Not-for-Publication Appendix to

"Has the Information Channel of Monetary Policy Disappeared? Revisiting the Empirical Evidence"

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Table of Contents

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I. Additional Results on the Information Advantage

I.A Information Advantage Coefficients

We report the coefficient $\beta_{GB,t}$ from the Information Advantage Fluctuation test in Figures S1-S2.

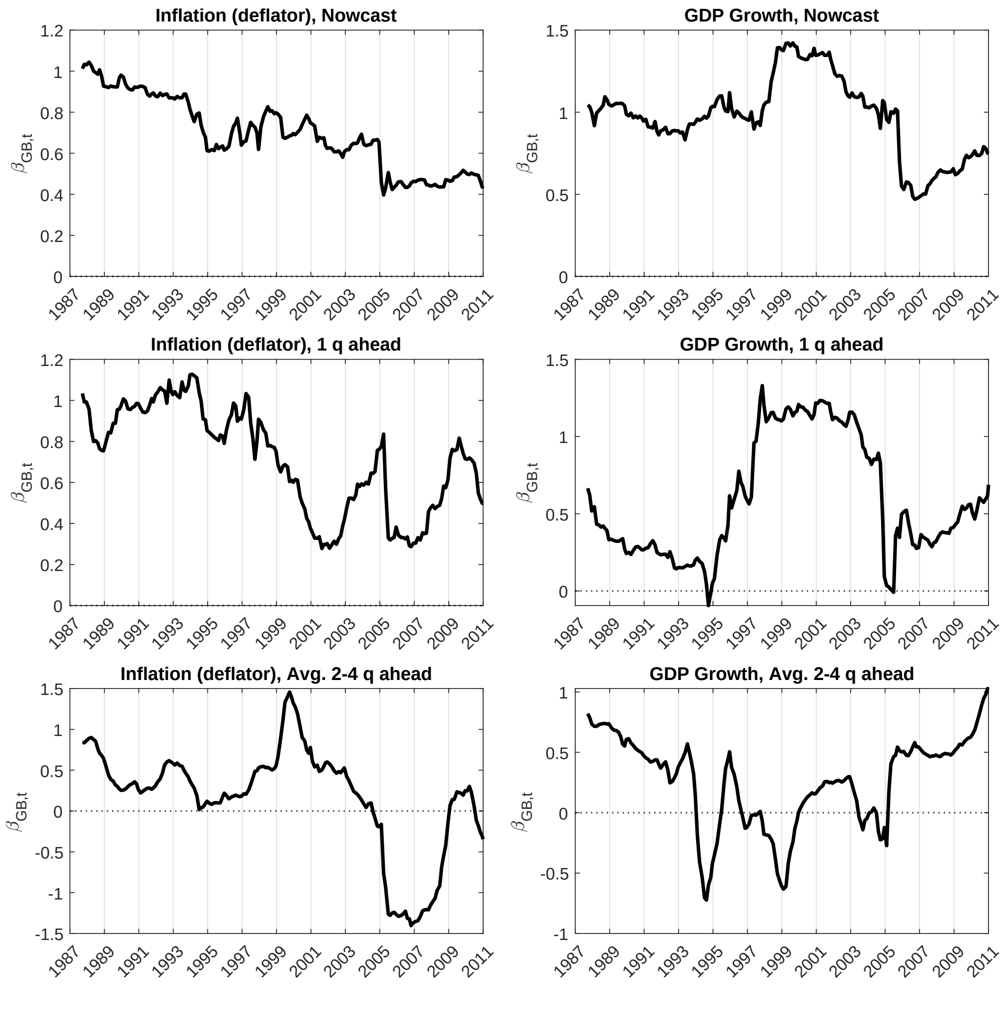

Figure S1: Information Advantage: $\beta_{GB,t}$ coefficients

Note: The figure shows the estimates $\hat{\beta}_{GB,t}$ from eq. (2) based on 60 meetings rolling windows. Horizontal axes correspond to mid-window dates.

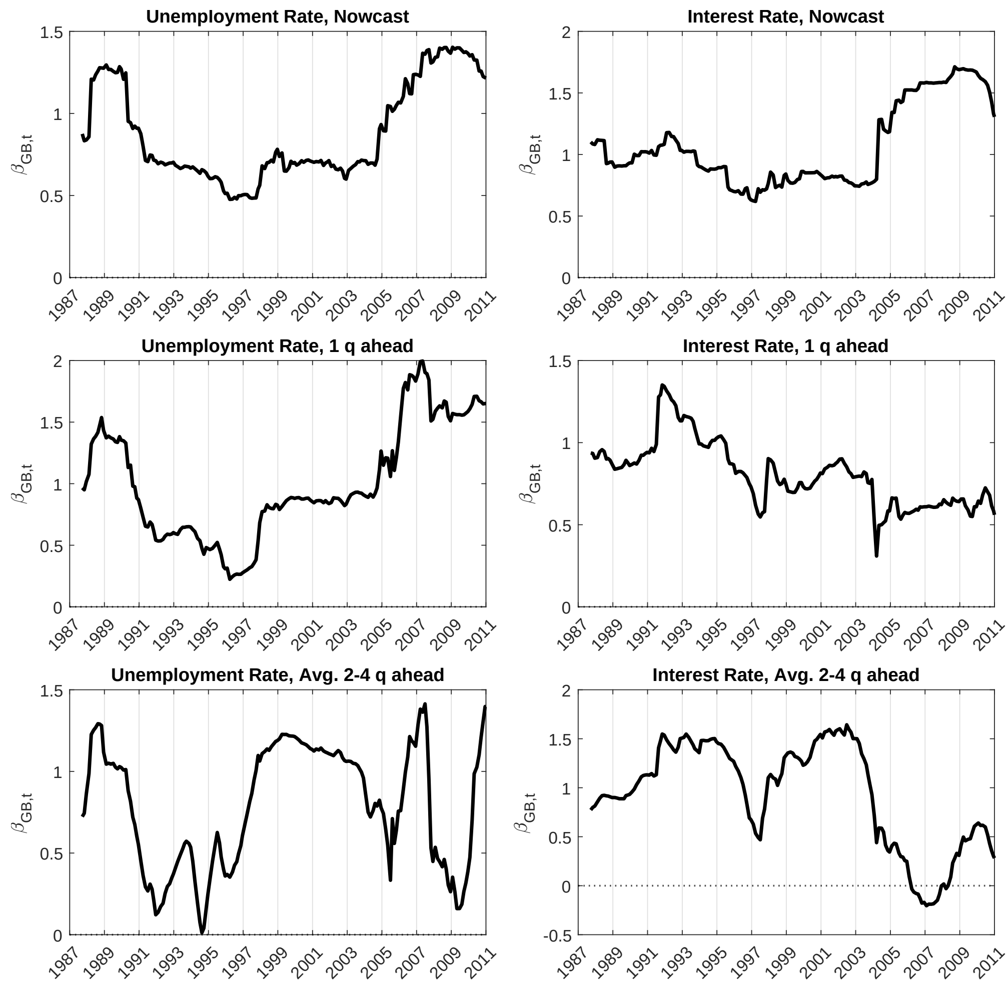

Figure S2: Information Advantage: $\beta_{GB,t}$ coefficients

Note: The figure shows the estimates $\hat{\beta}_{GB,t}$ from eq. (2) based on 60 meetings rolling windows. Horizontal axes correspond to mid-window dates.

I.B Robustness to the Rolling Window Size

We explore the robustness of the Information-Advantage Fluctuation test to different window sizes in Figures S3-S4.

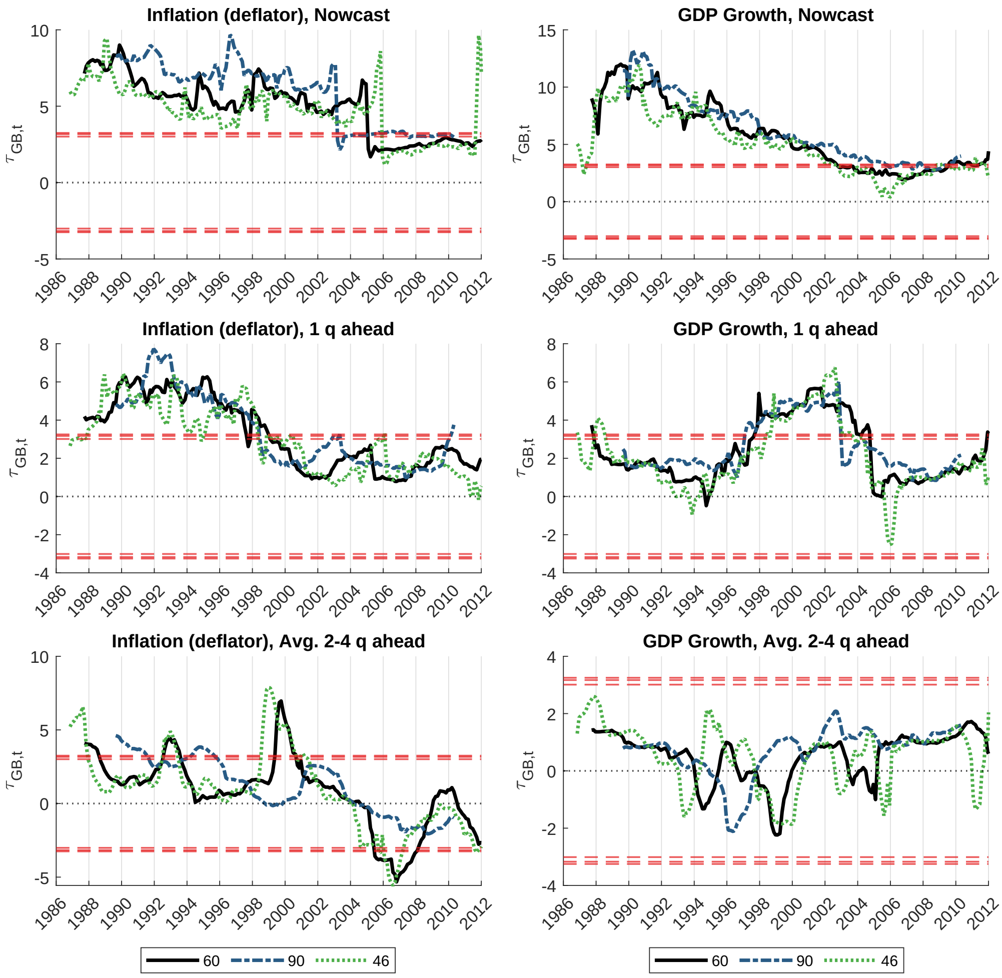

Figure S3: Information Advantage Window Size: GDP Growth and Inflation

Note: The figure shows $\tau_{GB,t}$ from eq. (2) based on: $m = 60$ (black solid line), $m = 90$ (blue dash-dotted line) and $m = 46$ (green dotted line) meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

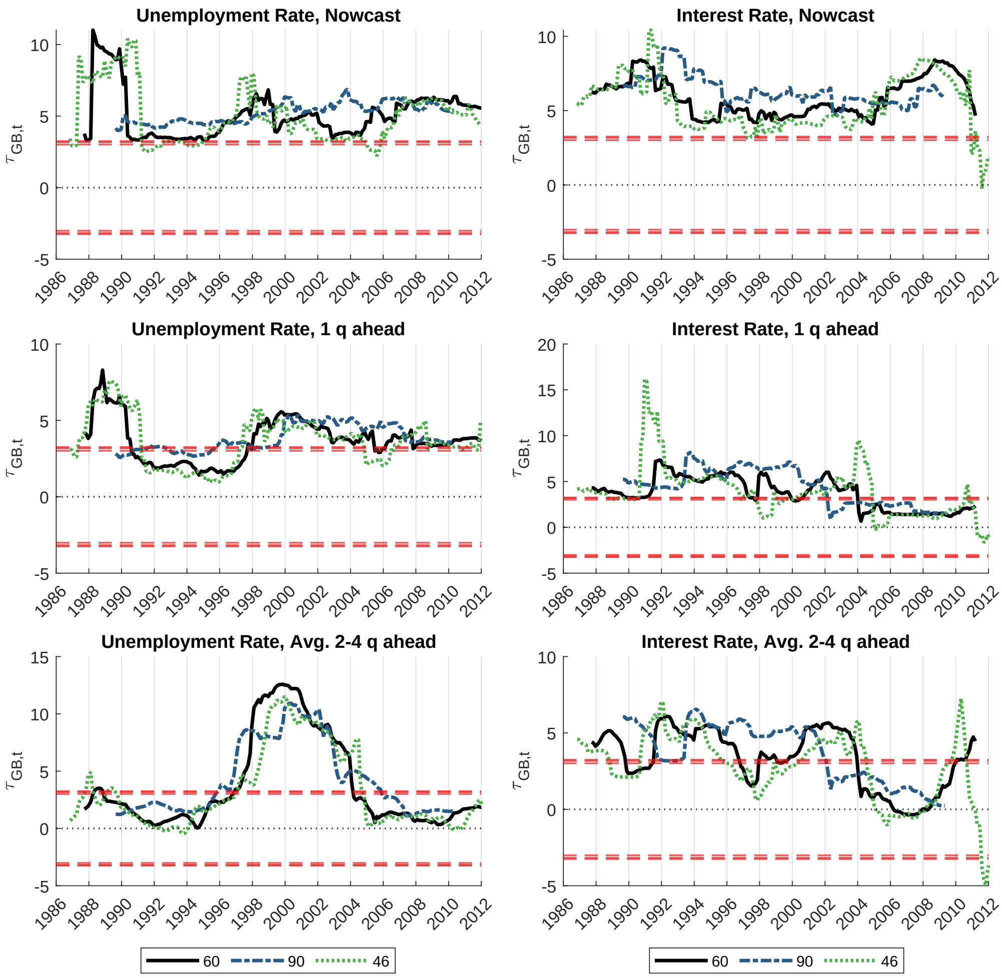

FIGURE S4: INFORMATION ADVANTAGE WINDOW SIZE: UNEMPLOYMENT AND INTEREST RATES

Note: The figure shows $\tau_{GB,t}$ from eq. (2) based on: $m = 60$ (black solid line), $m = 90$ (blue dash-dotted line) and $m = 46$ (green dotted line) meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

I.C Robustness to the Real-time Vintages

Figure S5 shows the Information-Advantage Fluctuation test when using different vintages (first, second and third releases) for the realizations of the target variable.

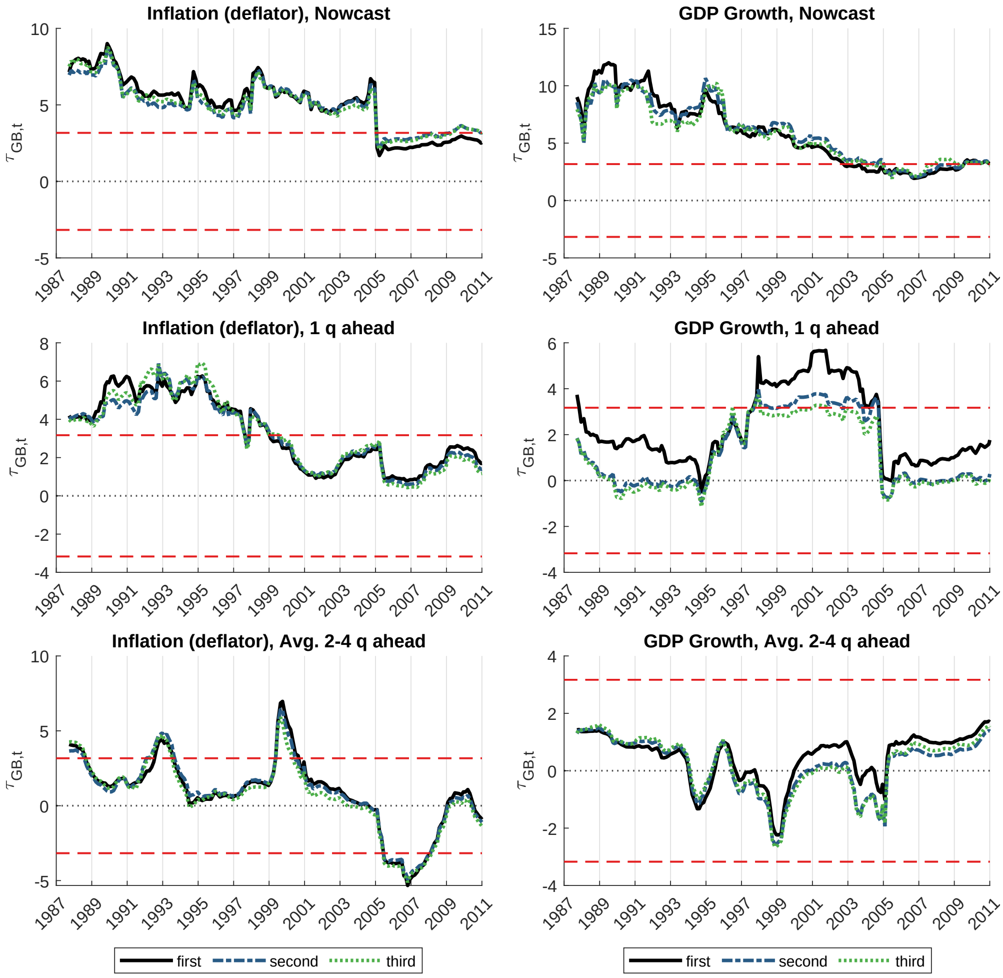

FIGURE S5: INFORMATION ADVANTAGE VINTAGES: GDP GROWTH AND INFLATION

Note: The figure shows $\tau_{GB,t}$ from eq. (2) based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$ for different real-time realizations: first release (black solid line), second release (blue dash-dotted line) and third release (green dotted line). Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

II. Forecast Accuracy and Information Advantage

II.A Insights from the Forecast Combination Literature

In this section, we address the relationship between the weights β_{GB} and β_{BCEI} in the information advantage regressions and the accuracy of the forecasts x_{t+h}^{GB} and x_{t+h}^{BCEI}, as measured by the mean squared forecast error (MSFE).

The intuition for the null hypothesis $\beta_{GB} = 0$ in our information advantage regressions is that, given two forecasts x_{t+h}^{GB} and x_{t+h}^{BCEI}, for the same target variable x_{t+h}, the best forecast should put all the weight on x_{t+h}^{BCEI} and zero weight on x_{t+h}^{GB}. In fact, this is evident by rewriting eq. (1) in the main paper as:

$$x_{t+h} = \delta + \beta_{GB} x_{t+h}^{GB} + \widetilde{\beta}_{BCEI} x_{t+h}^{BCEI} + \eta_{t+h}, \tag{S.1}$$

where $\widetilde{\beta}_{BCEI} = 1 + \beta_{BCEI}$.

Thus, one would expect that the magnitude of the coefficients β_{GB} and β_{BCEI} corresponds to the accuracy of the Greenbook/Tealbook and BCEI forecasts, respectively. However, that is not always the case when the two forecasts are not unbiased and uncorrelated.

More specifically, although typically the most accurate forecasts (in terms of the MSFE) get higher weight in the information advantage regression, it is also possible that forecasts with equal accuracy may have different information advantage coefficients. For example, when the forecasts are highly correlated, the coefficients in the information advantage regression could be large and different from each other, thus not reflecting their relative forecasting accuracy. Here below, we further provide a detailed discussion of the relationship between information advantage regression coefficients and their relative forecast accuracy.

For analytical convenience, it is easier to work with a restricted specification of eq. (S.1), where the constant $\delta = 0$ and the weights β_{GB} and $\tilde{\beta}_{BCEI}$ sum to one, i.e. $\beta_{GB} + \widetilde{\beta}_{BCEI} = 1$.[1] Let $fe_{t+h}^{GB} = y_t - x_{t+h}^{GB}$ and $fe_{t+h}^{BCEI} = y_t - x_{t+h}^{BCEI}$.

[1] As suggested in Granger and Ramanathan (1984), when the weights sum to one and each

The MSFE of the combined forecast can be written as

$$MSFE = E\left[w(y_t - x_{t+h}^{GB}) + (1-w)(y_t - x_{t+h}^{BCEI})\right]^2 \tag{S.2}$$

where w is the weight on the Greenbook/Tealbook forecasts, which we refer to as the forecast "one" in what follows. Moreover, let $s_1^2 = E(fe^{GB})^2$ be the MSFE of the Greenbook/Tealbook forecast, while the $s_2^2 = E(fe^{BCEI})^2$ be that of the BCEI forecast and $s_{12} = E(fe_{t+h}^{BCEI} fe_{t+h}^{GB})$. Further, let ρ define the cross correlations of the two forecasts. Minimizing the MSFE in eq. (S.2) results in the optimal weight w^* on the Greenbook/Tealbook forecast:

$$w^* = \frac{s_2^2 - s_{12}}{s_1^2 + s_2^2 - 2s_{12}} = \frac{1 - \rho\frac{s_1}{s2} - \frac{E(fe_{t+h}^{GB})E(fe_{t+h}^{BCEI})}{s_2^2}}{1 + \frac{{s_1}^2}{{s2}^2} - 2\rho\frac{s_1}{s2}} \tag{S.3}$$

This equation shows that the optimal weights summarize a variety of information about individual forecasts, i.e. their MSFEs (s_1^2 and s_2^2), their cross correlations (ρ) as well as their respective biases ($E(fe_{t+h}^{GB})$ and $E(fe_{t+h}^{BCEI})$). In fact, the numerator of w^* is the moment condition typically tested against zero in encompassing regressions.

In the simplest possible case, when the bias is zero and the forecasts are uncorrelated, the optimal weights simplify and are proportional to the MSFEs, such that the more accurate model gets more weight:

$$w^* = \frac{s_2^2}{s_1^2 + s_2^2} \tag{S.4}$$

Motivated by the empirical observation that our forecasts exhibit time-varying cross-correlations (see Figure S10) and are biased, at least at some points in time

forecast is unbiased then their combination is an unbiased forecast. In general, however, Granger and Ramanathan (1984) argue that the unrestricted specification in eq. (S.1) should be preferred, at least on a theoretical basis, since it results in an unbiased forecast combination with a smaller average squared error even when the individual forecasts are biased. Though the theory gives strict preference to the unrestricted specification, in practice the gains might not be very large as the empirical application in Granger and Ramanathan (1984) shows.

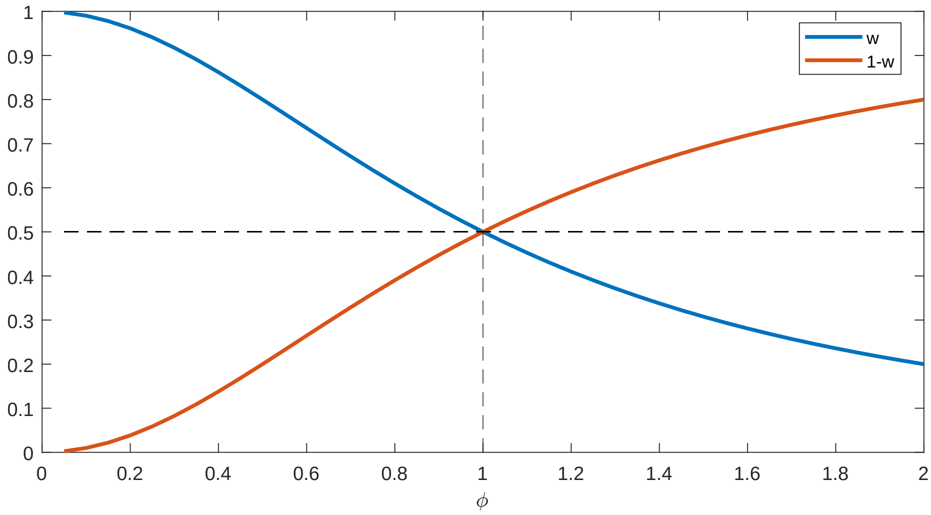

Figure S6: Benchmark Combination Weights

Note: w is the weight on forecast 1, while $1-w$ is the weight on forecast 2, $\phi < 1$ showcases the situation where the first forecast (Greenbook/Tealbook) is more accurate than the second one (BCEI).

(see Figures S11 and S12), below we study the behavior of the optimal weights resorting to a graphical implementation.

Let $s_1/s_2 = \phi$, where s_2 equals 1.[2] ϕ measures the relative forecast accuracy: $\phi < 1$ refers to the situation where the first forecast (Greenbook/Tealbook) is more accurate than the second (BCEI), while $\phi > 1$ indicates the opposite. First, we establish a benchmark case where the individual forecasts are unbiased and uncorrelated. Subsequently, we consider the cases of cross-correlated and biased forecasts. In all the cases, we consider $\phi \in [0.05 : 0.05 : 2]$.

Benchmark: Uncorrelated and Unbiased Forecasts: Figure S6 shows that, when the forecasts' relative accuracy is equal (i.e. when $\phi = 1$), then the forecasts get equal weight (0.5). Otherwise, the more accurate forecast gets a higher weight. The weights are determined by eq. (S.4).

[2]In fact, the exact value is irrelevant.

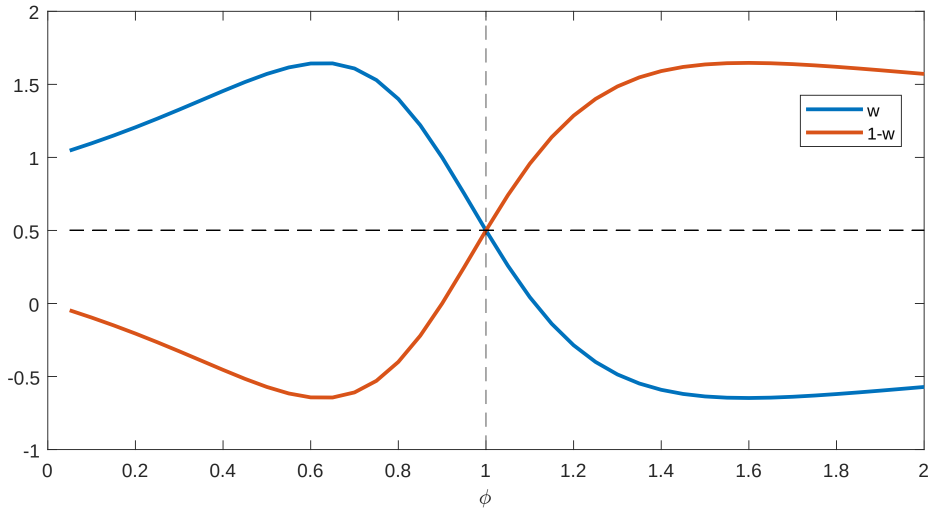

Figure S7: Combination Weights with Correlated Forecasts: Example

Note: w is the weight on forecast 1, while $1-w$ is the weight on forecast 2, $\phi < 1$ showcases the situation where the first forecast (Greenbook/Tealbook) is more accurate than the second one (BCEI).

Unbiased and cross-correlated forecasts: Let $\rho = 0.9$, a reasonable value for the real GDP growth nowcast across most of the considered sample period based on Figure S10.

Figure S7 shows that the presence of non-zero correlation can lead to weights that are negative and greater than 1 (in absolute value). In this case, the weights on each individual forecast reflect not only their respective accuracy, but also their correlation. In fact, $\frac{\delta w}{\delta \rho} = \frac{\phi - \phi^3}{(1+\phi^2-2\rho\phi)^2}$. This suggests that, when the forecasts are equally accurate, their correlation is irrelevant and the weights are equal. On the other hand, the weight on the first forecast is inversely proportional to the squared correlation. Figure S7 shows that when $\phi < 1$, i.e. the first forecast is more accurate, the increase in the correlation implies assigning a larger weight on the most accurate forecast. In fact, the ranking of the forecasts stays the same, the most accurate forecast gets a larger weight, but the value of the weight itself does not correspond to the MSFE, as it is "distorted" by the cross-correlations. Figure S8 demonstrates this point for various values of ρ, i.e. allowing for different cross-correlation patterns.

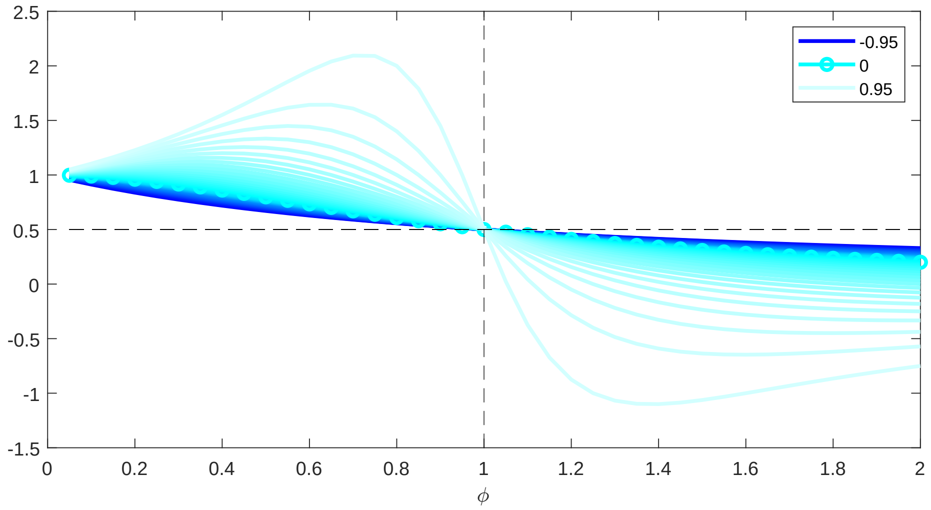

Figure S8: Combination Weights with Correlated Forecasts

Note: The figure shows the weight on the first forecast (w) as a function of ϕ. $\phi < 1$ showcases the situation where the first forecast (Greenbook/Tealbook) is more accurate than the second one (BCEI). Each line in the figure corresponds to a different correlation value, which ranges from -0.95 to 0.95, with a step size of 0.05.

Biased and uncorrelated forecasts: Figure S9 shows the optimal weight on the first forecast when the forecasts are biased and uncorrelated. Each line in the figure corresponds to a different bias value of the first forecast, which ranges from -1 to 1, with a step size of 0.1; the bias of the second forecast is always 0.5. Eq. (S.3) suggests that the product of the biases plays a key role in determining the weights. The bias distorts the mapping between the weights in the information advantage regressions and relative forecast accuracy. In fact, it is possible that the first model is better than the second one in terms of relative forecast accuracy, i.e. $\phi < 1$, yet the weight associated with the more accurate forecast in the information advantage regression is lower than that on the less accurate one. The existence of the bias not only "distorts" the magnitude of the weights, but it also does not preserve the ranking. In other words, the most accurate model does not always get the highest weight.

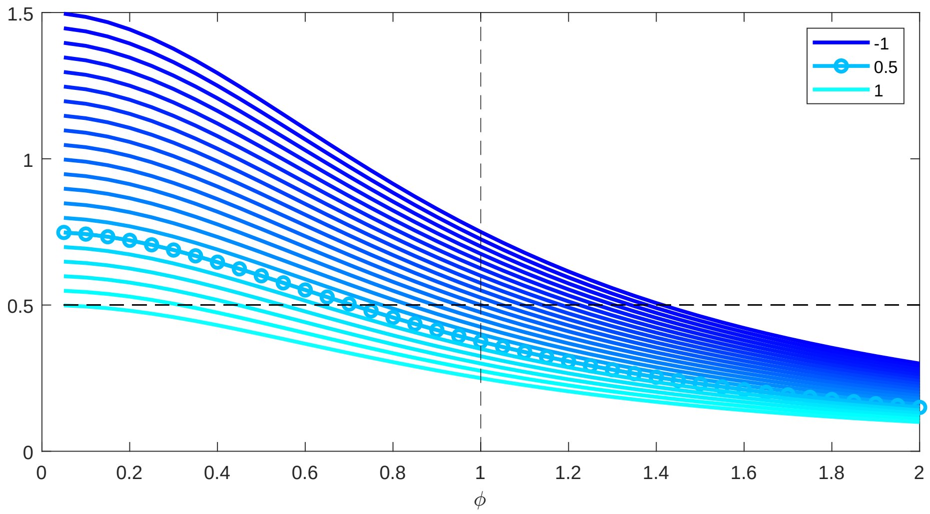

Figure S9: Combination Weights with Biased Forecasts

Note: The figure shows the weight on the first forecast (w) as a function of ϕ. $\phi < 1$ showcases the situation where the first forecast (Greenbook/Tealbook) is more accurate than the second one (BCEI). Each line in the figure corresponds to a specific value of the bias of the first forecast, which ranges from -1 to 1, with a step-size of 0.1. The bias of the second forecast is always 0.5.

II.B Time-varying Forecast Correlations

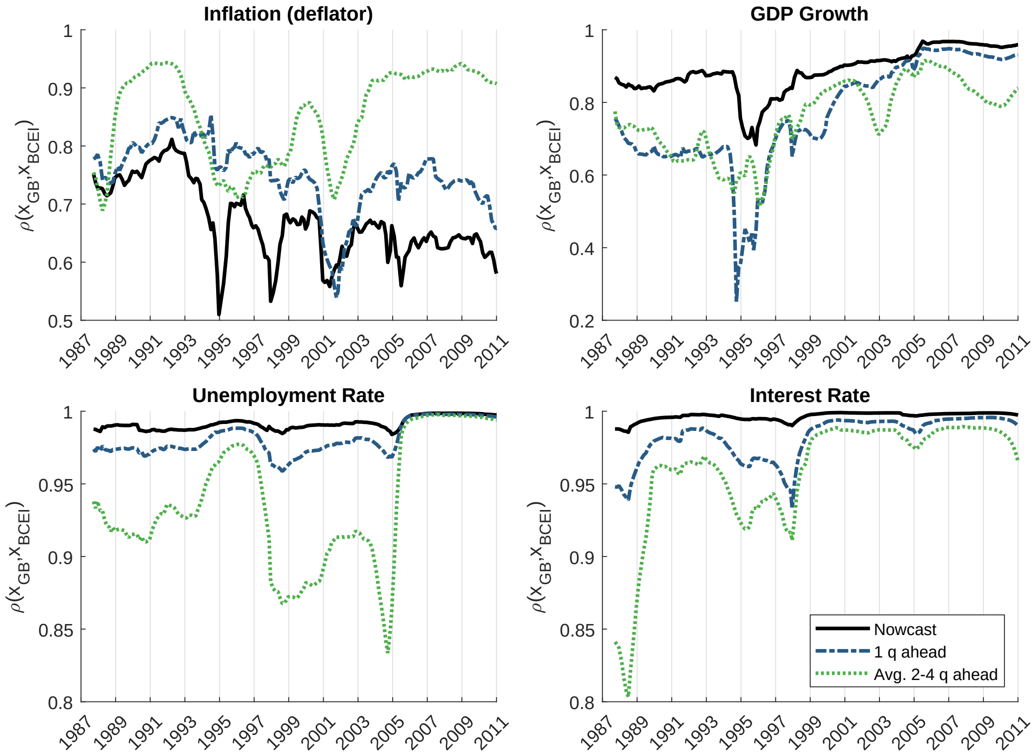

Figure S10: Correlations between Greenbook/Tealbook and BCEI forecasts

Note: Correlation between Greenbook/Tealbook and Blue-Chip forecasts based on 60 meetings rolling windows. Sample: Feb 1984 - Dec 2015. Horizontal axes correspond to mid-window dates.

II.C Forecast Unbiasedness Tests

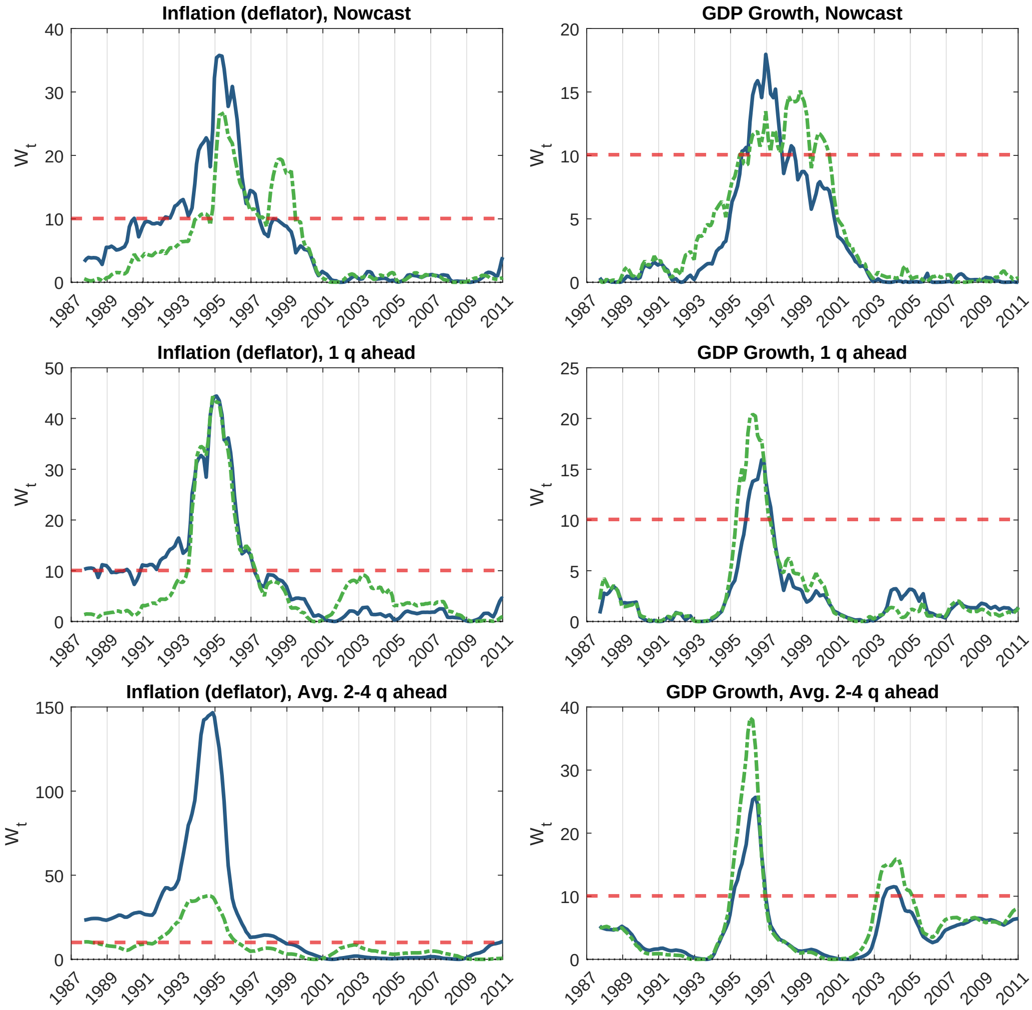

Figure S11: Forecast Unbiasedness Fluctuation Test: GDP Growth and Inflation

Note: Rossi and Sekhposyan (2016) forecast unbiasedness W_t-test based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. The dashed (red) line denotes the 5% critical value based on Rossi and Sekhposyan (2016)'s Fluctuation test. The sample is: Feb 1984 - Dec 2015.

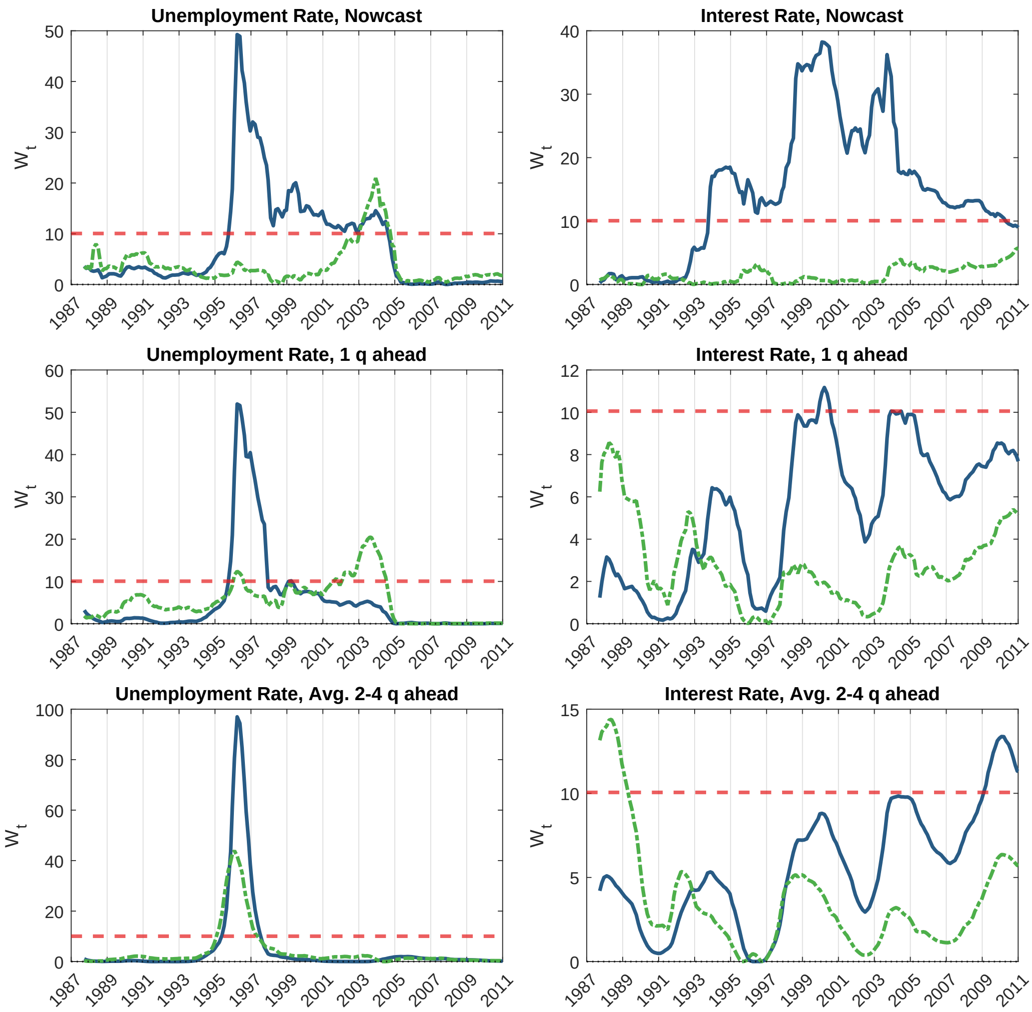

Figure S12: Forecast Unbiasedness Fluctuation Test: Unemployment and the Interest Rate

Note: Rossi and Sekhposyan (2016) forecast unbiasedness W_t-test based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. The dashed (red) line denotes the 5% critical value based on Rossi and Sekhposyan (2016)'s Fluctuation test. The sample is: Feb 1984 - Dec 2015.

II.D Forecast Rationality Tests

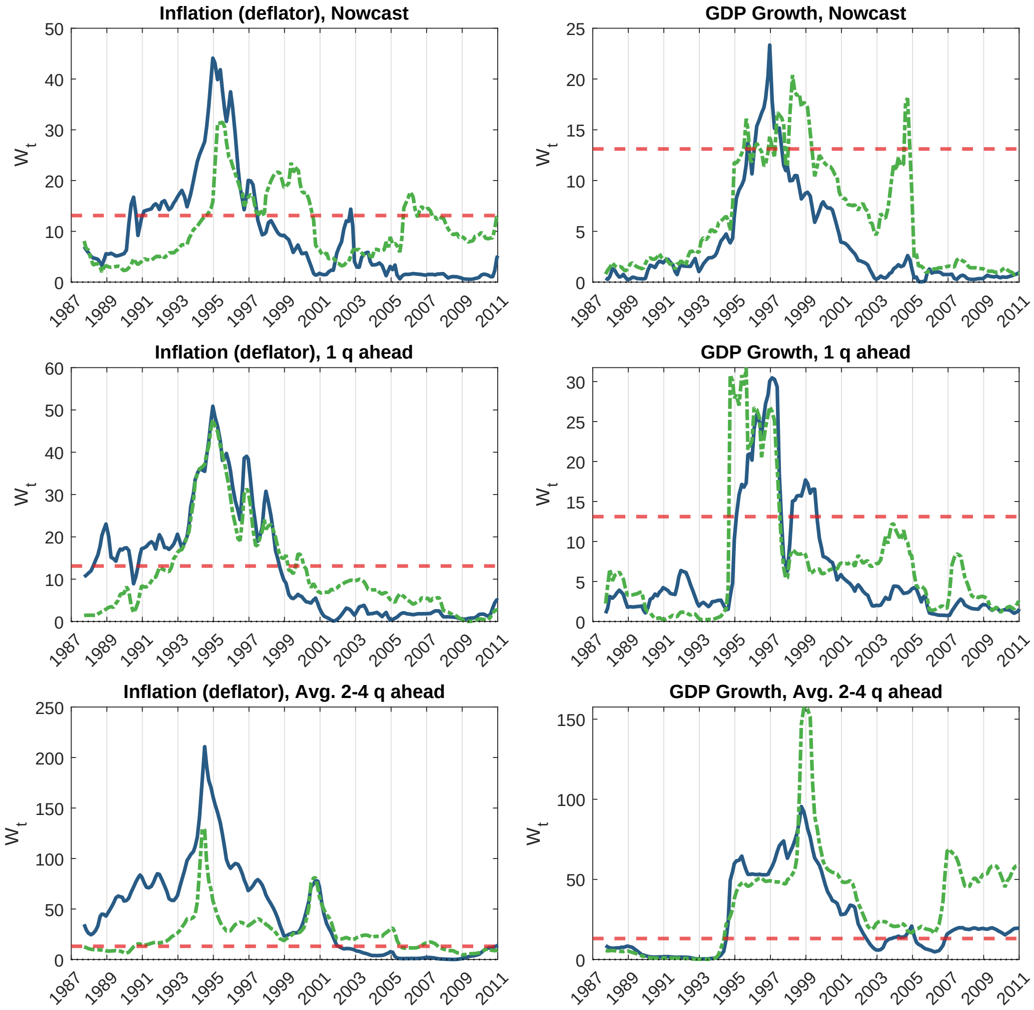

Figure S13: Forecast Rationality Fluctuation Test: GDP Growth and Inflation

Note: Rossi and Sekhposyan (2016) forecast rationality W_t-test based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. The dashed (red) line denotes the 5% critical value based on Rossi and Sekhposyan (2016)'s Fluctuation test. The sample is: Feb 1984 - Dec 2015.

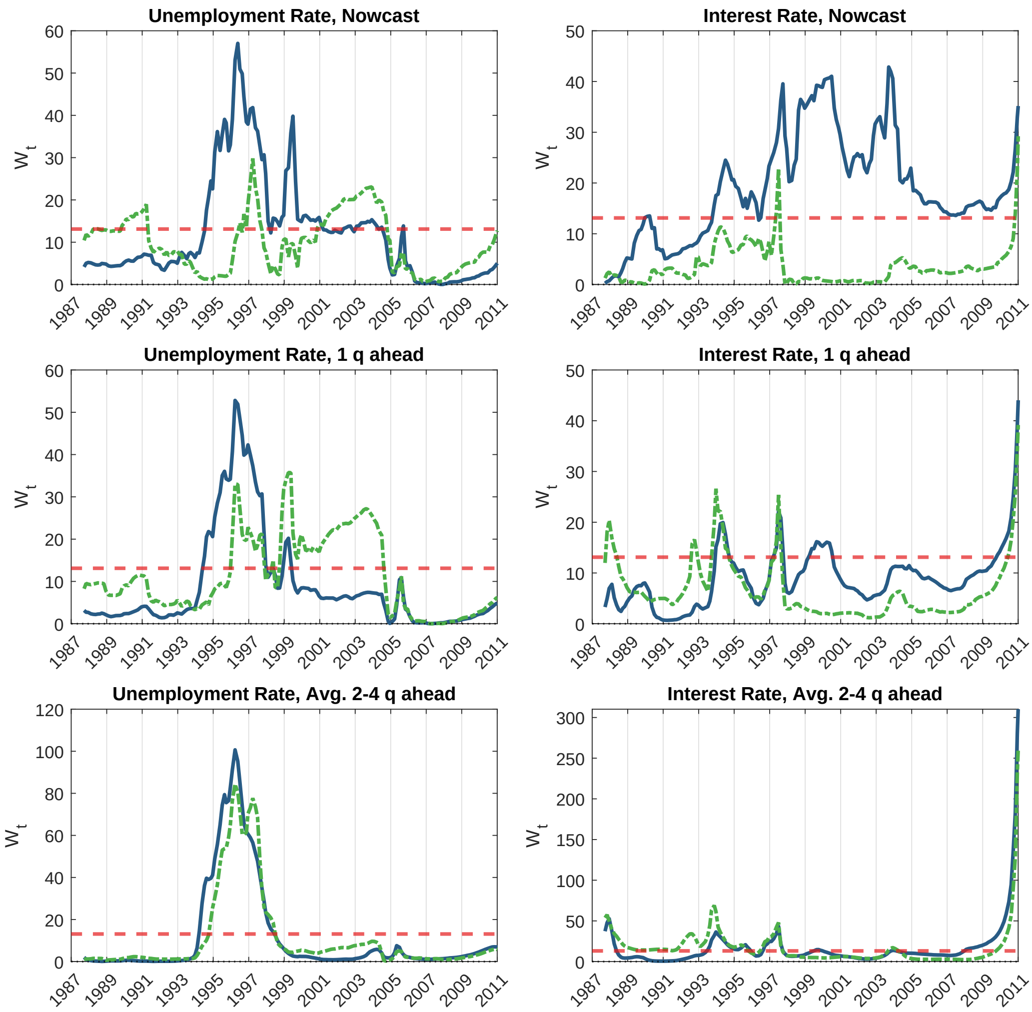

FIGURE S14: FORECAST RATIONALITY FLUCTUATION TEST: UNEMPLOYMENT AND THE INTEREST RATE

Note: Rossi and Sekhposyan (2016) forecast rationality W_t-test based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. The dashed (red) line denotes the 5% critical value based on Rossi and Sekhposyan (2016)'s Fluctuation test. The sample is: Feb 1984 - Dec 2015.

III. Additional SVAR Evidence

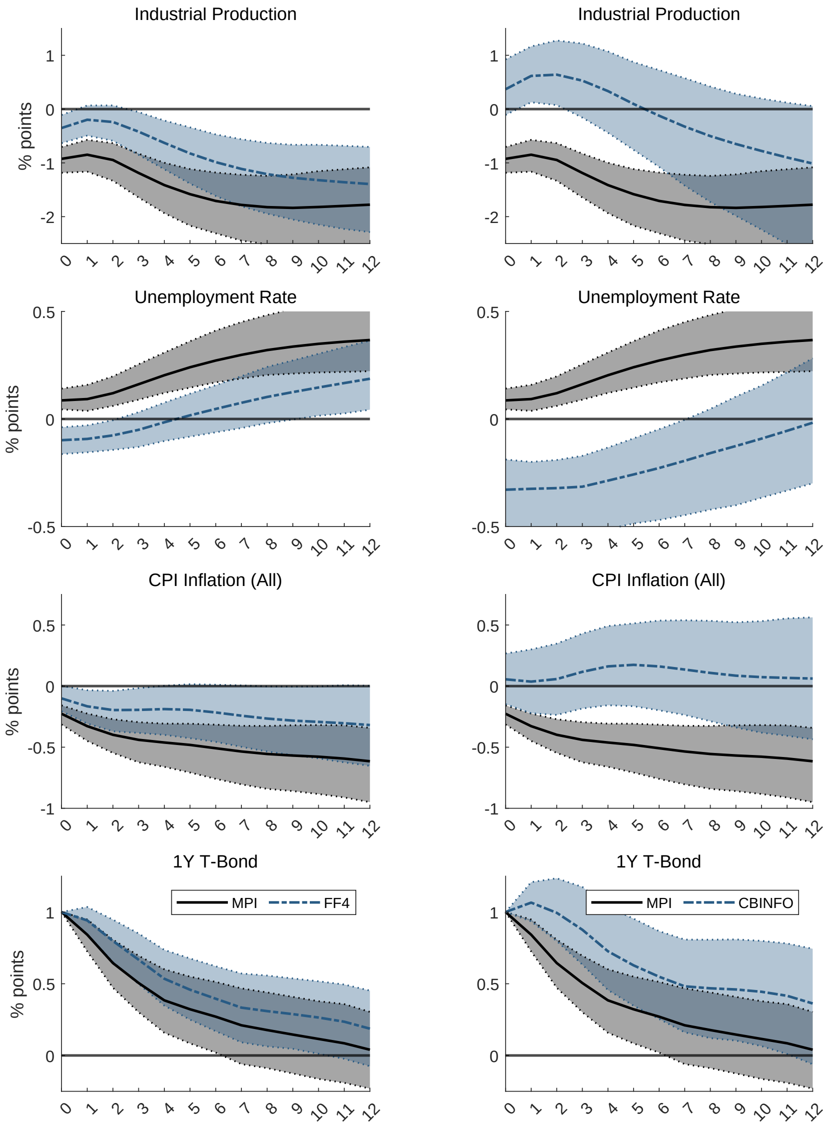

Figure S15: Responses to a monetary shock: Full Sample

Note: Bayesian VAR with standard macroeconomic priors and external instruments identification. VAR sample: January 1979 - December 2019. Information-robust instrument vs. FF4 (left panel) and information-robust instrument vs. information-component (right panel).

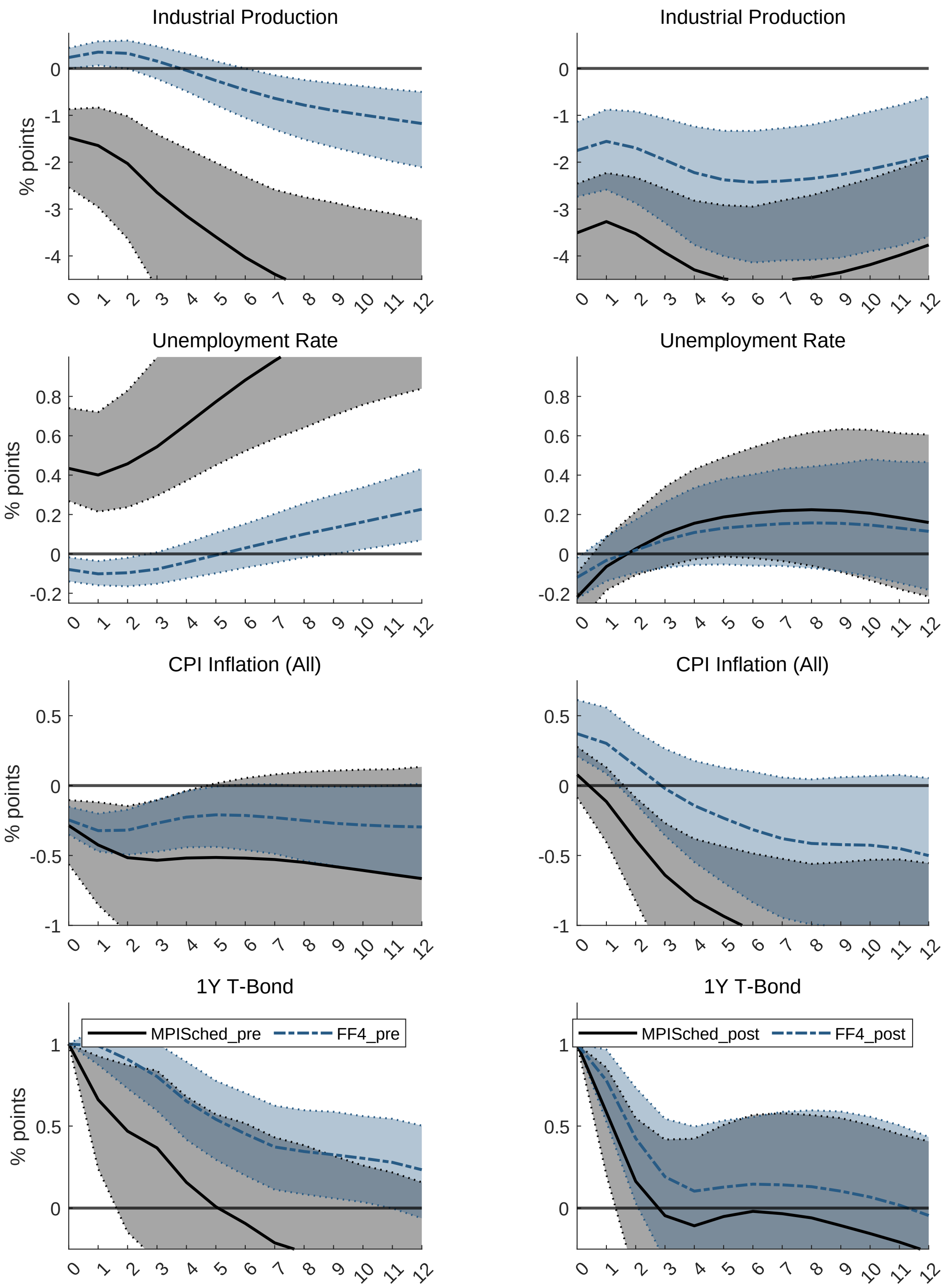

Figure S16: Responses to a monetary shock: Scheduled Announcements Only

Note: Bayesian VAR with standard macroeconomic priors and external instruments identification. VAR sample: January 1979 - December 2019. Instrument samples: February 1990 - July 2003 (left panel) and August 2003 - December 2015 (right panel).

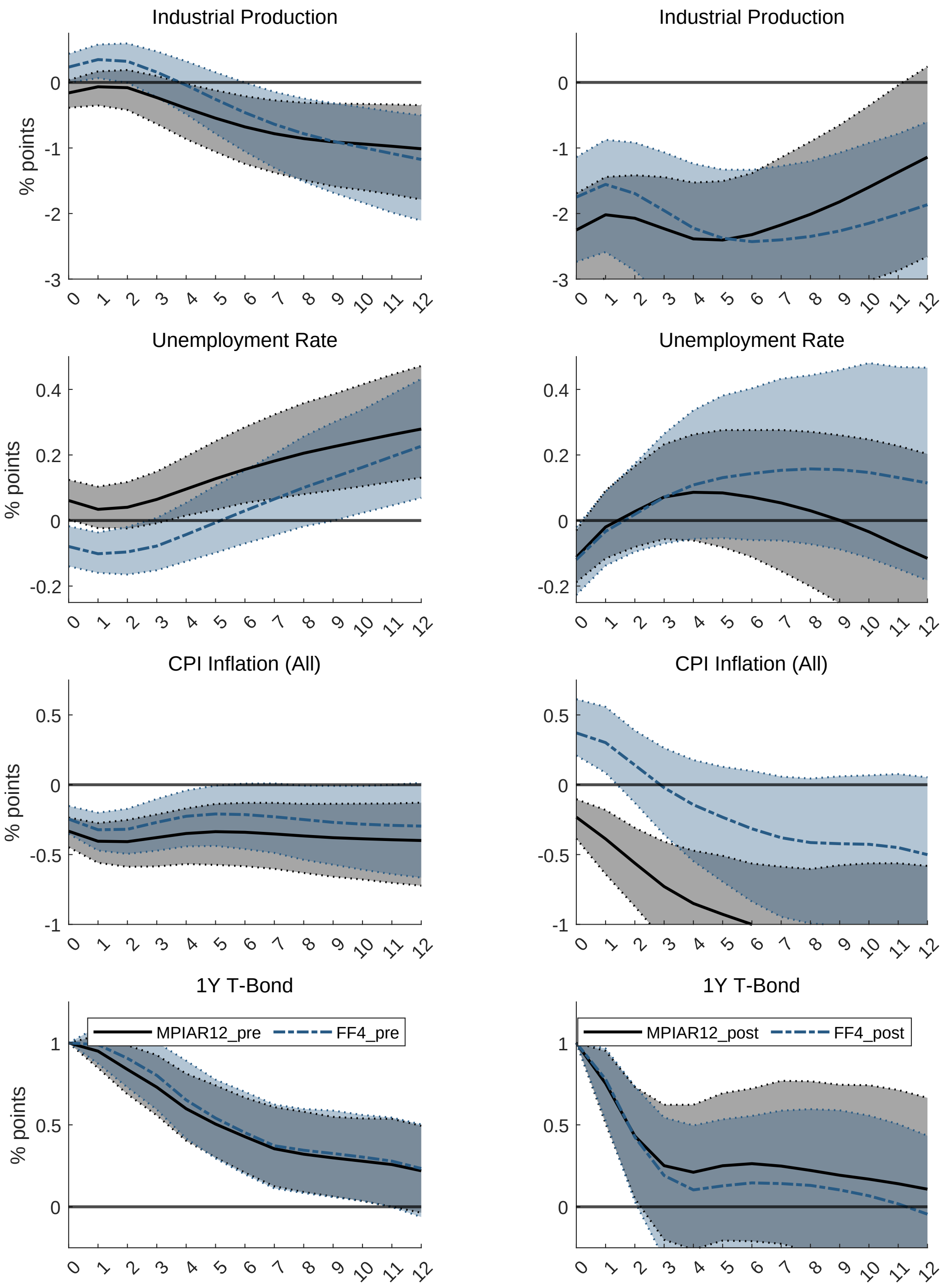

Figure S17: Responses to a monetary shock: AR(12) adjustment

Note: Bayesian VAR with standard macroeconomic priors and external instruments identification. VAR sample: January 1979 - December 2019. Instrument samples: February 1990 - July 2003 (left panel) and August 2003 - December 2015 (right panel).

References

Granger, Clive W. J., and Ramu Ramanathan. 1984. "Improved methods of combining forecasts." *Journal of Forecasting*, 3(2): 197–204.

Rossi, Barbara, and Tatevik Sekhposyan. 2016. "Forecast Rationality Tests in the Presence of Instabilities, with Applications to Federal Reserve and Survey Forecasts." *Journal of Applied Econometrics*, 31(3): 507–532.