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Reconsidering the Fed’s Forecasting Advantage*

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Abstract

Previous studies show the Fed has a forecast advantage over the private sector, either because it devotes more resources to forecasting or because it has an informational advantage in knowing the path of future monetary policy. We evaluate the Fed’s forecast advantage to determine how much of it results from the Fed’s knowledge of the conditioning path. We develop two tests—an instrumental variable encompassing test and a path-dependent encompassing test—to equalize the Fed’s information set with the private sector’s. We find that, generally, the Fed does not encompass the private sector when the latter has knowledge of the future of monetary policy. Further, we find that between 20 and 30 percent of the difference between the Fed’s average mean squared forecast error and the private sector’s can be explained by monetary policy.

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1 Introduction

Because monetary policy is inherently forward-looking, the Federal Reserve devotes a substantial amount of resources to forecasting economic variables. One set of forecasts produced by the Fed is contained in the Greenbook. A voluminous literature has arisen studying the accuracy and efficiency of these forecasts [e.g., Faust and Wright (2009); Patton and Timmermann (2012); Del Negro and Schorfheide (2013); Wolters (2015); and many others]. In particular, a number of these papers have focused on the accuracy of Greenbook forecasts relative to their private sector counterparts [see, for example, Romer and Romer (2000); henceforth RR]. In general, the broad conclusion from this literature is that private sector forecasts of inflation are encompassed by the Greenbook forecasts—that is, once the Greenbook forecasts are taken into account, private sector forecasts provide little or no additional predictive power. This result has been taken to imply that the Fed has some forecasting advantage, stemming from better information or from the use or availability of more resources devoted to forecasting. RR described the issue:

The key idea is that information the Federal Reserve has about the economy that is not known to market participants is likely to be reflected in the Federal Reserve’s internal forecasts. Because the Federal Reserve makes its forecasts public only after five years, the forecasts can contain information that is not known contemporaneously by market participants. [p. 429]

The more recent literature, however, has suggested that the Fed’s forecasting advantage has weakened over time—in particular, for inflation forecasts. Two possible explanations have been posited for this result: (i) the use and/or credibility of an inflation target has sufficiently anchored expectations to make inflation easier to forecast using simple models [see, for example, Atkeson and Ohanian (2001); Stock and Watson (1999); and Faust and Wright (2013)] or (ii) more Fed transparency has reduced market uncertainty about the future path of monetary policy [Sims (2002); Gamber and Smith (2009); and El-Shagi, Giesen, and Jung (2016)]. Which of these explanations is correct depends heavily on the source of the Fed’s

informational advantage.

In the first case, if the Fed adopts a credible inflation target, market participants know (or believe) the Fed conducts monetary policy to maintain the target. Regardless of the economic shocks, the Fed adjusts policy to keep inflation around the target. Thus, simple forecasting models of inflation may be comparable to complicated models developed by forecasters with more devoted resources to forecasting. As a result, the market's informational disadvantage relative to the Fed diminishes.

In the second case, the Fed's informational advantage is centered on what it knows about future monetary policy relative to the market. Greenbook forecasts are conditional forecasts, accounting for the future path of policy. Market forecasts, on the other hand, are produced with uncertainty about the future path of policy. Beginning in 1994, the Fed began to become increasingly transparent, issuing statements about the expected future path of policy, holding press conferences, and, inevitably, providing explicit forward guidance. As a result, market expectations about the future path of policy may have converged to the Fed's. Prior to the increased transparency, the market had to forecast both economic shocks and the Fed, while the Fed knew with relative certainty what it would do. More recently, the market's uncertainty about the Fed's path has diminished.

In this paper, we investigate these two hypotheses about the Fed's forecasting advantage relative to the market forecasts from the Blue Chip. Using standard encompassing tests, we replicate previous findings: (i) prior to the transparency period, private sector forecasts are encompassed by Greenbook forecasts and (ii) after the Fed became more transparent, the Fed's forecast advantage dissipates. We then propose a test that explicitly accounts for the fact that the Fed may know the path of future policy while the market may not. We find that, after equalizing the two forecaster's information sets, the Fed's forecasts no longer encompass the private sector's, regardless of the subsample used for estimation.

We then explore these results further. The previous literature's conjecture is that subsample differences in the encompassing results arise from the fact that the Fed has become more transparent. This implicitly assumes that during the early period, the market had less

knowledge about the conditioning path than it did in the later period. We take an alternative approach that narrows our focus on the market’s understanding of the conditioning path. Specifically, we use data from Eurodollar and fed funds futures markets and other sources to identify dates when the market’s expectation of future policy coincided with the Greenbook’s conditioning path. Our hypothesis is that if market expectations of future policy are aligned with the Greenbook’s path and the main source of the Fed’s informational advantage is knowledge of this path, Fed forecasts during these periods should no longer encompass the private sector’s. Indeed, we find that, using ordinary encompassing tests, the Fed seems to possess no informational advantage during periods where the market’s expectations of future policy are synched to the Fed’s.

The remainder of the paper is laid out as follows: In Section 2, we describe the forecast data—both from the Greenbook and the private sector forecasts—and the realizations to which they are compared. We outline both encompassing tests, the standard test which assumes that the Fed and the private sector have the same conditioning information and our new test that can account for the Fed’s certainty about the conditioning path. In Section 3, we present the results from a battery of tests comparing the two sets of forecasts. In Section 4, we describe the futures data used to separate the time sample into periods where the conditioning sets align and periods where they do not. We then present results of some of the same tests using the sample split along these lines. In Section 5, we quantify the importance of knowledge about the conditioning path for forecasting. In Section 6, we summarize the main results and link them back to the literature on the evaluation of monetary policy.

2 Baseline Empirical Framework

A common method of comparing the accuracy of forecasts is to compute their mean squared forecast errors (MSFEs). However, even if two forecasters produce forecasts with statistically similar MSFEs, one could still have an informational advantage over the other. For example, if A’s forecast has no predictive power once B’s forecast is known, B’s forecast is said to *encompass* A’s, suggesting B has an informational advantage.

Conventional encompassing tests, however, do not account for the fact that the Greenbook forecasts are conditional forecasts, constructed based on an assumed future policy path. This difference in conditioning information means the Fed is forming a horizon- h forecast, $\hat{y}_{t,h}^f = \pi(y_{t+h}|X_t, r_{t+1}, \dots, r_{t+h})$, while the private sector forms a forecast $\hat{y}_{t,h}^p = \pi(y_{t+h}, r_{t+1}, \dots, r_{t+h}|X_t)$, where the r_t 's are the period- t policy rates and X_t is the common information set. Thus, the Fed's job is to forecast inflation, while the private sector's job is to forecast both inflation and the Fed or monetary policy.

2.1 Conventional Encompassing Tests

Using data from the Greenbook as the Fed's forecast, RR estimate the (OLS) encompassing regression suggested by Fair and Shiller (1989):

$$y_{t+h} = \alpha + \beta_p \hat{y}_{t,h}^p + \beta_f \hat{y}_{t,h}^f + \eta_{t+h}, \quad (1)$$

where superscripts p and f denote the private sector's and Fed's forecasts, respectively. A formal test of the encompassing hypothesis is straightforward: jointly test the null hypothesis that $(\alpha, \beta_p, \beta_f)' = (0, 0, 1)'$.¹

RR find that, in general—and, in particular, for inflation—the estimate of β_f is close to one and statistically different from zero, while their estimate of β_p is close to zero and statistically insignificant. They interpret these results as supporting the idea that private sector forecasts provide no additional information above what is already contained in the Greenbook forecasts. While Romer and Romer do not formally test the joint null hypothesis that $(\alpha, \beta_p, \beta_f)' = (0, 0, 1)'$, their results *suggest* that the Greenbook forecasts encompass the private sector forecasts.

Explaining the origin of the Fed's forecast advantage is more complicated. RR argue that the quality of the Fed's forecasts are indicative of “the vast resources that it devotes to forecasting” and not due to any inside information about government statistics or future

¹Previous studies found that forecasts of inflation and output growth are biased [see Caunedo, DiCecio, Komunjer, and Owyang (2020)]. The joint hypothesis could be rejected because $\alpha \neq 0$. Thus, we also perform the encompassing test omitting the unbiasedness condition, making the null $(\beta_p, \beta_f)' = (0, 1)'$.

monetary policy (p. 430). In contrast, Sims (2002) argues that the Fed’s informational advantage arises from the fact that the Greenbook forecasts are constructed conditional on future monetary policy. Because monetary policy matters for future inflation, knowing the future path of monetary policy may give the Fed an advantage when forecasting inflation. The conventional encompassing test, regardless of whether we account for unbiasedness or not, is insufficient to distinguish between these two alternative theories of the origin of the Fed’s informational advantage.

2.2 Conditional Encompassing Tests

We want to test whether the Fed’s forecasts encompass the private sector’s because the Fed knows the future path of monetary policy (i.e., the conditioning path). To understand our approach, it is instructive to first delineate how a conditional forecast differs from an unconditional forecast. Let y_t be the variable to forecast and x_t be a vector of variables, some of which we may have future information about. Define $\hat{y}_{t,h}^{(c)}$ and $\hat{y}_{t,h}^{(u)}$ as the h -step-ahead (c)onditional and (u)nconditional forecasts of y_t , respectively. The conditional forecast is constructed based on hypothetical (known) values of x_{t+i} , $i = 1, \dots, h$, denoted $x_{t+i}^{(c)}$.

In the context of a Gaussian vector autoregression (VAR), Waggoner and Zha (1999) show that the minimum MSE *conditional* forecast of y_{t+h} takes the form:

$$\hat{y}_{t,h}^{(c)} = \hat{y}_{t,h}^{(u)} + \sum_{1 \leq i \leq h} \hat{\gamma}'_{i,t} (x_{t+i}^{(c)} - \hat{x}_{t,i}^{(u)}), \quad (2)$$

where $\hat{x}_{t,i}^{(u)}$ is the (u)nconditional forecast of x_{t+i} and $\hat{\gamma}_{i,t}$ is a vector of weights. If the forecasting model relating $Y_t = (y_t, x_t')'$ can be written as a VAR, the weights, $\hat{\gamma}_{i,t}$, are known functions of the estimated conditional mean parameters of the VAR, as well as the residual variance matrix. Thus, the conditional forecast, $\hat{y}_{t,h}^{(c)}$, is the unconditional forecast, $\hat{y}_{t,h}^{(u)}$, adjusted by a linear combination of deviations between the unconditional forecast, $x_{t+i}^{(u)}$, and the conditioning path, $x_{t+i}^{(c)}$. For our application, we assume that the Fed constructs its conditional forecasts, $\hat{y}_{t,h}^{(c)} = \hat{y}_{t,h}^f$, based on the future path of monetary policy, $x_{t+i}^{(c)} = x_{t+i}$.

Thus, $x_{t+i}^{(c)} - \hat{x}_{t,i}^{(u)}$ is (in large samples) the value of the time $t + i$ shock to the policy rate equation in the VAR.

Now, reconsider the encompassing regression in equation (1). Because of the conditioning, $\hat{y}_{t,h}^f$ is an endogenous regressor and OLS is inconsistent for the parameters α , β^f , and β^p .² In equation (2), the second term on the right hand side can be thought of as a linear combination of future shocks that are unpredictable, given information available to the private sector at time t . Thus, we can estimate the encompassing regression by instrumental variables (IV), provided there exists a set of time- t instruments that are correlated with the unobservable unconditional forecast, $\hat{y}_{t,h}^{(u)}$, but also uncorrelated with the future shocks, $x_{t+i}^{(c)} - \hat{x}_{t,i}^{(u)}$.

We can derive a test for encompassing with conditional forecasts that is similar to the standard encompassing test. Using a vector of instruments and an intercept, z_t , we run a first-stage regression

$$\hat{y}_{t,h}^f = \delta_z' z_t + \delta_p \hat{y}_{t,h}^p + u_t \quad (3)$$

to obtain an estimate of what the Fed's forecast would be without the conditioning information. We then run the encompassing regression:

$$y_{t+h} = \alpha + \beta_p \hat{y}_{t,h}^p + \bar{\beta}_f \bar{y}_{t,h}^f + \bar{\eta}_{t+h}, \quad (4)$$

where we have replaced the actual forecast, $\hat{y}_{t,h}^f$, with the fitted values from the first stage regression, $\bar{y}_{t,h}^f = \hat{\delta}_z' z_t + \hat{\delta}_p \hat{y}_{t,h}^p$. The conditional encompassing test then amounts to testing the null hypothesis $(\beta_p, \bar{\beta}_f)' = (0, 1)'$.

The key to our procedure is choosing instruments that are correlated with the Fed's unobserved *unconditional* forecast but uncorrelated with the informational advantage the Fed possesses about the conditioning path—i.e., $x_{t+i}^{(c)} - \hat{x}_{t,i}^{(u)}$. Fortunately, obtaining valid instruments is straightforward, because—apart from the conditioning path—the information set available

²This issue was also observed by Faust and Wright (2009) for evaluating the efficiency of the Greenbook forecasts. Their solution is to introduce additional regressors that approximate the conditioning term, $\sum_{1 \leq i \leq h} \hat{\gamma}_{i,t}^{(c)} (x_{t+i}^{(c)} - \hat{x}_{t,i}^{(u)})$. This requires that they explicitly know the Fed's conditioning information, whereas the IV allows us to have instruments correlated with the conditioning information without knowing the exact information.

to private sector agents overlaps—if not coincides—with that available to the Fed. For example, if we are comparing the Greenbook to the Blue Chip—i.e., if we set $\hat{y}_{t,h}^p = \hat{y}_{t,h}^{BC}$ —forecasts from the Survey of Professional Forecasters are a natural choice of instrument. In addition, if private agents form joint forecasts of multiple variables, the forecasts of these other variables can also serve as instruments. For example, private sector forecasts of the unemployment rate, the yield on the 3-month T-bill, and GDP growth—individually or collectively—could be used as instruments for evaluating an inflation forecast. Finally, the longer-horizon private sector forecast, $y_{t-1,h+1}^{BC}$ —a forecast of y_{t+h} formed in the previous period—could be used as an instrument. We continue this discussion later when we describe the data.

2.3 Data

The dataset for our initial set of results contains four elements: (i) the Greenbook forecasts, (ii) the private sector forecasts, (iii) the realizations, and (iv) the instruments used to conduct the conditional encompassing tests. The full sample period for the Greenbook is 1965:11 to 2012:12, while the Blue Chip and SPF start in 1980:01 and 1968:Q4, respectively.

2.3.1 Greenbook Forecasts

The Greenbook forecasts are predictions of various macroeconomic series at different horizons. They are prepared by the Board of Governors staff for each Federal Open Market Committee (FOMC) meeting. After a 5-year lag, the Greenbook forecasts are made available at the Federal Reserve Bank of Philadelphia.³ The Greenbook contains a large number of forecasted variables but, like RR, we concentrate on inflation.⁴

Similar to the schedule of the FOMC meetings, the Greenbook forecasts vary both in frequency and in timing over the sample period.⁵ At the beginning of the sample, the Greenbook

³These data are available here: <https://www.philadelphiafed.org/research-and-data/real-time-center/greenbook-data>. While the Greenbook forecasts are inputs into the policy process, they do not represent the forecasts—individually or collectively—of the FOMC members.

⁴Results for output growth and the unemployment rate are provided in the Appendix.

⁵The definitions of the forecasted variables also change over time. In 1992, the Greenbook changed from forecasting GNP growth to forecasting GDP growth. For inflation, the Greenbook forecasted the implicit GNP deflator through the end of 1991, the implicit GDP deflator until 1996:Q1, and the chain-weighted price index for GDP thereafter. In order to remain consistent, we change the realizations accordingly.

forecasts were available monthly; after 1981, the Greenbook was produced only for FOMC meetings. Thus, prior to 1981, twelve observations per year are available; after 1981, eight or nine observations per year are typically available. The maximum forecast horizon varies across Greenbooks.

2.3.2 Private Sector Forecasts

To ensure that the information sets for the forecasters are comparable, we consider only the private sector forecasts that are released in the same calendar month as an FOMC meeting.⁶ Similar to RR, we consider consensus-based forecasts from the Blue Chip survey and the Survey of Professional Forecasters (SPF). The former is released monthly within the first week of each month, while the latter is quarterly and is typically released the third week of the middle month of each quarter.

Much of the literature comparing Federal Reserve forecasts to private sector forecasts uses the SPF. Because of its quarterly frequency, there are relatively few compatible SPF observations that share the same calendar month as the Greenbook. On the other hand, we typically find more monthly Blue Chip forecasts per year that share the same month as Greenbook forecasts. Thus, we report our main set of results comparing the Greenbook to the Blue Chip forecasts and use the SPF forecasts to check robustness.⁷

2.3.3 Realizations

Because macroeconomic data are sometimes subject to revision, which data release forecasters target is not always obvious. Deflator-based inflation is revised a number of times, even within the first year. Importantly, the first release by the BEA occurs during the first month after the end of the quarter. The first release—also known as the advance release—is often thought to be the target for private forecasters; Stark (2010) shows that SPF forecasts of output growth become increasingly less accurate as the number of revisions increase over time. In contrast,

⁶For some periods, the Greenbook and the private sector forecasts will target different variable definitions. This occurs near those periods when the forecasted variable changes. In these cases, we drop these datapoints. Because they are few in number, these omissions do not significantly affect our conclusions.

⁷These results are available in the Appendix.

one might argue that the Federal Reserve is more interested in the true value of the variable. If revisions converge to the true value, the Fed may be targeting extensively revised data. We use the second revised value of deflator-based inflation—sometimes called first final—when evaluating the forecasts. For further discussion on this issue see Clements (2019).⁸

2.3.4 Instruments

To execute our conditional forecast encompassing tests, we require a set of instruments that proxy the (common) information set of the two forecasters. As we indicated above, given the nature of the forecasts we are comparing, three sets of possible instruments come to mind. First, we could use lags of the forecasts that are being compared. Second, we could use the other private sector forecast of the same data—i.e., when comparing the Greenbook inflation forecasts to the Blue Chip, we could use the SPF inflation forecasts as instruments. Finally, we could use the forecasts of other variables produced by the same private sector forecaster—e.g., when comparing the Greenbook forecast of inflation to the Blue Chip, we could use Blue Chip forecasts of unemployment and/or output growth.

Evaluation of the first stage F —statistics for the first set of instruments suggest that lags of the forecasts are weak instruments. Using the other private sector forecaster’s predictions (i.e., SPF) requires us to drop observations, as we need all three forecasts to be observed in the same period. This limitation reduces the number of observations dramatically, especially in our split sample analysis. Instead, we opt to report results for the third instrument set, using the same forecaster’s predictions of other variables. This ensures that we can maximize the number of available observations over the sample period.

3 Comparing the Forecasts

Based on the empirical framework outlined above, we compare the forecasts to determine if (and possibly when) the Fed has an informational advantage. In cases where the Fed does have an informational advantage, we assess whether the advantage is a result of its knowledge

⁸For the output growth and the unemployment rate results in the Appendix, we also use the second revision.

of the conditioning path.

3.1 Encompassing Tests

We compare the results of two types of forecast encompassing tests with the null hypothesis that $(\beta_p, \beta_f)' = (0, 1)'$.⁹ The first is based on OLS estimates of the encompassing regression in equation (1); the second is based on the IV approach discussed in Section 2.2.

Taken together, the results of these tests have a natural interpretation summarized by four possible outcomes. First, failure to reject the null using both OLS and IV suggests that the Fed has an absolute forecasting advantage, independent of its knowledge of the conditioning path. Second, failure to reject the null using OLS but rejecting the null using IV suggests that the Fed’s knowledge of the conditioning path gives them an advantage over the private sector. Moreover, once the conditioning path is accounted for, the Fed’s advantage dissipates. Third, rejecting the null under OLS but failing to reject using IV implies that either (i) policy does not coincide with the conditioning path or (ii) the Fed misunderstands how the conditioning path will affect future outcomes. In either case, from an MSFE standpoint, the Fed would be better off without using the conditioning information. Finally, rejecting the null using both OLS and IV implies that the Fed has no informational advantage regardless of any conditioning information.

Previous studies have hypothesized that increased transparency starting in 1994 led to synching the Fed’s and the private sector’s beliefs [e.g., Poole and Rasche (2003)]. This, in turn, coincides with previous studies’ findings that the Fed’s forecasting advantage has declined [e.g., Gamber and Smith (2009) and Hoesch, Rossi, and Sekhposyan (2020)]. If this is indeed the case, during the pre-transparency period, the Fed would have a forecasting advantage that would disappear once accounting for the conditioning path. Thus, we would expect to fail to reject encompassing using OLS but reject using IV. Moreover, during the transparent period, we would expect to reject encompassing even without accounting for the Fed’s knowledge of the conditioning path.

⁹Results for the three parameter joint test are in the Appendix.

3.1.1 Conventional Encompassing Tests

We first execute the conventional encompassing test, eq. (1), using Greenbook and private sector forecasts for a common sample and various forecast horizons.¹⁰ As indicated above, we consider three time samples: (i) the full sample, (ii) the pre-1994 period, and the post-1994 increased-transparency period.¹¹

Table 1: Conventional Encompassing Test Inflation

Table 1 shows the results for the conventional encompassing tests for inflation using the Blue Chip as our private sector forecaster. The three panels contain results for the full sample (left); the pre-1994 period (center), and the post-1994 period (right). Each panel is comprised of five columns. The first three columns in each panel report the estimated values of the coefficients— α , β_p , and β_f ,—with the p -value for the individual HAC-robust Wald statistic that the coefficient is zero (for α and β_p) or one (for β_f) in the parentheses. The fourth column in each panel reports the HAC-robust Wald statistic and associated p -value for the conventional encompassing test with the null of encompassing. The final column reports the number of observations used in the estimation. Each row of the table reports a different (quarterly) forecasting horizon.

The results in the center panel (pre-1994) are the most comparable to, and are broadly consistent with, those in Romer and Romer (2000). Based on the Wald tests, we reach more formal but similar conclusions. At horizon zero, the Fed does not have an informational advantage for inflation. At intermediate horizons, the Fed encompasses the private sector forecasts. At long horizons, the Fed’s informational advantage again disappears. Given our hypothesis that the Fed’s knowledge of the conditioning path is the source of its advantage, these results have a straightforward interpretation. The Fed has no informational advantage at very short horizons because only past monetary policy—known to both the Fed and the

¹⁰Our main results are reported for the Blue Chip, which has more temporally proximate observations to the Greenbook. Results for the SPF are provided in the Appendix.

¹¹Romer and Romer (2000) end their sample in 1991 due to changes in the definition of the forecasted inflation series. We consider this sample in our series of robustness checks.

private sector forecasters—matters. At intermediate horizons, the Fed’s knowledge of the conditioning path becomes relevant. At very long horizons, deviations from the conditioning path and possible unanticipated shocks make knowledge of the conditioning path less valuable.

Previous studies cite the decline in the magnitude of β_f and the increase in the magnitude of β_p over time as evidence that the Fed’s informational advantage has eroded. If the policy path is the source of the Fed’s informational advantage, increased transparency might weaken that advantage. Our results support that conclusion: In the post-1994 sample, the Fed forecasts never encompass those of the private sector. The full sample results are a mix of these split-sample results: There are only two horizons at which we fail to reject encompassing at a 5-percent level and none at which we fail to reject at the 10-percent level.

3.1.2 Conditional Forecast Encompassing Tests

The Greenbook forecasts are based on a presumed-known future monetary policy path; thus, the OLS estimated coefficients from conventional encompassing regressions are inconsistent, and the standard encompassing tests are invalid. To account for the Fed’s knowledge of the path, we construct a modified version of the encompassing test. Using the same forecast and realization data, we first estimate eq. (3) to cleanse the Fed’s forecast of the conditioning path and then estimate eq. (4). If RR’s hypothesis that the Fed is simply better at forecasting is true, correcting for the conditioning path should not materially change the encompassing results.

Table 2: Conditional Encompassing Test Inflation

We use the same period Blue Chip forecasts of the 3-month T-bill, the unemployment rate, and output growth as instruments. These variables should be correlated with the Fed’s unobservable, unconditional forecast but uncorrelated with the Fed’s private information about the future path of monetary policy. Table 2 shows the results for our two-stage procedure. As before, the table has three panels, each representing a different estimation sample. Each panel is comprised of six columns: the first-stage F –statistic; the estimated values of the

coefficients— α , β_p , and $\bar{\beta}_f$; the HAC-robust Wald statistic for the conditional encompassing test; and the number of observations used for the estimation. Each row again reports a different forecasting horizon.

If we believe that (i) the Fed’s informational advantage is its knowledge of the conditioning path and (ii) increased transparency after 1994 has reduced this advantage by imparting knowledge of the path to the market [Sims (2002); Gamber and Smith (2009); El-Shagi, Giesen, and Jung (2017)], we expect to find that the Fed’s unconditional forecast should not encompass the private sector’s. Indeed, results for the post-1994 period are broadly similar to the conventional encompassing results. On the other hand, for the pre-1994 period, encompassing is rejected for all but two horizons.

We take these results as evidence that a major component of the Fed’s forecasting advantage vanishes if its information set is the same as the private sector’s. If, as RR postulate, the Fed is simply better at forecasting, equalizing information sets would still leave the Fed with an advantage. However, based on this evidence alone, we cannot conclude that the source of the Fed’s informational advantage is specifically its knowledge of the conditioning path. We can only conclude that, mostly prior to 1994, the Fed had some knowledge the market did not have. As Faust and Wright (2009) suggest, this could be knowledge of the future path of oil prices or exchange rates, among other things.

4 Formalizing Fed’s Conditioning Path

Suppose that the conditioning path is the source of the Fed’s forecasting advantage. Then, during periods when the market “knows” the path, the Greenbook forecasts should not encompass private sector forecasts. Conversely, when the market path is either wrong or uncertain, the Fed should have a forecasting advantage.

In this section, we reconsider the conventional encompassing tests, partitioning the data into periods in which (i) the Fed gets the future path of policy correct but the market does not; (ii) both the Fed and the market get the path correct; and (iii) both the Fed and the

market miss the path.¹²

4.1 Identifying the Market’s Expectations of Future Policy

The key component of this analysis is determining when the market “knows” the path. We assume the path is “known” by the market if: (i) the market’s expected path is on or close to the realized path and (ii) the expected path is relatively certain. Ideally, we would use private sector density forecasts of expected future monetary policy; instead, we use the market-implied policy path derived from options data augmented with a measure of monetary policy uncertainty.¹³

4.1.1 Futures Data

Eurodollar futures contracts can be thought of as bets on future monetary policy outcomes [see Cochrane and Piazzesi (2002); Gürkaynak, Sack, and Swanson (2007); and Piazzesi and Swanson (2008); among others] and are available for a longer time period than fed funds futures.¹⁴ Eurodollar futures are contracts written on 3-month deposits of U.S. dollars in foreign banks at specific dates in the future. While not identical to the fed funds futures, a number of previous papers have shown that the rate implied by the Eurodollar futures generally approximates the fluctuations in the fed funds futures implied rate [Swanson (2006); Rigobon and Sack (2004); Lakdawala and Schaffer (2019); De Pooter, Martin, and Pruitt (2018); Bauer and Rudebusch. (2019)]. We can then compute the market’s expected policy rate at different horizons using the appropriate maturity Eurodollar futures.

To match the timing of our forecast dataset, we use Eurodollar contracts that mature around the 10th of each month—about when the Blue Chip forecasts are released. For each contract, we compute the average settlement price of days 8-12 (when available) of the current month to obtain a close approximation even when the 10th does not fall on a business day or when there is no volume for a particular contract on the 10th. For a given month, we

¹²Cases for which the market correctly forecasts the path but the Fed does not are too rare for proper analysis and are discarded.

¹³The options data are obtained from Fisher and Robertson (2016).

¹⁴Fed funds futures sample starts in 1993:01, while the Eurodollar futures sample starts in 1982:01.

form a path of Eurodollar future contracts maturing over the next calendar year. We linearly interpolate between observable contracts to fill in values for missing contracts that would theoretically mature in unobserved serial calendar months. In total we have observations ranging from 1982:01 through 2009:12.¹⁵ All Eurodollar futures are obtained from Haver.

4.1.2 Uncertainty

While futures contracts provide an average path, they do not reflect the market’s certainty about the path. Consider two cases: the market places (i) a 40 percent probability on a 25-basis-point increase and 30 percent each on no-change and a 50-basis-point increase or (ii) 100 percent certainty on a 25-basis-point increase. Using futures data alone, these two scenarios would be equivalent and, if the Fed moved the target 25 basis points, both cases would show the market knew the path.

One way of incorporating uncertainty is to interact the path variable with the monetary policy uncertainty index [MPU; see Baker, Bloom, and Davis (2016)]. The MPU is a subcategory of the economic policy index and is constructed by analyzing the frequency of newspaper articles containing several key search terms and is available for the sample 1985-2018.¹⁶

4.2 The Market’s Path

The Eurodollar futures data allows us to compute the market’s expected path at a forecast origin t for a variety of horizons up through h . Let $\mathbf{r}_t = (r_{t+1}, \dots, r_{t+h})$ represent the realized path. At time t , the market-based expected path is

$$\mathbf{r}_{t,h}^p = (\bar{r}_{t+1}, \dots, \bar{r}_{t+h})',$$

where $\bar{r}_{t+h}$ corresponds to the futures-implied rate at time $t + h$. We then construct an indicator that shows, at time t , whether the market correctly forecasts the h -period-ahead stance of monetary policy:

¹⁵To match the Eurodollar data to the Blue Chip forecasts, we use the quarterly average of the monthly values.

¹⁶See http://www.policyuncertainty.com/us_monthly.html

$$s_{t,h} = \begin{cases} 1 & \text{if } r_{t+1} + \tau^h > \bar{r}_{t+h} > r_{t+1} - \tau^h \\ 0 & \text{otherwise} \end{cases},$$

where $0 < \tau < 1$ allows some deviations that may result from outlier forecasts in a band that increases over the forecast horizon.

We could collect the $s_{t,h}$'s in a vector and use this as our measure of “on the path.” This would, however, allow forecasters to be simultaneously correct about the long-run path but incorrect about the short-run path. If we believe that the path *up to* h is relevant in determining the effects of monetary policy, we should, for horizon h , evaluate whether the market was on the path for $t + 1$ through $t + h$. We then define the market on-the-path indicator at time t for horizon h to be

$$S_{t,h} = \prod_{\eta=1}^h s_{t,\eta}.$$

Thus, the market is considered off the path at horizon h if it was off the path for any horizon less than h .

We then define a certainty indicator:

$$z_t = \begin{cases} 1 & \text{if } MPU < z^* \\ 0 & \text{otherwise} \end{cases},$$

which is logically combined with the path indicator in the results below. Note that we omit the horizon subscript; thus, during a period of uncertainty, we assume that the forecaster is uncertain for all horizons.

4.3 Results

Given our on-the-path indicators, we revisit the conventional encompassing regressions to evaluate how these results differ for periods where the Fed does and does not have an informational advantage based on the conditioning path. For each forecast horizon, we separate the time periods into periods in which (i) the Fed was on the conditioning path but the mar-

ket was not and (ii) the Fed and the market were both on or both off the conditioning path. The former corresponds to periods when the Fed had an informational advantage; the latter corresponds to periods when the information sets were essentially the same.¹⁷ Because we explicitly account for knowledge of the conditioning path, we no longer split the full sample into subperiods to proxy for an increase in transparency.

Table 3: Monetary Policy Path Encompassing Test

Table 3 displays the results for these cases. As before, the rows in the table reflect the various horizons. There are four panels, each of which has four columns. The first panel shows the results from the encompassing regressions when the Fed and the market are either both on or both off the conditioning path. The second panel shows the results when the Fed is on the path and the market is not. The third panel shows the results when the Fed is on the path but the market is either off the path or uncertain. The fourth panel shows the results when either (a) the Fed is on the path, the market is on the path, and uncertainty is low or (b) the Fed is off the path and the market is either off the path or uncertain. Each panel contains the slope coefficients in the encompassing regressions (omitting the intercepts), the HAC-robust Wald statistic for the conventional encompassing test, and the number of observations.

When the market and the Fed have the same information (the first and fourth panels), we reject the null of encompassing at all horizons except the shorter horizon. On the other hand, when the Fed knows the path but the market does not (panel 2) or is uncertain (panel 3), we reject encompassing only for the nowcast and the one-period-ahead. For these short horizons, the path of monetary policy is likely irrelevant, given the lags in the effects of monetary policy. For longer horizons, when the Fed has asymmetric knowledge about the true path, the Fed's forecasts dominate the private sector's; when they have the same information, the forecasts are essentially equivalent.

In the third and fourth panels of Table 3, the on-the-path indicator is interacted with the

¹⁷Periods in which the Fed and the market are both off the path may be subject to large shocks (e.g., after peaks) that complicate forecasting. Results splitting the same information for both on and off the path separately are available in the Appendix.

threshold uncertainty indicator. Results incorporating uncertainty are generally consistent with—and provide sometimes even stronger evidence than—our previous results controlling for whether the private sector was on or off the path.¹⁸

5 How Important Is Knowing the Path?

Our results suggest that the Fed’s informational advantage (at least for inflation forecasting) can be explained by its knowledge (and certainty of) the conditioning path. In this subsection, we investigate how the market’s knowledge of the conditioning path affects private sector forecast performance.

5.1 Forecast Performance and the Conditioning Path

Table 4: MSFE Dependent on Monetary Policy Path

Forecast encompassing is a binary result that tells us whether the information set of one forecaster strictly dominates that of another forecaster. We now consider how the private sector’s knowledge of the path affects its forecast performance relative to when the path is uncertain. Table 4 shows the MSFE of the Blue Chip forecasts during periods (i) when both the market and the Greenbook know the conditioning path, (ii) when the market is on the path (regardless of the status of the Greenbook), (iii) when the market is off the path (regardless of the status of the Greenbook); and (iv) when the Greenbook is on the path but the market is off the path.

We find that, at very short horizons (nowcast or one-period-ahead), knowing the conditioning path does not improve the performance of the Blue Chip forecasts; in fact, these short-horizon forecasts are often worse when the market is on the path. However, at short horizons, the effects of monetary policy may already be “baked in,” and knowledge of the conditioning path may be irrelevant. At longer horizons (2-quarters-ahead or more), the Blue Chip consensus forecasts perform better when the market knows the path. These results

¹⁸Results for output are mixed, possibly due to longer lags in the effects of monetary policy. Recall that we only use a four quarter horizon for the path variable. These results are reported in the Appendix.

suggest that, for horizons at which we expect monetary policy to matter, the private sector forecasts better when it is confident about the policy path.

5.2 Quantifying Monetary Policy’s Influence

Our main hypothesis is that the Fed and the private sector have similar forecasting performance once accounting for the information in the Greenbook’s conditioning path. In the previous section, we asked how much better the private sector forecasts when they are certain about the conditioning path. Here, we quantify the conditioning path’s contribution to the difference between the Fed’s and the private sector’s MSFE.

To evaluate this, we compute the Kitagawa–Blinder–Oaxaca (KBO) decomposition [Kitagawa (1955); Blinder (1973); and Oaxaca (1973)] of the expected difference in the MSFEs. Define $R_h = E[(y_{t+h} - \hat{y}_{t,h}^f)^2] - E[(y_{t+h} - \hat{y}_{t,h}^p)^2]$, the mean difference between the MSFEs of the Fed and the private sector. We then regress the horizon- h inflation prediction errors on a vector of state variables, s_{it} , that includes a constant and the squared forecast errors for output, unemployment, and the short term interest rate:

$$(y_{t+h} - \hat{y}_{t,h}^i)^2 = \lambda_h^i s_{ht}^i + \varepsilon_{ht}^i, \quad (5)$$

where $i = f, p$. Then, suppressing the horizon subscript, we can rewrite the mean difference in MSFEs as:

$$R = \lambda_p [E(s_f) - E(s_p)] + (\lambda_f - \lambda_p) E(s_p) + (\lambda_f - \lambda_p) [E(s_f) - E(s_p)], \quad (6)$$

where we have suppressed the horizon and time subscripts. The first term is the object of interest, indicating how differences in information (reflected by the expected difference in the state variables) would affect the MSFE difference, given the private sector’s forecast “ability,” the λ_{np} ’s. The second term indicates the contribution of the Fed’s forecast ability over the private sector’s with the private sector’s information. The final term is the residual.

Table 5: Kitagawa-Blinder-Oaxaca Decomposition

Table 5 shows the results of the KBO decompositions at various horizons. The first row shows the difference in the MSFE and indicates whether this is significantly different from zero based on a Diebold-Mariano (1995) and West (1996) test. The next three rows show the values of the three terms in equation (6). The next three rows show the breakdown of the first term attributable to each of the state variables in the regression, eq (5). The final rows show (i) the percentage of the difference in the MSFE associated with the difference in the Fed’s and the private sector’s policy paths (row 5 divided by row 1) and (ii) the percentage of the Fed’s superior information (rather than, say, forecast ability) attributed to the path (row 5 divided by row 2). As one might suspect from the results in previous sections, knowledge of the conditioning path does not matter much for the nowcast. For future horizons, knowledge of the future path of monetary policy accounts for between 20 to 30 percent (on average) of the difference in forecaster performance. Moreover, knowledge of the path accounts for almost all of the Fed’s informational advantage.

6 Conclusion

The Fed appears to have a forecasting advantage over the private sector. When comparing Greenbook forecasts to Blue Chip forecasts using standard encompassing tests, we find that the Fed encompasses the private sector prior to 1994 when the Fed became more transparent. However, when we equalize the information between the Fed and the private sector, the Fed’s forecasts no longer encompass the private sector’s forecasts. This result contrasts with RR’s preferred hypothesis that the Fed’s advantage stems from its use of better/more resources devoted to forecasting and suggests the advantage is informational.

We then focus specifically on the conditioning path as the source of the Fed’s advantage. Using Eurodollar futures as a measure of the market’s belief about future monetary policy, we compare periods when the Fed and the private sector have essentially the same conditioning

path to periods when the Fed knows the path but the private sector does not. In these cases, we find generally that the Fed's forecasts encompass those of the private sector when they have an informational advantage and fails to encompass when they do not.

The literature on the Fed's forecast advantage has implications for the identification of monetary policy shocks in VARs and their subsequent effects on macroeconomic variables. The recent literature explores the importance of the information channel in both standard VARs [Miranda-Agrippino and Ricco (2018) and Jarociński and Karadi (2020)] and using high frequency identification [Nakamura and Steinsson (2018)]. We validate and quantify the effect of the Fed informational advantage for forecasting, which supports this literature on the information channel.

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Table 1: Conventional Encompassing Test Inflation

h	Full Sample					Pre 1994					Post 1994				
	α	β_p	β_f	χ^2	N	α	β_p	β_f	χ^2	N	α	β_p	β_f	χ^2	N
0	-0.03 (0.84)	0.33 (0.00)	0.64 (0.00)	23.09 (0.00)	263	-0.14 (0.63)	0.32 (0.10)	0.66 (0.04)	7.21 (0.03)	113	0.31 (0.32)	0.20 (0.35)	0.60 (0.00)	17.53 (0.00)	150
1	0.24 (0.22)	-0.02 (0.91)	0.90 (0.51)	5.91 (0.05)	263	0.22 (0.56)	-0.22 (0.35)	1.12 (0.50)	2.06 (0.36)	113	0.96 (0.09)	0.02 (0.96)	0.48 (0.04)	10.64 (0.00)	150
2	0.43 (0.04)	-0.10 (0.59)	0.92 (0.67)	9.75 (0.01)	263	0.47 (0.29)	-0.28 (0.27)	1.11 (0.61)	4.17 (0.12)	113	1.32 (0.02)	-0.04 (0.92)	0.34 (0.02)	17.60 (0.00)	150
3	0.41 (0.08)	-0.19 (0.31)	1.02 (0.91)	8.26 (0.02)	263	0.29 (0.53)	-0.35 (0.19)	1.22 (0.32)	2.54 (0.28)	113	1.74 (0.00)	-0.16 (0.60)	0.24 (0.00)	27.28 (0.00)	150
4	0.51 (0.09)	-0.10 (0.65)	0.87 (0.62)	5.44 (0.07)	259	0.30 (0.66)	-0.32 (0.25)	1.18 (0.55)	1.71 (0.43)	109	2.15 (0.00)	-0.33 (0.19)	0.20 (0.00)	45.56 (0.00)	150
5	0.56 (0.07)	0.13 (0.61)	0.50 (0.16)	9.57 (0.01)	193	0.58 (0.44)	-0.23 (0.55)	0.93 (0.87)	3.44 (0.18)	81	2.37 (0.00)	-0.03 (0.91)	-0.38 (0.00)	77.10 (0.00)	112
6	0.62 (0.01)	0.56 (0.00)	-0.11 (0.00)	67.75 (0.00)	118	0.48 (0.40)	0.48 (0.02)	0.03 (0.00)	32.87 (0.00)	46	2.54 (0.00)	-0.24 (0.52)	-0.25 (0.00)	44.22 (0.00)	72
7	0.55 (0.10)	0.61 (0.00)	-0.22 (0.00)	60.71 (0.00)	61	0.82 (0.27)	0.29 (0.06)	0.10 (0.00)	29.63 (0.00)	26	0.85 (0.43)	0.94 (0.01)	-0.85 (0.00)	29.36 (0.00)	35

Table 1: Conventional Encompassing Test Inflation: Pre 1994 refers to a sample up to and including 1993:12, while post 1994 refers to a sample that begins in 1994:01. Values of α , β_p , and β_f are OLS estimated coefficients from eq. (1). χ^2 denotes a HAC-robust Wald statistic associated with testing the null $(\beta_p, \beta_f)' = (0, 1)'$. N and h denote the sample size and horizon, respectively. Parentheses indicate p -values associated with HAC-robust Wald tests. The null is zero for α and β_p , but is one for β_f . Bold means that we reject at the 5% level. There are definitional changes over the sample: Blue Chip: GNP deflator (1980:01 - 1991:12); GDP implicit deflator (1992:01 - 1995:12); GDP deflator, chain-weighted (1996:01 - 2012:12) and Greenbook: GNP implicit deflator (1968:11 - 1991:11), GDP implicit deflator (1991:12 - 1996:03), GDP deflator, chain-weighted (1996:05 - 2012:12).

Table 2: Conditional Encompassing Test Inflation

h	Full Sample						Pre 1994						Post 1994					
	F	α	β_p	$\bar{\beta}_f$	χ^2	N	F	α	β_p	$\bar{\beta}_f$	χ^2	N	F	α	β_p	$\bar{\beta}_f$	χ^2	N
0	3.51 (0.02)	0.08 (0.70)	0.20 (0.66)	0.73 (0.49)	5.66 (0.06)	256	1.44 (0.24)	-0.10 (0.92)	0.51 (0.68)	0.46 (0.59)	7.88 (0.02)	106	1.14 (0.33)	0.08 (0.89)	1.46 (0.39)	-0.56 (0.31)	2.11 (0.35)	150
1	14.28 (0.00)	0.22 (0.32)	0.73 (0.08)	0.09 (0.03)	9.85 (0.01)	256	6.31 (0.00)	0.52 (0.31)	-0.40 (0.45)	1.23 (0.63)	4.79 (0.09)	106	8.29 (0.00)	0.23 (0.73)	2.71 (0.00)	-2.03 (0.00)	17.03 (0.00)	150
2	40.53 (0.00)	0.55 (0.01)	0.30 (0.38)	0.42 (0.11)	16.44 (0.00)	256	38.86 (0.00)	0.84 (0.07)	-0.45 (0.19)	1.20 (0.57)	7.95 (0.02)	106	9.66 (0.00)	0.80 (0.30)	2.16 (0.08)	-1.86 (0.01)	13.23 (0.00)	150
3	43.54 (0.00)	0.44 (0.11)	-0.17 (0.60)	0.98 (0.96)	5.31 (0.07)	256	42.61 (0.00)	0.23 (0.68)	-0.46 (0.22)	1.37 (0.36)	2.09 (0.35)	106	10.83 (0.00)	1.60 (0.00)	0.61 (0.51)	-0.56 (0.08)	23.40 (0.00)	150
4	38.56 (0.00)	0.67 (0.01)	0.06 (0.86)	0.61 (0.26)	19.01 (0.00)	256	32.82 (0.00)	0.78 (0.10)	-0.28 (0.41)	0.99 (0.98)	7.97 (0.02)	106	22.16 (0.00)	2.15 (0.00)	-0.34 (0.43)	0.21 (0.08)	44.61 (0.00)	150
5	28.62 (0.00)	0.83 (0.00)	0.49 (0.15)	-0.06 (0.41)	40.87 (0.00)	190	31.25 (0.00)	1.46 (0.01)	-0.18 (0.64)	0.62 (0.35)	44.75 (0.00)	78	21.43 (0.00)	2.39 (0.00)	-0.11 (0.74)	-0.30 (0.00)	70.35 (0.00)	112
6	23.81 (0.00)	0.56 (0.02)	0.95 (0.00)	-0.56 (0.00)	58.77 (0.00)	118	19.34 (0.00)	0.47 (0.42)	0.55 (0.04)	-0.04 (0.00)	23.50 (0.00)	46	22.16 (0.00)	2.56 (0.00)	-0.33 (0.38)	-0.16 (0.00)	49.49 (0.00)	72
7	11.10 (0.00)	0.57 (0.06)	0.56 (0.07)	-0.17 (0.00)	43.65 (0.00)	61	10.41 (0.00)	0.76 (0.32)	0.46 (0.05)	-0.08 (0.00)	23.78 (0.00)	26	13.97 (0.00)	0.98 (0.36)	0.58 (0.16)	-0.46 (0.00)	13.38 (0.00)	35

Table 2: Conditional Encompassing Test Inflation: Pre 1994 refers to a sample up to and including 1993:12, while post 1994 refers to a sample that begins in 1994:01. Values of α , β_p , and $\bar{\beta}_f$ are 2SLS estimated coefficients from eqs. (3) and (4). We use the Blue Chip forecasts of the 3-m Treasury bill yield, the unemployment rate, and real GDP as instruments. F is the first-stage F-statistic. χ^2 denotes a HAC-robust Wald statistic associated with testing the null $(\beta_p, \bar{\beta}_f)' = (0, 1)'$. N and h denote the sample size and quarterly horizon, respectively. Parentheses indicate p -values associated with HAC-robust Wald tests, except for the first-stage F-statistic. The null is zero for α and β_p but is one for $\bar{\beta}_f$. Bold means that we reject at the 5% level. Sample changes are similar to the notes in Table 1.

Table 3: Monetary Policy Path Encompassing Test

h	Both on Path & Both off Path				Fed on Path & Market off Path				Market off Path/Uncertain Fed on Path & Market off Path/Uncertain				Both on Path with Certainty & Both off Path/Uncertain			
	β_p	β_f	χ^2	N	β_p	β_f	χ^2	N	β_p	β_f	χ^2	N	β_p	β_f	χ^2	N
0	0.00 (0.99)	0.81 (0.15)	4.39 (0.11)	92	0.14 (0.28)	0.69 (0.00)	12.00 (0.00)	114	0.09 (0.42)	0.74 (0.01)	11.64 (0.00)	149	0.25 (0.37)	0.76 (0.23)	1.55 (0.46)	42
1	-0.05 (0.78)	0.83 (0.37)	5.88 (0.05)	109	0.26 (0.15)	0.44 (0.03)	6.15 (0.05)	90	0.21 (0.25)	0.50 (0.05)	5.10 (0.08)	98	-0.03 (0.86)	0.77 (0.23)	9.85 (0.01)	104
2	0.07 (0.70)	0.65 (0.14)	12.15 (0.00)	140	0.02 (0.95)	0.70 (0.48)	2.92 (0.23)	62	0.08 (0.74)	0.65 (0.35)	2.31 (0.32)	67	0.13 (0.50)	0.57 (0.09)	12.90 (0.00)	137
3	0.02 (0.90)	0.69 (0.19)	6.68 (0.04)	148	-0.02 (0.95)	0.56 (0.40)	4.10 (0.13)	52	-0.03 (0.94)	0.58 (0.38)	3.76 (0.15)	57	0.03 (0.88)	0.68 (0.22)	6.68 (0.04)	144
4	0.09 (0.64)	0.61 (0.13)	6.95 (0.03)	160	0.10 (0.82)	0.54 (0.29)	2.15 (0.34)	42	0.18 (0.64)	0.48 (0.19)	2.24 (0.33)	46	0.05 (0.81)	0.66 (0.24)	6.25 (0.04)	157

Table 3: Monetary Policy Path Encompassing Test: The first panel shows the results from the encompassing regressions when the Fed and the market are either both on or both off the path. The second panel shows the results when the Fed is on the path and the market is not. The third panel shows the results when the Fed is on the path but the market is either off the path or uncertain. The fourth panel shows the results when either (a) the Fed is on the path and the market is both on the path, and uncertainty is low or (b) the Fed is off the path and the market is either off the path or uncertain. Let η be the horizon of the path, then this table shows results when $\eta = h$. χ^2 denotes a HAC-robust Wald statistic associated with testing the null $(\beta_p, \beta_f)' = (0, 1)'$. N and h denote the sample size and quarterly horizon respectively. Parentheses indicate p -values associated with HAC-robust Wald tests. The null is zero for β_p and is one for β_f . Bold means that we reject at the 5% level. Sample changes are similar to the notes in Table 1.

Table 4: MSFE Dependent on Monetary Policy Path

h	Both on Path			BC on Path			BC off Path			Fed on & BC off		
	BC	GB	N	BC	GB	N	BC	GB	N	BC	GB	N
0	1.07	0.70	85	1.21	0.80	90	0.78	0.57	121	0.73	0.57	114
1	1.38	0.81	31	1.55	1.06	43	1.14	0.90	168	0.95	0.79	90
2	0.93	0.76	23	0.85	0.72	32	1.46	1.06	179	1.27	0.91	62
3	0.79	0.66	18	0.75	0.57	29	1.85	1.21	182	1.68	1.27	52
4	1.20	0.62	16	1.66	0.93	25	1.86	1.19	186	1.30	1.15	42

Table 4: MSFE Dependent on Monetary Policy Path: Table shows MSFE for four permutations of being on or off the path, where BC refers to the Blue Chip forecasts and GB refers to the Fed forecasts. N and h denote the sample size and quarterly horizon, respectively. The sample is 1982:01 to 2008:09.

Table 5: Kitagawa–Blinder–Oaxaca Decomposition

	h = 0	h = 1	h = 2	h = 3	h = 4
(1) R	-0.320 (0.119)	-0.285 (0.124)	-0.405 (0.136)	-0.567 (0.164)	-0.763 (0.179)
(2) $\lambda_p[E(s_f) - E(s_p)]$	-0.122 (0.039)	-0.146 (0.046)	-0.108 (0.051)	-0.203 (0.078)	-0.266 (0.087)
(3) $(\lambda_f - \lambda_p)E(s_p)$	1.557 (0.519)	-0.103 (0.135)	-0.353 (0.142)	-0.430 (0.156)	-0.688 (0.177)
(4) $(\lambda_f - \lambda_p)[E(s_f) - E(s_p)]$	-1.754 (0.508)	-0.036 (0.072)	0.055 (0.065)	0.067 (0.055)	0.191 (0.081)
(5) policy path SFE	-0.057 (0.026)	-0.109 (0.036)	-0.115 (0.041)	-0.191 (0.070)	-0.263 (0.088)
(6) unemployment SFE	-0.053 (0.024)	-0.035 (0.022)	-0.005 (0.014)	-0.012 (0.020)	-0.003 (0.010)
(7) output SFE	-0.011 (0.021)	-0.001 (0.008)	0.013 (0.021)	0.000 (0.004)	0.000 (0.016)
(5)/(1)	0.178	0.382	0.284	0.337	0.345
(5)/(2)	0.467	0.747	1.06	0.941	0.989
N	526	526	526	526	526

Table 5: Kitagawa–Blinder–Oaxaca Decomposition: These are the results for the Kitagawa–Blinder–Oaxaca decomposition for inflation estimated using OLS across different horizons (h) with N total observations. All variables in the regression are in squared forecast errors (SFE) and standard errors are reported in the parentheses. R refers to the MSFE difference between the Greenbook and the Blue Chip forecasts. The next three lines decomposes R into three components. The middle panel decomposes the $\lambda_p[E(s_f) - E(s_p)]$ part of the decomposition into parts of the state vector, s , attributed to knowledge of the path, SFE of the unemployment rate, and the SFE of output. The bottom panel shows fractions as designated by the row numbers. Bold means the coefficient is statistically significant at the 5% level. The sample is 1982:01 to 2008:09.