Is the Fed Behind the Curve?*

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Abstract

The causes of the sustained high inflation in the U.S. since 2021 are widely debated. The Federal Reserve has gradually raised interest rates to nearly 20-year highs after COVID-19. However, it remains uncertain if the Fed has accurately predicted and effectively controlled inflation. By incorporating the dynamic effect, I employ a Bayesian VAR and a sufficient statistics method to quantitatively analyze the extent of lag in the Federal Reserve's monetary policy and to determine whether there have been deviations between reality and predictions. I show that creating policy counterfactual path is possible with only two statistics: (i) the forecast paths of policy objectives, and (ii) the policy objectives to policy shocks. I utilize multiple forecast data to measure the counterfactuals of the optimal policy. In conclusion, I find that about 12% of the inflation gap could be attributed to Fed policy bias, whereas inaccuracies in the Fed's forecasts account for approximately 7% of the inflation gap.

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1 Introduction

From 2021 to 2023, the United States experienced an anomalous and prolonged phase of high inflation. Federal Reserve's monetary policy has sparked questions and warnings from various economists and media including *The Associated Press*. Since 2020, the Fed maintained near-zero interest rates for approximately two years. In terms of stabilizing inflation and controlling unemployment, was this policy too delayed? Did it entail welfare losses for the U.S.? This paper aims to leverage extensive macroeconomic datasets and construct a theoretical model to empirically examine whether short-term interest rate policies within U.S. monetary policy from 2021 to 2023 exhibited significant lags, and if so, the extent to which improvements could have been made. Furthermore, through the integration of theoretical modeling and empirical data, this paper seeks to explore how implementing an optimized monetary policy might have impacted inflation, unemployment, and the policy's overall effectiveness.

Numerous studies have proposed methods to calculate optimal monetary policy, but how would the dynamics change if the economic policy environment were different? For instance, how would the economy respond under varying monetary policies? I propose a solution to this counterfactual policy assessment problem by building on the sufficient statistics approach to optimal monetary policy calculation developed by Barnichon and Mesters (2023). I extend this framework by incorporating the dynamic effects of policy adjustments and by accounting for the impact of these adjustments on forecasts, thereby deriving counterfactuals for both policy instruments and objectives. A common concern with this approach is that it may not align with the Lucas Critique. However, McKay and Wolf (2023) have demonstrated that the framework for calculating counterfactual paths based on impulse response functions is robust to the Lucas Critique.

The first statistic in this model is the forecasts for policy objectives. These forecasts are made at each point in time for the future and are adjusted in the counterfactual framework due to changes in information sets. Given that these forecasts are linked to actual macroeconomic variables, I assume they share the response of actual variables to policy shocks.

The second statistic is the dynamic causal effect of policy changes on current and future macroeconomic variables—i.e., what changes occur in macroeconomic variables following an adjustment in policy tools. For monetary policy, it's essential to understand the causal effect of interest rate changes on variables like inflation and unemployment. To capture such causal effects, the exogenous component of interest rate changes need to be isolated, namely the monetary policy shock. The response of macroeconomic variables to these exogenous shocks is generally termed the impulse response function.

To further construct counterfactuals for changes in monetary policy, I must account for the impact of policy shocks on expectations. Given that forecast variables are multidimensional, I use reduced-form regressions to estimate the changes in forecasts under shocks, and apply the corresponding impulse response functions for the actual variables. Together, I am able to build a period-by-period counterfactual framework under an optimal policy calculation.

The primary appeal of adopting a sufficient statistics approach that incorporates dynamic effects is its reliance on weaker assumptions compared to the typical DSGE framework, reducing the risks associated with model mis-specification.

Under the assumption that the causal effect of policy changes on macroeconomic variables remains stable, this counterfactual framework is influenced by both forecast data and the starting time. In baseline results, I utilize the Federal Reserve's Survey of Economic Projections (SEP), published at each FOMC meeting, as the source for forecast data. Would more aggressive or conservative forecasts yield different counterfactuals? To explore this, I collected data from the Fed's Survey of Professional Forecasters (SPF) and the University of Michigan's Michigan Survey of Consumers (MSC) as alternatives. Under comparable conditions, MSC forecasts indeed performed better than official projections. In scenarios of future inflation surges, moderately advanced, aggressive forecasts prove beneficial for policy formulation. Additionally, my results indicate that earlier implementation of an optimal policy framework leads to better inflation control, aligning with the economic intuition that earlier, well-calibrated policy actions yield superior macroeconomic outcomes.

Related Literature: This paper makes contributions to several branches of literature. One relates to the common approach of deriving optimal monetary policy based on structural models. In macroeconomics, many micro-founded models provide paradigms for optimal policy decision-making (Chari et al. (1994) and Woodford (2010)). However, parameter calibration often presents substantial challenges, as accurately obtaining values for each parameter in structural equations is typically difficult. More closely aligned with my work, the literature has proposed reduced-form methods to study policy rule counterfactuals (Sims and Zha (2006), Leeper and Zha (2003)), although these methods are not fully robust to the Lucas Critique.

The use of impulse responses from policy shocks as sufficient statistics for policy counterfactuals has also been explored in several studies (McKay and Wolf (2023), Barnichon and Mesters (2023)), though these works do not fully consider counterfactuals over a sustained period.

Additionally, this paper connects with the literature on measuring endogenous monetary policy (Romer and Romer (1989), Nakamura and Steinsson (2018a)), which emphasizes the need to isolate the monetary policy shock for causal identification. According to mainstream literature, there are several ways to identify monetary policy shocks. First, when a shock is large enough, it is possible to disregard other influencing factors and attribute the primary effect to monetary policy (Nakamura and Steinsson (2018b)). Furthermore, high-frequency evidence can aid in disentangling shocks, distinguishing between the effects of policy actions and policy statements (Gürkaynak et al. (2004), Gertler and Karadi (2015)). Another approach involves obtaining the shock series by controlling for confounding factors through structural vector autoregression (Romer and Romer (2004)). I adopt the method of Gürkaynak et al. (2004), using the impact of monetary policy on asset prices obtained from high-frequency data to separate the monetary policy shock.

The remainder of the paper is organized as follows. Section 2 introduces the theoretical motivation and empirical approach. Section 3 describes the data construction. Section 4 details the computation and construction of the key statistics. Section 5 presents the baseline results. Section 7 discusses the mechanisms. Section 8 provides the conclusions. Section A1 includes the theoretical foundation of the Bayesian VAR, robustness checks, and additional figures and tables not included in the main text.

2 Theoretical Motivation and Empirical Approach

In this section, I will introduce the theoretical model and empirical strategy used in this article. To estimate the optimality of the Federal Reserve's monetary policy, I develop a sufficient statistic model. The policy counterfactuals can be constructed using two statistics, (i) the forecast paths of policy objectives, and (ii) the impulse response of policy objectives to policy shocks. The model in this paper is based on the approach proposed by Barnichon and Mesters (2023) for assessing macroeconomic policies. The model is grounded in the New Keynesian framework and is robust to Lucas critique.

To estimate the impulse response, I follow the framework of Koop et al. (2010). I use a Bayesian VAR with inflation, unemployment, the Fed funds rate (FFR) and the monetary policy surprise. I estimate the reduced-form VAR coefficients using Bayesian methods following the default setup with an Independent Normal-Wishart Prior.

However, this model only allows for the calculation of the optimal policy adjustment for the current period based on past information and forecasts derived from it, without considering the impact of current policy adjustments on future policy objectives and policy instruments. To address this limitation, I further developed the model by incorporating the dynamic effect of policy adjustments. With the revised model, I can compute the counterfactuals of policy objectives and policy instruments, thereby evaluate the effect of optimal monetary policy.

2.1 Optimal Policy Perturbation

The method for calculating the optimal policy perturbation is based on the approach outlined in the paper by Barnichon and Mesters (2023). Let H represents the forecast horizon, and M_y represents the number of policy objectives in each period. Consider a loss function of the form $\mathcal{L}_t = \frac{1}{2}E_t\mathbf{Y}_t'\mathcal{W}\mathbf{Y}_t$, where $\mathcal{W} = diag(\beta \otimes \lambda)$ denotes a diagonal map of preferences with $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_{M_y})'$ capturing the weights on the different variables and $\beta = (\beta_0, \beta_1, \cdots)'$ the discount factors for the different horizon ,$\mathbf{Y}_t = (\mathbf{y}_t', \mathbf{y}_{t+1}', \ldots, \mathbf{y}_{t+H-1}')'$ represents the path of policy objectives, and $\mathbf{y}_t' = (y_{1,t}, y_{2,t}, \ldots, y_{M_y,t})'$ denotes the policy objectives in each period.

Now, consider imposing a perturbation $\boldsymbol{\delta}_t$ on policy at period t. According to the impulse response function, this perturbation will have a certain impact on the forecast in current period. To determine the optimal policy perturbation (OPP) $\boldsymbol{\delta}_t^*$ that minimizes the loss function at period t,

$$\boldsymbol{\delta}_t^* = \arg\min_{\boldsymbol{\delta}_t} \mathcal{L}_t(\boldsymbol{\delta}_t) \quad \text{s.t.} \quad E_t\mathbf{Y}_t(\boldsymbol{\delta}_t) = E_t\mathbf{Y}_t^0 + \mathcal{R}_y^0\boldsymbol{\delta}_t, \tag{1}$$

where $\mathcal{R}_y^0$ is the impulse response function capturing the impulse responses of the objectives to policy news shocks at different horizons–from horizon 0 to any horizon $h > 0$. For simplicity, I calculate the horizons of the impulse response function that match the forecast horizon H. The solution of optimal policy perturbation (OPP) is given by

$$\boldsymbol{\delta}_t^* = -\left(\mathcal{R}_y^{0\prime}\mathcal{W}\mathcal{R}_y^0\right)^{-1}\mathcal{R}_y^{0\prime}\mathcal{W}E_t\mathbf{Y}_t^0. \tag{2}$$

2.2 Dynamic Effects

To further simulate the genuine impact of policy tool adjustments on policy objectives, I extended the model proposed by Barnichon and Mesters (2023) through incorporating the dynamic effect of policy adjustments on the economy.

Now, I assume that starting from period t_0, the Federal Reserve adopts the OPP as its policy frame. Utilizing the impulse response function $\mathcal{R}_y^0$ and the optimal policy perturbation $\boldsymbol{\delta}_t^*$, I can iteratively compute the counterfactual paths for policy objectives,

$$\begin{cases} \mathbf{Y}_{t_0}^{counter,\,1} = \mathbf{Y}_{t_0}^0 + \mathcal{R}_y^0\boldsymbol{\delta}_{t_0}^* \\ \mathbf{Y}_t^{counter,\,I+1} = \mathbf{Y}_t^{counter,\,I} + \mathcal{R}_y^0\boldsymbol{\delta}_t^*, \end{cases} \tag{3}$$

where $I \leq H$ represents the number of iterations.

Similarly, I can iteratively compute the counterfactual paths for policy instruments,

$$\begin{cases} \mathbf{P}_{t_0}^{counter,\,1} = \mathbf{P}_{t_0}^{0} + \mathcal{R}_p^0 \boldsymbol{\delta}_{t_0}^* \\ \mathbf{P}_{t}^{counter,\,I+1} = \mathbf{P}_{t}^{counter,\,I} + \mathcal{R}_p^0 \boldsymbol{\delta}_{t}^*. \end{cases} \tag{4}$$

Furthermore, forecasts evolve alongside changes in policy instruments. In fact, if there are alterations in the past information set, the forecasts of policymakers for the current period will correspondingly change, leading to the formulation of current policies based on the revised forecasts. In my framework, alterations in the past information set modify the current period's forecasts, thereby influencing the measurement of the OPP for the current period. However, as it is hard to get the impulse response of forecasts to interest rate shocks in reality, I estimate the impact of interest rate shocks on forecasts by examining the relationship between changes in current policy objectives and changes in forecasts of policy objectives for the current period. I depict this relationship using the following equation,

$$\Delta \mathbb{E}_t \mathbf{Y}_{t+i} = \lambda_i \Delta \mathbf{Y}_t, \tag{5}$$

where $\lambda_i \Delta \mathbf{Y}_t$ represents the cumulative change in policy objectives or policy instrument at period t, $\Delta \mathbb{E}_t \mathbf{Y}_{t+i}$ denotes the change in forecasts of policy objectives or policy instrument for period $t+i$, $i = \{0, 4, 8\}$, representing the current year t, year $t+1$, and year $t+2$, and λ_i represents the coefficient capturing the relationship between changes in forecasts of policy objectives and changes in policy objectives. This coefficient is estimated through reduced-form regression.

Choosing different starting points for iteration can generate different counterfactual paths, reflecting the impact of the timing of the Federal Reserve's adoption of the OPP strategy.

3 Data

Forecast - To obtain the forecast data used for constructing the expected policy paths, I adopt the dataset compiled by Barnichon and Mesters (2023) covering unemployment rates, inflation rates, and FFR from 1980 to 2022. I extend this dataset to include data up to 2023. Forecast data from 2007 to 2023 is sourced from the Summary of Economic Projections (SEP), which is released every four years. This report provides median, central tendency, and forecast ranges for PCE inflation rates, core PCE inflation rates, unemployment rates, and the FFR for the next three or four years and the long term, as projected by FOMC members.

Forecast data before 2007 is obtained from the Monetary Policy Report (MPR), the predecessor of SEP, which was released semi-annually and reported FOMC members' forecasts for inflation rates and unemployment rates for the next two years. Additionally, long-term forecast data after 2007 is sourced from SEP, while data before 2007 is sourced from the Greenbook.

To further probe the impact of forecasts on OPP, I substitute the inflation rate, unemployment rate, and the FFR forecast data sourced from the SEP with alternative datasets. I source inflation and unemployment rate forecasts from the Survey of Professional Forecasters (SPF) by the Federal Reserve Bank of Philadelphia and the Michigan Survey of Consumers (MSC) by the University of Michigan. The SPF provides individual forecasts, forecast averages, and medians for various macroeconomic indicators each quarter. Specifically, I collect median forecasts for the next three years' PCE inflation rate and unemployment rate from the SPF. I linearly interpolate the quarterly forecast data for the fourth year. Despite this, I retain the long-term forecasts for inflation and unemployment rates from the Greenbook and SEP as indicators for the long term. In the case of the MSC, only consumer forecasts for the change in the price index for the next year and the subsequent five to ten years are surveyed. In practical terms, I utilize the average consumer forecasts for the change in the price index over the subsequent five to ten years as forecasts for the sixth year, while linearly interpolating any missing data for the third and fourth years. Subsequently, I employ long-term forecast data from the Greenbook and SEP to linearly interpolate forecast data for each quarter.

Backcast - To linearly interpolate data for each quarter and obtain the forecast path, backcast data were also required. I modify the dataset by replacing the data collected from the real-time database of the Federal Reserve Bank of Philadelphia with data from FRED Economic Data for backcasting. Through robustness test in Section A1.2, this substitution will not significantly affect the results of the OPP.

Impulse Response - To obtain the impulse response functions, I adopt data from database by Gürkaynak et al. (2022) regarding federal funds futures and on-the-run ten-year treasury yields as instrumental variables for policy shocks and supplement the data from 2019 to 2023. To ensure reasonable absolute values of the impulse response functions, I proportionally scale these datasets. Quarterly data for inflation, unemployment, and FFR are sourced from FRED Economic Data. Specifically, the inflation rate represents the quarterly average percent change from a year ago in Personal Consumption Expenditures Excluding Food and Energy, the unemployment rate represents the quarterly average of the Unemployment Rate, FFR represents the quarterly average of the Federal Funds Effective Rate, and the ten-year

Table 1: The Main Bayesian VAR Results

	UR_t	PI_t	$FF4_t$	FFR_t
constant	-0.023	0.040*	0.175	0.054
	(0.030)	(0.027)	(0.407)	(0.047)
Lag 1 of FF4	0.009	0.000	-0.099	-0.008
	(0.008)	(0.007)	(0.108)	(0.012)
Lag 2 of FF4	0.005	-0.009*	0.011	0.006
	(0.008)	(0.007)	(0.101)	(0.012)
Lag 3 of FF4	0.028***	-0.005	0.108	-0.014
	(0.007)	(0.007)	(0.102)	(0.012)
Lag 4 of FF4	0.032***	-0.018***	-0.066	-0.033***
	(0.008)	(0.007)	(0.104)	(0.012)
Lag 5 of FF4	0.022***	-0.004	0.053	-0.012
	(0.006)	(0.006)	(0.088)	(0.010)

Notes: This table presents the main results of the Bayesian Vector Autoregression, specifically the coefficients of the policy shocks, namely FF4, with respect to various lags of the dependent variables. $N = 116$, the prior distribution is chosen as Normal-Wishart, the Gibbs sampling is conducted for 10,000 iterations without any burn-in period.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

treasury yield represents the Market Yield on U.S. Treasury Securities at ten-Year Constant Maturity quoted on an Investment Basis at the end of each quarter. The shadow FFR is derived from the Wu-Xia Shadow FFR statistics by the Federal Reserve Bank of Atlanta, representing the simulated FFR if there is no zero lower bound constraint.

4 Preparations

4.1 Impulse Response Estimation

Table 1 reports the posterior results of the Bayesian Vector Autoregression (BVAR). Following the framework of Koop et al. (2010), a reduced-form regression was initially conducted using a Vector Autoregression (VAR) with a lag order of 5 and including a constant term. The regression coefficients obtained are used in conjunction with a Normal-Wishart prior to compute the posterior. For posterior computation, Gibbs sampling is employed with a total of 10,000 iterations. The sample period for the regression analysis spans from the first quarter of 1991 to the third quarter of 2019.

Figure 1: Impulse Response

Notes: Impulse responses of PCE inflation gaps, unemployment gaps and Fed funds rate gaps to the Fed funds rate shock with 83 and 95 percent confidence intervals. 20 periods of the results are saved.

The core coefficients are the coefficients corresponding to the dependent variable *lag i of FF4* and the independent variables *unemployment rate*, *inflation rate*, and *FFR*. Here, surprises in the FFR beyond market expectations serve as instrumental variables, representing policy shocks. By rescaling the policy objectives and instruments to include only the form of policy shocks and converting the VAR(5) to a Vector Moving Average (VMA) form, I estimate the impulse responses of policy objectives and instruments to policy shocks.

Figure 1 displays the impulse responses and their confidence intervals of the inflation rate, unemployment rate, and FFR to policy shocks. In practice, twenty periods of impulse responses are retained. It is observed that with each unit increase in monetary policy surprise, the impulse response of *unemployment rate* increases with the horizon until reaching a peak around the eleventh period, followed by a slight decline while remaining positive. The impulse response of *inflation* increases negatively with the horizon, reaching its maximum negative value around the tenth period before gradually approaching zero, yet consistently remaining negative. The impulse response of *FFR* initially starts positively, peaks around the third period, then gradually decreases with the horizon, reaching around zero by the ninth period and remaining near zero thereafter. It is notable that the impulse response of *FFR* is positive at time zero, contrasting with the near-zero responses of inflation and unemployment at the same period. This observation aligns closely with economic intuition, as unexpected changes in the FFR would likely lead to an overall change in the FFR exceeding the anticipated portion.

Based on the estimated impulse response functions, it is possible to assess how adjusting policy by one unit would alter policymakers' forecasts and its impact on future actual policy objectives and instruments, thereby constructing counterfactuals.

4.2 Forecast Adjustment

Due to the fact that policymakers forecast policy objectives and policy instruments for the future H periods including the current period, the impulse response functions of forecasts are difficult to compute directly. Theoretically, each period's forecast is based on past information sets, and when these sets change, the forecasts for the current period also change accordingly. Consequently, in constructing counterfactual paths, the adjustments in current forecasts due to changes in past policy objectives and instruments cannot be ignored. In practice, I utilize the impulse response functions of policy objectives and instruments to policy shocks to simulate the impulse response functions of forecasts to policy shocks.

However, adjustments to forecasts due to shocks and adjustments to actual values due to shocks are likely to be different in scale. I estimated the relationship between changes in current policy objectives and changes in forecasts of policy objectives for the current period. The reduced-form regression equation is as follows

$$D.Y_t^{forecast_{t+i}} = f(D.X_t^{actual})\beta + \varepsilon_t, \tag{6}$$

where $f(D.X_t^{actual})$ represents the first-order difference of policy objectives or policy instruments and its higher order terms at period t, and $D.Y_t^{forecast_{t+i}}$ represents the first-order difference of forecasts of policy objectives or policy instruments from period t to $t+i$, $i = \{0, 4, 8\}$. β corresponds to λ_i in the equation 5, which is the core coefficient I focus on. Table 2 reports the results. The relationship between the first difference of the current period variables and the first difference of the forecasts for the current year (t) and the next year ($t+4$) is particularly significant, indicating a good fit between actual values and forecasts.

5 Baseline Result

5.1 Baseline Counterfactuals

The starting period of iteration I set is the first quarter of 2019. The baseline period is from the first quarter of 2019 to the fourth quarter of 2023.

Figure 2 depicts the counterfactual outcomes within the framework of the theoretical model, including the median and confidence intervals of the counterfactual paths for inflation, unemployment, and FFR, derived using the iterative subset OPP method. Observations reveal that the adjusted optimal paths for inflation, unemployment, and FFR do not align closely with the actual paths, which is supported with 90% confidence. Overall, this suggests

Table 2: Reduced-form Regression

	(1) DUR_f0	(2) DUR_f1	(3) DUR_f2	(4) DPI_f0	(5) DPI_f1	(6) DPI_f2	(7) DFFR_f0	(8) DFFR_f1	(9) DFFR_f2
DUR0	0.293***	0.178***	0.157***						
	(0.0234)	(0.0178)	(0.0204)						
DUR0_DUR0	-0.0316***	-0.0191***	-0.0167***						
	(0.00230)	(0.00177)	(0.00186)						
DPI0				0.541***	0.148**	0.0551			
				(0.153)	(0.0622)	(0.0338)			
DFFR0							0.550***	0.336***	0.192**
							(0.0898)	(0.113)	(0.0810)
DFFR0_DFFR0							0.352***	0.143*	0.0728
							(0.0552)	(0.0746)	(0.0543)
N	44	44	44	44	44	44	24	24	24
R^2	0.653	0.375	0.304	0.243	0.160	0.032	0.899	0.412	0.160

Notes: This table presents the main results of reduced-form regression between the current genuine value and the forecasted value.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

that the Federal Reserve's policy has not consistently operated at an optimal level.

Specifically focusing on the FFR policy path, it is evident that the Federal Reserve should have raised the rate earlier, maintaining FFR approximately 1.5 percentage point higher than the prevailing rate from early 2020 until around the first quarter of 2023. Under optimal policy adjustments, the FFR need not ascend to the same elevated levels as observed in reality, indicating a lag in policy response by the Federal Reserve during this period. Notably, during the high inflation period spanning from 2021 to 2023, the counterfactual FFR path is flatter than the actual path.

Regarding inflation, the counterfactual inflation rate remains lower than the actual inflation rate from the fourth quarter of 2020 to the fourth quarter of 2023, approaching the long-term inflation target value during periods of significant inflation surge. By observing the confidence interval of the counterfactual inflation path, I can believe the conclusion above at a 90% confidence level.

Relatively speaking, within the observed window, the unemployment rate under the iteration of optimal policy adjustments is higher than the actual unemployment rate, but overall, there is no significant fluctuation, and it continues to approach the long-term unemployment rate target. Notably, the counterfactual unemployment rate hovers around 6% on average, lower than the real values observed during the period of declining unemployment rates in the fourth quarter of 2020.

Overall, implementing optimal policy has led to a reduction in high inflation levels from

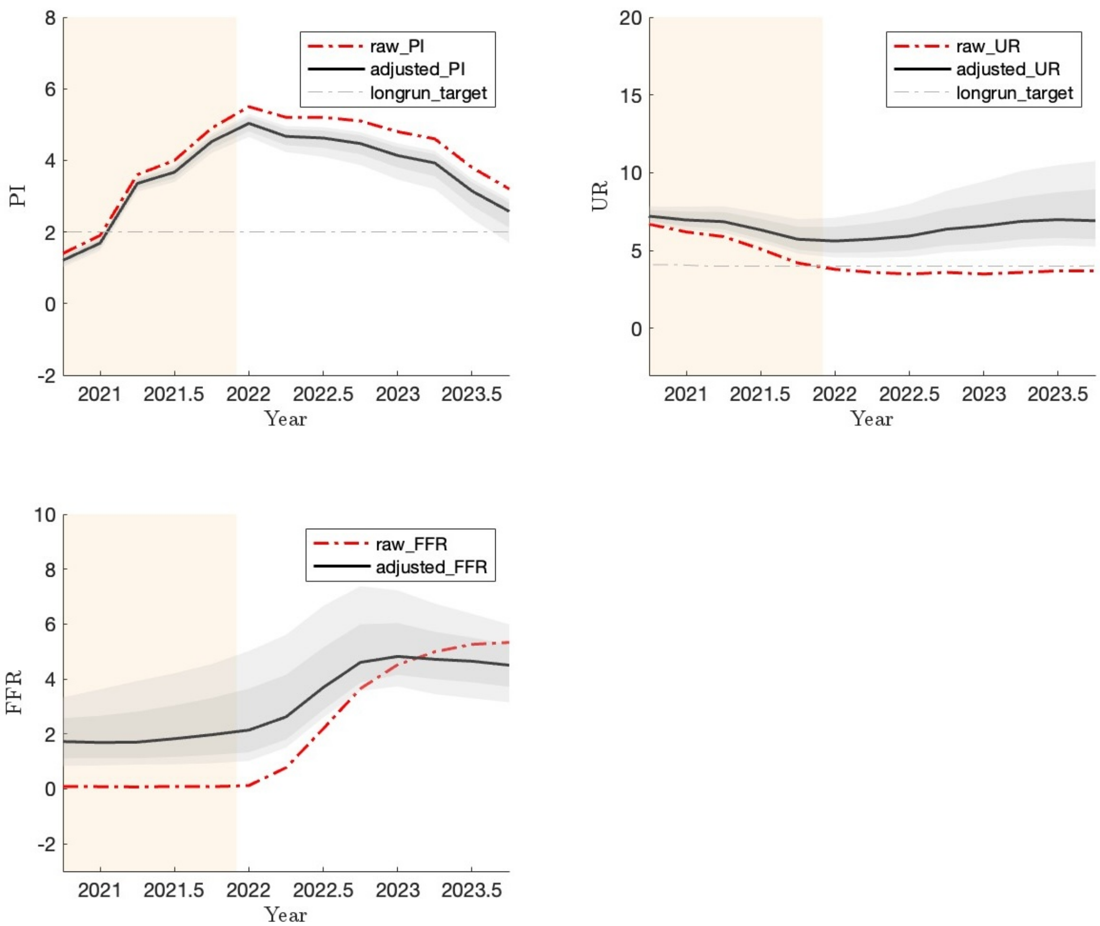

Figure 2: Inflation, Unemployment and FFR: Actual vs. Counterfactual, 2020Q4 to 2023Q4

Notes: Iterations start from 2019Q1. The red dashed line represents the original data, the black line indicates the counterfactual path. The beige shaded area corresponds to the period of imposing the zero lower bound (ZLB) constraint. The gray shaded areas denote the 80 and 90 percents confidence intervals.

2021 to 2023, indicating that a portion of the high inflation during this period was caused by the Federal Reserve's policy bias. The remaining portion, which cannot be reversed by policy adjustments, may be attributed to other factors such as supply-demand imbalances, rising production costs of factors like labor, and bias in the Fed's forecast. In the subsequent mechanism analysis, I will focus on how different forecasts lead to different counterfactual policy outcomes.

It can be concluded that, based on the proportion of the reduction in counterfactual inflation to the gap between the forecast and the long-term target, an average of 19.1% of the inflation surge in the United States from the second quarter of 2021 to the fourth quarter of 2023 can be attributed to the non-optimal implementation of monetary policies by the

Table 3: Baseline Counterfactuals vs. Actual

Year	FFR_adj	PI_adj	UR_adj
2021.00	1.34	-0.19	0.85
2021.25	1.26	-0.21	1.07
2021.50	1.26	-0.29	1.37
2021.75	1.38	-0.32	1.68
2022.00	1.50	-0.38	1.98
2022.25	1.37	-0.42	2.25
2022.50	1.07	-0.44	2.51
2022.75	0.59	-0.48	2.81
2023.00	0.01	-0.52	3.01
2023.25	-0.51	-0.52	3.12
2023.50	-0.84	-0.51	3.07
2023.75	-0.96	-0.46	2.88

Notes: This table presents part of the gaps of the FFR, inflation rate, and unemployment rate from the baseline results. The iteration starts from 2019Q1. Numbers represent the differences between the OPP paths and the original paths.

Fed.

Table 3 presents the numerical differences between the counterfactual and original paths for each period in the baseline results. It can be observed that until the first quarter of 2023, the Fed should have increased the FFR to varying degrees, with an average increase of 1.52 percentage points. Starting from 2023, the counterfactual FFR path indicates that the Fed does not need to maintain the FFR at the level observed in reality, but should decrease it by an average of approximately 0.57 percentage points.

Under these circumstances, it can be observed that the inflation rate decreases in each period, with an average decline of 0.39 percentage points. Moreover, with the cumulative implementation of the OPP FFR policy, it is noticeable that the inflation rate declines more rapidly over time. Additionally, the counterfactual unemployment rate increases by approximately 1.72 percentage points. These numerical findings indicate the extent to which the Fed was behind the curve until the first quarter of 2023.

5.2 Deviations

I further examine the disparity between the monetary policy adopted by the Federal Reserve and the optimal policy from 1985 to 2023, along with the welfare losses incurred.

To compare deviations across different periods, I set the iterative starting period to the first quarter of 1980 and excluded the high-interest-rate periods before 1985 from all benchmark periods. This ensures a relatively stable and predictable monetary policy period

Table 4: Summary Statistics of Deviation by Period

Benchmark Period	Mean *BM*	Std. *BM*	Exceed Std Count	Exceed Std%
Deviation	1.1635	0.8506	18	90.00%
1985-1989.75	-0.1543	0.0540	20	100.00%
1990-2007.75	0.0455	0.1400	19	95.00%
2008-2010.75	-0.1658	0.2195	19	95.00%
2011-2015.75	0.3274	0.3064	18	90.00%
2016-2018.75	0.9086	0.4692	18	90.00%

Notes: This table displays the percentage of abnormal OPP periods in the baseline period (2019Q2 to 2023Q4), using the standard deviation of each benchmark period as a measure. In part one, the benchmark period is 1985Q1 to 2019Q1. In part two, the benchmark periods are divided as follows: Major S&L crisis defaults (1985Q1 to 1989Q4), Great moderation (1990Q1 to 2007Q4), Financial crisis and Great Recession (2008Q1 to 2010Q4), Zero lower bound, recovery from Great Recession (2011Q1 to 2015Q4), Pre-pandemic and trade war (2016Q1 to 2018Q4).

for comparison with the baseline results.

Deviations refer to differences between the optimal FFR policy and the actual FFR policy, known as the OPP adjustments. I assume the expectation of OPP adjustment is zero and compute the standard deviation of OPP. I consider OPP adjustments exceeding one standard deviation to indicate significant policy bias by the Federal Reserve. A positive OPP suggests that the Federal Reserve should have raised the FFR level in that period, while a negative OPP implies that the FFR should have been lowered.

Table 4 reports the percentage of abnormal deviations in the baseline results, using the standard deviation of each different benchmark period as a measure. Part one of Table 4 indicates that approximately 90% of FFR policy decisions between 2019 and 2024 have experienced significant bias. Building on the evidence of deviations from the optimal policy path of FFR from 2019 to 2023, this further validates that a significant proportion of FFR policy deviations compared to historical deviations by the Federal Reserve are highly unusual.

Furthermore, using classification by Brunnermeier et al. (2021), I divide the period from 1985 to 2019 into five distinct periods, each characterized by different monetary policy styles. Part two of Table 4 presents the standard deviations of OPP calculated for different benchmark periods, along with the proportion of the baseline period OPP deviates by more than one standard deviation. The results further demonstrate that over 90% of the deviations in the baseline result period are abnormal. Specifically, using the first quarter of 1985 to the fourth quarter of 1989 as benchmark even suggests that all deviations of FFR policy from the optimal policy between 2019 and 2023 exceed the typical magnitude of deviation,

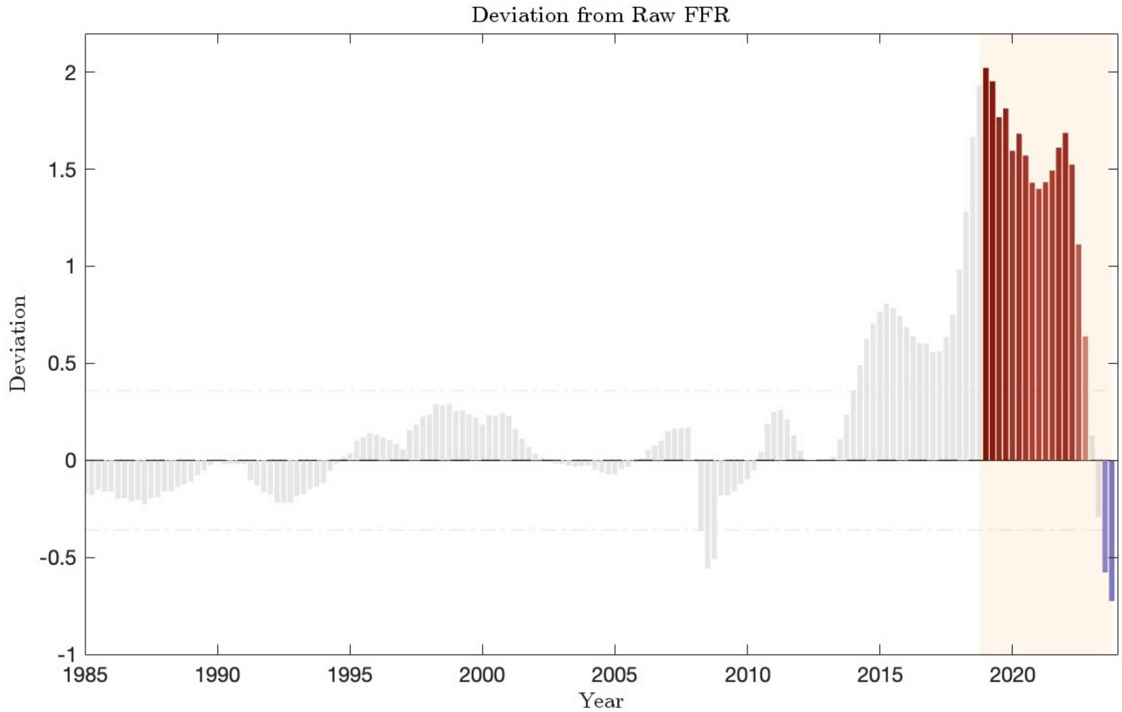

Figure 3: Deviations of FFR from 1990Q1 to 2023Q4

Notes: This figure presents the results of OPP. Colored bars represent OPP exceeding one standard deviation. The red bars represent periods when the FFR should be increased, while the blue bars represent periods when the FFR should be decreased. Dashed lines represent one standard deviation for the whole period. The shaded area represent the baseline period (2019Q1 to 2023Q4).

indicating a significant bias of the Fed.

Figure 3 illustrates the OPP adjustments over time using the period from 1985 to 2019 as a benchmark, with the colored bars representing OPP adjustments exceeding one standard deviation, indicating periods of significant decision bias by the Federal Reserve. This visualization provides a clearer depiction of the deviations between the Fed's monetary policy decisions and the optimal level. It displays that deviations between the FFR and the optimal policy path largely exceed 1 percentage point before the first quarter of 2023, and overall, there is a trend towards further increasing the FFR before 2023 and decreasing it thereafter. This further validates that the Fed's monetary policy has been somewhat sluggish.

5.3 Welfare Losses

Further attention is paid to the welfare losses caused by deviations from the optimal policy path.

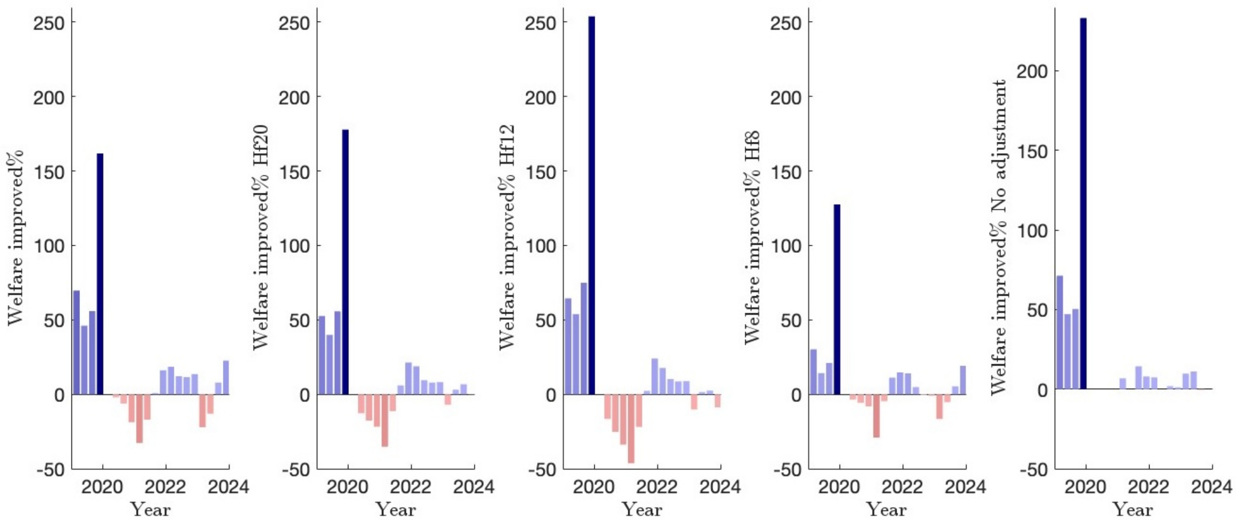

Figure 4: Welfare Improvements: Forecasts

Notes: This figure illustrates the average percentage of welfare improvements incurred from 2019Q1 to 2023Q4 due to adopting the optimal policy framework compared with following the original policy. It is calculated using the formula $(Loss_{raw} - Loss_{OPP})/Loss_{OPP}$. The colored bars represent the net percentage of welfare improvements (blue) or losses (red) for each period. The first subplot represents the baseline results, while the subsequent four subplots illustrate the outcomes under alternative forecast adjustments.

The first subplot of Figure 4 illustrates the percentage change in welfare improvements from adopting the optimal policy framework compared to the original policy from the first quarter of 2019 to the fourth quarter of 2023, based on different forecast adjustment mechanisms. This graph provides a visual representation of the welfare improvements, measured by the loss function.

In the baseline results, it can be observed that under the optimal policy, welfare improved by approximately 5% to nearly 250% for most periods, indicating a certain degree of improvement after adopting the optimal policy framework. However, a few periods experienced a decrease of around 25% in welfare. This decline can be attributed to various factors – Each period's policy adjustment, which inevitably leads to an improvement in welfare compared to the pre-adjustment scenario, is based on adjusted backcast and forecast data, as well as the current period's FFR. Nevertheless, it is challenging to determine whether the welfare in the current period relative to the original welfare has improved before previous periods' OPP adjustments. This is because the current counterfactual has already been influenced by OPP adjustments in the preceding periods, say, $H - 1$ periods. Moreover, previous periods' OPP adjustments aim to minimize the gap between the forecasts of policy objectives and long-term targets up to the current period, rather than minimizing the gap between the actual real-time values of current period's objectives and long-term targets. Consequently, in my theoretical framework, it is possible to observe a decline in welfare relative to the original policy path and policy expectations.

However, it is notable that even with a decline in welfare of some, the relative decrease is not substantial. Moreover, the majority of periods still experience welfare improvements. Additionally, it is evident that inflation can be well controlled in the counterfactuals. Raising the FFR earlier indeed helps to better suppress inflation without causing a significant increase in the unemployment rate, while maintaining a downward trend in unemployment.

The improvements or losses in welfare under alternative forecast adjustments are depicted in the subsequent four subplots of the Figure 4. It can be observed that welfare generally improves for most periods, but whether welfare increases or decreases for each period remains uncertain. As illustrated in the fifth subplot, assuming forecasts are entirely unaffected by changes in the existing information set, welfare improves for almost all periods, with the largest welfare improvement reaching approximately 250%. This further confirms that welfare conditions based on forecasts generally improve for the majority of periods under optimal policy.

6 Robustness Checks

I further examine the robustness of the counterfactual paths obtained from the model.

Figure A.3 displays the counterfactual paths of policy objectives and instruments under different horizons. In the baseline results, I select a horizon of 20, meaning that the OPP in each period would affect the inflation rate, unemployment rate, and FFR for the next 20 quarters including the current period. Now, I replace the horizon of 20 with 16, 24, 28, 32, and recalculated the counterfactual paths for different horizons. It can be observed that changing the horizon does not significantly alter the results.

Figure A.4 illustrates the counterfactual paths of policy objectives and instruments under random shocks to the OPP. Demanding policymakers to make optimal policy decisions based on past information and forecasts in each period is indeed a high requirement, and policymakers in different periods may have different decision-making styles. Therefore, I introduce random shocks to the OPP following a standard normal distribution in the model to verify the robustness of the baseline results.

It can be seen that even if there are deviations from the relatively optimal policies in each period, the resulting counterfactual paths of policy objectives and instruments are almost identical to the baseline results. This indicates that the baseline results are quite robust.

I also develop alternative ways of adjusting the forecast to further examine the robustness of the baseline results and provide other prospective of welfare accounting. I approximate the effect of adjustments in policy instruments on the forecasts of policy objectives using the estimated impact of policy instruments adjustments on policy objective. I depict this relationship using the following equation,

$$\Delta \mathbb{E}_{t+i} \mathbf{Y}_{t+i}^{t} = \lambda_{\mathbf{Y}} \mathcal{R}_{y,\,i}^{0} \boldsymbol{\delta}_t^{*}, \tag{7}$$

where $\Delta \mathbb{E}_{t+i} \mathbf{Y}_{t+i}^{t}$ represents the change in the forecast path at period $t+i$ ($i \leq H-1$), superscript t implies that it is the OPP at period t that influence the forecast for that period. $\mathcal{R}_{y,\,i}^{0}$ signifies the impulse response function that disregards the impact of policy shocks on policy objectives for the previous i periods, and $\lambda_{\mathbf{Y}}$ represents the ratio between the genuine value and the forecast. I choose the coefficient for the relationship between the change in forecast values for next year's policy objectives or policy instruments and the change in actual values for the current period as $\lambda_{\mathbf{Y}}$. Based on this, I compute the counterfactual paths under different periods of policy shock's impact on forecasts.

Figure A.5 displays the results under the baseline mechanism and different periods of forecast impact. It can be observed that the variations in the mechanism affecting the forecasts do not have a significant impact on the results of the counterfactual paths. All the counterfactual paths overlap closely, further confirming the reliability of the baseline results

In Section A1.2, I conduct more robustness checks to further validates the robustness of the baseline results.

7 Mechanisms

In this section, I will further examine the mechanisms influencing the Federal Reserve to make optimal decisions.

7.1 Forecasts

In my theoretical framework, forecast path serves as another sufficient statistic besides impulse response, affecting the calculation of the OPP and the counterfactual paths for policy objectives and policy instruments. Logically, under the assumption that the forecast for unemployment remains unchanged, if policymakers anticipate higher future inflation, they would naturally raise interest rates to curb inflation. In my previous discussions, counterfactual paths are calculated based on the forecast path fitted from the FOMC's SEP data. Subsequently, I collect forecast data on inflation rates and unemployment rates from the

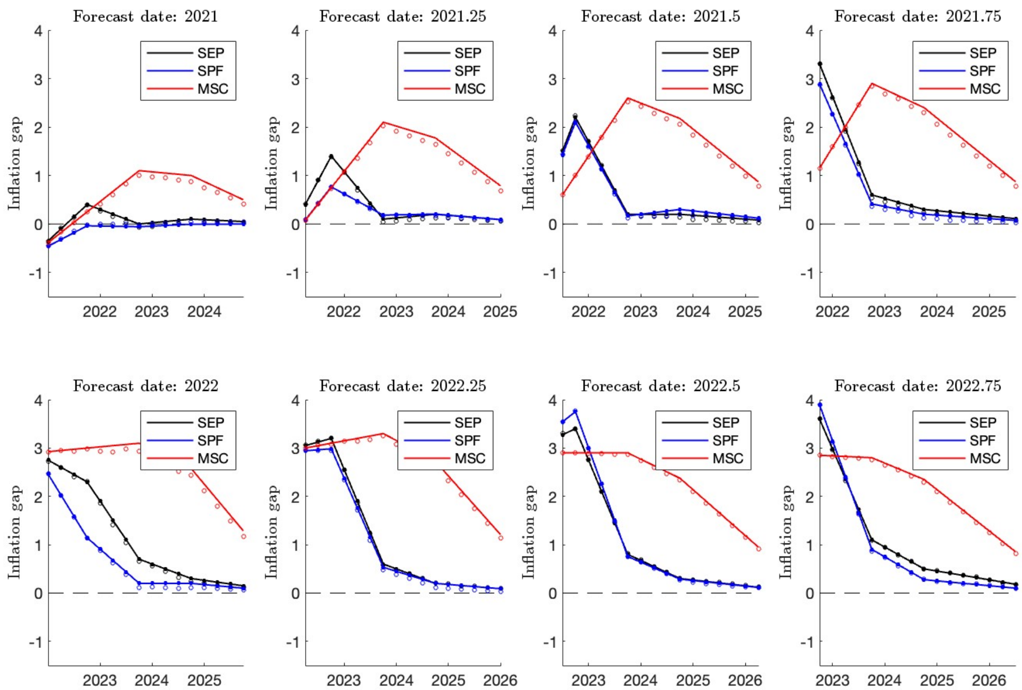

Figure 5: FFR Policy from 2021Q1 to 2022Q4 on Inflation.

Notes: This figure displays median forecasts for inflation. SEP represents the forecasts from the Summary of Economic Projections, SPF represents the forecasts from the Survey of Professional Forecasters, and MSC represents the forecasts from the Surveys of Consumers, Michigan College. Filled circles represent the original forecast path, while empty circles represent the forecast path after OPP adjustments.

Survey of Professional Forecasters (SPF) by the Federal Reserve Bank of Philadelphia and the Surveys of Consumers (MSC) by the University of Michigan, and compare the counterfactuals thereafter. As MSC does not provide forecast data for the unemployment rate, I supplement it with SEP data.

Figure 5 illustrates the gaps of the original forecast paths relative to the long-term target for inflation from the first quarter of 2021 to the fourth quarter of 2022 (filled circles), along with the gaps between the forecast paths after OPP adjustments and the long-term target (empty circles). It is evident that SPF is relatively optimistic about inflation for the years 2021 to 2022 compared to SEP. Additionally, due to the lack of inflation forecast values for the current year in MSC, I linearly interpolate the forecast values from the fourth quarter of the previous year and the next year, making it difficult to directly compare MSC's forecasts for inflation with those of SPF and SEP. Nevertheless, it can be observed that MSC's inflation

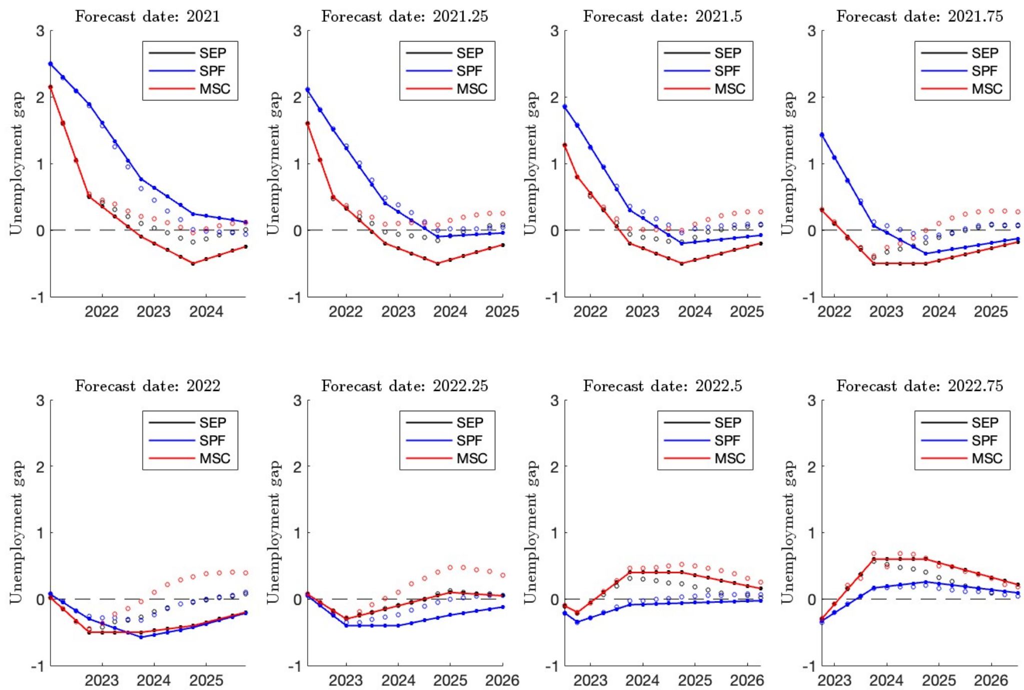

Figure 6: FFR Policy from 2021Q1 to 2022Q3 on Unemployment Rate

Notes: This figure displays median forecasts for unemployment. SEP represents the forecasts from the Summary of Economic Projections, SPF represents the forecasts from the Survey of Professional Forecasters, and MSC represents the forecasts from the Surveys of Consumers, Michigan College. Filled circles represent the original forecast path, while empty circles represent the forecast path after OPP adjustments.

forecasts are higher than those of SEP and SPF, with a slower declining trend, particularly for long-term inflation rate forecasts. After OPP adjustments, all inflation forecast paths show a decline, with MSC experiencing a more substantial decrease. It can be believed that MSC's forecasts for inflation are higher than those of the official SEP and SPF forecasts, and I will further elaborate on the implications of higher forecasts in subsequent discussions.

Thus, it can be inferred that part of the reason for the unusually high inflation in the United States from 2021 to 2023 is the deviation in the Fed's forecasts of inflation, unemployment rate, and FFR. Adopting the measurement in the last section, about 19.1% of the inflation gap is attribute to the bias of the monetary policy of the Fed under MSC forecast on average. Moreover, comparing SEP forecast and MSC forecast of inflation, about 7.6% of the inflation gap is due to the bias in forecast of the Fed on the premise that the first quarter of 2019 is set as the starting period.

Figure 6 presents the original forecast paths relative to the long-term target for the unemployment rate (filled circles) from the first quarter of 2021 to the fourth quarter of 2022, as well as the gap between the forecast paths after OPP adjustments and the long-term target (empty circles). As MSC does not provide forecasts for the unemployment rate, I use SEP's paths as a substitute. It can be observed that SPF's forecasts for the unemployment rate are relatively higher than SEP's in 2021 and lower in 2022, but the overall trend is nearly consistent. After OPP adjustments, the unemployment forecasts are almost near the long-term target. Furthermore, when inflation forecasts are relatively higher, there is a greater change in the unemployment rate after OPP adjustments. Overall, OPP adjustments help keep the unemployment rate near the long-term target in each period.

However, the above analysis only pertains to the optimal adjustments in each period, and the paths of policy objectives and policy instruments after iteration are still unknown. I select the first quarter of 2021 as the starting point for adopting the optimal policy framework and calculate the counterfactual paths for the inflation rate, unemployment rate, and FFR under different forecasts.

Figure 7 displays the counterfactual paths of policy objectives and policy instruments under different forecasts and confidence intervals from the first quarter of 2019 to the fourth quarter of 2023. The magnitude of the FFR increase is highest for MSC, while SPF's FFR is lower than SEP's before the second quarter of 2022. Under these circumstances, the counterfactual inflation rates are lowest for MSC, followed by SEP, and highest for SPF. Regarding the unemployment rate, MSC's forecast is higher than SEP's, which is higher than SPF's. Overall, the counterfactual paths for the median unemployment rate after 2021 remain at 8% or below. It can be seen that MSC's 90% confidence interval is wider, encompassing a 15% interest rate in MSC's FFR path, as well as extremely low inflation rates and relatively high unemployment rates. In terms of median counterfactuals, MSC's forecasts lead to paths closer to the long-term inflation target compared to SPF and SEP, keeping the FFR and unemployment rates within reasonable ranges.

It can be concluded that during the period from 2021 to 2023, monetary policy decisions made under higher inflation forecasts can better control inflation levels. The reasons behind the deviation between households' forecasts of inflation and those of professional forecasters are widely discussed, well accepted one such that Coibion and Gorodnichenko (2015) argued that oil price is the reason for the deviation of the forecasts for the period from 1981 to 2013. I will further explore the reason behind it for the period from 2021 to 2023, and link macroeconomic empirical results with microeconomic foundations.

Overall, an average of 7.6% of the inflation surge in the United States from the second quarter of 2021 to the fourth quarter of 2023 can be attributed to the bias in forecast of the

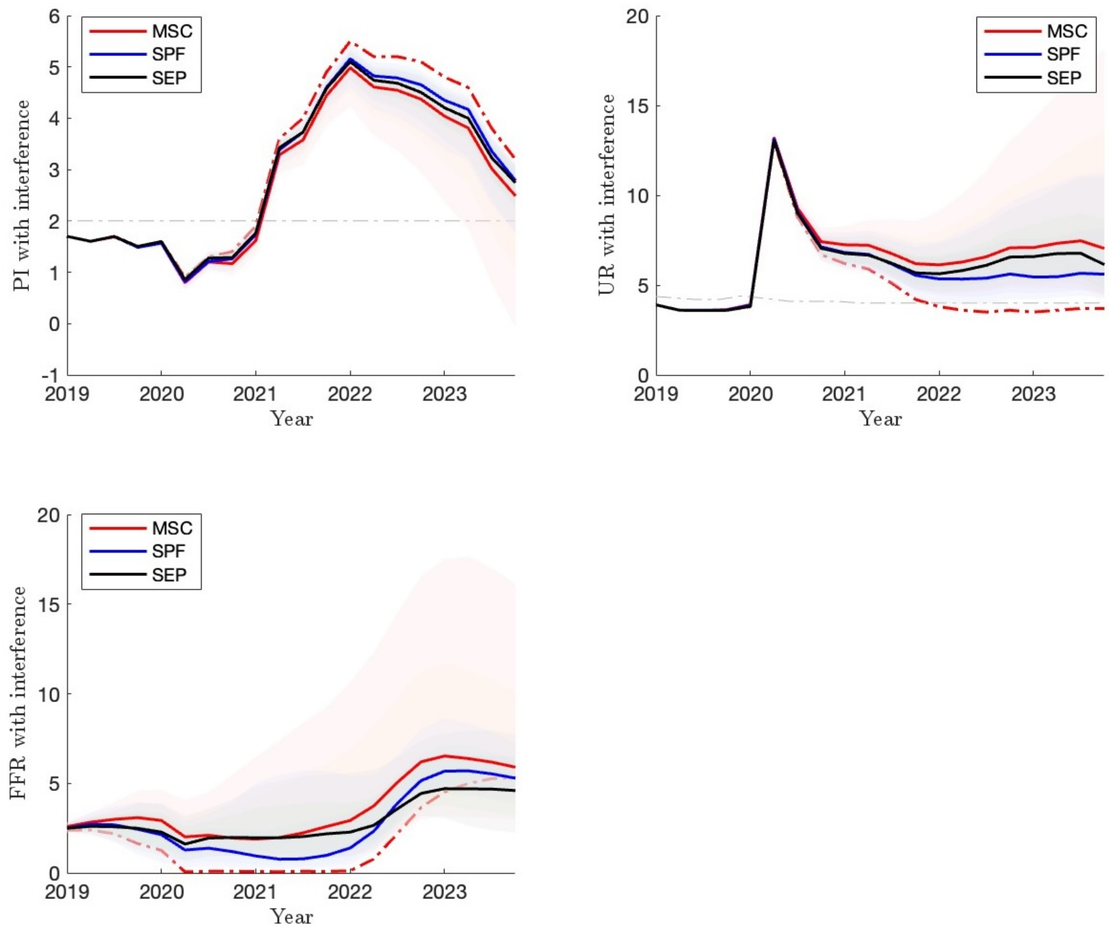

Figure 7: Different Forecasts for Iteration Starting in 2019Q1

Notes: Iterations start from 2019Q1. The red dashed line represents the original data, the coloured lines indicate the counterfactual paths with different forecasts (black = SEP, blue = SPF, red = MSC). The coloured shaded areas denote the 80 and 90 percents confidence intervals.

Fed.

7.2 Starting periods

In the baseline results, I select the first quarter of 2019 as the starting period for adopting the optimal policy framework. Next, I will examine how different starting periods affect the counterfactual paths and further explore how different forecasts under different starting periods will influence the counterfactual paths.

Figure 8 displays the counterfactual paths initiated in the first quarter of 2021 and the first quarter of 2022 under different forecast data. The earlier the optimal policy framework is adopted, the higher the counterfactual FFR paths, the lower the counterfactual inflation

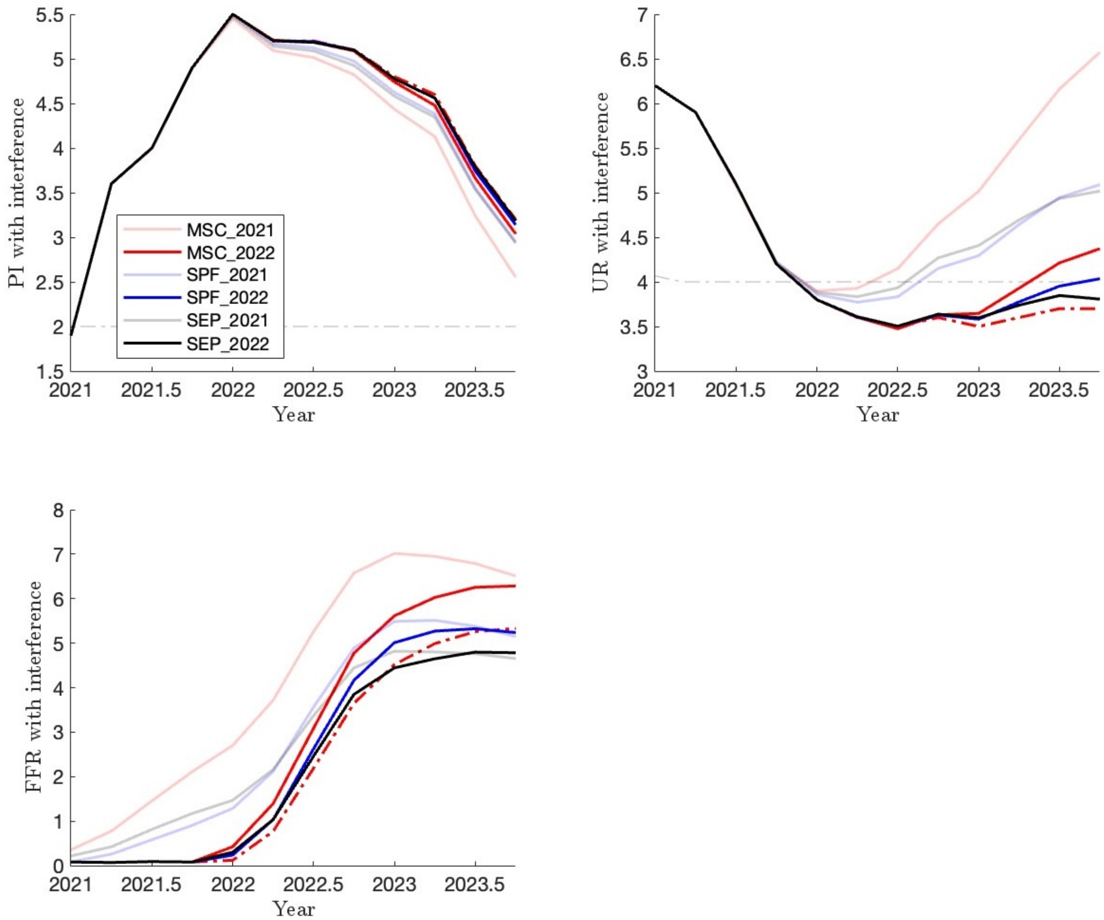

Figure 8: Different Forecasts for Iteration Starting in 2021 and 2022

Notes: Iterations start from 2021Q1 and 2022Q1. The red dashed line represents the original data, the coloured lines indicate the counterfactual paths with different forecasts (black = SEP, blue = SPF, red = MSC). The coloured shaded areas denote the 80 and 90 percents confidence intervals.

paths, and the higher the counterfactual unemployment rate paths. Furthermore, it is still observed that under the same starting period, the counterfactual FFR paths are higher, the counterfactual inflation paths are controlled the lowest, and the counterfactual unemployment paths are higher, but overall remains below 6.5% for MSC forecast data, followed by SPF, and SEP is closest to the original path.

I numerically examine the counterfactual inflation paths under the adoption of the optimal policy framework and the replacement of the forecast. Consequently, the average decline in inflation can be attributed to deviations in policy and forecast.

Table 5 depicts the results of the fraction of the bias. In the baseline results, the starting period is the first quarter of 2019, about 19.1% of the inflation gap can be attributed to Fed

Table 5: Explainable Fraction

Starting Period	2019Q1	2021Q1	2022Q1
Policy Bias %	19.1284	5.9957	0.4411
Forecast Bias %	7.5975	6.3956	2.1561
Unexplained %	73.2741	87.6087	97.4028

Notes: This table presents the results of the biases under different starting periods. Policy bias is computed using the gap between the original inflation paths and the paths under optimal policy framework with SEP forecast. Forecast bias is computed using the gap between the paths with SEP forecast and MSC forecast. Unexplained part is the gap between the counterfactual paths with MSC forecast and long-term targets.

policy bias, and 7.6% can be attributed to Fed forecast bias. Under the assumption that the starting period is the first quarter of 2021, only 6.0% of the inflation gap can be attributed to Fed policy bias, and 6.4% can be attributed to Fed forecast bias. In contrast, assuming the starting period is the first quarter of 2022, only 0.4% can be attributed to policy bias, and only 2.2% can be attributed to forecast bias. This further validates that the earlier adoption of the optimal policy framework leads to better control of inflation.

8 Conclusion

The main contribution of this paper is to propose a revised sufficient statistic approach to evaluating the U.S. monetary policy. The results show that the Fed's monetary policy has indeed been sluggish since 2019, and there are certain deviations in the forecasts of monetary policy objectives. By incorporating the dynamic effect of policy perturbation, I can ultimately derive the counterfactual paths of policy instruments and objectives. The gap between the original and the counterfactual paths can be explained by the bias in policy's decision-making process, while other contributing factors account for the remaining discrepancies. Comparing different forecast datasets, I find that inflation forecasts made by consumers outperform those by Fed professionals, yielding a lower inflation counterfactual curve from 2019 to 2023. The optimal policy rate consistently exceeds the original policy rate before 2022 regardless of the forecast, and higher FFR indeed would result in a lower inflation and improve welfare. Quantitatively, if the Fed adopt the optimal policy framework beginning from the first quarter of 2019, the inflation could have been eased by about 19%. Moreover, adopting the forecast made by consumer could further mitigate 7% of the inflation. The later the Fed adopts this decision-making framework, the smaller the improvement in inflation will be.

This paper suggests several paths to the future work. First, there is still no consensus on what a perfect forecast is. The gap between the counterfactuals and the original paths can hardly be closed due to the complexity of making forecast. Second, the weights on policy objectives may be dynamic. In the baseline results, the inflation gap and the unemployment gap are weighted equally in each period, but the actual weights are unknown, and the counterfactual will change as the weights change. In addition, it is conceivable that if the inflation gap is larger, it will be given a larger weight, and this dynamic change is not taken into account.

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A1 Appendix

A1.1 Bayesian Vector Autoregression

I implement the works of Kuttner (2001), Eberly et al. (2019), and Gürkaynak et al. (2004) to perform Bayesian VAR. I utilize the changes in the implied rate from the four-quarter-ahead federal funds future contract measured around the FOMC announcements within a 30-minute window as an instrumental variable for FFR, also known as the monetary policy surprise. It captures the disparity between the expected FFR and the actual FFR, serving to identify shocks to the contemporaneous FFR.

Considering a VAR(p) model, I define $A = (a_0\, A_1\, \cdots\, A_p)'$ where A_j is a $M \times M$ vector and $\alpha = vec(A)$ which is a $KM \times 1$ vector with $K = 1 + Mp$, and I can write the VAR either as

$$Y = XA + E, \tag{A.1}$$

or

$$y = (I_M \otimes X)\alpha + \varepsilon, \tag{A.2}$$

where $\varepsilon \sim N(0, \Sigma \otimes I_M)$, $\alpha|\Sigma, y \sim N\left(\widehat{\alpha}, \Sigma \otimes (X'X)^{-1}\right)$, and $\Sigma^{-1}|y \sim W\left(S^{-1}, T - K - M - 1\right)$.

The prior has the form

$$\begin{aligned} \alpha|\Sigma &\sim N\left(\underline{\alpha}, \Sigma \otimes \underline{V}\right), \\ \Sigma^{-1} &\sim W\left(\underline{S}^{-1}, \underline{\nu}\right), \end{aligned}$$

where $\underline{\alpha}$, $\underline{V}$, $\underline{S}$ and $\underline{\nu}$ are prior hyperparameters.

With this prior, the posterior becomes

$$\begin{aligned} \alpha|\Sigma, y &\sim N\left(\overline{\alpha}, \Sigma \otimes \overline{V}\right), \\ \Sigma^{-1}|y &\sim W\left(\overline{S}^{-1}, \overline{\nu}\right), \end{aligned}$$

where

$$\begin{aligned}
\overline{V} &= \left[\underline{V}^{-1} + X'X\right]^{-1}, \\
\overline{A} &= \overline{V}\left[\underline{V}^{-1}\underline{A} + X'X\widehat{A}\right], \\
\overline{S} &= S + \underline{S} + \widehat{A}'X'X\widehat{A} + \underline{A}'\underline{V}^{-1}\underline{A} - \overline{A}'\left(\underline{V}^{-1} + X'X\right)\overline{A}, \\
\overline{\nu} &= T + \underline{\nu}.
\end{aligned}$$

Using a Gibbs sampling algorithm, I can obtain the posterior distribution.

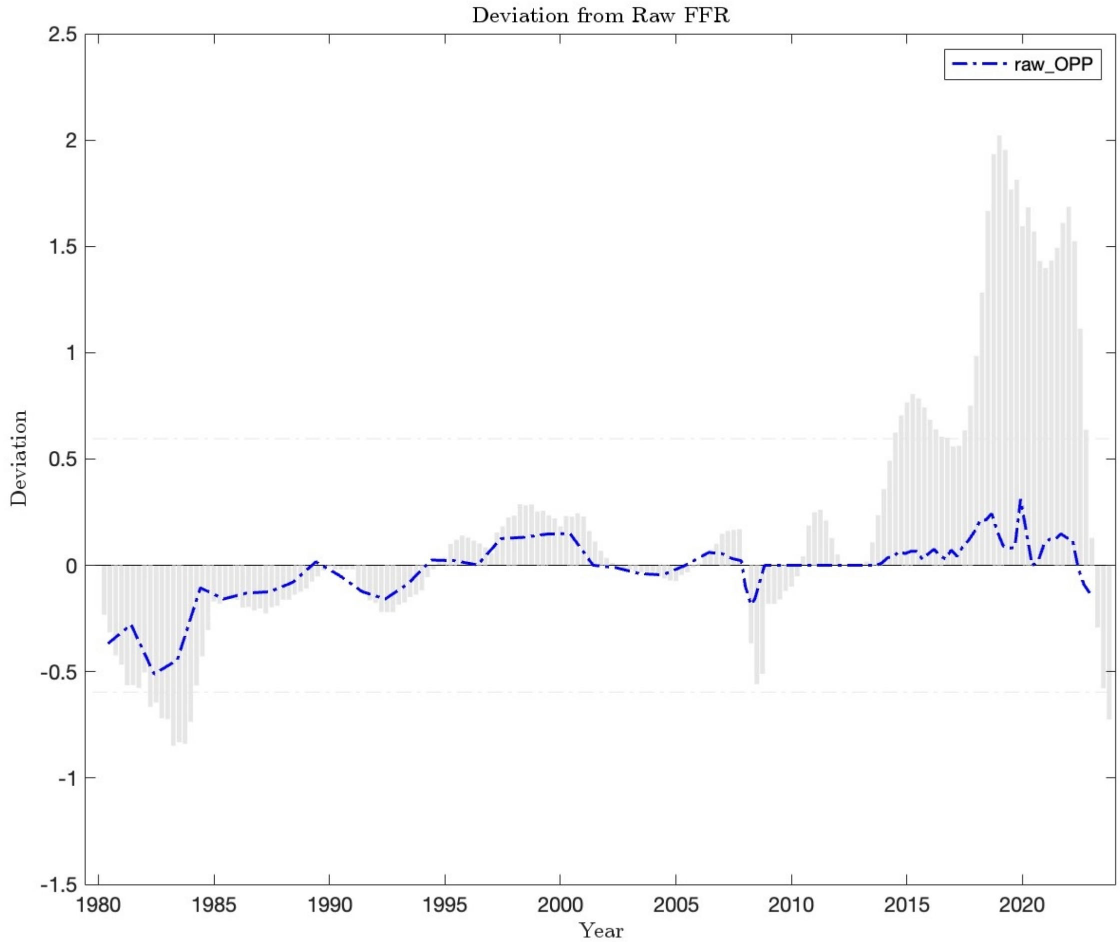

Figure A.1: Robustness Checks with Original OPP

Notes: This figure depicts the result of the optimal policy framework (gray bar) and the raw OPP from Barnichon and Mesters (2023) (blue dashed line). The gray dashed line represents one standard deviation of the optimal policy framework for the whole period.

A1.2 Robustness Checks

In Figure A.1, I compare the results of optimal policy framework with the original OPP results obtained from Barnichon and Mesters (2023). It can be observed that the OPP, after iterative computation, exhibits larger absolute values compared to the results obtained from calculating each period independently. However, the trends of the two are the same. This validates the robustness of the baseline results.

In Figure A.2, I also compare the results of the OPP obtained using real-time data from the FRED Economic Data that I employ as backcast data with the OPP obtained from using real-time data from the Federal Reserve Bank, Philadelphia, as backcast data,

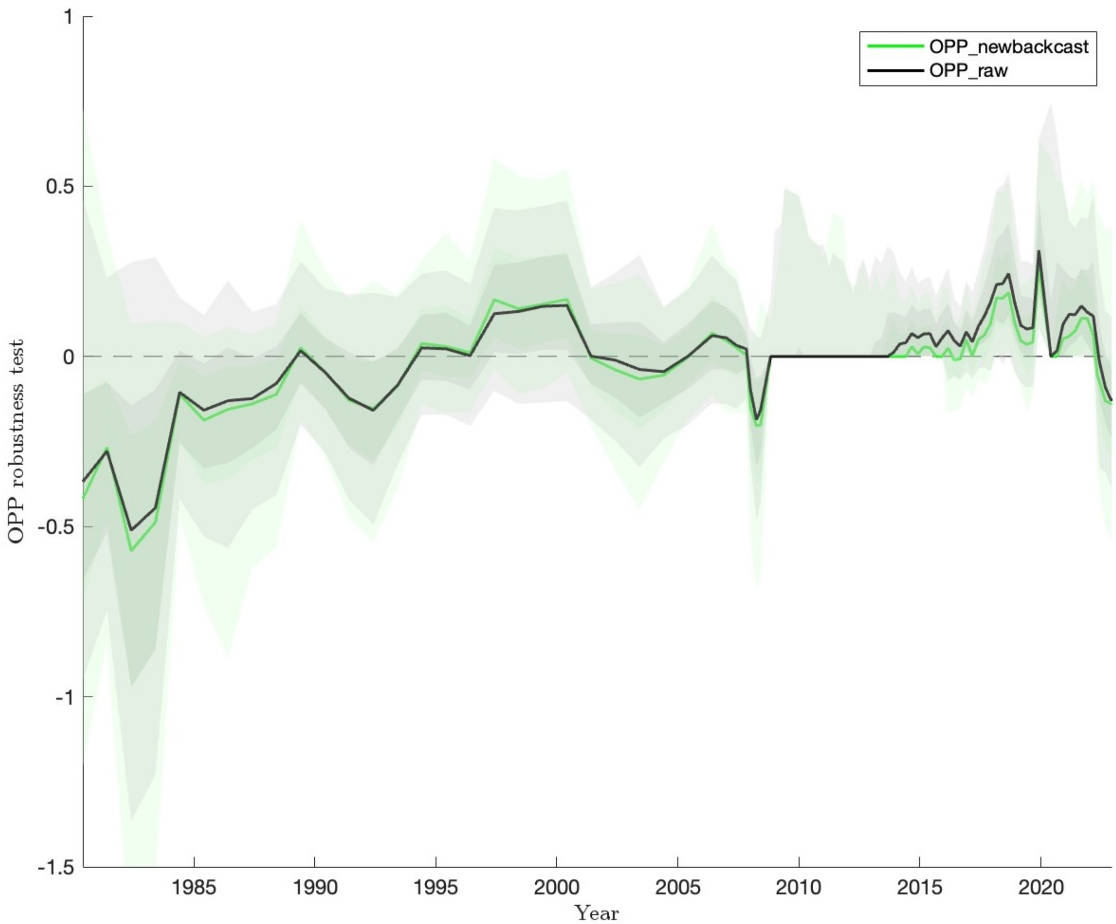

Figure A.2: Robustness Checks with New Backcast

Notes: This figure depicts the result of the OPP with new backcast data and the raw OPP from Barnichon and Mesters (2023) (green line). The gray and green shaded areas denote the 80 and 90 percents confidence intervals.

as in Barnichon and Mesters (2023). It can be observed that this change does not lead to significant variations in the calculated OPP results. This further validates the robustness of the baseline results.

A1.3 Appendix Figures and Tables

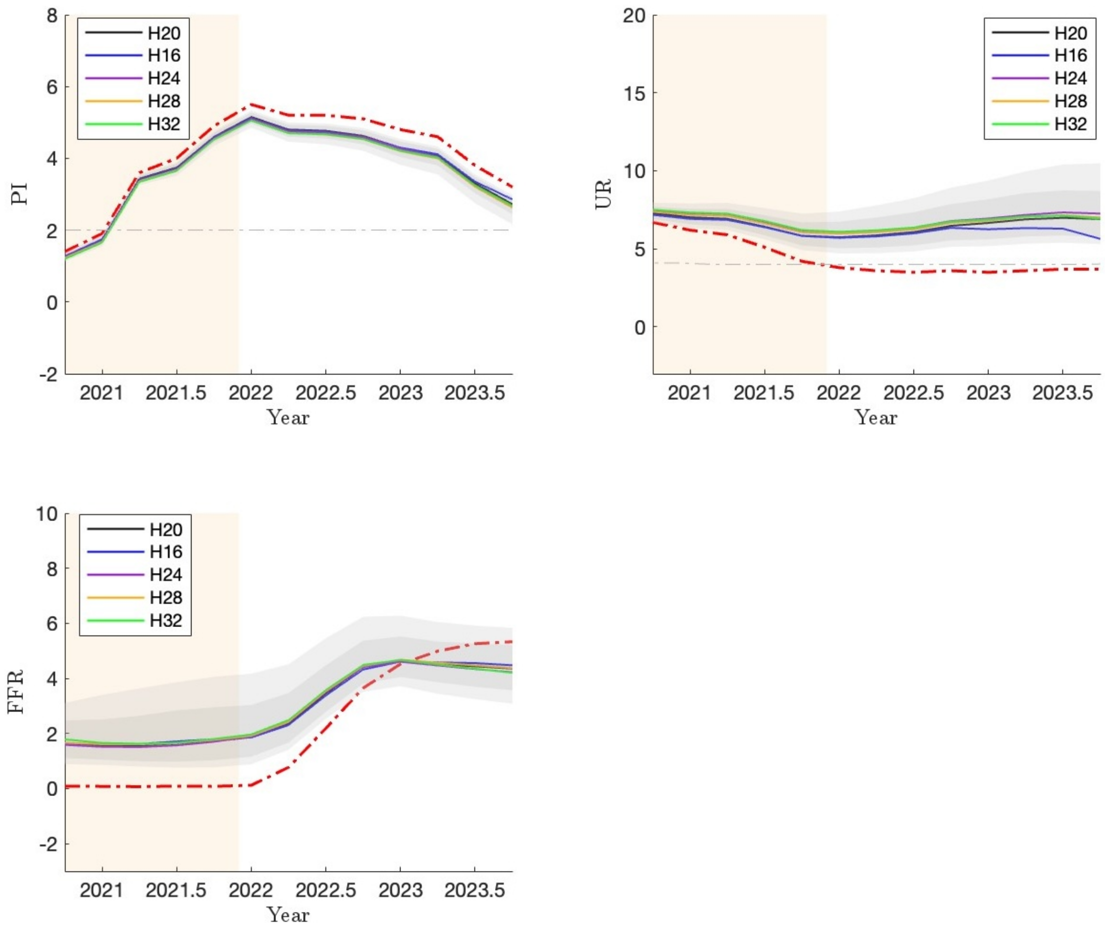

Figure A.3: Robustness Checks with Different Horizons

Notes: Iterations start from 2019Q1. The red dashed line represents the original data. Different colour lines indicates the counterfactual path with different horizons (black = 20 quarters, blue = 16 quarters, purple = 24 quarters, orange = 28 quarters, green = 32 quarters).

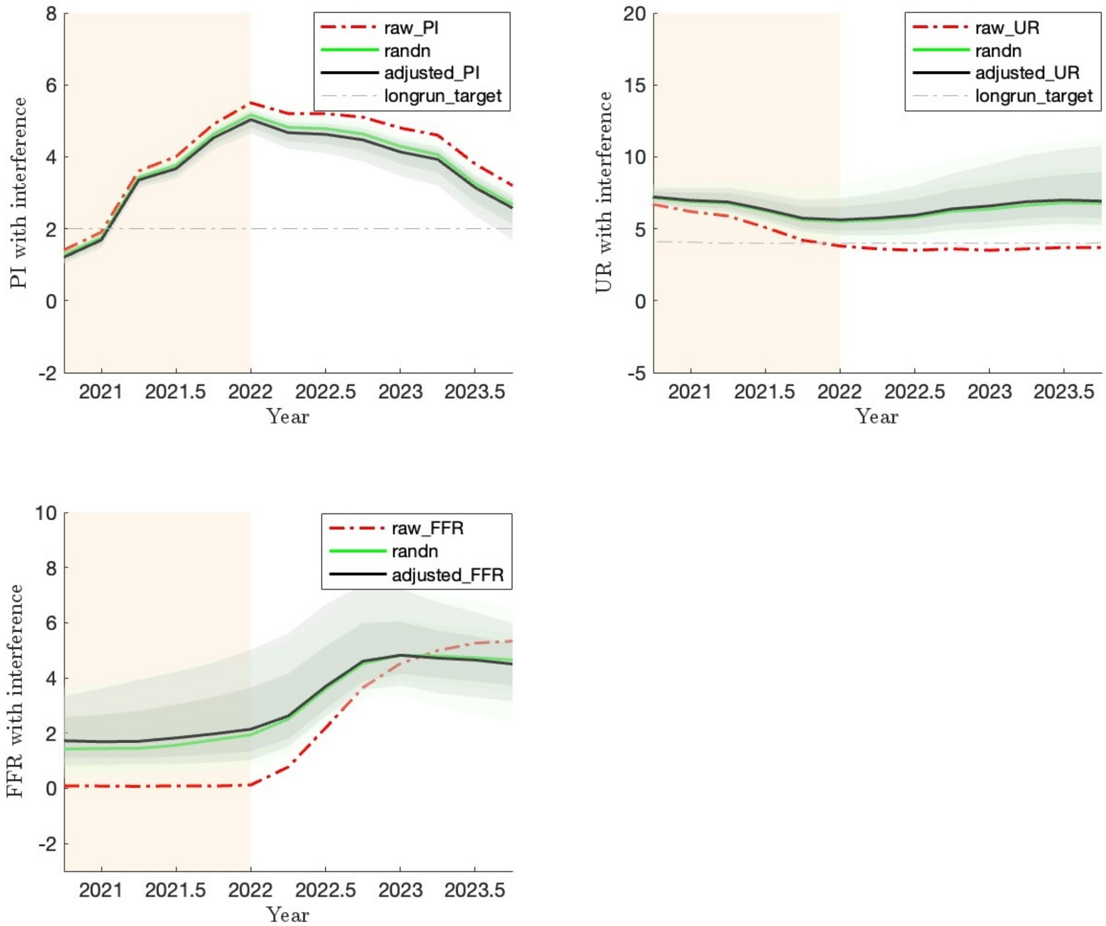

Figure A.4: Robustness Checks with Random Shocks

Notes: Iterations start from 2019Q1. The red dashed line represents the original data, the black and green line indicates the counterfactual path and path with random shocks. The gray and green shaded areas denote the 80 and 90 percents confidence intervals.

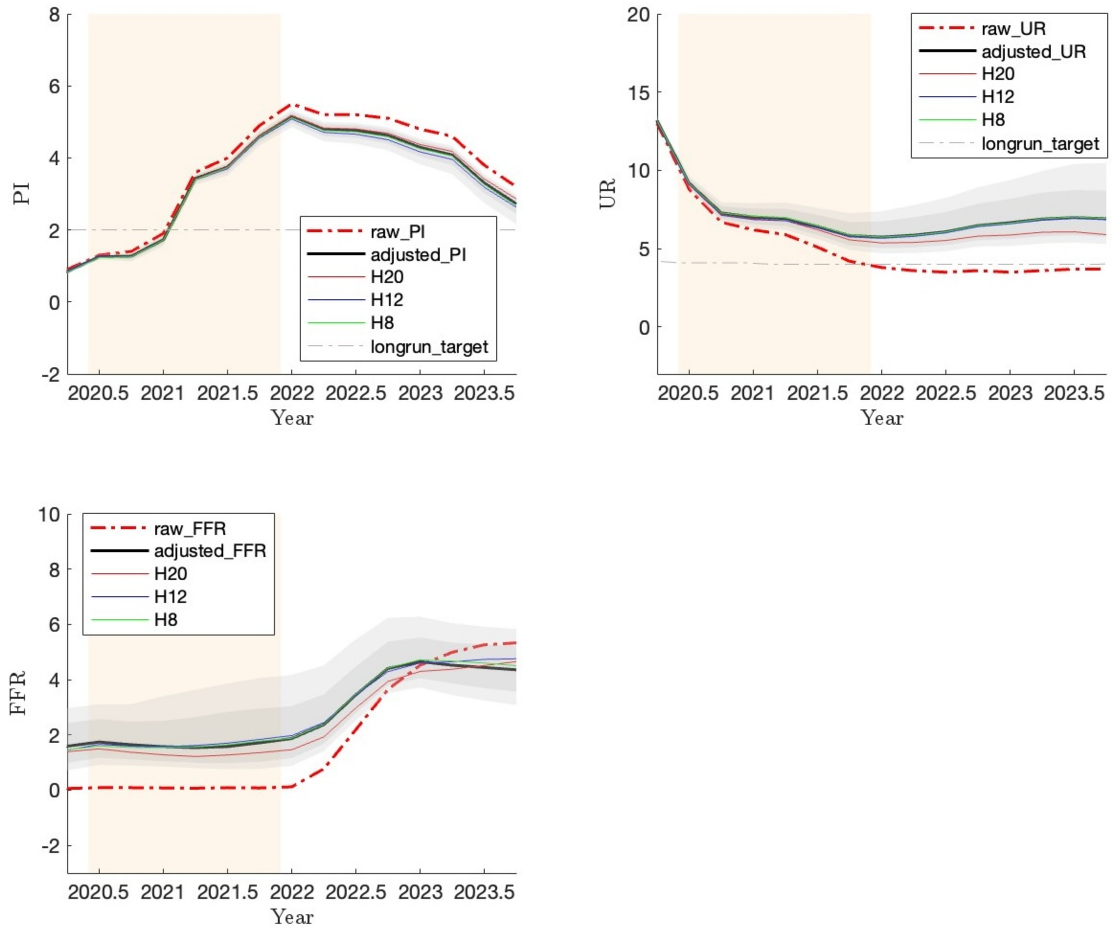

Figure A.5: Different Forecast Adjustment Mechanisms

Notes: This Figure depicts the results of different ways of adjusting the forecast. H represents the horizons of forecast adjustment. The shaded areas denote the 80 and 90 percents confidence intervals.

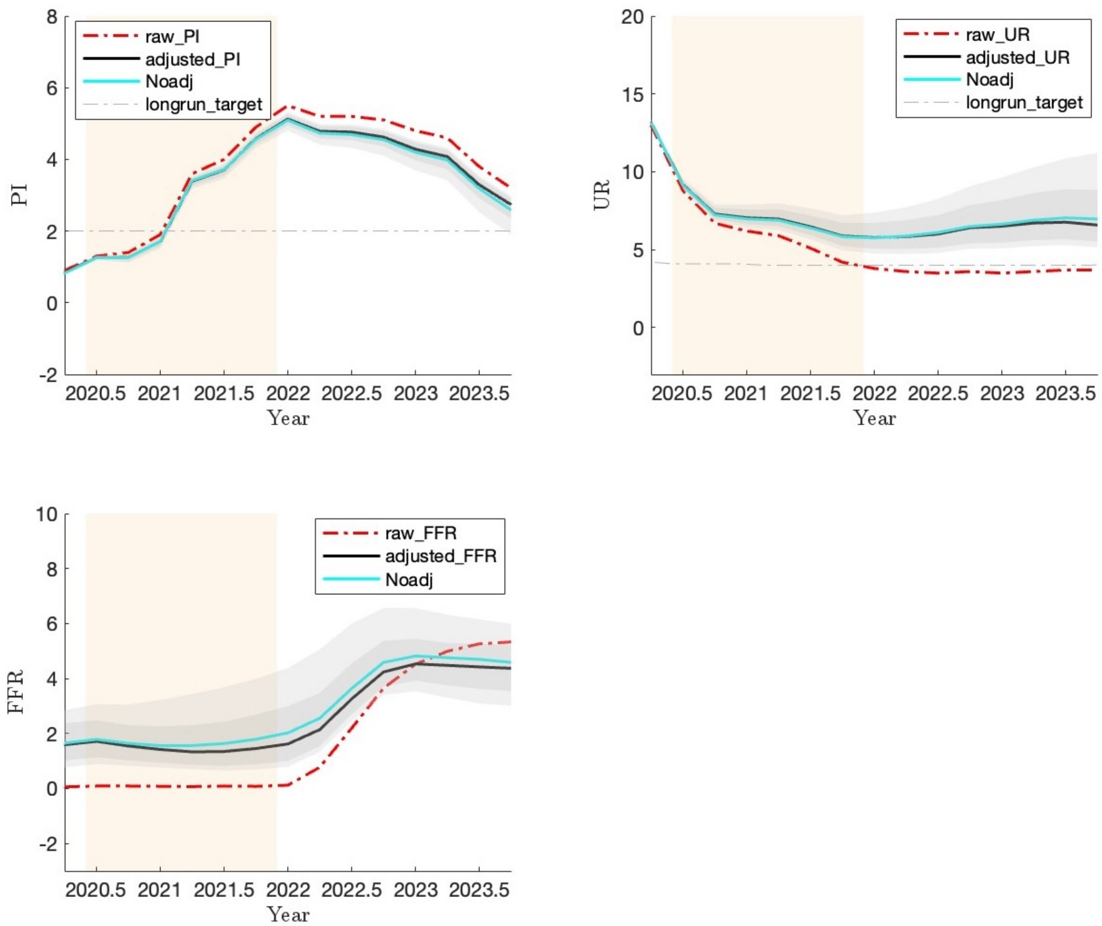

Figure A.6: No Forecast Adjustment

Notes: This Figure depicts the results of ignoring adjusting the forecast. H represents the horizons of forecast adjustment. The shaded areas denote the 80 and 90 percents confidence intervals.

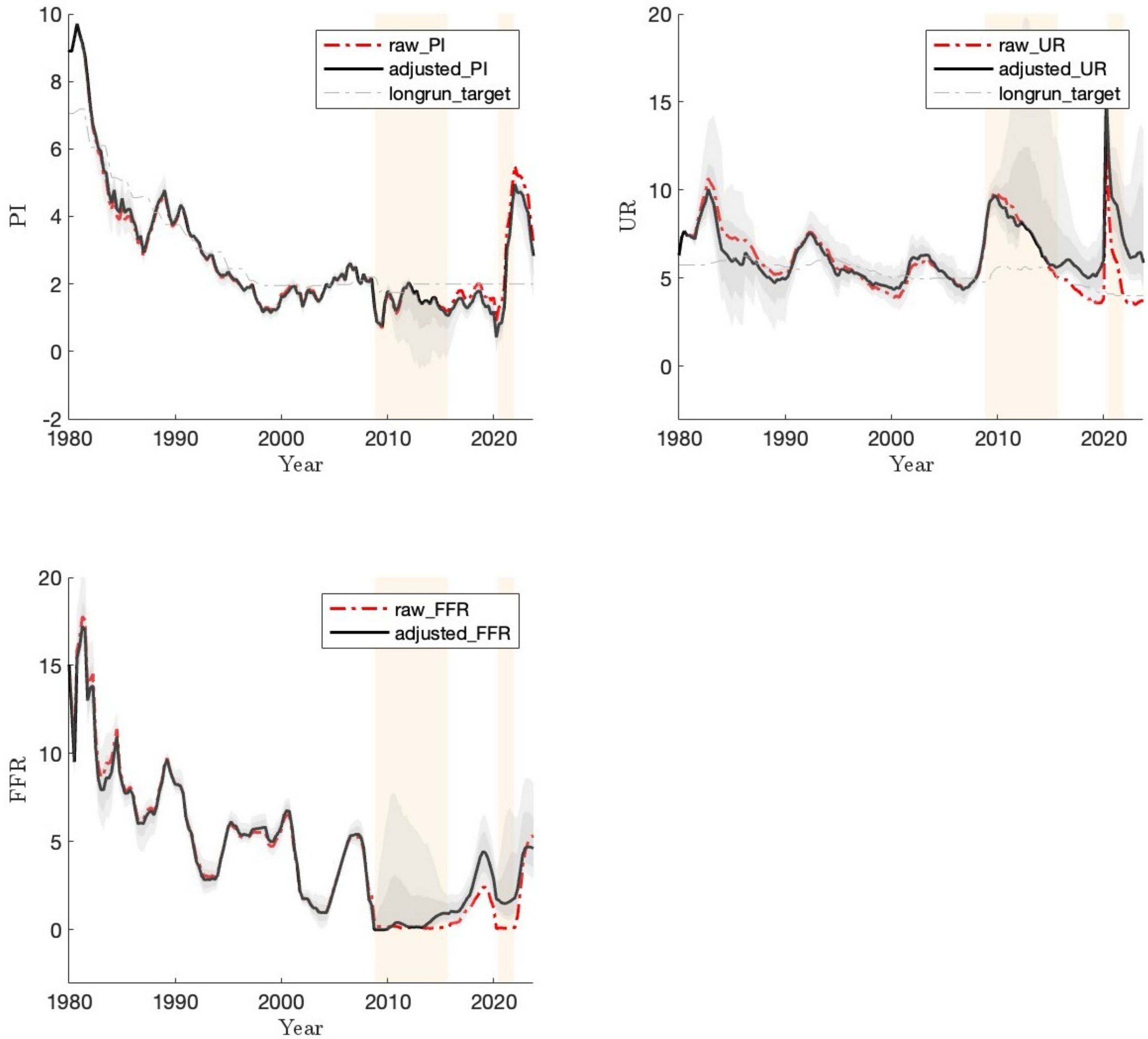

Figure A.7: Inflation, Unemployment and FFR Iteration Starting from 1980Q1.

Notes: Iterations start from 1980Q1. The red dashed line represents the original data, the black line indicates the counterfactual path. The beige shaded area corresponds to the period of imposing the zero lower bound (ZLB) constraint. The gray shaded areas denote the 80 and 90 percents confidence intervals.

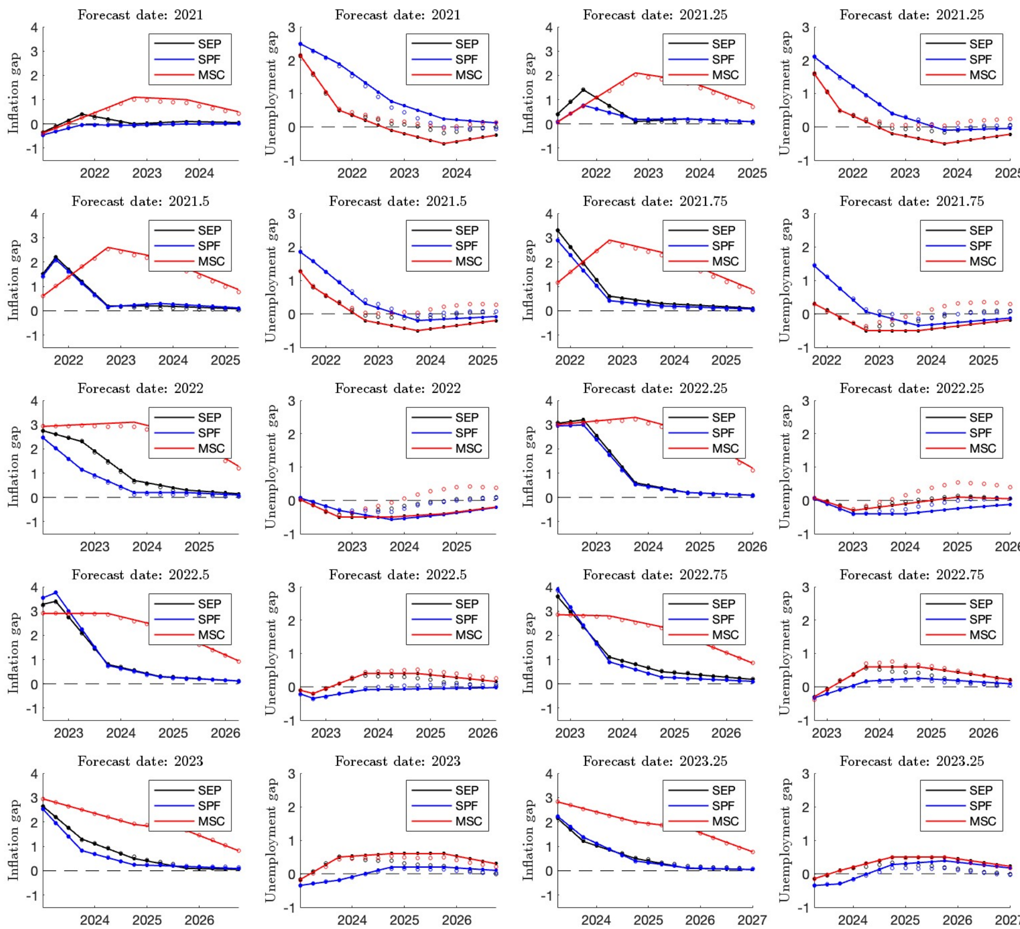

Figure A.8: FFR Policy from 2021Q1 to 2023Q2.

Notes: This figure displays median forecasts for inflation and unemployment. SEP represents the forecasts from the Summary of Economic Projections, SPF represents the forecasts from the Survey of Professional Forecasters, and MSC represents the forecasts from the Surveys of Consumers, Michigan College. Filled circles represent the original forecast path, while empty circles represent the forecast path after OPP adjustments.