Evaluating the Efficiency of the FOMC's New Economic Projections

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Abstract

Since 2007, FOMC policymakers have been publishing detailed numerical projections of macroeconomic series over the next three years. By testing whether the revisions to these projections are unpredictable, I find that FOMC's efficiency is generally accepted for inflation, but often rejected for real economic variables, notably for the unemployment rate. The rejection is due to the strong autocorrelation of revisions, which may reflect information rigidity of FOMC's unemployment projections. The joint efficiency of the entire projection is accepted in most cases.

Keywords: FOMC, economic projections, forecast revisions, forecast efficiency, information rigidity

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1 Introduction

Since October 2007, the Federal Open Market Committee (FOMC) has been publishing the "Summary of Economic Projections" after the meetings. These economic projections are numerical projections of four macroeconomic series submitted by individual FOMC policymakers. With a few years of these new projections in hand, researchers can now begin to assess their efficiency.

The assessment of FOMC's new economic projections is important for two reasons. First, given the findings that subjective forecasts are often more accurate than forecasts using reduced-form models,[1] analyzing the efficiency of another subjective forecast is a subject of interest. In particular, these projections are based on profound knowledge and judgment about economics since the FOMC has made considerable efforts to make them more accurate and consistent with economic narratives. Second, the assessment of the FOMC's new projections is important in practice because monetary policy decisions are now explicitly tied to these projections and the public is keenly aware of them.[2]

In this paper, I evaluate the efficiency of FOMC's new projections by testing if their revisions are unpredictable. Even though the efficiency could be evaluated by testing the unpredictability of forecast errors, the power of the tests would be very low due to the short sample in hand. Therefore, I focus on the unpredictability of forecast revisions. I propose different tests based on the time-series property of forecast revisions (bias, autocorrelation, and Wald statistic) and signs of forecast revisions (positive revisions and consecutive revisions). In addition, I propose the joint tests across different target years and series to improve the power of the tests.

One limitation of this analysis is that the period in which these projections have been made (2007—2014) is very short, and contains an extremely turbulent period for the US economy. Forecasting a macroeconomic series is difficult even during the normal times, and evaluating the efficiency by looking at this particularly unusual period may not be appropriate. However, an evaluation in this early stage can still be a useful benchmark, considering close attention paid to the new projections. To evaluate the size and power of the tests in the small sample, I provide a Monte Carlo exercise. The simulation results show that the size is generally close to the nominal size

[1] For details, see Ang et al. (2007) and Faust and Wright (2009).

[2] For example, in December 2012, Bernanke (2012a) explains that the FOMC's decision to use their unemployment projections to give guidance on how long they will keep the federal fund rate low is to "make FOMC's intention to maintain accommodation more explicit."

(though the joint tests tend to be slightly oversized), and some tests are powerful even with a small sample, against a reasonable set of simulations where the forecasts are not efficient.

The results show a stark contrast between the forecast efficiency of real economic projections and inflation projections. While the efficiency is accepted for inflation in almost all years, it is often rejected for real economic variables, notably for the unemployment rate. For unemployment, the rejections between 2009 and 2011 are so strong that they lead to the rejections in the joint tests.[3] The joint efficiency of the entire projection is accepted in most cases.

In order to compare the results, I apply the same tests to the Survey of Professional Forecasters (SPF) forecast. Similar to the FOMC's projections, the efficiency of the SPF's inflation forecast is accepted in most cases. On the other hand, the SPF's unemployment forecast is not as inefficient as FOMC's unemployment projections. This comparison highlights that the revisions of FOMC's unemployment projections have a much stronger autocorrelation, which may reflect information rigidity in FOMC's unemployment projections.

This strong rigidity in FOMC's unemployment projections is puzzling for two reasons. First, it is not consistent with Okun's law, which draws an negative association between unemployment and GDP growth. Second, the FOMC's projections should in principle be at least as efficient as the SPF forecast, since they have an access to the Greenbook forecast—a forecast that is prepared by the staff of the Federal Reserve and generally more accurate than the SPF forecast. In order to facilitate the accurate interpretation of these results, I discuss the following explanations: (1) slower updating of FOMC's beliefs about unemployment, (2) FOMC's conservatism about their unemployment projections, and (3) different predictability of GDP growth and the unemployment rate.

Lastly, I provide an extension to the main results. I analyze the relationship between the revisions of the FOMC's GDP growth and unemployment projections to assess if they follow Okun's law. The regression analysis shows that the FOMC's projections are consistent with Okun's law only at the shorter horizons.

The remainder of the paper is organized as follows: Section 2 explains the projections I use,

[3] For example, projections for the fourth quarter of 2009 are all revised upward through 2007 to 2009, as described in Figure 1, which is highly unlikely under the null hypothesis of unpredictable forecast revisions.

and Section 3 describes the method of forecast evaluations and provides a Monte Carlo exercise. Section 4 contains the main results and Section 5 provides a regression analysis focusing on Okun's law as an extension. Section 6 concludes.

2 Data

The FOMC's economic projections are numerical projections of four macroeconomic series, real GDP growth, the unemployment rate, PCE inflation and Core PCE inflation, over next two to three years. Each FOMC policymaker submits his/her own projections at the FOMC meeting, and the range and the central tendency of projections are published after the meeting. The central tendency is the range of projections from which the three highest and lowest projections are excluded. In this paper, I focus on the midpoints of the central tendency and range to analyze the revisions of these projections.[4]

The FOMC has introduced these projections as a part of the Fed's enhanced communication strategy.[5] In many respects, they are considerably more detailed and informative than the old projections that had been released twice a year with the monetary policy report to US Congress. First, these new projections have been published more frequently than the old projections, four times a year, in March, June, September, and December.[6] Because FOMC policymakers have a chance to revise their projections right after the meeting, these projections can be regarded as the forecasts conditional on the information set of the meeting day.

Second, the horizons of new projections have been extended to three years; the old projections had a two-year horizon. The new projections aim to forecast the level of unemployment rate in the fourth quarter, and the rate of changes of real GDP and prices in the fourth quarter from a year earlier.

There are at most fourteen projections, and thus thirteen consecutive revisions, for an individual target year. Since these projections are newly introduced, the number of revisions for some target

[4]The results based on the upper end or the lower end of the projections are generally similar as the results using the midpoint of the projections. Gavin and Pande (2008) and Fischer et al. (2014) discuss the implication and caveats of taking the midpoints of intervals of FOMC's projections.

[5]For details, see Bernanke (2007) and Mishkin (2007).

[6]The projections used to be released typically in January, April, June, and November. But the FOMC has changed the timing since 2012, by releasing five projections in 2012.

year is limited. In my dataset, I have eight revisions for 2009, twelve revisions for 2010 and 2011, thirteen revisions for 2012 and 2013, and eleven revisions for 2014. The projections for 2008 and 2015 are dropped because the sample is too small.

Even though more detailed distribution of FOMC's projections is published three weeks after the meeting, it is anonymous and I cannot match individual policymaker's responses across different series and periods. Accordingly, I primarily focus on the central tendency and range of the projections.

3 Method

This section describes the tests I use to evaluate the efficiency of FOMC's projections. Based on an implication of forecast efficiency that the revisions are unpredictable, I propose several tests focusing on time-series property or signs of forecast revisions. In addition, I propose the joint tests using the average across target years and series as the test statistics. Then, I describe the inference based on the bootstrap. Lastly, I provide a Monte Carlo exercise assessing the size and power of the tests to show that small sample issues are not too pronounced.

3.1 Testable Implication of Forecast Efficiency

The idea of a forecast efficiency test using revisions dates back to Nordhaus (1987). Essentially, it is based on the implication that forecast revisions are unpredictable.[7] To formalize the idea, suppose that y_t is a variable of interest, and denote $\hat{y}_{t+h|t}$ as a forecast for period $t+h$, based on the set of variables observed in period t, $\mathbf{X_t}$. Then define the forecast revision for period $t+h$ between t and $t+j$, for any j such that $0 < j < h$, as $r_{t+h|t,t+j} \equiv \hat{y}_{t+h|t+j} - \hat{y}_{t+h|t}$.

It is well known that the optimal forecast is the conditional expectation of the series under a symmetric loss function. Therefore, the realized value at period $t+h$ is the sum of the conditional expectation, $E[y_{t+h}|\mathbf{X}_t]$, and its uncorrelated forecast error, $e_{t+h|t}$:

$$y_{t+h} = E[y_{t+h}|\mathbf{X}_t] + e_{t+h|t}. \tag{1}$$

[7]Isiklar et al. (2006) also evaluate the efficiency of Consensus Economics forecast by testing the unpredictability of revisions. For more recent application, see Loungani et al. (2013) and Sheng (forthcoming).

Then, the revision between t and $t+j$ is described as the difference between forecast errors in period t and $t+j$:

$$
\begin{aligned}
r_{t+h|t,t+j} &= E[y_{t+h}|\mathbf{X}_{t+j}] - E[y_{t+h}|\mathbf{X}_t], \\
&= e_{t+h|t} - e_{t+h|t+j}. \qquad (2)
\end{aligned}
$$

Since $e_{t+h|t}$ is also uncorrelated to $\mathbf{X}_{t+j}$, $r_{t+h|t,t+j}$ is uncorrelated to $\mathbf{X}_{t+j}$. As a result, revisions of the efficient forecasts are uncorrelated to any observable variables. By setting the maximum forecast horizon as H, the sequence of consecutive forecast revisions are described as $\{r_{t+H|t+h-1,t+h}\}_{h=0}^{H-1}$. In this paper, I primarily focus on this sequence of forecast revisions.[8]

3.2 Test for Individual Year and Series

In order to test the efficiency of FOMC's projections for an individual target year and series, I propose the methods focusing on two different properties of forecast revisions: *time-series properties* and *signs* of forecast revisions.

3.2.1 Tests Using Time-Series Properties of Revisions

For the tests using time-series properties of forecast revisions, I use three summary statistics: (1) Bias, (2) First-order autocorrelation, and (3) Wald statistic of the first-order autoregression. To define these statistics formally, consider a first-order autoregression of forecast revisions:

$$
r_{t+H|t+h-1,t+h} = \alpha_{t+H} + \beta_{t+H} \cdot r_{t+H|t+h-2,t+h-1} + \varepsilon_{t+h}. \qquad (3)
$$

The forecast efficiency implies both the intercept, α_{t+H}, and the coefficient, β_{t+H}, are zero. The first test statistic, the bias of forecast revisions, tests if $\alpha_{t+H} = 0$. The sample bias is computed as

[8] As pointed out by Patton and Timmermann (2012), incorporating forecast revisions will make the forecast evaluation significantly more powerful, which could be even used to improve the accuracy of forecasts as discussed in Arai (2014).

the average of forecast revisions:

$$\bar{r}_{t+H} = \frac{1}{H}\sum_{h=0}^{H-1} r_{t+H|t+h-1,t+h}. \tag{4}$$

The second test statistic, the first-order autocorrelation of forecast revisions, tests if $\beta_{t+H} = 0$. The sample autocorrelation is computed as the ratio of autocovariance to its variance:

$$\hat{\rho}^1_{t+H} = \frac{\hat{\gamma}^1_{t+H}}{\hat{\gamma}^0_{t+H}}, \tag{5}$$

where

$$\hat{\gamma}^j_{t+H} = \frac{1}{H}\sum_{h=0}^{H-j-1} (r_{t+H|t+h-1,t+h} - \bar{r}_{t+H})(r_{t+H|t+h+j-1,t+h+j} - \bar{r}_{t+H}) \quad \text{for} \quad j = 0, 1.$$

I use the sample mean $\bar{r}_{t+H}$ to measure the deviations of lagged series, and the total number of revisions H to normalize.

The third test statistic, the Wald statistic, jointly tests if $\theta_{t+H} \equiv [\alpha_{t+H}, \beta_{t+H}]'$ is a zero vector. The sample Wald statistic is computed as follows:

$$\hat{W}_{t+H} = H\ \hat{\theta}'_{t+H}[(Avar(\hat{\theta}_{t+H}))]^{-1}\hat{\theta}_{t+H}, \tag{6}$$

where $Avar(\hat{\theta}_{t+H})$ is the asymptotic variance-covariance matrix of $\hat{\theta}_{t+H}$. I estimate the asymptotic variance without any autocorrelation correction because the forecast efficiency implies that revisions are serially uncorrelated.

3.2.2 Tests Using Signs of Revisions

For the tests using signs of forecast revisions, I use two summary statistics: (1) Ratio of positive forecast revisions and (2) Ratio of the cases in which the consecutive forecast revisions have the same sign. The advantage of focusing on signs is that it gives the exact distribution of test statistics, which enables us to do the exact test.

The first test statistic summarizes how often the forecast revision is positive. Since the sign of revisions can be regarded as an outcome of the Bernoulli trial under the forecast efficiency, the number of positive revisions should follow *Binomial* $(H, 0.5)$. I divide it by H to normalize as the ratio.

To define the test statistic, first define the indicator variable $i^P_{t+H|t+h}$ for a target period of $t+H$:

$$i^P_{t+H|t+h} = \begin{cases} 1 & \text{if} \quad r_{t+H|t+h-1,t+h} > 0 \quad \text{for} \quad h = 0, \dots, H-1, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

Then, the test statistic is defined as the ratio of the sum of these indicator variables to the total number of forecast revisions:

$$b^P_{t+H} = \frac{1}{H} \sum_{h=0}^{H-1} i^P_{t+H|t+h}. \tag{8}$$

Similarly, I can define the second test statistic, which summarizes how often the consecutive forecast revisions have the same sign, as being either positive or negative. Since such event can also be regarded as an outcome of Bernoulli trial under the forecast efficiency, the number of such cases should follow *Binomial* $(H-1, 0.5)$. I divide it by $H-1$ to normalize as the ratio.

Let $i^C_{t+H|t+h}$ be the indicator variable for a target period of $t+H$:

$$i^C_{t+H|t+h} = \begin{cases} 1 & \text{if} \quad r_{t+H|t+h-1,t+h} \cdot r_{t+H|t+h,t+h+1} > 0 \quad \text{for} \quad h = 0, \dots, H-2, \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

Then, the test statistic is defined as the ratio of the sum of these indicator variables to the total number of consecutive forecast revisions:

$$b^C_{t+H} = \frac{1}{H-1} \sum_{h=0}^{H-2} i^C_{t+H|t+h}. \tag{10}$$

When a value of the forecast revision is zero, I compute these test statistics in two steps. First, I randomly assign a sign with the probability of 0.5 to compute these statistics. Second, I repeat this random assignment many times (100 times in this paper) to treat the mean as the test statistic.

One concern about focusing on signs is that it may over-simplify the forecast revisions, and thus the tests may not have enough power. However, as presented in a Monte Carlo exercise and the empirical results, these tests reject the null as many cases as the tests based on time-series properties, which suggests that the loss of the power associated with this simplification is not detrimental.[9]

3.3 Joint Test Across Years and Series

One limitation of the efficiency tests for an individual year and series is that they may not have enough power due to the short sample. In order to make tests more powerful, I compute the joint test statistics across different years and series by averaging individual test statistics.

First, I compute the average of individual test statistics across different target years. Define the vector of individual test statistics for the target year t as $\mathbf{x}_t \equiv \{\bar{r}_t, \hat{\rho}_t^1, \hat{W}_t, b_t^P, b_t^C\}$ for some series. Then the vector of joint test statistics from year T_s to year T_e is defined as the average of individual test statistics:

$$\bar{\mathbf{x}} \equiv \frac{1}{T_e - T_s + 1} \sum_{t=T_s}^{T_e} \mathbf{x}_t. \tag{11}$$

Second, I compute the average of these statistics across all series as the test statistic for the entire projections. The formal expression is abbreviated to conserve space.

3.4 Inference

I conduct the exact tests for the individual tests using signs, and approximate tests based on the bootstrap for other individual tests and joint tests. I report one-sided p-values for the Wald statistics and their averages, and two-sided p-values for other test statistics.

The bootstrap p-values are computed based the null hypothesis that the FOMC's projections are efficient, and therefore their revisions are serially uncorrelated. However, to keep the correlation among the forecast revisions at different horizons, I construct the artificial projections by resampling a block of multiple forecast revisions made at the same period. In addition, I apply the wild bootstrap to the FOMC's forecast revisions, in which I flip the sign of the resampled revisions with the probability of 0.5. This is because the distribution of forecast revisions are symmetric under the null hypothesis.

[9] Campbell and Ghysels (1995, 1997) also apply the similar tests to budget forecasts in the US and Canada, and claim that these tests have good finite sample power.

After constructing artificial projections, I apply the same tests to obtain the bootstrap test statistics. By repeating this procedure arbitrarily many times, I can form the distribution of bootstrap test statistics and report the p-value based on the percentile of the sample test statistics.

3.5 Monte Carlo Exercise

I conduct a Monte Carlo exercise to assess the size and power of the tests. The simulation results show that the size is generally close to the nominal size and some tests are powerful even with a small sample.

By constructing artificial forecast revisions using a reduced-form VAR, I first check if the actual probability of rejections is close to the nominal size. Then, I construct three types of inefficient forecasts to assess the power: (1) Forecasts with the independent noise, (2) Forecasts with the persistent noise across multiple horizons, and (3) Forecasts with the sluggish adjustments.[10] I use the data from 1984 to 2012 to calibrate the series, which includes both the Great Moderation and the period after the Great Recession, but excludes the period before the Great Moderation. The specific steps are described in detail in the Appendix A.

The simulation results with the nominal size of 10% are presented in Tables 1 to 4. The size is generally close to the nominal size in most individual tests. However, the consecutive sign test tends to be slightly oversized, and the joint test across different years and series tends to be oversized, with the actual size up to 23.6%.

For the power of the tests, the results show that the autocorrelation, Wald, and consecutive sign tests are much more powerful than the other two tests, and their higher power is robust across different simulations.[11] In particular, the autocorrelation and consecutive sign tests have an extremely high power close to 1, in all joint tests. These results show that some tests used in this paper are considerably powerful even with a small sample, against a set of reasonable simulations where the forecasts are not efficient.

[10] The variance of the noise is set to be unity in both the first and second simulations. However, the results are generally similar when the sample variance of each series is used.

[11] However, the poor power of the bias and positive sign tests is primarily due to the design of the simulations, in which all inefficient forecasts have the same mean as the efficient forecasts.

4 Results

In this section, I present the efficiency evaluation of FOMC's projections, showing that the efficiency is rejected often for real economic variables, especially for the unemployment rate, while it is accepted for inflation. Then I compare the results with the SPF forecasts to highlight that the revisions of FOMCs unemployment projections have a much stronger autocorrelation, which may suggest information rigidity of the projections. Then I discuss that slow updating, conservatism, or different predictability could help explain such rigidity.

4.1 FOMC's Economic Projections

The results using the midpoints of the central tendency and the range are presented in Tables 5 and 6, respectively. The results show that there is a stark contrast between the forecast efficiency of real economic projections and inflation projections. While the efficiency is accepted for inflation in almost all target years, it is rejected in many cases for real economic variables, notably for the unemployment rate. In particular, for the unemployment rate, the efficiency is rejected in most individual tests for the target years of 2009–2011. Furthermore, the joint efficiency is rejected in most joint tests across different target years because the rejections between 2009 and 2011 are so strong. Unlike the case of unemployment projections, the efficiency of output growth projections is accepted in most cases. The joint efficiency of the entire projections is accepted in most cases, and both the central tendency and the range of the projections provide similar results.

4.2 SPF Forecasts

The results of the SPF forecasts using the mean and the median are presented in Tables 7 and 8, respectively. Similar to the FOMC's projections, the efficiency of the SPF's real GDP growth and unemployment forecasts is rejected more often than inflation forecasts. However, the efficiency of the SPF's unemployment forecast is rejected only in 2009, which is not as strong as the rejections of FOMC's projections.

The comparison between the FOMC's projections and the SPF forecast shows that the revisions of FOMC's unemployment projections have much stronger autocorrelations. For example, the autocorrelations of the revisions for 2010 and 2011 are 0.00 and -0.03 for the SPF forecast (mean) but 0.53 and 0.48 for FOMC's projections (central tendency), respectively.

Such significant autocorrelations in the revisions may reflect information rigidity in FOMC's unemployment projections. For example, Coibion and Gorodnichenko (2010) observe a substantial degree of correlation among the SPF's forecast revisions, and consider it as evidence of information rigidity. Coibion and Gorodnichenko (2012) also show that a broad range of survey forecasts substantially deviate from the null hypothesis of full information, and show that their finding is consistent with the predictions of macroeconomic models with information rigidity. However, it should be noted that the FOMC's projections and the SPF forecast forecast differ slightly with respect to their targets and horizons,[12] and these differences may lead to their divergent evaluations of forecast efficiency.

4.3 Discussion

The strong rigidity of FOMC's unemployment forecasts is puzzling for two reasons. First, it is inconsistent with Okun's law, which draws an negative association between unemployment and GDP growth. In other words, if forecasters follow Okun's law, evaluations of GDP growth forecasts and unemployment forecasts should be similar.[13] Second, the FOMC's projections should be in principle at least as efficient as the SPF forecast, because the FOMC has an access to the Greenbook forecast, which is generally more accurate than the SPF forecast. To facilitate the accurate interpretation of these results, I list a number of possible explanations.

First, FOMC policymakers may have gradually learned of the effect of the Great Recession on the unemployment rate over the course of multiple years. As a result, the updating of their beliefs about unemployment happens at a rate slower than that about GDP growth. Considering

[12] The SPF forecasts are different from the FOMC's projections in two ways. First, the availability of longer-horizon forecasts are limited; Three-year ahead SPF forecasts starts from 2009Q2 for GDP growth and unemployment, and two-year ahead SPF forecasts start from 2007Q1 for inflation. Second, the SPF forecasts have different targets for GDP growth and unemployment; the SPF forecasts aim to forecast the *annual average* rate of GDP growth and level of unemployment.

[13] For the analysis of Okun's law during the Great Recession, see Elsby et al. (2010) and Daly and Hobijn (2010). Some FOMC policymakers, such as Yellen (2010) and Bernanke (2012b), observe that both the jump in the unemployment rate in 2009 and its decline in 2011 were not anticipated by Okun's law. Ball et al. (2012) examine cross-country data and argue that Okun's law did not substantially change during the Great Recession. Daly et al. (2014) claim that the deviation is not substantial considering the recent data revisions.

that FOMC policymakers have made substantial revisions to their unemployment projections at time-horizons exceeding one year, slower updating could be a likely cause of inefficiency.

Second, FOMC policymakers may be conservative about their projections for various reasons. For example, they may be concerned about the signalling value of their projections. In other words, FOMC policymakers may be cautious about changing their projections, because such changes would convey a message about future economic conditions. As a result, this concern may lead to smoothing in their projections. In addition, FOMC policymakers may focus on worst-case scenarios in their projections.[14] More specifically, even if the FOMC policymakers were to correctly recognize developments within the labor market, they may be conservative in updating their beliefs, because their recognition is subject to misjudgment in real time. Such considerations may also lead to the inefficiency in their projections. Other factors—such as strategic behavior among committee members or concern for their reputations as forecasters—could also be causes of FOMC's conservatism. Using a dataset of FOMC's old projections presented by Romer (2010), which includes the individual forecasts of each policymaker, Nakazono (2013), Rülke and Tillmann (2011), and Tillmann (2011) each point out that the forecasting behavior of FOMC members varies with their status within the committee (i.e., governors vs. voting members vs. nonvoting members). For example, they find that governors tend to have views close to the consensus whereas non-governors tend to have extreme views, which suggests that FOMC members strategically use their forecasts to influence FOMC's decisions. Jain (2013) suggests that forecasters' reluctance to make substantial revisions is sufficiently strong to lead to substantial forecast smoothing.

Finally, differences in predictability between output growth and the unemployment rate may lead us to reject the efficiency of unemployment projections more frequently. As Tulip (2009) points out, output growth has essentially become unpredictable after the Great Moderation. Consistent with his argument, the output growth and unemployment rates simulated in the Monte Carlo exercise in Section 3.5 also exhibit substantially different predictability. When projecting the artificial realized series on the conditional expectation, average R-square is 0.202 for the output

[14] Responding to Romer and Romer's (2008) criticism of the FOMC in terms of its inferior forecasting performance relative to the Greenbook forecast, Ellison and Sargent (2012) provide a defense by allowing the FOMC to doubt the economic model that underpins the Greenbook forecast. They claim that it is inappropriate to evaluate FOMC's forecasting performance by using the same metric, because the FOMC's and Greenbook's forecasting objectives are different.

growth whereas 0.960 for the unemployment rate. Since the forecast evaluation proposed in this paper tests the unpredictability of forecast revisions, it could be easier for us to detect inefficiency in more predictable series, namely the unemployment rate.

5 Extension

To shed some light on the reason why the rejections of efficiency are stronger for the unemployment rate than GDP growth, I provide a regression analysis to assess if the FOMC's projections numerically follow Okun's law. Since Okun's law conventionally associates 1% faster GDP growth from the potential with 0.5% decline in the unemployment rate, the slope coefficient of the unemployment revisions on output growth revisions should be around -0.5. In addition to the analysis of revisions at individual horizons, I provide the analysis of cumulative revisions, which add up he revisions at all horizons, to see if these projections follow Okun's law in a medium term.

The confidence interval is computed by the block bootstrap, in which the artificial sample of a year is constructed by resampling from the sample of the same year. For example, an artificial sample of 2009 is made by resampling only from the sample of 2009. This is because the news at the current period could influence the forecasts both at shorter and longer horizons, and therefore its effect would likely to persist more than a year. As a result, I need to keep the correlation between the current revision and the revisions made more than a year before.

The results presented in Table 9 show that the FOMC's projections are consistent with Okun's law at shorter horizons, but inconsistent at the longer horizon. For nowcasts and 1-year ahead projections, correlations are negative: -0.41 and -0.81 for the central tendency and -0.41 and -0.72 for the range, respectively. On the other hand, the correlation in 2-year ahead projections is positive but the confidence interval is extremely wide. This is because FOMC participants substantially revise their 2-year ahead unemployment projections without changing the output growth projections. As a result, R^2 of the regression becomes very small. Furthermore, this large variation in unemployment revisions at 2-year horizon makes the slope coefficient of cumulative revisions strongly negative, -0.91 for the central tendency and -0.89 for the range. Figures 2 and 3 show the plots of the FOMC's GDP growth revisions and unemployment revisions based on the central tendency and the range, respectively, highlighting the difference between the projections at shorter and longer horizons.

6 Conclusion

In this paper, I evaluate the efficiency of FOMC's new economic projections by testing if their forecast revisions are unpredictable. These projections are released from 2007, and play an increasingly important role in formulation of U.S. monetary policy. Therefore, evaluating the quality of these projections is a matter of great importance for macroeconomists.

By applying several statistical tests focusing on the unpredictability of forecast revisions, I find that the efficiency of FOMC's projections is accepted for inflation in almost all target years, but often rejected for real economic variables, notably for the unemployment rate. Furthermore, the comparison with the SPF forecast shows that the inefficiency of FOMC's unemployment projections is due to the strong autocorrelation in revisions, which may reflect information rigidity in their unemployment projections.

I discuss that such strong rigidity may be related to three factors: slower updating of FOMC's beliefs about unemployment, FOMC's conservatism about their unemployment projections, and different predictability of GDP growth and the unemployment rate. Further research on disentangling these channels, especially using disaggregated data if it becomes public in the future, would yield a much better understanding of FOMC's decision making and their conduct of U.S. monetary policy.

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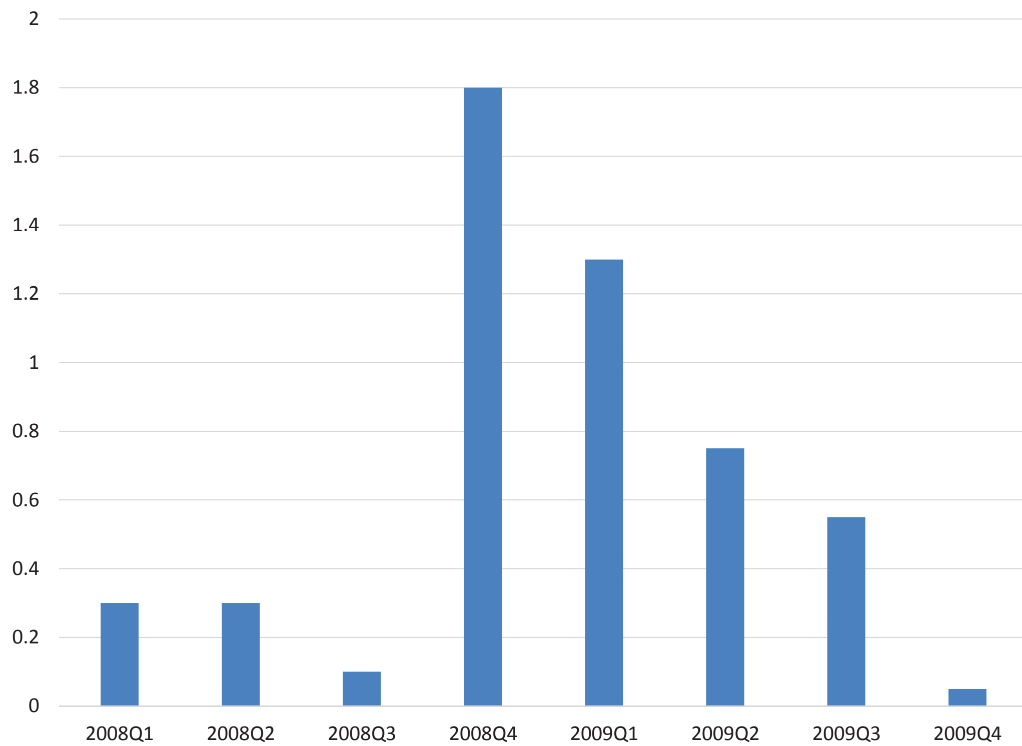

Figure 1: Revisions to FOMC's Unemployment Projections (Targeting 2009Q4)

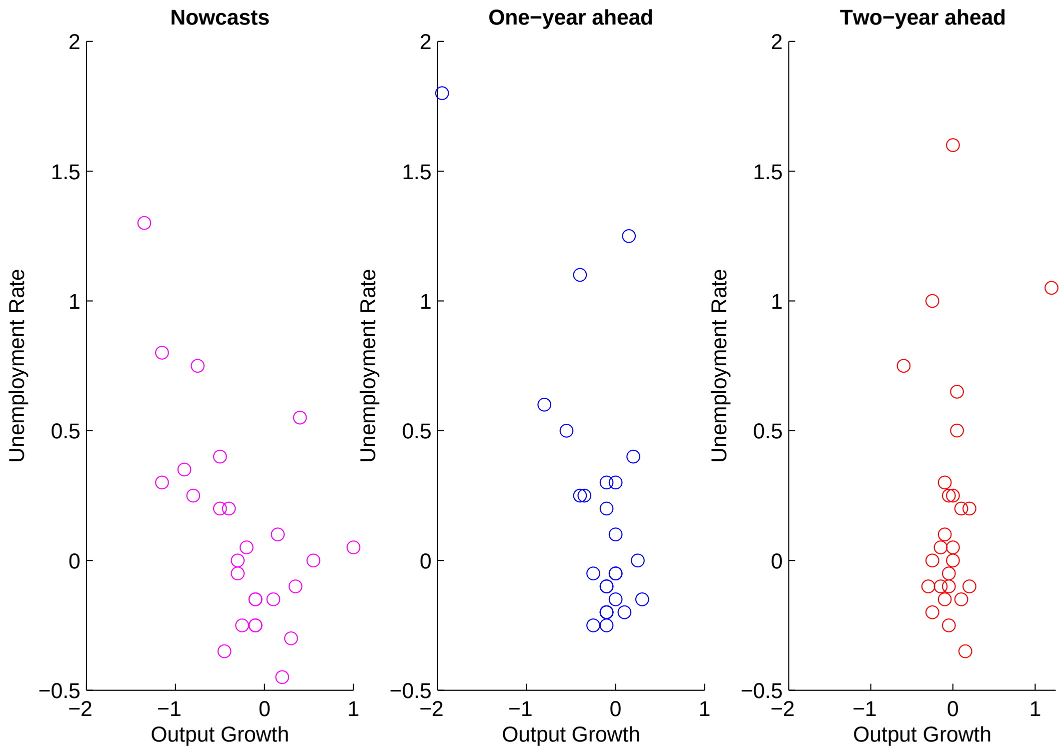

Figure 2: Revisions to FOMC's GDP Growth and Unemployment Projections (Central Tendency)

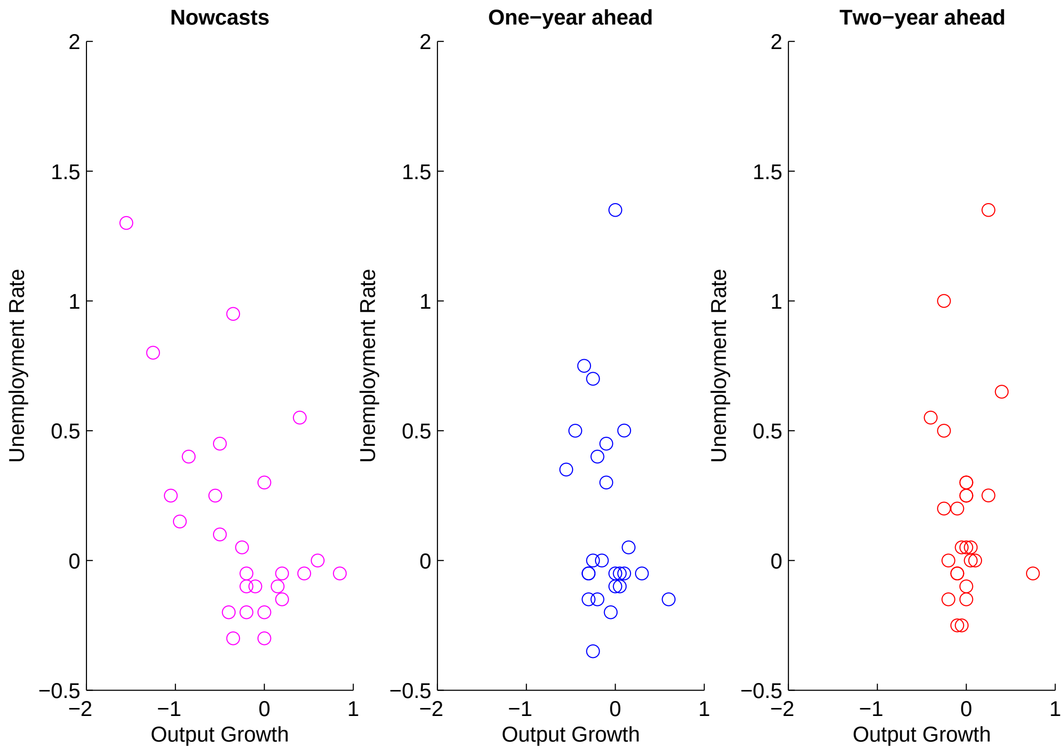

Figure 3: Revisions to FOMC's GDP Growth and Unemployment Projections (Range)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
Panel A: Size of the Test (Individual Year)					
GDP growth	0.099	0.126	0.117	0.089	0.150
Unemployment	0.096	0.105	0.090	0.087	0.144
PCE	0.105	0.113	0.096	0.101	0.148
Core PCE	0.096	0.097	0.087	0.102	0.125
Panel B: Size of the Tests (Average of Five Years)					
GDP growth	0.100	0.131	0.133	0.102	0.127
Unemployment	0.096	0.110	0.099	0.108	0.128
PCE	0.096	0.111	0.104	0.108	0.119
Core PCE	0.103	0.118	0.105	0.113	0.111
Panel C: Size of the Joint Test Across Years					
GDP growth	0.108	0.127	0.193	0.106	0.122
Unemployment	0.094	0.113	0.093	0.097	0.093
PCE	0.099	0.110	0.121	0.094	0.089
Core PCE	0.105	0.113	0.107	0.111	0.085
Panel D: Size of the Joint Test Across Years and Series					
	0.061	0.236	0.190	0.191	0.226

a. The results are based on 1,000 simulations, where the bootstrap with 1,000 replications is used for the inference in each simulation.

Table 1: Size of the Tests

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
Panel A: Power of the Tests (Individual Year)					
GDP growth	0.000	0.312	0.216	0.015	0.187
Unemployment	0.000	0.326	0.236	0.008	0.207
PCE	0.000	0.375	0.255	0.012	0.221
Core PCE	0.000	0.369	0.251	0.009	0.212
Panel B: Power of the Tests (Average of Five Years)					
GDP growth	0.001	0.287	0.190	0.024	0.134
Unemployment	0.000	0.292	0.206	0.020	0.149
PCE	0.000	0.310	0.215	0.017	0.151
Core PCE	0.000	0.315	0.216	0.018	0.153
Panel C: Power of the Joint Test Across Years					
GDP growth	0.002	0.816	0.274	0.013	0.664
Unemployment	0.004	0.848	0.324	0.015	0.693
PCE	0.000	0.867	0.342	0.017	0.714
Core PCE	0.000	0.883	0.334	0.009	0.732
Panel D: Power of the Joint Test Across Years and Series					
	0.000	1.000	0.578	0.011	0.998

a. Same as Table 1.

Table 2: Power of the Tests (Independent Noise)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
Panel A: Power of the Tests (Individual Year)					
GDP growth	0.003	0.283	0.210	0.008	0.179
Unemployment	0.000	0.326	0.215	0.009	0.190
PCE	0.000	0.338	0.239	0.005	0.194
Core PCE	0.001	0.349	0.262	0.010	0.192
Panel B: Power of the Tests (Average of Five Years)					
GDP growth	0.001	0.276	0.196	0.021	0.147
Unemployment	0.000	0.282	0.191	0.020	0.137
PCE	0.000	0.296	0.203	0.018	0.140
Core PCE	0.000	0.315	0.221	0.018	0.147
Panel C: Power of the Joint Test Across Years					
GDP growth	0.000	0.573	0.255	0.001	0.469
Unemployment	0.000	0.536	0.254	0.010	0.372
PCE	0.000	0.592	0.271	0.005	0.428
Core PCE	0.000	0.574	0.299	0.006	0.412
Panel D: Power of the Joint Test Across Years and Series					
	0.000	0.986	0.466	0.007	0.930

a. Same as Table 1.

Table 3: Power of the Tests (Persistent Noise)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
Panel A: Power of the Tests (Individual Year)					
GDP growth	0.219	0.298	0.274	0.160	0.426
Unemployment	0.244	0.532	0.363	0.192	0.489
PCE	0.228	0.393	0.312	0.198	0.479
Core PCE	0.249	0.407	0.313	0.192	0.484
Panel B: Power of the Tests (Average of Five Years)					
GDP growth	0.222	0.264	0.284	0.191	0.363
Unemployment	0.238	0.469	0.321	0.199	0.409
PCE	0.231	0.339	0.284	0.203	0.406
Core PCE	0.246	0.363	0.290	0.209	0.409
Panel C: Power of the Joint Test Across Years					
GDP growth	0.206	0.690	0.471	0.176	0.631
Unemployment	0.234	0.825	0.475	0.197	0.499
PCE	0.242	0.817	0.483	0.219	0.575
Core PCE	0.241	0.798	0.464	0.224	0.512
Panel D: Power of the Joint Test Across Years and Series					
	0.188	0.997	0.707	0.315	0.958

a. Same as Table 1.

Table 4: Power of the Tests (Sluggish Adjustment)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
Panel A: Real GDP Growth					
2009	-0.344*	0.370*	2.643	0.371	0.643
2010	-0.008	0.107	0.450	0.628	0.545
2011	-0.129	-0.058	4.432	0.335	0.404
2012	-0.185	0.146	6.054	0.236	0.627
2013	-0.138	-0.276	7.910*	0.231*	0.667
2014	-0.114	-0.185	4.669	0.322	0.392
Panel B: Unemployment Rate					
2009	0.644***	0.206	8.638*	1.000***	1.000***
2010	0.400**	0.527***	10.953**	0.833***	0.636
2011	0.250*	0.478**	8.454**	0.583	0.636
2012	0.054	0.036	0.486	0.464	0.500
2013	-0.008	0.073	0.061	0.309	0.667
2014	-0.109	-0.461	7.157	0.182*	0.600
Panel C: PCE Inflation					
2009	-0.088	0.235	0.658	0.554	0.490
2010	-0.038	0.046	0.653	0.539	0.455
2011	0.104	-0.129	2.377	0.583	0.364
2012	0.008	-0.632**	7.724*	0.494	0.320
2013	-0.050	-0.134	1.332	0.462	0.376
2014	-0.014	0.028	0.787	0.502	0.496
Panel D: Core PCE Inflation					
2009	-0.044	0.115	0.255	0.696	0.653
2010	-0.058	0.093	1.089	0.511	0.478
2011	0.029	-0.031	2.001	0.626	0.456
2012	0.023	-0.063	0.076	0.462	0.417
2013	-0.031	0.370*	3.206	0.460	0.498
2014	-0.018	-0.319	1.894	0.508	0.400
Panel E: Joint Tests Across Years					
GDP Growth	-0.153**	0.017	4.360	0.354**	0.546
Unemployment	0.205**	0.143*	5.958**	0.562	0.673**
PCE	-0.013	-0.098	2.255	0.522	0.417
Core PCE	-0.016	0.027	1.420	0.544	0.484
Panel F: Joint Test Across Years and Series					
	0.006	0.023*	3.498	0.495	0.530

a. Superscripts $*, **, ***$ denote the significance at the level of 10%, 5% and 1%, respectively. The bootstrap inference is based on 10,000 replications.

Table 5: Efficiency Tests of FOMC's Economic Projections (Central Tendency)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
		Panel A: Real GDP Growth			
2009	-0.331*	0.370*	2.469	0.500	0.429
2010	-0.004	0.008	0.064	0.616	0.640
2011	-0.150	0.078	2.964	0.376	0.453
2012	-0.162	-0.123	7.434*	0.268	0.542
2013	-0.131	-0.124	8.614*	0.272	0.582
2014	-0.132	0.113	69.335*	0.235	0.540
		Panel B: Unemployment Rate			
2009	0.656***	0.117	7.629*	0.750*	0.571
2010	0.400***	0.467**	10.763**	0.750**	0.818**
2011	0.242*	0.364*	6.692*	0.667	0.455
2012	0.077	0.139	1.406	0.580	0.545
2013	0.012	0.057	0.053	0.346	0.833**
2014	-0.114	0.186	13.909***	0.126**	0.766
		Panel C: PCE Inflation			
2009	-0.063	0.262	0.583	0.443	0.571
2010	-0.037	0.210	1.222	0.493	0.635
2011	0.133	-0.213	2.339	0.464	0.507
2012	0.035	-0.185	0.568	0.732*	0.459
2013	-0.012	0.136	0.318	0.466	0.617
2014	-0.023	-0.017	0.171	0.365	0.602
		Panel D: Core PCE Inflation			
2009	-0.037	0.110	0.378	0.549	0.397
2010	-0.050	-0.065	0.644	0.451	0.438
2011	0.046	-0.252	3.189	0.510	0.465
2012	0.035	0.071	0.431	0.467	0.543
2013	-0.008	0.080	0.122	0.465	0.410
2014	-0.018	-0.481	3.086	0.417	0.300
		Panel E: Joint Test Across Years			
GDP Growth	-0.152**	0.054	5.147*	0.378	0.531
Unemployment	0.212**	0.222**	6.742**	0.537	0.665**
PCE	0.006	0.032	0.867	0.494	0.565
Core PCE	-0.005	-0.089	1.308	0.476	0.426
		Panel F: Joint Test Across Years and Series			
	0.015	0.055**	3.516	0.471	0.547

a. Same as Table 5.

Table 6: Efficiency Tests of FOMC's Economic Projections (Range)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
		Panel A: Real GDP Growth			
2009	-0.723***	0.456**	8.728*	0.286	0.833**
2010	0.085	0.186	1.301	0.571	0.667
2011	-0.104	-0.134	1.148	0.300	0.444
2012	-0.071	-0.086	0.974	0.286	0.692*
2013	-0.095	-0.328	9.012**	0.200**	0.714*
2014	-0.109	-0.022	2.913	0.286	0.462
2015	-0.005	-0.813***	23.645***	0.500	0.111**
		Panel B: Unemployment Rate			
2009	0.587***	0.352*	10.617*	1.000***	1.000***
2010	0.143	0.005	0.085	0.571	0.500
2011	0.045	-0.032	0.127	0.600	0.556
2012	0.043	0.002	0.071	0.571	0.462
2013	0.008	-0.003	0.050	0.333	0.571
2014	-0.051	0.113	0.564	0.214*	0.692*
2015	-0.091	0.260	3.807	0.200	0.556
		Panel C: PCE Inflation			
2008	0.124	-0.228	1.120	0.714	0.500
2009	-0.089	-0.008	0.518	0.636	0.600
2010	-0.104	-0.286	5.864	0.364	0.500
2011	0.085	-0.035	0.811	0.545	0.500
2012	-0.024	-0.494	4.043	0.545	0.200
2013	-0.064	0.093	8.167	0.273	0.700
2014	-0.043	-0.052	1.629	0.200	0.778**
		Panel D: Core PCE Inflation			
2008	0.039	0.041	1.492	0.714	0.667
2009	-0.053	0.052	0.680	0.455	0.500
2010	-0.093*	-0.193	7.172*	0.182*	0.700
2011	0.021	0.230	0.640	0.545	0.600
2012	-0.019	-0.038	0.185	0.364	0.400
2013	-0.045	-0.036	4.420	0.455	0.700
2014	-0.038	-0.020	2.557	0.200	0.667
		Panel E: Joint Test Across Years			
GDP Growth	-0.146**	-0.106	6.817**	0.347**	0.561
Unemployment	0.098*	0.100	2.189	0.499	0.619
PCE	-0.016	-0.144	3.165	0.468	0.540
Core PCE	-0.027	0.005	2.449	0.416	0.605

a. Same as Table 5.

Table 7: Efficiency Tests of the SPF Forecast (Mean)

Projected Year	Bias	Autocorrelation	Wald	Signs, Positive	Signs, Consecutive
		Panel A: Real GDP Growth			
2009	-0.748***	0.478**	9.166*	0.286	0.833**
2010	0.073	0.145	0.884	0.571	0.667
2011	-0.075	-0.099	0.753	0.500	0.333
2012	-0.057	-0.434	4.381	0.429	0.462
2013	-0.096	-0.317	3.549	0.400	0.357
2014	-0.116	-0.237	2.684	0.357	0.385
2015	-0.000	-0.273	1.126	0.400	0.333
		Panel B: Unemployment Rate			
2009	0.597***	0.385*	11.784*	1.000***	1.000***
2010	0.121	-0.049	0.029	0.714	0.667
2011	0.034	-0.052	0.045	0.600	0.556
2012	0.029	-0.015	0.009	0.500	0.462
2013	0.009	-0.025	0.112	0.333	0.571
2014	-0.072	0.059	0.661	0.286	0.692
2015	-0.099	-0.164	3.003	0.200	0.556
		Panel C: PCE Inflation			
2008	0.109	-0.192	0.872	0.714	0.500
2009	-0.087	-0.026	0.379	0.455	0.500
2010	-0.094	-0.342	5.663	0.273	0.500
2011	0.078	-0.012	0.549	0.455	0.300
2012	-0.019	-0.288	1.063	0.545	0.400
2013	-0.073	0.543**	16.636**	0.273	0.500
2014	-0.027	-0.193	1.283	0.400	0.444
		Panel D: Core PCE Inflation			
2008	0.036	0.382*	1.719	0.714	0.667
2009	-0.064	0.111	1.008	0.364	0.500
2010	-0.087**	0.096	8.339**	0.091**	0.700
2011	0.009	0.190	0.503	0.545	0.500
2012	-0.013	0.164	0.410	0.273	0.600
2013	-0.045	0.402*	5.028	0.455	0.700
2014	-0.030	-0.026	1.198	0.100***	0.500
		Panel E: Joint Test Across Years			
GDP Growth	-0.146**	-0.105	3.220	0.420	0.481
Unemployment	0.089	0.067	2.235	0.519	0.643*
PCE	-0.016	-0.073	3.778	0.445	0.449
Core PCE	-0.028	0.189***	2.601	0.363	0.603***

a. Same as Table 5.

Table 8: Efficiency Tests of the SPF Forecast (Median)

	Nowcast	1-Year Ahead	2-Year Ahead	Cumulative
Panel A: Central Tendency				
Slope	-0.405	-0.812	0.288	-0.905
R^2	0.367	0.491	0.029	0.415
90% Conf. Int.	[-0.599, -0.166]	[-0.934, -0.277]	[-1.081, 0.745]	[-1.164, -0.421]
Panel B: Range				
Slope	-0.414	-0.720	0.112	-0.890
R^2	0.366	0.441	0.002	0.465
90% Conf. Int.	[-0.580, -0.170]	[-0.813, -0.324]	[-1.019, 1.200]	[-1.120, -0.500]

a. Analysis of cumulative revision is based on the sum of forecast revisions at all horizons.
b. Confidence interval is computed based on the block bootstrap.

Table 9: Regression Analysis of the FOMC's Unemployment Revisions on the GDP Growth Revisions

A Monte Carlo Exercise

A.1 Construction of Artificial Projections

1. Estimate a reduced-form quarterly VAR(1) of four variables, GDP growth, unemployment rate, PCE inflation and Core PCE inflation with a constant:

$$v_{t+1} = Av_t + \xi_t, \tag{12}$$

where

$$v_t = \begin{pmatrix} 1 \\ v_t^1 \\ \vdots \\ v_t^4 \end{pmatrix}, A = \left(\begin{array}{c|ccc} 1 & 0 & \cdots & 0 \\ \hline c_1 & a_{11} & \cdots & a_{14} \\ \vdots & \vdots & & \vdots \\ c_4 & a_{41} & \cdots & a_{44} \end{array}\right), \text{ and } \xi_t = \begin{pmatrix} 0 \\ \xi_t^1 \\ \vdots \\ \xi_t^4 \end{pmatrix}.$$

I use the vintage data of 2012 from 1984 to estimate A and the variance-covariance matrix of ξ_t. Denote estimates as $\hat{A}$ and $\hat{\Xi}$.

2. Generate the artificial realized series using $\hat{A}$ and $\hat{\Xi}$, by assuming that ξ_t is jointly normal.

3. Construct the efficient quarterly projections by iterations as in Table 10, under the null hypothesis that the forecast is the conditional mean. I assume that the realized value is not observable until the beginning of the next period. (For example, v_1 is observable at the beginning of period 2.)

	Nowcast	1Q ahead	$\cdots$	12Q ahead
Period 1	$\hat{A}v_0$	$\hat{A}^2v_0$	$\cdots$	$\hat{A}^{13}v_0$
2	$\hat{A}v_1$	$\hat{A}^2v_1$	$\cdots$	$\hat{A}^{13}v_1$
3	$\hat{A}v_2$	$\hat{A}^2v_2$	$\cdots$	$\hat{A}^{13}v_2$
$\vdots$	$\vdots$	$\vdots$		$\vdots$

Table 10: Simulated Quarterly Projections

4. Construct the efficient yearly projections in accordance with FOMC's projections, by assuming that period 1 is the fourth quarter of a year. Specifically, I pick the projection of the

unemployment rate for the fourth quarter, as in Table 11. Similarly, I compute the projection of GDP growth and inflation for the fourth quarter as the sum of realized values and quarterly projections, as in Table 12.[15]

	Nowcast	Year 1	Year 2	Year 3
Period 1	$\hat{A}v_0$	$\hat{A}^5v_0$	$\hat{A}^9v_0$	$\hat{A}^{13}v_0$
2	$\hat{A}^4v_1$	$\hat{A}^8v_1$	$\hat{A}^{12}v_1$	-
3	$\hat{A}^3v_2$	$\hat{A}^7v_2$	$\hat{A}^{11}v_2$	-
4	$\hat{A}^2v_3$	$\hat{A}^6v_3$	$\hat{A}^{10}v_3$	-
5	$\hat{A}v_4$	$\hat{A}^5v_4$	$\hat{A}^9v_4$	$\hat{A}^{13}v_4$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	

Table 11: Simulated Yearly Projections of the Unemployment Rate

	Nowcast	Year 1	Year 2	Year 3
Period 1	$\sum_{k=-2}^{0} v_k + \hat{A}v_0$	$\sum_{k=2}^{5} \hat{A}^k v_0$	$\sum_{k=6}^{9} \hat{A}^k v_0$	$\sum_{k=10}^{13} \hat{A}^k v_0$
2	$\sum_{k=1}^{4} \hat{A}^k v_1$	$\sum_{k=5}^{8} \hat{A}^k v_1$	$\sum_{k=9}^{12} \hat{A}^k v_1$	-
3	$v_2 + \sum_{k=1}^{3} \hat{A}^k v_2$	$\sum_{k=4}^{7} \hat{A}^k v_2$	$\sum_{k=8}^{11} \hat{A}^k v_2$	-
4	$\sum_{k=2}^{3} v_k + \sum_{k=1}^{2} \hat{A}^k v_3$	$\sum_{k=3}^{6} \hat{A}^k v_3$	$\sum_{k=7}^{10} \hat{A}^k v_3$	-
5	$\sum_{k=2}^{4} v_k + \hat{A}v_4$	$\sum_{k=2}^{5} \hat{A}^k v_4$	$\sum_{k=6}^{9} \hat{A}^k v_4$	$\sum_{k=10}^{13} \hat{A}^k v_4$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	

Table 12: Simulated Yearly Projections of GDP Growth and Inflation

A.2 Computation of Forecast Revisions (Size)

Based on the efficient yearly projections, I compute the revisions of the unemployment rate projections as in Table 13, and compute the revisions of GDP growth and inflation projections as in

[15]These series are in continuously compounding rate of growth.

Table 14. Then, I apply the tests in this paper to these revisions. By repeating the whole exercise many times, I report the probability of rejections as the size of the tests.

	1st Year	2nd Year	3rd Year	$\cdots$
1st Period	$\hat{A}^4 v_1 - \hat{A}^5 v_0$	$\hat{A}^8 v_1 - \hat{A}^9 v_0$	$\hat{A}^{12} v_1 - \hat{A}^{13} v_0$	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	
4th Period	$\hat{A} v_4 - \hat{A}^2 v_3$	$\hat{A}^5 v_4 - \hat{A}^6 v_3$	$\hat{A}^9 v_4 - \hat{A}^{10} v_3$	$\cdots$
$\vdots$		$\vdots$	$\vdots$	
8th Period		$\hat{A} v_8 - \hat{A}^2 v_7$	$\hat{A}^5 v_8 - \hat{A}^6 v_7$	$\cdots$
$\vdots$			$\vdots$	
12th Period			$\hat{A} v_{12} - \hat{A}^2 v_{11}$	$\cdots$

Table 13: Simulated Revisions of the Unemployment Projections

	1st Year	2nd Year	3rd Year	$\cdots$
1st Period	$\sum_{k=1}^{4} \hat{A}^k v_1 - \sum_{k=2}^{5} \hat{A}^k v_0$	$\sum_{k=5}^{8} \hat{A}^k v_1 - \sum_{k=6}^{9} \hat{A}^k v_0$	$\sum_{k=9}^{12} \hat{A}^k v_1 - \sum_{k=10}^{13} \hat{A}^k v_0$	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	
4th Period	$v_4 + \hat{A} v_4 - \sum_{k=1}^{2} \hat{A}^k v_3$	$\sum_{k=2}^{5} \hat{A}^k v_4 - \sum_{k=3}^{6} \hat{A}^k v_3$	$\sum_{k=6}^{9} \hat{A}^k v_4 - \sum_{k=7}^{10} \hat{A}^k v_3$	$\cdots$
$\vdots$		$\vdots$	$\vdots$	
8th Period		$v_8 + \hat{A} v_8 - \sum_{k=1}^{2} \hat{A}^k v_7$	$\sum_{k=2}^{5} \hat{A}^k v_8 - \sum_{k=3}^{6} \hat{A}^k v_7$	$\cdots$
$\vdots$			$\vdots$	
12th Period			$v_{12} + \hat{A} v_{12} - \sum_{k=1}^{2} \hat{A}^k v_{11}$	$\cdots$

Table 14: Simulated Revisions of the GDP Growth and Inflation projections

A.3 Construction of Inefficient Projections (Power)

To compute the power of the tests, construct the three types of inefficient forecasts. Denote the efficient forecast constructed in Section A.1 as $\hat{y}^{b,*}_{t+h|t+j}$, for time $t+h$ made at time $t+j$ for $0 < j < h$.

1. The forecast with the independent noise is computed as follows:

$$\hat{y}^{b,I}_{t+h|t+j} = \hat{y}^{b,*}_{t+h|t+j} + \varepsilon_{t+h|t+j}, \tag{13}$$

   where $\varepsilon_{t+h|t+j}$ is an independent white noise.

2. The forecast with the persistent noise across multiple horizons are computed as follows:

$$\hat{y}^{b,P}_{t+h|t+j} = \hat{y}^{b,*}_{t+h|t+j} + \eta^{h-j-1}\varepsilon_{t+j}, \tag{14}$$

   where η is the parameter of the persistence in the noise such that $0 < \eta < 1$, and ε_{t+j} is an independent white noise. The forecaster receives an independent noise every period, but this noise affects all forecasts at different horizons. I set $\eta = 0.8$ in the simulation.

3. The forecasts with a sluggish adjustment are computed as follows:

$$\hat{y}^{b,S}_{t+h|t+j} = \delta\hat{y}^{b,*}_{t+h|t+j} + (1-\delta)\hat{y}^{b,*}_{t+h|t+j-1}, \tag{15}$$

   where δ is the parameter of the sluggishness in the adjustment such that $0 < \delta < 1$. The forecast is computed as the weighted average of efficient forecasts in the current period and the previous period. I set $\delta = 0.5$ in the simulation.

Given these inefficient forecasts, I apply the tests in this paper to the revisions of these forecasts. By repeating the whole exercise many times, I report the probability of rejections as the power of the tests.