Forecasting Federal Fund Rates using Box-Jenkins Methodology

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Abstract- The paper explores the application of the ARIMA (Autoregressive Integrated Moving Average) model to forecast the Federal Funds Rate (FFR) for 2025 using data from 2010 to 2024. The study highlights the importance of the FFR in U.S. monetary policy and its influence on financial markets. The research applies the Box-Jenkins methodology for time series analysis, emphasizing stationarity tests and model selection. The best-fitting model, ARIMA (1,1,1), is used to predict a gradual decline in the FFR from 5.04% in October 2024 to 4.88% by December 2025.

The study discusses potential economic impacts of the forecasted rate cuts, including lower borrowing costs, potential inflationary pressures, and effects on employment and investments. It also considers limitations related to external shocks, such as the COVID-19 pandemic, and concludes that while the forecast predicts a decline in interest rates, unforeseen global events could influence actual trends.

Keywords: Federal Fund Rates, ARIMA Model, Forecasting, Monetary Policy.

1.Introduction:

The Federal Funds Rate (FFR) is defined as the interest rate at which depository institutions, especially banks, lend reserve balances to other banks on an overnight basis. It is arguably the most vital measure when it comes to the monetary policy of the United States (Mohajerani, 2015). In fact, for the last twenty years or so, its popularization in the context of the financial and monetary markets of the United States and the economy of the United States in general is beyond doubt. It is customary for those with excessive reserves in their Federal Reserve accounts, to lend out their funds for short periods only to institutions which need them. This activity serves to ensure the efficiency of the monetary system. The ARIMA model, known as Autoregressive Integrated Moving Average, is a standard approach used for forecasting time series data developed by Box and Jenkins in the 1970's. It comprises of three parts: Autoregression (AR) is the approach in which the current value is correlated with all its previous values; Integration (I) is the order of differencing required to make a time series stationary and; Moving Average (MA) is an approach where the close price is related to the moving average and estimates of residuals from this moving average of previous periods. The model is well known for its ability to learn the existing trends and make predictions over the short to medium range of time back and forward. (Ma et al., 2018) .In this research, ARIMA model will be applied focusing on FFR forecasts for the year 2025 and its upcoming trends. With the help of such practical applications as EViews, where ARIMA modeling processes are made easier, it is possible to carry out the forecast of the Federal Funds Rate for the greater part of the consecutive year to enhance monetary policy and financial planning perspectives. February 2020 recorded a significant decrease in the Federal Fund Rate (FFR) that was 1.58% to 0.05% in April 2020. This was in line with the decisions made by the Fed to mitigate adverse economic effects caused by the COVID-19 pandemic. By February 2024, the Federal Reserve increased the FFR to 5.33% seeking to limit and control spiraling tendencies of inflation due to high levels of expenditure (Johnson et al., 2024).

For financial firms and Federal Reserve policymakers, predicting the Federal Funds Rate is essential. Determining how this rate will move in the future is useful for making decisions about interest rates, managing inflation, and maintaining overall economic stability. This forecasting's use of ARIMA enables a methodical examination of the variables affecting the rate, offering useful information for the efficient execution of monetary policy.

2.Literature review:

The effective federal funds (FF) rate being a key benchmark interest rate in US financial markets is quite fundamental. The Fed implements its monetary policy by maintaining a certain level for the efficient segment of the FF rate. Therefore, it may be plausible to claim that the federal funds rate would provide more insight into future trajectory of real macroeconomic variables than any of the other interest rates or monetary aggregates. Estimating the FF rate is indeed an essential part of evaluating contemporary monetary policy. Other interest rates, as viewed through the market expectation of monetary policy measures, are actually connected to the FF rate that directly affects it (SARNO et al., 2005). In addition to lagged FF rate data, FF futures rates and no-arbitrage criteria are likely to be related to the FF rate.

The federal open market committee meets eight times a year, and it decides on the target rate about seven weeks apart. It is the "reaction function" through which the Federal Reserve determines their interest rates. This has been a subject of conjecture for years. It is an excellent model to fit interest to economists. Many different studies rely greatly upon it. The Federal Reserve mandate is to keep prices stable and watch economic indicators. The variables the Fed uses in determining its funds are yet still debated (Mohajeryami, 2015). The Fed adjusts the effective federal funds rate (EFFR) with open market operations in terms of attempts to achieve the target set by the FOMC for the federal funds rate. Since the EFFR has strong effects on daily life, monetary policy practice realizes its implementation by targeting it. Modern analysis of monetary policy is related to the ability of market participants to predict the federal funds rate. That rate would be the benchmark against which other interest rates in the economy are measured; and it would be determined on the basis of market expectation of what actions of monetary policy would impact it (Alão & Ferreira, 2023).

Even in different continents, there are observable effects that the Fed rates have on countries' economies. In 2022 when the U.S. Federal Reserve Board raised its interest rate in response This, there was a spillover effect into the ChiNext market. Increasing interest rates encourage short-term closing prices but with long term unfavorable effects on closing prices. As observed, high interest rates also contributed to the conditions in ChiNext and the whole of Chinese stock markets that included the retreat of the RMB, and external capital flight (Sha, 2024). The dynamic development of the so-called foundations of future financing (FF) has been modeled in many ways, for example: univariate, multivariate, linear and nonlinear. The final remarks on the stationarity of the series in question is not clear. A number of other studies, including Campbell (1987), Hamilton (1996) and Lanne (1999) have all dismissed the unit root hypothesis. For instance, some authors such as Stock and Watson (1999) and the works citing these authors, defend the argument that there is a single root. This is important because I (0) processes are expected to return to their mean, while I (1) or random-walk processes do not return to a mean. Therefore, this controversy may be attributed to changes in the structure of the FF mechanism.

Moving ahead, the re-examination of the stationarity of the time series of the effective federal funds rate - the most salient parameter of the U.S. monetary policy - was performed using the unit root tests Lee and Strazicich (2003 and 2004) which allow for up to two changes in level and trend under the null of unit root as well as the alternative of stationarity and it was established that a two break stationary process explains the behavior of monthly federal funds rate the best (Bec & Bassil, 2009). However, regressions for the daily campaigns of the federal funds rates are then carried out subject to random walk forecasting of funds rate relevant for that particular day and implementing a moving average model computation. It has been anticipated that the ARIMA approach would incorporate intra-week seasonal fluctuations of the funds rate as well as the presence of negative first order autocorrelation. In addition, the scope of last resort may be considered broader because the operating procedures of the Fed may influence the behavior of the structural time series models. It is because all such variables are omitted from the random walk model that it is reasonable to think that ARIMA estimates are superior (Hein & Spudeck, 1988).

Hamilton (2000) emphasizes the considerations of when and how the Fed intends to alter the FFR. This article focuses on the comparison between ACD and ACH models. As a matter of fact, Hamilton's ACH model has been able to forecast the probability of changing FFR targets in the very near future. For the firms, the correct prediction of FFR targets is helpful in implementing appropriate and prudent decisions for financial planning (Johnson et al., 2024).

3.Methodology

Based on the methodology of Box - Jenkins, the ARIMA (autoregressive integrated moving average) model aims to forecast fed fund rates of fifteen months in future. The paper applies quantitative data modeling of a univariate time series for the purpose of forecasting. Data is collected by using a secondary source of the Federal Reserve Economic Data (FRED) database. Model is based on monthly data beginning from January 2010 to avoid the effects of the 2008-2009 economic crisis that may lead to erroneous predictions by the model and going to the latest available data. Although fed funds rates are overnight lending rates monthly data was taken into account to reduce volatility. A similar ARIMA modeling on daily FFR was ran by the researchers and the results were spurious. The correlogram had no spike which depicts the data as white noise and no pattern across time lags. Yearly data was also not considered as it lacks in detail. Monthly data provides a balance and highlights important trends and shifts in policies.

The ARIMA modeling process will adopt the Box-Jenkins approach, which encompasses four processes: identification, estimation, diagnostic checking and forecasting. The first step is to test the series for stationarity using the Augmented Dickey-Fuller (ADF) test. If the series is non-stationary, differencing is used. After the Stationarity test, model identification the next step is model identification, where we determine the appropriate ARIMA model by selecting the values for the autoregressive (AR), and moving average (MA) components. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are then used to establish the lag orders of the AR (p) and MA (q) components. Succeeding model selection, best fitted model is estimated using OLS estimation. After estimating the ARIMA model, residuals are checked for stationarity, this process is known as diagnostic tests. If the residuals are not stationary at level the model is rejected and another equation needs to be estimated. After the equation passes the diagnostic test, the model is forecasted. Further heteroscedasticity was tested to assess the feasibility of implementing an ARCH model on the FFR. The results indicated homoscedasticity, hence the ARCH model couldn’t be applied. The entire process is done through student-version of EViews software.

4. Data and model

4.1 Data description

Data is collected from the Federal Reserve Economic Data (FRED) database, beginning from January 2010 and going to the latest available data. Presented below is the line graph of the time series:

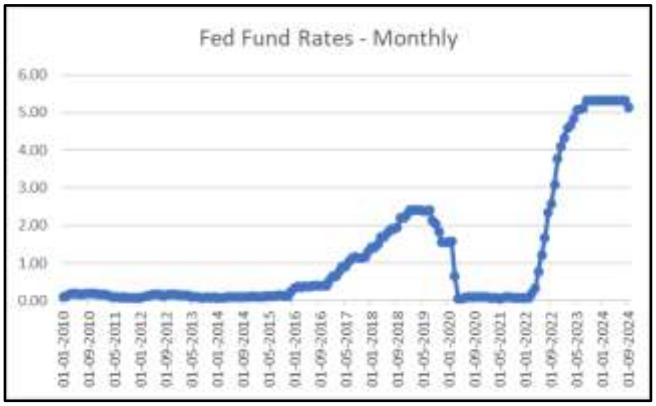

Fig:1 Source: Federal Reserve Economic Data

Fig 1 shows a calendar month view of Federal Funds Rate for 2010-2024 (till September). The rate remains slightly above zero from 2010 till 2016, which is therefore an extended period of loose monetary policy after the 2008 financial crisis. Starting from 2016, the Fed slowly turns around and raises rates up until around 2.5 percent. Then to combat COVID-19 pandemic, rates are again turned sharply down to near zero by 2020, USA also experienced economic recession during this period. However, from mid-2022, the Fed reversed plans to inflict big rate hikes to reach around 5.5 percent by 2024 in response to inflationary pressures and shifts toward tightening monetary policy to curb inflation.

4.2. Box- Jenkins Methodology

Box-Jenkins analysis technique refers to an analyzing method of identifying the model, estimating, diagnostic, and using it to forecast by using integrated autoregressive, moving average (ARIMA) time series models. (Abdulqader, 2023). The model is based on ARMA (auto regressive moving average) and ARIMA (auto regressive integrated moving average) models. It is used for forecasting time series data. Major assumption of the methodology is that the model should be stationary. Below are the two major components of models –

<u>Auto Regressive</u>: Autoregressive means that the model relies solely on past data to predict future values. It expresses the value of the time series at time(t) as a linear function of its previous values (lags). The equation of model at AR(p) is given below:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \cdots + \rho_p u_{t-p} + \varepsilon_t$$

<u>Moving average</u>: Moving averages is used to reflect the average change in a data series over a specific period of time. It expresses the current value of the series as a linear combination of past errors. The equation of model at MA(q) is given below

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \cdots + \beta_q u_{t-q}$$

ARMA model is used if the data is stationary at level otherwise ARIMA model is used.

4.3 Identification

4.3.1.StationarityTest

In Figure 2, the Augmented Dickey-Fuller (ADF) test statistic for the fed funds rate (FFR) is 0.5743, which is greater than the critical value at the 0.05 significance level. This result indicates that the FFR series is non-stationary, meaning that it contains trends or patterns that change over time.

Augmented Dickey-Fuller Unit Root Test on FFR

Null Hypothesis: FFR has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.468523	0.5473
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Fig: 2: Augmented dickey fuller Test at Level

To achieve stationarity, we take the first difference of the Fed Funds Rate (FFR). The ADF test is then applied to this differenced series. Here, ADF = 0.0084 As a result, the D(FFR) sequence fails to accept the null hypothesis of non-stationarity, implying that the first-order differenced series is stationary. The first-order differencing yields a new sequence, D(FFR) (differenced log FFR), and the ADF test results for the D(FFR) sequence are presented in Figure 3.

Augmented Dickey-Fuller Unit Root Test on D(FFR)

Null Hypothesis: D(FFR) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.526278	0.0084
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Fig: 3: Augmented dickey-fuller Test at 1st Difference

4.3.2 Identification of order

AR and MA order are identified using a correlogram. These models are fully specified using Autocorrelation (ACF) and Partial Autocorrelation (PACF) functions. ACF and PACF plots are graphical representations of the correlation between a variable and its lagged values.

Correlogram of D(FFR)

Date: 10/12/24 Time: 22:18
Sample (adjusted): 2010M02 2024M09
Included observations: 176 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.639	0.639	73.166	0.000
		2	0.442	0.056	108.29	0.000
		3	0.467	0.280	147.80	0.000
		4	0.412	0.015	178.67	0.000
		5	0.404	0.158	208.51	0.000
		6	0.356	-0.032	231.84	0.000
		7	0.255	-0.061	243.91	0.000
		8	0.168	-0.118	249.15	0.000
		9	0.140	-0.014	252.81	0.000
		10	0.070	-0.124	253.73	0.000
		11	0.051	0.040	254.21	0.000
		12	0.057	0.013	254.84	0.000
		13	-0.006	-0.027	254.85	0.000
		14	-0.039	-0.008	255.14	0.000
		15	-0.041	0.008	255.47	0.000
		16	-0.057	-0.011	256.11	0.000
		17	-0.102	-0.081	258.17	0.000
		18	-0.071	0.063	259.17	0.000
		19	-0.060	-0.008	259.90	0.000
		20	-0.085	-0.002	261.34	0.000

Fig:4: Autocorrelation and Partial Autocorrelation function graphs of D(FFR) Series

ACF is used to determine the order of MA process and PACF is used to determine the order of AR process. Figure 4, demonstrates that the spike of ACF is significant at lag 1; it indicates that the current value of the series is highly correlated with its past values at those time points. The plot also shows that autocorrelation gradually decreases as lag value increases. The significant spike at lag 1 in PACF suggests an AR (1) process. From the correlogram, it could be deciphered that AR (1) and MA (1) processes would be suitable to estimate the equation for the model.

4.3.3 Model selection

From the correlogram result we would make three equations and estimate them to select the best fitted model for our study. To select the best model from the set of the fitted models, criteria for model selection like Adjusted R-squared, AIC, SIC values, and standard error of regression will be significant determinants. The model with the greatest number of significant variables, low variance (Sigma sq.), a higher Adjusted R^2 and low values for AIC and SIC is ideal.

Model	F[AR(1), MA(1)]	F[AR(1)]	F[MA(1)]
	(1,1,1)	(1,1,0)	(0,1,1)
Significance	2	1	1
Sigma Square	0.012677	0.012855	0.014017
Adjusted R2	0.412398	0.407567	0.354021
AIC	-1.481231	-1.47898	-1.392287
SIC	-1.481231	-1.424937	-1.338345

Fig: 5: Test results of ARIMA (p,d,q)

Figure 5 concludes that the most fitted model for the study is ARIMA (1,1,1), since it has a maximum number of significant variables, lower volatility and is most fitted.

4.4Estimation -

Figure 6 presents the results of an ARIMA (1,1,1) model using Ordinary Least Squares (OLS) for the dependent variable D(FFR). Below are the interpretations of each variable with their gradient graphs:

Dependent Variable: D(FFR)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/12/24 Time: 22:35
Sample: 2010M02 2024M09
Included observations: 176
Convergence achieved after 70 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.024736	0.036070	0.685764	0.4938
AR(1)	0.826989	0.044423	18.61625	0.0000
MA(1)	-0.348283	0.085877	-4.055583	0.0001
SIGMASQ	0.012677	0.000440	28.84130	0.0000

R-squared	0.422471	Mean dependent var	0.028523
Adjusted R-squared	0.412398	S.D. dependent var	0.148578
S.E. of regression	0.113893	Akaike info criterion	-1.481231
Sum squared resid	2.231119	Schwarz criterion	-1.409174
Log likelihood	134.3483	Hannan-Quinn criter.	-1.452005
F-statistic	41.94018	Durbin-Watson stat	1.836545
Prob(F-statistic)	0.000000		

Inverted AR Roots	.83
Inverted MA Roots	.35

Fig: 6: Estimation of Equation on F[AR (1) , MA(1)]

4.3.1 Interpretation of the intercept:

The null hypothesis (H0) is that intercept is zero or there is no baseline effect or constant on differentiated fed fund rates (d(ffr)) when AR (1) or MA (1) processes are accounted for. Alternate hypothesis (H1) is that intercept has a significant impact on d(ffr). The p value is 0.498, at 5% level of significance, we accept the null hypothesis which means that the constant term is not statistically significant, indicating that it has no significant impact on d(ffr).

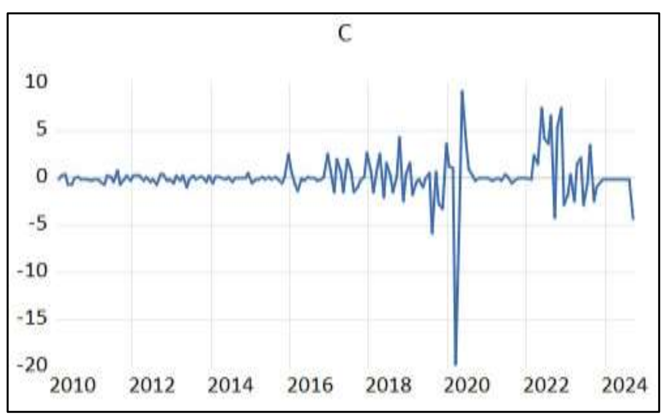

Fig :7: Gradient of intercept

The gradient analysis shows that from 2010 to 2016, the series remained relatively stable, followed by increased volatility from 2016 to 2019. Around 2020, there was a sharp decline and subsequent rapid recovery, likely reflecting the impact of significant events like the COVID-19 pandemic, with continued fluctuations and a recent downward trend towards 2024.

4.3.2 Interpretation of AR (1)

The null hypothesis (H0) is that the AR (1) coefficient is equal to zero, indicating no autoregressive effect on d(FFR). The alternative hypothesis (H1) is that the AR(1) coefficient has a significant impact on d(FFR). The coefficient for AR(1) is 0.826989, and the p-value is 0.0000. At the 5% level of significance, we fail to accept the null hypothesis, indicating that the AR(1) term is statistically significant and positively influences d(FFR), implying that past values of the Fed Fund Rate strongly affect current changes.

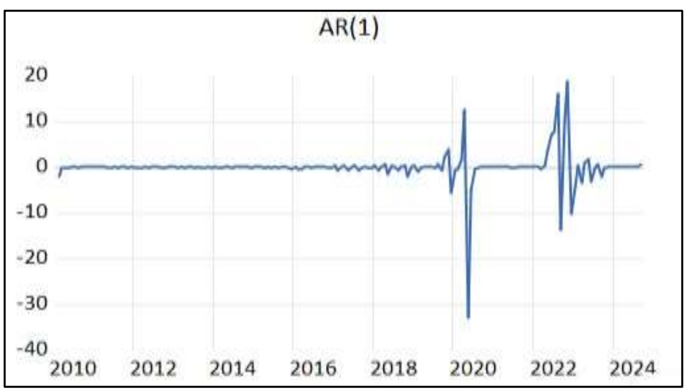

Fig :8: Gradient of AR (1)

From 2010 to 2019, the AR (1) series displays a relatively flat gradient, indicating stable behavior. However, around 2020, the gradient experiences a sharp drop followed by a rapid recovery, reflecting sudden changes and increased volatility. This heightened fluctuation continues up to 2023, with some stabilization appearing in the trend as it approaches 2024.

4.3.3 Interpretation of MA (1)

The null hypothesis (H0) is that the MA (1) coefficient is equal to zero, indicating no moving average effect on d(FFR). The alternative hypothesis (H1) is that the MA (1) coefficient has a significant impact on d(FFR). The coefficient for MA (1) is -0.348283, and the p-value is 0.0000. At the 5% level of significance, we fail to accept the null hypothesis, indicating that the MA (1) term is statistically significant and negatively influences d(FFR), indicating that past errors effect d(ffr).

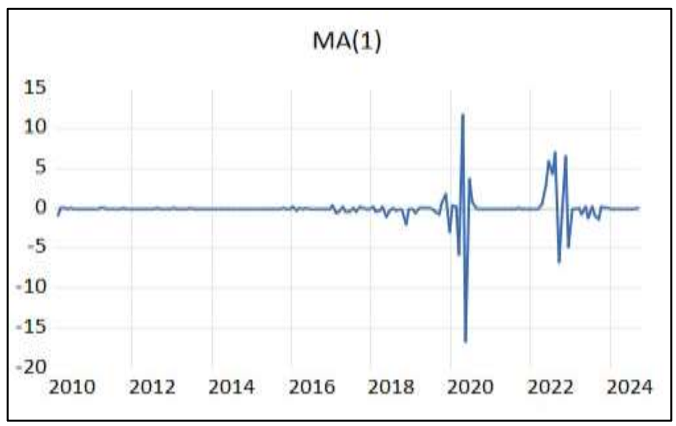

Fig:9: Gradient of MA (1)

The MA (1) series shows minimal fluctuations and stability from 2010 to around 2019. However, there is a noticeable increase in volatility starting around 2020, with sharp spikes and drops indicating sudden changes. This pattern of heightened fluctuations persists up to 2023, before showing signs of returning to a more stable state as it approaches 2024.

The final equation of the model is as follows: $\mathbf{D(FFR)_t = 0.024736 + 0.826989 \cdot D(FFR)_{t-1} - 0.348283 \cdot u_{t-1} + u_t}$

4.3.4 Actual vs. Fitted Values with Residuals (2010-2024)

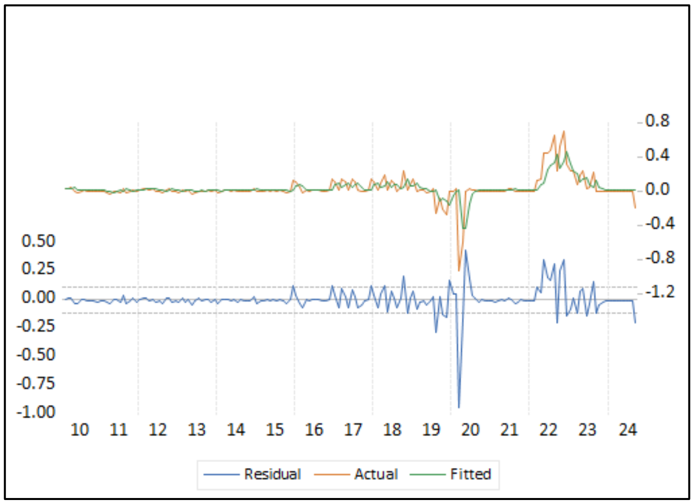

Fig: 10: Actual Fitted residual graph

The graph presents three lines: Actual, Fitted, and Residual values. The Actual and Fitted lines closely align, indicating that the model fits the data well. However, there are deviations around periods 2019 and 2020, where the residuals (difference between actual and fitted values) show significant volatility. This suggests that the model underperforms in capturing dynamics during these periods, possibly due to external shocks or sudden changes in the data. After 2020, the residuals stabilize again, implying that the model resumes its accuracy. Overall, the residuals mostly hover around zero, indicating that the errors are minimal in most periods, except during the highlighted anomaly.

4.4 Diagnostic Test

After estimating the equation, the next step involves calculating the residuals, followed by an examination of their stationarity.

Augmented Dickey-Fuller Unit Root Test on RESID01

Null Hypothesis: RESID01 has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.336210	0.0005
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Fig:11: Stationarity test of residual series

It could be interpreted from Figure 11, that ADF = 0.0005, which means we fail to reject null hypothesis.

4.5Forecasting

Forecasted FFR		
Year	Month	FFR (%)
2024	October	5.040825
2024	November	4.971359
2024	December	4.918190
2025	January	4.878500
2025	February	4.849956
2025	March	4.830630
2025	April	4.818927
2025	May	4.813528
2025	June	4.813343
2025	July	4.817470
2025	August	4.825162
2025	September	4.835803
2025	October	4.848882
2025	November	4.863978
2025	December	4.880742

Table 1: Forecasted FFR

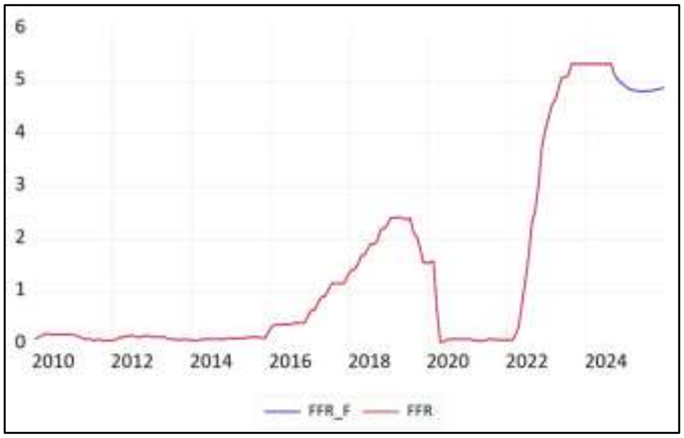

Fig:12: Graph of forecasted and actual FFR

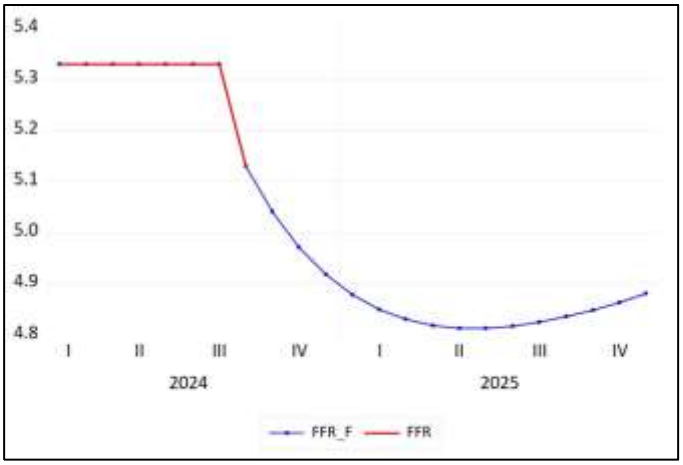

Fig:13: Graph of forecasted FFR

The subsequent table accompanied by graphs illustrates an outlook of the Federal Funds Rate (FFR) covering the period from October 2024 through December 2025. In the legend FFR_F represents the forecasted rate and FFR represents the actual rates. The general tendency is shown to be a downward trend with minor fluctuations. As presented in the table, the FFR hits 5.04% at the beginning of October 2024 and experiences a gradual decline to 4.88% by the end of December 2025. In particular, the rate undergoes slight declines in the middle of the months March 2025 (4.83%) and April 2025 (4.81%) before declination and partial growth toward the mid-2025, thus indicating very minor volatility amidst an overall drop.

5 Results and findings

It can be seen that the ARIMA (1,1,1) model depicts the Federal Funds Rate (FFR) forecasted that the fed fund rates would decline in the coming fifteen months. The model shows that it would remain near to 4.8%. This implies that the US is loosening its monetary policy. Lower interest rates can lead to reduced borrowing costs for consumers and businesses, stimulating economic activity and encouraging spending and investment. This, in turn, can support job creation and economic growth.

The variables of the model effects fed fund rates in the following way - The autoregressive coefficient AR(1) is significant and is equal to 0.826998 and moving average coefficient MA(1) is significant and is equal to –0.342883 which implies that the current rate of the FFR and the shock from it depends on the past values and shocks of the two preceding values. AR has a positive effect on fed fund rates and MA has a negative relationship with fed fund rates.

On the contrary, the constant value (C = 0.024736, p = 0.4938) is insignificant statistically, which suggests that the FFR series does not have an upward or downward movement of consistent non-zero vertical slope. Lack of significance of constant values may also mean that the changes in Fed Funds Rate are temporary shocks or changes as a result of policy rather than a constant tendency. The fitted model showed an R-squared value of 0.422471, indicating that about 42.2% of the variability in the FFR can be accounted for by the model, which is reasonably fair for any time series data. Deviations in the coefficients and spikes in volatility of the residuals indicate that a number of structural breaks especially between the years 2020 and 2022, such as the Covid 19 pandemic, were experienced. The model however is able to hold well except during those unusual periods as illustrated in the actual versus fitted residual graph, in which residuals go back to normal post 2020.

As discussed in literature review, the fed fund rates are a crucial macroeconomic variable and have a significant impact on the economy of not just the United States but also many other economies. The subsequent discussion will elaborate on these impacts.

6. Discussion:

"The U.S. economy is in good shape. It is growing at a solid pace. Inflation is coming down." - Fed chair, Jerome Powell, September 2024. (Lo, 2024). Economic projections of Federal Reserve Board members and Federal Reserve Bank presidents, under their individual assumptions of projected appropriate monetary policy, September 2024 is around 3.1 - 3.6% margin. This is a notable decrease from the earlier June 2024 forecast, which estimated a range of 3.9-4.4%. However, the machine learning-based prediction of a 4.8% federal funds rate for 2025 deviates from the Fed's projections. This higher prediction is based on historical data and past behavior of fed. The cut signals a shift towards looser monetary policy, with further reductions in the Federal Funds Rate expected through 2025. (Vantage Markets, 2024)

Nonetheless, a lower fed funds rate would lead to a lower borrowing costs, which could stimulate consumer spending and business investment. Sectors such as real estate, technology, and consumer goods could particularly benefit due to increased liquidity and reduced cost of capital. For businesses, lower interest rates mean reduced costs for financing expansion or operations, which can lead to increased hiring, higher wages, and more capital investment. For developing markets like India there is a high possibility of similar cuts. Experts predict that the Reserve Bank of India (RBI) might follow the Fed's lead with a rate cut by December. (Deva, 2024). The stock market is sensitive to changes in the FFR. A decline in rates may see a boost in stock market prices. Additionally, investors would prefer equities more as the rate of government bonds and debt would decrease. Lower interest rates generally make stocks more attractive, as businesses tend to perform better due to cheaper credit and increased consumer demand. This may particularly benefit small-cap and growth stocks, which are more sensitive to changes in interest rates.

The effectiveness of these cuts depends on prevailing economic conditions. The prevalent times of geopolitical tension between countries have affected global trade patterns and inflationary pressures remain uncertain. The tensions in the middle east and Russia-Ukraine has created an environment of heightened uncertainty, with energy prices soaring due to disruptions in supply. These situations might lead to economic instability even though, USA is a strong economy. The effect of such conditions would affect the nation and fed fund rates. (Gopinath, 2024) It should be noticed that such qualitative aspects are not taken into account by machine learning models and their forecasting is completely based on past data which is why there is a significant difference in rates forecasted by the ARIMA model and the experts.

7. Conclusion:

The prediction for the near-term future , as provided by the ARIMA model for the effective federal funds rate, is that interest rates are to decline shortly. This could fuel inflation since an increase in borrowings and spending would lead to more money floating around. When demand increases faster than supply, inflationary pressure may drive the need to raise prices. In any case, this prediction may also help boost employment. As businesses take advantage of cheaper borrowing to expand and invest, they may begin hiring more workers, reducing the level of unemployment and strengthening the labor market. The impact could also be higher wages. In the current scenario , The US unemployment is nearly up 1% from its record low in April 2023, to 4.2%. While this isn't alarmingly high-continuing unemployment increases this way often does, the former Fed

economist Claudia Sahm reports that when three-month average unemployment rate increases 0.5% from its recent trough over the past year, a recession is probably already in place. This has been a consistent predictor of every US recession since 1970. To prevent the slowdown, the Fed has reduced the rates by 0.5% in recent times, and the recent trends also reflect more cuts in the rates. The US is one of the largest players in the international economy, and most of the central banks observe the Fed rates of the country to frame guidelines for their own economic policy. So, a cut in the rates may reduce the unemployment level in the US but might, once more, raise the inflation level in the US.

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