Is the Fed Behind the Curve? *

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Abstract

The surge in inflation experienced by the United States from 2021 to 2023 has sparked controversy over the Federal Reserve's conservative monetary policy. I focus on whether the high inflation in the United States since 2021 is caused by the Federal Reserve's monetary policy being behind the curve. I employed BVAR and iterative sufficient statistics method to generate counterfactual paths for inflation, unemployment rate, and the Fed Funds Rate, demonstrating that the high inflation is largely attributed to the Federal Reserve's excessively lagging monetary policy. Specifically, about 18.6% of the inflation gap can be attributed to Fed policy errors. Furthermore, I combined different forecasts and starting periods to analyze, from a micro perspective, the reasons for the counterfactual paths of various macroeconomic policy objectives and instruments, and delved into the mechanisms influencing optimal policy decisions. About 7.8% of the inflation gap can be attributed to Fed forecast errors. Consequently, the later the optimal policies are adopted, the harder it will be to control inflation.

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1 Introduction

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2 Theoretical Motivation and Empirical Approach

In this section, I will introduce the theoretical model and empirical strategy used in this article. The model employed to estimate the optimality of the Federal Reserve's monetary policy in this paper is based on the sufficient statistic approach proposed by Barnichon and Mesters (2023) for assessing macroeconomic policies. The model is grounded in the New Keynesian framework and incorporates Lucas critique robustness.

To estimate the impulse response, I follow the framework of Koop, Korobilis, et al. (2010). I use a Bayesian VAR with inflation, unemployment, the Fed funds rate 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 an iterative model incorporating policy objectives, policy instruments, and forecasts using the impulse response function to create counterfactual paths.

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 δ_t on policy at period t. According to the impulse response function, this perturbation will have a certain impact on the forecast of current-period policy. To determine the optimal policy perturbation (OPP) δ_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

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

Indeed, all the information necessary to compute OPP is impossible to obtain. In other words, the OPP we get are derived from the information that is only partially representative of the whole dataset. It is called the *subset* OPP, namely $\boldsymbol{\delta}_{a,t}'$.

2.2 Iteration

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

Now, I assume that starting from period t_0, the Federal Reserve adopts the OPP as its policy guideline. 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 observe the impulse response of forecasts to interest rate shocks in reality, I estimated 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 on policy objectives and policy instruments within my theoretical framework.

3 Data

Forecast - To obtain the forecast data used for constructing the expected policy paths, I adopted the dataset compiled by Barnichon and Mesters (2023) covering unemployment rates, inflation rates, and the Fed funds rate (FFR) from 1980 to 2022. I extended this dataset to include data up to 2023. Forecast data from 2007 to 2023 were 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 were 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 were sourced from SEP, while data before 2007 were sourced from the Greenbook.

To further probe the impact of forecasts on OPP, I substituted the inflation rate, unemployment rate, and the Fed funds rate (FFR) forecast data sourced from the SEP with alternative datasets. I sourced 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 collected median forecasts for the next three years' PCE inflation rate and unemployment rate from the SPF. I linearly interpolated the quarterly forecast data for the fourth year. Despite this, I retained 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 utilized 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 employed 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 modified the dataset by replacing the data collected from the real-time database of the Federal Reserve Bank of Philadelphia, as used by Barnichon and Mesters (2023), with data from FRED Economic Data for backcasting. Through robustness test, 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 R. Gürkaynak, Karasoy-Can, and Lee (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 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.

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.

4 Preparations

4.1 Impulse Response Estimation

Table 1 reports the posterior results of the Bayesian Vector Autoregression (BVAR). Following the framework of Koop, Korobilis, 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 were used in conjunction with a Normal-Wishart prior to compute the posterior. For posterior computation, Gibbs sampling was employed with a total of 10,000 iterations without any burn-in period. The sample period for the regression analysis spans from the first quarter of 1991 to the third quarter of 2019.

Of particular interest are the coefficients between lag i of FF4 and the unemployment rate, inflation rate, and FFR. Here, the explanatory variables serve as instrumental variables

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.

representing policy shocks, specifically, surprises in the FFR beyond market expectations. 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, impulse responses of policy objectives and instruments to policy shocks can be estimated.

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 were 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 targets 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 targets and instruments cannot be ignored. In practice, I utilized the impulse response functions of policy targets 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

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

where $D.X_t^{actual}$ represents the first-order difference of policy objectives or policy instruments 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 7, which is the core coefficient we 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.

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	0.0938***	0.0583**	0.0518*						
	(0.0333)	(0.0282)	(0.0277)						
DPI0				0.516***	0.146***	0.0461			
				(0.144)	(0.0526)	(0.0453)			
DFFR0							0.760***	0.410***	0.232*
							(0.105)	(0.125)	(0.129)
constant	-0.0628	-0.0144	0.00804	0.0857	0.0062	0.0310*	0.0372	0.0365	0.0141
	(0.0529)	(0.0447)	(0.0440)	(0.0556)	(0.0202)	(0.0175)	(0.0566)	(0.0675)	(0.0698)
N	44	44	44	44	44	44	24	24	24
R^2	0.159	0.092	0.077	0.233	0.155	0.024	0.704	0.327	0.127

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.

5 Baseline Result

5.1 Baseline Counterfactuals

The starting period of iteration 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 the Fed funds rate, 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 that the Federal Reserve's policy has not consistently operated at an optimal level.

Specifically focusing on the FFR policy path, within the iterative subset OPP framework, it is evident that the Federal Reserve should have initiated rate hikes earlier, maintaining rates approximately 1.5 percentage point higher than the prevailing rates from early 2020

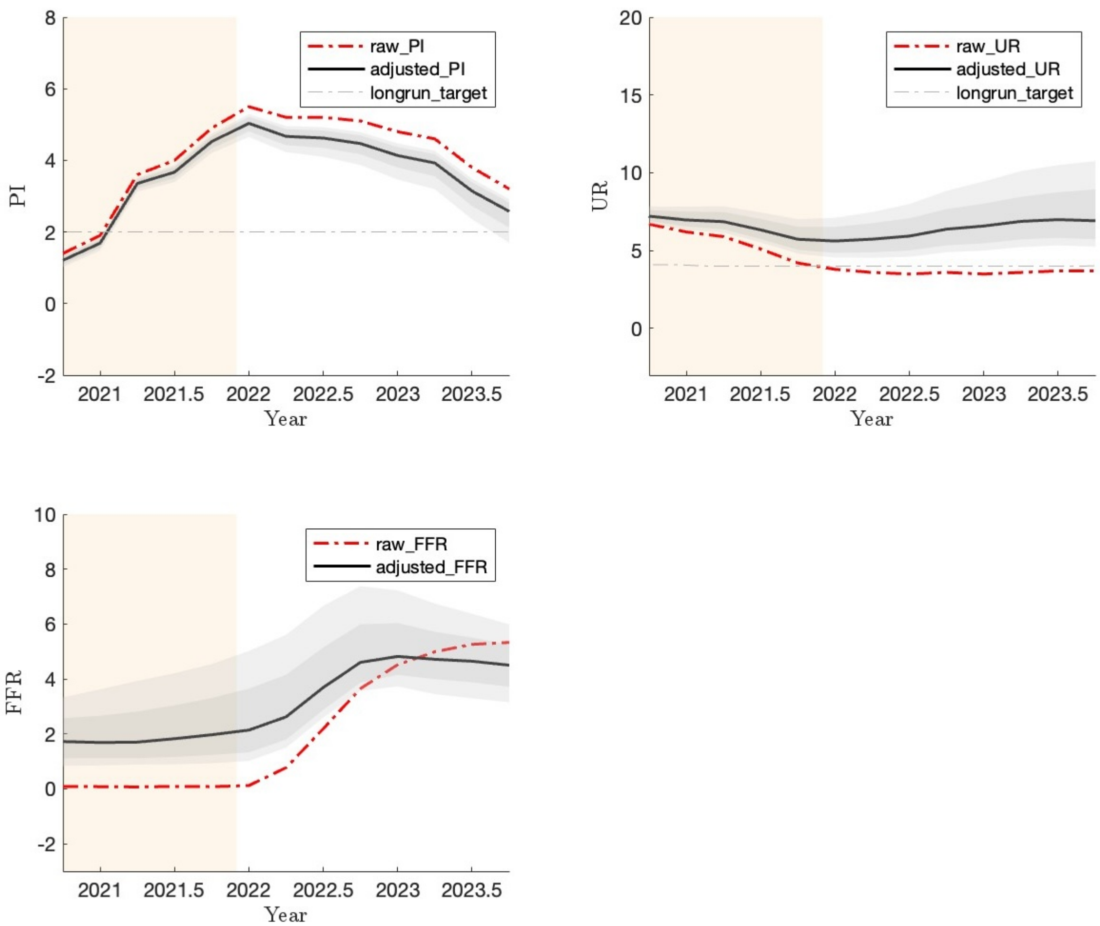

Figure 2: Inflation, Unemployment and FFR: Actual vs. Counterfactual, 2020Q4 to 2023Q4

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.

until around the first quarter of 2023. Under iterative 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, we 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 iterative OPP method has led to a reduction in high inflation levels from 2021 to 2023, indicating that a portion of the high inflation during this period was caused by the Federal Reserve's policy errors. 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 biases in the Fed's forecasts. 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 18.6% 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 non-optimal implementation of monetary policies by the Fed.

Table 3 presents the numerical differences between the counterfactual and actual 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

Table 3: Baseline Counterfactuals vs. Actual

Year	FFR_adj	PI_adj	UR_adj
2020.00	1.32	-0.03	0.05
2020.25	1.63	-0.09	0.11
2020.50	1.74	-0.08	0.30
2020.75	1.63	-0.19	0.51
2021.00	1.61	-0.21	0.77
2021.25	1.63	-0.25	0.96
2021.50	1.74	-0.33	1.23
2021.75	1.89	-0.38	1.53
2022.00	2.02	-0.47	1.82
2022.25	1.85	-0.53	2.14
2022.50	1.50	-0.58	2.44
2022.75	0.95	-0.63	2.78
2023.00	0.30	-0.67	3.08
2023.25	-0.27	-0.67	3.28
2023.50	-0.61	-0.66	3.29
2023.75	-0.83	-0.62	3.22

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.

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 Alternative Forecast Adjustment

I developed alternative ways of adjusting the forecast to further examine the robustness of the baseline results and provide other prospectives of welfare accounting. I approximated 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,

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

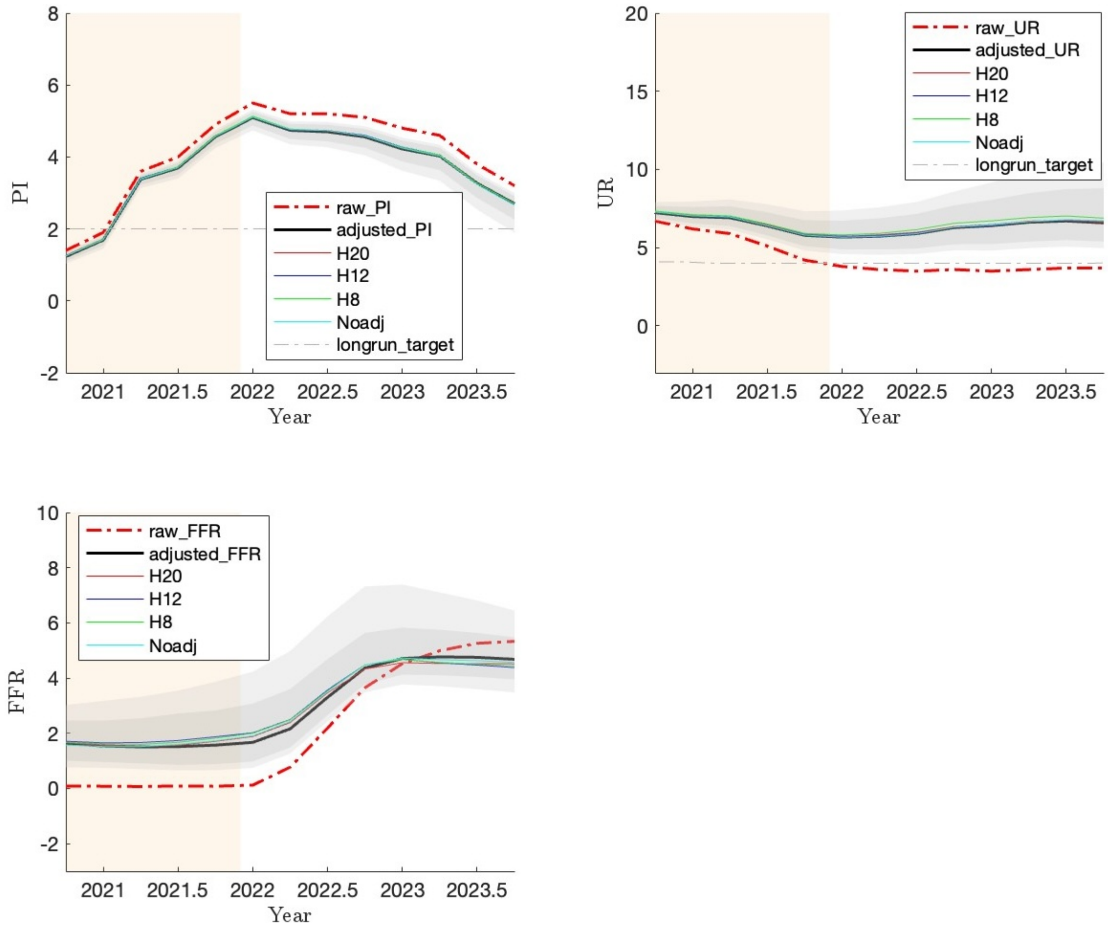

Figure 3: Different Forecast Adjustment Mechanisms

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.

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 targets 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 forecasted 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 computed the counterfactual paths under different periods of policy shock's impact on forecasts.

Figure 3 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.

5.3 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 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, assuming an expected OPP adjustment of zero and computing the standard deviation of OPP. I consider OPP adjustments exceeding one standard deviation to indicate significant policy errors 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 experienced significant errors. 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 divided 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

Table 4: Summary Statistics of Deviation by Period

Benchmark Period	Mean *BM*	Std. *BM*	Exceed Std Count	Exceed Std%
1985 - 2018.75	1.3901	1.0694	18	90.00%
1985 - 1989.75	-0.2960	0.1379	20	100.00%
1990 - 2007.75	0.0497	0.2279	19	95.00%
2008 - 2010.75	-0.1737	0.2401	19	95.00%
2011 - 2015.75	0.3201	0.3443	19	95.00%
2016 - 2018.75	1.1704	0.5928	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: Volcker disinflation (1985Q1 to 1989Q4), Major S&L crisis defaults (1990Q1 to 2007Q4), Great moderation (2008Q1 to 2010Q4), Financial crisis and Great Recession (2011Q1 to 2015Q4), Zero lower bound, recovery from Great Recession (2016Q1 to 2018Q4).

benchmark periods, along with the proportion of the baseline period OPP deviates by more than one standard deviation. The results further demonstrate that deviations between the FFR and the optimal policy path during the benchmark periods indicate 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, indicating a significant policy mistake of the Fed.

Figure 4 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 errors 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.

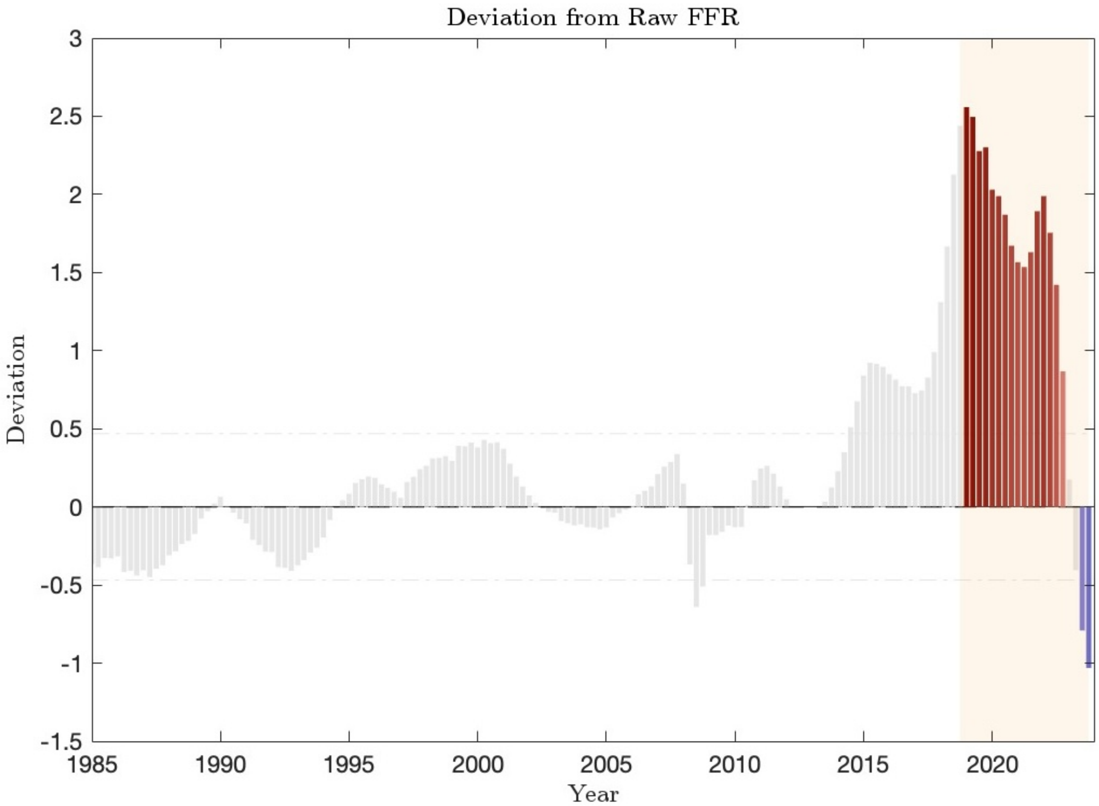

Figure 4: Deviations of FFR from 1990Q1 to 2023Q4

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).

5.4 Welfare Losses

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

The first subplot of Figure 5 illustrates the percentage change in welfare improvements from adopting the iterative OPP policy 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 under the iterative OPP path relative to the original path, measured by a loss function based. Specifically, the loss function represents the sum of squared differences between the forecasts of policy objectives and the

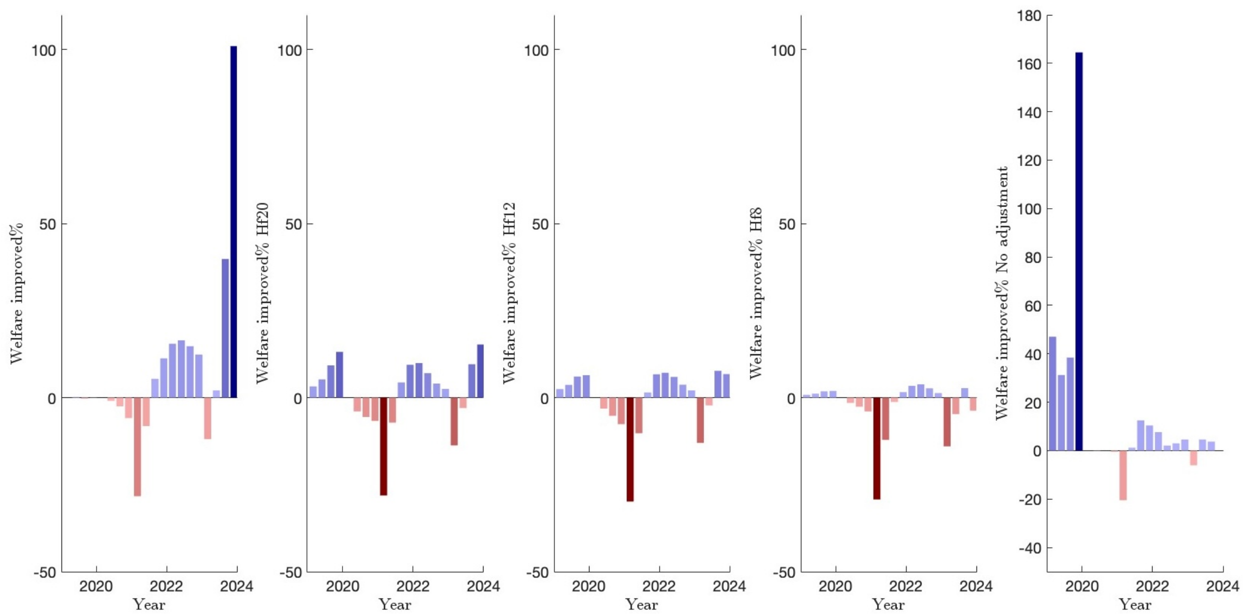

Figure 5: Welfare Improvements: Forecasts

Notes: This figure illustrates the average percentage of welfare improvements incurred from 2019Q1 to 2023Q4 due to adopting the iterative OPP method 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.

long-term targets.

In the baseline results, it can be observed that under the iterative OPP policy, welfare improved by approximately 5% to nearly 100% for most periods, indicating a certain degree of improvement after adopting the iterative OPP policy. 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 our theoretical framework, it is possible to observe a decline in welfare relative to the original policy path and policy expectations, despite the adjustment to the optimal policy.

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, on the counterfactual paths constructed using the iterative OPP method, it is evident that inflation, which we pay more attention to, can be well controlled. 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 5. 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 160%. This further confirms that welfare conditions based on forecasts within the iterative OPP framework generally improve for the majority of periods.

5.5 Robustness Checks

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

Figure 6 displays the counterfactual paths of policy objectives and instruments under different horizons. In the baseline results, I selected 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 replaced the horizon of 20 with 16, 24, 28, 32, and recalculated the counterfactual paths for different horizons. It can be observed that

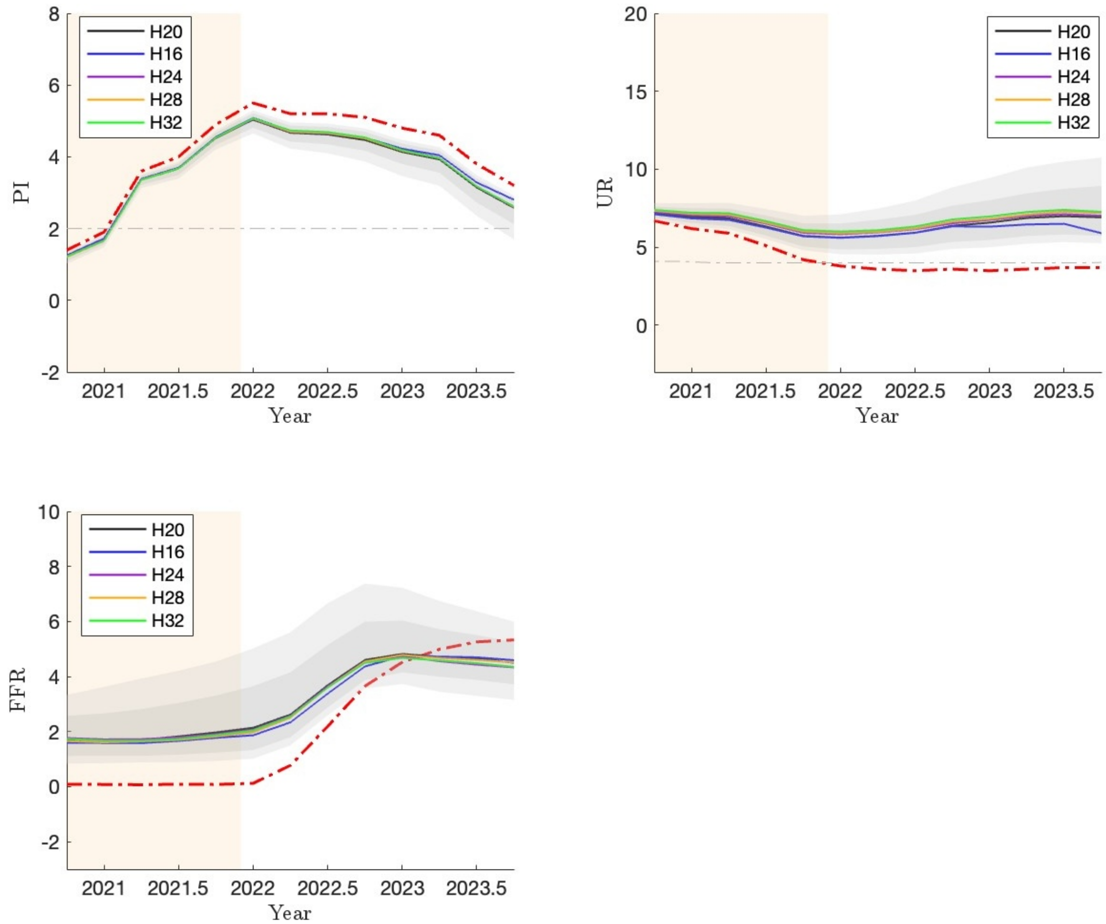

Figure 6: Robustness Checks with Different Horizons

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).

changing the horizon does not significantly alter the results.

Figure 7 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 introduced 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

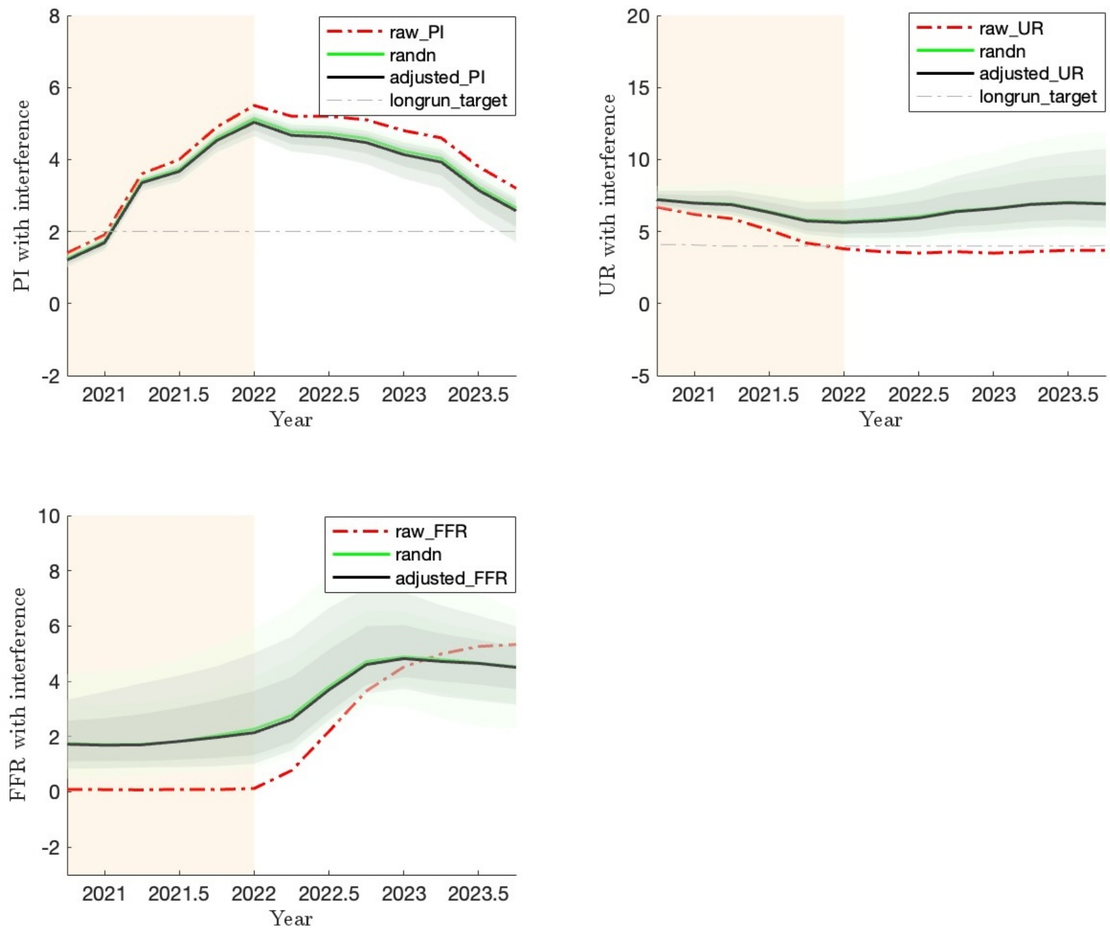

Figure 7: Robustness Checks with Random Shocks

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.

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.

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

6 Mechanisms

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

6.1 Forecasts

In our 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 our previous discussions, counterfactual policy target and instrument paths were calculated based on the forecast path fitted from the FOMC's SEP data, iterated to obtain the OPP. Subsequently, I collected forecast data on inflation rates and unemployment rates from the Survey of Professional Forecasters (SPF hereafter) by the Federal Reserve Bank of Philadelphia and the Surveys of Consumers (MSC hereafter) by the University of Michigan, and compared the calculated optimal policy adjustments and OPP-adjusted policy target paths for each period. As MSC does not provide forecast data for the unemployment rate, I supplemented it with SEP data.

Figure 8 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 interpolated 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 forecasts are higher than those of SEP and SPF, with a slower declining trend, particularly

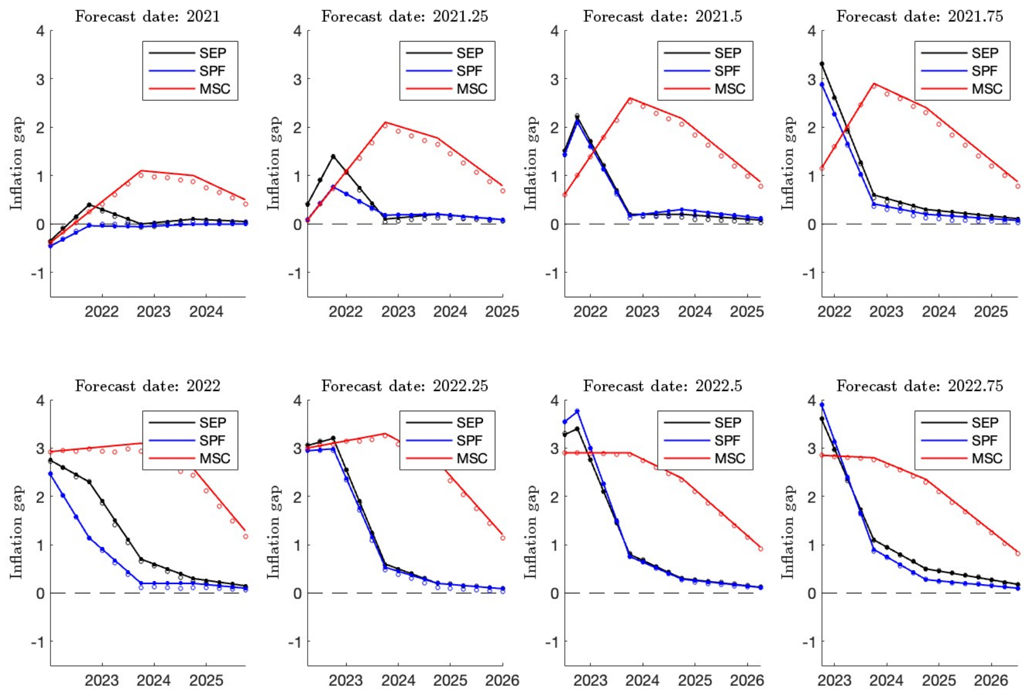

Figure 8: FFR Policy from 2021Q1 to 2022Q4 on Inflation.

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.

for long-term inflation rate forecasts. After OPP adjustments, all inflation forecast paths show a decline, with MSC experiencing a more substantial decrease. We have reason to believe 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, as well as the non-optimal FFR policies implemented based on forecast data. Adopting the measurement in the last section, about 19% of the inflation gap

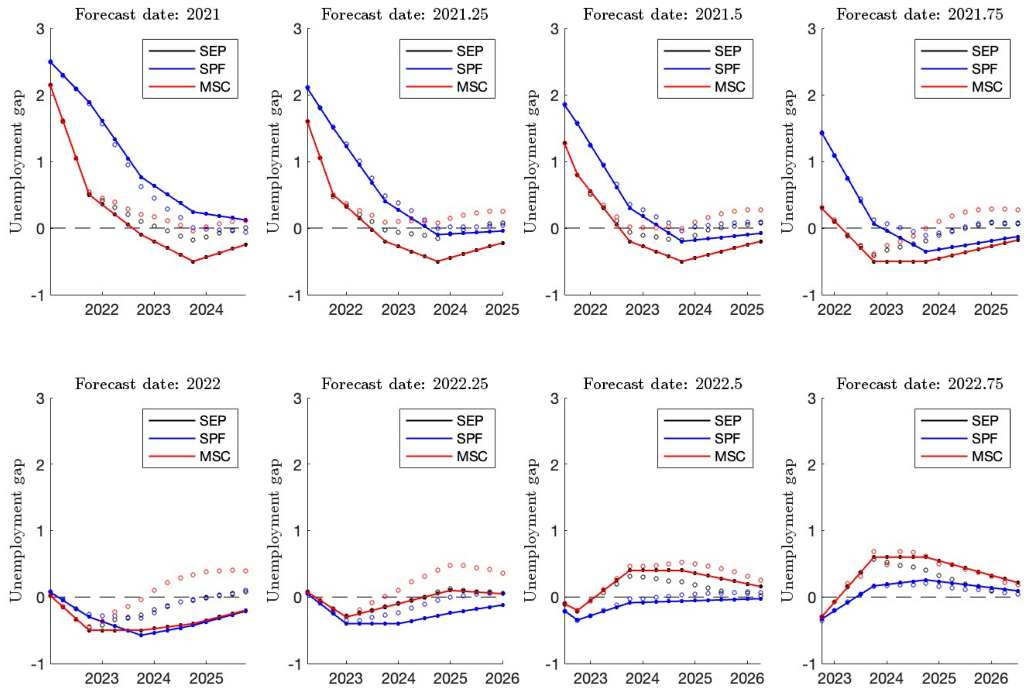

Figure 9: FFR Policy from 2021Q1 to 2022Q3 on Unemployment Rate

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.

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% of the inflation gap is due to the error in forecast of the Fed on the premise that the first quarter of 2019 is set as the starting period.

Figure 9 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 used 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. However, 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 targets and policy instruments after iteration are still unknown. I selected the first quarter of 2021 as the starting point for adopting the iterative OPP as the monetary policy decision framework and calculated the counterfactual paths for the inflation rate, unemployment rate, and FFR under different forecasts.

Figure 10 displays the counterfactual paths of policy targets 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. However, 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.

We have reason to believe that during the period from 2021 to 2023, when inflation is rising, 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

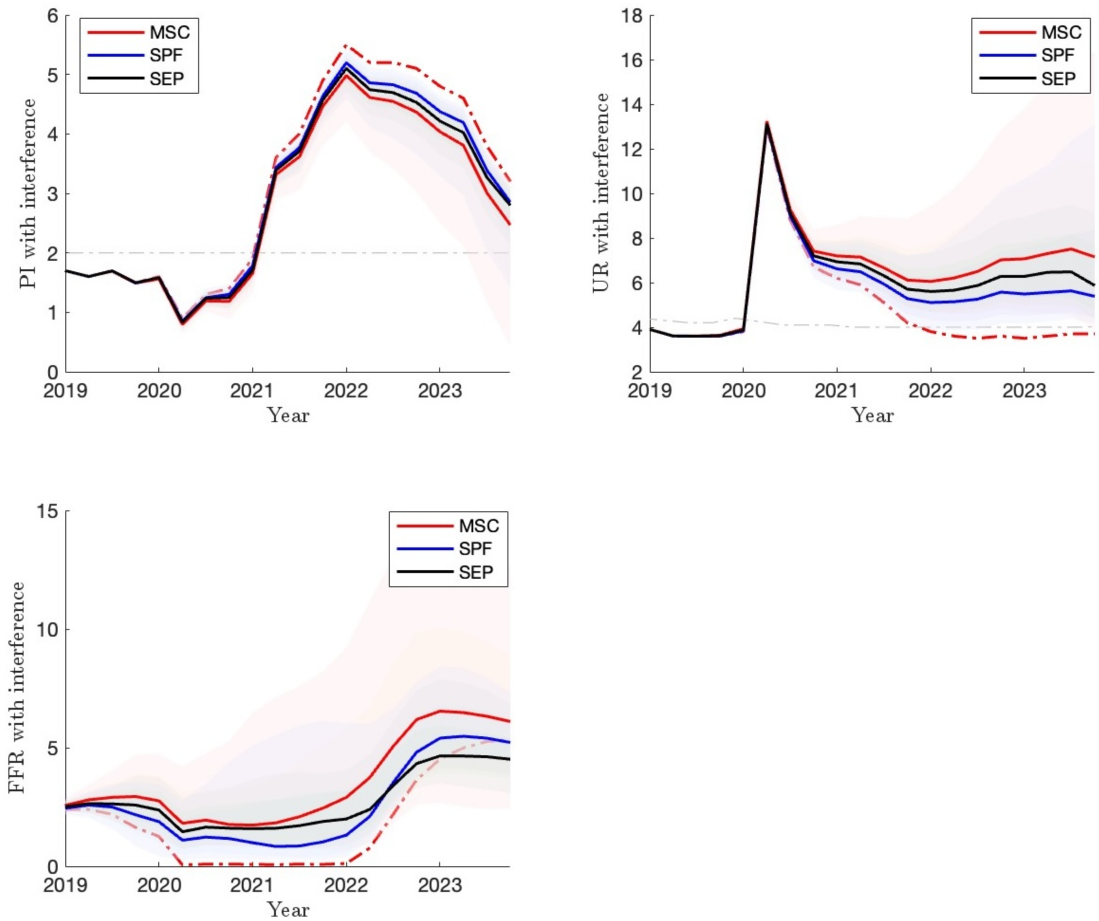

Figure 10: Different Forecasts for Iteration Starting in 2019Q1

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.

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, 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 6.4% 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 Fed.

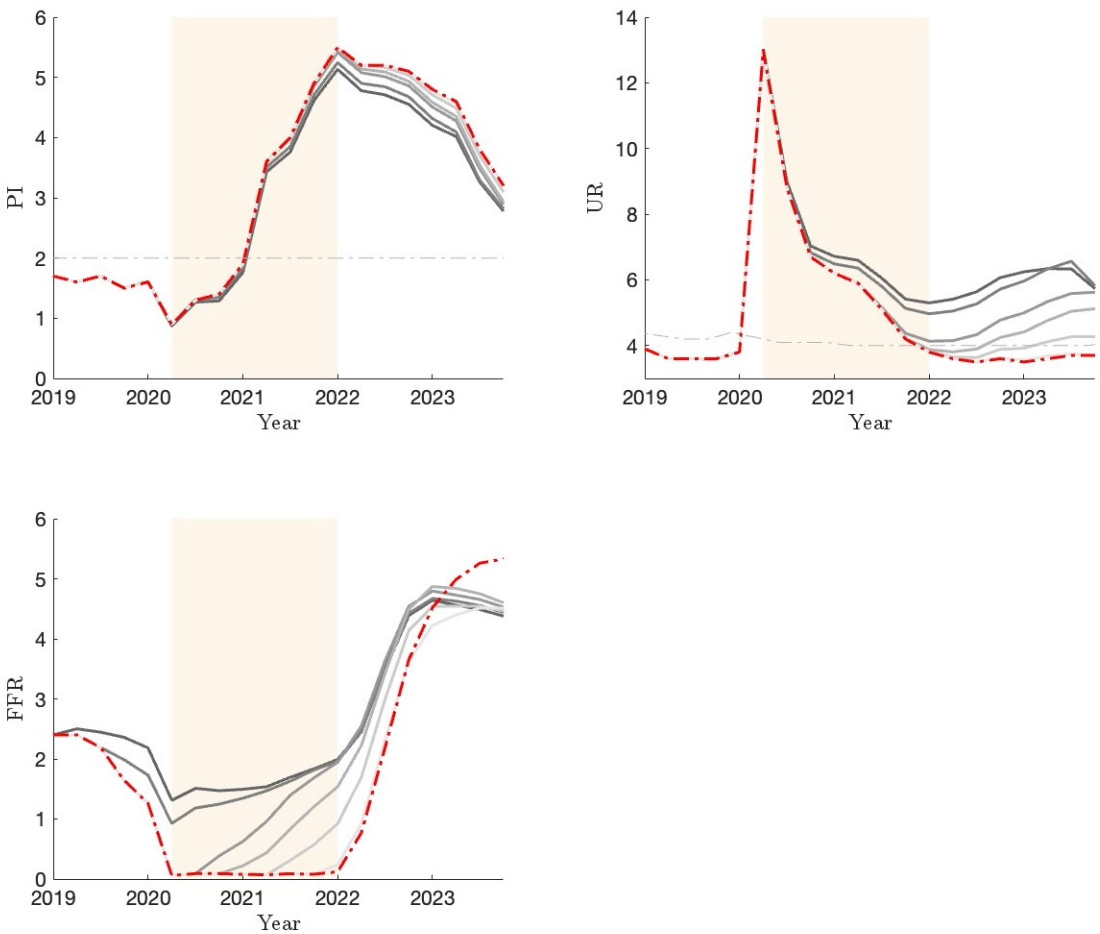

Figure 11: Inflation, Unemployment and FFR Iterated from 2019Q2 to 2022Q1

Notes: Iterations start from 2019Q2 to 2022Q1. The red dashed line represents the original data, the gray lines indicate the counterfactual paths. The later the iteration begins, the lighter the colour of the line. The shaded area corresponds to the period of imposing the zero lower bound (ZLB) constraint.

6.2 Starting periods

In the baseline results, I selected the first quarter of 2019 as the starting period for adopting iterative OPP. 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 11 illustrates the counterfactual path results obtained by taking the SEP forecast data as the forecast path, in steps of two quarters, from the second quarter of 2019 to the first

Table 5: Explainable Fraction

Starting Period	2019Q1	2021Q1	2022Q1
Policy Bias %	18.6216	5.9957	0.4411
Forecast Bias %	7.8914	6.3956	2.1561
Unexplained %	73.4871	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 iterative OPP 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.

quarter of 2022. It can be observed that the earlier the adoption of iterative OPP method, the earlier the FFR will be raised, with the highest increase of about 1.5 percentage points. The counterfactual inflation is lower, with the highest decrease of about 0.6 percentage points. For the unemployment rate, it tends to be higher but generally remains below 6%. Additionally, it can be observed that the earlier the adoption of iterative OPP policy, the smoother the path of FFR increases, consistent with the baseline result. However, regardless of the starting period chosen, the FFR is raised compared to the original path before the fourth quarter of 2022, further indicating that the FFR policy originally implemented by the Fed was too conservative.

Figure 12 displays the counterfactual paths initiated in the first quarter of 2021 and the first quarter of 2022 under different forecast data. Consistently with our previous conclusions, the earlier the adoption of iterative OPP strategy, the higher the counterfactual FFR path, the lower the counterfactual inflation path, and the higher the counterfactual unemployment rate path. Furthermore, we still observe that under the same starting period, the counterfactual FFR path is higher, the counterfactual inflation rate is controlled the lowest, and the counterfactual unemployment rate is higher, but overall remains below 6.5% for MSC forecast data, followed by SPF, and SEP is closest to the original path.

We numerically examine the counterfactual inflation paths under the adoption of the iterative OPP strategy and further adjustments to the forecast. The average decline in inflation can be attributed to deviations in policy and forecast.

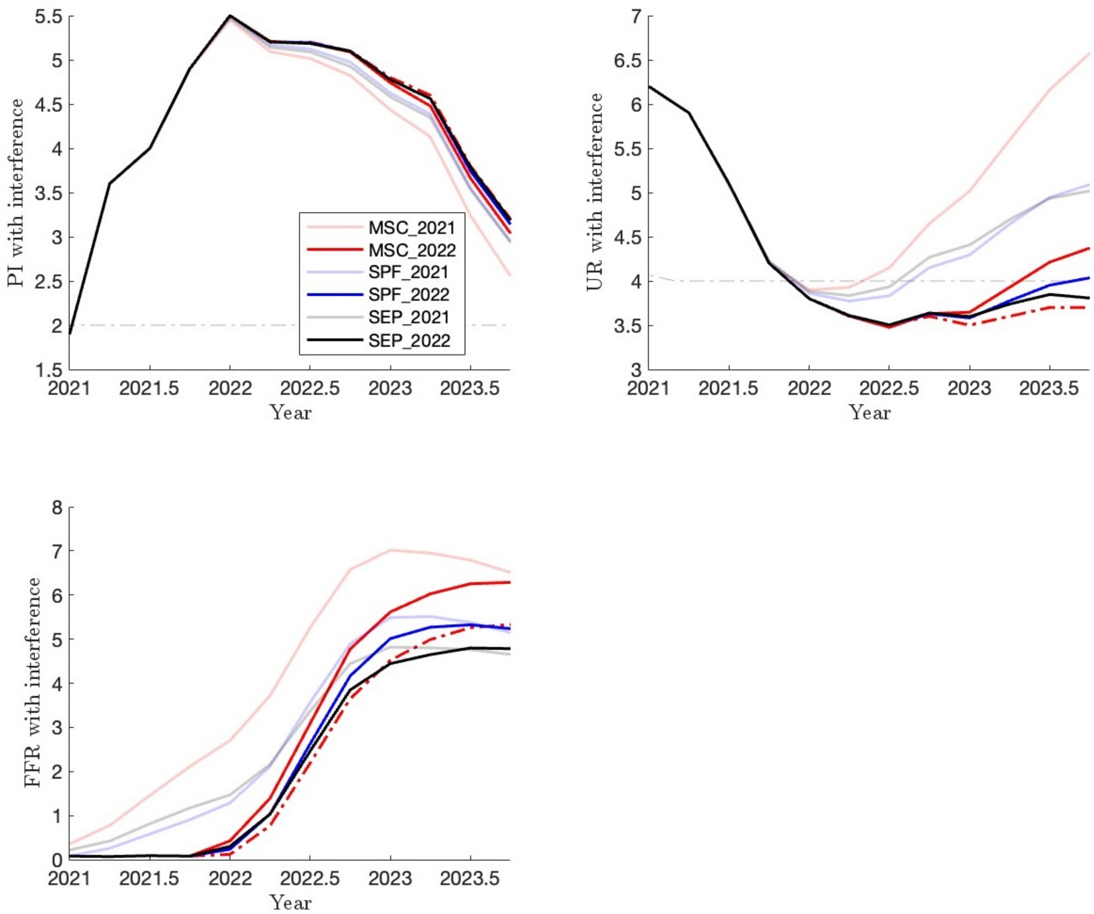

Figure 12: Different Forecasts for Iteration Starting in 2021 and 2022

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.

Table 5 depicts the results of the fraction of the biases. In the baseline results, the starting period is the first quarter of 2019, about 18.6% of the inflation gap can be attributed to Fed policy errors, and 7.8% can be attributed to Fed forecast errors. Under the assumption that the starting period is the first quarter of 2021, only 5.9% of the inflation gap can be attributed to Fed policy errors, and 6.3% can be attributed to Fed forecast errors. In contrast, assuming the starting period is the first quarter of 2022, only 0.4% can be attributed to policy errors, and only 2.1% can be attributed to forecast errors. This further validates that the earlier adoption of the iterative OPP strategy leads to better control of inflation.

7 Conclusion

This part has not been completed yet.

References

Barnichon, Régis and Geert Mesters (2023). "A sufficient statistics approach for macro policy". In: *American Economic Review* 113.11, pp. 2809–2845.

Brunnermeier, Markus et al. (2021). "Feedbacks: financial markets and economic activity". In: *American Economic Review* 111.6, pp. 1845–1879.

Coibion, Olivier and Yuriy Gorodnichenko (2015). "Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation". In: *American Economic Journal: Macroeconomics* 7.1, pp. 197–232.

Eberly, Janice C, James H Stock, and Jonathan H Wright (June 2019). "The Federal Reserveâs Current Framework for Monetary Policy: A Review and Assessment". In: Working Paper Series 26002.

Gürkaynak, Refet, HatiÌce Gökçe Karasoy-Can, and Sang Seok Lee (2022). "Stock market's assessment of monetary policy transmission: The cash flow effect". In: *The Journal of Finance* 77.4, pp. 2375–2421.

Gürkaynak, Refet S, Brian P Sack, and Eric T Swanson (2004). "Do actions speak louder than words? The response of asset prices to monetary policy actions and statements". In: *The Response of Asset Prices to Monetary Policy Actions and Statements (November 2004).*

Koop, Gary, Dimitris Korobilis, et al. (2010). "Bayesian multivariate time series methods for empirical macroeconomics". In: *Foundations and Trends® in Econometrics* 3.4, pp. 267–358.

Kuttner, Kenneth N (2001). "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market". In: *Journal of monetary economics* 47.3, pp. 523–544.

A Appendix

A.1 Bayesian Vector Autoregression

I drew upon the works of Kuttner (2001), Eberly, Stock, and Wright (2019), and R. S. Gürkaynak, Sack, and Swanson (2004). 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 the Fed funds rate, also known as the monetary policy surprise. It captures the disparity between the expected Fed funds rate and the actual Fed funds rate, serving to identify shocks to the contemporaneous Fed funds rate.

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

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

or

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

where $\varepsilon \sim N\left(0, \Sigma \otimes I_M\right)$, $\alpha|\Sigma, y \sim N\left(\widehat{\alpha}, \Sigma \otimes (X'X)^{-1}\right)$, 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

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

where

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

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

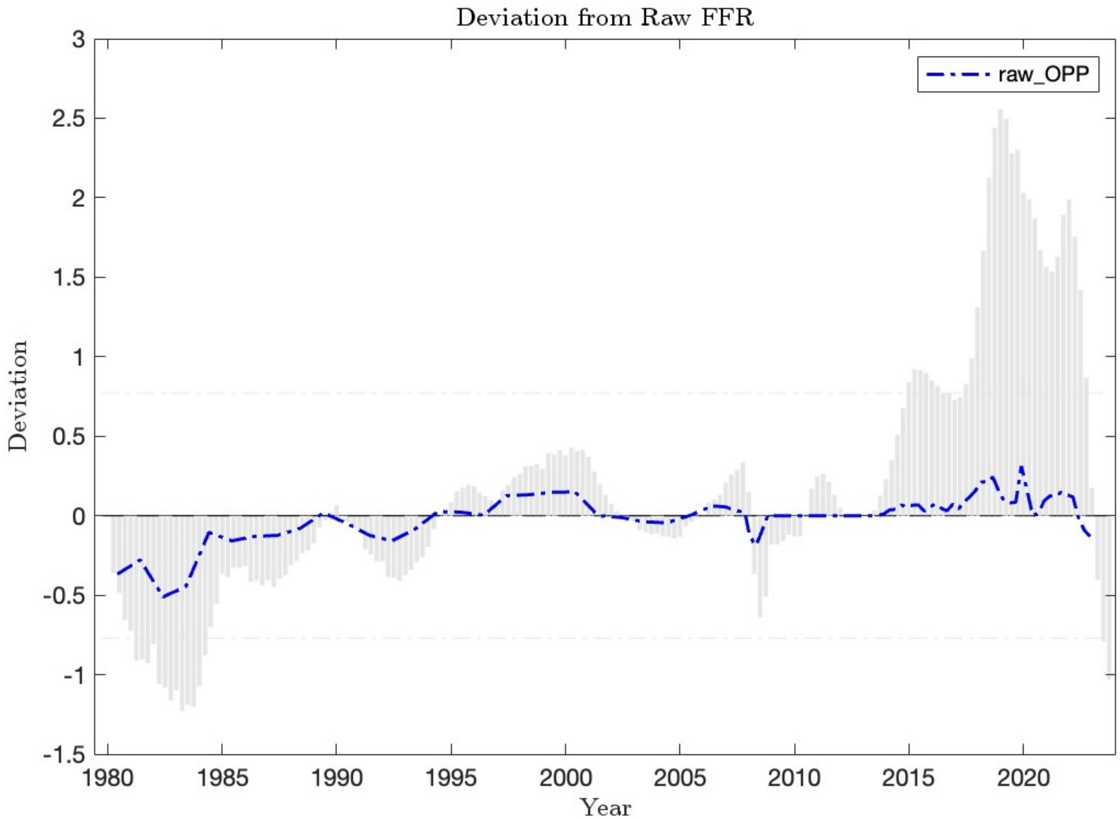

Figure A1: Robustness Checks with Original OPP

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

A.2 Robustness Checks

In Figure A1, I compared the results of iterative OPP 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 A2, I also compared the results of the OPP obtained using real-time data from the FRED Economic Data that I employed as backcast data with the OPP obtained from using real-time data from the Federal Reserve Bank, Philadelphia, as backcast data, as in

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

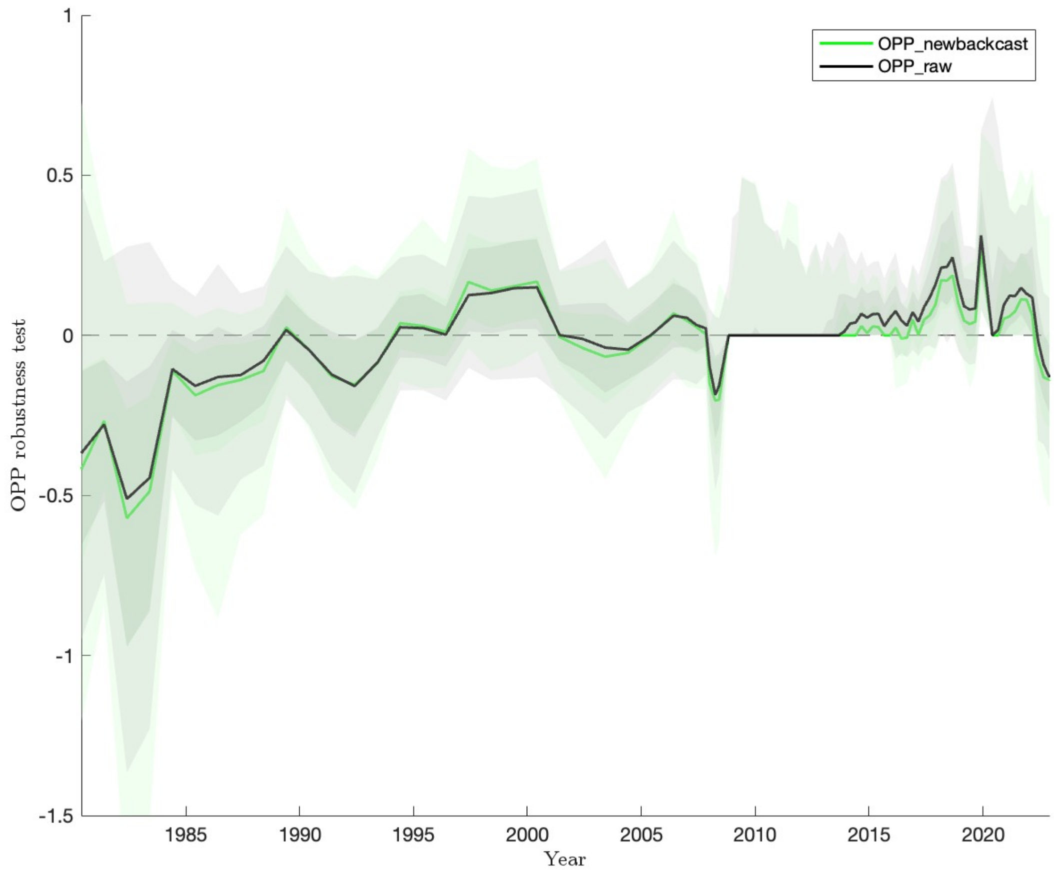

Figure A2: Robustness Checks with New Backcast

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.

A.3 Appendix Figures and Tables

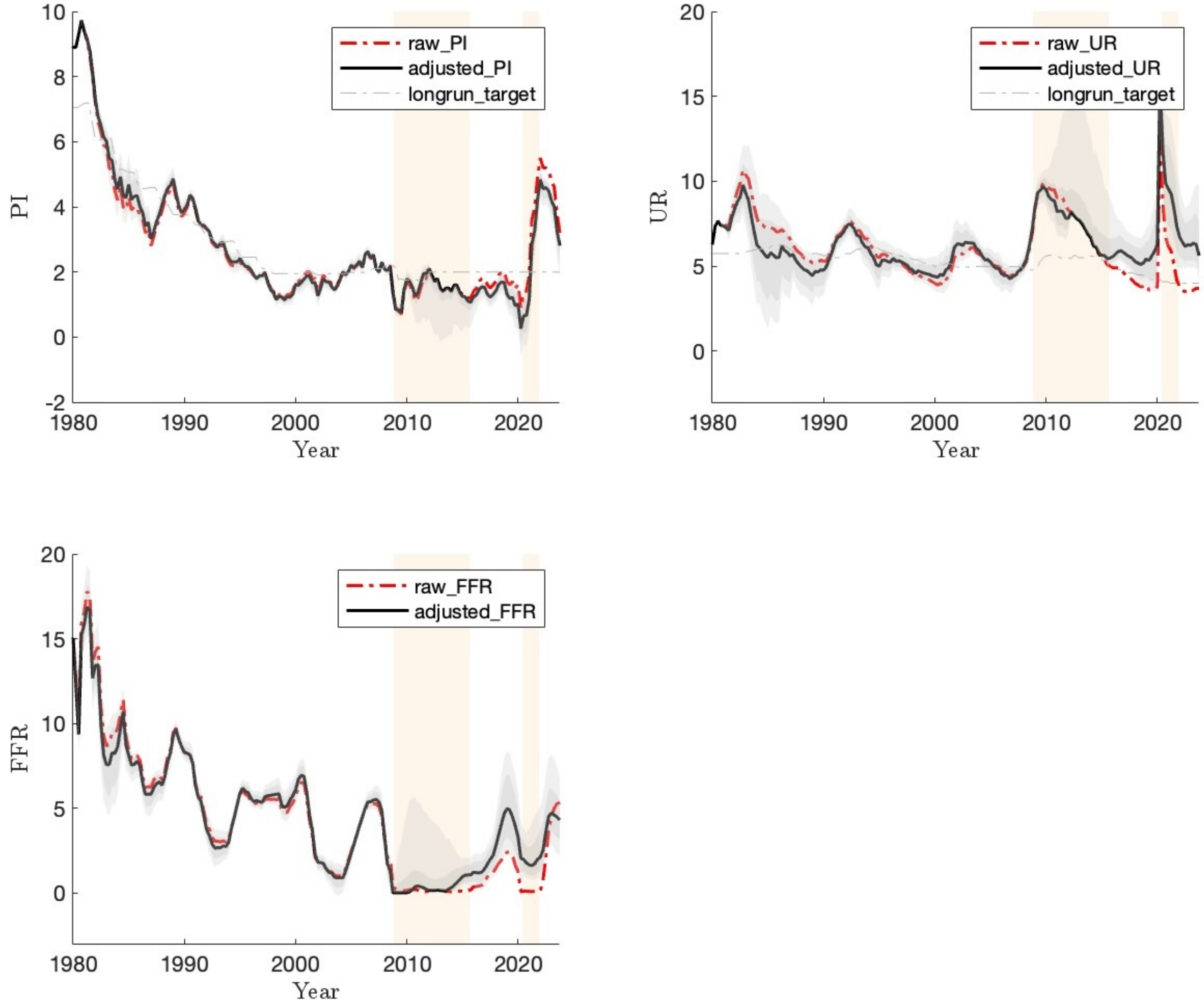

Figure A3: Inflation, Unemployment and FFR Iteration Starting from 1980Q1.

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.

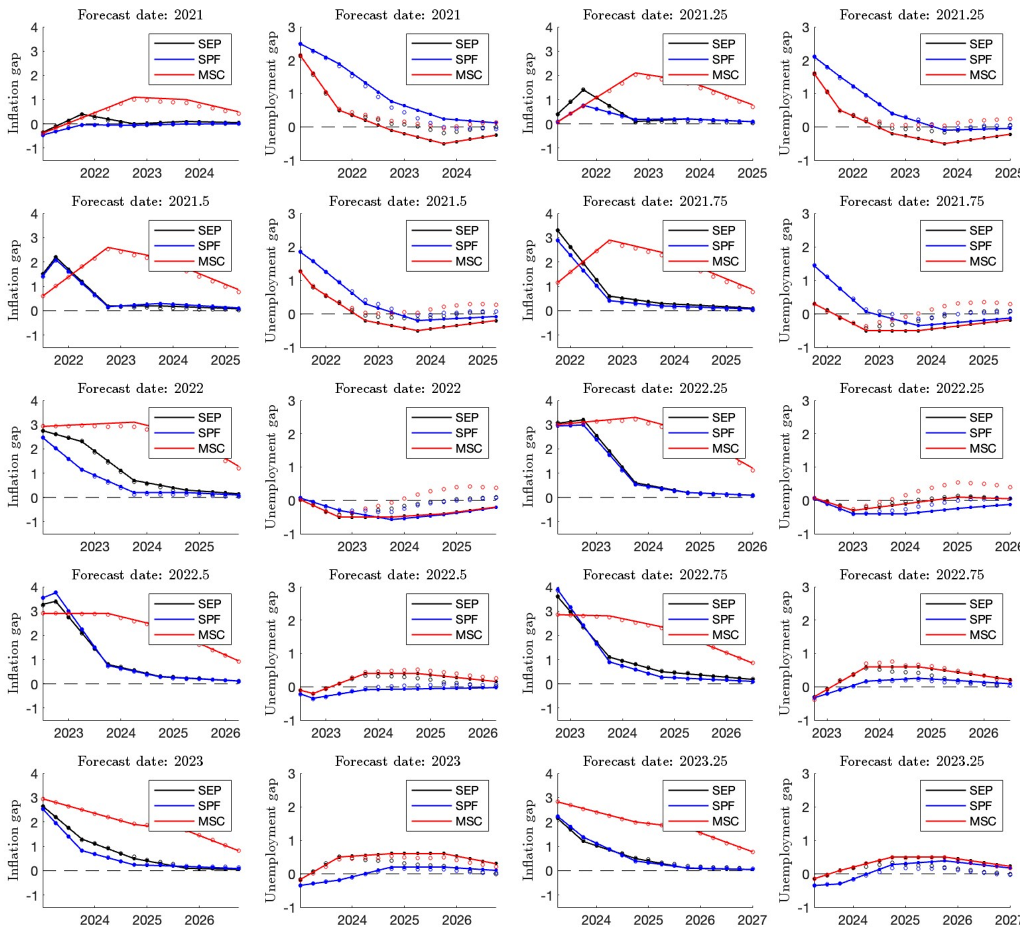

Figure A4: FFR Policy from 2021Q1 to 2023Q2.

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.