UNIVERSITY OF CALIFORNIA SAN DIEGO

Essays on Monetary Policy and Asset Prices

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy

in

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by

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The Dissertation of Linyan Zhu is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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Chapter 1, 2 and 3, in part, are currently being prepared for submission for publication of the material. The dissertation author was the primary researcher and author of this material.

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ABSTRACT OF THE DISSERTATION

Essays on Monetary Policy and Asset Prices

by

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Professor James Hamilton, Chair

This dissertation consists of three essays on monetary policy and asset prices.

The first chapter proposes a novel methodology to disentangle in real-time the signaling effect of a Fed announcement from exogenous monetary shocks. The method relies on the different ways monetary news and non-monetary news change the short end of the yield curve at high frequency, with the latter informed by market responses to macroeconomic data releases. The estimated revelation of Fed information is strongly correlated with the difference between market forecasts and the Fed's own forecasts. The policy shock is found to have a bigger effect on the economy than suggested using an instrument without adjustment for the signaling effect.

The second chapter studies the structural forces driving the financial market responses

to data releases and Fed announcements. I estimate a coherent, realistic framework that prices Treasury bonds based on macroeconomic fundamentals. The framework explicitly recognizes agents' information frictions in regard to contemporaneous aggregate outcomes, successfully matches the market responses to macroeconomic events and sheds light on the nature of news learned by investors at various events.

The third chapter proposes a state-space approach to decomposing a stock's idiosyncratic volatility into a common component and an idiosyncratic one. The measure of the common idiosyncratic volatility is persistent at the daily frequency. It accounts for idiosyncratic volatilities in sample better than GARCH(1,1) and a principal component approach. It also forecasts the future levels of idiosyncratic volatilities better than GARCH(1,1) in the medium- to long-run. I assess its pricing implication in the cross section of stock returns.

Chapter 1

Let the Market Speak: Using Interest Rates to Identify the Fed Information Effect

1.1 Introduction

Quantifying the causal effects of monetary policy is a challenging task in empirical macroeconomics because in setting interest rates a central bank responds endogenously to other conditions in the economy. To identify exogenous monetary shocks, recent studies have favored a high-frequency event-study approach (Kuttner, 2001; Gürkaynak et al., 2005a; Piazzesi and Swanson, 2008; Wright, 2012; Gertler and Karadi, 2015; Hanson and Stein, 2015; Swanson, 2021). The idea is to look at how one or more interest rates change within a narrow window around a Federal Open Market Committee (FOMC) announcement. Under the assumption that only monetary information gets incorporated into asset prices within the window, the rate changes serve as direct measures of policy shocks.

However, rate changes can also signal a central bank's opinion on economic developments (Melosi, 2017). Earlier findings by Campbell et al. (2012) and Nakamura and Steinsson (2018) provide suggestive evidence for this channel by looking at how private economic forecasts as measured by Blue Chip respond to an announcement. If the FOMC announcement results in lower interest rates than the market had forecast, corresponding to an easing of monetary policy, one would expect private forecasts of variables like GDP and inflation to increase. In fact, forecasts of these variables decline, consistent with the interpretation that the FOMC announcement revealed to private forecasters information the Fed had of weaker economic fundamentals. These studies and the subsequent literature refer to the revelation of the Fed information on the state of the economy through FOMC announcements as "the Fed information effect".

The Fed information effect confounds the estimation of monetary policy effects. Figure 1.1 relates the high-frequency rate changes to *actual* economic outcomes. Each red bar plots a 30-minute change in one of five commonly-used interest rates around an FOMC announcement, averaged across the announcements one quarter following which an NBER recession occurred. The blue bars plot the averages across the rest of the announcements. Clearly, the Fed tended to surprise the market with large rate cuts when the economy was going into a recession.[1] This suggests that the Fed may have foreseen an upcoming recession better than the market. In this case, if one were to treat these rate changes directly as policy shocks, the estimates of monetary policy effects would be biased toward zero.

This paper proposes a novel approach to controlling for the Fed information effect when identifying monetary shocks at high frequency. Using only interest rate data, the approach isolates the contribution of the revelation of Fed information to rate responses from that of a policy shock in real-time. The key intuition is to think of an FOMC announcement as a sum of a macroeconomic data release and a pure monetary announcement, and use responses of a cross section of interest rates to the data release to pin down the Fed information component.

The approach postulates that two common, orthogonal shocks drive the responses of interest rates with various maturities s to an announcement. One is an economic news shock that captures the market learning of Fed's information on economic fundamentals from the

[1] One may notice that for each asset the *unconditional* mean of the rate change is also negative. Instead of looking for the driving forces behind the secular decline in interest rates, this paper focuses on the potential revelation of Fed information on business cycles. Even when the unconditional mean is subtracted from the whole sample, surprising rate cuts before recessions are still evident as shown in Figure A.1 in the Appendix.

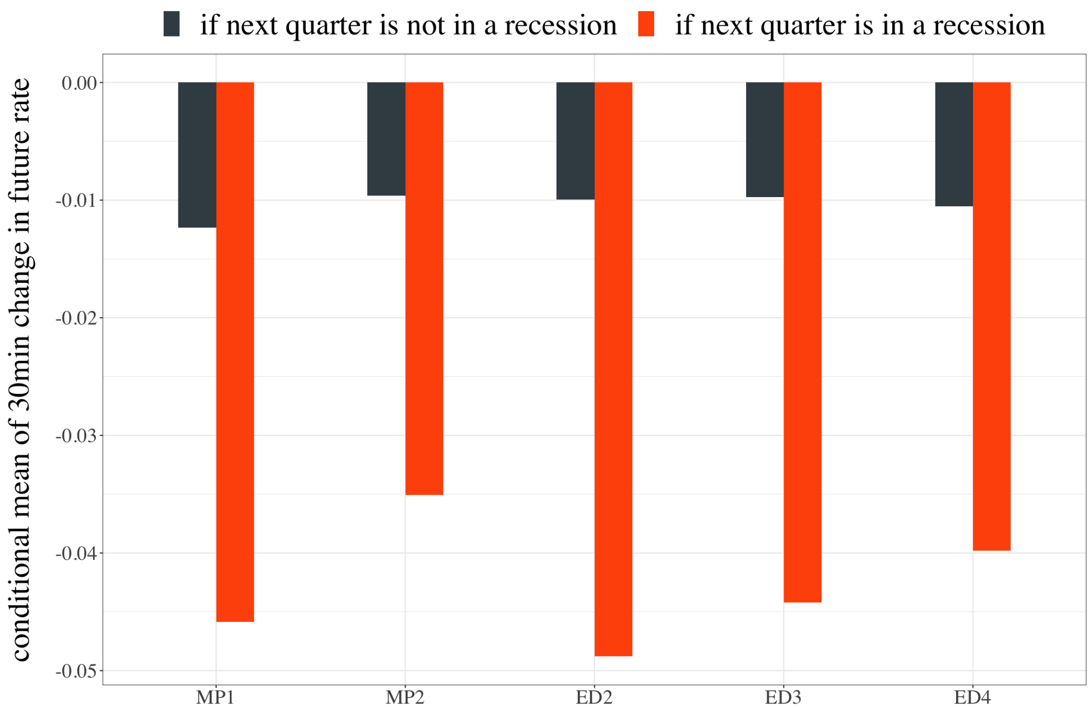

Figure 1.1. Easing policy consistently surprised interest rate futures market before recession

Notes: Listed on the x-axis are five assets reflecting market expectations of interest rates for various horizons. Y-axis plots the average change in the rate of each asset during a 30-minute window around an FOMC announcement across two samples. MP1 and MP2: federal funds future contracts to be settled at the end of the current month and the third month after the FOMC announcement. ED2, ED3 and ED4: Eurodollar future contracts to be settled at the end of the second, third and fourth quarter. Sample from February 1990 to March 2019.

announcement. I hereafter refer to this as an "information shock". The other is an exogenous monetary shock, capturing the Fed's deviation from its policy rule.

For identification, the approach relies on key assumptions that: (1) the two shocks elicit different responses of short-term interest rates over a 30-minute window around an FOMC announcement; (2) the *relative* magnitude of the responses across maturities to an information shock is the same as that to economic news caused by macroeconomic data releases; (3) the two shocks are orthogonal to each other over a sample of FOMC announcement windows. The method identifies the *market-perceived* information effect and the *market-perceived* monetary shock with publicly available data.

I apply the method to the FOMC announcements from 1991 to 2019. I find that communications on the assessment of economic prospects play a nontrivial role in driving high-frequency interest rate movements. My decomposition can directly account for the revision in Blue Chip forecasts following an FOMC announcement. I find that the positive revision of private forecasts of output and inflation to a contractionary announcement can be explained entirely by my measure of the information component of the FOMC announcement.

I provide further corroborating evidence by comparing Blue Chip forecasts with those prepared by Fed staff as reported in the Greenbook. I find that the information component is biggest when Greenbook forecasts differ the most from Blue Chip forecasts, and that Blue Chip forecasts get revised in the direction that would be implied if the Fed had simply announced the Greenbook forecast itself. This evidence is consistent with approaches to eliminating the information component with forecast data suggested by Romer and Romer (2000), Zhang (2019), Miranda-Agrippino and Ricco (2020) and Bachmann et al. (2021).

My approach has several desirable features relative to the ones that rely on forecast data. First, for scheduled announcements for which Fed forecasts were prepared, the measure proposed here can be constructed in real-time from publicly available data, whereas researchers have to wait five years for release of the Fed forecasts.

Second, the approach works for unscheduled FOMC announcements for which no Fed forecasts were prepared. The Fed information effect is likely to be substantial precisely for those events, because when the Fed found it urgent and necessary enough to hold an unscheduled meeting, it was likely to review aspects of economic and financial developments that the market had yet to know. Indeed, Lakdawala (2019b) provide suggestive evidence for the special role of unscheduled meetings in studying the Fed information effect. Hence, we would not want to leave unscheduled meetings out of such discussions.

Third, the approach can capture the information gap between the Fed and the private sector at any instant as it takes advantage of the efficiency in asset prices, whereas the forecast data are not directly comparable due to their timing inconsistency. Blue Chip solicits private forecasts at the beginning of every month whereas Fed staff make forecasts right before every FOMC announcement which could take place at any date during a month. If an announcement is made towards the end of a month, private forecasters may have already updated their economic outlook by the time of the announcement given various news arriving in the month. What appears to be a Fed information advantage in the forecast data may well be an advantage that the Fed had in timing.

Another interesting approach taken by researchers to identifying the Fed information effect is to impose sign restrictions on financial data. Jarociński and Karadi (2020) and Cieslak and Schrimpf (2019) exploit the opposing signs of the effect of monetary news versus non-monetary news on interest rates and stock prices. Along the same lines but focusing on forward guidance policy, Andrade and Ferroni (2021) impose sign restrictions on future interest rates and breakeven inflation rates. These methods are appealing in that they impose limited restrictions on a model and also achieve identification in real-time. Nonetheless, having limited restrictions is also a liability in that they do not yield point estimates; in fact, a range of estimates would be consistent with sign restrictions, and the confidence ranges typically reported by researchers significantly understate the range of possible answers that are consistent with the data (Moon and Schorfheide, 2012; Baumeister and Hamilton, 2015; Baumeister and Hamilton, 2020; Baumeister and Hamilton, 2022; Watson, 2019; Giacomini and Kitagawa, 2021). By contrast, the shocks in this paper are point identified and the analysis based on them can be interpreted in a classical way. Different from Bu et al. (2020) which also impose fully identifying assumptions on financial data, this paper brings other macro events into the picture and makes use of the valuable information in their impact on short-term interest rates.

Using the newly-constructed monetary shocks, I evaluate the effect of monetary policy on output, inflation and risk premium in a vector autoregression (Christiano et al., 1996; Faust et al., 2004; Cochrane and Piazzesi, 2002; Boivin et al., 2010; Barakchian and Crowe, 2013; Gertler and Karadi, 2015; Amir-Ahmadi and Uhlig, 2015). When the Fed surprisingly lowers the interest rate because it views the economy as becoming weaker than the market projects, traditional monetary surprises can introduce positive omitted variable biases to the estimate of the effect of monetary policy; if any, the economic downturn is the reason for, not a consequence of, policy easing. Likely for this reason, the VAR literature often finds the effect of monetary policy on price levels or output growth with puzzling signs when the high-frequency identification approach is used. I show in this paper that, once the Fed information effect is removed, a tightening of monetary policy clearly dampens the economy, leading to a significant drop of output growth and price level. Not only are the signs consistent with standard monetary models but the magnitudes of the effects are also larger than what one would obtain with direct high-frequency measures. For the sample from 1991m7 to 2019m3, a monetary shock that raises the three-month-ahead fed funds futures rate by 1% leads the industrial production to drop on impact and eventually decreases by as much as 4.0% in 10 months. It causes CPI to adjust quickly and shift down by nearly 1.5% in the long run. The pronounced effect on output and the quick adjustment of the price level are consistent with the findings of Miranda-Agrippino and Ricco (2020). The VAR exercise here points to the time-varying risk premium in the financial sector as the potential transmission channel of monetary policy (Jarociński and Karadi, 2020).

To justify the identification method, I compare the monetary shocks proposed here with several alternative proposals in the literature. A monetary shock that corresponds to a policy easing should have the following characteristics: (1) it has no forecasting ability to predict current and future recessions, and (2) it does not lead Blue Chip forecasters to revise down their economic outlook or inflation expectations following the FOMC announcement. In these regards, the shocks proposed here perform better than the other proposals that take no account of the Fed information effect. They are also comparable to estimates by other researchers that deal with the information effect.

This paper contributes to a growing literature that discusses asymmetric information between central banks and the public on the state of the economy and its relevation by policy announcements. Romer and Romer (2000) show that the Fed possesses private information on future inflation and signals it to the public via FOMC announcements, which explains why long-term Treasury yields respond to surprise changes in federal funds futures around an announcement. Hamilton (2018) discusses the relevance of information asymmetry for evaluating the efficacy of Quantitative Easing programs in narrow windows around FOMC announcements. Lakdawala (2019a) provides evidence for information asymmetry in a structural vector autogression. Bauer and Swanson (2020) question the econometric specifications of Campbell et al. (2012) and Nakamura and Steinsson (2018) and interpret their evidence as the Fed's and the market's common responses to public news. The analysis here points out the key role of stale news in reconciling these two views and provides suggestive evidence that the Fed interpreted stale news differently from the private sector.

A closely related paper is Nunes, Ozdagli, and Tang (2022).[2] They also propose using the response to macroeconomic news releases to identify the macro news component of FOMC announcements. They estimate this response using a structural VAR that summarizes interest rates using the one-year Treasury yield and an excess bond premium. By contrast, my method uses the observed market response of the entire short end of the yield curve without requiring the assumptions behind a VAR — my approach is to "let the market speak". My methodology also allows for a different variance of the macro news component of every FOMC statement, with this variance inferred directly from the observed market response on that day. Furthermore, the

[2] I learned of their research three months after my paper had been publicly circulated.

identifying assumptions here allow the news component in an FOMC announcement to have a different realization from that of a data release in the same month. My analysis also develops additional corroboration of the estimates using direct analysis of Greenbook and Blue Chip forecasts, which their paper does not. However, they reach the same substantive conclusion that I do that correcting for the information effect leads to significantly larger effects estimated for monetary policy. The fact that they reach a similar conclusion using a very different method lends additional corroboration to the results presented here.

Last but not least, the paper contributes to the macroeconomic event study literature by presenting another reason why different types of macroeconomic events should be analyzed within a single framework. A few papers have recently advocated modeling them together to compare or justify the relative magnitude of asset price responses across events, including Bauer (2015b), Gilbert et al. (2015), Ehrmann and Sondermann (2012) and Lapp and Pearce (2012). Importantly, Gürkaynak et al. (2018) find that news across various data releases, whether observed or unobserved, elicit the same hump-shaped response from the yield curve. This paper confirms the findings of Gürkaynak et al. (2018) for the short end of the yield curve. I show it is useful to consider FOMC announcements together with macroeconomic data releases for the purpose of identifying the Fed information effect.

1.2 Methodology

This section presents the identification framework to disentangling a monetary shock from the Fed information effect given a set of interest rate changes around an FOMC announcement. The approach achieves identification by connecting the market response to FOMC announcements with that to macro data releases. In Section 1.2.1, I describe short-term interest rate changes around major macro data releases. I show that one latent factor is sufficient to capture the market response to news across various releases. I embed this insight into modeling the interest rate responses to FOMC announcements in Section 1.2.2, and use it to motivate the identifying assumptions in Section 1.2.3.

Throughout the analysis, I will focus on the short end of the yield curve. Specifically, I consider the three-month-ahead federal funds future contract, the two-, three-, and four-quarter-ahead Eurodollar future contracts and the two-year Treasury bond.[3]

To demonstrate the key idea of my approach, I use a sample from 1990m1 to 2008m12 in this section and the next. Later on in Section 1.4, I extend the sample to 2019m3 and show robustness of the approach.

1.2.1 Interest rates around macroeconomic data releases

I begin the analysis by studying the factor structure of interest rate responses to macro data releases.

Let t denote a day and $\tilde{y}_t$ be an $N \times 1$ vector of daily changes in the set of interest rates from the end of Day $t-1$ to the end of Day t. Building on the framework of Gürkaynak et al. (2018), I estimate the response of interest rates to a macroeconomic data release with a factor model:

$$\tilde{y}_t = \tilde{d}_t \quad \tilde{\gamma}\tilde{\xi}_t + \tilde{u}_t. \tag{1.1}$$

Here $\tilde{d}_t$ is a dummy variable taking a value of 1 if there is at least one major data releases (to be defined below) on Day t and 0 otherwise.[4] A latent factor, $\tilde{\xi}_t \sim \text{iid}\ (0,1)$, captures the news content of the release. The response of interest rates of various maturities is described by an $N \times 1$ loading vector, $\tilde{\gamma}$. In addition to the release, some background noise unobservable to econometricians could also change the yield curve on a release day, just as they do on a

[3]It is conventional in the literature to consider the short end of the yield curve, especially these particular assets, for identifying monetary shocks. See Gürkaynak et al. (2005a), Nakamura and Steinsson (2018), Kuttner (2001) for example. I omit the current-month federal funds future contract because its rate was insensitive to shocks during the zero lower bound period. Following Gürkaynak et al. (2005a) and Swanson (2021), I also skip some contracts with maturities in between the listed ones to avoid overlapping information.

[4]An FOMC announcement could take place on a day with data releases. To isolate the effect of data releases, I omit all the days with FOMC announcements in the analysis of Section 1.2.1.

no-release day. I summarize them in an $N \times 1$ vector, $\tilde{u}_t \sim \text{iid}\ (0, \Sigma_{\tilde{u}})$. I assume the covariance matrix of $\tilde{u}_t$ to be identical across the two types of days and allow it to be non-diagonal.

I define a data release to be a major one if it has historically increased the short-end yield curve volatility significantly. For each type of release listed in the first column of Table 1.1, I conduct a bootstrap test developed by Wright (2012) and a Box's M-test to determine significance. The null hypothesis is that the covariance matrix of daily rate changes on that specific type of release days are identical to that on no-release days. Whenever I reject the null at the 10% level, I consider the release to be a major one. By focusing on the overall rate changes instead of the rate responses to a particular variable contained in the release, I am able to capture all the news content in a release. Gürkaynak et al. (2018) establish the importance of doing so for identifying non-headline news. For a sample from 1990m1 to 2008m12, I report the p-value of the test for each release in the second and third columns of Table 1.1. Clearly, all the data releases listed here pass the significance test and will be included for the identification of market response to macro news.

In general, one may use more than one latent factor to capture the market response to these major data releases in Equation (1.1). However, I find that one factor is sufficient to do so in my sample. To see this, I conduct another bootstrap test of Wright (2012). Grouping all the release days together regardless of the release type, I test the null hypothesis that the difference between release days and non-release days can be summarized with a one-dimensional vector against the alternative that the information on release days is multidimensional. In particular, I test whether the difference between the covariance matrices on release days and non-release days can be restricted as $\Sigma_1 - \Sigma_0 = \tilde{\gamma}\tilde{\gamma}'$ for $\tilde{\gamma}$ a one-dimensional vector. Table 1.2 shows that one cannot reject the null hypothesis that they are statistically identical at the 5% level. That is, one factor is sufficient to capture the variations in the changes of short-term interest rates around different types of releases.[5] This implies that the bond market consistently perceived and cared

[5]Relatedly, Gürkaynak et al. (2018) find that different types of macroeconomic data releases have similar relative effects at different points on the entire yield curve and that one factor is sufficient to capture those effects. The analysis here confirms their findings specifically for interest rates on the short end.

about only one dimension of economic news as reflected in these short-term interest rates.

As further evidence in support of this specification, Figure 1.2 graphs the responses of interest rates to different data releases. For each type of data release, the figure plots the estimated eigenvector associated with the first principal component of the covariance matrix of $\tilde{y}_t$. Strikingly, no matter which economic indicator got released, the short end of the yield curve turned out to always respond with a hump shape, with the maximum effect on the rate of the Eurodollar future contract maturing in four quarters. In the next two sections, I will bring this insight into modeling the interest rate responses to FOMC announcements.

Table 1.1. List of major macroeconomic data releases

Type of release	P-value from Wright (2012) $\times 10^{-2}$	P-value from Box's M-test $\times 10^{-2}$	Included
CPI / Core CPI	0.02	0.00	Yes
Nonfarm PayrollsI	0.00	0.00	Yes
Employment Cost Index	0.02	0.11	Yes
GDP Advance	0.02	0.00	Yes
ISM Manufacturing	0.38	0.00	Yes
Industrial Production	0.56	0.00	Yes
Initial Jobless Claims	0.10	0.00	Yes
PPI / Core PPI	0.38	0.00	Yes
Retail Sales Advance	0.28	0.00	Yes

Notes: The first column lists the types of data releases that I start with. The second column shows the bootstrapped p-value from the Wright (2012) test H_0: $\Sigma_k = \Sigma_0$, where Σ_k is the variance-covariance matrix of daily rate changes on a day with a data release of Type k and Σ_0 on a day with no releases. The third column displays the p-value from the Box's M-test for the same null hypothesis. The last column shows that a type of release is included in the analysis if I reject the null at the 10% level for both tests.

1.2.2 Interest rates around FOMC announcements

This section models the responses of the same set of interest rates as above to an FOMC announcement. As a key innovation to the high-frequency identification approach, I treat an

Table 1.2. Wright (2012)'s test for the number of news shocks

	Sample period	Dimension of $\tilde{\xi}_t$ ($N_{\tilde{\xi}}$)	p-value
pre-ZLB	1991m7 - 2008m12	1	0.079

Notes: The null hypothesis is $\Sigma_1 - \Sigma_0 = \tilde{\gamma}\tilde{\gamma}'$, where $\tilde{\gamma}$ is an $N \times N_{\tilde{\xi}}$ matrix, Σ_1 is the covariance matrix of daily interest rate changes on the days with a major data release (defined in Table 1.1 with a "Yes"), and Σ_0 is the sample covariance matrix on the days with no major data release.

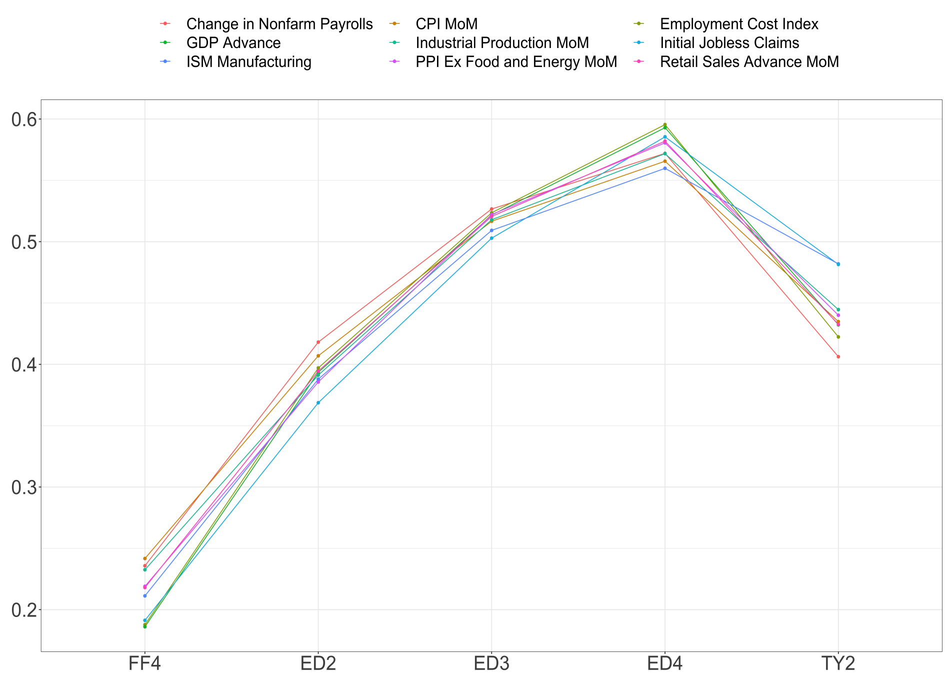

Figure 1.2. Similarity of normalized interest rate responses to major data releases

Notes: For each type of major data release, the line plots the eigenvector associated with the first principal component of the sample covariance matrix of $\tilde{y}_t$. Sample: 1991m7 - 2008m12.

FOMC announcement as the sum of a macro data release and a purely monetary announcement.

Let y_t ($N \times 1$) collect changes in the market-based interest rates during a thirty-minute window around the time of an FOMC announcement on Day t. Again, I use a factor model to summarize the various reasons why the interest rates would move in this window:

$$y_t = \underbrace{\gamma\xi_t}_{\text{Fed information}} + \underbrace{\beta\eta_t}_{\text{monetary}} + \underbrace{u_t}_{\text{idiosyncratic}} + \theta_0 \tag{1.2}$$

where $\xi_t \sim \text{iid}\ (0, \Sigma_\xi)$ is a Fed information shock, $\eta_t \sim \text{iid}\ (0,1)$ is an exogenous monetary shock, and $u_t \sim \text{iid}\ (0, \Sigma_u)$ is an $N \times 1$ vector of white noises with a diagonal covariance matrix, capturing the idiosyncratic movement of an individual interest rate.

Fed information shock, ξ_t

The first latent factor captures the first reason why the market might be surprised by an FOMC announcement: the market learned something new about the state of the economy from the announcement. Because the Fed sets interest rates partly by reacting to changes in output growth and inflation, any private information held by the Fed that indicates a worsening economy would lead to an announcement cutting the interest rate relative to what the market expected. A non-zero ξ_t corresponds to the relevation of such information to the market.

Monetary shock, η_t

The second latent factor accounts for the changes of interest rates due to the Fed announcing an unexpected course of policy commitments. Because the factor summarizes the information in interest rates of a range of maturities, it captures the Fed's commitment to changing the federal funds rate not only in the near term but also at longer horizons.[6] This is important because changes in the near-term federal funds rate have largely been anticipated by the market since the onset of the Great Financial Crisis and Fed has increasingly used forward guidance as a policy tool (Gürkaynak et al., 2005a; Nakamura and Steinsson, 2018; Swanson, 2021; Zhang, 2019).

[6]Thus, it corresponds to the term, Odyssean forward guidance, in Campbell et al. (2012).

1.2.3 Identifying assumptions

My main assumption is that the revelation of Fed information about economic fundamentals, ξ_t, has similar effects on the cross section of short-term interest rates as the information $\tilde{\xi}_t$ associated with macro data releases described in the previous section. Since the information about economic fundamentals in a typical macro data release can be described by a scalar $\tilde{\xi}_t$, I assume that the information about economic fundamentals that is revealed by an FOMC announcement can also be described by a scalar, ξ_t.

Assumption 1: $\gamma = \tilde{\gamma}$, with Σ_ξ free.

Assumption 1 formalizes the partial resemblance of FOMC announcements to data releases. Note that the size and the sign of ξ_t is estimated to be different for every day t. The amount of information about economic fundamentals revealed by a typical FOMC announcement might be considerably greater or smaller than that for a typical data release, which would show up as having a different sample variance on monetary announcement days compared to news announcements. Hence, by allowing Σ_ξ to be different from 1 which is the normalized variance of news content in data releases, Assumption 1 only requires that interest rates of different maturities respond in the same proportions to any news about the state of the economy.

This also flexibly accommodates the different lengths of event windows for FOMC announcements versus macro data releases. In this paper, I use a 30-minute window to compute the changes in interest rates around an FOMC announcement and a daily window for data releases (hence the tilde in $\tilde{y}_t$). Although the choice of windows is mainly dictated by data availability, it should not raise concern about the validity of the strategy. On the one hand, daily changes seem to capture the market response to data releases better than intraday changes. Altavilla et al. (2015) find that macro data releases have a persistent effect on nominal bond yields. Bauer (2015a) also argues for a slightly delayed response of the TIPS market to such events that can be missed by intraday windows. On the other hand, the yield curve tends to respond to a FOMC announcement fairly quickly within the 20 minutes after the event (Gürkaynak et al., 2005a).

Using a daily window instead would introduce too much noise into the identification of their impact (Nakamura and Steinsson, 2018).

One concern that researchers may have about Assumption 1 is what if the market would want to learn certain aspects of fundamentals only from FOMC announcements. In Section 1.3, I provide corroborating evidence to show that this is not the case.

To fully identify the model, I rule out the possibility that the monetary shock changes the short-term interest rate responses relative to each other in the same way as the Fed information shock does, i.e.

Assumption 2: There exists no constant c such that $c\beta = \gamma$.

Finally, I impose the orthogonality condition in sample below. Even though Assumption 3 is not essential for the identification of the model, it is imposed here to give monetary shock the usual interpretation that it is the deviate from the Fed's policy rule. It also helps with the interpretations of results in the next section.

Assumption 3: $\xi_t \perp \eta_t$ in FOMC announcement windows.

With all the identifying restrictions above, I impose normality for the shocks and frame the model as a constrained maximization problem of a likelihood function. Details of the estimation procedure are outlined in Appendix B. In the next section, I validate these identifying restrictions by testing two predictions of the model with the estimated η_t and ξ_t.

1.3 Corroborating evidence

This section validates the structural interpretations of the identified shocks. I do so by relating them to two sets of forecasts data, one by the Fed and the other by the private sector. Section 1.3.1 shows that when the information shock is identified to have raised interest rates during an announcement, the Fed did on average anticipate a stronger economy going forward than the private sector. Section 1.3.2 shows that the identified shocks explain the changes in the private sector's economic forecasts following an FOMC announcement.

1.3.1 Differences in forecasts between the Fed and the private sector

If the information component captures the Fed information effect, one would expect it to be disproportionately positive when the Fed is more optimistic about the economy than the private sector at the time. To test this prediction, I use two sets of forecast data below.

The first data set is called the Greenbook. Before every FOMC meeting the research staff of the Federal Reserve Board of Governors makes projections for key macroeconomic variables for up to nine quarters into the future. The Greenbook contains these projections and serves as an important input for policy decisions in the upcoming FOMC meeting. A number of researchers have used them to study the Fed information effect (Campbell et al., 2012; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2020; Zhang, 2019).

The second data set is the Blue Chip Economic Indicators. It is widely used in the literature to characterize the private sector's view of the state of the economy at a monthly frequency. During the first two to three business days of every month [7], Blue Chip solicits projections for key macroeconomic variables from about fifty professional forecasters. Following Campbell et al. (2012) and Nakamura and Steinsson (2018), I use the mean forecast of a given variable in a given horizon at the beginning of the month to capture the market expectation for it before an FOMC announcement. Figure 1.3 sketches the timeline of the two sets of data around a typical FOMC announcement.

Conveniently, six variables are commonly predicted by the Greenbook and the Blue Chip. For each of them and for each horizon, I look at the difference between their projections and regress the information shock on that difference:[8]

$$\xi_{t(m)} = \phi_0^h + \phi_\xi^h \left(EI_{GB,t(m)}^h - EI_{BC,m}^h \right) + e_{t(m)}^h \tag{1.3}$$

[7]According to Bauer and Swanson (2020), the Blue Chip Economic Indicators forecast survey was carried out during the first three business days of every month prior to 2000m12 and the first two business days after 2000m12. The forecast data is published on the 10th of each month.

[8]For regressions involving Greenbook data in this section, I include only those FOMC meetings for which a Greenbook was prepared.

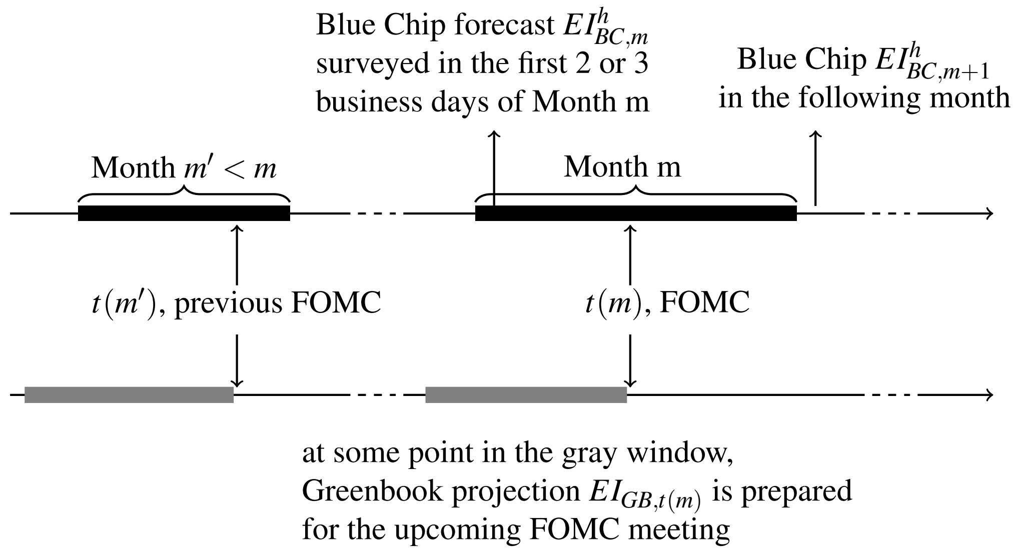

Figure 1.3. Timeline of actions around an FOMC announcement

where $t(m)$ indexes the day of FOMC announcement in Month m; $EI^h_{GB,t(m)}$ is the Greenbook forecast of h-quarter-ahead EI (economic indicator) prepared for that announcement; $EI^h_{BC,m}$ is the Blue Chip mean forecast of the same variable at the beginning of Month m; ξ_t is my estimated information shock, normalized to raise the three-month-ahead federal funds future rate by 1% on average during announcement windows from 1991m7 to 2008m12.[9]

Table 1.3 shows the OLS estimate, ϕ^h_ξ, from Equation (1.3), using one variable for one horizon at a time. Column (1)-(3) present the results for pro-cyclical, real economic indicators, including real GDP, real personal consumption expenditures and industrial production. A positive forecast difference on the right-hand side suggests that the Fed expects a stronger economy than the market prior to an FOMC announcement. In that case, one would expect ξ_t to be positive, reflecting the market's learning of the more optimistic view on the economy. The consistently positive coefficients in Column (1)-(3) confirm this prediction. To highlight a few significant

[9]The forecast horizon h is computed relative to the date of the announcement. A Greenbook is typically dated in the same month with the upcoming announcement. However, when an announcement took place at the beginning of a month, the corresponding Greenbook was typically ready late in the previous month.

correlations at the 5% level, an increase in interest rates due to ξ_t is strongly associated with the Fed projecting a higher growth rate of real GDP for two quarters into the future and a higher growth rate of industrial production for the current quarter than professional forecasters.

By contrast, one would expect $\phi_{\xi}^{h} < 0$ for a counter-cyclical variable, such as the unemployment rate. This is because if the revelation of information raised interest rates we would expect the Fed to have predicted a lower unemployment rate than the private sector, as reflected by a negative forecast difference in Equation (1.3). Column (4) shows that it is indeed the case for all horizons even though none of the coefficients is significantly different from zero.

Finally, Column (5) and (6) show the estimated ϕ_{ξ}^{h} for two price variables, GDP Price Index and CPI. At the 5% significance level, the coefficient on CPI for the current quarter and that on GDP Price Index in six quarters are significantly positive at the 5% level, again consistent with what one would expect for a pro-cyclical indicator.

The exercise above confirms the prediction that the information component tends to be positive when the Fed is more optimistic about the state of the economy than the market. It suggests that ξ_t does capture some Fed information that the market does not know. However, does it capture all that information? I check this by replacing the dependent variable in Equation (1.3) with the monetary shock $\eta_{t(m)}$. If the monetary shock no longer predicts the forecast differences in the same way as ξ_t does, the answer is yes. Table 1.4 shows that most of the predictive coefficients for the monetary shock are insignificant at the 10% level. A contractionary monetary shock is correlated with the Fed predicting a significantly lower GDP Price Index in six quarter, lower real personal consumption expenditures in one quarter and a slightly higher unemployment rate in six quarter than Blue Chip forecasters. It could be the case that the staff of the Fed were able to factor in the contractionary effect of the monetary shock on the macroeconomy because they were better informed of the shock itself than the private sector. It could also be the case that significance arises as false positive cases due to the size of the tests. In either case, the additional evidence on η_t leads me to conclude that ξ_t is able to capture all the Fed information effect in interest rate surprises.

1.3.2 Revisions of private sector forecasts

This section tests for the second prediction: if the market responds to an FOMC announcement as if ξ_t is the revealed Fed information, one would expect the private sector to disproportionally revise up their economic outlook following an announcement with a positive ξ_t. The opposite holds for the identified monetary shock, η_t.

Similarly to the previous section, I use the Blue Chip forecasts to measure the private sector's belief about the state of the economy. For an announcement in Month m, a one-month change in the mean forecast from the beginning of Month m to Month $m+1$ indicates the revision of private sector's expectation following that announcement. Table 1.5 lists the expected direction of change in these expectations to the two types of shocks.

Before looking at the identified shocks, let's first look at how Blue Chip forecasters respond to an FOMC announcement overall. I summarize the information in an announcement with the first principal component of y_t, normalized to increase $FF4$ by one percent. I then regress the Blue Chip forecast revisions on that information:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_t \tag{1.4}$$

where $\Delta EI^h_{BC,m+1}$ is the change in Blue Chip mean forecast of EI in h quarters from Month m to $m+1$.

Table 1.3. Predictability of GB-BC forecast differences for Fed information shock ξ_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	**1.79*****	0.63	**0.53****	-0.24	**1.33****	-0.23
	(0.56)	(0.53)	(0.22)	(5.71)	(0.53)	(0.73)
1	**2.17****	**1.25****	**0.53***	-0.19	0.59	-1.46
	(0.95)	(0.53)	(0.30)	(0.39)	(0.67)	(1.27)
2	**1.39****	0.49	0.18	-2.32	-0.78	-1.22
	(0.69)	(0.40)	(0.29)	(2.14)	(1.15)	(1.65)
3	0.95	0.76	0.18	-2.05	-0.06	-1.65
	(0.79)	(0.58)	(0.47)	(1.65)	(1.36)	(1.33)
4	**1.41***	1.59**	0.49	-2.11	1.00	-0.10
	(0.84)	(0.80)	(0.48)	(1.55)	(1.48)	(0.91)
5	1.30	**2.18****	0.49	-2.41	0.23	-0.42
	(0.99)	(0.97)	(0.65)	(1.66)	(1.79)	(1.11)
6	1.29	2.10	0.91	-2.62	-0.89	**0.38*****
	(1.56)	(1.83)	(1.00)	(2.29)	(2.21)	(0.08)
7	1.84	**3.95***	-0.43	-3.33	-1.76	-2.16
	(2.15)	(2.01)	(2.13)	(2.70)	(2.42)	(2.00)

Each cell of the table reports the estimated ϕ_ξ^h from regression $\xi_{t(m)} = \phi_0^h + \phi_\xi^h(EI^h_{GB,t(m)} - EI^h_{BC,m}) + e^h_{t(m)}$, where $EI^h_{GB,t(m)}$ is the Greenbook forecast for EI in h quarters prepared by the Fed staff for the FOMC meeting on Day t of Month m, $EI^h_{BC,m}$ is the Blue Chip forecast for the same variable at the beginning of Month m. Sample is from 1991m7 to 2008m12. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.4. Predictability of GB-BC forecast differences for monetary shock η_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	-0.33	0.03	-0.10	-1.48	-0.21	0.13
	(0.37)	(0.23)	(0.10)	(2.14)	(0.23)	(0.30)
1	-0.42	**-0.69****	0.07	-0.11	-0.07	0.31
	(0.54)	(0.31)	(0.14)	(0.15)	(0.28)	(0.65)
2	-0.29	-0.15	-0.20	-0.08	0.21	1.45
	(0.48)	(0.33)	(0.20)	(1.29)	(0.57)	(1.00)
3	-0.34	-0.49	0.03	0.36	1.11	0.97
	(0.56)	(0.36)	(0.19)	(1.04)	(0.90)	(0.83)
4	-0.28	-0.37	0.30	0.27	0.48	0.07
	(0.57)	(0.59)	(0.24)	(0.92)	(0.89)	(0.53)
5	0.61	0.26	0.42	1.11	0.05	-0.24
	(0.49)	(0.54)	(0.27)	(0.81)	(1.05)	(0.51)
6	0.52	0.02	-0.03	**1.47***	0.37	**-0.24*****
	(0.64)	(0.83)	(0.32)	(0.87)	(1.26)	(0.03)
7	-0.20	-0.82	-0.60	1.59	1.65	1.47
	(1.11)	(1.18)	(1.04)	(1.63)	(1.63)	(0.87)

Each cell of the table reports the estimated ϕ_η^h from regression $\eta_{t(m)} = \phi_0^h + \phi_\eta^h(EI^h_{GB,t(m)} - EI^h_{BC,m}) + e^h_{t(m)}$, where $EI^h_{GB,t(m)}$ is the Greenbook forecast for Variable EI in h quarters prepared by the Fed staff for the FOMC meeting on Day t of Month m, $EI^h_{BC,m}$ is the Blue Chip forecast for the same variable at the beginning of Month m. Sample is from 1991m7 to 2008m12. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.5. Expected directions of private sector forecast revisions in response to shocks in FOMC announcements

Economic indicator	information shock $\xi_t > 0$	monetary shock $\eta_t > 0$
Pro-cyclical variables		
Industrial production	$\uparrow$	$\downarrow$
Real GDP	$\uparrow$	$\downarrow$
GDP Price Index	$\uparrow$	$\downarrow$
CPI	$\uparrow$	$\downarrow$
PPI	$\uparrow$	$\downarrow$
Counter-cyclical variable		
Unemployment rate	$\downarrow$	$\uparrow$

Table 1.6. Blue Chip regressions - real variables

(a) Industrial Production				(b) Real GDP				(c) Unemp. Rate			
h	PC	ξ	η	h	PC	ξ_t	η_t	h	PC	ξ_t	η_t
0	**2.62***	**3.04****	0.74	0	0.66	0.79	0.63	0	**-0.17***	**-0.20***	-0.24
	(1.42)	(1.51)	(2.44)		(0.64)	(0.70)	(1.31)		(0.09)	(0.10)	(0.22)
1	**1.34****	**1.51****	0.88	1	**0.75****	**0.90****	0.48	1	0.00	-0.06	0.05
	(0.64)	(0.68)	(1.56)		(0.37)	(0.39)	(0.98)		(0.25)	(0.25)	(0.34)
2	0.37	0.47	-0.28	2	0.10	0.19	-0.50	2	**-0.34***	**-0.38****	-0.40
	(0.34)	(0.37)	(0.85)		(0.26)	(0.27)	(0.52)		(0.18)	(0.18)	(0.42)
3	0.28	0.40	-0.69	3	0.11	0.15	-0.35	3	-0.30	**-0.37***	-0.11
	(0.33)	(0.36)	(0.56)		(0.22)	(0.24)	(0.32)		(0.19)	(0.19)	(0.45)
4	0.13	0.25	**-1.10***	4	0.21	0.25	0.23	4	-0.06	-0.12	0.41
	(0.23)	(0.23)	(0.58)		(0.16)	(0.18)	(0.42)		(0.19)	(0.19)	(0.75)
5	0.30	0.35	-0.60	5	0.18	0.21	-0.42	5	-0.24	-0.27	-0.21
	(0.24)	(0.24)	(0.50)		(0.15)	(0.15)	(0.41)		(0.15)	(0.17)	(0.52)

i. Columns labeled "PC" present estimated α_{PC}^h from regression: $EI_{t(m)}^h = \alpha_0^h + \alpha_{PC}^h PC_{t(m)} + e_{t(m)}^h$ while the other columns present estimated α_{ξ}^h and α_{η}^h from regression: $EI_{t(m)}^h = \alpha_0^h + \alpha_s^h \xi_{t(m)} + \alpha_m^h \eta_{t(m)} + e_{t(m)}^h$.

ii. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

iii. Sample is from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Table 1.7. Blue Chip regressions - price variables

(a)	CPI			(b)	PPI			(c)	GDP Price	Index	
h	PC	ξ_t	η_t	h	PC	ξ_t	η_t	h	PC	ξ_t	η_t
0	1.20	**1.60***	-1.13	0	**2.83***	**3.44****	-0.38	0	0.13	0.15	0.15
	(0.87)	(0.96)	(1.59)		(1.48)	(1.67)	(2.67)		(0.30)	(0.34)	(0.38)
1	0.00	-0.11	0.37	1	0.43	0.59	-1.03	1	0.14	0.15	0.13
	(0.57)	(0.74)	(1.74)		(0.37)	(0.43)	(0.85)		(0.17)	(0.18)	(0.26)
2	0.04	0.04	**0.35***	2	-0.05	-0.04	-0.33	2	0.00	0.01	-0.02
	(0.12)	(0.13)	(0.20)		(0.21)	(0.24)	(0.40)		(0.16)	(0.19)	(0.24)
3	0.12	0.11	0.13	3	0.19	0.21	-0.41	3	0.09	0.13	-0.28
	(0.12)	(0.14)	(0.22)		(0.25)	(0.28)	(0.28)		(0.14)	(0.16)	(0.27)
4	0.09	0.11	0.03	4	0.05	0.09	-0.24	4	-0.05	-0.06	-0.19
	(0.12)	(0.14)	(0.25)		(0.20)	(0.22)	(0.59)		(0.14)	(0.16)	(0.30)
5	0.14	0.18	0.08	5	0.14	0.18	**-0.97****	5	2.34	2.94	-8.31
	(0.21)	(0.23)	(0.38)		(0.22)	(0.19)	(0.43)		(2.32)	(2.85)	(8.48)

i. Columns labeled “PC” present estimated α^h_{PC} from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_{t(m)}$ while the other columns present estimated α^h_ξ and α^h_η from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_s \xi_{t(m)} + \alpha^h_m \eta_{t(m)} + e^h_{t(m)}$.

ii. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

iii. Sample is from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

The columns labeled "PC" in Table A.3 and A.4 present the estimated α^h_{PC} for a sample from 1990m7 to 2008m12. Table A.3 focuses on real variables, and Table A.4 on price variables. Column "PC" in Panel (a)-(c) of Table A.3 shows that, following a tightening of surprise changes, professional forecasters tend to predict a stronger economy than they previously had for two quarter into the future. On average, they significantly increased the mean forecast of industrial production for the contemporaneous quarter by 2.6% and for the following quarter by 1.3%. The upward revision declined greatly for longer horizons. Expectations of real GDP display a similar pattern. A better economic outlook can also be witnessed from the significant decreases in projected unemployment rates in the current and the second quarter. According to Table A.4, Blue Chip forecasters also significantly raised their projections of current PPI by 2.8% on average.

These results confirm the concerns raised by Campbell et al. (2012) and Nakamura and Steinsson (2018) about using the high-frequency approach directly to measure monetary shocks. An exogenous policy tightening is supposed to dampen the economy and reduce inflation from a theory's perspective. To understand why we find the opposite, I replace the regressor in Equation (1.4) by the Fed information shock and the monetary shock identified from my approach:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + e^h_t \tag{1.5}$$

The rest of the columns in A.3 and A.4 report the estimated α^h_ξ and α^h_η. Looking at the columns labeled "ξ_t", I find that the information shock plays a dominant role in driving the updates of Blue Chip forecasts. The estimated α^h_ξ's are generally larger than α^h_{PC}'s in absolute value, have signs largely consistent with Table 1.5 and share similar dynamics across horizons with α^h_{PC}'s. To highlight a few significant responses at the 5% level, a positive information shock that raises $FF4$ by one percent is associated with an upward forecast revision of (1) industrial production in the current and the next quarter by 3.0% and 1.5%, respectively; (2) real GDP in the next quarter by 0.9%; and (3) current PPI by 3.4%. On the other hand, they lowered their expected unemployment rate for the third quarter by 0.4%. These variables and horizons, along with those of 10% significance, largely match the ones for which Greenbook projections significantly differ from Blue Chip's in Section 1.3.1. These results suggest that our information shock successfully captures the market's learning of new information about economic fundamentals from FOMC announcements.

Again, does it capture all that information? Once the information shock is accounted for, our proposed measure of the monetary shock is associated with insignificant changes in Blue Chip forecasts for most indicators and horizons, as the columns labeled "η_t" show. There are a few exceptions. Expectations for industrial production in four quarters got adjusted downward significantly by 1.1% at the 10% level and PPI in five quarters by almost 1.0% at the 5% level. The signs of the effects are consistent with our predictions in Table 1.5. The coefficient associated with CPI in two quarters looks puzzling but should not be much of a concern given the consistent performance of our shocks for the other variables. It can result from the size of the test by construction.

Combining the analysis above with that of Section 1.3, one would find the argument for the Fed information effect complete: (1) market participants did expect a stronger economy than they would otherwise have after an announcement surprises them with a tightening of interest rates; (2) the surprise tightening is a result of the Fed foreseeing a stronger growth of economy or a higher inflation than the private sector; and (3) ξ_t captures precisely that information gap.

1.3.3 Reconciliation with Bauer and Swanson (2020)

This section investigates how the previous results relate to the "Fed response to news" channel recently proposed by Bauer and Swanson (2020). First, I explain this channel by replicating the key results in Bauer and Swanson (2020). Then, I examine whether taking their evidence into account changes my results.

Bauer and Swanson (2020) challenge specifications like Equation (1.4) which have been used as supporting evidence for the Fed information effect in previous studies. Campbell et al.

(2012), as a leading example in this literature, study the response of private sector's expectations to FOMC announcement in a set-up similar to Equation (1.4). Specifically, they estimate the following regression over a sample from 1990m2 to 2007m12:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_{Target}\text{Target}_m + \alpha^h_{Path}\text{Path}_m + e^h_m \tag{1.6}$$

where m indexes a month when an FOMC announcement was made; Target_m and Path_m are two dimensions of monetary policy that are constructed with daily data based on the method of Gürkaynak et al. (2005a). Nakamura and Steinsson (2018) as another example estimate the following equation over a sample from 1995m1 to 2014m3.

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_P\text{Policy}_m + e^h_m \tag{1.7}$$

where Policy_m is their proposed monetary shock. Both studies find the signs of their coefficients puzzling, just as shown in the previous section.[10]

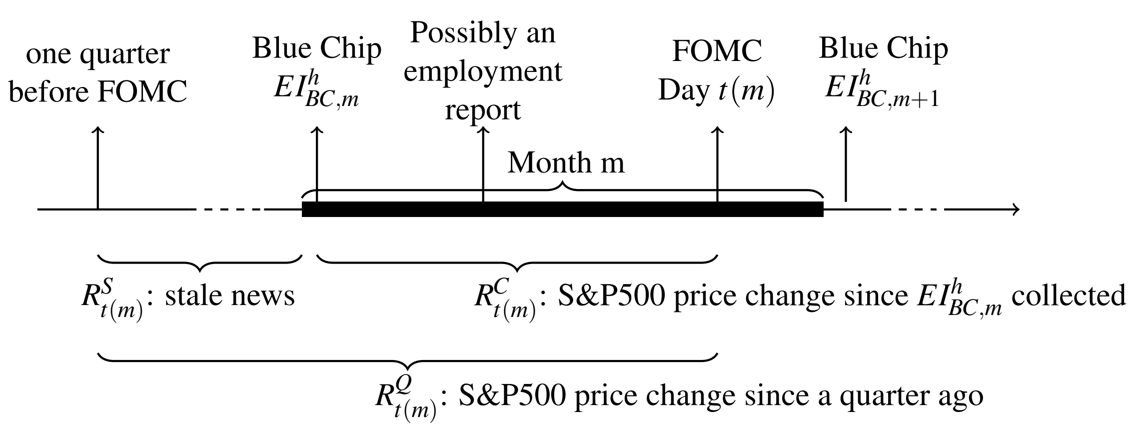

Figure 1.4. Timeline of actions around an FOMC announcement, with control variables

[10] I replicate their results in the highlighted cells of Table A.2. For completeness, I extend their analyses to a full range of relevant economic indicators and horizons reported by the Blue Chip survey. For consistency with Bauer and Swanson (2020), I show results of the regressions run at the meeting frequency. Running the regressions at the monthly frequency makes negligible difference.

Figure 1.4 illustrates Bauer and Swanson (2020)'s concern about these specifications. If an unsatisfactory employment report got released between an FOMC announcement and the Blue Chip survey at the beginning of the month, it may have led the Fed to lower interest rate further than publicly expected and simultaneously caused Blue Chip forecasters to revise down their economic outlook. That is, what these researchers claim to be the Fed information effect could simply be a result of an omitted variable bias in Equation (1.6) and (1.7).

In order to take this concern into account, I re-estimate the Blue Chip forecast response to shocks by controlling for public news that may arrive between the Month-*m* Blue Chip survey and the targeted FOMC announcement. Two proxies for such public news arise naturally. One is the unexpected change in non-farm payrolls released in Month m for Month $m-1$, which I denote with NFP_m. The other is the change in the S&P500 index, accumulated from the last day of the Month-*m* Blue Chip survey to one day before the FOMC announcement. I denote it with $R^C_{t(m)}$ where C standards for contemporaneous news.

To carefully examine what variable(s) can cause the omitted variable bias, I add these proxies as control variables to Equation (1.5) step by step, yielding:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^h_c Control_{t(m)} + e^h_t \tag{1.8}$$

where $Control_{t(m)}$ is one of the following sets of control variables:

C1: NFP_m

C2: NFP_m and $R^C_{t(m)}$

Panel C1 and C2 of Table A.5 and A.6 show the estimated α^h_ξ and α^h_η from Equation (1.8). Not only do the effects of an information shock on Blue Chip forecasts remain, they become even stronger. The variables with significance become even more consistent with the ones for which the Greenbook differs the most from the Blue Chip in the previous section, especially in Panel C2 when both control variables are used.

In fact, Bauer and Swanson (2020) propose a larger set of control variables. They also include: (1) the change in the S&P500 index over the entire quarter prior to an FOMC announcement (denoted by $R^{Q}_{t(m)}$ in Figure 1.4); (2) a news index constructed by Brave et al. (2019). Such a set captures not only contemporaneous news but also stale news arriving to the financial market in previous months. I re-estimate Equation (1.8) with these additional control variables and show the results in Panel C3 and C4. Clearly, as soon as stale news is controlled for, the signs of estimated α^{h}_{ξ}'s reverse for real variables.

The sign reversion suggests that the identified information shock is positively correlated with stale news and not with contemporaneous news. This correlation stems from the behavior of the five interest rates from which the information shock is constructed. To see this, I take the S&P500 returns earned only over *previous* months as a measure of stale news and label it with $R^{S}_{t(m)}$ where S stands for stale. I regress each of the five interest rates on NFP_m and public news arriving during a particular window:

$$y_{t(m)} = \phi^{i}_{0} + \phi^{i}_{R} R^{i}_{t(m)} + \phi^{i}_{NFP} NFP_m + u^{i}_{t(m)} \qquad i = S, C, Q \tag{1.9}$$

Table 1.10 reports the estimated coefficients ϕ^{i}_{R}. As the first two rows show, stale news as measured by $R^{S}_{t(m)}$ dominates the positive correlations between those interest rates and the quarterly stock return. Holding NFP_m constant, a 1% decline in the stock price in previous months driven by bad news strongly predicts that the market would be surprised at a rate cut during the contemporaneous announcement and adjust down their expected interest rates in various horizons by between 0.24% and 0.38%. The finding is consistent with the "Fed put" pattern documented in Cieslak and Vissing-Jorgensen (2020) where they conduct a text analysis of FOMC documents and show that the Fed has reacted to negative intermeeting stock returns with an accommodative policy since the mid-1990s. By contrast, the third row shows that contemporaneous news as measured by $R^{C}_{t(m)}$ has no significant effect on these interest rates.

Stale news is relevant for the high-frequency responses of bond markets to FOMC announcements for two possible reasons. First, the Fed may read more into the stale news as to what the news means for the economy than the private sector. That is, given the same decline in the stock market, the Fed may form a more pessimistic view of the economy than the private sector. Second, given that the Fed and the private sector interpret the stale news in the same way, the Fed may react more aggressively than publicly believed. To the extent that the Blue Chip survey at the beginning of a month has already captured the private sector's reading of any stale news and to the extent that the Blue Chip forecasts responded to the information shock with the expected signs, I find the first explanation more plausible. In fact, one can check this by regressing the difference in projections by the Fed and by the Blue Chip on the stale news:

$$EI^h_{GB,t(m)} - EI^h_{BC,m} = \alpha^h_0 + \alpha^h_R R^S_{t(m)} + \alpha^h_{NFP} NFP_m + e^h_{t(m)} \tag{1.10}$$

Table 1.11 reports the estimated α^h_R from Equation (1.10). It shows that the Greenbook did tend to project a worse economy than the private sector following stock market declines. Since large rate cuts indeed tend to precede a recession, as Figure 1.1 showed earlier, I view Table 1.10 and 1.11 as suggestive evidence that the Fed was better at figuring out what stale news meant for the economy than the private sector. This way of interpreting the Fed information is also shared by the theoretical model in Miranda-Agrippino and Ricco (2020) and reconciles Bauer and Swanson (2020) with the literature arguing for the existence of a Fed information effect.

To conclude this section, I show the success of my approach by showing the behavior of ξ_t and η_t in the spirit of Figure 1.1. I take the three-month-ahead federal funds future contract as a target of decomposition. Figure 1.5 plots the mean of the information component ($\hat{\gamma}_j\hat{\xi}_t$) and the monetary component ($\hat{\beta}_j\hat{\eta}_t$) over a sample of FOMC announcements that preceded a recession by one quarter. The information shock nicely captures the Fed's superior knowledge of a worsening economy while the monetary component displays no correlation with business cycles. In Section 1.5, I will provide a formal test of cyclicality when I compare η_t with alternative monetary instruments in the literature.

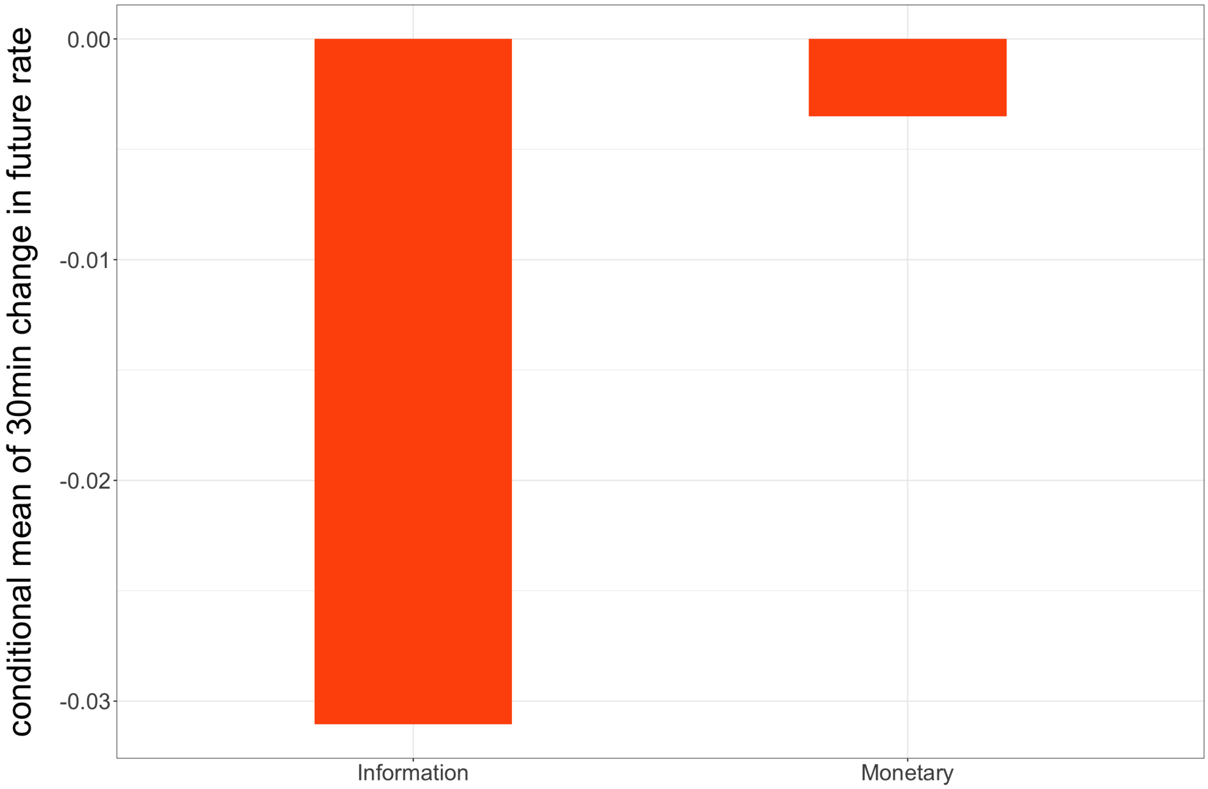

Figure 1.5. Decomposition of interest rates into identified shocks before recessions

Notes: The figure shows a decomposition of the three-month-ahead federal funds futures rate into the information shock and the monetary shock. For $j = FF4$, the left bar plots the sample mean of $\hat{\gamma}_j\hat{\xi}_t$ from $y_{j,t} = \hat{\theta}_{j,0} + \hat{\gamma}_j\hat{\xi}_t + \hat{\beta}_j\hat{\eta}_t + \hat{u}_{j,t}$, taken across FOMC announcement windows that preceded a recession by one quarter, and the right bar plots that of $\hat{\beta}_j\hat{\eta}_t$.

1.4 Composite shock measures from 1991m7 to 2019m3

This section extends the series of Fed information shocks and monetary shocks to 2019m3. Due to the zero lower bound (ZLB), parameters in my model changed at the end of 2008. In order to deal with such structural breaks, I re-estimate the model separately for the ZLB period from 2009m1 to 2016m12 and for the post-ZLB period from 2017m1 to 2019m3. Combining the estimated series from each subsample together yields two composite measures, one of the Fed information shock and the other of the monetary shock, both for all the FOMC statements

Table 1.8. Robustness to the Fed response to economic news channel - real variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
Industrial Production	0	**2.80***	-0.13	**3.22****	-0.61	0.78	-0.37	0.16	0.09
		(1.51)	(2.64)	(1.32)	(2.13)	(1.62)	(2.36)	(1.47)	(2.17)
	1	**1.43****	0.62	**1.72*****	0.30	-0.30	0.42	-0.59	0.63
		(0.67)	(1.61)	(0.59)	(1.19)	(0.75)	(1.19)	(0.70)	(1.08)
	2	0.44	-0.38	0.62	-0.57	**-0.78***	-0.52	**-0.90****	-0.43
		(0.37)	(0.87)	(0.42)	(0.71)	(0.43)	(0.60)	(0.44)	(0.57)
	3	0.41	-0.66	0.51	-0.78	-0.41	-0.76	-0.46	-0.73
		(0.36)	(0.59)	(0.40)	(0.55)	(0.35)	(0.48)	(0.37)	(0.48)
	4	0.26	-0.98	0.30	-1.04	-0.11	**-0.94***	-0.11	**-0.94***
		(0.23)	(0.63)	(0.24)	(0.63)	(0.23)	(0.54)	(0.23)	(0.55)
	5	0.36	-0.54	0.37	-0.58	0.30	-0.57	0.30	-0.57
		(0.25)	(0.54)	(0.25)	(0.52)	(0.28)	(0.53)	(0.28)	(0.53)
Real GDP	0	0.56	-0.13	0.78	-0.52	**-1.07***	-0.46	**-1.26****	-0.20
		(0.65)	(1.42)	(0.59)	(1.02)	(0.64)	(1.09)	(0.59)	(1.00)
	1	**0.82****	0.23	**0.99*****	-0.08	-0.48	-0.03	-0.64*	0.19
		(0.39)	(1.03)	(0.37)	(0.76)	(0.43)	(0.73)	(0.38)	(0.60)
	2	0.17	-0.57	0.27	-0.74	**-0.60***	-0.73	**-0.70****	-0.59
		(0.28)	(0.54)	(0.32)	(0.54)	(0.32)	(0.49)	(0.30)	(0.42)
	3	0.13	-0.41	0.19	**-0.51***	-0.28	**-0.49***	-0.31	**-0.44***
		(0.24)	(0.31)	(0.26)	(0.30)	(0.25)	(0.25)	(0.25)	(0.24)
	4	0.26	0.33	**0.31***	0.24	-0.03	0.34	-0.02	0.36
		(0.18)	(0.44)	(0.17)	(0.38)	(0.21)	(0.40)	(0.17)	(0.38)
	5	0.22	-0.38	0.23	-0.42	**0.23***	-0.37	0.23	-0.38
		(0.15)	(0.44)	(0.16)	(0.42)	(0.13)	(0.43)	(0.14)	(0.43)
Unemployment Rate	0	**-0.19***	-0.20	**-0.22****	-0.16	0.06	-0.17	0.10	-0.20
		(0.10)	(0.23)	(0.09)	(0.20)	(0.12)	(0.20)	(0.12)	(0.17)
	1	-0.03	0.13	-0.07	0.18	0.22	0.16	0.25	0.14
		(0.23)	(0.35)	(0.23)	(0.31)	(0.25)	(0.32)	(0.23)	(0.31)
	2	**-0.34***	-0.28	**-0.42*****	-0.19	0.06	-0.23	0.15	-0.29
		(0.18)	(0.44)	(0.16)	(0.35)	(0.22)	(0.37)	(0.21)	(0.33)
	3	**-0.33***	0.03	**-0.41****	0.12	0.17	0.09	0.27	0.01
		(0.19)	(0.48)	(0.18)	(0.41)	(0.25)	(0.38)	(0.22)	(0.31)
	4	-0.11	0.56	-0.20	0.73	**0.44***	0.51	**0.43****	0.49
		(0.19)	(0.78)	(0.19)	(0.61)	(0.26)	(0.56)	(0.21)	(0.45)
	5	-0.24	-0.08	**-0.29***	0.12	-0.02	0.00	0.04	0.05
		(0.18)	(0.55)	(0.16)	(0.44)	(0.18)	(0.44)	(0.17)	(0.43)
Control:		C1		C2		C3		C4	
NFP		✓		✓		✓		✓	
R^C				✓					
R^Q						✓		✓	
$NewsIndex$								✓	

Estimated α^h_ξ and α^h_η from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^h_C Control_{t(m)} + e^h_{t(m)}$. Definitions of variables in $Control_{t(m)}$ are plotted in Figure 1.4.Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Sample is from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Table 1.9. Robustness to the Fed response to economic news Channel - price variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
CPI	0	**1.50***	-1.48	**1.72****	-1.73	0.23	-1.64	-0.01	-1.46
		(0.90)	(1.67)	(0.86)	(1.51)	(0.90)	(1.57)	(0.85)	(1.60)
	1	0.03	0.83	-0.41	1.33	2.08	1.07	2.42	0.82
		(0.72)	(1.86)	(0.87)	(1.89)	(1.32)	(1.82)	(1.47)	(1.78)
	2	0.04	**0.36***	0.04	0.35	0.02	**0.35***	0.02	0.35
		(0.13)	(0.21)	(0.13)	(0.21)	(0.15)	(0.21)	(0.15)	(0.21)
	3	0.13	0.18	0.13	0.18	0.11	0.18	0.08	0.20
		(0.14)	(0.24)	(0.14)	(0.24)	(0.16)	(0.24)	(0.16)	(0.22)
	4	0.12	0.07	0.11	0.08	0.13	0.07	0.13	0.07
		(0.13)	(0.26)	(0.14)	(0.26)	(0.15)	(0.26)	(0.15)	(0.26)
	5	0.17	0.03	0.19	-0.04	0.14	0.02	0.13	0.02
		(0.24)	(0.39)	(0.22)	(0.40)	(0.26)	(0.40)	(0.26)	(0.39)
PPI	0	**3.30****	-0.85	**3.74****	-1.34	0.95	-1.13	0.54	-0.83
		(1.62)	(2.80)	(1.60)	(2.73)	(1.83)	(2.72)	(1.79)	(2.81)
	1	0.58	-1.07	**0.78***	-1.30	-0.39	-1.18	-0.58	-1.04
		(0.43)	(0.89)	(0.44)	(0.83)	(0.68)	(0.90)	(0.69)	(0.82)
	2	-0.01	-0.24	0.06	-0.32	-0.23	-0.27	-0.29	-0.22
		(0.24)	(0.41)	(0.26)	(0.40)	(0.28)	(0.43)	(0.28)	(0.42)
	3	0.28	-0.20	0.28	-0.20	**0.45****	-0.18	**0.45****	-0.18
		(0.26)	(0.30)	(0.26)	(0.30)	(0.22)	(0.29)	(0.22)	(0.29)
	4	0.11	-0.05	0.09	-0.01	0.34	-0.07	0.34	-0.07
		(0.21)	(0.57)	(0.23)	(0.62)	(0.23)	(0.59)	(0.24)	(0.60)
	5	0.20	**-0.91****	0.19	-0.87*	0.18	**-0.91****	0.15	**-0.94****
		(0.19)	(0.42)	(0.20)	(0.44)	(0.20)	(0.41)	(0.19)	(0.41)
GDP Price Index	0	0.14	0.12	0.18	0.07	-0.06	0.09	-0.10	0.12
		(0.33)	(0.40)	(0.33)	(0.39)	(0.31)	(0.41)	(0.31)	(0.40)
	1	0.14	0.12	0.16	0.10	0.07	0.11	0.03	0.14
		(0.18)	(0.28)	(0.17)	(0.27)	(0.21)	(0.29)	(0.21)	(0.27)
	2	0.01	-0.04	0.02	-0.06	0.05	-0.04	0.04	-0.03
		(0.19)	(0.25)	(0.19)	(0.25)	(0.21)	(0.24)	(0.21)	(0.24)
	3	0.14	-0.25	0.15	-0.27	0.11	-0.25	0.09	-0.24
		(0.16)	(0.27)	(0.16)	(0.27)	(0.17)	(0.28)	(0.17)	(0.27)
	4	-0.07	-0.32	-0.06	-0.35	-0.06	-0.32	-0.06	-0.32
		(0.17)	(0.30)	(0.16)	(0.28)	(0.17)	(0.30)	(0.17)	(0.28)
	5	2.61	-9.79	3.06	-11.80	3.58	-9.44	3.95	-9.08
		(2.55)	(9.58)	(2.93)	(11.13)	(3.36)	(9.22)	(3.68)	(8.81)
Control:		C1		C2		C3		C4	
NFP		✓		✓		✓		✓	
R^C				✓					
R^Q						✓		✓	
$NewsIndex$								✓	

Estimated α_ξ^h and α_η^h from regression: $EI_{t(m)}^h = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{f,t(m)} + \alpha_C^h Control_{t(m)} + e_{t(m)}^h$. Definitions of variables in $Control_{t(m)}$ are plotted in Figure 1.4. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Table 1.10. Predictability for interest rate surprises by stock returns over different windows

	FF4	ED2	ED3	ED4	2-year T yield
$R^{Q}_{t(m)}$	0.11	0.24**	0.32***	0.32***	0.19**
	(0.07)	(0.10)	(0.11)	(0.12)	(0.08)
$R^{S}_{t(m)}$: stale news	0.14*	0.29**	0.38***	0.38***	0.24***
	(0.08)	(0.11)	(0.12)	(0.13)	(0.09)
$R^{C}_{t(m)}$: contemporaneous news	-0.01	0.04	0.03	0.03	0.00
	(0.15)	(0.15)	(0.18)	(0.20)	(0.15)

Notes: Each cell reports a coefficient, ϕ^{i}_{R}, from regression: $y_{t(m)} = \phi^{i}_{0} + \phi^{i}_{R}R^{i}_{t(m)} + \phi^{i}_{NFP}NFP_{m} + u^{i}_{t(m)}$, where $y_{t(m)}$ is the surprise change in one of the five interest rates within a 30-minute window around an FOMC announcement. Definitions of $R^{Q}_{t(m)}$, $R^{S}_{t(m)}$, $R^{C}_{t(m)}$ and NFP_{m} are plotted in Figure 1.4.

Table 1.11. Predictability for GB-BC forecast differences by stale news

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)
0	0.64	1.75	1.19	-0.05	1.46
	(0.76)	(1.11)	(2.61)	(0.13)	(2.12)
1	3.89***	3.48**	6.01***	-0.57**	0.84
	(0.95)	(1.33)	(2.12)	(0.23)	(1.54)
2	3.46***	3.03***	3.62*	-0.73***	-0.83
	(0.88)	(1.05)	(1.91)	(0.27)	(1.00)
3	2.30**	3.53***	2.77*	-1.06***	-0.57
	(1.01)	(1.20)	(1.66)	(0.39)	(0.47)
4	2.45***	3.32***	2.68**	-1.17***	-0.10
	(0.85)	(0.78)	(1.13)	(0.44)	(0.37)
5	1.19	3.99***	0.45	-1.45***	-0.70
	(1.06)	(0.99)	(1.45)	(0.53)	(0.54)
6	1.39	5.45***	1.55	-2.56***	-1.74*
	(2.02)	(1.67)	(2.47)	(0.87)	(0.98)
7	0.01	4.17***	0.03	-2.91**	-2.67**
	(1.44)	(1.21)	(1.73)	(1.21)	(1.21)

Notes: Each cell reports a coefficient, ϕ_{R}, from regression: $EI^{h}_{GB,t(m)} - EI^{h}_{BC,m} = \phi_{0} + \phi_{R}R^{S}_{t(m)} + \phi_{NFP}NFP_{m} + u_{t(m)}$. Definitions of $R^{S}_{t(m)}$ and NFP_{m} are plotted in Figure 1.4

from 1991m7 to 2019m3.[11]

Key intuition and results in Section 1.2 and 1.3 remain to hold for the composite measures. Table 1.12 shows that one factor continues to be sufficient for capturing the market response to various types of data releases in early 2009. Table 1.13 and 1.14 relate the composite measures to the forecast differences between the Greenbook and the Blue Chip. They confirm the results in Section 1.3.1; the composite Fed information shock fully captures the information asymmetry between the Fed and the private sector as measured by the difference in forecasts between the Greenbook and the Blue Chip. Most evidently, the Fed and the Blue Chip disagreed the most on output growth and inflation in the very near future. I also repeat the Blue Chip regressions in Section 1.3.2 with the composite measures, controlling for news between the initial Blue Chip survey and the FOMC announcement. Table 1.15 highlights the results for three economic indicators and confirms my findings in Section 1.3.2. An information shock identified to lower FF4 is associated with Blue Chip forecasters (1) revising down their expectations on real GDP for the next quarter and PPI for the current quarter. It also led the unemployment forecasts to drop for a set of horizons. For a more complete set of variables and specifications of control variables that showed up in Section 1.3.2, see Appendix.

Table 1.12. Wright (2012)'s test for the number of news shocks

	Sample period	Dimension of $\tilde{\xi}_t$ ($N_{\tilde{\xi}}$)	p-value
ZLB	2009m1 - 2016m12	1	0.631
post-ZLB	2017m1 - 2019m3	1	0.450

Notes: The null hypothesis is $\Sigma_1 - \Sigma_0 = \tilde{\gamma}\tilde{\gamma}'$, where $\tilde{\gamma}$ is an $N \times N_{\tilde{\xi}}$ matrix, Σ_1 is the covariance matrix of daily interest rate changes on the days with a major data release (defined in Table 1.1 with a "Yes"), and Σ_0 is the sample covariance matrix on the days with no major data release.

[11] The estimated series is normalized to raise FF4 by 1% in each subsample for consistency.

Table 1.13. Predictability of GB-BC forecast differences for Fed information shock ξ_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	**1.48*** **	0.52	**0.35** **	-0.21	**1.16** **	-0.20
	(0.44)	(0.45)	(0.16)	(4.16)	(0.46)	(0.53)
1	**1.82** **	**1.11** **	**0.41***	-0.18	0.48	-0.96
	(0.84)	(0.48)	(0.21)	(0.38)	(0.53)	(0.94)
2	**1.18** **	0.44	0.15	-1.85	-0.62	-0.91
	(0.60)	(0.37)	(0.24)	(1.86)	(0.92)	(1.31)
3	0.73	0.65	0.14	-1.59	-0.03	-1.29
	(0.63)	(0.51)	(0.39)	(1.41)	(1.04)	(1.03)
4	0.93	**1.24** **	0.36	-1.62	0.89	0.01
	(0.60)	(0.63)	(0.40)	(1.31)	(1.06)	(0.83)
5	0.65	**1.50** **	0.24	-1.75	0.53	-0.27
	(0.64)	(0.73)	(0.50)	(1.37)	(1.23)	(1.04)
6	0.59	1.23	0.50	-1.73	0.13	0.16
	(0.83)	(1.16)	(0.68)	(1.74)	(1.39)	(0.16)
7	0.47	1.68	-0.25	-1.91	-0.42	-1.61
	(0.84)	(1.19)	(0.83)	(1.84)	(1.77)	(1.82)

Each cell of the table reports the estimated ϕ_ξ^h from regression $\xi_{t(m)} = \phi_0^h + \phi_\xi^h(EI_{GB,t(m)}^h - EI_{BC,m}^h) + e_{t(m)}^h$, where $EI_{GB,t(m)}^h$ is the Greenbook forecast for Variable EI in h quarters prepared by the Fed staff for the FOMC meeting on Day t of Month m, $EI_{BC,m}^h$ is the Blue Chip forecast for the same variable at the beginning of Month m. Sample is from 1991m7 to 2013m12. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.14. Predictability of GB-BC forecast differences for monetary shock η_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	-0.21	0.02	-0.05	-1.27	-0.19	0.09
	(0.29)	(0.19)	(0.07)	(1.63)	(0.21)	(0.23)
1	-0.49	**-0.64****	0.03	-0.07	-0.09	0.20
	(0.46)	(0.27)	(0.10)	(0.14)	(0.22)	(0.48)
2	-0.33	-0.15	-0.18	0.18	0.14	1.02
	(0.42)	(0.30)	(0.16)	(1.08)	(0.44)	(0.82)
3	-0.36	-0.51	0.00	0.60	0.99	0.98
	(0.45)	(0.33)	(0.16)	(0.83)	(0.70)	(0.64)
4	-0.31	-0.42	0.21	0.48	0.66	0.17
	(0.42)	(0.49)	(0.20)	(0.72)	(0.60)	(0.50)
5	0.30	0.09	0.23	**1.06***	0.27	-0.18
	(0.31)	(0.42)	(0.21)	(0.63)	(0.67)	(0.48)
6	0.24	-0.05	-0.06	**1.16***	0.37	-0.08
	(0.33)	(0.51)	(0.20)	(0.61)	(0.67)	(0.11)
7	-0.02	-0.39	-0.21	0.96	1.26	**1.41***
	(0.36)	(0.57)	(0.35)	(0.96)	(1.05)	(0.74)

Each cell of the table reports the estimated ϕ_η^h from regression $\eta_{t(m)} = \phi_0^h + \phi_\eta^h (EI_{GB,t(m)}^h - EI_{BC,m}^h) + e_{t(m)}^h$, where $EI_{GB,t(m)}^h$ is the Greenbook forecast for Variable EI in h quarters prepared by the Fed staff for the FOMC meeting on Day t of Month m, $EI_{BC,m}^h$ is the Blue Chip forecast for the same variable at the beginning of Month m. Sample is from 1991m7 to 2013m12. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.15. Blue Chip regressions controlling for news, 1991m7 - 2019m3

(a) Real GDP				(b) Unemp. Rate				(c) PPI			
h	PC	ξ_t	η_t	h	PC	ξ_t	η_t	h	PC	ξ_t	η_t
0	0.65	0.79	-0.23	0	**-0.20****	**-0.22****	-0.25	0	**3.17****	**3.80****	-0.69
	(0.52)	(0.58)	(1.02)		(0.09)	(0.09)	(0.22)		(1.39)	(1.58)	(2.57)
1	**0.79****	**0.95*****	-0.02	1	-0.08	-0.09	0.18	1	0.51	**0.71***	-1.06
	(0.32)	(0.34)	(0.76)		(0.20)	(0.22)	(0.31)		(0.34)	(0.41)	(0.76)
2	0.17	0.25	-0.66	2	**-0.36****	**-0.40****	-0.23	2	0.05	0.06	-0.32
	(0.27)	(0.30)	(0.49)		(0.15)	(0.16)	(0.36)		(0.22)	(0.25)	(0.40)
3	0.10	0.16	-0.44	3	**-0.37****	**-0.41****	0.04	3	0.18	0.24	-0.33
	(0.21)	(0.25)	(0.29)		(0.17)	(0.17)	(0.40)		(0.23)	(0.27)	(0.31)
4	0.24	0.30*	0.23	4	-0.18	-0.20	0.57	4	-0.02	0.06	-0.26
	(0.15)	(0.17)	(0.36)		(0.18)	(0.18)	(0.62)		(0.19)	(0.21)	(0.56)
5	0.22	0.25	-0.43	5	**-0.28***	**-0.29***	0.02	5	0.19	0.23	**-1.07*****
	(0.15)	(0.15)	(0.42)		(0.16)	(0.16)	(0.47)		(0.20)	(0.18)	(0.37)

i. Columns labeled “PC” present estimated α^h_{PC} from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + \alpha^h_C Control_{t(m)} + e^h_{t(m)}$ while the other columns present estimated α^h_ξ and α^h_η from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_s \xi_{t(m)} + \alpha^h_m \eta_{t(m)} + \alpha^h_C Control_{t(m)} + e^h_{t(m)}$. $Control_{t(m)}$ includes NFP_m and $R^C_{t(m)}$.

ii. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

iii. Sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

1.5 Effects of monetary policy on output and inflation

One of the goals of properly identifying monetary shocks is to understand their effects on the macro economy. In this section, I embed the estimated series of η_t in a vector-autoregressive model to evaluate their impact on output and inflation.

My baseline model takes the exogenous variable approach (Paul, 2020) and estimate the following system of equations:

$$Y_t = B_0 + \sum_{i=1}^{p} B_i Y_{t-i} + \nu \eta_t + e_t \tag{1.11}$$

where Y_t is a vector of endogenous variables, including log industrial production, log CPI and excess bond premium in the baseline specification. The sample for both Y_t and η_t spans from 1991m7 to 2019m3. The impulse response function of Y_t to η_t is computed by forward iteration with estimated ν and $\{B_i\}_{i=1}^{p}$.[12]

Figure 1.6 plots the dynamic responses of these endogenous variables to a positive shock η_t that raises FF4 by 1% around an announcement. Industrial production drops on impact by roughly 1% although the effect is hardly significant. The decline, however, continues and becomes significant 5 months after the shock. In 10 months, output declined by as much as 4% in comparison to its original level. Risk premium in the bond market seems to play an important role for the slowdown of the economy. As the third figure shows, the excess bond premium jumps up immediately and significantly by nearly 1.3% and does not return to its original level until 10 months later. CPI adjusts fairly quickly within the first half of the year after the shock. It eventually shifts down by nearly 1.5% in the long run.

To show how controlling for the Fed information effect improves our understanding of the transmission of monetary policy, I compare the impulse responses to η_t with those to a shock in the high-frequency literature that does not adjust for the information effect. A popular

[12] Paul (2020) proves that the exogenous variable approach delivers numerically equivalent impulse response functions as the external instrument approach (Gertler and Karadi (2015)) under normal assumptions.

benchmark is the VAR specification of Gertler and Karadi (2015) along with their preferred policy instrument, denoted in this paper with $FF4^{GK}$. This instrument is a monthly aggregate of changes in the three-month federal funds future rate across all FOMC announcement windows during the month. I apply Gertler and Karadi (2015)'s aggregation procedure and extend their shock series to 2019m3. Figure 1.7 plots the dynamic responses of industrial production and CPI to a positive $FF4^{GK}$ shock in red and to a positive η_t shock in blue for a sample from 1979m7 to 2019m3. For comparison, I normalize both shocks to raise the one-year Treasury bond rate by 1% on impact.

Relative to $FF4^{GK}$, the responses of the macro economy to η_t display no output puzzle and are evidently larger in magnitude in all horizons. At the trough, industrial production decreases by more than 4% in response to a positive η_t shock. In contrast, $FF4^{GK}$ has a significantly positive effect on industrial production shortly after its realization, and its impact remains close to zero for any horizon within the first three years. CPI also declines more quickly and shifts down more dramatically following a positive η_t shock than following a positive $FF4^{GK}$ shock.

The Fed information effect can potentially explain Gertler and Karadi (2015)'s underestimation of impulse responses. As Section 1.3.2 illustrates, a rise in $FF4$ during an announcement window contains a Fed information component that leads the Blue Chip professionals to increase their forecasts for CPI, industrial production and real GDP significantly in the near future. Derived from such daily measures, $FF4^{GK}$ likely display a similar feature. Either if changes in market expectations upon announcements have self-fulfilling real effects or if the Fed information predicts the economy well, the estimated effects of monetary shocks on output and inflation would be biased upward if one were to use $FF4^{GK}$ directly in a VAR model. This is precisely what we see in Figure 1.7.

For a robustness check, I estimate the impulse responses of industrial production and CPI to η_t without incorporating the excess bond risk premium into the VAR model. This choice of specification is motivated by a recent finding of Miranda-Agrippino and Ricco (2020) that the behavior of Gertler and Karadi (2015)'s $FF4^{GK}$ is sensitive to including the excess bond premium. In particular, including this very variable is key to avoiding an output puzzle in their dynamic responses. I show in Figure 1.8 that deleting this variable from my baseline specification does not qualitatively change my results. Not surprisingly, the 90% confidence intervals widens as the level of precision for estimating ν and B drops.

In summary, studying the transmissions of monetary policy with η_t, I find that an exogenous, contractionary monetary shock has a larger negative impact on output and inflation than one would observe with high-frequency monetary instruments themselves. The deviation potentially comes from the fact that existing monetary instruments are confounded by the Fed information effect. The estimated impulse response functions are robust to alternative specifications.

1.6 A comparison with existing monetary instruments

A number of previous studies have proposed alternative measures of monetary shocks. In this section, I compare η_t proposed in this paper with a number of popular ones.

1.6.1 Overview

The first two columns of Table 1.16 list the sources and abbreviations of the shocks considered in the comparison. Some of them are daily measures. They take non-zero values only on Fed announcement days. For this category, I consider Gürkaynak et al. (2005a)'s target and path factors, Nakamura and Steinsson (2018)'s policy news shock, Zhang (2019)'s daily measure and Bu et al. (2020)'s BRW shock. The rest are monthly measures. They either construct the shocks with monthly data from the very beginning, such as the Romer and Romer (2000) shock, or aggregate daily shocks from FOMC days into monthly measures for a month with multiple announcements, such as Gertler and Karadi (2015)'s $FF4^{GK}$, Miranda-Agrippino and Ricco (2020)'s information-robust shock, Zhang (2019)'s monthly measure and Jarociński and Karadi (2020)'s monetary shock. For comparison with the latter category, I also create a monthly version of η_t by aggregating my daily values by month and treating the shock as zero for those months with no FOMC announcements.

Table 1.16 also shows the correlation coefficients of η_t with these alternative constructions. As one might expect from my earlier discussions, η_t largely co-moves with the ones that are also identified to remove the Fed information effect, such as Miranda-Agrippino and Ricco (2020), Zhang (2019) and Jarociński and Karadi (2020). Even though η_t also has a nontrivially positive correlation with $FF4^{GK}$ and with $Target$, they display drastically different behavior in terms of their relations to business cycles, as I show in the next section.

Table 1.16. Overview of monetary shocks in the literature

Shock	Abbrev.	Corr. w/ η_t	Availability
Monthly			
Romer and Romer (2000)	RR	0.12	1969m3 - 2007m12
Gertler and Karadi (2015)	$FF4^{GK}$	0.29	1990m1 - 2012m6
Miranda-Agrippino and Ricco (2020)	MAR	0.42	1991m2 - 2010m1
Zhang (2019)	Zhang	0.22	1988m3 - 2013m12
Jarociński and Karadi (2020)	JK	0.41	1990m2 - 2015m12
η_t, this paper	η_t	n.a.	1991m7 - 2019m3
Daily			
Path, Gürkaynak et al. (2005a)	Path	-0.50	1990m2 - 2004m12
Target, Gürkaynak et al. (2005a)	Target	0.57	1990m2 - 2004m12
Nakamura and Steinsson (2018)	NS	0.19	1995m2 - 2014m3
Zhang (2019)	Zhang	0.22	1988m3 - 2013m12
Bu et al. (2020)	BRW	-0.05	1994m2 - 2019m9
η_t, this paper	η_t	n.a.	1991m7 - 2019m3

1.6.2 Cyclicality

Exogenous monetary shocks ought to display no patterns of cyclicality with business cycles. If a series tends to be negative during and before a recession, it is likely a response of policymakers to their understanding of the state of the economy. I check if the shocks listed above are exogenous in this sense by running the following Probit regression.

$$IsRecession_t^h = \kappa_0^h + \kappa^h Shock_t + e_t^h \tag{1.12}$$

where $IsRecession_t^h$ is binary, taking the value of 1 if the economy is in an NBER recession h quarters following the shock and zero otherwise. I consider $h = 0, \ldots, 6$.

Table 1.17 shows that the target factor, the NS shock, the RR shock and the GK shock tend to precede a recession by 0-3 quarters when they take negative values. It indicates that they have captured some Fed information on bad economic fundamentals. In contrast, the proposed shock here along with the others that take care of the Fed information effect do not significantly predict recessions.

Notably, when I replace the regressor in Equation (1.12) with my constructed information shock, I show in Table 1.18 that it significantly predicts a recession in the current quarter or the next at the 5% level. This again proves the success of my decomposition.

1.6.3 Revisions of Blue Chip forecasts

For comparison, I repeat my exercise in Section 1.3.2 for all of the monetary shocks considered here. If a monetary shock is well identified to be expansionary, it should revise up Blue Chip forecasts for pro-cyclical variables. For each shock, I use the raw series as posted on the authors' websites and filter the data in the same way as Bauer and Swanson (2020) when running the regressions. Nonfarm payrolls and current-month cumulative stock returns are added in the regressions to control for the Fed response to news channel.

Table 1.19, 1.20 and 1.21 repeat the results for each of the proposed monetary shocks along with ξ_t and η_t. I highlight in red the coefficients that are statistically significantly different from zero but of the wrong sign. The first three columns confirm the findings in the literature (Campbell et al. (2012); Nakamura and Steinsson (2018)). A shock that is constructed to be contractionary leads Blue Chip forecasters to significantly predict higher CPI, higher industrial

Table 1.17. Estimated κ^h from Equation (1.12)

h (quarters)	0	1	2	3	4	5	6
Path	-0.69	-0.68	0.29	1.20	2.35**	2.00**	4.01***
	(0.89)	(1.15)	(1.15)	(1.29)	(0.96)	(0.91)	(1.50)
Target	-3.00**	-2.12	-2.33	-0.50	2.03	1.91	2.29
	(1.28)	(1.65)	(1.53)	(2.03)	(1.32)	(1.68)	(2.87)
NS	-7.18***	-8.13***	-5.31**	-2.16	0.05	0.09	2.04
	(2.78)	(3.06)	(2.65)	(2.59)	(2.68)	(2.66)	(3.33)
Zhang	-0.07	-0.93	0.09	0.66	-0.21	-2.07	-0.69
	(3.26)	(3.41)	(3.29)	(2.63)	(2.28)	(2.00)	(1.95)
BRW	-1.80	-0.87	1.44	0.69	1.34	0.83	1.42
	(4.47)	(4.07)	(3.48)	(2.96)	(3.07)	(2.73)	(2.60)
η_t (pre-ZLB)	0.54	-1.49	-1.58	-1.28	0.48	1.23	-1.16
	(7.93)	(8.48)	(7.74)	(7.39)	(6.78)	(6.60)	(3.37)
η_t (full sample)	0.39	-1.36	-1.43	-1.10	0.88	1.73	-0.97
	(9.79)	(11.23)	(10.60)	(10.08)	(9.10)	(8.77)	(4.38)
RR	-0.41*	-0.44*	-0.29	-0.08	-0.09	-0.13	0.05
	(0.22)	(0.24)	(0.21)	(0.17)	(0.17)	(0.16)	(0.18)
$FF4^{GK}$	-6.41***	-4.85**	-3.78**	0.08	0.75	0.83	4.15
	(2.01)	(1.94)	(1.86)	(2.16)	(2.29)	(2.42)	(2.66)
MAR	-0.45	-0.54	-1.68	1.67	1.05	0.43	1.09
	(3.02)	(3.22)	(2.81)	(3.06)	(2.63)	(2.43)	(1.71)
Zhang (monthly)	0.80	-0.52	-1.69	1.35	0.46	-0.47	0.25
	(4.41)	(3.96)	(3.48)	(3.16)	(2.90)	(2.78)	(2.23)
JK	-3.24	-2.91	-1.85	0.73	2.03	1.98	2.76
	(2.61)	(2.70)	(2.90)	(3.26)	(3.07)	(3.18)	(3.00)
η_t (monthly, pre-ZLB)	0.33	-1.27	-1.67	0.11	0.82	1.37	5.14
	(8.71)	(8.55)	(7.98)	(7.12)	(6.80)	(6.64)	(4.12)
η_t (monthly, full sample)	0.01	-1.41	-1.58	0.43	1.25	1.88	6.57
	(10.16)	(10.98)	(11.11)	(9.88)	(9.39)	(9.11)	(5.02)

Notes: Each cell reports the estimate of κ^h from Probit regression $IsRecession_t^h = \kappa_0^h + \kappa^h Shock_t + e_t^h$. Robust standard errors in parenthesis. $IsRecession_t^h$ is determined by the NBER labeling of recessions. The sample period for each shock can be found in Table 1.16.

Table 1.18. Information shock ξ_t predicts near-future recessions

h (quarters)	0	1	2	3	4	5	6
Pre-ZLB	**-5.53****	**-5.21****	-2.38	-0.13	0.79	0.15	1.98
	(2.45)	(2.51)	(2.23)	(2.00)	(2.19)	(1.99)	(2.42)
Full sample	**-6.08****	**-5.89****	-2.76	-0.07	1.10	0.29	2.66
	(2.68)	(2.93)	(2.77)	(2.61)	(2.99)	(2.63)	(3.47)

Notes: Each cell reports an estimate of κ_ξ^h from Probit regression $IsRecession_t^h = \kappa_0^h + \kappa_\xi^h \xi_t + e_t^h$. Robust standard errors in parenthesis. $IsRecession_t^h$ is determined by the NBER labeling of recessions.

production, higher real GDP or lower employment rate for at least one quarter in the future. These three shocks yield the most puzzling results because they do not control for the Fed information effect at all. Miranda-Agrippino and Ricco (2020)'s information-robust shock performs slightly better in the sense that it results in fewer significant, incorrectly-signed coefficients. However, the shock is significantly correlated with an upward change in the forecasts for industrial production in the next quarter, and for CPI and PPI in the third quarter. This suggests that the shock may still contain some remaining Fed information.[13]

On the other hand, there is no overwhelming evidence for remaining Fed information in Jarociński and Karadi (2020) and Bu et al. (2020). The responses of Blue Chip forecasts are mostly insignificant. Notably, Zhang (2019) and the shocks proposed here perform particularly well; whenever a coefficient is significant, it always implies that a positive disturbance leads to a downward revision of public forecasts for pro-cyclical indicators and an upward revision for the unemployment rate. The desirable behavior of these proposals points out the importance of using asset prices of multiple dimensions and explicitly disentangling the Fed information effect for the identification of monetary policy.

To summarize the findings in this section, I conclude that the series proposed by Zhang (2019) and this paper display expected features of monetary shocks. My approach is further desirable in its real-time availability and its point-identified feature.

[13]For a monthly measure, I omit those FOMC announcements if multiple take place in a month because its timing relative to Blue Chip surveys is uncertain.

1.7 Conclusion

As the FOMC announcements in the past three decades have increasingly accompanied policy decisions with discussions about economic fundamentals, it is reasonable to say that the Fed would want to sync its non-monetary information with the market through announcements. It is an empirical question to ask how much of what it discusses is new to the market, or equivalently whether or not there is a Fed information effect in the language of the literature. This paper proposes a novel approach to answering this question with limited point-identifying assumptions and the requirement of only public data. From a sample from late 1990 to early 2019, I decompose the high-frequency interest rate surprises around FOMC announcements into a Fed information shock and a monetary shock. With the decomposed Fed information shock, I am able to explain private forecast revisions for a variety of economic indicators after an announcement. The information shock captures the market's learning of industrial production, CPI and PPI in the current quarter and real GDP in the fifth quarter from an FOMC announcement. Reconciliating this result with those of Bauer and Swanson (2020), this paper suggests that the information asymmetry may come from the FOMC's better judgment of public news instead of its better access to information per se. Without the confounding effect of non-monetary news, the resulting monetary shock delivers theoretically-consistent dynamic responses of industrial production and CPI that are more pronounced and long-lasting than those without adjusting for the Fed information effect.

Table 1.19. Blue Chip forecast revisions in response to various shocks

Industrial Production:

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	0.46	1.75	**3.70****	0.50	**2.14***	1.37	**2.18***	-0.13
	(0.72)	(1.26)	(1.72)	(1.59)	(1.12)	(1.05)	(1.22)	(2.11)
1	0.15	0.35	**2.18*****	0.60	0.18	**1.21***	0.69	0.22
	(0.31)	(0.47)	(0.77)	(0.66)	(0.70)	(0.64)	(0.64)	(1.23)
2	0.13	-0.02	**0.86***	0.22	-0.43	0.59	-0.21	-0.60
	(0.17)	(0.25)	(0.49)	(0.42)	(0.45)	(0.40)	(0.45)	(0.69)
3	0.15	-0.07	0.77	0.26	0.11	0.40	-0.32	-0.77
	(0.17)	(0.26)	(0.48)	(0.39)	(0.34)	(0.34)	(0.39)	(0.51)
4	0.12	-0.13	0.14	-0.05	-0.12	0.18	-0.32	**-1.11***
	(0.13)	(0.15)	(0.27)	(0.24)	(0.25)	(0.17)	(0.20)	(0.60)
5	0.09	-0.08	0.13	0.15	0.28	0.20	-0.21	-0.60
	(0.12)	(0.14)	(0.34)	(0.25)	(0.31)	(0.18)	(0.24)	(0.52)

Real GDP:

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	0.01	0.24	**1.40****	0.15	0.22	0.45	0.18	-0.23
	(0.29)	(0.58)	(0.68)	(0.66)	(0.66)	(0.47)	(0.63)	(1.02)
1	0.22	0.37	**1.27*****	0.35	0.18	0.55	0.17	-0.02
	(0.14)	(0.24)	(0.41)	(0.38)	(0.47)	(0.41)	(0.41)	(0.76)
2	0.06	0.19	0.49	-0.11	-0.14	0.13	-0.16	-0.66
	(0.11)	(0.15)	(0.37)	(0.34)	(0.35)	(0.34)	(0.31)	(0.49)
3	0.15	0.15	0.33	0.00	0.09	0.25	-0.06	-0.44
	(0.09)	(0.11)	(0.28)	(0.22)	(0.19)	(0.17)	(0.18)	(0.29)
4	0.12	0.06	0.30	0.10	0.28	0.22	-0.02	0.23
	(0.08)	(0.10)	(0.22)	(0.17)	(0.17)	(0.16)	(0.17)	(0.36)
5	**0.22****	-0.11	0.04	0.10	0.06	0.02	-0.12	-0.43
	(0.09)	(0.19)	(0.30)	(0.21)	(0.14)	(0.13)	(0.27)	(0.42)

Table 1.20. Blue Chip forecast revisions in response to various shocks (cont.)

Unemployment Rate:

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	-0.05	**-0.15****	**-0.23***	0.07	-0.20	0.00	**-0.19***	-0.25
	(0.05)	(0.07)	(0.12)	(0.15)	(0.21)	(0.12)	(0.11)	(0.22)
1	**-0.17****	0.23	-0.20	0.26	-0.11	0.83	0.00	0.18
	(0.08)	(0.27)	(0.19)	(0.20)	(0.29)	(0.85)	(0.19)	(0.31)
2	-0.11	**-0.17***	-0.35	0.04	-0.10	-0.11	-0.18	-0.23
	(0.08)	(0.09)	(0.22)	(0.19)	(0.29)	(0.20)	(0.16)	(0.36)
3	-0.09	-0.13	**-0.40***	0.19	-0.27	-0.04	-0.16	0.04
	(0.07)	(0.09)	(0.24)	(0.20)	(0.34)	(0.23)	(0.19)	(0.40)
4	-0.07	-0.03	-0.24	**0.36***	-0.17	0.02	-0.01	0.57
	(0.08)	(0.07)	(0.25)	(0.20)	(0.39)	(0.23)	(0.20)	(0.62)
5	**-0.15****	0.01	-0.35	0.24	-0.65	-0.17	-0.26	0.02
	(0.06)	(0.08)	(0.22)	(0.22)	(0.39)	(0.18)	(0.18)	(0.47)

CPI:

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	0.38	0.13	**1.86***	0.50	-0.10	0.16	-0.08	-0.19
	(0.27)	(0.28)	(1.11)	(0.65)	(0.88)	(0.65)	(0.67)	(1.45)
1	-0.01	**0.34*****	-1.31	0.11	-1.50	-0.94	1.22	0.78
	(0.08)	(0.12)	(1.19)	(0.51)	(1.35)	(0.95)	(1.03)	(1.67)
2	-0.01	0.07	0.11	0.05	0.25	-0.03	0.04	0.32
	(0.07)	(0.07)	(0.16)	(0.14)	(0.19)	(0.11)	(0.11)	(0.21)
3	-0.06	**0.14***	**0.27****	0.00	0.13	**0.22****	0.10	0.15
	(0.09)	(0.07)	(0.13)	(0.15)	(0.18)	(0.10)	(0.09)	(0.24)
4	0.05	-0.03	0.12	-0.06	-0.05	0.01	-0.06	-0.04
	(0.08)	(0.08)	(0.15)	(0.14)	(0.17)	(0.09)	(0.11)	(0.27)
5	0.14	-0.01	0.22	0.06	0.16	0.04	0.15	-0.11
	(0.10)	(0.13)	(0.30)	(0.19)	(0.21)	(0.18)	(0.18)	(0.38)

Table 1.21. Blue Chip forecast revisions in response to various shocks (cont.)

PPI:

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	**0.81***	0.66	**4.71****	1.52	2.48	0.95	0.72	-0.69
	(0.47)	(0.73)	(2.08)	(1.23)	(1.90)	(1.25)	(1.46)	(2.57)
1	-0.06	0.27	0.81	0.34	0.73	0.09	-0.19	-1.06
	(0.13)	(0.19)	(0.56)	(0.37)	(0.72)	(0.49)	(0.51)	(0.76)
2	-0.01	-0.11	0.15	-0.09	0.20	-0.03	-0.31	-0.32
	(0.10)	(0.15)	(0.32)	(0.27)	(0.31)	(0.23)	(0.24)	(0.40)
3	**0.15****	-0.09	0.24	-0.06	0.27	**0.42*****	0.11	-0.33
	(0.08)	(0.10)	(0.29)	(0.26)	(0.31)	(0.16)	(0.17)	(0.31)
4	0.10	-0.07	0.10	-0.18	-0.28	0.00	0.04	-0.26
	(0.10)	(0.13)	(0.25)	(0.22)	(0.34)	(0.18)	(0.19)	(0.56)
5	0.10	-0.07	0.22	-0.01	0.48	0.08	0.05	**-1.07*****
	(0.11)	(0.12)	(0.28)	(0.21)	(0.33)	(0.17)	(0.16)	(0.37)

GDP Price Index:

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	-0.10	0.03	0.23	-0.04	-0.25	0.06	-0.06	0.15
	(0.13)	(0.16)	(0.36)	(0.28)	(0.26)	(0.22)	(0.23)	(0.38)
1	0.03	0.05	0.14	-0.03	0.06	-0.04	0.03	0.09
	(0.08)	(0.13)	(0.18)	(0.18)	(0.19)	(0.17)	(0.15)	(0.26)
2	0.02	-0.08	0.05	-0.16	0.13	-0.06	0.03	-0.09
	(0.12)	(0.08)	(0.21)	(0.17)	(0.14)	(0.15)	(0.12)	(0.24)
3	0.00	0.06	0.12	-0.03	**0.29****	-0.03	0.08	-0.29
	(0.09)	(0.11)	(0.20)	(0.15)	(0.12)	(0.13)	(0.14)	(0.26)
4	-0.03	-0.09	-0.12	-0.16	0.09	-0.10	-0.11	-0.28
	(0.09)	(0.09)	(0.18)	(0.15)	(0.12)	(0.12)	(0.11)	(0.27)
5	2.49	-1.47	2.08	2.02	1.42	0.38	-0.23	-9.97
	(2.26)	(1.51)	(2.18)	(2.14)	(1.27)	(0.98)	(0.61)	(9.51)

Notes: Each cell reports an estimated α^h from regression $\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h Shock_{t(m)} + \alpha^h_C Control_{t(m)} + e^h_t$, where *Shock* takes one of the monetary instruments in the head row and $Control_{t(m)}$ contains NFP_m and $R^C_{t(m)}$ defined in Figure 1.4. In the rightmost column, the point estimates repeat those in Column "η_t" in Panel C2 of Table A.5 and A.6.

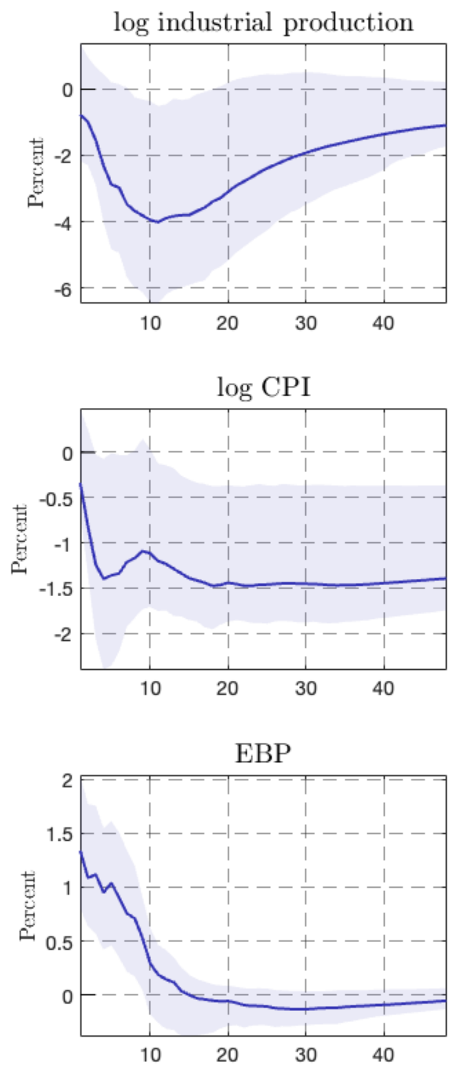

Figure 1.6. Dynamic responses to a monetary tightening shock - baseline

Notes: Impulse response functions from the baseline VAR model, $Y_t = B_0 + \sum_{i=1}^{p} Y_{t-i} + \nu\eta_t + e_t$. Endogenous variables Y_t include log industrial production, log CPI and excess bond premium. The shock η_t is normalized to raise FF4 by 1% on average. The sample for both Y_t and η_t goes from 1991m7 to 2019m3. The number of lags is 12 months. Shaded areas are 90% confidence interval constructed by a moving-block bootstrap.

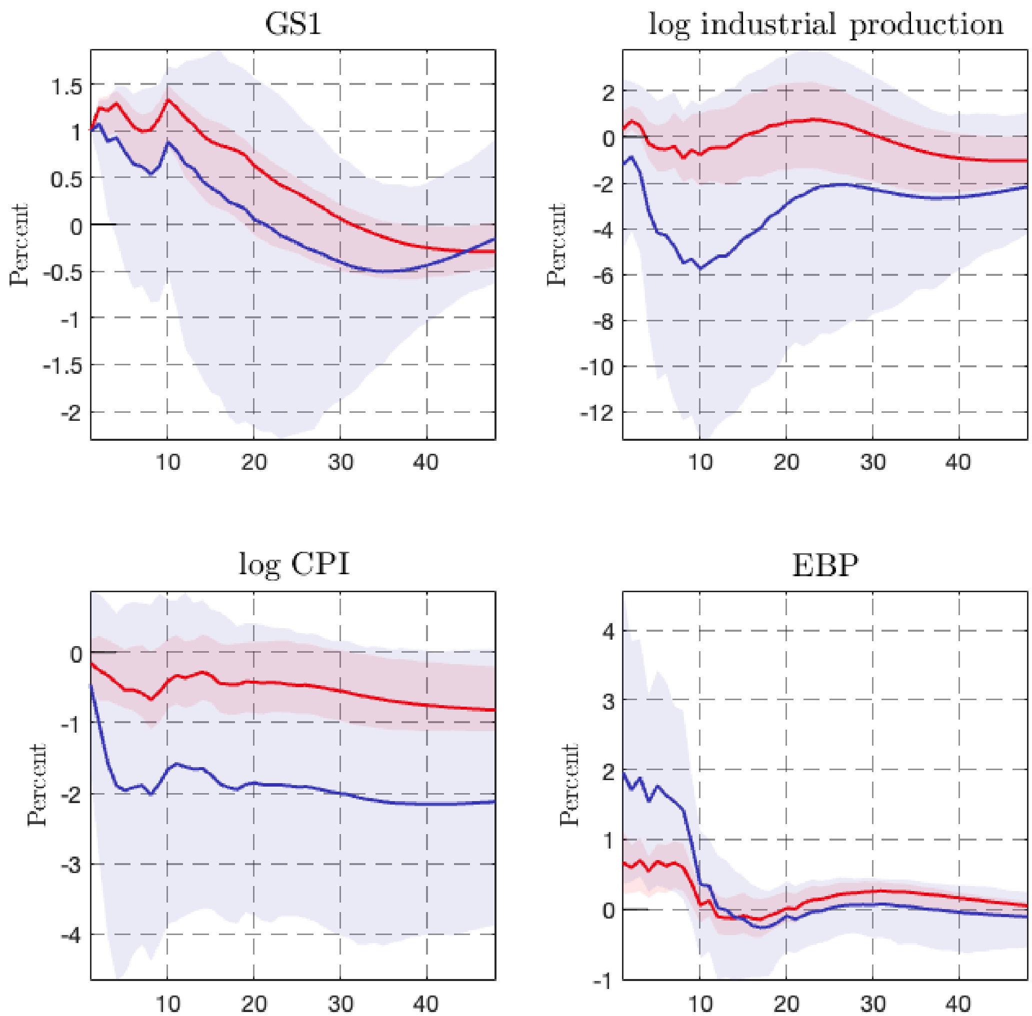

Figure 1.7. Dynamic responses to a monetary tightening shock - a comparison with Gertler and Karadi (2015)

Notes: The red curves show the impulse responses to Gertler and Karadi (2015)'s policy instrument $FF4^{GK}$, while the blue ones show those to η_t. The sample for both endogenous variables and the shock series runs from 1991m7 to 2019m3.

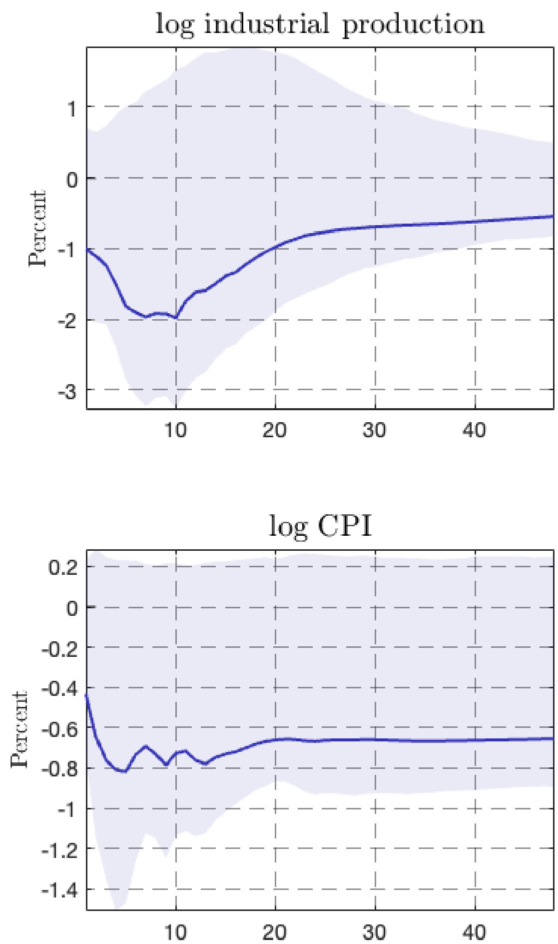

Figure 1.8. Dynamic responses to a monetary tightening shock - a robustness check

Notes: Impulse response functions from a VAR model that differs from my baseline only by not having the excess bond risk premium in Y_t. See notes under Figure 1.6 for detailed specifications.

Chapter 2

A Macro-Finance Term Structure Model of Interest Rates with Data Revisions

2.1 Introduction

Financial markets, especially the nominal Treasury bond market, move substantially in response to key macroeconomic events. Numerous attempts have been made in the event-study literature to explain such a phenomenon. Some relate the movement of the yield curve to the market surprise at a particular headline number but fail to match the magnitude of the response, while others replicate the magnitude but are muted on the fundamental driving forces of the response (Gürkaynak et al., 2018).

A satisfactory account of the market response needs to address a few things. First, why does the yield curve move around statistical releases that pertain to economic indicators of *past* periods? Second, why does it move so much? If econometricians need variables beyond surprises at headline numbers to explain the magnitude of the movements, how can we summarize that multi-dimensional information? This paper proposes a coherent, realistic framework of Treasury bond pricing that answers these questions simultaneously. It explicitly recognizes agents' information frictions in regard to contemporaneous aggregate outcomes, successfully matches the market responses to macroeconomic events and sheds light on the nature of news learned by investors at various events.

The framework consists of three blocks. In the first block, I model the quarterly dynamics of macroeconomic variables, recognizing the asyncronicity of data generating, collecting and publishing processes commonly seen in an economy. Treating these macro variables as unobserved state variables, I build an affine term structure model of interest rates in the second block. The pricing model provides a mapping between a fundamental innovation and the shape of its immediate impact on the yield curve. Using this mapping, the last block zooms into a day with a macroeconomic news event and recovers the composition of information that investors learn about on that day.

The bond pricing model in this paper belongs to the group of macro-based term structure models of interest rates (Diebold et al., 2006; Rudebusch and Wu, 2008). It is most different from previous models in that it aligns asset prices with investors' appropriate information sets. The asyncronicity of data generating, collecting and publishing processes usually leads econometricians to use the most up-to-date data for modeling asset prices. However, Aruoba (2008) documents that initial data releases in the US were systematically biased. Using the most recent values available, one would fail to capture the appropriate information set of bond investors at the time when the assets were priced.

As a starting point, I model the decision-making processes of economic agents when they possess imperfect information about the state of the economy. The model is an adapted version of a three-equation, linearized New-Keynesian economy. A representative household, a representative firm and a central bank all share the same information set. At the end of each quarter, they were fully informed of macroeconomic statistics only up to the previous quarter, and therefore had to act based on their rational expectations of contemporaneous aggregate outcomes. In addition, shocks to the IS curve and the Phillips curve are forward-looking, capturing the feature that part of the decisions they make in this quarter will have to manifest themselves in the following period.

The macro block forms the basis upon which Treasury bonds are priced. I establish a pricing relationship between economic fundamentals and nominal Treasury bond prices in an affine term structure model. The rational expectations solution to the macro model characterizes the state equation of the pricing model. Yields of various maturities are connected to the state vector by no-arbitrage restrictions.

Throughout the framework, macroeconomic variables are treated as unobserved. In a state-space representation of the framework, econometricians use two sets of data to identify those latent variables. The first set contains the first three releases of macroeconomic data. They approximate latent variables with decreasing measurement errors, indicating that each round of data revision embodies news to the market. The second set contains data of the yield curve. They identify the level of risk aversion in the bond market.

Zooming into a day within the quarter, I use the bond pricing model to study the various forces driving the financial market's responses to a macroeconomic event. As an important feature of the framework, each event is allowed to reveal news about all five fundamental shocks. As a result, the model captures news not only about the headline number of an event but also of other dimensions of information which econometricians cannot fully observe (Gürkaynak et al., 2018). For each macroeconomic data release or FOMC announcement, bond investors update their perceptions of the fundamental shocks by a bit, as is characterized by a weight vector. The weight vector represents the linear combination of the fundamental shocks that best approximate the observed movement of the yield curve around the event in the data. Joining a variety of events together, the approach characterizes the process in which investors overcome information frictions and learn about the state of the economy during the quarter.

The model is able to match the secular declines in Treasury bond yields over the past three decades. This is because agents in the macro block form expectations not only of the output gap and inflation but also of trend variables. Both the long-run inflation expectations and the equilibrium real rate of interest are allowed to change over time. Flexibility of this kind leads the short nominal rate to feature a shifting long-run mean. Linked by no-arbitrage restrictions, yields of all maturities also end up featuring time-varying long-run averages in the pricing model. It is well known that macroeconomic data is usually too limited in size to characterize the long-run characteristics of an economy. The yield data here is much richer and can serve as an additional source of identification.

It turns out that learning about the equilibrium real rate of interest is key to understanding the volatility of long yields around all kinds of data releases and FOMC announcements. Gürkaynak et al. (2005b) point out the importance of a time-varying inflation expectation for accounting for the large variations of the long forward rates around data releases. I complement their argument with another trend variable which has displayed a more dramatic decline over the last fifteen years.

For short and medium yields, the shock to the IS curve plays a predominant role in driving their variations around macroeconomic events, including the FOMC announcements. Even though the latter events are usually treated as of a monetary nature, my framework suggests that they also disclose information about economic fundamentals. This is consistent with a series of recent studies that argue for the existence of non-monetary news in FOMC announcements (Cieslak and Schrimpf, 2019; Nakamura and Steinsson, 2018).

The paper proceeds as follows. Section 2.2 introduces the framework in which macroeconomic fundamentals are determined, investors' expectations are formed and Treasury bonds are priced. Section 2.3 and 2.4 explain the data and the procedure from which model parameters are calibrated and estimated. Section 2.5 discusses my findings for a variety of macroeconomic events.

2.2 Framework

The framework consists of three blocks. The first block is a variant of a stylized small-scale New Keynesian model, describing the fundamental dynamics of macroeconomic variables such as the output gap, the inflation rate and the nominal interest rate. A key feature of this block is that the macro agents do not know aggregate outcomes of the economy contemporaneously and have to learn them through rounds of data revisions. The second block prices nominal Treasury bonds from the perspective of a bond investor who takes the fundamentals from the first block as given. Finally, the last block uses the pricing implications from the second block and the intra-day responses of the yield curve to macroeconomic data releases to identify the information learned by market participants from different releases.

2.2.1 Macro dynamics

This first block describes the decision-making of macro agents in the economy at the quarterly frequency. To simplify the analysis, I assume that both households make consumption decisions and firms set prices at the end of a quarter, by which date they must have heard the relevant monetary announcement(s) in the quarter and thus do not need to guess the prevailing policy rate.

Let t denote a quarter. On the last day of Quarter t, a household consumes and invests in response to the ex-ante real interest rate like in a New-Keynesian economy,

$$\tilde{y}_t = \mu_{y,1}\,\mathbb{E}_t(\tilde{y}_{t+1}) + \mu_{y,2}\tilde{y}_{t-1} - \beta\left[i_t - \mathbb{E}_t(\pi_{t+1}) - r_t^*\right] + g_{t+1}$$

where $\tilde{y}_t$ is the output gap of Quarter t, π_t is the inflation rate, r_t^* is the agent's perception of the equilibrium real rate of interest, and the expectation operator with a t subscript denotes an individual's expectation of a variable as of the last day in Quarter t. The last term of the equation, g_{t+1}, is a demand shock to this otherwise standard IS curve. The unusual subscript $t+1$ on g captures the asynchronicity of data generation and data releases of macroeconomic outcomes; the latest information about the aggregate output is of the previous quarter, so part of the outcome resulting from her decision in Quarter t must be revealed in Quarter $t+1$. The division of information revelation is determined by ρ_g in the assumed AR(1) process of g_{t+1}:

$$g_{t+1} = \rho_g g_t + e_{g,t+1} \qquad e_{g,t+1} \sim \text{iid } N(0, \sigma_g^2)$$

I assume that the equilibrium rate of interest follows a random walk, i.e.

$$r_t^* = r^* + z_t$$

$$z_t = z_{t-1} + e_{z,t}$$

$$z_0 = 0$$

$$e_{z,t} \sim N(0, \sigma_z^2)$$

Similarly, firms at the end of Quarter t are informed of statistics for only up to Quarter $t-1$. As a result, a firm has to set the price at the end of Quarter t based on their *expectation* of aggregate output gap for the current quarter and that of inflation for the next quarter. Though made in Quarter t, individual price setter's decision will eventually be completely reflected and made available in the data releases in Quarter $t+1$. Thus, an adapted Phillips curve follows,

$$\tilde{\pi}_t = \mu_{\pi,1}\,\mathbb{E}_t(\tilde{\pi}_{t+1}) + \mu_{\pi,2}\tilde{\pi}_{t-1} + \kappa\,\mathbb{E}_t(\tilde{y}_t) + a_{t+1}$$

where $\tilde{\pi}_t \equiv \pi_t - \pi_t^*$ is the deviation of inflation from its trend, $a_{t+1} = \rho_a a_t + e_{a,t+1}$ and $e_{a,t+1} \sim N(0, \sigma_a^2)$. The trend inflation is assumed to follow a random walk, i.e.

$$\pi_t^* = \pi^* + v_t$$

$$v_t = v_{t-1} + e_{v,t}$$

$$v_0 = 0$$

$$e_{v,t} \sim N(0, \sigma_v^2)$$

Finally, a central bank faces the same information frictions as the other agents in the economy with respect to all the shocks. As the policymaker, it may be better informed of the monetary shock prior to an FOMC announcement than the public, but at the end of a quarter by which the announcement has been made, the information asymmetry will have been eliminated.

The short nominal interest rate is set to follow a Taylor rule and track the long-run inflation target of the economy.

$$
\begin{aligned}
i_t &= \tilde{i}_t + \pi_t^* \\
\tilde{i}_t &= \tau_i \tilde{i}_{t-1} + (1-\tau_i)\left[\phi_y \mathbb{E}_t(\tilde{y}_{t+1}) + \phi_\pi \mathbb{E}_t(\tilde{\pi}_{t+1})\right] + \eta_t
\end{aligned}
$$

where $\eta_t \sim N(0, \sigma_\eta^2)$ is a monetary shock.

2.2.2 Term structure of interest rates

In the second block, I describe the behavior of nominal Treasury bonds at quarter ends with the macro variables above acting as pricing factors. An affine term structure model (ATSM) is well-suited to fit Treasury yields of many maturities. I take the state variables from the first block as pricing factors and show they are priced in Treasury bond prices.

Let ξ_t be an N_ξ-by-1 vector collecting the state variables that govern the macro dynamics above. The pricing model features a stochastic discount factor in the following form,

$$
M_{t,t+1} = \exp\left[-i_t - \tfrac{1}{2}\lambda_t'\lambda_t - \lambda_t'\mathscr{E}_{t+1}\right]
$$

where λ_t is an $N_\xi \times 1$ vector of risk prices summarizing investors' attitude towards fluctuations in the state vector ξ_t, and $\mathscr{E}_t$ is an $N_\mathscr{E}$-by-1 vector of innovations to ξ_t ($N_\mathscr{E} = 5$) satisfying $\mathscr{E}_t \sim iidN(0, \Omega\Omega')$. The risk prices are further assumed to be affine in ξ_t as

$$
\lambda_t = \lambda + \Lambda \xi_t
$$

Here, λ is an $N_\mathscr{E}$-by-1 vector capturing the constant risk aversion of bond investors against the five shocks in the economy, and Λ governs how the risk aversion changes with state variables.

The rational expectations solution method delivers the state equation under the P-measure,

$$\xi_t = c + \Phi\xi_{t-1} + \mathscr{E}_t$$

With the specifications of λ_t and $M_{t,t+1}$, the state equation under the Q-measure is,

$$\xi_t = c^Q + \Phi^Q\xi_{t-1} + \mathscr{E}_t^Q$$

where

$$c^Q = c - \lambda\Sigma$$
$$\Phi^Q = \Phi - \Lambda\Sigma$$

Rewriting (4) into $i_t = \delta_0 + \delta_1\xi_t$, the model implies that the interest rate on an n-quarter nominal bond as of the last day of Quarter t is given by:

$$i_{n,t} = a_n + b_n'\xi_t \tag{2.1}$$

where

$$b_n = \frac{1}{2}\left[I + \Phi^Q + \cdots + \left(\Phi^Q\right)^{n-1}\right]\delta_1$$
$$a_n = \delta_0 + \left[b_1' + 2b_2' + \cdots + (n-1)b_{n-1}'\right]c^Q/n - \left[b_1'\Sigma\Sigma'b_1 + \cdots + (n-1)^2 b_{n-1}'\Sigma\Sigma'b_{n-1}\right]/2n$$

2.2.3 Daily changes in interest rates

The pricing equation above connects Treasury yields to important macroeconomic variables. It provides a natural way of interpreting the financial market's response to macroeconomic events and analyzing the information flow through which market participants learn about the aggregate state of economy. I explain how to do so in this subsection.

Suppose bond investors maintain the same pricing kernel day by day within a quarter. The yield curve at the end of any day s can be expressed as a snapshot of Equation (2.1),

$$i_{n,t}(s) = a_n' + b_n' \xi_t(s)$$

where $i_{n,t}(s)$ denotes the yield of maturity n at the end of Day s in Quarter t.

Differencing the equation above by one day provides a mapping between the change in the yield in any given day s and the change in the state vector on that day. If a fraction of information about the five macro shocks arrives to the market on Day s and the fraction is summarized in a vector $w(s) = \left(w_{g,t}(s), w_{a,t}(s), w_{\eta,t}(s), w_{v,t}(s), w_{z,t}(s) \right)'$, the mapping becomes the following,

$$i_{n,t}(s) - i_{n,t}(s-1) = b_n' \mathscr{E}_t(s)$$

where $\mathscr{E}_t(s) \sim N\left(0, \Omega \operatorname{diag}[w(s) \odot w(s)] \Omega'\right)$.

The main focus of this paper is on the revelation of information through macroeconomic events, so I look particularly at those event days and associate each type of event with a weight vector.

2.3 Data

For the macro variables, I use the first three releases of the real GDP to calculate the year-over-year real GDP growth, and those of the PCE Price Index to calcualte a year-over-year inflation rate. Both series come from the "Real-Time Data Set for Macroeconomists" by the Federal Reserve Bank of Philadelphia.

I obtain the daily fitted yields with 1-, 2-, 5-, 7-, and 10-year of maturity from Gurkaynak et al. (2006). For the short nominal interest rate at quarter ends, I use the 3-month Treasury bill rate in the secondary market from the Board of Governors' Release of "H.15 Selected Interest Rates".

2.4 Estimation

In this section, I explain the procedure with which I determine the model parameters for the framework. The procedure is based on a state-space representation of the macro block and the asset pricing block.

The state equation of the state-space representation is derived from a rational expectations solution to the macro block. In doing so, I assume that investors are able to forecast current and future macro variables correctly on average at the end of each quarter. This is a realistic assumption, as Gilbert (2011) provides evidence that equity investors were able to infer accurately information about revised statistics from initial releases. This approach circumvents the difficult decision that econometricians usually have to make on which release to use for measuring a macro variable. With the state equation derived from the rational expectations approach, bond prices later on are aligned with the true information set of investors.

Specifically, collect the deviations of the three macro variables from their stochastic steady states into a vector $x_t = \left(\tilde{y}_t, \tilde{\pi}_t, \tilde{i}_t\right)'$. Stack the five fundamental shocks into a vector $u_t = \left(v_t, z_t, \eta_t, a_t, g_t\right)'$. The rational expectations solution method of Klein (2000) is convenient to yield the following solution to the model.

$$x_t = Px_{t-1} + Qu_t + S\Sigma e_{t+1}$$

where

$$
\begin{aligned}
e_{t+1} &\sim N\left(0, I_{5\times 5}\right) \\
\Sigma &= \text{diag}\left(\sigma_v, \sigma_z, \sigma_\eta, \sigma_a, \sigma_g\right) \\
S &= \begin{pmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}
\end{aligned}
$$

Augmenting the equation with a number of lags gives the state equation of the state-space representation,

$$
\underbrace{\begin{pmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ u_{t+1} \end{pmatrix}}_{\xi_t} = \underbrace{\begin{pmatrix} P & 0 & 0 & 0 & Q \\ I & 0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & 0 & 0 & 0 & \Phi \end{pmatrix}}_{F} \underbrace{\begin{pmatrix} x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ u_t \end{pmatrix}}_{\xi_{t-1}} + \underbrace{\begin{pmatrix} S \\ 0 \\ 0 \\ 0 \\ I \end{pmatrix}}_{\Omega} \Sigma e_{t+1}
$$

Measurements of the state vector fall into two groups. The first group contains macro data on the output growth, the inflation and the short nominal interest rate. The measurement equations connecting them to the state vector can be written as follows.

$$
\begin{aligned}
y_{j,t-4,t} &= \Delta y + \frac{1}{4} \sum_{j=0}^{3} \tilde{y}_{t-j} + v_{j,t}^{y} \\
\pi_{j,t-4,t} &= \pi_t^* + \tilde{\pi}_t + v_{j,t}^{\pi} \\
i_t &= \tilde{i}_t + \pi_t^*
\end{aligned}
$$

where $y_{j,t-4,t}$ is the j-th release of the year-over-year real GDP growth from Quarter $t-4$ to t,

$\pi_{j,t-4,t}$ is the j-th release of the year-over-year PCE inflation rate from Quarter $t-4$ to t, i_t is the three-month Treasury bill rate on the last day of the Quarter t, $v_{j,t}^k$ is a measurement error associated with variable k in the j-th release.

I assume that each data release adds only a news component to the information set of an investor. Therefore, the measurement errors associated with both output and inflation are parameterized to decrease with the number of revisions:

$$\begin{pmatrix} v_{3,t}^k \\ v_{2,t}^k \\ v_{1,t}^k \end{pmatrix} \sim \begin{pmatrix} \sigma_{k,3}^2 & 0 & 0 \\ 0 & (\sigma_{k,2}+\sigma_{k,3})^2 & 0 \\ 0 & 0 & (\sigma_{k,1}+\sigma_{k,2}+\sigma_{k,3})^2 \end{pmatrix} \qquad k = y, \pi$$

The second group of measurements contain data on yields of 1, 2, 5, 7, and 10 years of maturity at the end of each quarter. I assume that they are measured with i.i.d errors.

$$i_{n,t} = a_n' + b_n' \xi_t + v_{i,n,t} \tag{2.2}$$

where $v_{i,n,t} \sim N(0, \sigma_n^2)$ is the measurement error capturing potentially the mis-pricing of the n-quarter bond yield due to market dysfunctions, liquidity disruptions, etc.

Let Θ collect all the parameters of the framework. It can be divided into three groups $\Theta = \left(\Theta^m, \Theta^y, \Theta^d\right)'$.

$$\begin{aligned} \Theta^m &= \left(\mu_{y,1}, \mu_{y,2}, \mu_{\pi,1}, \mu_{\pi,2}, \phi_y, \phi_\pi, \rho_y, \rho_\pi, \beta, \kappa, \tau_i, \mathrm{vec}(\Sigma)', \{\sigma_{k,h}\}_{k=y,\pi,h=1,2,3}\right)' \\ \Theta^y &= \left(\lambda', vec(\Lambda), \{\sigma_n\}_{n=4,8,20,28,40}\right)' \\ \Theta^d &= \{w_s'\}_{s=1}^S \end{aligned}$$

The first group Θ^m characterize the dynamics of macro variables. A subset of them are calibrated to standard values in the New-Keynesian literature (see Table 2.1) . The measurement errors associated with the releases and the standard deviations of fundamental shocks are chosen to maximize the likelihood function of the state-space model where Equation (2.2) is the measurement equation.

Table 2.1. Calibration

parameter	value
$\mu_{y,1}$	0.36
$\mu_{y,2}$	0.63
$\mu_{\pi,1}$	0.00
$\mu_{\pi,2}$	0.77
β	0.11
ϕ_{π}	1.50
ϕ_{y}	0.80
κ	0.01

The second group, Θ^y, contains parameters governing the risk aversion of bond investors. To estimate λ, Λ and σ_n's, I choose their values to maximize the likelihood function of the state-space model where quarter-end data on the yields of 1-year, 2-year, 5-year, 7-year and 10-year maturities act as observables.

The last group Θ^d pertains to the fractions of fundamental innovations being allocated to each type of data release. For a release type s, the weight vector is estimated to approximate the sample variance of the yield changes across it as closely as possible. That is,

$$\widehat{w(s)} = \arg\min_{w(s)} \sum_{n=1}^{N} \left| \widehat{Var}[i_{n,t}(s)] - b_n' F \Omega \operatorname{diag}[w(s) \odot w(s)] \; \Omega' F' b_n \right|$$

2.5 Results and discussions

This section discusses the results estimated from the framework above. I first evaluate the model fit. Then, I characterize the information flow during various macroeconomic events that led to the substantial movements of the yield curve we see in the data.

2.5.1 Model fit

The model features two trend variables. Figure 2.1 plots their filtered estimates. The long-run inflation expectation declined mostly before 1998 and has remained at a steady level of around two percent since 1998. This is consistent with the change in the Fed's policy implementation that has successfully anchored the long-term inflation expectations since 1994. On the other hand, the equilibrium real rate of interest has displayed a more dramatic downward trend since 2000.

Table 2.2 shows the variances of the measurement errors associated with the first three releases of real GDP growth and PCE inflation. By construction, the initial releases of both statistics are less accurate than later revisions. What is interesting is that the third estimates do not seem to add much more information than the second.

The model fits the yields of 1, 2, 5, 7, 10 years of maturity remarkably well. Table 2.3 shows the measurement errors of actual yields in the data when compared to their model predictions. They are so small that the fitted curves are almost indistinguishable from the data, as shown in Figure 2.2.

Table 2.2. Variances of measurement errors in data releases

	1st	2nd	3rd
PCE inflation	0.12	0.07	0.07
Real GDP growth	0.17	0.11	0.11

2.5.2 Variance decomposition

Figure 2.3 plots the changes in Treasury yields with maturities from 1 quarter to 10 years in response to each innovation of the size of its quarterly variation. The demand shock has a hump-shaped effect on the yield curve, with the largest effect taking place on the maturity of two years. The monetary shock is the least persistent, exerting the most impact on the short end of the yield curve. The shock to the r star changes the 1-year yield little, but its impact on the yield curve increases monotonically as the maturity rises.

Given the calibrated effect of each shock on the yield curve, I assign weights to these shocks so that a combination of their effects on the yield curve best matches the yield changes in the data around a given macro event. In each panel of Figure 2.5 and 2.4, each red dot displays the sample variance of the change in the yield of a given maturity around a specific event while the blue curve shows the model-implied variance curve. Using the fundamental shocks to identify the information revealed in a data release instead of a particular series, the model is able to match the large variations in yields of all maturities across different types of events.

To see which macroeconomic shock drives the movement of the yield curve for each event, I decompose the variance of a yield into contributions of the five shocks. For each type of event s, the contribution of shock j to the variance is calculated as

$$\text{Fraction}_{j,s,n} = \frac{b_n' F\Omega \text{ diag}\left[e_j \odot w(s)\right] \text{ diag}\left[e_j \odot w(s)\right] \Omega' F' b_n}{b_n' F\Omega \text{ diag}[w(s)] \text{ diag}[w(s)] \Omega' F' b_n}$$
$$j: \text{ shock} \quad s: \text{ event type} \quad n: \text{ maturity}$$

where e_j is a 5×1 vector with 1 in the j-th element and 0 everywhere else.

Figure 2.6 and 2.7 display the variance decomposition of yield changes given our estimated weights. Every panel considers a macro event. Within each panel, the x-axis lists the five maturities that I aim to match. For each maturity, the y-axis shows the proportion of the variance of yield changes that is attributed to each of the five shocks, defined as follows and labeled with five different colors.

Several patterns emerge as common features across different types of macroeconomic events. First, investors learn information about all the fundamental shocks across all seven data releases. The decomposition here displays the multi-dimensional nature of information revelation of these events. Second, the demand shock plays a predominant role in driving the yields with less than 5 years of maturity regardless of the type of the event. Consistent with the hump-shaped effect we saw earlier, the 2-year yield is affected the most by it. Third, the shock to the r star has an increasingly large footprint in moving the yields as the maturity goes up. In fact, it becomes the most important source of movement for the 10-year yield for all eight events, partially explaining why the long end of the yield curve is so volatile in event studies. Fourth, the supply shock contributes to the yield curve movements like a demand shock but to a much less degree. Finally, an FOMC announcement not only surprises the market with a monetary shock but also reveals information about economic fundamentals in both the short and the long run. This is consistent with the Fed information effect documented in the literature.

2.5.3 Importance of macro events

Finally, I ask which macro event was the most critical for revealing information about each shock. To compare the events against each other, I compute for each shock j its proportion that got revealed by event of type s among all the events:

$$\text{Importance}_{j,s} = \frac{w_j^2(s)}{\sum_{s=1}^{S} w_j^2(s)}$$

$$j: \text{ shock} \quad s: \text{ event type}$$

In Figure 2.8, each vertical bar represents an innovation to one of the five equations in our macro model. Each color block in a bar shows the contribution of an event to investors' learning of the corresponding innovation, measured by the *Importance* index above. Two findings immediately follow. First, the employment report is the most informative macroeconomic event for all innovations. It tells investors more information about the long-run inflation, the monetary shock and the supply shock and less so about the equilibrium real rate of interest and the demand shock. Second, FOMC announcements disclose a disproportionally large amount of information regarding the monetary shock relative to data releases. This is expected given the nature of a monetary policy announcement.

2.6 Conclusion

This paper proposes and estimates a macro-based bond pricing model. In the model, Treasury bonds are priced in line with investors' true information set as macroeconomic statistics are released only with a lag. I use the model to recover the nature of information that investors learn at each macroeconomic event. I find that the shock to the IS curve is most responsible for the hump-shaped change in the yield curve for a variety of data releases. In addition, learning about the equilibrium real rate of interest results in the high volatility of long-term yields for both data releases and FOMC announcements.

Several avenues for future research are in line. First, it would be interesting to extend the sample in this study to the zero lower bound period and its afterward. Second, the current study rules out the direct role that uncertainty may play in determining the first moment of macro dynamics. Allowing such a possibility would require a more involved analysis and is a next step worth taking.

Table 2.3. Standard deviations of measurement errors in yields

1-year	2-year	5-year	7-year	10-year
0.0475	0.0061	0.0006	0.1598	0.0109

Table 2.4. Standard deviation of quarterly innovations

σ_v	σ_z	σ_η	σ_a	σ_g
0.1323	0.3558	0.6838	0.4271	2.6683

Table 2.5. Risk prices

	$e_{v,t}$	$e_{z,t}$	$e_{\eta,t}$	$e_{a,t}$	$e_{g,t}$
λ	-2.3062	-7.0609	1.9232	-0.0903	-3.3061
Λ	0.0266	0.0274	0.1567	0.0029	-0.0569
	0.0130	-0.2242	0.0294	0.0455	0.1201

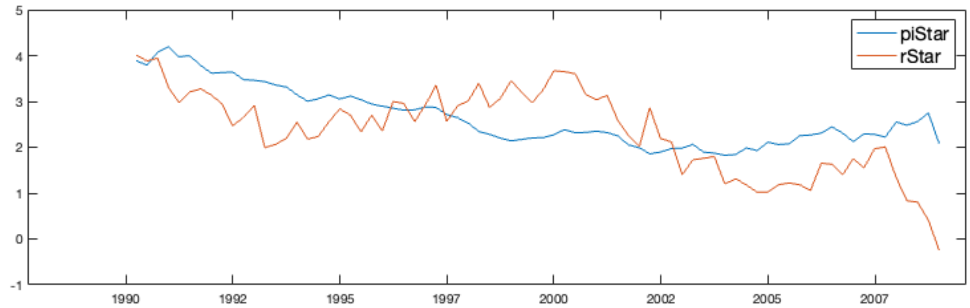

Figure 2.1. Trend variables

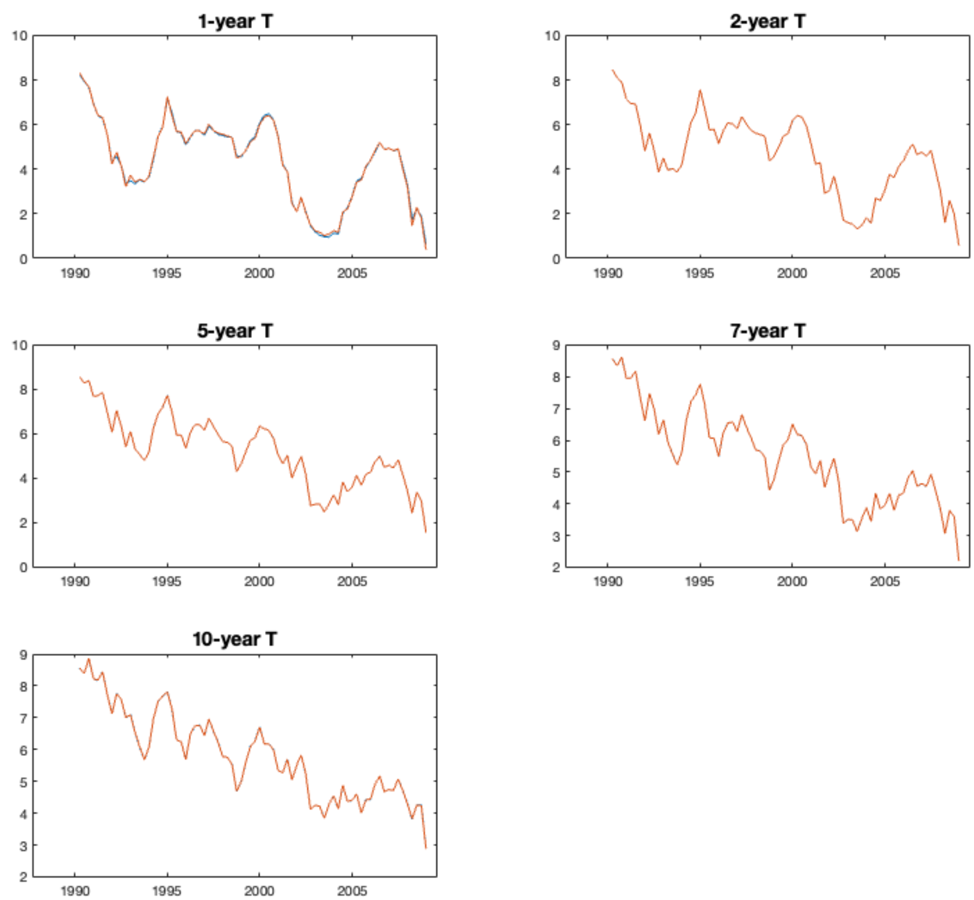

Figure 2.2. Fitted yields

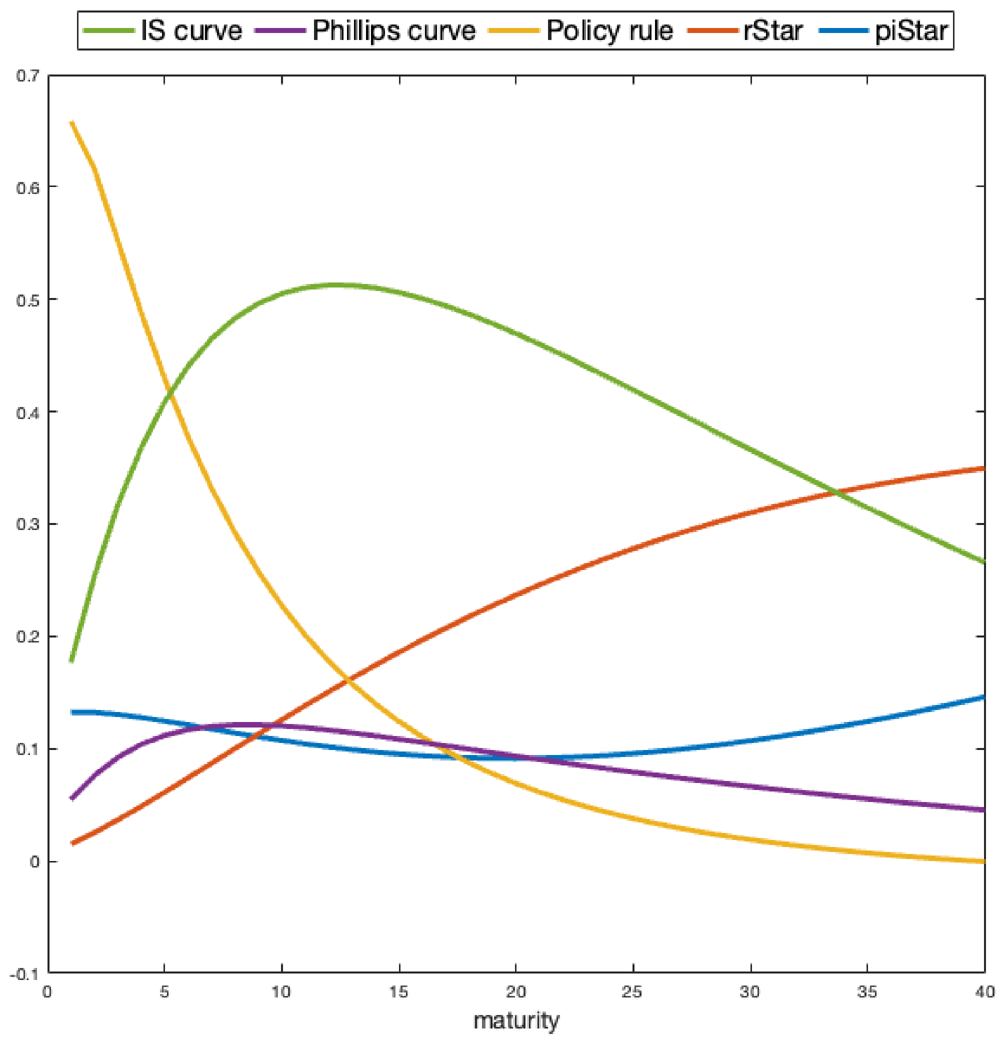

Figure 2.3. Responses of the yield curve to macroeconomic shocks by maturity

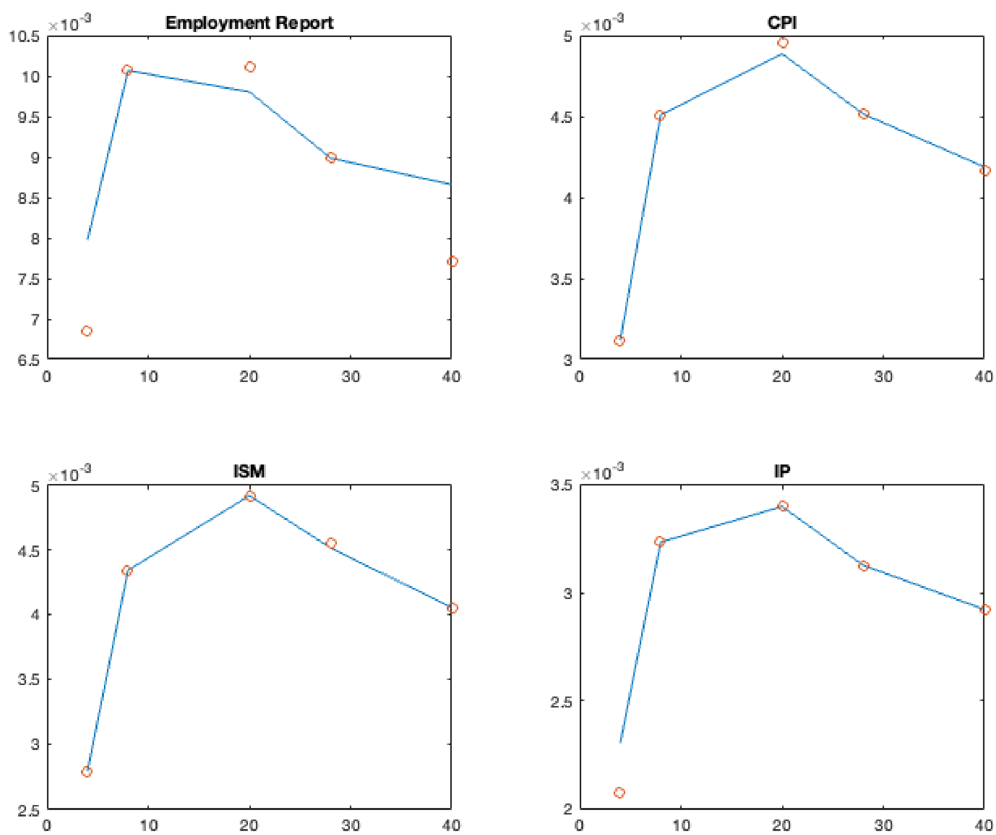

Figure 2.4. Fitted yield responses to data releases

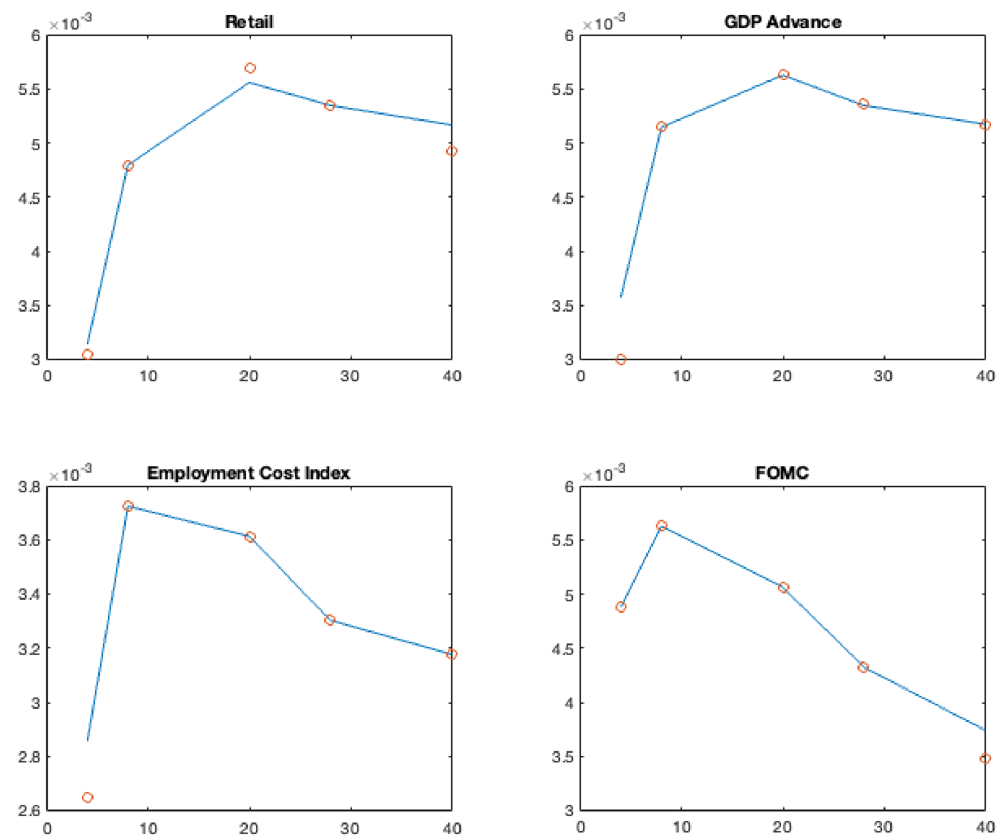

Figure 2.5. Fitted yield responses to data releases

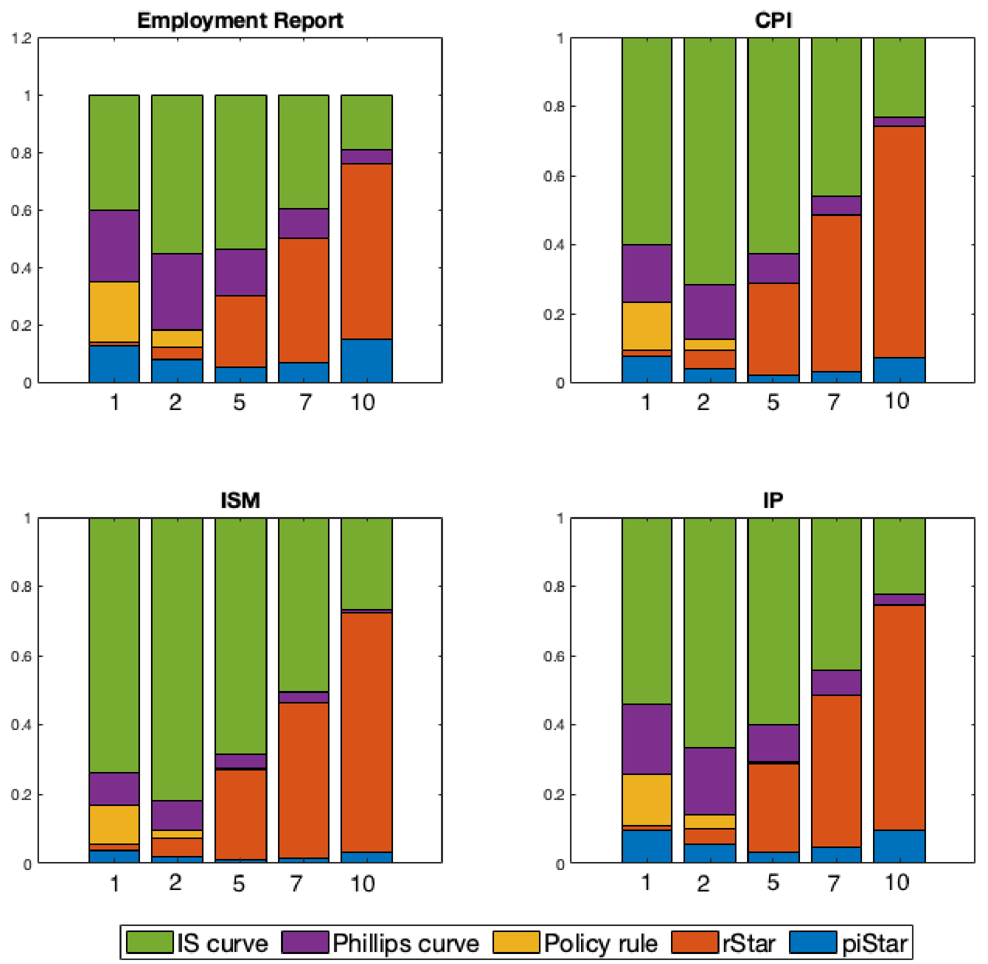

Figure 2.6. Variance decomposition

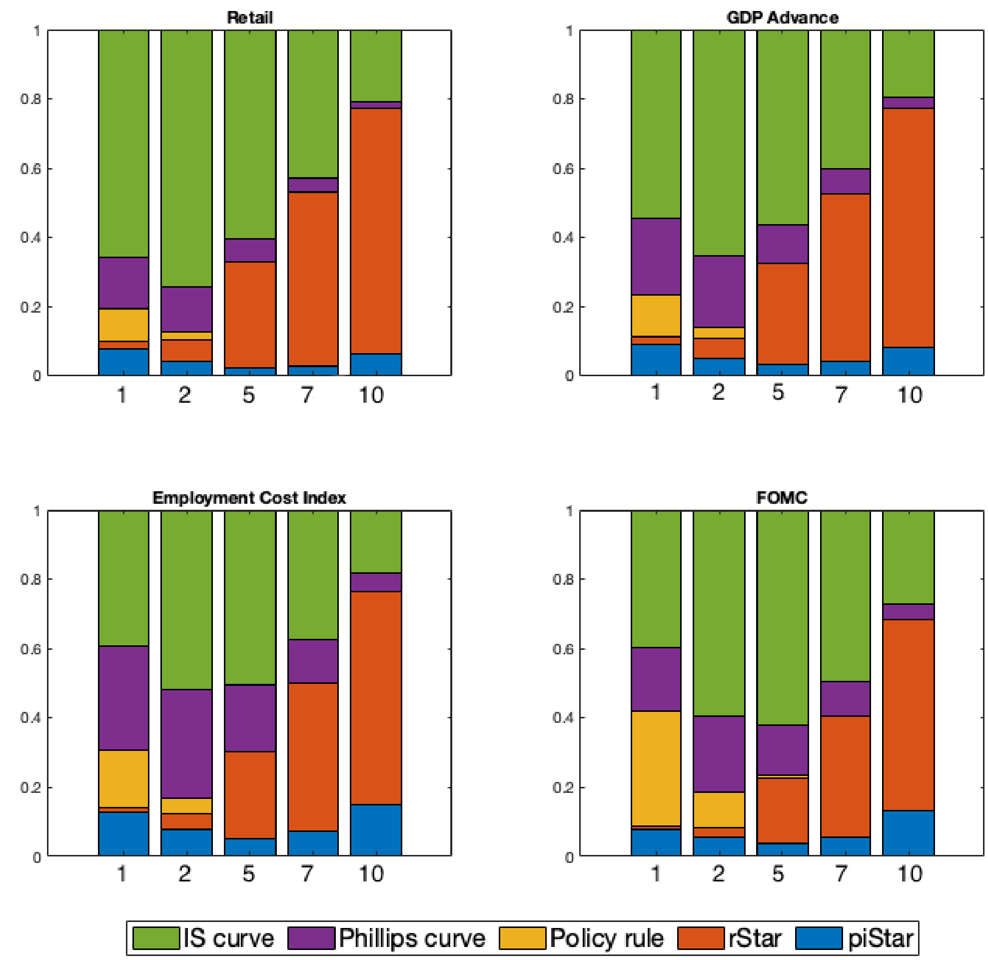

Figure 2.7. Variance decomposition

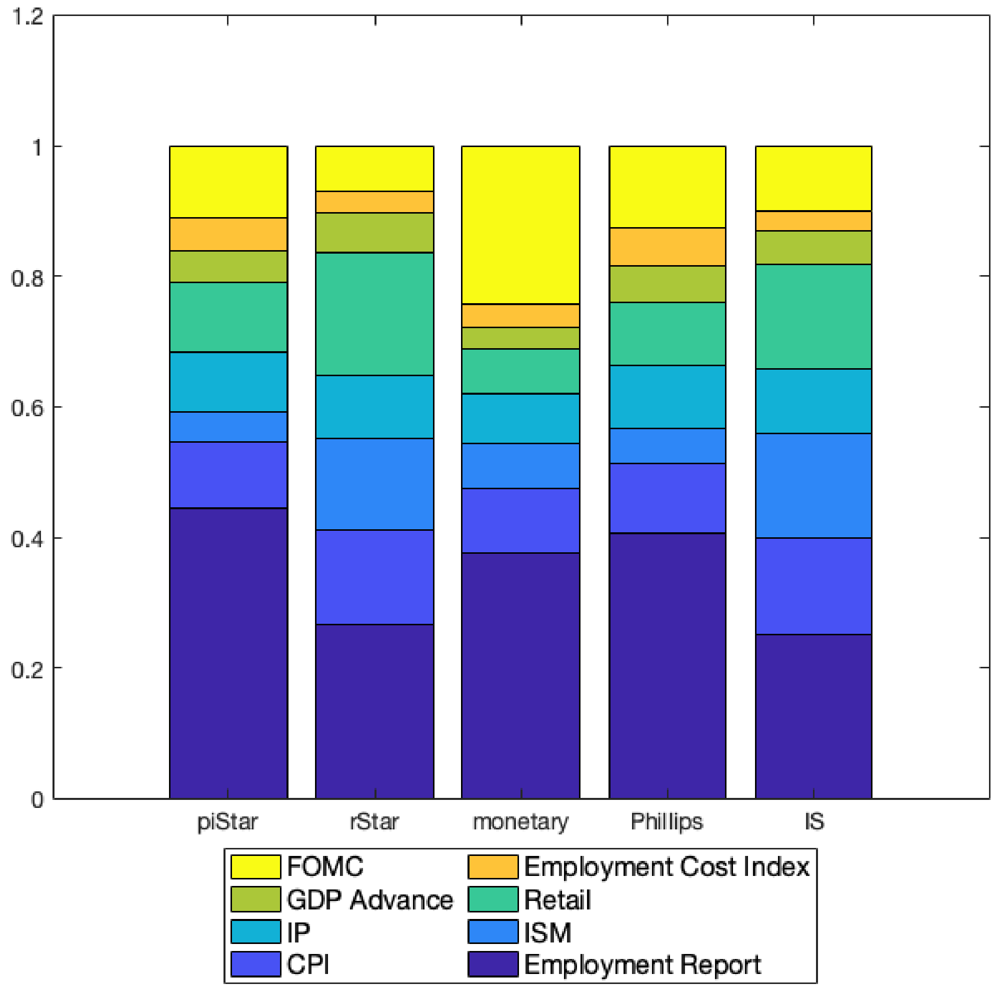

Figure 2.8. Rank of events for each macro shock

Chapter 3

A Dynamic Factor Analysis on Idiosyncratic Volatilities of Stock Returns

3.1 Introduction

The main goal of this paper is to study the pricing implications of idiosyncratic volatilities in the cross section of stock returns. In order to do so, I propose a state-space modeling approach to decomposing a stock's idiosyncratic volatility into a common component and an idiosyncratic one.

Specifically, I consider a market-factor model with heteroskedastic idiosyncratic errors for a panel of stock returns. The *levels* of returns are modeled as follows.

$$r_{jt} = \alpha_j + \underbrace{\beta_{jt} r_{mt}}_{\text{systematic level risk}} + \underbrace{u_{jt}}_{\text{idiosyncratic level risk}} \qquad j = 1, \ldots, N$$

where r_{jt} is the excess return of Stock j in Day t; $\beta_{jt} r_{mt}$ is the systematic risk component capturing Stock j's time-varying exposure to the market risk in Day t; u_{jt} is the idiosyncratic risk component.

Our main focus is on the second moments of idiosyncratic risk components, u_{jt}'s. I characterize u_{jt}'s in a stochastic volatility model with a novel feature: stochastic volatilities of all u_{jt}'s share a common factor following an AR(1) process. I shall call this common factor my measure of common idiosyncratic volatility from now on (denoted by ξ_t below).

This modeling choice is motivated by the recent finding that idiosyncratic volatility proxies of stock returns in the CRSP universe co-move closely over time (Herskovic et al., 2016). My common factor summarizes the overall, undiversifiable level of idiosyncratic volatilities in the cross section. As such, one could think of the model as predicting idiosyncratic volatilities conditioning on not only its own past values but also other stocks'. As a result, we are able to fit the panel of idiosyncratic volatilities in sample better than a univariate GARCH(1,1).

Unlike the existing studies that either take a simple average of or conduct a principal component analysis on idiosyncratic volatilities, I employ an explicitly dynamic factor approach so my measure of the common idiosyncratic volatility is persistent. For the feasibility of estimation, I make an assumption that only one volatility factor completely explains conditional idiosyncratic volatilities. It turns out that modeling the persistence explicitly is necessary; my model fits the panel of IVs better than a static principal component approach. The assumption is also sufficient; the model is able to forecast IV's as well as GARCH(1,1) in the short run and better in the medium- to long- run.

Due to the advantage of the modeling choice, my measure of the common idiosyncratic volatility has a daily frequency. As a result, I am assess whether the volatility factor is priced in the cross section of stock returns at the daily frequency in different sub-samples. In contrast with most existing studies that use monthly idiosyncratic volatility measures, I find that the daily measure is not a strong predictor of stock returns in the cross-section.

The paper is related to a few strands of literature. First, it is connected to a large literature on studying the pricing implications of idiosyncratic volatilities. Ang et al. (2006) are among the first ones to show that stocks with high idiosyncratic volatilities earn low returns on average. Chen and Petkova (2012) explain the finding by proposing the average volatility as a pricing factor. In light of the co-movement of idiosyncratic volatilities, Herskovic et al. (2016) propose a common factor in stock variances that is orthogonal to the market variance and also priced in the stocks. This paper is similar to the latter two studies in that it focuses on the common, systematic part of idiosyncratic volatilities and assesses its potential in pricing stocks in the cross section.

However, this paper differs from the previous ones by providing a dynamic view on idiosyncratic volatilities. The dynamic view disentangles the conditional part of volatilities from unpredictable disturbances and allows us to produce a *daily* volatility factor.

Closest to this paper is Barigozzi and Hallin (2016). They apply a generalized dynamic factor approach to the market volatility and a panel of idiosyncratic volatilities. Sharing the same dynamic view on idiosyncratic volatilities, this paper chooses a different state-space approach. To this regard, I view the current study as a complement to their work.

Finally, I offer a parsimonious way to conduct multivariate stochastic volatility modeling. Harvey et al. (1994) proposed a stochastic volatility model with a common factor and estimated it with a quasi maximum-likelihood method. I generalize the model by allowing individual heterogeneous constant terms and factor loadings. I also provide an MCMC estimation procedure in our setting. Carriero et al. (2016) apply a similar model to a VAR setting where the stochastic volatilities of the VAR errors share a common volatility component.

The remainder of the paper is organized as follows. Section 3.2 describes my stochastic volatility model with a common factor for idiosyncratic components of stock returns. Section 3.3 explains a Bayesian Gibbs sampling procedure to estimate the model. Section 3.4 describes my choice of data. Section 3.5 shows the estimation results. Finally, I study the pricing implication of our measure in the cross section of stock returns in section 3.6.

3.2 Model

I consider a panel of returns for stocks, $j = 1, \ldots, N$, in periods, $t = 1, \ldots, T$. Their levels are captured by a market-factor model with heteroskedastic idiosyncratic errors.

$$r_{jt} = \alpha_j + \underbrace{\beta_{jt} r_{mt}}_{\text{systematic risk}} + \underbrace{u_{jt}}_{\text{idiosyncratic risk}} \qquad j = 1, ..., N$$

where r_{jt} is the excess return of Stock j in Day t; r_{mt} is the excess market return in Day t; β_{jt} measures the time-varying exposure of Stock j to the market risk in Day t. The heteroskedasticity of the idiosyncratic risk component, u_{jt}, is described by a stochastic volatility model.

$$\begin{aligned} u_{jt} &= \sigma_{jt}\varepsilon_{jt} \\ \varepsilon_{jt} &\sim iidN(0,1) \\ \sigma_{jt} &= e^{\frac{1}{2}h_{jt}} \end{aligned}$$

where I call h_{jt} the idiosyncratic stochastic volatility of Stock j in Day t. As a novel feature of the model, I assume that the dynamics of all the *conditional* idiosyncratic volatilities are completely driven by a common potentially persistent factor, ξ_t.

$$\begin{aligned} h_{jt} &= \mu_j + \gamma_j \xi_t \\ \xi_t &= \phi \xi_{t-1} + v_t \\ v_t &\sim N(0,1) \\ E(v_t \varepsilon_{jt}) &= 0 \qquad j = 1, \ldots, N \end{aligned}$$

3.3 Estimation method

I estimate the model in two steps following the literature on idiosyncratic volatilities. In the first step, $\hat{\alpha}_{jt}$ and $\hat{\beta}_{jt}$ are re-estimated every month by OLS. This is to capture the potentially time-varying systematic exposure to the market risk. The idiosyncratic risk component $\hat{u}_{jt}$ is then constructed as $\hat{u}_{jt} = r_{jt} - \hat{\alpha}_{jt} - \hat{\beta}_{jt} r_{mt}$.

In the second step, I estimate μ_j, γ_j and ϕ by a Bayesian Gibbs sampling procedure. Note that once $\hat{\alpha}_{jt}$ and $\hat{\beta}_{jt}$ are known the model can be transformed into the following state-space model with non-Gaussian disturbances. Specifically, it can be written in a matrix form:

$$\underbrace{\begin{bmatrix} ln(\hat{u}_{1t}^2) \\ ... \\ ln(\hat{u}_{Nt}^2) \end{bmatrix}}_{\text{Observables } ln(\hat{u}^2)} = \underbrace{\begin{bmatrix} \mu_1 \\ ... \\ \mu_N \end{bmatrix}}_{\mu} + \underbrace{\begin{bmatrix} \gamma_1 \\ ... \\ \gamma_N \end{bmatrix}}_{\gamma} \xi_t + \underbrace{\begin{bmatrix} ln(\varepsilon_{1t}^2) \\ ... \\ ln(\varepsilon_{Nt}^2) \end{bmatrix}}_{ln(\varepsilon_t^2)}$$

$$\xi_t = \phi \xi_{t-1} + v_t \qquad E(v_t v_t^{'}) = 1$$

$$ln(\varepsilon_{jt}^2) \sim iid\ ln\chi^2(1)$$

To deal with the non-Gaussian disturbances in the observation equation, I generalize the method of Chib and Greenberg (1998) to a multivariate setting where I use an offset mixture of normals approximation to a log-chi-square distribution. Conditioning on knowing which normal distribution $ln(\varepsilon_{jt}^2)$ is approximated by (indexed by $s_{jt} \in \{1, \ldots, 7\}$), the model has a Gaussian state-space representation. Specifically, I divide our parameters and state variable besides s_{jt}'s into three blocks and the Gibbs sampler proceeds as follows.

0. Initialize S, μ, γ, ϕ, ξ.

1. $p(S|ln(\hat{u}^2), \mu, \gamma, \phi, \xi)$

2. $p(\phi|ln(\hat{u}^2), \mu, \gamma, S, \xi) = p(\phi|\xi)$

3. $p(\mu, \gamma|ln(\hat{u}^2), S, \gamma, \phi, \xi) = p(\mu, \gamma|ln(\hat{u}^2), \xi)$

4. $p(\xi|ln(\hat{u}^2), \mu, \gamma, \phi, S)$

The posterior of Step 1 has the following distribution. Step 2 and 3 are standard regressions. To sample the posterior distribution in Step 4, I apply a Kalman filtering algorithm provided that ξ

follows a Gaussian distribution.

$$p(s_{jt} = s) = \frac{\frac{\pi_s}{\tau_s} \exp\left[-\frac{(ln(\hat{u}_{jt}^2) - \mu_j - \gamma_j \xi_t - \delta_s)^2}{2\tau_s^2} \right]}{\sum_{i=1}^{7} \frac{\pi_i}{\tau_i} \exp\left[-\frac{((ln(\hat{u}_{jt}^2) - \mu_j - \gamma_j \xi_t - \delta_i)^2}{2\tau_i^2} \right]}$$

To complete our model specification, I list the prior distributions for model parameters below. The hyperparameters, ϕ_0, μ_0's and γ_0, are set by a first-pass quasi maximum likelihood estimation.

$$\begin{aligned}
&\phi \sim N(\phi_0, V_\phi) \\
&\mu_j \sim N(\mu_{j0}, V_{\mu,j}) \qquad \forall j = 1, \ldots, N \\
&\gamma_j \sim N(\gamma_{j0}, V_{\gamma,j}) \qquad \forall j = 1, \ldots, N \\
&\xi_0 \sim N(\xi_{0|0}, P_{0|0})
\end{aligned}$$

3.4 Data

I use daily returns and factors for my analysis. The market factor, r_{mt}, is obtained from the Fama-French data library[1]. For our panel of returns, we choose those of the thirty companies in the Down Jones Industrial Average (DJIA) Index, available from the CRSP database.

I make this choice of the panel for a few reasons. First, it is a good representation of stock performances in various industries. Second, the size of the panel is large enough to illustrate our idea of the dynamic co-movement of idiosyncratic volatilities, and at the same time small enough to render our Bayesian estimation feasible. Even though our panel seems biased towards medium to large companies, we argue that they are sufficient to provide a meaning measure of common idiosyncratic volatilities because large companies tend to drive the dynamics of volatilities of smaller ones (J. et al., 2022; Gabaix, 2011).

[1]Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. See Fama and French, 2021.

The sample spans from July 1, 1963 to June 60, 2009. The components of the DJIA Index gradually changed over this period. As we will elaborate in the evaluation design, I re-estimate the model every two years. For any given two-year period, I include a company in my sample only if: (1) it was a component of the Index for the entire two years; and (2) it was continuously traded during the two years.

3.5 Results

3.5.1 Smoothed estimates of the volatility factor

Figure 3.1 shows the loadings of 29 stocks' idiosyncratic volatilities on the common factor, ξ_t, for the sample period from July 2005 to June 2007. The lower the factor loading is, the higher its exposure to ξ_t is. The unconditional log idiosyncratic volatilities is shown in Figure 3.2.

Figure 3.3 plots the *daily* smoothed common factor in blue for the sample period from July 2005 to June 2007. I employ again a Kalman filtering algorithm for the smoothed inference.

For comparison, I show alongside the log of the square of a widely-used measure of common idiosyncratic volatility in the literature. This measure first defines the idiosyncratic volatility of Stock j in Month m by the sample standard deviation of its daily idiosyncratic components.

$$IVOL_{jm} = \frac{1}{N_m} \sum_{t=1}^{N_m} STD(\hat{u}_{jt})$$

where N_m is the number of trading days in Month m. The common idiosyncratic volatility is then a simple or weighted average of idiosyncratic volatilities across stocks.

$$CIVOL_m = \sum_{j=1}^{N} w_{jm} IVOL_{jm}$$

Because this widely-used measure requires a sufficient amount of data for computing

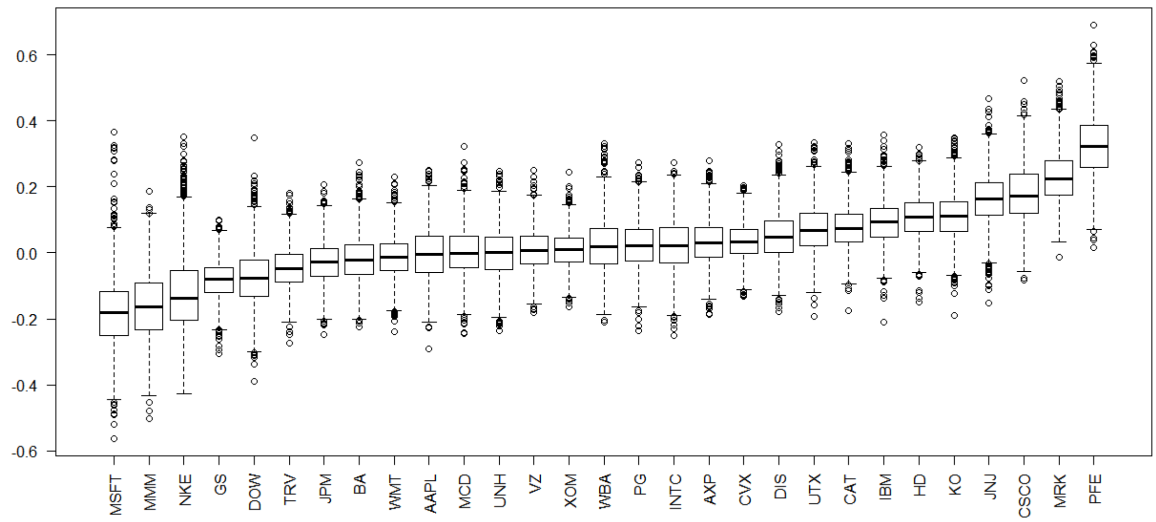

Figure 3.1. γ: loadings of idiosyncratic volatilities on the volatility factor.

Sample: from 2005/07/01 to 2007/06/30

sample standard deviations, it is at most at the monthly frequency. As the figure shows, the monthly measure tracks the average of the daily volatility factors in most periods. However, it misses out much information that arrives daily in the stock market. This point is made clearer in Figure 3.4. I plot there in blue a series of daily shocks to our volatility factor, $\hat{v}_t$, which is the unpredictable part of the smoothed volatility factor.

$$\hat{v}_t = \hat{\xi}_{t|T} - \hat{\phi}\hat{\xi}_{t-1|T}$$

where $\hat{\xi}_{t|T}$ and $\hat{\phi}$ are the medians of our sampled draws from the corresponding posterior distribution after a burn-in period of 3000 draws. For comparison, I plot the first difference of $CIVOL_m$, $\Delta CIVOL_m = CIVOL_m - CIVOL_{m-1}$ in red. This is the pricing factor proposed by Chen and Petkova (2012) that explains the pricing of individual stocks' idiosyncratic volatilites in the cross section. I conclude that the daily measure proposed here captures much more variations of the common idiosyncratic volatility than the typical monthly measures.

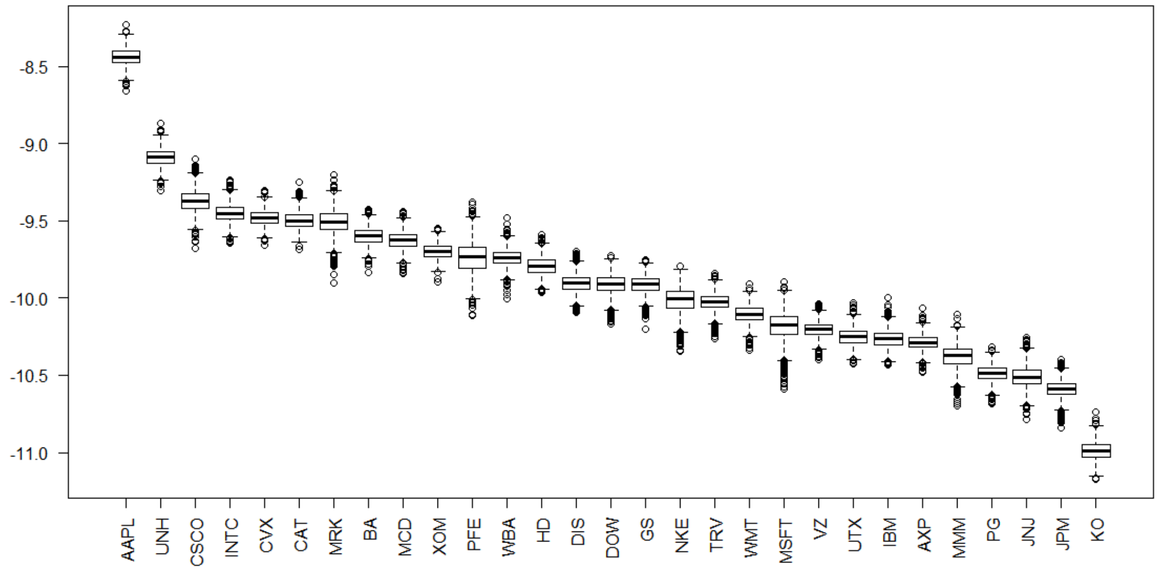

Figure 3.2. μ: unconditional idiosyncratic volatilities.

Sample: from 2005/07/01 to 2007/06/30

3.5.2 Model fit

In this section, I evaluate the ability of the model to fit the panel of idiosyncratic volatilities, $ln(u_{jt}^2)$'s, both in sample and out of sample. The evaluation framework is shown below. I split our data into twenty-three two-period training samples and estimate the model above on each of them. Then for each training sample, I forecast the h-day-ahead idiosyncratic volatilities, $ln(u_{j,t+h}^2)$'s, for $h = 1, \dots, H$ and $H = 400$.

3.5.3 In-sample fit

I first show that my model explains the cross section of idiosyncratic volatilities in sample well. It is more likely to fit the realized variances of daily returns better than a GARCH(1,1) model. GARCH(1,1) emerges as a natural univariate benchmark as it is widely-used for its convenience and performance. I could also compare the model against a univariate stochastic volatility model but I choose not to because of its overwhelming computational burden.

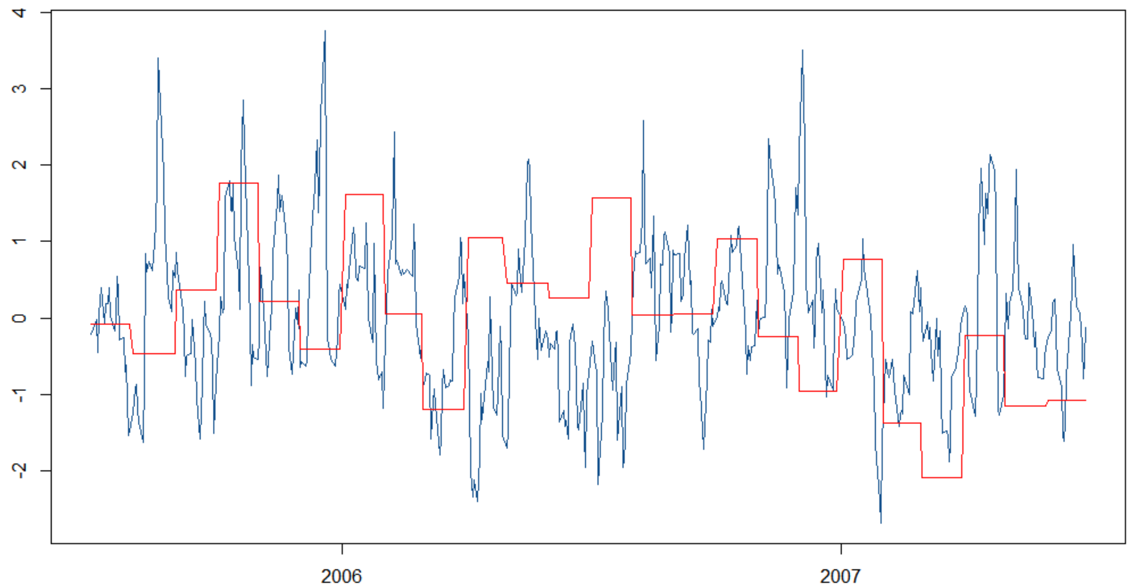

Figure 3.3. Smoothed volatility factor, $\hat{\xi}_{t|T}$

Sample: from 2005/07/01 to 2007/06/30

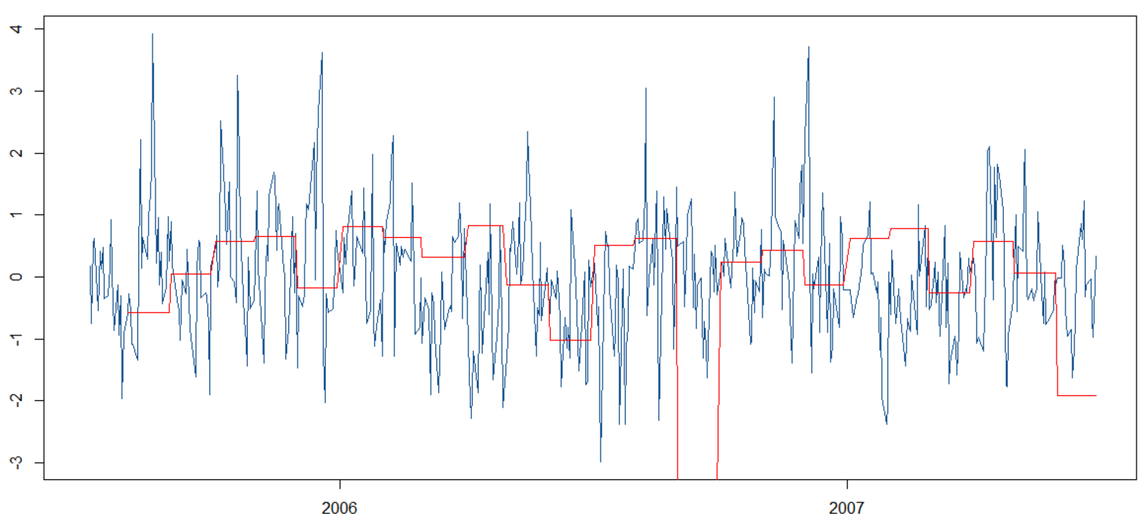

Figure 3.4. Daily shock to our volatility factor, $\hat{v}_t$

Sample: from 2005/07/01 to 2007/06/30

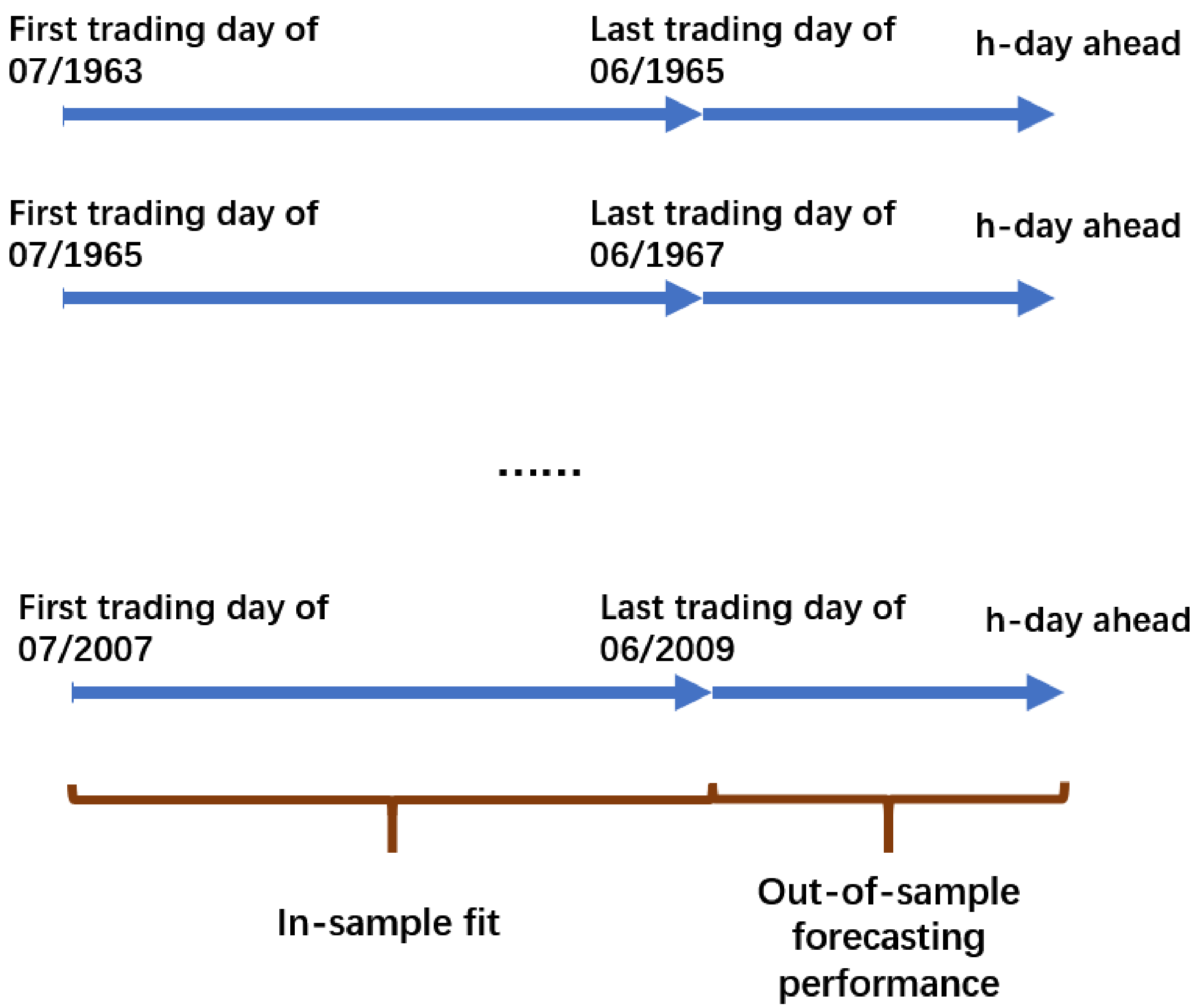

Figure 3.5. Evaluation design

I now construct our fitted values for idiosyncratic volatilities and evaluation metrics. The fitted idiosyncratic volatility for Stock j in Day t builds upon the smoothed volatility factor, $\hat{\xi}_{t|T}$.

$$\hat{\sigma}^2_{jt} = \exp(\hat{\mu}_j + \hat{\gamma}_j \hat{\xi}_{t|T})$$

For Sample s and Stock j, we define the sum of squared errors from Model i by

$$SSE^{(i)}_{js} = \sum_{t \in s} (\hat{\sigma}^{2,(i)}_{jt} - \hat{u}^2_{jt})^2 \qquad i = \{SVC, GARCH(1,1)\}$$

Then our model (denoted by SVC) fits the panel strictly better than GARCH(1,1) if and only if

$$SSE^{SVC}_{js} < SSE^{GARCH(1,1)}_{js}$$

I do this comparison for each stock and each sample. Figure 3.6 displays for each stock the percentage of samples where the model performs strictly better than GARCH(1,1). We see that for all stocks this number exceeds 50%. If I pool all the stocks together, in 71.9% of the twenty-three samples the model provides a smaller sum of squared errors than GARCH(1,1). These results justify the modeling of a factor structure on the idiosyncratic volatilities as imposing it does improve the fitting in sample.

I next show that a *dynamic* factor approach is critical for an improved fit. Duarte et al. (2014) take a static approach and fit the panel idiosyncratic volatilities by their exposure to the first principal component. Using the same metric as above, I compare the model's fitting performance against that of their approach in Figure 3.7. For every stock except for Apple, Inc., my model dominates the principal component approach in more samples. If I pool all the stocks together, in 88.7% of the twenty-three samples, my model provides a smaller sum of squared errors than the other approach.

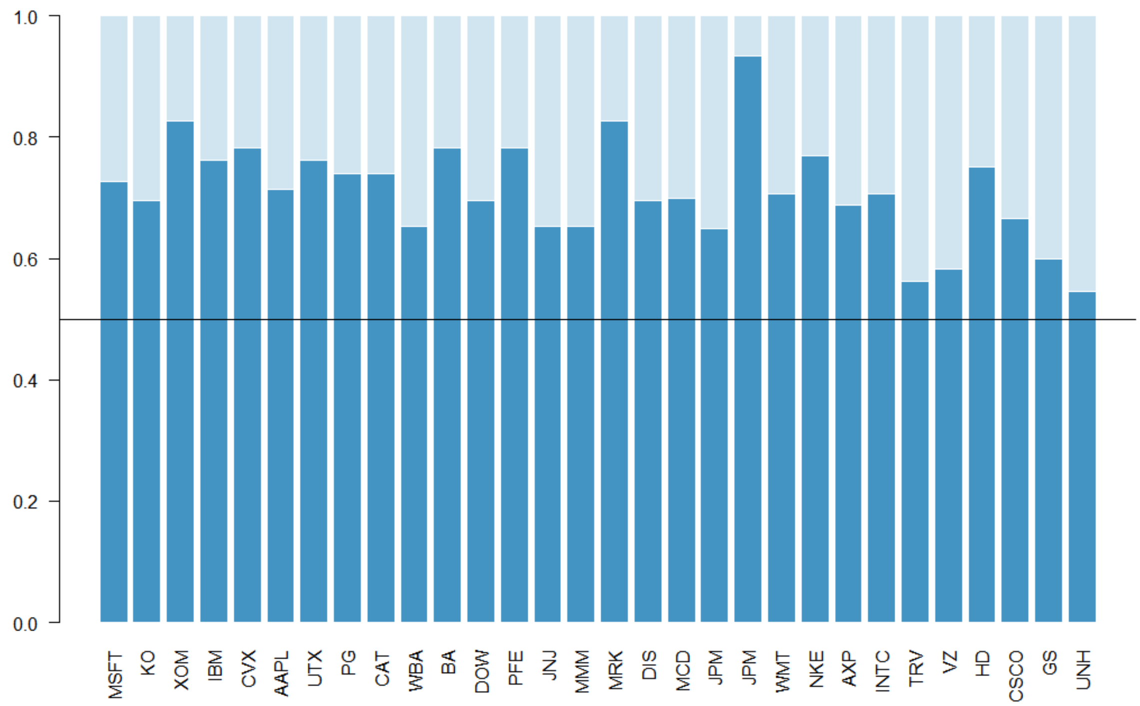

Figure 3.6. Percentage of samples where our model fits better than GARCH(1,1) in sample, by stock

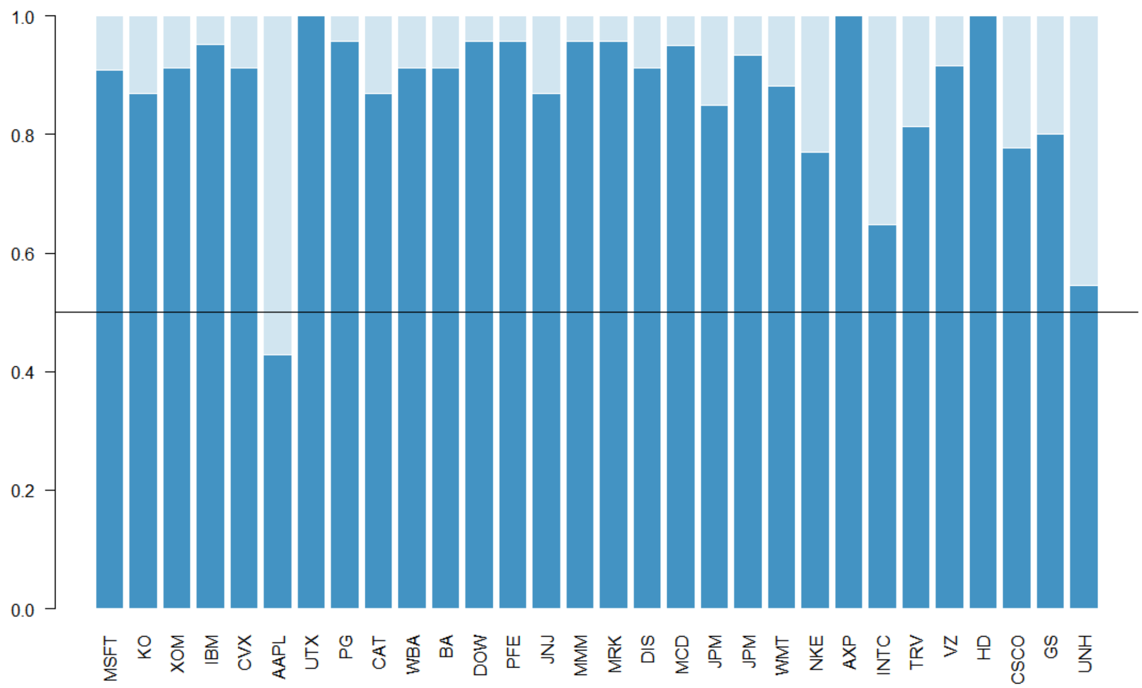

Figure 3.7. Percentage of samples where our model fits better than a principal component approach in sample, by stock

3.5.4 Out-of-sample performances

One of the advantages of the model here over static factor approaches is that I could use it to forecast idiosyncratic volatilities out of sample. In this section, I compare its out-of-sample performances against those of GARCH(1,1). Forecasting horizons ranging from $h = 1$ to $h = 400$ are considered.

Specifically, the forecast of the h-day-ahead idiosyncratic volatility for Stock j in Day t based on a training sample ending in day T is computed as follows.

$$\hat{\xi}_{T+h|T} = \hat{\phi}^h \hat{\xi}_{T|T}$$
$$\hat{\sigma}^{2,SVC}_{j,T+h} = \exp(\hat{\mu}_j + \hat{\gamma}\hat{\xi}_{T+h|T})$$

Using the same metric as for the in-sample fit, Figure 3.8 plots the percentage of samples where our model does better than GARCH(1,1) for h-day ahead forecasting when we pool all stocks together. For horizons ranging from $h = 1$ to $h = 80$ days, GARCH(1,1) outperforms our model.

However, when I summarize the overall magnitude of the deviation of a forecast from its realized counterpart by the root mean squared error (RMSE), my stochastic volatility model with a common volatility factor does a much better job than GARCH(1,1) in the medium- to long-run at forecasting future idiosyncratic volatilities. In particular, I compute for each stock j its RMSEs from the two models as follows. Figure 3.9 shows the $Ratio_{j,h}$ averaged over j for each horizon h. For a forecasting horizon ranging from 30 days to even further into the future, my model produces a much lower RMSE than GARCH(1,1).

$$RMSE^{(i)}_{j,h} = \sqrt{\frac{1}{23}\sum_{T\in s}\left[\hat{\sigma}^{2,(i)}_{j,T+h} - \hat{u}^2_{j,T+h}\right]^2} \qquad i = \{SVC, GARCH(1,1)\}$$
$$Ratio_{j,h} = RMSE^{SVC}_{j,h} / RMSE^{GARCH(1,1)}_{j,h}$$

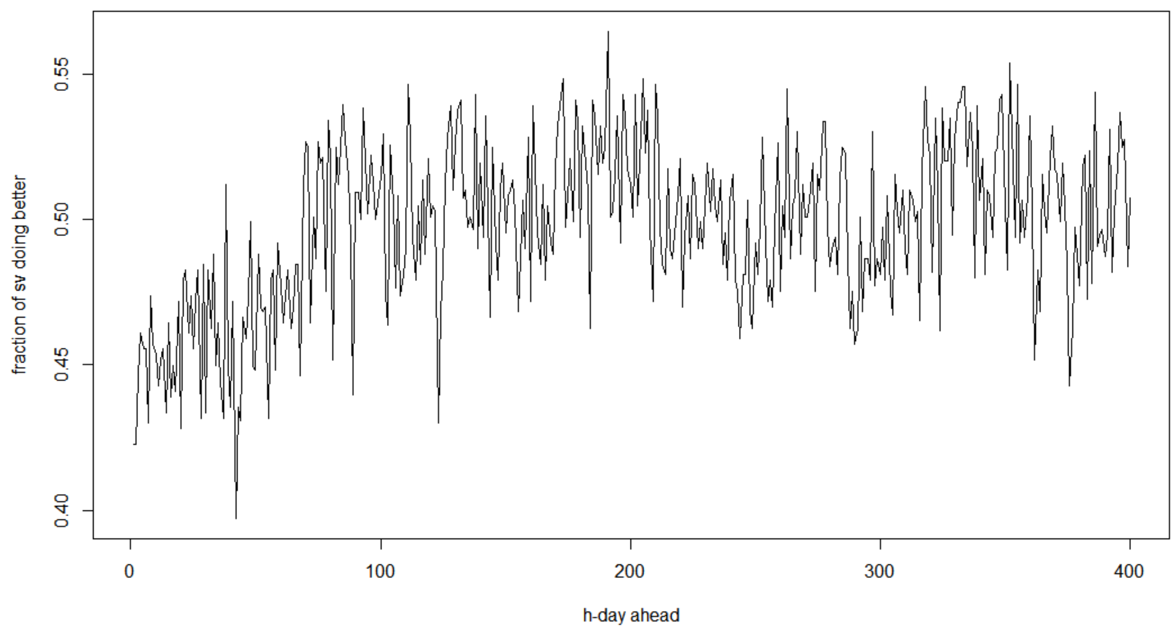

Figure 3.8. Percentage of samples where our model forecasts better than a principal component approach out of sample, by horizon

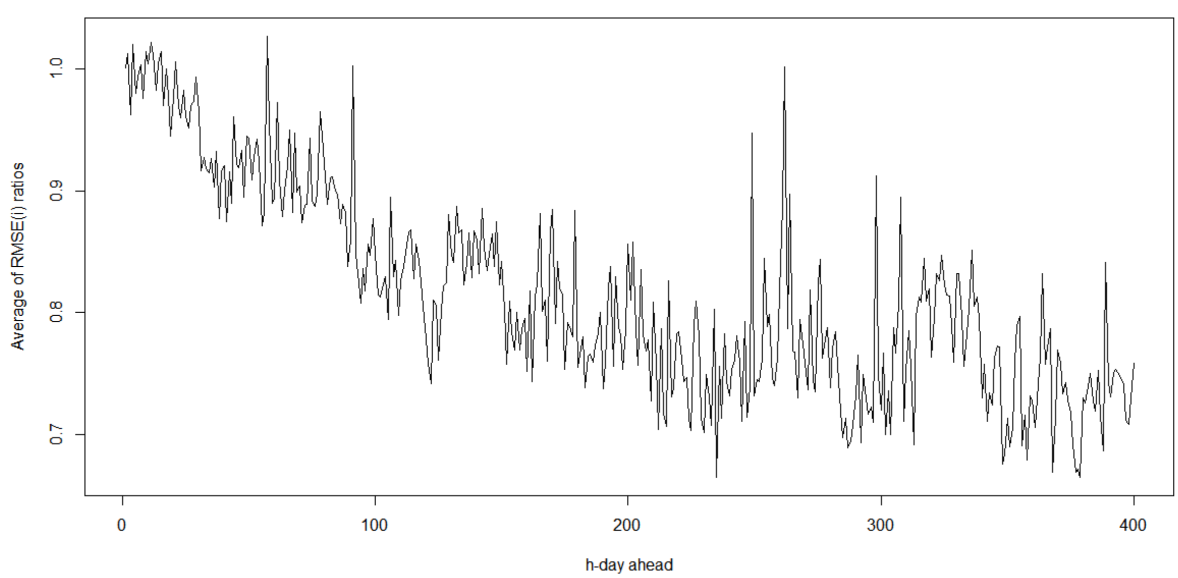

Figure 3.9. Ratios of $RMSE_{jh}$ with our model over $RMSE_{jh}$ with GARCH(1,1) averaged over stocks $j = 1,\ldots,N$, by horizon h

3.6 Pricing implications

With the newly-constructed volatility factor at hand, I revisit the question of whether or not idiosyncratic volatility is priced in the cross section of stock returns. Unlike the rest of the literature that uses monthly measures, my volatility factor enables a pricing analysis at the daily frequency by subsamples. For test assets, I use all the stocks in the CRSP database that were continuously traded in the corresponding sample period.

As a first pass, I answer the question by running a standard Fama-Macbeth procedure (Fama and MacBeth, 1973). Specifically, I estimate the loading of Return j on our volatility factor $\hat{\xi}_{t|T}$ in a time regresion for each stock $j = 1, \ldots, N$. Next, I estimate risk premium of our volatility factor by a cross section regression of unconditional returns on those factor loadings.

$$\text{Time-series: } r_{jt} = \beta_{j0} + \beta_j \hat{\xi}_{t|T} + \varepsilon_{jt}$$

$$\text{Cross-section: } \bar{r}_j = \lambda_0 + \lambda \beta_j + v_j$$

Giglio and Xiu (2021) claim that the standard Fama-Macbeth procedure may uncover risk premia of factors falsely due to a failure to control for omitted variables. I therefore apply their proposed three-pass test on our volatility factor as a robustness check. The basic idea of the test is as follows.

Step 1. Prevailing risk factors are extracted as the first K principal components (PCs) from a principal component analysis on a panel of returns of test assets ($K = 4, 5, 6$).

Step 2. The risk premia of the first K PCs are estimated by a cross sectional regression of returns on the PCs.

Step 3. Run a time series regression of our proposed factor on these K PCs. The risk premium of the factor is the projected loadings on the PCs times their respective risk premium.

Figure 3.10 summarizes the pricing implications of our volatility factor. I find that

From July of	To June of	Fama-Macbeth λ0	Fama-Macbeth t-statistic	Giglio & Xiu 4 PCs λ0	Giglio & Xiu 4 PCs t-statistic	Giglio & Xiu 6 PCs λ0	Giglio & Xiu 6 PCs t-statistic	Giglio & Xiu 6 PCs λ0	Giglio & Xiu 6 PCs t-statistic
1963	1965	5.507	1.360	-0.021	-0.065	-0.021	-0.065	-0.002	-0.008
1965	1967	-0.950	-1.279	0.011	0.091	0.053	0.481	0.076	0.711
1967	1969	**29.283**	**3.702**	**4.737**	**1.982**	**4.515**	**1.911**	**4.579**	**1.936**
1969	1971	-0.688	-0.649	-0.026	-0.221	-0.027	-0.223	-0.068	-0.620
1971	1973	-11.461	-1.309	-0.793	-1.111	-0.767	-1.097	-0.800	-1.153
1973	1975	0.397	0.547	0.045	0.620	0.045	0.627	0.045	0.625
1975	1977	0.431	0.486	0.124	1.079	0.126	1.100	0.130	1.172
1977	1979	-1.612	-1.542	**-0.531**	**-2.309**	**-0.525**	**-2.359**	**-0.532**	**-2.408**
1979	1981	-1.303	-0.624	-0.474	-1.151	-0.252	-0.761	-0.253	-0.761
1981	1983	3.429	1.063	0.711	0.875	0.713	0.871	0.830	1.022
1983	1985	3.322	1.795	0.309	0.866	0.285	0.802	0.234	0.741
1985	1987	0.226	0.537	0.006	0.137	0.008	0.200	0.008	0.205
1987	1989	-3066	-1.454	-23.285	-0.201	-24.385	-0.220	-22.762	-0.199
1989	1991	**7.994**	**2.511**	0.510	1.101	0.430	0.944	0.418	0.955
1991	1993	**4.251**	**2.519**	0.310	1.402	0.114	0.570	0.101	0.516
1993	1995	**10.814**	**3.580**	0.422	0.922	0.452	0.990	0.416	0.975
1995	1997	-2.835	-1.167	-0.161	-0.559	-0.141	-0.521	-0.102	-0.379
1997	1999	-0.469	-0.602	-0.121	-1.788	-0.120	-1.774	-0.073	-1.294
1999	2001	0.916	1.180	-0.022	-0.250	0.006	0.093	0.016	0.244
2001	2003	-0.348	-0.391	-0.054	-0.356	-0.006	-0.062	0.053	0.423
2003	2005	2.173	0.353	-0.733	-0.770	-0.839	-0.880	-0.950	-0.975
2005	2007	-9.591	-1.780	-0.437	-0.692	-0.447	-0.727	-0.453	-0.733
2007	2009	0.745	0.323	-0.080	-1.176	-0.073	-1.103	-0.052	-1.001

Figure 3.10. Pricing of our volatility factor in the cross section of stock returns

except for the sample from 1967 to 1969 and the one from 1977 to 1979, the common factor in idiosyncratic volatility is not priced in the cross section of stock returns.

3.7 Future work

There are two potential avenues for future research. First, a stochastic volatility in mean model might provide a more coherent framework for studying the interaction between the levels and the variances of returns than this widely-used two-step estimation procedure. In that case, sampling from the posterior distribution of ξ_t would involve a Metropolis-Hastings step because the standard Kalman filtering procedure cannot be applied.

Second, the parsimonious model for idiosyncratic volatilities can be useful for reducing the dimensionality for predicting variance covariance matrices of stock returns. It would be interesting to analyze how the dynamic modeling choice may affect portfolio allocations.

Appendix A

Additional Figures and Tables

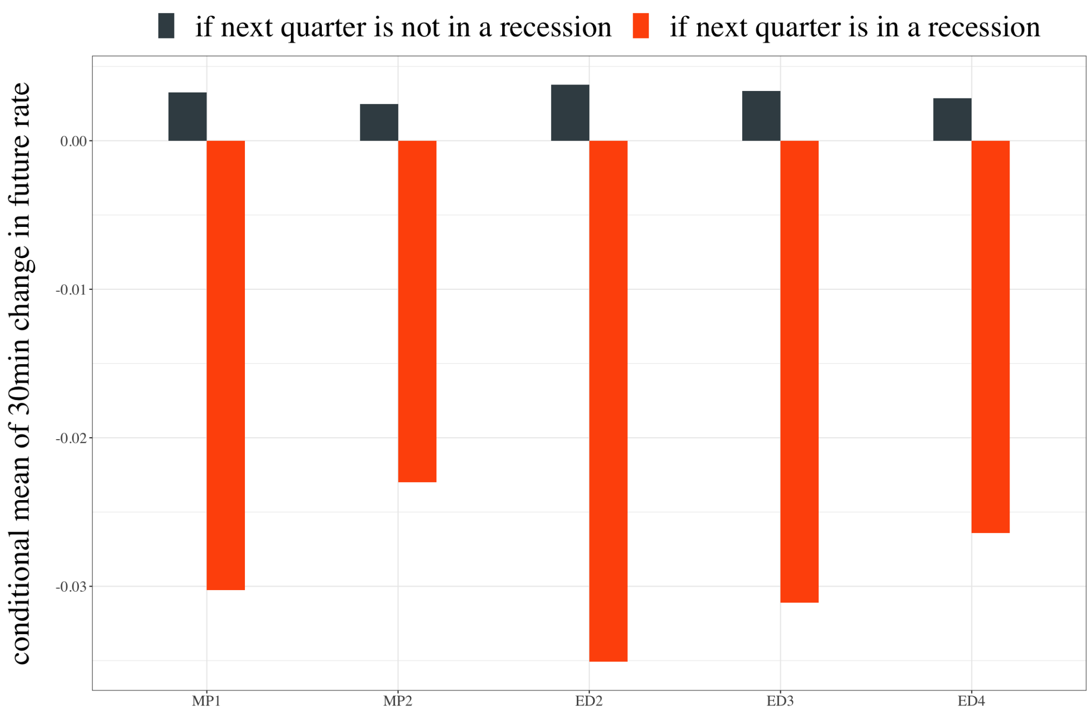

Figure A.1. Easing policy consistently surprised interest rate futures market before recession

Notes: Listed on the x-axis are five assets reflecting market expectations of interest rates for various horizons. Y-axis plots the average change in the rate of each asset during a 30-minute window around an FOMC announcement across two samples. MP1 and MP2: federal funds future contracts to be settled at the end of the current month and the third month after the FOMC announcement. ED2, ED3 and ED4: Eurodollar future contracts to be settled at the end of the second, third and fourth quarter. The figure differs from Figure 1.1 only in that here all series are demeaned before being split into subsamples.

Table A.1. Replication of Campbell et al. (2012) and Nakamura and Steinsson (2018)

(a) Real variables

EI	h	Campbell et al. (2012) Target	Campbell et al. (2012) Path	NS (2018) Policy
Industrial Production	0	**2.21***	-0.09	**3.71***
		(1.28)	(0.83)	(2.19)
	1	0.40	-0.18	**2.07***
		(0.52)	(0.44)	(1.08)
	2	-0.18	-0.38	0.73
		(0.25)	(0.43)	(0.47)
	3	-0.32	-0.17	0.66
		(0.24)	(0.24)	(0.43)
	4	**-0.34***	0.18	0.06
		(0.17)	(0.15)	(0.28)
	5	-0.15	**0.37****	0.09
		(0.17)	(0.16)	(0.32)
Real GDP	0	0.58	-0.22	1.48
		(0.59)	(0.37)	(0.90)
	1	**0.42***	0.04	**1.16****
		(0.24)	(0.18)	(0.53)
	2	0.09	-0.01	0.39
		(0.14)	(0.12)	(0.34)
	3	0.07	0.12	0.26
		(0.11)	(0.10)	(0.27)
	4	-0.02	**0.23*****	0.22
		(0.09)	(0.09)	(0.22)
	5	-0.18	**0.27*****	0.01
		(0.15)	(0.09)	(0.26)
Unemployment Rate	0	**-0.17****	-0.04	-0.20
		(0.07)	(0.06)	(0.14)
	1	0.14	-0.10	-0.23
		(0.29)	(0.08)	(0.22)
	2	**-0.24*****	-0.07	-0.36
		(0.09)	(0.07)	(0.26)
	3	**-0.18****	-0.02	-0.39
		(0.09)	(0.09)	(0.29)
	4	-0.06	0.01	-0.17
		(0.07)	(0.08)	(0.29)
	5	-0.06	-0.06	-0.33
		(0.07)	(0.10)	(0.23)

(b) Price variables

EI	h	Campbell et al. (2012) Target	Campbell et al. (2012) Path	NS (2018) Policy
CPI	0	0.06	0.62	1.86
		(0.33)	(0.40)	(1.26)
	1	0.30**	0.33	-1.07
		(0.14)	(0.30)	(1.09)
	2	0.06	-0.07	0.09
		(0.07)	(0.10)	(0.16)
	3	0.08	-0.12	0.20
		(0.07)	(0.09)	(0.15)
	4	-0.02	0.07	0.10
		(0.08)	(0.08)	(0.15)
	5	0.01	0.10	0.24
		(0.12)	(0.10)	(0.30)
PPI	0	0.80	1.53**	4.49**
		(0.77)	(0.68)	(2.27)
	1	0.17	0.44	0.61
		(0.25)	(0.42)	(0.60)
	2	-0.09	-0.06	-0.02
		(0.16)	(0.13)	(0.28)
	3	-0.04	0.10	0.08
		(0.10)	(0.12)	(0.31)
	4	0.04	-0.02	0.02
		(0.13)	(0.14)	(0.25)
	5	-0.05	0.06	0.13
		(0.12)	(0.17)	(0.30)
GDP Price Index	0	-0.05	0.06	0.22
		(0.16)	(0.18)	(0.39)
	1	0.11	0.10	0.12
		(0.12)	(0.18)	(0.21)
	2	0.00	0.02	0.05
		(0.08)	(0.13)	(0.21)
	3	0.07	0.06	0.08
		(0.11)	(0.11)	(0.21)
	4	-0.11	-0.02	-0.09
		(0.07)	(0.08)	(0.17)
	5	-0.50	0.69	2.22
		(0.59)	(0.64)	(2.34)

Columns labeled "Campbell et al. (2012)" present estimated α^h_{Target} and α^h_{Path} from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{Target} Target_{t(m)} + \alpha^h_{Path} Path_{t(m)} + e^h_{t(m)}$, where $Target_{t(m)}$ and $Path_{t(m)}$ are replicated following the authors' procedure. Sample goes from 1990m2 to 2007m6, excluding the announcement in 2001m9 , those in the first three business days of a month before 2000m12 and in the first two business days in and after 2000m12. Columns labeled "NS (2018)" present estimated α^h_P from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_P Policy_{n,t(m)} + e^h_{t(m)}$, where $Policy_{t(m)}$ is taken from authors' website. The sample goes from 1995m1 to 2014m4, excluding announcements that are unscheuled, made in the first week of a month, between 2008m7 and 2009m6 or in 2001m9. Robust standard errors in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively.

Table A.2. Replication of Bauer and Swanson (2020)

(a) Real variables | (b) Price variables

EI	h	Campbell et al. (2012) Target	Campbell et al. (2012) Path	NS (2018) Policy	EI	h	Campbell et al. (2012) Target	Campbell et al. (2012) Path	NS (2018) Policy
Industrial Production	0	1.00	-0.98	0.56	CPI	0	-0.10	0.11	0.21
		(0.76)	(0.61)	(1.13)			(0.32)	(0.56)	(0.57)
	1	0.58	-0.85**	-0.27		1	-0.10	0.84	1.10
		(0.43)	(0.36)	(0.53)			(0.45)	(0.83)	(0.69)
	2	-0.09	-0.89**	**-0.69****		2	0.02	-0.06	0.02
		(0.24)	(0.36)	(0.29)			(0.06)	(0.10)	(0.11)
	3	-0.21	-0.41**	**-0.42***		3	0.07	-0.13	0.06
		(0.18)	(0.20)	(0.24)			(0.07)	(0.09)	(0.10)
	4	-0.22*	0.04	**-0.30***		4	0.01	-0.02	0.06
		(0.13)	(0.13)	(0.16)			(0.05)	(0.10)	(0.10)
	5	-0.06	0.38**	0.00		5	-0.02	0.03	0.07
		(0.13)	(0.16)	(0.19)			(0.08)	(0.09)	(0.18)
Real GDP	0	0.22	-0.88***	-0.69	PPI	0	0.44	1.03	0.89
		(0.33)	(0.29)	(0.48)			(0.84)	(0.93)	(1.12)
	1	0.28	-0.58***	-0.27		1	0.16	0.06	-0.28
		(0.21)	(0.20)	(0.29)			(0.26)	(0.50)	(0.39)
	2	-0.21**	-0.37**	**-0.49****		2	-0.07	-0.17	-0.32*
		(0.11)	(0.16)	(0.21)			(0.11)	(0.16)	(0.18)
	3	-0.04	-0.16	-0.24		3	0.16	-0.03	0.13
		(0.07)	(0.13)	(0.16)			(0.10)	(0.15)	(0.16)
	4	0.04	0.06	0.00		4	0.12	-0.17	0.08
		(0.09)	(0.09)	(0.13)			(0.12)	(0.18)	(0.16)
	5	-0.08	0.22**	0.06		5	-0.10	-0.08	-0.05
		(0.09)	(0.10)	(0.14)			(0.09)	(0.15)	(0.17)
Unemployment Rate	0	-0.04	0.02	0.01	GDP Price Index	0	-0.06	-0.03	0.00
		(0.05)	(0.07)	(0.10)			(0.11)	(0.19)	(0.21)
	1	0.09	-0.02	0.20		1	0.08	0.05	0.08
		(0.15)	(0.11)	(0.18)			(0.10)	(0.15)	(0.15)
	2	-0.11	0.09	0.06		2	0.01	0.03	0.01
		(0.10)	(0.10)	(0.16)			(0.08)	(0.11)	(0.13)
	3	-0.03	0.13	0.16		3	-0.01	0.05	0.06
		(0.11)	(0.12)	(0.16)			(0.09)	(0.09)	(0.11)
	4	0.05	0.15	**0.27***		4	-0.08	-0.01	-0.09
		(0.12)	(0.11)	(0.15)			(0.05)	(0.06)	(0.11)
	5	-0.01	-0.05	0.10		5	-0.15	1.04	1.47
		(0.13)	(0.08)	(0.16)			(0.27)	(0.96)	(1.47)

Estimated α^h_{MP} from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{MP} MP_{t(m)} + \alpha^h_{NFP} NFP_m + \alpha^h_{SP} R^Q_{t(m)} + \alpha^h_{index} NewsIndex_m + e^h_{t(m)}$, where $MP_{t(m)}$ is either $(Target_{t(m)}, Path_{t(m)})'$ constructed based on Campbell et al. (2012) or $Policy_{t(m)}$ constructed based on Nakamura and Steinsson (2018). The sample goes from 1991m7 to 2019m3, excluding the announcement in 2001m9 , those in the first three business days of a month before 2000m12 and in the first two business days in and after 2000m12. Robust standard errors are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively.

Table A.3. Blue Chip regressions - real variables

(a) IP

PC	ξ	η
2.78**	**3.08****	0.66
(1.37)	(1.46)	(2.41)
1.35**	**1.50****	0.56
(0.61)	(0.64)	(1.55)
0.38	0.47	-0.45
(0.33)	(0.36)	(0.85)
0.30	0.41	-0.74
(0.33)	(0.35)	(0.55)
0.12	0.25	**-1.18****
(0.23)	(0.23)	(0.57)
0.32	0.37	-0.62
(0.25)	(0.25)	(0.50)

(b) Real GDP

h	PC	ξ_t	η_t
0	0.72	0.81	0.44
	(0.61)	(0.68)	(1.30)
1	**0.76****	**0.88****	0.26
	(0.35)	(0.37)	(0.98)
2	0.12	0.19	-0.57
	(0.24)	(0.27)	(0.51)
3	0.08	0.13	-0.38
	(0.20)	(0.24)	(0.31)
4	0.20	0.25	0.19
	(0.16)	(0.18)	(0.41)
5	0.20	0.22	-0.41
	(0.15)	(0.15)	(0.41)

(c) Unemploy. Rate

h	PC	ξ_t	η_t
0	**-0.19***	**-0.20****	-0.26
	(0.10)	(0.10)	(0.23)
1	-0.08	-0.08	0.10
	(0.21)	(0.23)	(0.34)
2	**-0.36****	**-0.38****	-0.34
	(0.17)	(0.18)	(0.42)
3	**-0.36***	**-0.39****	-0.07
	(0.19)	(0.19)	(0.46)
4	-0.13	-0.14	0.45
	(0.19)	(0.19)	(0.75)
5	**-0.27***	-0.27	-0.21
	(0.16)	(0.16)	(0.52)

Columns labeled "PC" present estimated α^h_{PC} from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_{t(m)}$ while the other columns present estimated α^h_ξ and α^h_η from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_s \xi_{t(m)} + \alpha^h_m \eta_{t(m)} + e^h_{t(m)}$. Bootstrapped standard errors are shown in parentheses. Determined by p-values based on bootstrapped sampling distributions, statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively. Sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Table A.4. Blue Chip regressions - price variables

(a) CPI

h	PC	ξ_t	η_t
0	1.26	**1.63***	-1.08
	(0.86)	(0.95)	(1.57)
1	-0.13	-0.15	0.44
	(0.57)	(0.73)	(1.71)
2	0.07	0.04	**0.33***
	(0.12)	(0.13)	(0.20)
3	0.09	0.10	0.09
	(0.12)	(0.14)	(0.21)
4	0.12	0.12	-0.06
	(0.12)	(0.14)	(0.26)
5	0.17	0.19	0.02
	(0.20)	(0.22)	(0.39)

(b) PPI

h	PC	ξ_t	η_t
0	**2.98****	**3.54****	-0.49
	(1.46)	(1.65)	(2.66)
1	0.41	0.58	-1.02
	(0.36)	(0.42)	(0.84)
2	-0.02	-0.03	-0.39
	(0.20)	(0.24)	(0.40)
3	0.12	0.18	-0.45
	(0.24)	(0.28)	(0.28)
4	-0.04	0.04	-0.37
	(0.19)	(0.21)	(0.58)
5	0.16	0.19	**-1.00****
	(0.22)	(0.18)	(0.42)

(c) GDP Price Index

h	PC	ξ_t	η_t
0	0.10	0.15	0.13
	(0.30)	(0.33)	(0.38)
1	0.11	0.14	0.09
	(0.16)	(0.18)	(0.26)
2	0.03	0.03	-0.07
	(0.16)	(0.19)	(0.23)
3	0.13	0.15	-0.30
	(0.14)	(0.16)	(0.26)
4	-0.04	-0.05	-0.18
	(0.13)	(0.16)	(0.29)
5	2.38	2.84	-8.21
	(2.28)	(2.72)	(8.30)

Columns labeled "PC" present estimated α^h_{PC} from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_{t(m)}$ while the other columns present estimated α^h_ξ and α^h_η from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_s \xi_{t(m)} + \alpha^h_m \eta_{t(m)} + e^h_{t(m)}$. Bootstrapped standard errors are shown in parentheses. Determined by p-values based on bootstrapped sampling distributions, statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively. Sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Table A.5. Robustness to the Fed response to economic news channel - real variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
Industrial Production	0	**2.85***	-0.06	**3.14****	-0.13	0.95	-0.19	0.24	-0.39
		(1.47)	(2.54)	(1.32)	(2.11)	(1.53)	(2.29)	(1.42)	(2.15)
	1	**1.41****	0.27	**1.61*****	0.22	-0.23	0.15	-0.45	0.09
		(0.64)	(1.58)	(0.57)	(1.23)	(0.69)	(1.19)	(0.67)	(1.14)
	2	0.44	-0.57	0.56	-0.60	-0.65	-0.64	**-0.74***	-0.67
		(0.36)	(0.85)	(0.39)	(0.69)	(0.40)	(0.60)	(0.41)	(0.58)
	3	0.41	-0.76	0.48	-0.77	-0.27	**-0.80***	-0.32	**-0.82***
		(0.35)	(0.56)	(0.38)	(0.51)	(0.33)	(0.46)	(0.35)	(0.45)
	4	0.26	**-1.09***	0.30	**-1.11***	-0.15	**-1.02****	-0.16	**-1.04****
		(0.23)	(0.60)	(0.24)	(0.60)	(0.22)	(0.50)	(0.22)	(0.50)
	5	0.39	-0.56	0.40	-0.60	0.26	-0.60	0.25	-0.62
		(0.25)	(0.52)	(0.25)	(0.52)	(0.26)	(0.52)	(0.26)	(0.52)
Real GDP	0	0.62	-0.13	0.79	-0.23	-0.95	-0.34	**-1.15****	-0.37
		(0.63)	(1.35)	(0.58)	(1.02)	(0.61)	(1.05)	(0.58)	(0.98)
	1	**0.81****	0.05	**0.95*****	-0.02	-0.34	-0.10	-0.50	-0.13
		(0.37)	(0.99)	(0.34)	(0.76)	(0.39)	(0.73)	(0.36)	(0.65)
	2	0.17	-0.62	0.25	-0.66	**-0.54***	-0.71	**-0.64****	**-0.73***
		(0.27)	(0.52)	(0.30)	(0.49)	(0.29)	(0.46)	(0.29)	(0.42)
	3	0.11	-0.41	0.16	-0.44	-0.26	**-0.46***	-0.30	**-0.47***
		(0.23)	(0.31)	(0.25)	(0.29)	(0.24)	(0.25)	(0.24)	(0.24)
	4	0.26	0.25	**0.30***	0.23	0.01	0.28	0.00	0.23
		(0.18)	(0.42)	(0.17)	(0.36)	(0.19)	(0.38)	(0.17)	(0.36)
	5	0.23	-0.38	0.25	-0.43	0.22	-0.38	0.21	-0.41
		(0.15)	(0.42)	(0.15)	(0.42)	(0.14)	(0.43)	(0.14)	(0.43)
Unemployment Rate	0	**-0.20***	-0.26	**-0.22****	-0.25	0.05	-0.24	0.12	-0.22
		(0.10)	(0.24)	(0.09)	(0.22)	(0.12)	(0.21)	(0.12)	(0.17)
	1	-0.06	0.17	-0.09	0.18	0.26	0.19	0.32	0.21
		(0.23)	(0.35)	(0.22)	(0.31)	(0.26)	(0.32)	(0.22)	(0.30)
	2	**-0.35***	-0.25	**-0.40****	-0.23	0.05	-0.22	0.16	-0.19
		(0.18)	(0.43)	(0.16)	(0.36)	(0.20)	(0.36)	(0.20)	(0.34)
	3	**-0.36***	0.03	**-0.41****	0.04	0.13	0.06	0.27	0.10
		(0.19)	(0.47)	(0.17)	(0.40)	(0.22)	(0.37)	(0.21)	(0.32)
	4	-0.13	0.53	-0.20	0.57	0.39	0.45	**0.42****	0.56
		(0.19)	(0.77)	(0.18)	(0.62)	(0.24)	(0.55)	(0.19)	(0.45)
	5	-0.25	-0.12	**-0.29***	0.02	0.10	0.00	0.17	0.15
		(0.17)	(0.54)	(0.16)	(0.47)	(0.19)	(0.42)	(0.18)	(0.41)
Control:		C1		C2		C3		C4	
NFP		✓		✓		✓		✓	
R^C				✓					
R^Q						✓		✓	
$NewsIndex$								✓	

Estimated α_ξ^h and α_η^h from regression: $EI_{t(m)}^h = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + \alpha_C^h Control_{t(m)} + e_{t(m)}^h$. Bootstrapped standard errors are shown in parentheses. Determined by p-values based on bootstrapped sampling distributions, statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively. Sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Table A.6. Robustness to the Fed response to economic news channel - price variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
CPI	0	**1.50***	-1.48	**1.72****	-1.73	0.23	-1.64	-0.01	-1.46
		(0.90)	(1.67)	(0.86)	(1.51)	(0.90)	(1.57)	(0.85)	(1.60)
	1	0.03	0.83	-0.41	1.33	2.08	1.07	2.42	0.82
		(0.72)	(1.86)	(0.87)	(1.89)	(1.32)	(1.82)	(1.47)	(1.78)
	2	0.04	**0.36***	0.04	0.35	0.02	**0.35***	0.02	0.35
		(0.13)	(0.21)	(0.13)	(0.21)	(0.15)	(0.21)	(0.15)	(0.21)
	3	0.13	0.18	0.13	0.18	0.11	0.18	0.08	0.20
		(0.14)	(0.24)	(0.14)	(0.24)	(0.16)	(0.24)	(0.16)	(0.22)
	4	0.12	0.07	0.11	0.08	0.13	0.07	0.13	0.07
		(0.13)	(0.26)	(0.14)	(0.26)	(0.15)	(0.26)	(0.15)	(0.26)
	5	0.17	0.03	0.19	-0.04	0.14	0.02	0.13	0.02
		(0.24)	(0.39)	(0.22)	(0.40)	(0.26)	(0.40)	(0.26)	(0.39)
PPI	0	**3.30****	-0.85	**3.74****	-1.34	0.95	-1.13	0.54	-0.83
		(1.62)	(2.80)	(1.60)	(2.73)	(1.83)	(2.72)	(1.79)	(2.81)
	1	0.58	-1.07	**0.78***	-1.30	-0.39	-1.18	-0.58	-1.04
		(0.43)	(0.89)	(0.44)	(0.83)	(0.68)	(0.90)	(0.69)	(0.82)
	2	-0.01	-0.24	0.06	-0.32	-0.23	-0.27	-0.29	-0.22
		(0.24)	(0.41)	(0.26)	(0.40)	(0.28)	(0.43)	(0.28)	(0.42)
	3	0.28	-0.20	0.28	-0.20	**0.45****	-0.18	**0.45****	-0.18
		(0.26)	(0.30)	(0.26)	(0.30)	(0.22)	(0.29)	(0.22)	(0.29)
	4	0.11	-0.05	0.09	-0.01	0.34	-0.07	0.34	-0.07
		(0.21)	(0.57)	(0.23)	(0.62)	(0.23)	(0.59)	(0.24)	(0.60)
	5	0.20	**-0.91****	0.19	**-0.87***	0.18	**-0.91****	0.15	**-0.94****
		(0.19)	(0.42)	(0.20)	(0.44)	(0.20)	(0.41)	(0.19)	(0.41)
GDP Price Index	0	0.14	0.12	0.18	0.07	-0.06	0.09	-0.10	0.12
		(0.33)	(0.40)	(0.33)	(0.39)	(0.31)	(0.41)	(0.31)	(0.40)
	1	0.14	0.12	0.16	0.10	0.07	0.11	0.03	0.14
		(0.18)	(0.28)	(0.17)	(0.27)	(0.21)	(0.29)	(0.21)	(0.27)
	2	0.01	-0.04	0.02	-0.06	0.05	-0.04	0.04	-0.03
		(0.19)	(0.25)	(0.19)	(0.25)	(0.21)	(0.24)	(0.21)	(0.24)
	3	0.14	-0.25	0.15	-0.27	0.11	-0.25	0.09	-0.24
		(0.16)	(0.27)	(0.16)	(0.27)	(0.17)	(0.28)	(0.17)	(0.27)
	4	-0.07	-0.32	-0.06	-0.35	-0.06	-0.32	-0.06	-0.32
		(0.17)	(0.30)	(0.16)	(0.28)	(0.17)	(0.30)	(0.17)	(0.28)
	5	2.61	-9.79	3.06	-11.80	3.58	-9.44	3.95	-9.08
		(2.55)	(9.58)	(2.93)	(11.13)	(3.36)	(9.22)	(3.68)	(8.81)
Control:		C1		C2		C3		C4	
NFP		✓		✓		✓		✓	
R^C				✓					
R^Q						✓		✓	
$NewsIndex$								✓	

Estimated α^h_ξ and α^h_η from regression: $EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{f,t(m)} + \alpha^h_C Control_{t(m)} + e^h_{t(m)}$. Bootstrapped standard errors are shown in parentheses. Determined by p-values based on bootstrapped sampling distributions, statistical significance at the 1%, 5% and 10% levels is denoted by ***, ** and *, respectively. Sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12.

Appendix B

Estimation Procedure

Given the parameter vector, $\Theta = (\tilde{\gamma}, \gamma, \beta, \text{vec}(\Sigma_\xi), \text{vec}(\Sigma_{\tilde{u}}), \text{vec}(\Sigma_u))'$, and data y_t and $\tilde{y}_t$, the model implies the following log-likelihood for Day t,

$$
\begin{aligned}
l\left(\Theta; y_t, \tilde{y}_t\right) = & \left(-\frac{N}{2}log(2\pi) - \frac{1}{2}log|\Sigma| - \frac{1}{2}y_t'\Sigma^{-1}y_t\right)d_t \\
& + \left(-\frac{N}{2}log(2\pi) - \frac{1}{2}log|\Sigma_1| - \frac{1}{2}\tilde{y}_t'\Sigma_1^{-1}\tilde{y}_t\right)\tilde{d}_t\left(1-d_t\right) \\
& + \left(-\frac{N}{2}log(2\pi) - \frac{1}{2}log|\Sigma_{\tilde{u}}| - \frac{1}{2}\tilde{y}_t'\Sigma_{\tilde{u}}^{-1}\tilde{y}_t\right)\left(1-\tilde{d}_t\right)\left(1-d_t\right)
\end{aligned}
$$

where

$$
d_t = \begin{cases} 1, \text{ if Day t has an FOMC announcement} \\ 0, \text{ else} \end{cases}
$$

$$
\tilde{d}_t = \begin{cases} 1, \text{ if Day t has a major data release} \\ 0, \text{ else} \end{cases}
$$

$$
\Sigma = \gamma\Sigma_\xi\gamma' + \beta\beta' + \Sigma_u
$$

$$
\Sigma_1 = \tilde{\gamma}\tilde{\gamma}' + \Sigma_{\tilde{u}}
$$

The model parameters are estimated to maximize the log-likelihood function defined below for all days subject to constraints implied by the identifying assumptions.

$$\min_{\Theta} \quad L\left(\Theta; \{y_t, \tilde{y}_t\}_{t=1}^{T}\right) = \sum_{t=1}^{T} l\left(\Theta; y_t, \tilde{y}_t\right) \tag{B.1}$$

$$s.t. \quad \gamma = \tilde{\gamma} \tag{B.2}$$

$$\sum_{t=1}^{T} d_t \hat{\xi}_t \hat{\eta}_t = 0 \tag{B.3}$$

I numerically solve this problem by using a function called *constrOptim.nl* in the *alabama* R package.

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