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Evaluating the Efficiency of the FOMC's New Economic Projections

Since 2007, Federal Open Market Committee (FOMC) policymakers have been publishing detailed numerical projections of macroeconomic series over the next 3 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.

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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

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1. For details, see Ang, Bekaert, and Wei (2007) and Faust and Wright (2009).

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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 article, 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 (2007–14) is very short and contains an extremely turbulent period for the U.S. 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 (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. Simulation results also suggest that the bias due to the aggregation is quantitatively negligible.

The results show a stark contrast between the forecast efficiency of real economic projections and inflation projections. Although 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 from 2009 to 2011, 2014, and 2015 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.

To compare the results with the forecasts over the same period, I apply the same tests to the Survey of Professional Forecasters (SPF) forecast.[4] 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

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

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.

4. Although the Greenbook forecast—the forecast prepared by the staff of the Federal Reserve—would be an ideal candidate to compare the efficiency, it is only available for 2008 because of the 5-year embargo policy.

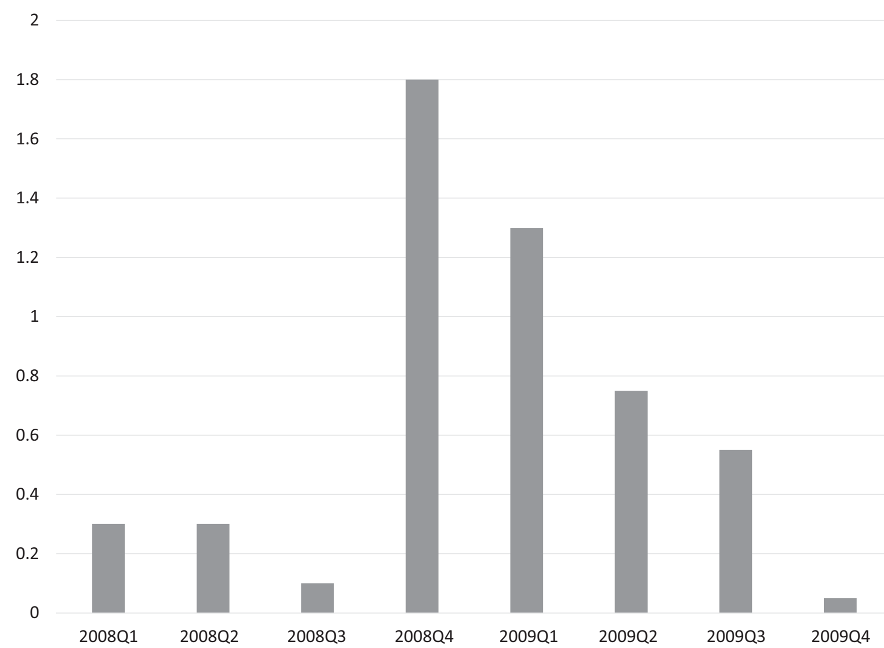

Fig. 1. Revisions to FOMC's Unemployment Projections (Targeting 2009Q4).

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 a negative association between unemployment and GDP growth. Second, the FOMC's projections should in principle be at least as efficient as the SPF forecast, because they have an access to the Greenbook forecast, which is generally more accurate than the SPF forecast. To facilitate the accurate interpretation of these results, I discuss the following explanations: (i) slower updating of FOMC's beliefs about unemployment, (ii) FOMC's conservatism about their unemployment projections, and (iii) different predictability of GDP growth and the unemployment rate.

The inefficiency of FOMC's projections could have important implications in the theoretical and empirical contexts. For example, even though FOMC's projections have been introduced as a part of the Federal Reserve's enhanced communication strategy,[5] whether the guidance based on inefficient projections helps or disrupts the monetary transmission mechanism is an open question in the literature. On the other hand, the inefficiency of the projections could help explain empirical

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

macroeconomic puzzles such as interest rate inertia during the Great Moderation and missing disinflation during the Great Recession.

Lastly, I provide two extensions to the main results. First, I analyze the relationship between the forecast revisions of GDP growth and unemployment to assess if the forecasts follow Okun's law. The regression analysis shows that both the FOMC's projections and the SPF forecast are consistent with Okun's law only at the shorter horizons. Second, I compare the performance of FOMC's projections and the SPF forecast prior to the Great Recession. The comparison suggests that the FOMC's projections are generally more accurate than the SPF forecast, but their forecast errors for inflation are systematic, which leads to the inefficiency of their projections.

The remainder of the article is organized as follows: Section 1 explains the projections I use, and Section 2 describes the method of forecast evaluations and provides a Monte Carlo exercise. Section 3 contains the main results and Section 4 provides extensions. Section 5 concludes.

1. DATA

The FOMC's economic projections are numerical projections of four macroeconomic series, real GDP growth, the unemployment rate, Personal Consumption Expenditure (PCE) inflation, and Core PCE inflation, over next 2–3 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 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 U.S. 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 3 years; the horizon of the old projections is fewer than 2 years. 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 14 projections, and thus 13 consecutive revisions, for an individual target year. Because these projections are newly introduced, the number of revisions for some target year is limited. In my data set, I have 8 revisions for 2009, 12 revisions for 2010 and 2011, 13 revisions from 2012 to 2014, and 9 revisions for 2015. The projections for 2008 and 2016 are dropped because the sample is too small.

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.

Even though more detailed distribution of FOMC's projections is published 3 weeks after the meeting, it is anonymous and I cannot match individual policymaker's responses across different series and periods.[7] Accordingly, I primarily focus on the midpoints of the central tendency and the range of the projections.[8]

2. 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 or aggregation issues are not too pronounced.

2.1 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.[9] 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, $e_{t+h|t}$:

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

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

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

7. Alichi et al. (2015) argue that the FOMC could improve the effectiveness of the policy by publishing a baseline projection that is more explicit about the conditions on which the projections are based.

8. The results based on the lowest or highest value of the projections are generally similar as the results using the midpoints. Gavin and Pande (2008) and Fischer et al. (2014) discuss the implication and caveats of taking the midpoints of intervals of FOMC's projections.

9. Isiklar, Lahiri, and Loungani (2006) also evaluate the efficiency of Consensus Economics forecast by testing the unpredictability of revisions. For more recent application, see Loungani, Stekler, and Tamirisa (2013) and Sheng (2015).

Because $e_{t+h|t}$ 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 article, I primarily focus on this sequence of forecast revisions.[10]

The inefficiency of the forecasts—a systematic relationship among the forecast revisions—has important implications in terms of economic theories. More specifically, the inefficiency could be associated with the economic models with dynamic properties or information frictions. For example, Ehrbeck and Waldmann (1996) showed that forecast revisions could be driven by reputational considerations of forecasters; thus, the forecast revisions became serially correlated under the framework of rational expectation. Coibion and Gorodnichenko (2010) observed a substantial degree of correlation among the SPF's forecast revisions and consider it as evidence of information rigidity. Coibion and Gorodnichenko (2012a) also showed that a broad range of survey forecasts substantially deviated from the null hypothesis of full information, and showed that their findings were consistent with the predictions of the macro-economic models with information rigidity.

2.2 Test for Individual Year and Series

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.

Tests using time-series properties of revisions. For the tests using time-series properties of forecast revisions, I use three summary statistics: (i) bias, (ii) first-order autocorrelation, and (iii) Wald statistic of the first-order autoregression. To define these statistics formally, consider a first-order autoregression of forecast revisions:

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

The forecast efficiency implies 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 the average of forecast revisions:

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

10. 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 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

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

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.

Tests using signs of revisions. For the tests using signs of forecast revisions, I use two summary statistics: (i) ratio of positive forecast revisions and (ii) 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. Because 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 $t + H$:

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

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 an 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 $t + H$:

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

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 article) to treat the mean as the test statistic.

One concern about focusing on signs is that it may oversimplify 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.[11]

2.3 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. 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 $\mathbf{x}_t \equiv \{\bar{r}_t, \hat{\rho}^1_t, \hat{W}_t, b^P_t, b^C_t\}$ 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:

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

11. Campbell and Ghysels (1995, 1997) also apply the similar tests to budget forecasts in the United States and Canada and claim that these tests have good finite sample power.

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.

2.4 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.

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.

2.5 Monte Carlo Exercise

I conduct a Monte Carlo exercise to assess (i) the size and power of the tests and (ii) effects of aggregating the projections by taking midpoints. The simulation results show that the size is generally close to the nominal size and some tests are powerful even with a small sample. The results also suggest that the aggregation bias is quantitatively negligible. The specific steps of both exercises are described in detail in the Appendix.

Size and power of the tests. 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: (i) forecasts with the independent noise, (ii) forecasts with the persistent noise across multiple horizons, and (iii) forecasts with the sluggish adjustments.[12] I use the data from 1984 to 2012 to calibrate the series, which include the Great Moderation and the period after the Great Recession, but excludes the period before the Great Moderation.

The simulation results with the nominal size of 10% are presented in Tables 1–4. The size is generally close to the nominal size in most individual tests. However, the

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

TABLE 1

Size of the Tests

	Bias	Autocorrelation	Wald	Signs, positive	Signs, consecutive
Panel A. Size of the test (individual year)					
GDP growth	0.093	0.127	0.117	0.089	0.160
Unemployment	0.095	0.112	0.112	0.097	0.125
PCE	0.100	0.106	0.096	0.101	0.149
Core PCE	0.088	0.102	0.100	0.098	0.122
Panel B. Size of the tests (average of 6 rears)					
GDP growth	0.089	0.120	0.127	0.111	0.121
Unemployment	0.099	0.106	0.099	0.115	0.106
PCE	0.101	0.113	0.098	0.114	0.122
Core PCE	0.100	0.114	0.098	0.112	0.112
Panel C. Size of the joint test across years					
GDP growth	0.096	0.103	0.169	0.103	0.084
Unemployment	0.099	0.116	0.091	0.106	0.097
PCE	0.105	0.113	0.099	0.099	0.105
Core PCE	0.104	0.114	0.094	0.082	0.084
Panel D. Size of the joint test across years and series					
	0.075	0.223	0.159	0.181	0.214

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

TABLE 2

Power of the Tests (Independent Noise)

	Bias	Autocorrelation	Wald	Signs, positive	Signs, consecutive
Panel A. Power of the tests (individual year)					
GDP growth	0.000	0.313	0.231	0.015	0.170
Unemployment	0.000	0.339	0.233	0.020	0.182
PCE	0.000	0.370	0.254	0.016	0.203
Core PCE	0.000	0.350	0.259	0.013	0.209
Panel B. Power of the tests (average of 6 years)					
GDP growth	0.001	0.300	0.211	0.023	0.141
Unemployment	0.000	0.318	0.211	0.023	0.143
PCE	0.000	0.315	0.213	0.024	0.151
Core PCE	0.000	0.317	0.218	0.021	0.142
Panel C. Power of the joint test across years					
GDP growth	0.000	0.899	0.349	0.013	0.776
Unemployment	0.001	0.921	0.367	0.017	0.796
PCE	0.000	0.928	0.378	0.012	0.805
Core PCE	0.001	0.951	0.379	0.012	0.800
Panel D. Power of the joint test across years and series					
	0.000	1.000	0.695	0.016	1.000

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

TABLE 3

Power of the Tests (Persistent Noise)

	Bias	Autocorrelation	Wald	Signs, positive	Signs, consecutive
Panel A. Power of the tests (individual year)					
GDP growth	0.002	0.315	0.220	0.014	0.203
Unemployment	0.000	0.355	0.251	0.019	0.196
PCE	0.000	0.348	0.240	0.010	0.203
Core PCE	0.000	0.352	0.230	0.013	0.205
Panel B. Power of the tests (average of 6 years)					
GDP growth	0.002	0.277	0.191	0.023	0.148
Unemployment	0.000	0.303	0.216	0.026	0.142
PCE	0.000	0.315	0.219	0.020	0.155
Core PCE	0.000	0.313	0.224	0.017	0.153
Panel C. Power of the joint test across years					
GDP growth	0.000	0.651	0.299	0.007	0.536
Unemployment	0.000	0.673	0.310	0.010	0.467
PCE	0.000	0.674	0.329	0.007	0.516
Core PCE	0.000	0.676	0.333	0.003	0.488
Panel D. Power of the joint test across years and series					
	0.000	0.997	0.554	0.007	0.974

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

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 21.4%.

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.[13] 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 article are considerably powerful even with a small sample, against a set of reasonable simulations where the forecasts are not efficient.

Aggregation bias. In this article, I focus on the midpoints of the central tendency and the range. However, one may have a concern that aggregating forecasts—reducing 19 or so forecasts to a single prediction—may substantially affect the properties of forecast revisions. For example, it is natural to assume that the individual policymakers take both of their previous projections and the consensus in the committee into account when submitting the projections. Yet such information is not

13. 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.

TABLE 4

Power of the Tests (Sluggish Adjustment)

Projected year	Bias	Autocorrelation	Wald	Signs, positive	Signs, consecutive
Panel A. Power of the tests (individual year)					
GDP growth	0.224	0.296	0.279	0.170	0.429
Unemployment	0.236	0.513	0.361	0.203	0.488
PCE	0.246	0.405	0.324	0.208	0.492
Core PCE	0.237	0.459	0.345	0.194	0.470
Panel B. Power of the tests (average of 6 years)					
GDP growth	0.222	0.262	0.268	0.198	0.360
Unemployment	0.237	0.462	0.327	0.223	0.403
PCE	0.237	0.342	0.298	0.217	0.393
Core PCE	0.243	0.396	0.310	0.215	0.399
Panel C. Power of the joint test across years					
GDP growth	0.235	0.776	0.447	0.187	0.729
Unemployment	0.231	0.867	0.499	0.208	0.565
PCE	0.236	0.900	0.568	0.212	0.632
Core PCE	0.239	0.886	0.536	0.206	0.583
Panel D. Power of the joint test across years and series					
	0.185	1.000	0.772	0.326	0.974

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

incorporated in aggregated projections, which may lead to substantial bias in the efficiency evaluation.

To see the effect of aggregating the projections, I generate multiple projections based on the Bayesian interpretation of the VAR estimates presented in the previous section. More specifically, I take multiple draws—20 draws in this exercise—from the posterior distribution of the estimated VAR with a noninformative prior, and formulate different projections based on each draw. These multiple draws from the posterior distribution could be interpreted as different views about the economy. I then compare (i) the average size and power of the tests based on these multiple projections and (ii) the size and power of the tests using the average of these multiple projections, to determine if there is any difference in the simulation results. The results reported in the online appendix show that the simulation results are very similar, suggesting that the effects of aggregation bias are quantitatively negligible.[14]

14. Isiklar (2005) also notes that problems arising from aggregation in the fixed-event forecast evaluation are not as serious as they are in the fixed-horizon forecast evaluation such as the Mincer–Zarnowitz test.

3. 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 forecast to highlight that the revisions of FOMC's unemployment projections have a much stronger autocorrelation, which may suggest information rigidity of the projections. I discuss that slow updating, conservatism, or different predictability could help explain such rigidity. I also discuss the possible implications of these results on empirical macro-economic issues such as interest rate inertia and missing disinflation.

3.1 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. Although 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 2009–11 and 2014–15. In other words, the FOMC policymakers fail to forecast efficiently, either the hike of the unemployment during the Great Recession or its drop in the recent recovery. The joint efficiency of unemployment projections is rejected in most joint tests across different target years because the rejections during these periods 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 the central tendency and the range of the projections provide similar results.

3.2 SPF Forecast

The results of the SPF forecast 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, 2014, and 2015, 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. However, it should be noted that the FOMC's

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	−0.34*	0.37*	2.64	0.38	0.63
2010	−0.01	0.11	0.45	0.63	0.55
2011	−0.13	−0.06	4.43	0.33	0.41
2012	−0.18	0.15	6.05	0.23	0.62
2013	−0.14	−0.28	7.91*	0.23*	0.67
2014	−0.08	−0.15	2.82	0.36	0.40
2015	−0.07	−0.44	6.77*	0.15	0.72
Panel B. Unemployment rate					
2009	0.64***	0.21	8.64*	1.00***	1.00***
2010	0.40***	0.53***	10.95**	0.83***	0.64
2011	0.25*	0.48**	8.45**	0.58	0.64
2012	0.05	0.04	0.49	0.47	0.50
2013	−0.01	0.07	0.06	0.31	0.67
2014	−0.11	−0.46*	10.17**	0.15**	0.67
2015	−0.13	−0.42	16.52***	0.11**	0.75*
Panel C. PCE inflation					
2009	−0.09	0.24	0.66	0.56	0.49
2010	−0.04	0.05	0.65	0.54	0.45
2011	0.10	−0.13	2.38	0.58	0.36
2012	0.01	−0.63**	7.72*	0.51	0.36
2013	−0.05	−0.13	1.33	0.47	0.38
2014	−0.04	−0.03	1.89	0.47	0.49
2015	−0.07	−0.07	2.88	0.29	0.48
Panel D. Core PCE inflation					
2009	−0.04	0.12	0.26	0.69	0.64
2010	−0.06	0.09	1.09	0.51	0.47
2011	0.03	−0.03	2.00	0.62	0.45
2012	0.02	−0.06	0.08	0.46	0.42
2013	−0.03	0.37*	3.21	0.47	0.49
2014	−0.02	−0.30	1.85	0.50	0.43
2015	−0.03	−0.44	5.39	0.27	0.40
Panel E. Joint tests across years					
GDP growth	−0.14**	−0.04	4.44*	0.33**	0.57
Unemployment	0.16*	0.06	7.90***	0.49	0.69***
PCE	−0.02	−0.10	2.50	0.49	0.43
Core PCE	−0.02	−0.04	1.98	0.50	0.47
Panel F. Joint test across years and series					
	−0.01	−0.03	4.20**	0.45	0.54

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

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	−0.33*	0.37*	2.47	0.50	0.43
2010	−0.00	0.01	0.06	0.63	0.64
2011	−0.15	0.08	2.96	0.38	0.44
2012	−0.16	−0.12	7.43*	0.26	0.55
2013	−0.13	−0.12	8.61*	0.26	0.59
2014	−0.09	0.07	3.04	0.28	0.51
2015	−0.08	−0.50	12.40**	0.22	0.63
Panel B. Unemployment rate					
2009	0.66***	0.12	7.63*	0.75*	0.57
2010	0.40***	0.47**	10.76**	0.75**	0.82**
2011	0.24*	0.36*	6.69*	0.67	0.45
2012	0.08	0.14	1.41	0.57	0.54
2013	0.01	0.06	0.05	0.35	0.83**
2014	−0.12	0.16	20.82***	0.11**	0.80*
2015	−0.12	−0.74***	51.43***	0.11**	0.75*
Panel C. PCE inflation					
2009	−0.06	0.26	0.58	0.45	0.57
2010	−0.04	0.21	1.22	0.50	0.64
2011	0.13	−0.21	2.34	0.46	0.51
2012	0.03	−0.19	0.57	0.73*	0.46
2013	−0.01	0.14	0.32	0.46	0.63
2014	−0.04	0.02	1.38	0.30	0.58
2015	−0.05	−0.38	3.39	0.39	0.25
Panel D. Core PCE inflation					
2009	−0.04	0.11	0.38	0.56	0.42
2010	−0.05	−0.07	0.64	0.46	0.46
2011	0.05	−0.25	3.19	0.50	0.46
2012	0.03	0.07	0.43	0.46	0.55
2013	−0.01	0.08	0.12	0.47	0.40
2014	−0.02	−0.45	3.40	0.43	0.33
2015	−0.02	−0.49	3.63	0.39	0.37
Panel E. Joint test across years					
GDP growth	−0.14**	−0.03	5.28*	0.36*	0.54
Unemployment	0.16**	0.08	14.11***	0.47	0.68***
PCE	−0.01	−0.02	1.40	0.47	0.52
Core PCE	−0.01	−0.14	1.69	0.47	0.43
Panel F. Joint test across years and series					
	0.00	−0.03	5.62***	0.44	0.54*

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

TABLE 7

Efficiency Tests of the SPF Forecast (Mean)

Projected year	Bias	Autocorrelation	Wald	Signs, positive	Signs, consecutive
Panel A. Real GDP growth					
2009	−0.72***	0.46**	8.73*	0.29	0.83**
2010	0.08	0.19	1.30	0.57	0.67
2011	−0.10	−0.13	1.15	0.30	0.44
2012	−0.07	−0.09	0.97	0.29	0.69*
2013	−0.10	−0.33	9.01**	0.20**	0.71*
2014	−0.07	−0.23	2.60	0.33	0.43
2015	−0.01	−0.81***	24.64***	0.45	0.10**
2016	−0.00	−0.22	0.30	0.29	0.50
Panel B. Unemployment rate					
2009	0.59***	0.35*	10.62*	1.00***	1.00***
2010	0.14	0.00	0.09	0.57	0.50
2011	0.04	−0.03	0.13	0.60	0.56
2012	0.04	0.00	0.07	0.57	0.46
2013	0.01	−0.00	0.05	0.33	0.57
2014	−0.06	0.12	0.80	0.20**	0.71*
2015	−0.10	0.29	5.67	0.18*	0.60
2016	−0.13	−0.10	5.26	0.14	0.67
Panel C. PCE inflation					
2008	0.12	−0.23	1.12	0.71	0.50
2009	−0.09	−0.01	0.52	0.64	0.60
2010	−0.10	−0.29	5.86	0.36	0.50
2011	0.09	−0.04	0.81	0.55	0.50
2012	−0.02	−0.49	4.04	0.55	0.20
2013	−0.06	0.09	8.17*	0.27	0.70
2014	−0.07	−0.43	7.86*	0.18*	0.70
2015	−0.04	−0.41	4.07	0.43	0.50
Panel D. Core PCE inflation					
2008	0.04	0.04	1.49	0.71	0.67
2009	−0.05	0.05	0.68	0.45	0.50
2010	−0.09**	−0.19	7.17*	0.18*	0.70
2011	0.02	0.23	0.64	0.55	0.60
2012	−0.02	−0.04	0.19	0.36	0.40
2013	−0.05	−0.04	4.42	0.45	0.70
2014	−0.05	−0.35	6.57*	0.18*	0.60
2015	−0.02	−0.24	2.67	0.43	0.50
Panel E. Joint test across years					
GDP growth	−0.12**	−0.15	6.09*	0.34**	0.55
Unemployment	0.07	0.08	2.84	0.45	0.63
PCE	−0.02	−0.22	4.06	0.46	0.53
Core PCE	−0.03	−0.07	2.98	0.42	0.58

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

TABLE 8

Efficiency Tests of the SPF Forecast (Median)

Projected year	Bias	Autocorrelation	Wald	Signs, positive	Signs, consecutive
Panel A. Real GDP growth					
2009	−0.75***	0.48**	9.17*	0.29	0.83**
2010	0.07	0.15	0.88	0.57	0.67
2011	−0.08	−0.10	0.75	0.50	0.33
2012	−0.06	−0.43	4.38	0.43	0.46
2013	−0.10	−0.32	3.55	0.40	0.36
2014	−0.08	−0.40	3.59	0.40	0.36
2015	−0.01	−0.28	1.38	0.36	0.30
2016	−0.01	0.04	0.01	0.29	0.67
Panel B. Unemployment rate					
2009	0.60***	0.38*	11.78**	1.00***	1.00***
2010	0.12	−0.05	0.03	0.71	0.67
2011	0.03	−0.05	0.04	0.60	0.56
2012	0.03	−0.01	0.01	0.50	0.46
2013	0.01	−0.03	0.11	0.33	0.57
2014	−0.07	0.06	0.75	0.27	0.71*
2015	−0.10	0.17	3.78	0.18*	0.60
2016	−0.13	−0.24	14.91**	0.00**	0.67
Panel C. PCE inflation					
2008	0.11	−0.19	0.87	0.71	0.50
2009	−0.09	−0.03	0.38	0.45	0.50
2010	−0.09	−0.34	5.66	0.27	0.50
2011	0.08	−0.01	0.55	0.45	0.30
2012	−0.02	−0.29	1.06	0.55	0.40
2013	−0.07	0.54**	16.64**	0.27	0.50
2014	−0.05	−0.42	5.04	0.36	0.40
2015	−0.03	−0.16	1.13	0.43	0.50
Panel D. Core PCE inflation					
2008	0.04	0.38*	1.72	0.71	0.67
2009	−0.06	0.11	1.01	0.36	0.50
2010	−0.09**	0.10	8.34**	0.09**	0.70
2011	0.01	0.19	0.50	0.55	0.50
2012	−0.01	0.16	0.41	0.27	0.60
2013	−0.05	0.40*	5.03	0.45	0.70
2014	−0.04	−0.39	5.19	0.09**	0.50
2015	−0.02	−0.33	1.49	0.29	0.17
Panel E. Joint test across years					
GDP growth	−0.12**	−0.11	2.96	0.40	0.50
Unemployment	0.06	0.03	3.93	0.45	0.65*
PCE	−0.02	−0.11	3.92	0.44	0.45
Core PCE	−0.03	0.08*	2.96	0.35	0.54**

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

projections and the SPF forecast forecast differ slightly with respect to their targets and horizons,[15] and these differences may lead to their divergent evaluations of forecast efficiency.

3.3 Discussion

The strong rigidity of FOMC's unemployment projections 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.[16] This point is further examined in Section 4.1. 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 that FOMC policymakers have made substantial revisions to their unemployment projections at time-horizons exceeding 1 year, slower updating could be a likely cause of inefficiency. Lansing and Pyle (2015) also observe that the FOMC policymakers are persistently optimistic about their growth projections over the period.

Second, FOMC policymakers may be conservative about their projections for various reasons. For example, they may be concerned about the signaling 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.[17] 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

15. The SPF forecast is different from the FOMC's projections in two ways. First, the availability of longer horizon forecasts are limited; Three-year ahead SPF forecast starts from 2009Q2 for GDP growth and unemployment, and 2-year ahead SPF forecast starts from 2007Q1 for inflation. Second, the SPF forecast has different targets for GDP growth and unemployment; the SPF forecast aims to forecast the *annual average* rate of GDP growth and level of unemployment.

16. For the analysis of Okun's law during the Great Recession, see Elsby, Hobijn, and Sahin (2010) and Daly and Hobijn (2010). Some FOMC policymakers, such as Yellen (2010) and Bernanke (2012), observe that the jump in the unemployment rate in 2009 and its decline in 2011 were not anticipated by Okun's law. Ball, Leigh, and Loungani (2013) 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.

17. 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.

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 data set 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 versus voting members versus nonvoting members). For example, they find that governors tend to have views close to the consensus whereas nongovernors 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 2.5 also exhibit substantially different predictability. When projecting the artificial realized series on the conditional expectation, average R^2 is 0.20 for the output growth whereas 0.96 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.

3.4 Implications for Macroeconomic Debates

The results presented in this article have particularly relevant implications for two controversial macroeconomic issues: interest rate inertia and missing disinflation. First, there is a debate about whether the substantial degree of inertia in the U.S. interest rate is driven by interest rate smoothing by policymakers (or gradualism) or persistent shocks in the variables omitted in the reaction function of the central bank, such as financial stability.[18] It is likely that the FOMC's sluggish revisions on unemployment projections found in this paper could help explain interest rate inertia without appealing to any financial stability story as in Rudebusch (2002, 2006).

Second, a number of papers propose various explanations for the "missing disinflation" during the Great Recession; that term refers to the fact that inflation did not decline as much as one might have expected given the severity of the slump.[19] This paper finds no evidence that the FOMC's inflation projections are inefficient, indicating that their inflation projections, which are often interpreted as their implicit

18. For details, see Bernanke (2004), Rudebusch (2002, 2006), and Coibion and Gorodnichenko (2012b) among others.

19. For example, Bernanke (2010) claims that the proactive stance of the Federal Reserve against disinflation makes the inflation expectation well anchored. Ball and Mazumder (2011) argue that using the median inflation and introducing a time-varying coefficient could resolve the puzzle. Coibion and Gorodnichenko (2015) point out that inflation expectation by households did not fall during this period due to the surge in oil prices. Gilchrist et al. (2015) observe that financially constrained firms maintain prices to preserve their cash revenue.

inflation targets, are well anchored. In fact, Watson (2014) documents that the change in the persistence of inflation—the long-run inflation is more anchored now—is an important reason why only a mild decline in inflation occurred. Therefore, these results may reflect the credibility of the Federal Reserve's long-run inflation target, which in turn could be a candidate explanation for the missing disinflation.

4. EXTENSIONS

In this section, I provide two extensions to the main results: regression analysis of Okun's law using the revisions of GDP growth and the changes in unemployment, and comparison of FOMC's projections and the SPF forecast prior to the Great Recession. The regression analysis shows that both the FOMC's projections and the SPF forecast are consistent with Okun's law only at the shorter horizons. The comparison suggests that the FOMC's projections are generally more accurate than the SPF forecast, but their forecast errors for inflation are systematic, which leads to the inefficiency.

4.1 Okun's Law and Forecasts

I conduct a simple regression analysis to explain why the rejections of efficiency are stronger for the unemployment rate than GDP growth, which is surprising if the forecasts embody a tight Okun's law relationship. Consider a version of Okun's law described in first differences:

$$\Delta y_t = \alpha + \beta \Delta u_t, \tag{12}$$

with the typical values of $\alpha = 3\%$ per year and $\beta = -2$. In this specification, each additional percentage point in the growth rate of GDP above 3% is associated with a decline in the unemployment rate of about 0.5%. Therefore, the slope coefficient of the *revisions* of the changes in the unemployment rate regressed on the *revisions* of output growth should be around -0.5 under Okun's law.

In the regression, I analyze the revisions at each horizon (year-end, end of next year, and the end of subsequent year) and the cumulative revision, which adds the revisions at all horizons to see the effect over the whole forecast horizon. The changes in the unemployment at the year's end are computed using the real-time data released by the Federal Reserve Bank of Philadelphia. By following Faust and Wright (2009), I treat the data released two quarters after the forecasted quarter as the realized value.

To see whether the actual estimate is significantly different from -0.5, I construct the confidence intervals by the block bootstrap. In the block bootstrap, I construct the artificial sample of a year 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 among the current revision and the revisions made 1 year later or earlier.

TABLE 9

Regression Analysis of the Changes in Unemployment Revisions on the GDP Growth Revisions

	End of the year	End of the next year	End of the second year	Cumulative
Panel A. Central tendency (FOMC)				
Slope	−0.35	−0.47	−0.20	−0.37
R^2	0.37	0.78	0.19	0.63
90% Conf. Int.	[−0.49, −0.17]	[−0.50, −0.33]	[−0.32, −0.12]	[−0.46, −0.22]
Panel B. Range (FOMC)				
Slope	−0.36	−0.35	−0.66	−0.28
R^2	0.36	0.62	0.26	0.53
90% Conf. Int.	[−0.47, −0.18]	[−0.40, −0.09]	[−1.00, −0.27]	[−0.36, −0.14]
Panel C. Mean (SPF)				
Slope	−0.38	−0.54	−0.17	−0.20
R^2	0.44	0.73	0.10	0.26
90% Conf. Int.	[−0.29, 0.13]	[−0.37, 0.04]	[−0.39, −0.00]	[−0.29, −0.01]
Panel D. Median (SPF)				
Slope	−0.37	−0.52	−0.14	−0.12
R^2	0.43	0.77	0.09	0.09
90% Conf. Int.	[−0.26, 0.14]	[−0.40, −0.06]	[−0.34, 0.09]	[−0.25, 0.05]

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

The results presented in Table 9 show that the FOMC's projections are largely consistent with Okun's law at shorter horizons—year-end and end-of-next-year—but the relationship weakens at the longer horizon of the end of the second year. For the projections for the year-end and end-of-next-year, correlations are negative and relatively close to −0.5, −0.35, and −0.47 for the central tendency and −0.36 and −0.35 for the range, respectively. However, the correlation in the projections for the end of the second year is close to zero and R^2 becomes substantially smaller. This is because the FOMC participants revise their longer term unemployment projections without changing the output growth projections. Figure 2 shows the plot of the FOMC's revisions for GDP growth and the changes in the unemployment rate at each horizon for the central tendency, highlighting the difference between the projections at the shorter and longer horizons.

Table 9 also shows the same analysis for the SPF forecast. The results for the SPF forecast are similar to the FOMC's projections: the forecasts are consistent with Okun's law only at the shorter horizons.[20]

20. The first few samples of the SPF forecast are dropped for the inference due to the missing data, which makes some estimates to be out of the confidence intervals.

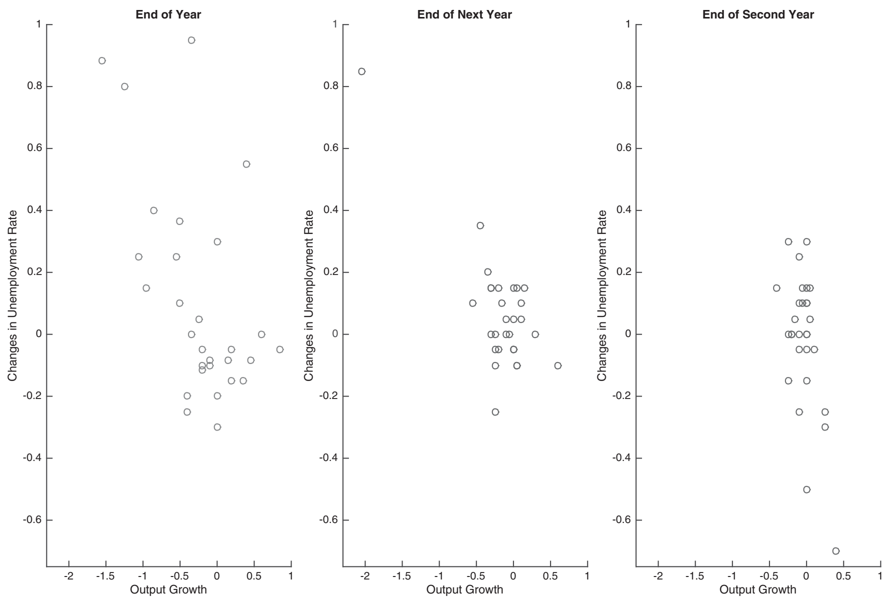

FIG. 2. Revisions to FOMC's GDP Growth and Changes in Unemployment Projections (Central Tendency).

4.2 *Comparison of FOMC and SPF Prior to the Great Recession*

I compare the performances of the FOMC's projections and the SPF forecast to see whether they are systematically different prior to the Great Recession. The results show that the FOMC's projections are generally more accurate than the SPF forecast, but the FOMC's forecast errors for inflation are systematic, which leads to the inefficiency of their projections.

I use the FOMC's previous projections covering the target years between 1980 and 2007. Since they are released only twice a year (February and July) with a shorter horizon, I can only provide the forecast evaluation based on the Mincer–Zarnowitz regression:

$$y_{t+h} = \alpha_0 + \beta_0 \cdot \hat{y}_{t+h|t} + \varepsilon_{t+h}, \tag{13}$$

jointly testing the null hypothesis of $\alpha_0 = 0$ and $\beta_0 = 1$. The rejection implies that there is a predictable variation in the forecast errors, suggesting that the forecaster does not incorporate all of the available information into the forecast.

The FOMC has projected three variables: inflation, real growth, and the unemployment rate. Data of the FOMC's projections are based on Romer and Romer (2008) and extended by using the data on the Federal Reserve's website. Because there have been changes in the measures of inflation (1979–1988: GNP deflator, 1989–2000: CPI, 2001–07: PCE), I change the measures of the SPF forecast in the same manner to

TABLE 10

COMPARISON OF THE FOMC AND SPF PRIOR TO THE GREAT RECESSION (MINCER–ZARNOWITZ REGRESSION)

	FOMC		SPF	
	Cent. Tend.	Range	Mean	Median
Panel A. Real growth				
Const.	0.04	0.16	1.20	1.65
Coef.	1.00	0.96	0.49	0.34
F-Stat	0.00	0.03	0.84	1.30
Panel B. Inflation				
Const.	0.59	0.58	0.20	0.29
Coef.	0.79	0.79	0.85	0.82
F-Stat	2.84*	2.71*	1.86	1.77
Panel C. Unemployment rate				
Const.	0.11	−0.15	−0.15	0.02
Coef.	0.97	1.00	1.02	0.98
F-Stat	0.25	0.48	0.05	0.17

NOTES: This table presents the forecast evaluation of three-quarter ahead forecasts based on the Mincer–Zarnowitz regression. *F*-stat jointly tests the constant and coefficient equals zero and one, respectively. Superscript * denotes the significance at the level of 10%.

compare the forecast accuracy.[21] Because the horizon of the SPF forecast is limited, I compare the performance of forecasts three quarters ahead. More specifically, I compare the efficiency of the forecasts made at the first quarter forecasting the value at the fourth quarter. The realized value is constructed from the real-time data in the same manner as the previous subsection.

Table 10 presents the results of the Mincer–Zarnowitz regression. Even though the efficiency of the FOMC's inflation projections is rejected with a 10% significance level, in most cases the efficiency is accepted for the FOMC's projections and the SPF forecast. For real growth and the unemployment rate, the efficiency of both forecasts are accepted, which may be due to the high predictability of the series and the relatively short forecast horizon. For inflation, the FOMC tends to make systematic errors, which results in the rejection of efficiency. Although the SPF forecast also shows some systematic tendency to forecast inflation, that tendency is not statistically significant.

Table 11 shows the Diebold–Mariano (DM) statistics comparing the accuracy of the FOMC projections and the SPF forecast. The DM statistic tests whether the root mean squared prediction errors of two nonnested forecasts are equal. Because I subtract the prediction errors of the SPF forecast from the errors of the FOMC's projections, the negative DM statistics presented in the table suggest that the FOMC's projections

21. Because the SPF's PCE forecast is only available from 2007, I subtract 40 basis points from their CPI forecast to use it as a proxy for their PCE forecast by following Hakkio (2008).

TABLE 11

COMPARISON OF THE FOMC AND SPF PRIOR TO THE GREAT RECESSION (DIEBOLD–MARIANO TEST)

	Real growth	Inflation	Unemployment
Cent. tend (FOMC) and median (SPF)	-1.85^{*}	-2.34^{**}	-0.09
Range (FOMC) and mean (SPF)	-1.74^{*}	-0.97	-1.22

NOTES: This table presents the Diebold–Mariano test statistics comparing the central tendency of FOMC and the median of SPF, and the range of FOMC and the mean of SPF. Superscripts *,** denote the significance at the level of 10% and 5%, respectively.

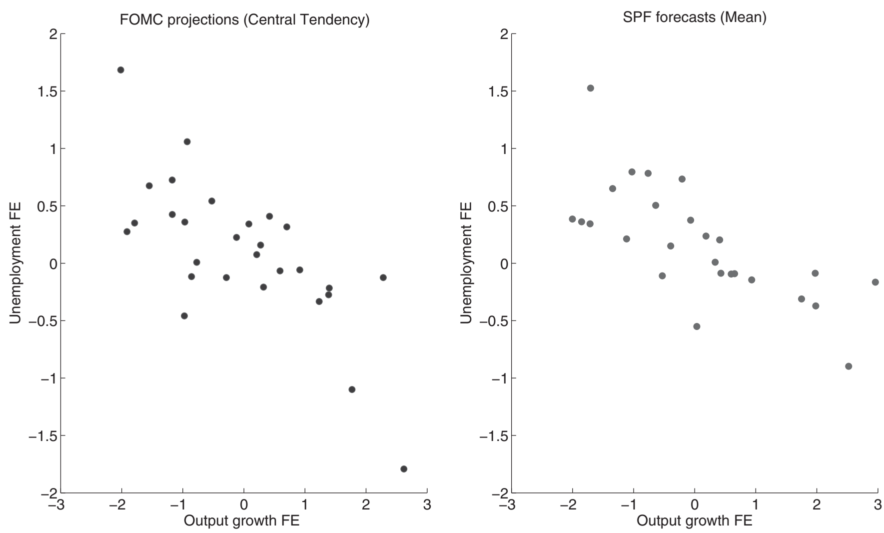

FIG. 3. GDP Growth and Unemployment Forecast Errors by FOMC and SPF Prior to the Great Recession.

are more accurate. In particular, the FOMC's projections perform significantly better than the SPF forecast for real growth and inflation.

Figure 3 shows the forecast errors of the FOMC's projections and the SPF forecast for GDP growth and the unemployment rate. As evident from the figure, there is a negative relationship between the forecast errors of GDP growth and the unemployment rate for both forecasters. In other words, the FOMC and SPF seem to follow Okun's law when forecasting at three-quarter horizon. Therefore, the FOMC projections and the SPF forecast are consistent with Okun's law at a short horizon, especially at less than a year, during prior and during the Great Recession.

These results are markedly different from the results that used the projections after the Great Recession. More specifically, there are no meaningful differences between GDP growth and unemployment projections, and inflation projections are significantly inefficient before the Great Recession. Therefore, this comparison suggests that the main patterns documented in this article, significant inefficiency in unemployment projections and efficiency in inflation projections, are unique to the period after the Great Recession. However, it should be noted that the forecast horizon for the new projections after the Great Recession is substantially longer than the old projections before the Great Recession: 3 years for the new and 9 months for the old. Accordingly, the difference in the results could be simply due to a different nature of nowcasts and forecasts.

5. CONCLUSIONS

In this article, 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.

APPENDIX A: MONTE CARLO EXERCISE

A.1 Construction of Yearly Projections

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

$$w_{t+1} = c + A_1 w_t + \xi_t, \tag{A1}$$

where w_t is a vector of variables, and ξ_t is a vector of errors. To simplify the notation, I denote the system as

$$v_{t+1} = A v_t + \zeta_t, \tag{A2}$$

where

$$v_t = \begin{pmatrix} 1 \\ w_t \end{pmatrix}, \; A = \begin{pmatrix} 1 & 0' \\ c & A_1 \end{pmatrix}, \; \text{and} \; \zeta_t = \begin{pmatrix} 0 \\ \xi_t \end{pmatrix}.$$

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

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

iii. Construct the efficient quarterly projections by iterations as in Table A1, 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.)

iv. Construct the efficient yearly projections in accordance with the timing of 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 A2. Similarly, I compute the projection of GDP

TABLE A1
Simulated Quarterly Projections

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

TABLE A2
Simulated Yearly Projections of the Unemployment Rate

	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	$\hat{A}v_4$	$\hat{A}^5v_4$	$\hat{A}^9v_4$	$\hat{A}^{13}v_4$
⋮	⋮	⋮	⋮	

TABLE A3
SIMULATED YEARLY PROJECTIONS OF GDP GROWTH AND INFLATION

	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 A4
SIMULATED REVISIONS OF THE UNEMPLOYMENT PROJECTIONS

	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			$\hat{A} v_{12} - \hat{A}^2 v_{11}$	$\cdots$

growth and inflation for the fourth quarter as the sum of realized values and quarterly projections, as in Table A3, since they are described in a continuously compounding rate of growth.

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 A4 and compute the revisions of GDP growth and inflation projections as in Table A5. Then, I apply the tests in this article to these revisions. By repeating the whole exercise many times, I report the probability of rejections as the size of the tests.

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 $0 < j < h$.

TABLE A5

Simulated Revisions of the GDP Growth and Inflation 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			$v_{12} + \hat{A} v_{12} - \sum_{k=1}^{2} \hat{A}^k v_{11}$	$\cdots$

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

$$\hat{y}_{t+h|t+j}^{b,I} = \hat{y}_{t+h|t+j}^{b,*} + \varepsilon_{t+h|t+j}, \tag{A3}$$

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

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

$$\hat{y}_{t+h|t+j}^{b,P} = \hat{y}_{t+h|t+j}^{b,*} + \eta^{h-j-1} \varepsilon_{t+j}, \tag{A4}$$

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.

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

$$\hat{y}_{t+h|t+j}^{b,S} = \delta \hat{y}_{t+h|t+j}^{b,*} + (1-\delta) \hat{y}_{t+h|t+j-1}^{b,*}, \tag{A5}$$

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 article 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.

A.4 Aggregation Bias

By defining the sets of vectors, the whole system can be described in a matrix form:

$$W = VA_0 + \Xi, \tag{A6}$$

where

$$W = \begin{pmatrix} w_2' \\ \vdots \\ w_T' \end{pmatrix}, \; V = \begin{pmatrix} v_1' \\ \vdots \\ v_{T-1}' \end{pmatrix}, \; A_0 = \begin{pmatrix} c \\ A_1 \end{pmatrix}, and \;\; \Xi = \begin{pmatrix} \xi_2' \\ \vdots \\ \xi_T' \end{pmatrix}.$$

By applying the Bayesian interpretation of VAR with a noninformative prior for $\alpha_0 = vec(A_0)$ and Ω, given data vector $w = vec(W)$, the posteriors are given as follows:

$$\alpha_0 \mid \Omega, w \sim N(\hat{\alpha_0}, \Omega \otimes (V'V)^{-1}), \text{ and} \tag{A7}$$

$$\Omega \mid w \sim IW(S^{-1}, T - 10), \tag{A8}$$

where $\hat{A_0} = (V'V)^{-1}V'W$ is the OLS estimates of A_0 and $\hat{\alpha_0} = vec(\hat{A_0})$, $S = (W - V\hat{A_0})'(W - V\hat{A_0})$ is the estimates of variance–covariance matrix based on the OLS residuals, and IW denotes the inverse-Wishart distribution.

To take a draw from the posterior, I first take a draw of Ω from the posterior in equation (A8), then take a draw of α_0 from the posterior in equation (A7), given the draw of Ω. By taking multiple draws of α_0 from the posterior, which could be interpreted as different views about the economy, I compute multiple forecasts and their revisions in the same way described in Section A.1 Based on these multiple projections, I compare the average size and power of the tests and the size and power of the tests using the mean of these projections.

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