

The Fed’s Response to Economic News Explains the “Fed Information Effect”*

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Abstract

High-frequency changes in interest rates around FOMC announcements are a standard method of measuring monetary policy shocks. However, some recent authors have found that these shocks have puzzling effects on private-sector forecasts of inflation, unemployment, or real GDP that is opposite in sign to what standard macroeconomic models would predict; they argue this is evidence of a “Fed information effect” channel of monetary policy, whereby an FOMC tightening (easing) communicates that the economy is stronger (weaker) than the public had expected. We show that these empirical results are also consistent with a “Fed response to news” channel, in which incoming, publicly available economic news causes *both* the Fed to change monetary policy *and* the private sector to revise its forecasts. We provide substantial new evidence that distinguishes between these two channels and strongly favors the latter; for example, (i) high-frequency stock market responses to Fed announcements, (ii) a new survey that we conduct of individual Blue Chip forecasters, and (iii) regressions that include the previously omitted public macroeconomic data releases all indicate that the Fed and forecasters are simply responding to the same public news, and that there is little if any role for a “Fed information effect”.

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1 Introduction

When the Federal Reserve surprises markets with a monetary policy announcement, is that surprise an exogenous “shock”, as is typically assumed in the monetary policy VAR literature (e.g., [Christiano, Eichenbaum and Evans, 1996](#); [Cochrane and Piazzesi, 2002](#); [Faust, Swanson and Wright, 2004b](#))? Or is it something else, such as a revision in the private sector’s beliefs about the state of the economy, as argued by more recent “Fed information effect” studies, such as [Romer and Romer \(2000\)](#), [Campbell, Evans, Fisher and Justiniano \(2012\)](#), and [Nakamura and Steinsson \(2018\)](#)? These questions have been debated for about as long as monetary policy shocks themselves have been studied (e.g., [Christiano, Eichenbaum and Evans, 1999](#)).

In this paper, we present substantial new evidence that contradicts the empirical relevance of the “Fed information effect” channel in the U.S. We do not dispute the empirical evidence presented in [Campbell et al. \(2012\)](#) and [Nakamura and Steinsson \(2018\)](#), but instead show that their results are consistent with an alternative explanation, which we call the “Fed response to news” channel. Importantly, the Fed response to news channel is also consistent with all of our new empirical evidence, while the Fed information effect is not.

To highlight the difference between the Fed response to news channel and the Fed information effect, it’s useful to write out the Federal Reserve’s monetary policy reaction function,

$$i_t = f(X_t) + \varepsilon_t, \tag{1}$$

where i_t denotes the monetary policy instrument at time t , X_t is a vector describing the state of the economy, the function f describes how the Fed sets policy as a function of the state X_t , and ε_t is a pure monetary policy “shock”, or exogenous random deviation from the Fed’s normal policy rule f . When the Fed sets a value of i_t that differs from the private sector’s *ex ante* expectation, $E_{t-\delta}i_t$, where δ is some small time interval, then there are three possible sources of that surprise: 1) an exogenous monetary policy shock ε_t ; 2) a Fed information effect, in which the Fed’s observation of X_t differs from the private sector’s *ex ante* estimate $\hat{X}_{t|t-\delta}$, conditional on information at time $t - \delta$; or 3) a difference between the Fed’s actual policy response function f and the the private sector’s *ex ante* estimate of that function, $\hat{f}_{t-\delta}$. It

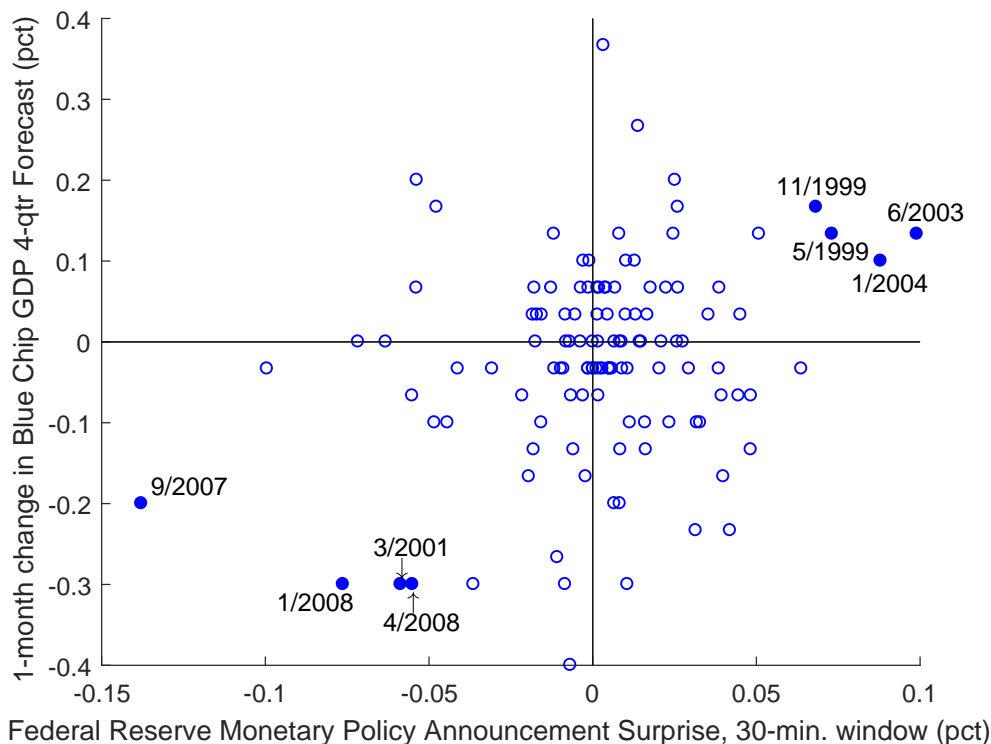
is this last channel that causes the Fed’s response to publicly available economic news to differ from the private sector’s expectation of that response, and drives the Fed response to news channel, as we discuss in more detail below. [Campbell et al. \(2012\)](#) and [Nakamura and Steinsson \(2018\)](#) devote much attention to distinguishing between channels 1 and 2, above, essentially assuming that the Fed’s monetary policy reaction function is known, $\hat{f}_{t-\delta} = f$. We relax this assumption and show that the empirical evidence in [Campbell et al. \(2012\)](#) and [Nakamura and Steinsson \(2018\)](#) is also consistent with channel 3, above, in which the Fed is responding to publicly available economic news, but by more than the private sector expected.

For example, Figure 1 summarizes the main evidence supporting the Fed information effect in [Nakamura and Steinsson \(2018\)](#). Each circle in the figure corresponds to a Federal Reserve Federal Open Market Committee (FOMC) announcement between January 1995 and March 2014. The change in short-term interest rates in a 30-minute window around each announcement is plotted on the horizontal axis, while the change in the Blue Chip consensus GDP forecast for the next four quarters is plotted on the vertical axis.¹ Because the Blue Chip survey is conducted only once per month (at the beginning of each month), the change in Blue Chip GDP forecasts on the vertical axis includes Blue Chip forecasters’ revisions over the entire month in which the FOMC announcement was made.

If FOMC announcements were exogenous shocks to monetary policy (channel 1, above), then standard Macroeconomic theory and VARs would predict a negative relationship in Figure 1: exogenously tighter monetary policy would imply lower GDP over the subsequent four quarters. Instead, there is a statistically significant *positive* relationship in the figure (slope 0.92, *t*-statistic 2.85). [Nakamura and Steinsson \(2018\)](#) argue that this surprising empirical result is evidence of a Fed information effect (channel 2, above): that is, the Fed observes a value for X_t that is substantially stronger than the private sector’s estimate $E_{t-\delta}X_t$ and

¹To match [Nakamura and Steinsson \(2018\)](#), we use exactly the same sample in Figure 1 that they do: we begin the sample in 1995 and end it in March 2014, and we exclude unscheduled FOMC announcements, all FOMC announcements from July 2008 through June 2009, and any FOMC announcement that occurred in the first 7 days of the month (to ensure the announcement post-dates the Blue Chip GDP forecast). We measure the change in short-term interest rates as the first principal component of the change in five short-term interest rate futures in a 30-minute window around the FOMC announcement: the current federal funds rate (measured using federal funds futures, as in [Kuttner, 2001](#)), the expected federal funds rate after the next FOMC meeting (measured in a similar manner), and the 2-, 3-, and 4-quarter-ahead Eurodollar futures contracts. Figure 1 thus replicates Figure II from Nakamura and Steinsson, except that they group the data into bins while we plot the data directly and highlight the most influential observations.

Figure 1: Blue Chip GDP Forecast Revisions and FOMC Monetary Policy Surprises



Change in Blue Chip consensus forecast for real GDP from one month to the next, plotted against the 30-minute change in short-term interest rates around FOMC announcements, from January 1995 to March 2014, excluding July 2008 to June 2009. Each circle represents an FOMC announcement; the eight solid circles denote the most influential observations in the relationship and are labeled with the month and year in which they occurred. Negative observations occurred when the economy was weakening and positive observations when the economy was strengthening. See text for details.

tightens interest rates in response; the private sector sees this interest rate change and infers from it that the economy must be stronger than they thought, leading them to revise their GDP forecasts upward.

However, the evidence in Figure 1 is also consistent with an alternative explanation, the “Fed response to news” channel that we propose in this paper. The solid circles in Figure 1 denote the eight most influential observations underlying the relationship in the figure. The four observations at the bottom-left all correspond to months in which the U.S. economy was in a sustained downturn: March 2001, September 2007, January 2008, and April 2008. A plausible explanation for these observations is that the clearly weakening economy caused *both* the Fed to lower interest rates (by more than financial markets expected) *and* the Blue

Chip forecasters to revise their GDP forecasts downward. Similarly, the four observations at the top-right of the figure all correspond to months in which the U.S. economy was in a sustained expansion: May 1999, November 1999, June 2003, and January 2004. Again, it seems plausible that the clearly strengthening economy caused *both* the Fed to raise interest rates *and* Blue Chip forecasters to revise their GDP forecasts upward. This is the essence of the Fed response to news channel that we propose here.

To distinguish between the Fed information effect and the Fed response to news channel, we present several new empirical findings, all of which strongly favor the latter. First, we show that standard information effect regressions along the lines of [Romer and Romer \(2000\)](#), [Campbell et al. \(2012\)](#), and [Nakamura and Steinsson \(2018\)](#) are sensitive to sample period and the variable being forecast (i.e., GDP, unemployment, or inflation). If these regression results are truly due to a Fed information effect, it suggests that the information content of FOMC announcements would have to be changing over time, sometimes conveying information about GDP but not unemployment or inflation, other times conveying information about unemployment but not GDP or inflation, and so on. Instead, if these regression results are driven by the Fed's response to publicly available economic news, then we would expect the coefficients to vary over time in line with the nature of the news that is being released.

Second, we analyze the high-frequency, 30-minute responses of the stock market to FOMC announcements. Several authors (e.g., [Jarocinski and Karadi, 2019](#); [Cieslak and Schrimpf, 2019](#)) have argued that the stock market responds positively to a monetary policy tightening surprise when a substantial information effect is present. We show that Federal Reserve monetary policy surprises have a strong, highly statistically significant *negative* effect on stock prices on average, and that this effect is even *more* negative for the most influential observations in the standard information effect regressions. (For example, every one of the four highlighted observations in the upper-right corner of Figure 1 led to large decreases in the S&P 500 in the 30-minute window surrounding those announcements.) These high-frequency stock market responses contradict the presence of a strong Fed information effect, but we show below that they are consistent with the Fed changing interest rates in response to publicly available economic news—the Fed response to news channel.

Third, we present new, high-frequency evidence from individual Blue Chip forecasters

on how they revise their forecasts on the day of an FOMC announcement, rather than over the one-month window surrounding the announcement. For example, we have high-frequency, daily “GDP tracking” estimates from one award-winning Blue Chip forecaster, Macroeconomic Advisors, that shows that they have *never* revised their current-quarter or next-quarter GDP forecast in response to an FOMC announcement going back to 2002, when their GDP tracking dataset begins. In contrast, Macroeconomic Advisors revises their GDP tracking forecasts in response to many other macroeconomic announcements over the course of each month, such as the Employment Report, retail sales, CPI, etc. This suggests that the Fed information effect is very small, at least for this one award-winning Blue Chip forecaster. We follow up this analysis with our own direct survey of all 52 individual forecasters in the Blue Chip panel, and ask them directly if they revise their GDP, unemployment, and/or inflation forecasts in response to FOMC announcements, and if so, in which direction. According to our survey, essentially every Blue Chip forecaster either does not revise their GDP, unemployment, and inflation forecasts in response to FOMC announcements, or revises them in the traditional direction, with a hawkish monetary policy surprise causing them to revise their GDP and inflation forecasts downward, and their unemployment forecasts upward. This is direct evidence, from the Blue Chip survey participants themselves, that there is no Fed information effect in the U.S. In contrast, our Fed response to news channel is consistent with all of these observations.

Fourth, we show that economic news released in the days between the Blue Chip survey and the FOMC announcement is an omitted variable in standard Fed information effect regressions. For example, the Employment Report in a given month is a strong predictor of *both* the Blue Chip forecast revision *and* the FOMC monetary policy announcement surprise later that month. Controlling for this economic news renders the statistical relationship between policy surprises and Blue Chip forecast revisions statistically insignificant and *reverses its sign* back to what would be predicted by standard macroeconomic models. In other words, we show that the positive relationship in Figure 1 is in fact entirely driven by the omitted economic news variable, exactly as would be predicted by our Fed response to news channel, and not by a Fed information effect.

Finally, we conduct a detailed comparison of Blue Chip and Federal Reserve forecasts of GDP, unemployment, and inflation. Many authors, such as [Romer and Romer \(2000\)](#) argue

that the Fed information effect exists because the Fed’s economic forecasts are substantially better than the private sector’s. In fact, we show that the Fed and the Blue Chip consensus forecasts are very similar to each other and perform very comparably. This might seem puzzling at first, since the Fed employs a much larger staff of Ph.D. economists than any single Blue Chip forecasting firm, but [Faust, Swanson and Wright \(2004a\)](#) point out that markets aggregate information (see, e.g., [Hayek, 1945](#); [Grossman, 1981, 1989](#)), and there are very large, liquid markets in the U.S. that are closely tied to interest rate and inflation forecasts, such as the markets for nominal and real Treasury bonds and the markets for Treasury, interest rate, and inflation futures, options, and swaps. As a result, it would be very surprising if the Fed’s own forecasts of these variables was substantially better than the market’s forecasts.² Even if the Fed devotes more resources to forecasting than any one private-sector firm, the Blue Chip forecasting firms and the financial markets as a whole devote far more resources to forecasting than does the Federal Reserve.³

After a brief literature review, the remainder of the paper proceeds as follows. Section 2 reviews the standard “Fed information effect” regressions and shows that those results are sensitive to sample period and the variable being forecast. Section 3 looks at the high-frequency response of stock prices to Fed announcements and shows that those responses are negative and highly statistically significant on average, and are even more so for the most influential observations in the standard information effect regressions. Section 4 presents results using high-frequency forecast data from Macroeconomic Advisors and our own survey of individual Blue Chip forecasters and shows that they do not revise their forecasts in the way predicted by the “Fed information effect” literature. Section 5 demonstrates that economic news released between the Blue Chip survey and the FOMC announcement is an omitted variable from the standard “Fed information effect” regressions. We show that this omitted variable is correlated with the right-hand-side variables in those regressions and thus leads to a substantial omitted variable bias. Section 6 compares the Fed’s internal forecasts and Blue Chip

²Although there is not an explicit market for GDP forecasts, those forecasts are nevertheless closely tied to the future path of interest rates and many other market outcomes, so again it would be very surprising if the Fed’s forecast for GDP was substantially better than the private sector’s.

³One should also bear in mind that the Federal Reserve’s large staff of economists is not devoted exclusively to forecasting the U.S. economy. They produce forecasts of other economies, conduct extensive counterfactual “what-if” analysis, produce a wide variety of economic statistics and reports, and conduct basic research.

consensus forecasts and shows that they have essentially equal predictive power for future GDP, unemployment, and inflation; thus, neither forecast is substantially better than the other. Section 7 discusses the broader implications of our findings for the measurement of monetary policy shocks using high-frequency data and the use of those high-frequency shocks in empirical studies. Section 8 concludes. An Appendix contains additional tables and results related to our main findings.

1.1 Related Literature

Theoretical models of monetary policy have allowed for the possibility that the central bank possesses asymmetric information about the economy since at least the 1970s (e.g., [Sargent and Wallace, 1975](#); [Barro, 1976](#); [Barro and Gordon, 1983](#)), but the first paper to argue for the empirical relevance of the Fed information effect is [Romer and Romer \(2000\)](#). They found that the Fed has substantial information about future inflation that private sector forecasters do not have, and that the Fed’s interest rate changes could be used to infer that information.⁴

[Faust et al. \(2004a\)](#) showed that the Fed’s monetary policy announcements cannot be used to improve private-sector forecasts of upcoming macroeconomic data releases, such as GDP, retail sales, CPI, etc. They also showed that private-sector forecasters do not revise their forecasts of these releases in response to FOMC announcements, even though they do revise those forecasts in response to other major macroeconomic data releases, such as the Employment Report. They conclude that the Federal Reserve’s monetary policy surprises do not contain substantial information about the state of the economy that the private sector doesn’t already possess. They also show that the [Romer and Romer \(2000\)](#) results for inflation are entirely due to the Volcker disinflation in the early 1980s; excluding that one episode (the third quarter of 1984 in particular), the Fed’s inflation forecasts are no better than those of the private sector.

⁴[Romer and Romer \(2000\)](#) appealed to this Fed information effect to explain why long-term U.S. Treasury yields seemed to rise in response to changes in the federal funds rate. However, [Gürkaynak, Sack and Swanson \(2005a\)](#), using a futures-based measure of federal funds rate surprises, showed that far-ahead forward U.S. Treasury yields actually *fall* in response to surprise FOMC tightenings. Thus, an information effect is not needed to explain the response of long-term Treasury yields to FOMC announcements.

Campbell et al. (2012) study how the Fed’s monetary policy announcements affect Blue Chip forecasts of unemployment and inflation. Consistent with Faust et al. (2004a), they find no evidence that Fed announcements affect Blue Chip inflation forecasts, but they do find that monetary policy tightenings are associated with a statistically significant *downward* revision in Blue Chip unemployment forecasts. Campbell et al. conclude that a Fed information effect is present, and they use the term “Delphic forward guidance” to refer to situations in which forward guidance by the FOMC conveys this information about the future evolution of the economy to the private sector.

Nakamura and Steinsson (2018) analyze how the Fed’s monetary policy announcements affect Blue Chip forecasts of real GDP. Like Campbell et al. (2012), they find a statistically significant relationship with a puzzling, opposite sign and conclude that a Fed information effect is present. In Section 2, below, we explore both the Campbell et al. and Nakamura-Steinsson results in more detail and show that they are sensitive to sample period and the variable being forecast. For example, using Nakamura and Steinsson’s sample and methods, there is no significant information effect for unemployment (contrary to Campbell et al.) or for inflation (contrary to Romer and Romer, 2000, but consistent with Campbell et al. and Faust et al., 2004a).

Lunsford (2019) performs a detailed analysis of the Fed’s forward guidance announcements from February 2000 to May 2006, and finds evidence of a Fed information effect in the period from February 2000 to August 2003, but not afterward. (Lunsford does not consider the period before 2000 or after May 2006 due to data limitations.) Like Lunsford, we find no evidence of an information effect in the period after 2003; unlike Lunsford, we attribute the appearance of a “Fed information effect” from 2000–2003 to the Fed’s response to the deteriorating economy in early 2001 and the improving economy in mid-2003.

Jarocinski and Karadi (2019) decompose monetary policy surprises in the U.S. and euro area into “pure monetary” shocks and “information” shocks, depending on whether stock prices move in the opposite direction or the same direction as interest rates, respectively.⁵ They estimate a Bayesian VAR using their high-frequency monetary and information shocks

⁵See also Cieslak and Schrimpf (2019), who similarly classify monetary policy surprises according to the minute-by-minute covariance of stock price changes and bond yield changes in a narrow window of time around each announcement.

as instruments, and find that pure monetary policy shocks cause future GDP to decline, while pure information shocks cause future GDP to increase. In our analysis below, we will also use stock market responses to FOMC announcements to assess whether they have a large information component or not; in contrast to [Jarocinski and Karadi \(2019\)](#), we find essentially no evidence for a significant information effect in U.S. monetary policy announcements.

Finally, [Miranda-Agrippino \(2017\)](#) documents that Federal Reserve monetary policy announcement surprises are predictable using publicly available information about output and interest rate changes that predate the FOMC announcement. Miranda-Agrippino interprets this predictability as a risk premium that compensates investors for holding interest rate risk around FOMC announcements. However, [Piazzesi and Swanson \(2008\)](#) find that this risk premium is relatively small, and we propose an alternative explanation below: that this *ex post* predictability could be due to the futures markets being *ex ante* rational and efficient but not knowing the Fed’s true monetary policy reaction function f (cf. equation (1)). This can lead to *ex post* predictability of the high-frequency monetary policy surprises even if the futures market is *ex ante* rational and efficient.

2 The “Fed Information Effect”

We begin by replicating the main empirical evidence for a “Fed information effect”. Although [Romer and Romer \(2000\)](#) is the original paper finding evidence of a Fed information effect for Blue Chip inflation forecasts, researchers using more recent samples have consistently found little or no evidence of such an effect for inflation. Thus, we focus on replicating the results in [Campbell et al. \(2012\)](#) (henceforth CEFJ) for unemployment and [Nakamura and Steinsson \(2018\)](#) (henceforth NS) for real GDP growth, although we consider inflation as well.

2.1 Data: Blue Chip Forecasts and Monetary Policy Surprises

The Blue Chip Economic Indicators survey of forecasters has been conducted once per month, over the first three business days of each month, since 1976.⁶ The professional forecasting

⁶Beginning in December 2000, the Blue Chip survey is completed by the second business day of each month.

teams at about 50–60 financial institutions, major corporations, forecasting firms and publishers of economic newsletters are surveyed about their predictions for a number of macroeconomic indicators for each quarter over the current and next calendar years. Thus, the maximal forecast horizon ranges from four quarters (when the survey is conducted in the last quarter of a calendar year) to seven quarters (when it is conducted in the first quarter). The survey covers real U.S. Gross Domestic Product (GDP) growth, the unemployment rate, the consumer price index (CPI) inflation rate, the 3-month Treasury bill rate, 10-year Treasury yield, and a few other macroeconomic variables such as industrial production, disposable personal income, and net exports. Empirical work using the Blue Chip survey has typically focused on the most prominent variables: real GDP, the unemployment rate, and CPI inflation, and we focus on these three variables in our analysis below.

Blue Chip reports the “consensus” forecast for each variable in each quarter, which is the arithmetic mean of the individual forecasts. In addition, the names and individual forecasts of each professional forecasting team are reported for each calendar year as a whole. In our regressions below, we focus on how the Blue Chip consensus forecast changed from one month to the next, and how those changes were related to FOMC monetary policy announcements. For simplicity, to reduce the number of reported coefficients in the tables below, we follow NS and consider the change in the *average* of the 1-quarter-ahead, 2-quarter-ahead, and 3-quarter-ahead consensus forecasts. (These are also the horizons for which the evidence of a Fed information effect is the strongest; including the current-quarter “nowcast” or the 4-quarter-ahead forecast in the average generally weakens the statistical significance of the coefficient estimates in Table 1, below.)

We relate these Blue Chip forecast revisions to FOMC monetary policy announcements. Over our sample, there are eight regularly-scheduled FOMC announcements per year, occurring after each scheduled FOMC meeting, spaced roughly six to eight weeks apart. In addition, the FOMC has occasionally made unscheduled monetary policy announcements that lie in between regularly-scheduled meetings, typically when the FOMC wanted to lower interest rates in response to a weakening economy and did not want to wait until the next scheduled meeting.⁷ We consider samples that both include and exclude these unscheduled FOMC

⁷For example, on January 22, 2008, the FOMC made an unscheduled announcement that it was cutting the

announcements in our analysis, below.

Financial markets and professional forecasters are forward-looking, so we would not expect them to respond to changes in monetary policy that were widely anticipated ahead of time. For this reason, researchers typically focus on monetary policy *surprises*—the unexpected component of FOMC announcements. We compute monetary policy announcement surprises in two different ways, following the approaches used by CEFJ and NS. CEFJ use the “target factor” and “path factor” computed by [Gürkaynak, Sack and Swanson \(2005b\)](#), which correspond to the surprise change in the federal funds rate target and the surprise change in forward guidance, respectively (where forward guidance is defined to be any additional information about the future path of the federal funds rate over the next several months). These surprises are computed using changes in short-maturity federal funds futures contracts and two- to four-quarter-ahead Eurodollar futures contracts in a narrow, 30-minute window surrounding each FOMC announcement. The scale of the target factor is normalized so that it moves one-for-one with surprise changes in the target for the federal funds rate, while the scale of the path factor is normalized so that a one-unit change increases the four-quarter-ahead Eurodollar future rate by one percentage point.⁸ NS use the same set of federal funds futures and Eurodollar futures contracts over the same 30-minute window, but condense the monetary policy surprise into a single dimension by taking the first principal component of those changes, which is then scaled so that a one-unit change on average increases the one-year zero-coupon Treasury yield (as measured by [Gürkaynak, Sack and Wright, 2007](#)) by one percentage point. Our high-frequency futures data for computing these monetary policy surprises, using either method, begins in January 1990, as discussed in [Gürkaynak et al. \(2005b\)](#).

2.2 “Fed Information Effect” Regressions

Table 1 reports results from our replication and extension of the basic “information effect” regressions in CEFJ and NS. The first set of columns in Table 1, labeled “Campbell et al.”,

federal funds rate by 75 basis points “in view of a weakening of the economic outlook and increasing downside risks to growth” (FOMC statement, Jan. 22, 2008, available on the Federal Reserve Board’s website). Although the next scheduled FOMC meeting was only about nine days away, Chairman Bernanke argued that “seven trading days is a long time in financial markets” and “I think we have to take a meaningful action” (FOMC transcript of January 21, 2008, available on the Federal Reserve Board’s website).

⁸For details see [Gürkaynak et al. \(2005b\)](#) and [Campbell et al. \(2012\)](#).

considers Blue Chip forecast revision regressions of the form

$$BCrev_t = \alpha + \beta target_t + \gamma path_t + \varepsilon_t, \quad (2)$$

where t indexes FOMC announcements, $target_t$ denotes the surprise change in the federal funds rate target in a 30-minute window bracketing the FOMC announcement, $path_t$ denotes the surprise change in forward guidance in the same 30-minute window, computed as described above, and $BCrev_t$ denotes the one-month revision in the Blue Chip consensus forecast of a given variable averaged over the 1-, 2-, and 3-quarter-ahead horizons. Note that $target_t$ and $path_t$ are high-frequency changes in the 30-minute window surrounding the FOMC announcement at date t , while $BCrev_t$ is a lower-frequency, one-month change over the calendar month containing the FOMC announcement. The last column of Table 1, labeled “Nakamura-Steinsson”, considers analogous regressions of the form

$$BCrev_t = \phi + \theta mps_t + \varepsilon_t, \quad (3)$$

where mps_t denotes the monetary policy surprise calculated as the the first principal component of the 30-minute changes in five short-term interest rate futures rates around the FOMC announcement, as described above.⁹

For each regression, we need to ensure that the Blue Chip forecast revision brackets the FOMC announcement. Since the Blue Chip survey is conducted during the first three business days of each month (two days after Dec. 2000), we thus drop from our analysis any FOMC announcement that occurs within the first three business days of a month (two days after Dec. 2000), since the timing of those announcements with respect to the Blue Chip forecasts is not clear.

In each panel of Table 1, (A) through (D), we consider the Blue Chip forecast of three different variables: the unemployment rate, real GDP growth, and the CPI inflation rate, as

⁹Note that regularly-scheduled FOMC announcements are spaced far enough apart that adjacent announcements never occur in the same month. In cases where we consider unscheduled as well as scheduled FOMC announcements, if an unscheduled announcement occurs in the same month as a scheduled announcement, then we follow [Campbell et al. \(2012\)](#) and add those two announcement surprises together to get one “total monetary policy announcement surprise” for that month.

Table 1: “Fed Information Effect” Regression Results

	(1) Campbell et al.	(2) Nakamura-Steinsson	
Blue Chip forecast	fed funds rate “target factor”	fwd. guidance “path factor” first princip. comp. “MP surprise”	
(A) Replication sample: 1/1990–6/2007 for Campbell et al., 1/1995–3/2014 for NS			
Unemployment rate	−0.10 (.093)	−0.22* (.124)	−0.17 (.286)
Real GDP growth	0.23 (.202)	0.31 (.268)	0.92** (.359)
CPI inflation	0.18 (.127)	0.06 (.172)	0.06 (.246)
(B) Full sample: 1/1990–6/2019, including unscheduled announcements			
Unemployment rate	−0.17 (.104)	−0.21 (.133)	−0.39** (.183)
Real GDP growth	0.25 (.189)	0.34 (.244)	0.34 (.274)
CPI inflation	0.19 (.136)	0.38** (.176)	0.29* (.158)
(C) Full sample: 1/1990–6/2019, excluding unscheduled announcements			
Unemployment rate	0.04 (.171)	−0.29** (.141)	−0.30 (.246)
Real GDP growth	0.11 (.271)	0.59** (.230)	0.56* (.301)
CPI inflation	0.17 (.224)	0.46** (.189)	0.27 (.200)
(D) Full sample: 1/1990–6/2019, excl. unscheduled announcements and 7/2008–6/2009			
Unemployment rate	−0.03 (.148)	−0.20 (.125)	−0.25 (.203)
Real GDP growth	0.23 (.227)	0.38* (.192)	0.65*** (.244)
CPI inflation	0.13 (.197)	0.16 (.168)	0.20 (.187)

Replication and extension of [Campbell et al. \(2012\)](#) and [Nakamura and Steinsson \(2018\)](#) Blue Chip forecast regression results. Campbell et al. coefficients are β and γ from regression $BCrev_t = \alpha + \beta target_t + \gamma path_t + \varepsilon_t$, where t indexes FOMC announcements, $target_t$ denotes the surprise change in the federal funds rate in a 30-minute window bracketing the FOMC announcement, $path_t$ denotes the surprise change in forward guidance in the same 30-minute window, and $BCrev_t$ denotes the one-month change in the Blue Chip consensus forecast for the next 3 quarters, over the month bracketing the FOMC announcement. Nakamura-Steinsson coefficient is θ from regression $BCrev_t = \phi + \theta mps_t + \varepsilon_t$, where mps_t denotes the policy surprise, calculated as the first principal component of the 30-minute changes in five short-term interest rate futures rates around the FOMC announcement. Bootstrapped standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Replication sample for Campbell et al. includes unscheduled announcements; that for Nakamura-Steinsson excludes unscheduled announcements, 7/2008–6/2009, and announcements in the first 7 days of the month. See text for details.

discussed above. In each row, coefficients reported in the “Campbell et al.” column report the coefficients β and γ estimated using regression specification (2), while the coefficient reported in the “Nakamura-Steinsson” column reports the θ estimated using regression specification (3). Standard errors are reported in parentheses below each coefficient estimate. Because the right-hand side variables in equations (2) and (3) are generated regressors, we compute these standard errors using a bootstrap procedure with 10,000 bootstrap samples in order to take into account the extra sampling variability associated with the computation of the target factor, path factor, and NS first principal component.¹⁰

In the top panel (A), we consider exactly the same sample used by CEFJ for each regression in the first set of columns, and exactly the same sample used by NS for each regression in the last column.¹¹ We are able to replicate the main features of their results in each case. For the CEFJ specification and sample, we find that a surprise tightening in forward guidance is associated with a *downward* revision in the Blue Chip consensus unemployment forecast, by about 0.2 percentage points for every percentage point surprise in forward guidance. This relationship is borderline statistically significant, at the 10% level. As CEFJ pointed out, this response is puzzling if one thought the change in forward guidance was a pure monetary policy shock: in that case, standard macroeconomic models and VARs predict that unemployment should increase following a monetary policy tightening. NS did not look at unemployment and instead focused on Blue Chip forecasts of real GDP. Using their specification and sample in panel (A), we find that a surprise tightening of interest rates is associated with a significant *upward* revision in the Blue Chip consensus forecast for real GDP growth, by about

¹⁰The CEFJ and NS regressors are computed using a factor model that does not fit the data perfectly, hence there is some extra sampling variability associated with the factor computation itself that our bootstrapping takes into account. See the Appendix for details. Note that both CEFJ and NS treat their regressors as fixed in repeated samples, which ignores this additional source of uncertainty. However, our bootstrapped standard errors are only slightly larger than the asymptotic ones in general (cf. Table A.1), because the factor models used to compute the GSS/CEFJ/NS factors are relatively robust and fit the data well, a result that was also found by [Gürkaynak et al. \(2005b\)](#).

¹¹CEFJ use January 1990 to June 2007 as their baseline sample and include unscheduled as well as scheduled FOMC announcements. NS use January 1995 to March 2014 as their baseline sample, but exclude unscheduled FOMC announcements and also any FOMC announcement from July 2008 to June 2009. In addition, NS exclude any FOMC announcement that occurred in the first seven calendar days of a given month, while CEFJ exclude announcements that occurred in the first three business days of a month, so we do that in each case in panel (A) as well, although in all other panels we exclude FOMC announcements only for the first three business days of each month prior to Dec. 2000, and first two business days from Dec. 2000 onward, which is sufficient to ensure that the FOMC announcement post-dates the Blue Chip survey.

0.9 percentage points for each percentage point surprise in the NS monetary policy measure. Again, this coefficient estimate contradicts the pure monetary policy shock view of an FOMC announcement, according to which a monetary policy tightening should cause future GDP to decrease. Both CEFJ and NS interpret their results as evidence of a Fed information effect channel of monetary policy, as discussed in the Introduction, above.

However, even within panel (A) of Table 1, there are potential concerns with this interpretation. First, there is little or no evidence that FOMC announcements communicate any information about inflation, despite the fact that this was the original Fed information effect channel documented by [Romer and Romer \(2000\)](#). Apparently, updating the sample period to either the one used by CEFJ or NS invalidates that earlier empirical finding, an observation that was also made by [Faust et al. \(2004a\)](#). Second, the CEFJ finding of an information effect for unemployment applies only to unemployment—there is no evidence in their sample that Blue Chip forecasters revise their projections for real GDP, in contrast to the findings in NS. Similarly, the NS finding of an information effect for real GDP in their sample applies only to GDP and not to unemployment, in contrast to the findings in CEFJ. This is very concerning, both because it implies these results are not robust and because a true Fed information effect channel ought to imply that Blue Chip forecasts of both unemployment and real GDP should be affected.

In panels (B) through (D) of Table 1, we extend the CEFJ and NS analyses to the full sample for which we have data, January 1990 to June 2019.¹² In panel (B), we include unscheduled as well as scheduled FOMC announcements during this period.¹³ In panel (C), we exclude the unscheduled FOMC announcements, and in panel (D), we exclude both the unscheduled FOMC announcements and announcements from July 2008 to June 2009.

In panels (B) through (D), there is some evidence of a systematic relationship in these

¹²The FOMC did not explicitly announce its monetary policy decisions in official press releases until February 1994; however, it still conveyed its decisions to financial markets through changes in the discount rate or through the size and type of open market operation conducted the following morning, as discussed in [Gürkaynak et al. \(2005b\)](#). As a robustness check, we also consider starting our sample in February 1994 and the results are essentially unchanged—see Table A.2 in the Appendix.

¹³Consistent with the rest of the literature, we exclude the unscheduled FOMC announcement on September 17, 2001, as it occurred before the markets opened and after they had been closed for several days following the September 11 terrorist attacks, so it's not possible to get a good high-frequency measure of the surprise component of the announcement on that date.

regressions: several of the estimated coefficients are statistically significant and in the same direction as observed by CEFJ and NS over their samples. However, the evidence is not as consistent as a true Fed information effect story ought to imply: for example, looking down the last column of Table 1, the results for real GDP are really only significant when July 2008 to June 2009 is excluded (panels A and D), while the results for unemployment are significant only in panel (B), a sample in which the results for GDP are insignificant. According to the Fed information effect story, this would imply that in some samples there is information about real GDP but not unemployment, while in other samples there is information about unemployment but not real GDP. The CEFJ results have similar problems: the results for unemployment are marginally significant or better only in panels (A) and (C), while the results for GDP are significant only in panels (C) and (D). In panel (A), the results for unemployment are marginally significant, but those for GDP are not, while in panel (D), the opposite is true. For inflation, there is some evidence of an information effect when the July 2008 through June 2009 period is included (panels B and C), but not when it is excluded. This July 2008 to June 2009 period is interesting because inflation fell dramatically while the Fed was cutting interest rates dramatically, suggesting that perhaps it is not due to an information effect, but rather that the Fed and Blue Chip forecasters were *both* responding to economic news during this period. This is exactly the “Fed response to news” channel that we propose in this paper.

If the Federal Reserve and Blue Chip forecasters were both responding to the same economic news (and the Fed responded by more than financial markets expected), that could explain all of the results in Table 1 and Figure 1, in fact more consistently than the Fed information effect. First, the observation that, in some samples the news is predominantly about real GDP, while in other samples the news is about unemployment, is consistent with the Fed and Blue Chip both responding to incoming news about GDP (in the first case) and unemployment (in the second). In contrast, the information effect offers no explanation why there would be differential information in FOMC announcements in different subsamples. Second, the significant coefficients for Blue Chip inflation forecasts that are specific to the July 2008 to June 2009 period can be explained by both the Fed and Blue Chip receiving significant news about inflation during this period. The Fed information effect channel has difficulty explaining why FOMC announcements would contain information about inflation in this period

and not others. Third, the “Fed response to news” channel is consistent with the finding in Figure 1 that all of the influential observations in the upper-right corner of the figure occurred when the economy was in a sustained boom, while all of the influential observations in the lower-left corner occurred when the economy was in a sustained downturn: according to this channel, both the Fed and Blue Chip forecasters were responding to incoming news about the economy. In contrast, the Fed information effect does not explain why negative information about the economy is only revealed by FOMC announcements in sustained recessions, while positive information about the economy is only revealed in sustained booms.

3 The “Fed Information Effect” and the Stock Market

Standard economic theory predicts that a pure monetary policy shock that raises interest rates should cause stock prices to fall, as discussed, for example, by [Bernanke and Kuttner \(2005\)](#). First, higher interest rates imply that future corporate profits should be discounted more heavily, implying a lower present value, and second, higher interest rates imply that future GDP and future corporate profits will be lower, reducing the present value of those profits further.

If higher interest rates have a significant Fed information component, however, then the effect on the stock market is ambiguous. Higher interest rates imply that future corporate profits should be discounted more heavily, as above, but now the higher interest rates signal that GDP and corporate profits will be *higher* in the future, rather than lower. The net effect of these two forces on the stock market is ambiguous.

Recent papers on the Fed information effect, however, have argued that the net effect is typically positive—that is, that higher interest rates cause stock prices to rise when a strong information effect is present ([Jarocinski and Karadi, 2019](#); [Cieslak and Schrimpf, 2019](#); [Lunsford, 2019](#)). In fact, [Jarocinski and Karadi \(2019\)](#) and [Cieslak and Schrimpf \(2019\)](#) identify information shocks (as opposed to pure monetary policy shocks) based on how the stock market responds to higher interest rates, with a positive stock market response to higher interest rates indicating an information shock and a negative stock market response to higher rates a pure monetary policy shock.

In this section, we likewise use the stock market response to FOMC announcements to help discern whether and when a significant information effect is present.

3.1 The Stock Market Response to FOMC Announcements

As a benchmark for comparison, we first estimate the typical response of stock prices to FOMC announcements. We run regressions analogous to (2)–(3), but now with the dependent variable being the percent change in the S&P 500 stock price index in a 30-minute window surrounding each FOMC announcement:

$$\Delta \log \text{S\&P500}_t = \alpha + \beta \text{target}_t + \gamma \text{path}_t + \varepsilon_t \quad (4)$$

and

$$\Delta \log \text{S\&P500}_t = \phi + \theta \text{mps}_t + \varepsilon_t. \quad (5)$$

The results are reported in Table 2. The first set of columns in each row reports the estimated coefficients β and γ from regression (4), along with the regression R^2 and number of observations N , while the last set of columns reports the corresponding results for the coefficient θ from regression (5). As in Table 1, bootstrapped standard errors from 10,000 bootstrap samples are reported in parentheses beneath each coefficient, to account for the generated regressors in (4)–(5). The four panels (A) through (D) report results for each of the four samples considered in Table 1.

The results are very much in line with [Bernanke and Kuttner \(2005\)](#), although the measures of monetary policy surprises in Table 2 are somewhat different. A one percentage point surprise increase in the federal funds rate target causes stock prices to fall about 3–4 percent, consistent with the estimates in [Bernanke and Kuttner \(2005\)](#), [Gürkaynak et al. \(2005b\)](#), and others.¹⁴ A surprise increase in forward guidance (that raises the one-year-ahead expected federal funds rate by one percentage point) causes stock prices to fall about 2–3 percent, consistent with [Gürkaynak et al. \(2005b\)](#), [D’Amico and Farka \(2011\)](#), and [Swanson \(2019\)](#). An increase in the NS monetary policy surprise that raises the one-year Treasury yield by

¹⁴See also [D’Amico and Farka \(2011\)](#) and [Swanson \(2019\)](#).

Table 2: Stock Market Response to FOMC Announcements

(1) Campbell et al.				(2) Nakamura-Steinsson		
fed funds rate “target factor”	fwd. guidance “path factor”	R^2	N	first princip. comp. “MP surprise”	R^2	N
(A) Replication sample: 1/1990–6/2007 for CEFJ, 1/1995–3/2014 for NS						
−4.24*** (0.46)	−2.05*** (0.65)	0.39	158	−5.95*** (1.03)	0.19	146
(B) Full sample: 1/1990–6/2019, including unscheduled announcements						
−4.37*** (0.45)	−2.52*** (0.54)	0.32	259	−7.82*** (0.72)	0.31	259
(C) Full sample: 1/1990–6/2019, excluding unscheduled announcements						
−3.11*** (0.64)	−3.14*** (0.51)	0.21	236	−6.53*** (0.82)	0.21	236
(D) Full sample: 1/1990–6/2019, excl. unscheduled announcements and 7/2008–6/2009						
−2.81*** (0.64)	−3.02*** (0.51)	0.21	228	−6.03*** (0.78)	0.21	228

Regression results for stock market response to FOMC announcements. Campbell et al. coefficients are β and γ from regression $\Delta \log \text{S\&P500}_t = \alpha + \beta \text{target}_t + \gamma \text{path}_t + \varepsilon_t$, where t indexes FOMC announcements, target_t and path_t denote the surprise change in the federal funds rate and forward guidance in a 30-minute window bracketing the FOMC announcement, and $\Delta \log \text{S\&P500}_t$ denotes the percent change in the S&P 500 stock price index over the same 30-minute window. Nakamura-Steinsson coefficient is θ from regression $\Delta \log \text{S\&P500}_t = \phi + \theta \text{mps}_t + \varepsilon_t$, where mps_t denotes the NS monetary policy surprise measure in a 30-minute window bracketing the FOMC announcement. Bootstrapped standard errors in parentheses; *** denotes statistical significance at the 1% level. See notes to Table 1 and text for details.

one percentage point has an even larger, 6–8 percent negative effect on stock prices, roughly equal to the combined target and path factor effects from the first set of columns. All of the estimated coefficients in Table 2 are highly statistically significant over all of the sample periods considered.

Note that the high statistical significance in Table 2 and the robustness of the coefficients across samples contrast sharply with the “Fed information effect” regressions in Table 1. In Table 2, there is no question that the U.S. stock market responds negatively, on average, to a monetary policy tightening surprise. By itself, this result is not surprising—it corresponds to the conventional wisdom described in [Bernanke and Kuttner \(2005\)](#) and others. But compared

Table 3: Ten Most Influential Observations in Nakamura-Steinsson GDP Forecast Regression

Date	Effect on t -statistic	MP surprise mps_t	$BCrev_t$, GDP	$\Delta \log$ S&P500 $_t$	bus. cycle indicator
9/2007	0.554	-0.138	-0.2	1.33	-0.29
1/2008	0.351	-0.076	-0.3	0.76	-0.81
6/2003	0.312	0.099	0.133	-0.27	-0.38
3/2001	0.291	-0.059	-0.3	-0.68	-1.45
4/2008	0.278	-0.055	-0.3	0.31	-1.52
11/1999	0.240	0.068	0.167	-0.42	0.86
1/2004	0.224	0.088	0.1	-0.97	0.38
5/1999	0.224	0.073	0.133	-1.44	0.19
12/1995	0.207	-0.036	-0.3	0.26	-0.08
3/1997	0.155	0.051	0.133	-0.67	0.80

Ten most influential observations in Nakamura-Steinsson regression (3), as measured by the change in the t -statistic due to inclusion vs. exclusion of the observation. Also shown is the NS measure of the monetary policy surprise mps_t , the change in the Blue Chip consensus forecast of real GDP ($BCrev_t$), the 30-minute-window response of the S&P 500 to the FOMC announcement, and a business cycle indicator. See text for details.

to Table 1, it presents something of a challenge for the Fed information effect story: If a Fed information effect is truly present in the data, and information shocks have a positive effect on stock prices as described by Jarocinski and Karadi (2019) and Cieslak and Schrimpf (2019), then why are the results in Table 2 so strongly and consistently negative? The results in Table 2 suggest that, if there is a Fed information effect in the data, then it must not be very large on average.

3.2 Stock Market Response to Influential FOMC Announcements

Perhaps the Fed information effect is not very large on average, but is very important on a few special dates. To investigate this possibility, Table 3 reports the 10 most influential observations in the Nakamura and Steinsson (2018) GDP regression from Table 1 and Figure 1, over their original sample. These are the 10 observations that provide by far the most evidence for a Fed information effect in their regressions and in Figure 1.

These top 10 influential observations are ordered by their contribution to the t -statistic in regression (3), reported in the second column of Table 3.¹⁵ The first column of Table 3

¹⁵This “Effect on t -statistic” is computed as the difference between the t -statistic for the coefficient θ in

reports the month and year of each influential observation (and the first eight of these are also labeled in Figure 1). The NS measure of the monetary policy surprise for each announcement is listed in the third column, followed by the change in the Blue Chip forecast for GDP that month in the fourth column, the percent change in the S&P 500 stock price index in the 30-minute window bracketing the announcement in the fifth column, and a business cycle indicator variable from [Brave, Butters and Kelley \(2019\)](#) for that month in the last column. For simplicity, we focus on the Blue Chip GDP forecast revisions in Table 3, but for every observation in the table, the inflation forecast revision has the same sign as the GDP revision, and the unemployment forecast revision has the opposite sign.¹⁶

By construction, the ten observations in Table 3 display a positive relationship between the NS monetary policy surprise and Blue Chip GDP forecast revision, because those are the ten observations that are the most important for the “Fed information effect” result in Figure 1 and panel (A) of Table 1. But even for these ten supposedly very information-laden FOMC announcements, the relationship between the monetary policy surprise and the stock market response remains strongly *negative*: on nine of these ten dates, the stock market responded strongly *and in the opposite direction to* the monetary policy surprise.

In fact, on the ten dates listed in Table 3, the stock market responded *more negatively* than it did for the NS sample as a whole. Table 4 reports the results for regression (5) for the ten information-laden observations in Table 3 compared to the rest of the NS sample, excluding those ten observations. If a “Fed information effect” were present, then the stock market should respond positively—or, at least, less negatively—to these ten announcements than to the rest of the observations in the NS sample. In fact, the opposite is true. The response of the stock market to even these supposedly very informative FOMC announcements is inconsistent with the “Fed information effect”.

As an alternative, we propose that both the Fed and Blue Chip forecasters are reacting to incoming news about the economy—the “Fed response to news” channel—which is consistent with the evidence in Table 3. The last column of the table reports the business cycle indicator variable from [Brave et al. \(2019\)](#), which provides a univariate summary of the state

regression (3) including vs. excluding that one observation from the sample.

¹⁶See Table A.3 for details.

Table 4: Stock Market Response to Ten Most “Information-Laden” Observations

first princip. comp. “MP surprise”	R^2	N
(A) Ten most information-laden observations in NS sample (cf. Table 3)		
-8.04*** (2.13)	0.64	10
(B) NS sample, excluding the ten observations from Table 3		
-4.96*** (1.24)	0.11	136

Coefficient θ from regressions $\Delta \log \text{S\&P500}_t = \phi + \theta \text{mps}_t + \varepsilon_t$, where t indexes the FOMC announcements described in each panel, mps_t denotes the NS monetary policy surprise in a 30-minute window bracketing the FOMC announcement, and $\Delta \log \text{S\&P500}_t$ denotes the percent change in the S&P 500 stock price index over the same 30-minute window. Standard errors in parentheses; *** denotes statistical significance at the 1% level. See notes to Table 2 and text for details.

of the business cycle based on a wide variety of economic data releases, with higher numbers indicating a stronger economy. Note that all five observations in Table 3 with negative policy surprises and downward GDP forecast revisions occurred when the economy was weak. In all five of these cases, the FOMC cut the federal funds rate in response to the weak economy, but the market was partly surprised by these decisions, according to the measured policy surprise. And in response to the monetary policy easing, the stock market rallied strongly in four out of those five cases, consistent with the standard view of the effects of monetary policy on the stock market (e.g., [Bernanke and Kuttner, 2005](#)). For the five positive monetary policy surprises in Table 3, the same observations hold, but in the opposite direction.¹⁷

It appears that the state of the economy might be an important omitted variable that could be the underlying driver of the correlation between the FOMC policy surprise and the Blue Chip forecast revision. Of course, this evidence concerning a few individual observations is only suggestive, but we provide more thorough systematic support for our Fed response to news channel in the following sections.

¹⁷The June 2003 announcement is an exception in that the economy was weak and the Fed lowered the federal funds rate in response, but by *less* than the markets had expected, resulting in a surprise monetary policy tightening on the day of the FOMC announcement.

4 High-Frequency Macroeconomic Forecast Responses

One of the main advantages of financial market data such as stock prices is its high frequency. Using daily or even intra-daily data, it's possible to focus on how a given asset price responds to a single important event in isolation, such as an FOMC announcement. By contrast, the Blue Chip survey of forecasters is conducted only monthly, so it's impossible to isolate the effects of an FOMC announcement on Blue Chip forecasts using those data.

In this section, we present new, high-frequency data from private-sector forecasters that *does* allow us to isolate the effects of FOMC announcements on the forecast. First, we obtained daily “GDP tracking” forecasts of real GDP from Macroeconomic Advisers, a multiple-award-winning participant in the Blue Chip survey of forecasters.¹⁸ These daily forecast revisions allow us to see how Macroeconomic Advisers revised its real GDP forecast on the days of FOMC announcements, and compare those revisions to other days on which other economic data was released.

Second, we contacted the chief economist of every participating firm in the Blue Chip survey of forecasters, and asked them directly how they revise their real GDP, unemployment, and inflation forecasts in response to FOMC announcements.

4.1 Macroeconomic Advisers GDP Tracking Estimates

Macroeconomic Advisers (MA) is a private firm specializing in macroeconomic forecasting and analysis since 1982. In 2017 they were purchased by IHS Markit and are now known as Macroeconomic Advisers by IHS Markit. One of the many products they offer to subscribers is a daily “GDP Tracking” estimate of current-quarter and next-quarter real GDP. Figure 2 provides an example of their current-quarter GDP Tracking for 2011Q1 from the company's public blog in April 2011.¹⁹ Each month, the GDP Tracking report begins with a base Macroeconomic Advisers forecast for current-quarter real GDP growth. (Note that because real GDP for 2011Q1 is not released by the U.S. Bureau of Economic Analysis until the end of April

¹⁸Macroeconomic Advisers won Blue Chip's annual Lawrence R. Klein award for overall forecast accuracy on two separate occasions, and was named by *The Wall Street Journal* as the most accurate macroeconomic forecaster of 2017.

¹⁹See <http://macroadvisers.blogspot.com/2011/04/q1-gdp-advance-estimate-is-18-02-pp.html>.

2011, it is still referred to as “current-quarter” GDP tracking by MA in April 2011.) That base forecast is then updated after every major macroeconomic data release that month. For example, when the monthly Retail Sales report from the U.S. Census Bureau for March 2011 came in substantially stronger than expected on April 13, 2011, MA revised up their forecast for 2011Q1 Personal Consumption Expenditures from 1.8 percent to 2.3 percent growth, implying an upward revision to their 2011Q1 real GDP growth forecast from 1.5 percent to 1.8 percent. They make analogous revisions for each of the other statistical releases listed in the figure, such as Business Inventories, the Consumer Price Index, Industrial Production, etc. A quick glance over the statistics in Figure 2 reveals, however, that the FOMC announcement on April 27, 2011 is not listed. Apparently, the FOMC announcement on that date was not informative for MA’s current-quarter real GDP forecast at that time.

Of course, one might worry that April 2011 was special, or that the FOMC announcement did affect MA’s forecast of real GDP in future quarters, just not in the current quarter. To resolve these questions, we obtained copies of MA’s current-quarter and next-quarter GDP Tracking forecasts for every month from January 2002 up to the present. Over that 18-year period, we found that MA *never* revised its current-quarter or next-quarter GDP forecast in response to an FOMC announcement. This suggests that the Fed information effect is very small, at least for this one multiple-award-winning Blue Chip forecaster.

4.2 New Survey of Individual Blue Chip Forecasters

One might still worry that Macroeconomic Advisers only reports daily GDP Tracking forecasts for the current quarter and next quarter, or that MA is only one firm that is not representative of the Blue Chip panel of forecasters as a whole. To address these concerns, we conducted our own survey of all 52 individual forecasting firms in the Blue Chip panel to ask them directly how they revise their forecasts in response to FOMC announcements.

We began by collecting the names and contact information for the Chief Economist for each of the 52 forecasting firms in the Blue Chip panel as of March 2019. The vast majority of these Chief Economists hold a Ph.D. from a highly ranked Economics Department. Several of them also have previous experience as Economists working within the Federal Reserve

Figure 2: Macroeconomic Advisers 2011Q1 Real GDP Tracking Estimate, April 2011

Release Title	Reference		GDP		Final Sales to Domestic Purchasers										Net Exports		CIPI		
	Date	Month	Chng	% ch	Total	PCE	Struct.	E&S	Res	Gov.	C&G	Level	Chng	Exports	Imports	Level	Chng		
MA Base Forecast	1-Apr-11	Feb	68	2.1	1.1	0.6	1.8	-18.6	9.7	4.8	-3.8	na	na	14.4	8.4	-382	16	47	31
Man. Ship. Inv. Orders	31-Mar-11	Feb	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
Construction	1-Apr-11	Feb	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
Unit Vehicle Sales	1-Apr-11	Mar	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
Chain Store Sales	7-Apr-11	Mar	71	2.1	1.1	0.7	1.8	-18.6	9.7	4.8	-3.8	na	na	14.4	8.4	-382	16	47	31
Wholesale Trade	8-Apr-11	Feb	71	2.1	1.1	0.7	1.8	-18.6	9.7	4.8	-3.8	na	na	14.4	8.4	-382	16	47	31
International Trade	12-Apr-11	Feb	50	1.5	0.3	0.6	1.8	-18.6	8.4	4.8	-3.8	na	na	5.7	6.7	-408	-10	55	39
Retail Sales	13-Apr-11	Mar	59	1.8	0.6	1.0	2.3	-18.6	8.4	4.8	-3.8	na	na	5.7	6.7	-408	-10	52	35
Business Inventories	13-Apr-11	Feb	49	1.5	0.6	1.0	2.3	-18.6	8.4	4.8	-3.8	na	na	5.7	6.7	-408	-10	43	26
Consumer Price Index	15-Apr-11	Mar	46	1.4	0.6	0.9	2.2	-18.6	8.4	4.8	-3.8	na	na	5.7	6.7	-408	-10	43	26
Industrial Production	15-Apr-11	Mar	47	1.4	0.5	0.9	2.2	-18.6	8.3	4.8	-3.8	na	na	5.7	6.7	-408	-10	44	28
Boeing Deliveries & Ords	15-Apr-11	Mar	46	1.4	0.5	0.9	2.2	-18.6	8.1	4.8	-3.8	na	na	5.5	6.7	-409	-11	44	28
Housing Starts	19-Apr-11	Mar	46	1.4	0.5	0.9	2.2	-18.6	8.1	5.2	-3.8	na	na	5.5	6.7	-409	-11	44	28
Existing Home Sales	20-Apr-11	Mar	47	1.4	0.5	0.9	2.2	-18.6	8.1	5.8	-3.8	na	na	5.5	6.7	-409	-11	44	28
New Home Sales	25-Apr-11	Mar	47	1.4	0.5	0.9	2.2	-18.6	8.1	6.2	-3.8	na	na	5.5	6.7	-409	-11	44	28
Durable Goods Orders	27-Apr-11	Mar	52	1.8	0.5	0.9	2.2	-18.6	8.1	8.2	-3.8	na	na	5.9	7.0	-409	-11	49	32
CQ Forecast as of	27-Apr-11		52	1.6	0.5	0.9	2.2	-18.6	8.1	6.2	-3.8	na	na	5.9	7.0	-409	-11	49	32
BEA's Advance Est.	28-Apr-11		58	1.8	0.8	0.9	2.7	-21.7	11.6	-4.1	-5.2	na	na	4.9	4.4	-400	-2	44	28

Release Notes:

Man Ship, Inv. and Ords: These data were available prior to completion of the base forecast and, hence, incorporated therein.
 Construction: These data were available prior to completion of the base forecast and, hence, incorporated therein.
 Unit Vehicle Sales: These data were available prior to completion of the base forecast and, hence, incorporated therein.
 Chain Store Sales: ICSC chain-store sales rose sharply in March, suggesting more growth of PCE in March than we previously expected.
 Wholesale Trade: Nonautomotive wholesale inventories rose in line with expectations in February and were little revised for January.
 International Trade: Net exports were well below expectations through February.
 Retail Sales: While core sales rose less than expected in March, large upward revisions in previous months imply more growth of core sales in the first quarter than we previously expected.
 Business Inventories: Nonautomotive retail inventories rose much less than expected in February.
 Consumer Price Index: The components of the CPI that we use to deflate retail sales came in higher than expected. This implies less real retail sales and PCE in Q1 than we expected.
 Industrial Production: Vehicle assemblies were above expectations in March, suggesting more inventory investment in Q1 than previously estimated.
 Boeing Deliveries and Ords: Boeing delivered 43 civilian aircraft in March, 2 fewer than expected, and at lower average value than assumed.
 Housing Starts: Starts and permits were above expectations in March and revised higher in previous months. This suggests more residential investment in Q1 than previously thought.
 Existing Home Sales: Existing home sales rose more than expected in March, suggesting more brokers' commissions in Q1 than previously assumed.
 New Home Sales: New home sales through March were above expectations, suggesting slightly higher brokers' commissions in Q1 than previously assumed.
 Durable Goods Orders: While shipments of nondurable capital goods ex air were close to expectations, manufacturing inventories exceeded expectations, implying more CIPI in Q1.

Explanatory Note: This table summarizes how the monthly data affect our current-quarter forecast of real GDP growth. Components labeled "Level" are expressed as billions of chained 2005 dollars at annual rates. Components labeled "Change" are the changes in the annualized levels of the component from the previous quarter. All other table entries are annualized growth rates of the real GDP components listed in the column headers. The first row of the table indicates the component growth rates, levels, and changes which constitute our most recent model-based forecast. Where data releases have implications for our current-quarter forecast of GDP components, the table cells bold. The reference month is the month for which new data will become available with the indicated release. GDP growth is calculated off-line by chain-weighting. STE denotes "stronger than expected," WTE denotes "weaker than expected," CMI denotes "change in private inventories," and E&S denotes "equipment and software." Please contact Ben Herzon if you have any questions.
 Disclaimer: The forecasts provided herein are based upon sources believed by Macroeconomic Advisers, LLC, to be reliable and to be developed from models which are generally accepted as methods for producing economic forecasts. Macroeconomic Advisers, LLC, cannot guarantee the accuracy or completeness of the information upon which this report and such forecasts are based. This report does not purport to disclose any risks or benefits of entering into particular transactions and should not be construed as advice with regard to any specific investment or insurance. The opinions and judgments expressed within this report made as of this date are subject to change without notice. Copyright © 2011 Macroeconomic Advisers, LLC

Source: Macroeconomic Advisers public blog, <http://macroadvisers.blogspot.com/2011/04/q1-gdp-advance-estimate-is-18-02-pp.html>.

System.²⁰ Each Chief Economist typically oversees a team of several economists who assist with the forecast and other economic analysis provided to clients.

We sent each Chief Economist a brief survey via email, reported in Figure 3. The goal of the survey is to find out whether they revise their forecasts of GDP, unemployment, and/or inflation in response to FOMC announcements and, if so, in which direction they revise those forecasts. Note that FOMC announcements consist of several components, including the federal funds rate decision itself, the FOMC statement, and sometimes a “dot plot” forecast of the FOMC’s views regarding the appropriate path for the federal funds rate over the next two years, and an “SEP” Summary of the FOMC’s own Economic Projections for GDP, unemployment, and inflation for the next two years. It’s possible that the Blue Chip forecasters respond differently to different components of these FOMC announcements: for example, the change in the federal funds rate might be viewed as a “pure monetary policy” shock, while the FOMC statement might have a significant informational component, and the SEP might even be viewed as a pure “information” shock, since it explicitly communicates the FOMC’s own forecast of macroeconomic variables. To allow for this kind of heterogeneity, we broke our main survey question into four components, asking how the private sector forecaster responds to each of: 1) changes in the federal funds rate, 2) the FOMC statement, 3) the “dot plot”, and 4) the FOMC’s SEP forecasts. See Figure 3 for the details of these questions.

We conducted our survey throughout July and August 2019. If we did not receive an initial response, we followed up with two brief reminder emails, with about 1.5 weeks between each email. In some cases, the initial response was vague regarding the direction in which they revise their forecasts (e.g., just replying “yes” to the questions). In those cases, we followed up with a brief email asking for clarification on the direction of those revisions, which cleared up the ambiguity. Sometimes, the initial response was a brief “no” to each of the four questions; in these cases, we followed up with a brief email asking for clarification regarding whether they viewed surprise FOMC announcements as having no significant effect on GDP, unemployment, or inflation vs. whether they viewed surprise FOMC announcements as having a significant effect but were just rarely surprised in practice over the past several years. Again, our followup

²⁰For example, Lewis Alexander of Nomura, Seth Carpenter of UBS, Julia Coronado of MacroPolicy Perspectives, and Dean Maki of Point72 Asset Management each worked at the Federal Reserve Board for many years, while Carl Tannenbaum of Northern Trust worked at the Federal Reserve Bank of New York.

Figure 3: Email Survey of Blue Chip Chief Economists

Eric Swanson

Subject: quick question about how FOMC announcements affect your forecast

Dear Dr. XXXX,

An important question in Macroeconomics is whether and how FOMC announcements affect private sector economic forecasts. We (Michael Bauer and Eric Swanson) are working on a new research paper that looks at this important question and would be extremely interested to learn **how FOMC announcements affect your own group's forecasts of GDP, unemployment, and inflation**. We'd be very grateful if you would take a minute to answer the following, very brief one-time survey on this topic:

1. Do you revise any of your macroeconomic forecasts (GDP, unemployment, or inflation) in response to the FOMC's **federal funds rate decision**?
If yes, please briefly explain which forecasts you revise and which direction you revise those forecasts (i.e., do you revise them up or down if the decision is more hawkish/dovish than expected):
2. Do you revise any of your macroeconomic forecasts in response to the **FOMC statement**?
If yes, please briefly explain which forecasts you revise, and which direction you revise those forecasts (i.e., do you revise them up or down if the statement is more hawkish/dovish than expected):
3. Do you revise any of your macroeconomic forecasts in response to the **dot plot** released by the FOMC in the Summary of Economic Projections (SEP)?
If yes, please briefly explain which forecasts you revise and which direction you revise those forecasts (i.e., do you revise them up or down if the dot plot is more hawkish/dovish than expected):
4. Do you revise any of your macroeconomic forecasts in response to **SEP forecasts of GDP, unemployment, and inflation** in the Summary of Economic Projections?
If yes, please briefly explain which FOMC forecasts matter for you, which forecasts you revise, and which direction you revise those forecasts:

Individual responses will be kept confidential, and we will only publish aggregated results. We'd like to emphasize that there are no right or wrong answers to these questions—there are theoretical reasons why the answers could go in any direction, or no direction. The point of our research is to find out what professional forecasters like yourself do in practice. If you are interested, we'd be happy to send you our overall results and analysis of this topic once we have a draft of our paper. Thank you very much for your time and help on this.

Sincerely,

Michael Bauer
Research Advisor
Federal Reserve Bank of San Francisco
michael.bauer@sf.frb.org
<https://www.frbsf.org/economic-research/economists/michael-bauer/>

Eric Swanson
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Email survey sent to Chief Economists of professional forecasting firms in the Blue Chip survey of forecasters.

Table 5: Blue Chip Forecaster Responses to FOMC Announcements: Results from Our Survey

	Response to hawkish surprise in:		
	fed funds rate	FOMC statement	“dot plot”
Do not revise GDP forecast	13	16	14
Revise GDP forecast downward	18	15	18
Revise GDP forecast, but direction depends on other factors	5	5	4
Revise GDP forecast upward	0	0	0
	Response to FOMC’s Summary of Economic Projections (SEP)		
Do not revise GDP forecast		24	
Revise GDP forecast towards SEP forecast of GDP if substantially different		4	
Use SEP to help forecast fed funds rate, effect on GDP standard		3	
Use SEP to help forecast fed funds rate, effect on GDP depends on other factors		1	
Revise GDP, but revision depends on multiple factors		2	

Number of private-sector forecasting firms (out of 36 total) reporting how they revise their GDP forecast in response to four main components of FOMC announcements: the federal funds rate, FOMC statement, FOMC “dot plot” projection of future federal funds rates, and FOMC “SEP” forecast of future real GDP, unemployment, and inflation. Two survey respondents did not provide answers for how they respond to the SEP forecasts. See text for details.

email essentially always resolved the ambiguity.

The results of our survey are summarized in Table 5. Overall, we received 36 responses out of 52 possible, a response rate of about 70 percent. Many forecasters noted that they rarely responded to FOMC announcements because the FOMC typically communicated the outcome of each meeting well in advance in speeches by FOMC members. Table 5 nevertheless reports in which direction they revise their GDP forecasts in those rare instances when the FOMC announcement is a substantial, hawkish surprise. Note that we focus on revisions to GDP forecasts in Table 5 for simplicity, but in every case survey respondents noted that they would revise unemployment in the opposite direction to GDP and inflation in the same direction as

GDP, consistent with standard macroeconomic models. The top panel of Table 5 reports how respondents revised their GDP forecasts in response to a hawkish surprise in the federal funds rate, in the FOMC statement, and in the “dot plot” of federal funds rate projections. The bottom panel of the table report how respondents revised their GDP forecasts in response to the FOMC’s SEP forecasts of GDP, unemployment, and inflation.

There are several important points to take away from Table 5. First, a large majority of the survey respondents, 24 out of 34, do not revise their forecasts in response to the SEP. This observation directly contradicts the existence of a Fed information effect—after all, the FOMC is explicitly communicating its GDP, unemployment, and inflation forecasts to the public through the SEP and a large majority of the Blue Chip forecasters simply do not find that information useful.²¹

Second, Macroeconomic Advisers is not an outlier: many survey respondents do not revise their GDP (or unemployment or inflation) forecasts in response to any component of FOMC announcements. Of the 34 respondents, 13 do not revise their forecasts in response to changes in the funds rate, 16 do not revise in response to the FOMC statement, 14 do not revise in response to the dot plot, and 24 do not revise in response to the SEP (as mentioned above). The overlap across these groups is substantial, so there are 13 respondents who do not revise their forecasts in response to any component of FOMC announcements. This is surprising, given that standard macroeconomic models and VARs imply that tighter monetary policy should cause GDP to fall slightly over the next several quarters. Our survey respondents gave several different reasons for their unresponsiveness to FOMC announcements: Some forecasters said that the announcements have not been a surprise for many, many years and are just not informative about monetary policy, relative to FOMC member speeches and press conferences.²² Other forecasters said that if they were surprised by an FOMC announcement,

²¹For example, one forecaster commented that “I trust my outlook more than the Fed’s. . . Their forecasting ability is pretty poor.” Another noted, “My view is that the Fed does not have superior information. . . The FOMC forecast tends to be off by a lot.” Other forecasters said, “We tend to find that the Fed has no better information advantage over economists like myself. . . In fact, what we have found many times is Fed forecasts (per the SEP) tend to be somewhat stale,” and “I would be responding to the change in the policy outlook, not to the possibility that the Fed ‘knew’ something that I did not.” Even one of the respondents who *does* revise their GDP forecast in response to the SEP noted that “We would not be updating our forecasts because we think the SEP forecasts are good. But if we think they signal something about future policy and portend a market shock then we might change some forecasts in anticipation of that.”

²²For example, one forecaster said, “I have not been surprised by an FOMC announcement since well before

then they viewed that surprise as an FOMC “mistake” that the FOMC would later have to unwind, resulting in no net change to the GDP forecast.²³ A few forecasters said that they could find only very small effects of changes in interest rates on GDP, so that changes in the federal funds rate or dot plot just didn’t have any significant effect on their forecast.²⁴

The third main point to take away from Table 5 is that, of our survey respondents who *do* revise their forecasts in response to FOMC announcements, the vast majority (18 out of 23) revise those forecasts in the standard way—that is, a hawkish monetary policy surprise causes them to revise their GDP forecast downward. In contrast, *none* of our survey respondents said that they would revise their GDP forecast upward, although 5 did say that their GDP forecast revision would depend on other factors.²⁵ Although this last group of 5 forecasters does allow for the existence of an information effect, and one of those respondents even explicitly raised that possibility, those forecasters are vastly outnumbered (by 18–5, 31–5, 27–4, or 32–4, depending on exactly how one counts) by respondents who say they simply do not revise their forecasts in the way that the information effect channel would require. In fact, several of these latter forecasters explicitly commented on the Fed’s SEP forecasts as being “somewhat stale”, “pretty poor”, “off by a lot”, or “not...good” (see footnote 21). Given this huge imbalance, it’s essentially impossible for the Blue Chip consensus forecast (the average of the individual firms’ forecasts) to be significantly affected by a Fed information effect.

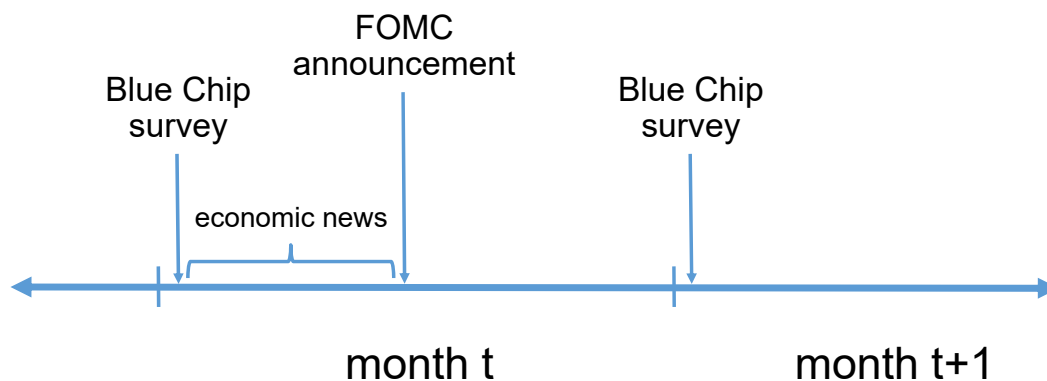
2008 (including January 2008 [a 75bp intermeeting interest rate cut]).” A second noted, “In the end, we are likely to get more information from speeches and press conferences than we are from the statement, the decision, or the dots. So by the time we get those things, it tends to be relatively ‘old news’, if you will.” A third stated, “I make my forecasts based on the data, not Fed assumptions. I haven’t been surprised by them in a very long time.”

²³One forecaster explained, “My view is that the Fed does not have superior information. As a result, over time, if my forecast is right and the Fed’s action at some meeting is wrong, they will come to see the forecast as ‘true’ and adjust policy in response.” A second stated, “If we think the Fed is about to make a decision that is inconsistent with our expected outlook, we often think that will lead to a change in financial conditions that will in turn push the Fed back to where we think is appropriate for the economy.”

²⁴For example, “I could never find an effect of interest rates on any component of investment except residential [which was too small to have a significant effect on the GDP forecast].”

²⁵For example, one forecaster said “There is no simple answer to that question, it depends on what else is happening.” Another stated that they would ask themselves, “Does the Fed know something?” A third forecaster said, “If the Fed was particularly concerned with maintaining price stability or...curbing rising inflation expectations then we might lower our GDP forecast...[but] If such a policy stance reduced the volatility in inflation or inflation expectations [as measured by TIPS vs. nominal Treasuries] then we might raise our GDP forecast as a result.”

Figure 4: Illustration of the “Fed Response to News” Channel



The Blue Chip survey of forecasters is conducted in the first 2–3 business days of each month, while FOMC announcements can occur at any point throughout the month. In between the time of the Blue Chip survey and the FOMC announcement, significant economic news, such as the Employment Report, is often released. See text for details.

5 Economic News as an Omitted Variable

Instead of a “Fed information effect”, we have proposed that the puzzling signs of the Blue Chip forecast regressions in Section 2 can be explained by a “Fed response to news” channel. The idea is illustrated in Figure 4. The Blue Chip survey of forecasters is conducted in the first 2 business days of each month (first 3 business days prior to December 2000). In contrast, the FOMC announcement can occur at any point throughout the month. In between the second business day and the day of the FOMC announcement, significant economic news can be released. For example, the Employment Report (including nonfarm payrolls, the unemployment rate, average weekly hours, and average hourly earnings) is typically released on the first Friday of each month; Retail Sales, International Trade, Industrial Production, Capacity Utilization, and many other indicators are released around the second week of each month; and new financial market data on stock prices, bond yields, and exchange rates arrives every day throughout the month.

This economic news is an omitted variable in regression equations (2) and (3). We focus on economic news released *before* the FOMC announcement because that news is clearly publicly available and common knowledge as of the time of the FOMC announcement, and thus cannot represent a “Fed information effect” about future data releases, although in principle any

economic news released after the FOMC announcement is an omitted variable in regressions (2) and (3) as well.

If this pre-FOMC economic news depicted in Figure 4 is correlated with the right-hand side variables in regressions (2) and (3), then the estimated coefficients in those regressions will be biased. Although one might hope that the high-frequency measure of monetary policy surprises used in those regressions controls for economic data that’s released up until the FOMC announcement, the scatter plot in Figure 1 raises serious concerns that there is still significant correlation remaining. In that figure, positive monetary policy surprises seem to be correlated with periods of sustained economic expansion, while negative monetary policy surprises are correlated with periods of sustained economic contraction.

In this section, we document three important empirical findings: first, the high-frequency monetary policy surprises used in regressions (2) and (3) are in fact correlated with economic data released before the FOMC announcement. Second, economic news released during the month is extremely informative about Blue Chip forecast revisions (which is not surprising). And third, including pre-FOMC economic news as additional right-hand-side variables in regressions (2) and (3) drives away the empirical evidence for the “Fed information effect”. We conclude that the Fed’s response to economic news explains the “Fed information effect”.

5.1 Economic News Predicts Monetary Policy Surprises

We first show that publicly available economic news that predates the FOMC announcement is correlated with the high-frequency monetary policy surprise at that upcoming meeting. To show this, we run regressions of the form

$$mps_t = \alpha + \beta news_t + \varepsilon_t, \tag{6}$$

where t indexes FOMC announcements, mps_t is a high-frequency measure of the monetary policy surprise at that FOMC meeting (either the “target” factor, the “path” factor, or the Nakamura-Steinsson first principal component), and $news_t$ denotes a measure of economic news that is publicly released before the FOMC announcement. Because we will eventually be looking at Blue Chip forecast revisions as well, we drop from the sample any FOMC

announcement that occurs in the first 2–3 business days of the month, to ensure that the FOMC announcement occurs after the Blue Chip forecast was made.

We consider three different variables for $news_t$ in regression (6). First, we use the nonfarm payrolls release from the Employment Report that month, as long as it occurs after the second business day of the month (third business day before Dec. 2000) and before the FOMC announcement.²⁶ This has the advantage of being a very simple yet informative measure of economic news for the month, as the nonfarm payrolls release has the largest effect on financial markets of all the data releases in general. Second, we consider a more comprehensive measure of economic news, the “big data” business cycle indicator of [Brave et al. \(2019\)](#). This index incorporates information from hundreds of statistics from dozens of statistical releases each month to come up with a single index of economic activity; it is thus much broader than nonfarm payrolls alone, but has the disadvantage of including data that are released after the FOMC announcement as well as before.²⁷ Third, we use the log change in the S&P 500 stock price index from the day after the previous FOMC announcement to the day before the FOMC announcement at date t . Although stock prices are noisy, they are also a reasonably good summary statistic for all of the economic news that is released each day and, unlike the Brave et al. index, we can isolate the effects of economic news leading up to the FOMC announcement while excluding news released afterward.²⁸

The results from these regressions are reported in Table 6. There are four panels in the Table, corresponding to the four sample periods considered in Table 1 and 2. The first column of Table 6 considers the “target factor” from [Campbell et al. \(2012\)](#) and [Gürkaynak et al. \(2005b\)](#) as the measure of the monetary policy surprise in regression (6), the second column considers the “path factor” from those papers, and the third column considers the monetary

²⁶The nonfarm payrolls release reports the change in nonfarm payrolls from the previous month, in thousands of workers; we divide this number by 100 (to make it in units of 100,000 workers) to improve the scaling of the coefficients in Table 6. We also considered the unemployment rate and average hourly earnings releases as well, but these did not significantly predict the monetary policy surprise once the nonfarm payrolls release was included. Note that all of these data refer to the previous month, because it is data for the previous month that is released in the runup to the FOMC announcement at t .

²⁷In regression (6), we use the [Brave et al. \(2019\)](#) index for the previous month as our $news_t$ variable, since it is the data for the previous month that is being released in the runup to the FOMC announcement at t .

²⁸In principle, we could use the log change in the S&P 500 from the second business day of the month up to the day before the FOMC announcement to measure the news released over the course of the month. In practice, however, this shorter-horizon stock index change is noisier and does not predict the FOMC announcement surprise as well as the longer-horizon stock price change going back to the previous FOMC announcement.

Table 6: Economic News Predicts High-Frequency Monetary Policy Surprises

Economic News Measure	(1) Campbell et al. “target factor”	(2) Campbell et al. “path factor”	(3) Nakamura-Steinsson “MP surprise”
(A) Replication sample: 1/1990–6/2007 for Campbell et al., 1/1995–3/2014 for NS			
Nonfarm payrolls	1.65*** (.528)	0.28 (.303)	0.41** (.195)
Brave-Butters-Kelley index	.037*** (.014)	.016** (.0078)	.013** (.0066)
$\Delta \log S\&P500$	0.26* (.153)	0.18** (.091)	0.099* (.055)
(B) Full sample: 1/1990–6/2019, including unscheduled announcements			
Nonfarm payrolls	0.95*** (.311)	0.24 (.274)	0.58*** (.207)
Brave-Butters-Kelley index	.017** (.0074)	.013** (.0057)	.014*** (.0049)
$\Delta \log S\&P500$	0.22* (.114)	0.16* (.082)	0.18*** (.067)
(C) Full sample: 1/1990–6/2019, excluding unscheduled announcements			
Nonfarm payrolls	0.44** (.215)	0.27 (.285)	0.35* (.201)
Brave-Butters-Kelley index	.007 (.0058)	.017*** (.0060)	.011*** (.0049)
$\Delta \log S\&P500$	0.08 (.065)	0.24*** (.080)	0.15** (.059)
(D) Full sample: 1/1990–6/2019, excl. unscheduled announcements and 7/2008–6/2009			
Nonfarm payrolls	0.48** (.237)	0.08 (.256)	0.28* (.162)
Brave-Butters-Kelley index	.012 (.0088)	.023*** (.0068)	.017*** (.0051)
$\Delta \log S\&P500$	0.04 (.062)	0.18** (.077)	0.11** (.048)

Estimated coefficients β from regressions $mps_t = \alpha + \beta news_t + \varepsilon_t$, where t indexes FOMC announcements, mps_t denotes the 30-minute window measure of the monetary policy surprise listed at the top of each column, and $news_t$ denotes the measure of economic news listed in each row. Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Replication sample for Campbell et al. includes unscheduled announcements; that for Nakamura-Steinsson excludes unscheduled announcements and 7/2008–6/2009. See text for details.

policy surprise measure from [Nakamura and Steinsson \(2018\)](#). The three rows of each panel consider the three measures of economic news described above. Each element of the table reports the coefficient estimate β from regression (6).²⁹ Note that, in contrast to Table 1, here the monetary policy surprises are on the *left*-hand side of each regression, rather than the right-hand side.

The clear takeaway from Table 6 is that there is significant predictability in these high-frequency monetary policy surprises. This predictability is robust across samples and across different measures of economic news. In other words, publicly available information that predates the FOMC announcement nevertheless has substantial predictive power for the 30-minute change in interest rate futures around that announcement. The signs of the coefficients in Table 6 imply that, when the economic news is positive, the FOMC is more likely to surprise markets with a monetary policy tightening, and when the economic news is negative, the FOMC is more likely to surprise markets with an easing, consistent with our observations in Figure 1.

This predicability is surprising, although similar results have been documented previously by [Miranda-Agrippino \(2017\)](#). According to the Efficient Markets Hypothesis, futures markets should efficiently incorporate all publicly available information within a few minutes of that information being released; thus, the 30-minute change in futures rates around the FOMC announcement should be unpredictable based on information that is publicly available prior to that announcement.³⁰ The results in Table 6 contradict that hypothesis. [Miranda-Agrippino \(2017\)](#) interprets this predictability as a risk premium that compensates investors for the risks associated with holding interest rate futures around FOMC announcements. However, [Piazzesi and Swanson \(2008\)](#) estimate that this risk premium is relatively small, and there are alternative potential explanations: for example, the futures market could be efficient *ex ante*, but market participants did not know the FOMC’s true monetary policy reaction function f (cf. equation 1) and underestimated how responsive the FOMC would be to economic news.

²⁹Thus, each coefficient in Table 6 corresponds to its own regression. In principle, one can include all three measures of news in regression (6) simultaneously, but there is enough collinearity between the three measures that they lose individual statistical significance, even though they are jointly highly statistically significant. In the interest of simplicity and clarity, we just report the univariate regression results in the table.

³⁰Note that the FOMC announcement should be unpredictable whether or not the “Fed information effect” is true. The results in Table 6 are thus surprising in either case.

This would lead to *ex post* predictability of monetary policy surprises of the type seen in Table 6 even if the futures market was *ex ante* rational and efficient. We do not take a stand on why market participants might have underestimated the FOMC’s responsiveness to news, but one possibility is that the FOMC has gradually become more responsive to news about output over time—i.e., Volker was less responsive to output than was Greenspan, who in turn was less responsive than Bernanke, who was less responsive than Yellen. Regardless, the important point for our analysis is that the high-frequency monetary policy surprises in the “Fed information effect” regressions (2) and (3) are predictable and correlated with economic news released after the Blue Chip forecast was made.

5.2 Economic News Predicts Blue Chip Forecast Revisions

We next show that the economic news considered above is a very strong predictor of Blue Chip forecast revisions. This should not be surprising: economic data is released every month, and the professional forecasters in the Blue Chip survey will typically revise their forecasts for GDP, unemployment, and inflation as those data come in.

We check the predictability of these Blue Chip forecast revisions by running regressions of the form

$$BCrev_t = \alpha + \beta news_t + \varepsilon_t, \tag{7}$$

where t indexes all months in the sample, $BCrev_t$ denotes the one-month revision over the course of month t in the Blue Chip consensus forecast of a given variable averaged over the 1-, 2-, and 3-quarter-ahead horizons, as in Section 2, and $news_t$ denotes one of the three economic news measures described above. In contrast to previous tables, here we include all months in our sample (not just the months of FOMC announcements) since the corresponding data are available for every month.³¹

The results are reported in Table 7. The first column reports the results for Blue Chip

³¹Nonfarm payrolls announcements are only included in regression (7) if they occur after the first 2 business days of the month (3 business days before Dec. 2000), to make sure that the announcement occurs after the Blue Chip forecast at the beginning of the month. As in Table 6, the nonfarm payrolls data and Brave et al. (2019) index correspond to month $t - 1$, since the data for that month are released in month t . The stock price change $\Delta \log S\&P500$ in these regressions is computed from the beginning of month $t - 1$ to the end of month t ; this two-month stock price change is less noisy than the one month change and has higher explanatory power for the Blue Chip forecast revision.

Table 7: Economic News Predicts Blue Chip Forecast Revisions

Economic News Measure	(1) Blue Chip real GDP forecast	(2) Blue Chip unemployment rate forecast	(3) Blue Chip inflation forecast
(A) Nakamura-Steinsson replication sample: 1/1995–3/2014, excluding 7/2008–6/2009			
Nonfarm payrolls	1.31** (.632)	−2.47*** (.639)	−0.13 (.401)
Brave-Butters-Kelley index	.077*** (.0171)	−.077*** (.0171)	−.002 (.0117)
$\Delta \log S\&P500$	1.02*** (.165)	−0.69*** (.195)	0.09 (.128)
(B) Campbell et al. replication sample: 1/1990–6/2007			
Nonfarm payrolls	1.11 (.690)	−2.99*** (.574)	0.45 (.414)
Brave-Butters-Kelley index	.062*** (.0177)	−.080*** (.0150)	.014 (.0105)
$\Delta \log S\&P500$	0.93*** (.192)	−0.53** (.218)	−0.20 (.168)
(C) Full sample: 1/1990–6/2019			
Nonfarm payrolls	2.02*** (.646)	−3.32*** (.406)	0.66 (.451)
Brave-Butters-Kelley index	.073*** (.0161)	−.081*** (.0081)	.027** (.0104)
$\Delta \log S\&P500$	1.30*** (.190)	−0.77*** (.148)	0.32* (.162)
(D) Full sample: 1/1990–6/2019, excluding 7/2008–6/2009			
Nonfarm payrolls	1.33** (.557)	−2.47*** (.492)	0.02 (.337)
Brave-Butters-Kelley index	.063*** (.0149)	−.074*** (.0118)	.003 (.0096)
$\Delta \log S\&P500$	0.93*** (.143)	−0.54*** (.157)	−0.03 (.127)

Estimated coefficients β from regressions $BCrev_t = \alpha + \beta news_t + \varepsilon_t$, where t indexes all months, $BCrev_t$ denotes the one-month change over the course of month t in the Blue Chip consensus forecast for the next 3 quarters for the variable listed in each column, and $news_t$ denotes the measure of economic news listed in each row. Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See text for details.

forecast revisions for real GDP, the second column for the unemployment rate, and the third column for inflation. The table is divided into four panels, which differ slightly from previous tables since the samples here include every month rather than just months containing an FOMC announcement.

Not surprisingly, economic news has a great deal of explanatory power for Blue Chip forecast revisions of GDP and unemployment. The coefficients in the first two columns of Table 7 all have the expected sign and are highly statistically significant except for one case. In many cases the t -statistics exceed 5 or even 10. There is no question that these news measures are associated with subsequent Blue Chip forecast revisions.

For inflation forecasts, in the third column, there is relatively evidence that the three news measures in Table 7 predict forecast revisions, except over the full sample from 1990–2019. This is perhaps not surprising, since the nonfarm payrolls statistic primarily reveals information about economic activity rather than inflation, and the [Brave et al. \(2019\)](#) index is explicitly constructed to provide information about output. If we instead include news measures such as the CPI and PPI releases in regression (7), then we do find significant effects on the Blue Chip inflation forecasts, but results are not reported here in the interest of space.

5.3 Economic News Drives Out the “Fed Information Effect”

The results above show that economic news is an omitted variables in regressions (2) and (3) and that this omitted variable is correlated with the monetary policy surprise measures in those regressions. As a result, the “Fed informatoin effect” coefficients on those variables will be biased.

To better control for the omitted news variables, and get a sense of the size of this bias, we re-estimate regressions (2) and (3) with explicit controls for economic news, that is,

$$BCrev_t = \alpha + \beta target_t + \gamma path_t + \delta news_t + \varepsilon_t, \quad (8)$$

and

$$BCrev_t = \alpha + \theta mps_t + \phi news_t + \varepsilon_t, \quad (9)$$

Table 8: Economic News Drives Out the “Fed Information Effect”

Blue Chip forecast	(1) Campbell et al.		(2) Nakamura-Steinsson
	fed funds rate “target factor”	fwd. guidance “path factor”	first princip. comp. “MP surprise”
(A) Replication sample: 1/1990–6/2007 for Campbell et al., 1/1995–3/2014 for NS			
Unemployment rate	0.09 (.085)	−0.01 (.109)	0.24 (.256)
Real GDP growth	−0.02 (.162)	−0.05 (.207)	0.35 (.286)
(B) Full sample: 1/1990–6/2019, including unscheduled announcements			
Unemployment rate	0.093 (.084)	0.088 (.104)	0.23 (.153)
Real GDP growth	−0.11 (.143)	−0.12 (.177)	−0.28 (.216)
(C) Full sample: 1/1990–6/2019, excluding unscheduled announcements			
Unemployment rate	0.28** (.124)	0.12 (.109)	0.49*** (.183)
Real GDP growth	−0.27 (.199)	−0.12 (.176)	−0.32 (.243)
(D) Full sample: 1/1990–6/2019, excl. unscheduled announcements and 7/2008–6/2009			
Unemployment rate	0.13 (.125)	0.05 (.110)	0.23 (.177)
Real GDP growth	−0.02 (.176)	−0.09 (.155)	0.13 (.207)

Coefficients in Campbell et al. columns are β and γ from regressions $BCrev_t = \alpha + \beta target_t + \gamma path_t + \delta news_t + \varepsilon_t$, where t indexes FOMC announcements, $target_t$, $path_t$, and $BCrev_t$ are as defined in Table 1, and $news_t$ is a vector that contains the three measures of economic news described above. Coefficients in Nakamura-Steinsson column are θ from regressions $BCrev_t = \alpha + \theta mps_t + \phi news_t + \varepsilon_t$, where mps_t is as defined in Table 1. Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See notes to Table 1 and text for details.

where t indexes FOMC announcements and the variables in (8) and (9) are as defined previously, although here we let $news_t$ be a vector that contains all three measures of economic news simultaneously.³²

The results are reported in Table 8. The structure of the table is essentially the same

³²Because the Brave-Butters-Kelley index is not completely known by the time of the FOMC announcement, we also consider a version of Table 8 that excludes that index from the $news_t$ variable, and the results are very similar. See Appendix Table A.4.

as Table 1, with the first two columns reporting the coefficients β and γ from regression (8), and the last column reporting the coefficient θ from (9). The table is divided into four panels, which consider the same four samples as in Table 1. Each row of the table corresponds to the Blue Chip forecast revision for a different variable—the unemployment rate or real GDP—but we don’t consider forecasts for inflation because our main news measures had relatively little explanatory power for Blue Chip inflation forecast revisions and because there was relatively little evidence of an information effect for inflation in Table 1 anyway.

The results in Table 8 are strikingly different from Table 1. First, there is essentially no evidence of a “Fed information effect” in Table 8, which controls for economic news released after the Blue Chip forecast at the beginning of the month. In fact, every coefficient in Table 8 has the *traditional* (i.e., non-information-effect) sign—positive for the unemployment rate and negative for real GDP—with the exception of the two Nakamura-Steinsson real GDP coefficients when the July 2008 to June 2009 period is excluded. Thus, controlling for economic news, the effects of Federal Reserve monetary policy announcements on Blue Chip forecasts looks very standard.

We conclude that economic news is an omitted variable from the information effect regressions (2) and (3), that economic news is correlated with the right-hand-side variables in those regressions, and that the resulting econometric bias is substantial. Once we control for this omitted variable, as we do in regressions (8) and (9), the sign of the coefficients on the Federal Reserve’s monetary policy announcement surprises reverses sign and looks conventional.

6 Forecast Accuracy: the Fed vs. Blue Chip

To motivate the existence of a “Fed information effect” many authors argue that the Fed produces better forecasts than the private sector because the Fed devotes more resources to forecasting than does any single private-sector firm. For example, Romer and Romer (2000) note that “the Federal Reserve commits far more resources to forecasting than even the largest commercial forecasters. As a result, it is able to produce superior forecasts from publicly available information,” (p. 437). However, Faust et al. (2004a) point out that markets aggregate information, as discussed by Hayek (1945), Grossman (1989), and others, and there

are very large markets in the U.S. that are closely tied to interest rate and inflation forecasts, such as nominal and real Treasury bond markets, interest rate futures and options markets, and inflation swaps and swaptions markets. As a result, it would be very surprising if the Fed’s own forecasts of these variables was substantially better than the private sector’s. Although there is not an explicit market for GDP forecasts, those forecasts are nevertheless closely tied to the future path of interest rates and many other market outcomes, so again it would be very surprising if the Fed’s forecast for GDP was substantially better than the private sector’s.

In this section, we conduct a detailed comparison of Blue Chip and Federal Reserve internal forecasts of GDP, unemployment, and inflation. The Fed’s internal forecasts are produced as part of the “Greenbook” a few days prior to each scheduled FOMC meeting, and those Greenbook (GB) forecasts are made available to the public with a five-year lag.³³ Our sample consists of the GB forecasts from January 1980 to December 2013, for a total of 274 forecast dates.

To compare the Blue Chip (BC) forecasts to these GB forecasts, we need to contend with the fact that the frequency and publication dates of these two forecast series differ: the BC survey is conducted monthly at the beginning of each month, while the GB forecasts are made eight times per year before each scheduled FOMC meeting, which can occur at any point within a month. For our baseline results, below, we match each GB forecast with whichever BC forecast is the *closest*; this BC forecast could have been made either before or after the corresponding GB forecast, depending on whether that particular GB forecast was made closer to the beginning or the end of the month. As a result, the BC forecasts have a slight informational advantage over the GB for 124 of the GB forecast dates, whereas the GB forecasts have a slight informational advantage over the BC for the other 150 forecast dates. In the Appendix, we report results for the alternative schemes of always comparing the GB forecast to the previous BC forecast (giving the GB an informational advantage), or always comparing the GB forecast to the next BC forecast (giving BC an informational advantage).

We obtain the corresponding macroeconomic data releases from FRED. For real GDP

³³Beginning in June 2010, the Fed’s separate “Greenbook” and “Bluebook” documents were combined into a single “Tealbook”. For simplicity, we will use the term “Greenbook forecast” to refer to the Fed’s internal forecast throughout our entire sample, even though the Greenbook was replaced by the Tealbook from June 2010 onward.

growth and CPI inflation, forecasts are made for quarterly growth rates at an annualized rate, whereas for the unemployment rate forecasts pertain to the quarterly average.³⁴ We consider forecast horizons of zero (i.e., nowcasts) to three quarters, as well as forecasts of the average realized values over these four quarters.

We estimate “encompassing regressions” similar to those of [Romer and Romer \(2000\)](#),

$$X_{t+h} = \alpha + \beta \hat{X}_{t+h|t}^{GB} + \gamma \hat{X}_{t+h|t}^{BC} + \varepsilon_{t+h}, \quad (10)$$

where the realized value of a macroeconomic variable X in quarter $t+h$ is regressed on both the GB and BC forecasts of that variable, $\hat{X}_{t+h|t}^{GB}$ and $\hat{X}_{t+h|t}^{BC}$, at time t to see which forecast receives more weight, and h denotes the forecast horizon in quarters.³⁵ However, [Sims \(2002\)](#) cautions against the use of encompassing regressions in this context, because the forecasts are serially correlated and have very similar information content; instead, Sims recommends focusing on accuracy measures for each forecast considered separately. Thus, we also calculate root-mean-squared errors (RMSEs) for each of the BC and GB forecasts considered separately, and perform a [Diebold and Mariano \(1995\)](#) test for equal predictive accuracy.

The results of these tests are reported in [Table 9](#). The top panel of the table compares the GB and BC forecasts for real GDP growth, the second panel compares their forecasts for the unemployment rate, and the bottom panel compares their forecasts for the CPI inflation rate.³⁶

The main conclusion from [Table 9](#) is that neither the Fed nor the Blue Chip had significantly better forecasts over this sample, 1980–2013. For horizons $h > 0$, the encompassing regression coefficients on the GB forecasts are never significantly different from the coefficients

³⁴For CPI inflation we first take quarterly averages of the price level index and then calculate quarterly growth rates.

³⁵To conduct statistical inference we need to account for serial correlation in the forecast errors due to the overlap in the observations, which depends on the forecast horizon. Like [Romer and Romer \(2000\)](#), we use the Hansen-Hodrick long-run covariance estimator and, because of our sample frequency, we use $2(h+1)$ lags, where h is the forecast horizon in quarters (and we take $h = 3$ when we forecast the average over 0-3 quarters). (In quarterly data, the overlap would induce serial correlation in the residuals up to order $h+1$, while in monthly data (as in [Romer and Romer, 2000](#)) there is serial correlation up to order $3(h+1)$). Our sample of GB forecast dates generally has about 8 observations per year (the number of FOMC meetings), which implies serial correlation up to order $2(q+1)$.)

³⁶The R^2 for the unemployment rate are naturally much higher (and RMSEs much lower) than for the other series, because this data series is highly persistent and therefore easier to forecast over the next few quarters.

Table 9: Comparison of Greenbook and Blue Chip forecasts

Horizon (quarters)	Encompassing regressions				RMSEs		
	GB	BC	R^2	$H_0: GB=BC$	GB	BC	$H_0: GB=BC$
(A) Real GDP growth							
0	1.07*** (.249)	-0.10 (.348)	.50	.047	2.17	2.32	.032
1	-0.09 (.515)	1.09* (.619)	.19	.284	2.94	2.80	.247
2	0.64 (.495)	-0.20 (.854)	.07	.508	2.87	2.89	.931
3	0.18 (.514)	-0.19 (.882)	.00	.769	2.98	2.89	.681
0-3 avg.	0.38 (.531)	0.55 (.724)	.27	.892	1.83	1.78	.675
(B) Unemployment rate							
0	0.65*** (.117)	0.34*** (.117)	.99	.194	0.20	0.22	.280
1	0.77*** (.209)	0.21 (.213)	.95	.190	0.39	0.41	.322
2	0.74** (.320)	0.23 (.312)	.88	.417	0.59	0.61	.660
3	0.81* (.414)	0.13 (.404)	.79	.404	0.76	0.79	.644
0-3 avg.	0.79*** (.282)	0.18 (.276)	.93	.276	0.46	0.47	.539
(C) CPI inflation							
0	0.98*** (.106)	-0.11 (.098)	.86	.000	1.10	1.40	.102
1	0.73*** (.250)	-0.06 (.314)	.46	.160	2.21	2.15	.580
2	0.16 (.236)	0.58 (.352)	.37	.468	2.07	1.94	.123
3	0.64* (.345)	0.12 (.463)	.36	.517	2.02	2.04	.841
0-3 avg.	0.89*** (.245)	-0.16 (.270)	.73	.038	1.21	1.20	.884

Comparison of forecast accuracy for Federal Reserve Greenbook (“GB”) and Blue Chip (“BC”) forecasts from 1980–2013 (274 observations). For encompassing regressions, the realized value for each macro series is regressed on a constant and both the GB and BC forecasts, and the table reports the coefficients, the regression R^2 , and p -value for the null hypothesis that the coefficients are equal. Hansen-Hodrick standard errors with $2(h+1)$ lags for forecast horizon h in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Root-mean-squared errors (RMSEs) are reported for each forecast, with a Diebold-Mariano p -value (using the same long-run covariance estimator and a small-sample correction) for the null hypothesis that the forecasts are equally accurate. See text for details.

on the BC forecasts. Similarly, for $h > 0$, the RMSEs for the two forecasts are generally very close to each other and neither the GB nor BC forecasts are ever significantly more accurate. Only for the current quarter, $h = 0$ —the “nowcast”—does the Fed appear to be significantly more accurate than Blue Chip, at least for real GDP growth and CPI inflation. Results in the Appendix using different timing assumptions lead to similar conclusions: When BC forecasts are given a timing advantage, GB nowcasts lose their advantage (see Table A.5), while when GB forecasts are given a timing advantage, then the GB advantage in nowcasting increases, and the GB forecasts for the unemployment rate are significantly more informative than BC forecasts, but not for real GDP growth or CPI inflation (see Table A.6).

Overall, the results suggest that the Fed does not have a systematic advantage in forecasting macro variables beyond the current quarter. Although Romer and Romer (2000) documented a systematic advantage of the Fed over private-sector forecasters, their sample covered only 12 years, from 1980–1991. We use 22 more years of data. Sims (2002) also reports that the Fed predicts future inflation more accurately than the Survey of Professional Forecasters, but his sample is only slightly longer than that of the Romers. More recent evidence suggests that the Fed’s forecasting advantage has eroded over time (Gamber and Smith, 2009; Paul, 2019), consistent with our results. Finally, our results on the Fed’s accuracy in nowcasting is consistent with Faust and Wright (2009), who document the accuracy of GB nowcasts for inflation and GDP growth in a comparison with various model-based methods.

Our finding that the GB and BC forecasts have very similar accuracy casts doubt on one of the main motivations for the “Fed information effect”: that the Fed’s forecasts are much better than the private sector’s.

7 Implications for Measuring Monetary Policy Shocks

In this section, we use a simple model to discuss the broader implications of our findings for the measurement of monetary policy shocks using high-frequency data and the use of those high-frequency shocks for empirical analysis of the effects of monetary policy.

For example, our results do not necessarily imply that interest rate futures markets are inefficient. Instead, we would argue that the FOMC’s monetary policy reaction function was

unknown and underestimated by the futures markets at the time, perhaps because the FOMC has become more responsive to output over time (e.g., Volker responded less to output than did Greenspan, who responded less than Bernanke, who responded less than Yellen). Thus, we view the futures market's expectation as being *ex ante* rational but *ex post* underestimating how responsive the FOMC would be to news about the economy.

This also implies that high-frequency federal funds futures surprises are still good measures of monetary policy shocks. A surprise innovation in the FOMC's monetary policy response to output, ϕ_y , is isomorphic in its effects to a series of innovations in ε (deviations from the monetary policy rule). If output is below potential, then a positive innovation in ϕ_y is isomorphic to a series of easing surprises in ε (until output recovers). The point of this section is to illustrate this in a simple model.

[To be written]

8 Conclusions

[To be written]

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A Appendix

Table A.1: “Fed Information Effect” Regression Results (White standard errors)

Blue Chip forecast	(1) Campbell et al.		(2) Nakamura-Steinsson
	fed funds rate “target factor”	fwd. guidance “path factor”	first princip. comp. of futures rates
(A) Replication sample: 1/1990–6/2007 for Campbell et al., 1/1995–3/2014 for NS			
unemployment rate	−0.10 (.085)	−0.22** (.104)	−0.17 (.267)
real GDP growth	0.23 (.189)	0.31* (.167)	0.92*** (.323)
CPI inflation	0.18 (.115)	0.06 (.194)	0.06 (.253)
(B) Full sample: 1/1990–6/2019, including unscheduled announcements			
unemployment rate	−0.17 (.119)	−0.21* (.103)	−0.39** (.196)
real GDP growth	0.25 (.242)	0.34** (.169)	0.34 (.257)
CPI inflation	0.19 (.164)	0.38* (.230)	0.29** (.143)
(C) Full sample: 1/1990–6/2019, excluding unscheduled announcements			
unemployment rate	0.04 (.221)	−0.29*** (.109)	−0.30 (.313)
real GDP growth	0.11 (.417)	0.59*** (.184)	0.56 (.356)
CPI inflation	0.17 (.353)	0.46* (.250)	0.27 (.198)
(D) Full sample: 1/1990–6/2019, excl. unscheduled announcements and 7/2008–6/2009			
unemployment rate	−0.03 (.152)	−0.20** (.091)	−0.25 (.176)
real GDP growth	0.23 (.237)	0.38*** (.147)	0.65*** (.218)
CPI inflation	0.13 (.165)	0.16 (.168)	0.20 (.184)

Same as Table 1, except that asymptotic heteroskedasticity-consistent (White) standard errors are reported rather than bootstrapped standard errors. See notes to Table 1 for details.

Table A.2: “Fed Information Effect” Regression Results (1994-2019)

Blue Chip forecast	(1) Campbell et al.		(2) Nakamura-Steinsson
	fed funds rate “target factor”	fwd. guidance “path factor”	first princip. comp. of futures rates
(A) Replication sample: 2/1994–6/2007 for Campbell et al., 1/1995–3/2014 for NS			
unemployment rate	0.06 (.111)	−0.25** (.124)	−0.17 (.288)
real GDP growth	0.12 (.196)	0.52** (.225)	0.92** (.368)
CPI inflation	0.02 (.151)	0.14 (.170)	0.06 (.253)
(B) Full sample: 2/1994–6/2019, including unscheduled announcements			
unemployment rate	−0.07 (.133)	−0.24 (.150)	−0.30 (.240)
real GDP growth	0.17 (.227)	0.51** (.258)	0.58 (.351)
CPI inflation	0.07 (.170)	0.47** (.195)	0.23 (.246)
(C) Full sample: 2/1994–6/2019, excluding unscheduled announcements			
unemployment rate	0.09 (.187)	−0.31** (.150)	−0.27 (.269)
real GDP growth	0.02 (.304)	0.67*** (.244)	0.60 (.369)
CPI inflation	0.11 (.248)	0.49** (.200)	0.27 (.307)
(D) Full sample: 2/1994–6/2019, excl. unscheduled announcements and 7/2008–6/2009			
unemployment rate	0.03 (.158)	−0.22* (.128)	−0.22 (.213)
real GDP growth	0.14 (.248)	0.46** (.201)	0.71*** (.267)
CPI inflation	0.05 (.217)	0.19 (.171)	0.21 (.193)

Same as Table 1 except that samples begin in February 1994 rather than January 1990. Bootstrapped standard errors in parentheses. See notes to Table 1 for details.

Table A.3: Top 10 Influential Observations in Nakamura-Steinsson GDP Forecast Regression (Additional Statistics)

Date	Change coeff.	Change t -stat.	Policy surprise	BC GDP	BC unempl.	BC infl.	S&P 500	Macro indic.
9/2007	0.059	0.554	-0.138	-0.200	0.067	-0.133	1.331	-0.285
1/2008	0.123	0.351	-0.076	-0.300	0.233	0.033	0.756	-0.814
6/2003	0.050	0.312	0.099	0.133	0.100	-0.100	-0.272	-0.381
3/2001	0.101	0.291	-0.059	-0.300	0.067	-0.033	-0.680	-1.448
4/2008	0.096	0.278	-0.055	-0.300	0.033	0.067	0.311	-1.518
11/1999	0.063	0.240	0.068	0.167	-0.067	0.067	-0.418	0.864
1/2004	0.028	0.224	0.088	0.100	-0.100	-0.100	-0.968	0.376
5/1999	0.048	0.224	0.073	0.133	-0.067	0.067	-1.436	0.194
12/1995	0.069	0.207	-0.036	-0.300	0.000	-0.033	0.264	-0.081
3/1997	0.040	0.155	0.051	0.133	-0.067	-0.033	-0.666	0.801

Ten most influential observations in Nakamura-Steinsson regression, measured by the change in the t -statistic due to inclusion of the observation (“Change t -stat.”). Also shown is the resulting change in the regression coefficient (“Change coeff.”), the measured policy surprise, the changes in the Blue Chip consensus forecasts of real GDP, the unemployment rate, CPI inflation, the intraday response of the S&P 500 stock market index to the policy surprise, and a macro indicator that summarizes the current state of the business cycle. The macro indicator is the “Big Data” index of U.S. economic activity of [Brave et al. \(2019\)](#), and it is lagged by one month to account for data availability at the time of the monetary policy surprise.

Table A.4: Economic News Drives Out the “Fed Information Effect” (excluding Brave et al. index from news)

	(1) Campbell et al.		(2) Nakamura-Steinsson
Blue Chip forecast	fed funds rate “target factor”	fwd. guidance “path factor”	first princip. comp. “MP surprise”
(A) Replication sample: 1/1990–6/2007 for Campbell et al., 1/1995–3/2014 for NS			
Unemployment rate	0.046 (.090)	−0.09 (.114)	0.24 (.260)
Real GDP growth	0.13 (.168)	0.08 (.214)	0.49 (.301)
(B) Full sample: 1/1990–6/2019, including unscheduled announcements			
Unemployment rate	0.10 (.092)	−0.03 (.112)	0.16 (.167)
Real GDP growth	−0.06 (.153)	0.01 (.185)	−0.14 (.226)
(C) Full sample: 1/1990–6/2019, excluding unscheduled announcements			
Unemployment rate	0.28** (.136)	−0.03 (.118)	0.28 (.202)
Real GDP growth	−0.21 (.211)	0.03 (.183)	−0.15 (.250)
(D) Full sample: 1/1990–6/2019, excl. unscheduled announcements and 7/2008–6/2009			
Unemployment rate	0.099 (.131)	−0.091 (.112)	0.02 (.182)
Real GDP growth	0.06 (.185)	0.08 (.158)	0.30 (.206)

Same as Table 8 except that the variable $news_t$ excludes the Brave et al. (2019) index. See notes to Table 8 for details.

Table A.5: Accuracy of Greenbook and Blue Chip forecasts: Blue Chip always lagged

Horizon (quarters)	Encompassing regressions				RMSEs		
	GB	BC	R^2	equal?	GB	BC	equal?
<i>Real GDP growth</i>							
0	0.20 (0.333)	0.85** (0.408)	0.39	0.369	2.50	2.44	0.405
1	-0.04 (0.397)	0.95** (0.475)	0.16	0.235	2.81	2.69	0.174
2	0.37 (0.517)	-0.04 (0.845)	0.02	0.749	2.99	2.93	0.736
3	0.30 (0.551)	-0.26 (0.879)	0.01	0.667	3.00	2.96	0.871
0-3 avg.	0.24 (0.555)	0.65 (0.752)	0.23	0.743	1.88	1.80	0.512
<i>CPI inflation</i>							
0	0.77*** (0.159)	0.11 (0.152)	0.77	0.030	1.43	1.54	0.478
1	0.31 (0.302)	0.42 (0.422)	0.41	0.872	2.23	2.03	0.038
2	0.00 (0.321)	0.81* (0.456)	0.37	0.292	2.10	2.00	0.140
3	0.64 (0.389)	0.12 (0.504)	0.34	0.555	2.06	2.09	0.719
0-3 avg.	0.60* (0.336)	0.18 (0.353)	0.70	0.535	1.25	1.19	0.520
<i>Unemployment rate</i>							
0	0.26 (0.169)	0.73*** (0.172)	0.98	0.166	0.25	0.23	0.097
1	0.15 (0.338)	0.84** (0.345)	0.94	0.318	0.44	0.42	0.235
2	0.30 (0.469)	0.68 (0.467)	0.87	0.685	0.63	0.61	0.535
3	0.53 (0.559)	0.41 (0.548)	0.77	0.915	0.81	0.80	0.919
0-3 avg.	0.30 (0.462)	0.67 (0.459)	0.91	0.688	0.50	0.48	0.490

Same as Table 9, except that BC forecasts are always lagged by one month. See notes to Table 9 for details.

Table A.6: Accuracy of Greenbook and Blue Chip forecasts: Blue Chip never lagged

Horizon (quarters)	Encompassing regressions				RMSEs		
	GB	BC	R^2	equal?	GB	BC	equal?
<i>Real GDP growth</i>							
0	1.23*** (0.158)	-0.33 (0.221)	0.55	0.000	2.10	2.35	0.004
1	0.33 (0.387)	0.62 (0.466)	0.19	0.715	2.82	2.75	0.578
2	0.63 (0.430)	-0.19 (0.795)	0.07	0.479	2.88	2.89	0.941
3	0.21 (0.471)	-0.10 (0.805)	0.01	0.783	3.00	2.91	0.694
0-3 avg.	0.50 (0.387)	0.41 (0.550)	0.29	0.918	1.77	1.74	0.792
<i>CPI inflation</i>							
0	1.01*** (0.134)	-0.13 (0.136)	0.89	0.000	0.95	1.30	0.022
1	0.77*** (0.254)	-0.11 (0.298)	0.51	0.107	1.97	1.95	0.897
2	0.01 (0.306)	0.78** (0.395)	0.36	0.264	2.18	2.03	0.070
3	0.35 (0.445)	0.40 (0.588)	0.33	0.958	2.08	2.07	0.926
0-3 avg.	0.70*** (0.210)	0.06 (0.268)	0.74	0.171	1.16	1.12	0.617
<i>Unemployment rate</i>							
0	0.82*** (0.105)	0.16 (0.105)	0.99	0.002	0.17	0.21	0.002
1	1.07*** (0.158)	-0.11 (0.162)	0.96	0.000	0.35	0.41	0.005
2	1.02*** (0.212)	-0.07 (0.207)	0.90	0.009	0.55	0.60	0.153
3	1.06*** (0.291)	-0.14 (0.277)	0.81	0.034	0.73	0.80	0.266
0-3 avg.	1.09*** (0.175)	-0.14 (0.173)	0.94	0.000	0.42	0.47	0.064

Same as Table 9, except that BC forecasts are never lagged by one month. See notes to Table 9 for details.