Three Essays on Modeling Information Around Monetary Policy

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Abstract

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This dissertation revolves around robustly measuring and using the information sets of the central bank and financial markets in order to measure exogenous monetary policy. Modern central banks aggressively use all the available information at their disposal to effectively set monetary policy. This problem of "foresight" renders traditional time series methods ineffective; the information edge of central banks is too large. In the first chapter, I discuss refinements to existing narrative methods, which attempt to the central bank's own forecasts to capture the information set of the central bank, thus removing their information edge over the econometrician. In the second chapter, I explore how the information sets of financial agents differ central banks and show that there is little direct information transfer between central banks and financial markets around monetary policy actions. Finally, the third chapter details how to use the information sets of financial sector actors to estimate exogenous monetary policy actions that is robust to financial sector revisions about the economy which can be due to the monetary policy actions.

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Introduction

In her handbook of Macroeconomics chapter [1] highlights the problem of “foresight” as the defining challenge when evaluating the effects of monetary and fiscal policy, by which she meant that policy makers themselves have expectations about the future of the economy and react according to these expectations. Therefore, to evaluate monetary and fiscal policy in a rigorous manner, the econometrician needs to be able to control for these expectations. In the context of monetary policy, this problem was first described by [2] who proposed using reduced form methods such as Vector Autoregressions to control for the historical path of the economy that policy makers respond to in place of many-equationed semi-structural models that were at the time in vogue.

Vector Autoregressions became the standard tool of macroeconomists to study monetary policy, although subtle assumptions around information sets available to the policy maker remained. This tool worked well when analyzing the post-war macroeconomy in the U.S., but performed less well as monetary policy became more sophisticated. By the early 90’s [3] argued that historical variables did a poor job fully capturing the information set available to policy makers. Multiple methods were proposed to solve this “foresight” problem such as incorporating fast moving, forward looking economic variables like commodity prices [3], including more variables in the VAR [4] or including factors capturing information from a wide range of sources [5].

At the turn of the millennium, researchers turned to using alternative methods to directly control for the information set of policy makers. Two approaches were devised, the first is the so-called narrative method pioneered by [6] which attempts to use narrative sources such as meeting transcripts and real-time forecasts to control for the information set of policy makers at the time of the policy decision directly. The other is the high-frequency method put forth by [7] and [8] which uses asset markets to control for all publicly available data at the time of the policy decision. More recently some authors ([9]) have started to combine these methods in an effort to combine these information sets.

The narrative and high frequency methods each have their own advantages and disadvantages. Narrative methods look to directly control for the thing that makes monetary policy endogenous, information of the central bank that is beyond the information available in historical variables. This leaves useful variation in monetary policy that can be used to identify its effects. For example, if the central bank publicly commits a policy action that is not justified by its forecast, narrative methods will capture this non-systemic action as an exogenous monetary policy shock. The disadvantage is that obtaining, and even defining, this information set is a challenge.

On the other hand, the identification of information in high frequency methods is seemingly straight forward; if asset prices fully incorporate all available information, then looking at their changes around monetary policy actions gives us a clear measure of unexpected, and therefore, non-systematic monetary policy. This identification assumption has been challenged in the recent literature, on the grounds that the central bank does not just release information about it's policy actions but also, either explicitly or implicitly, releases information about its own forecasts. These two points of information then interact in ways that make identify the portion of asset price movements that are due solely to policy actions difficult. More fundamentally, because asset markets incorporate all public information, they also incorporate public information about future monetary policy actions. Unfortunately, monetary policy has became very transparent, including about the future path of monetary policy which means that asset markets incorporate information about central bank actions before they even take them which severally limits the amount of information that one can hope to obtain by looking only at asset prices.

We can therefore see these two approaches as complementary. This dissertation improves our understanding of both methods. In Chapter 1, I focus on the narrative method and how to efficiently represent the information set of the central bank. Existing narrative methods aim to fully control for the central bank's information set by including a large number of variables from central bank forecasts at the time of policy actions. I show that when taken together, many of these variables are redundant and including all of them introduces estimation challenges. I propose to exploit the underlying sparsity in the information and replace the long list of forecast variables, with a compact set of factors estimated from these forecast variables. Doing so markedly improves the quality of the estimation. I then also show that using a compact set of factors derived from a large dataset of macroeconomic variables marginally improves the estimation quality.

In Chapter 2, I explore how information sets of the central bank and financial markets differ. I show that financial markets have at least as much information as the central bank by attempting to predict the high frequency returns with the central bank's information set. I show that the central bank's information set is not informative about the high frequency returns, but public information about the existing state of the economy is. Furthermore, I show that this pattern holds around other non-monetary economic news releases. This indicates that non-information effects are present around these news releases.

In Chapter 3, I improve the estimation of high frequency monetary policy shocks by incorporating information from non-monetary economic news releases in the estimation process. In particular, I show how to use asset returns around macroeconomic data releases as a way to control for non-monetary information effects by exploiting the inherit heteroskedasticity in monetary policy shocks between monetary and non-monetary news releases. This approach requires a second asset return which allows me to use equity returns which carry meaningful information about monetary and non-monetary news. I show that this method produces monetary shocks that align with conventional theory without needing to control for the central bank's information set.

Chapter 1: Robust Narrative Methods

Identifying exogenous monetary policy actions is a central challenge in macroeconomics. Monetary policy is highly endogenous and forward looking. Central bank actions are taken not just in response to the current state of the economy, but the forecasted future state as well. Traditional Vector Auto Regressive analysis attempts to control for both of these by controlling for the history of past economic shocks. The canonical VAR analysis by [4] find large effects of monetary policy in the U.S. during the pre-Volcker period but smaller effects in latter periods. They also find the so-called "price puzzle" in latter periods where contractionary monetary policy is followed by a short term rise in inflation. Ramey highlights the argument in [3] that the foresight of monetary policy makers on future economic conditions cannot be fully captured by looking only at current economic conditions.

To avoid this problem of foresight, [6] introduce narrative methods and utilize the forecasts of the policy makers themselves. Specifically they make use of the Greenbook forecasts which are prepared by the economic staff of the Federal Reserve Board of Governors before every scheduled FOMC meeting. These Greenbook forecasts contain the Federal Reserve Staff's estimate of the current state of the economy, along with their forecasts of the economy. Romer and Romer use the transcripts of the FOMC meetings to show that FOMC largely uses the Greenbook forecasts as the baseline for their own forecasts. By controlling for the forecasts of policy makers, Romer and Romer aim to control for all available information possessed by policy makers when they implement monetary policy. The goal is to produce a measure of monetary policy which is orthogonal to the FOMC's information set.

The subsequent narrative literature has followed the two step procedure introduced by Romer and Romer, controlling for different information at different stages of the estimation process which makes evaluating the effectiveness of the narrative method challenging. We propose a simple single step procedure for using narrative sources which easily allows us to evaulate the effectiveness of this method. To preview our results, we find the existing variables used in narrative methods perform poorly at producing exogenous measures of monetary policy. We explore how assumptions made in the Greenbook forecasting process can produce a wedge between the FOMC information set and the Greenbook forecasts, but rule this out as the driving factor of the poor results of narrative methods.

Next we explore the possibility that the large number of variables used in the narrative method can produce overfitting, leading to their poor performance. We exploit the sparse nature of the underlying information contained in the Greenbook forecasts and estimate a factor model for the forecast variables. Using these factors in place of the Greenbook forecasts, we are able to produce robust, exogenous measures of monetary policy which have effects that align with traditional economic theory but have longer lasting effects than traditional VAR methods.

This paper is organized as follows: Section 1.1 summarizes the goals and methods of the traditional narrative analysis. Section 1.2 details the data used. Section 1.3 presents a simple model for the possible effects of the Financial Assumptions process on narrative estimates. Next, Section 1.4 details the exact procedure and results of our new narrative method and Section 1.5 concludes.

1.1 Greenbook Narrative Method

The narrative method attempts to identify exogenous movements in monetary policy by controlling for policy makers' information sets at the time monetary policy was set. In the context of monetary policy, the goal is to control for the central bank's economic forecasts. For the U.S., [6] propose to use the Greenbook forecasts prepared for every scheduled FOMC meeting and provide evidence from meeting transcripts that the FOMC's forecasts are heavily based on the Greenbook forecasts. By controlling for these forecasts, [6] claim that they can separate out non-systematic monetary policy by regressing the intended changes in the Federal Funds rate on these forecasts. Specifically they run the following regression where Δff_m is the change in the intended Federal

Funds rate at meeting m, ffb_m is the policy rate at the start of the meeting, $\Delta\tilde{y}_{mi}$ is the Greenbook forecast of output growth for the relative quarter i, $\Delta\tilde{y}_{mi} - \Delta\tilde{y}_{m-1,i}$ is the change in the forecast between meeting m and $m-1$, $\tilde{\pi}_{mi}$ is the forecasted quarterly inflation rate, $\tilde{\phi}_{mi} - \tilde{\phi}_{m-1,i}$ is the meeting over meeting change in the forecasted quarterly inflation rate and $\tilde{u}_{mi}$ is the forecasted unemployment rate.

$$\Delta ff_m = \alpha + \beta ffb_m + \sum_{i=-1}^{2} \gamma_i \Delta\tilde{y}_{mi} + \sum_{i=-1}^{2} \lambda_i \left(\Delta\tilde{y}_{mi} - \Delta\tilde{y}_{m-1,i}\right) + \sum_{i=-1}^{2} \phi_i \tilde{\pi}_{mi} + \sum_{i=-1}^{2} \theta_i \left(\tilde{\pi}_{mi} - \tilde{\pi}_{m-1,i}\right) + \rho\tilde{u}_{mi} + \epsilon_m \quad (1.1)$$

The goal of this regression is not to estimate the FOMC's reaction function, but only to control for information that they use when systematically setting monetary policy. If these Greenbook forecast variables are able to capture the full extent of the information that the FOMC systematically uses when setting monetary policy, then the residual of this regression can be used as a proxy for exogenous monetary policy actions.

The general practice in the narrative literature is to take a two step procedure where one first estimates the narrative based exogenous shock from equation (1.1) and then uses the residual from this equation in a second regression, possibly with additional controls. As shown by [10], this two step procedure is sensitive to the exact form of the regression used in the second step. Alternatively, one can use the narrative method in a single step procedure where one regresses the variable of interest on the change in the Federal Funds rate, Δff_m while controling for Greenbook forecast variables along with any controls that would otherwise be used in the second stage regression.

1.2 Data

In this section we detail the data used in our analysis. Following [6], we produce a series of monetary shocks by regressing the intended Federal Funds rate on Greenbook forecast variables and also include variables from the Greenbook Financial Assumptions. Our intended Federal Funds rate series is taken from [11] and accessed via FRED. [11] builds on the narrative approach of [6] and analyzes the verbatim transcripts of FOMC meetings, the FOMC Blue Book, the Report of Open Market Operations and Money Market Conditions, and data that the author obtained from the Desk for the Federal Reserve Bank of New York dealing with open market operations over the period March 1984 through December 1996. This series ends in 1994 when the FOMC began to publicly announce its intended Federal Funds rate, after which we use this announced policy rate as the intended policy rate.

Greenbook forecast data is accessed from the Federal Reserve Bank of Philadelphia's Greenbook data set. The dataset contains the Greenbook forecasts for fifteen macroeconomic variables, along with the publication date of each Greenbook for Greenbooks published between 1967 and 2012. The length of the forecast horizon within the Greenbook grows over time, and some forecasts did not start to be produced until after 1967. This data can be accessed at https://www.philadelphiafed.org/research-and-data/real-time-center/greenbook-data.

The Greenbook Financial Assumptions are also produced by the Federal Reserve Bank of Philadelphia in their "Financial Assumptions: Interest Rates and Equity Prices" dataset. The dataset contains the Financial Assumptions, including the three-month Treasury yield, used during the production of the Greenbook for each FOMC meeting from the start of 1981 to the sixth FOMC meeting of 2008. This data is available at https://www.philadelphiafed.org/research-and-data/ real-time-center/greenbook-data/gap-and-financial-data-set.

Finally, we use several macroeconomic variables in our VAR including Industrial Production, unemployment, and the Consumer Price Index which are accessed via FRED. Daily effective Federal Funds rate data were obtained from the Federal Reserve Board's H.15 release and then aggregated to a monthly frequency by taking averages.

1.3 Modeling Financial Assumptions

In this section, I show how ignoring the Financial Assumptions process can cause narrative methods to misidentify monetary policy shocks. As discussed earlier, the primary challenge when estimating the effects of monetary policy is that changes in the policy rate can be due to forecasted changes in the economy. In particular, assume that the state of the economy can be summarized by the mean zero variable x_t and that the realization of x_t depends on the monetary policy rate set in the previous period i_{t-1} and the first lag of a mean zero, unobserved exogenous shock ϵ_{t-1} so that we have the following:

$$x_t = \beta i_{t-1} + \epsilon_{t-1} \tag{1.2}$$

Note that because the realization of x_t at time t depends only on lagged realizations of the exogenous shock process, it is not possible to recover ϵ_t using only the observed state variables up to time t, i.e. the exogenous shock is a news shock.

Turning now to monetary policy, let's assume that the central bank can observe the exogenous shocks ϵ_t on impact and systematically sets the policy rate i_t following a Taylor rule with a non-systemic component ν_t. The coefficient on the Taylor rule is chosen to minimize deviations in x_{t+1} from its steady state value of zero. This gives us:

$$i_t = -\beta^{-1}\epsilon_t + \nu_t = -\beta^{-1}\,\mathbb{E}_t[x_{t+1}|i_t = 0] + \nu_t \tag{1.3}$$

It's clear that the policy rate is correlated with the non-monetary shocks in the economy and simply regressing x_t on i_{t-1} will yield a biased estimator for β. The econometrician cannot fully control for the history of the exogenous structural shocks using only realizations of x_t so traditional VAR methods will fail. However, if the econometrician can control for the forecasts $\mathbb{E}_t[x_{t+1}|i_t = 0]$ of the central bank, then they can recover the exogenous component of monetary policy ν_t which can then be used to estimate β in a regression. This insight is the core of narrative methods.

Now let's consider a case where the econometrician does not have access to the true conditional forecasts but instead observes an alternative forecasts conditional on some other non-zero monetary policy actions, i.e.

$$\mathbb{E}_t[x_{t+1}|i_t = \widetilde{i_t}] = \beta\widetilde{i_t} + \epsilon_t \tag{1.4}$$

If the non-neutral policy rate used in the forecast is uncorrelated with the actual realized policy shock then this forecast is still a valid proxy for the economic shocks. While the true non-systemic component of monetary policy can no longer be recovered, β can still be consistently identified by regressing x_t on i_{t-1} and controlling for the central bank forecast. This continues to hold even if the non-neutral policy is correlated with economic shock; however, if the non-neutral policy rate used in the forecast is correlated with the non-systemic monetary policy shock then these forecasts will fail to be a valid proxy and the estimate of β from the previous regression will be biased.

In order to quantify how important these financial assumptions are, we plot the distribution of implied rate changes from the Financial Assumptions in Figure 1.1. We see that approximately half of the time, Federal Reserve staff assume no rate changes over the course of the following three quarters; however, occasionally the Federal Reserve staff incorporate large policy rate changes into their forecasts with quarterly rate changes ranging from -2.0 to 1.5%. Relatedly [12], show that these financial assumptions can vary significantly between consecutive Greenbook forecasts. These facts indicate that if the econometrician does not account for the role of financial assumptions in the Greenbook forecasting process, then narrative methods will fail to identify parameters of interest.

Next we quantify how much the Financial Assumptions process affects the information contained in the Greenbook forecasts by comparing the R^2 of the standard Greenbook narrative regression and the R^2 of the same regression but including the change in the one quarter ahead assumed Federal Funds rate between the current and previous Greenbook Forecast as shown in equation (1.5). This change is calculated identically to the change in the Greenbook forecast variables included in the standard Greenbook narrative regression. If the Financial Assumptions process does not introduce a wedge between the stated Greenbook forecasts and the FOMC's own forecasts, then the change in the assumed Federal Funds rate should not have any predictive power for FOMC actions.

Table 1.1: Predictive Power of Financial Assumptions

	Baseline	Including F.A.
$\tilde{ff}_{m,i+1} - \tilde{ff}_{m-1,i+1}$	—	0.28^{***}
		0.05
Obs:	186	186
Adj. R^2:	0.47	0.60

Notes: Table presents the estimate for the coefficient on the Financial Assumptions innovation term for the Greenbook narrative regression along with the adjusted R^2. The baseline regression is equation (1.1) and the Including F.A. regression is equation (1.5). The remaining coefficients have been suppressed. The sample period is January 1984 – June 2008. *** indicate statistical significance at the 0.1% level.

$$\Delta ff_m = \alpha + \beta ffb_m + \sum_{i=-1}^{2} \gamma_i \Delta\tilde{y}_{mi} + \sum_{i=-1}^{2} \lambda_i \left(\Delta\tilde{y}_{mi} - \Delta\tilde{y}_{m-1,i}\right) + \sum_{i=-1}^{2} \phi_i \tilde{\pi}_{mi}$$
$$+ \sum_{i=-1}^{2} \theta_i \left(\tilde{\phi}_{mi} - \tilde{\phi}_{m-1,i}\right) + \rho\tilde{u}_{mi} + \kappa\left(\widetilde{ff}_{m,i+1} - \widetilde{ff}_{m-1,i+1}\right) + \epsilon_m \quad (1.5)$$

Table (1.1) compares the adjusted R^2 for each regression. We see a large increase of 13% in the adjusted R^2 when including the change in the one quarter ahead assumed Federal Funds rate from the Financial Assumptions process. The coefficient on the Financial Assumptions innovation is also highly statistically significant at the 0.1% level. The positive value of this coefficient indicates for two Greenbook forecasts that are identical, except for the Financial Assumptions, the FOMC is more likely to raise its policy rate after observing the forecast that is based on the higher assumed interest rate. These results indicate that the Financial Assumptions process introduces a large wedge between the FOMC's information set and the Greenbook Forecasts.

1.4 Narrative Estimates

In this section we propose a new method for estimating the effects of monetary policy with narrative methods. Our method is based on the single equation local projections framework of [13].

Our single equation approach is easier to implement than the traditional two step narrative approach while also making it easier to incorporate additional information in the estimation procedure. We then show that this method produces estimates for the effect of monetary policy that are in line with the existing VAR literature.

Our proposed regression framework is the following:

$$y_{t+h} - y_t = \alpha + \beta \Delta ff_t + \gamma_i x_t \tag{1.6}$$

where y_t is the macroeconomic variable of interest, Δff_t is the change in the effective Federal Funds rate at time t and the vector x_t contains the Greenbook forecast variables in equation 1.1 and possibly lags of additional macroeconomic variables and the measure of the intermeeting change in the Financial Assumptions. Unlike traditional narrative methods, we use the change in the effective Federal Funds rate. We do this to avoid the issues of scale raised by [10] when using intended changes in the target Federal Funds rate. Across our analysis, we consider a shock that produces a 100 basis point increase in the effective federal funds rate. Our baseline model contains the same variables as the Romer and Romer regression in equation 1.1. We also only include months for which the FOMC issues a rate decision to avoid interpolating missing values for the Greenbook variables.

We analyze the impulse responses of industrial production, CPI inflation, the unemployment rate and the Federal Funds rate to a monetary policy shock. We do not impose the restriction that the monetary shock has no effect on our dependent variables on impact, i.e. the growth of these variables is calculated from the end of the period before the impact of the shock. The growth rate of industrial production is calculted as the log difference in the industrial produciton index. For inflation, we calculate the change in the 12-month CPI inflation rate. The IRFs of the Unemployment rate and the Federal Funds rate are calculated as changes in their levels. We use the sample period of January 1984 – June 2008 in order to begin after the the Volker period (which [10] shows has outsized effects on narrative method estimates) and end before the Financial crisis.

We plot our baseline results which use the full set of Greenbook forecast variables as controls in Figure 1.2. We immediately see that the predicted IRFs do not align with traditional theory. Looking first at the Federal Funds rate, we see that the increase in the Federal Funds rate is extremely persistent, never returning to the orignal value even after 60 months. Looking at industrial production, the contractionary monetary policy shock leads to a small but generally positive change in the industrial production index over the following four years with a larger increase of about 1% between years four and five. Inflation also generally increases over the first three years before decling at the end of the horizon. Finally looking at unemployment, we see a generally flat response to the shock with an increase of a couple tenths of a percent starting around three years after the shock. Overall, it appears the Greenbook forecast variables do not do a sufficient job capturing the FOMC's full information set and that even after controlling for the forecasts, a significant amount of the variation in the Federal Funds rate is endogenous.

Next we estimate the same IRFs except control for lags of output, inflation and unemployment in place of the Greenbook forecasts. This offers us a baseline where we use no explicitly forward looking variables and only use backward looking information at the time of the shock. In particular, we continue to use the change in the Federal Funds rate as our policy variable and control for the first 12 lags of ouput growth and changes in monthly inflation and unemployment. Figure 1.3 plots these results. Comparing to the IRFs using the Greenbook variables, the path of the Federal Funds rate is very similiar, with an immediate peak response of around 1.25 in both cases and remaining elevated even 60 months out. The increase in inflation peaks at around half a percent for both sets of IRFs and follows a similiar pattern thereafter. In both cases Industrial Production increases on impact before quickly declining to around zero, although it declines by more when controling for the lags of macroeconomic variables. Finally, looking at unemployment, we continue to see a small decline on impact, but unlike the Greenbook forecasts, there is a larage and sustained increase peaking at 0.6% at the end of the horizon. Summarizing these results, it appears that the Greenbook forecasts are strictly worse at controling for the endogenous component of monetary policy than historical macroeconomic variables, casting doubts on their ability to fully control for the FOMC's information set.

As discussed in Section 1.3, one possible explanation for this finding is that the Financial Assumptions process generates a wedge between the Greenbook Forecasts and the FOMC's information set. To address this concern we include the intermeeting change in the assumed 1-quarter ahead Federal Funds rate in the Financial Assumptions. This captures the change in the assumed stance of monetary policy between Greenbook forecasts. Figure 1.4 plots the results of this exercise. Comparing to Figure 1.2, the estimates are even more puzzling. The increase in the Federal Funds rate is more persistent while output, inflation and Unemployment all move in a permanently expansionary direction.

Next we explore the possibility that the Greenbook forecasts variables are individually only weakly informative about the FOMC's information set. The standard narrative regression contains nine variables containing information about the forecast of real economic activitity and eight variables containing information about the forecast of inflation. By including so many redunent variables, it is possible that narrative regressions overfit the policy variable and do worse at removing systemic monetary policy than a sparser model would.

To explore this possibility we make use of a factor model to exploit the underlying information sparseness. We estimate PCA factors from the Greenbook forecast variables and then rerun the narrative regression using these factors. Our first task is to estimate the appropriate number of factors. Traditionally this would be estimated with information criteria methods; however, in our case because the subcomponents are heavily correlated, information criteria methods tend to over estimate the number of common factors. Instead we use the ability of the factors to predict monetary policy actions as criteria. To do so, we run 11 regressions, the first including only a constant and add an additional factor for each subsequent regression, i.e. the second regression includes the first factor and the third regression contains the first two factors. We then compare the adjusted R^2 of each regression to the baseline narrative regression. Table 1.2 contains the results of this exercise. The adjusted R^2 of the baseline narrative regression is 0.378. Looking at the factor regressions, we see that the adjusted R^2 quickly increases for the first four factors reaching

Table 1.2: Adjusted R^2 for Different Factor Models

N Factors	Adj. R^2
0	0.000
1	0.001
2	0.246
3	0.245
4	0.324
5	0.321
6	0.360
7	0.373
8	0.373
9	0.387
10	0.400
Baseline Regression	0.378

Notes: Table presents the adjusted R^2 value for the regression of the change in target Federal Funds rate on PCA factors estimated from the components of the Greenbook forecast included in the narrative baseline regression (1.1). "N Factors" indicates the number of PCA factors used in the regression. "Baseline Regression" is (1.1). Each regression contains a constant. The sample period is January 1984–June 2008. Each regression contains 186 observations.

a value of 0.324, before plateauing for additional factors. At nine included factors, the adjusted R^2 is 0.387, above the adjusted R^2 of the baseline narrative regression, indicating that there is indeed redundant information across all the variables in the Greenbook forecasts.

In light of these results, we reestimate the narrative regression including a constant and the first six PCA factors estimated from the Greenbook forecasts variables. Looking at Table 1.5 we see that the reaction of the Federal Funds rate is much less persistent, with the effect declining to zero after three years. Industrial production shows a small initial increase on impact to the shocks, but quickly begins to decline, staying below the initial value for the entirety of the estimation horizion, with the peak decline of about 1.5% occuring four years after the initial impact of the shock. Unemployment has an insigificant decline after the impact of the shock, but quickly begins to rise hitting a peak of around a 0.9% increase four years after impact. Finally looking at inflation, we see an initial increase, followed by sustained downward trajectory over the rest of estimation horizon, ending at a decrease of half a percent at the end of the estimation horizon. For robustness, we also estimate the same model using only four factors in Table 1.6 with similiar results. These estimated IRFs are generally in line with conventional theory, other than the initial reaction in the first month. This is evidence that the Greenbook forecasts do contain information about the FOMC's information set when setting monetary policy but naively including each forecast variable is inefficient.

We round out our analysis of the Greenbook variables, by testing if our Greenbook Factors contain all the information used by the FOMC when setting monetary policy by also including factors estimated off the FRED-MD dataset compiled by [14]. The FRED-MD dataset contains over a houndred macroeconomic series at a monthly frequency. [14] show that the information contained in these series can be efficiently represented by eight factors. Using these factors is an efficient way to incorporate a large amount of data [5]. By including these eight factors in our model, we can test if their inclusion alters the estimated IRFs to our monetary shock. Figure 1.8 plots these results. We see that including the FRED-MD factors make a small difference in our estimated IRFs. The effect on the Federal Funds rate declines to zero slightly more quickly when including the macroeconomic information. The decline in output is quicker when including macroeconomic information but levels out at a similiar trough as before. Unemployment also increases faster but has a lower peak at an increase of 0.6%. Finally, the response of inflation is broadly similiar between the models.

Finally we test if there is additional information in the Greenbook factors, beyond what is in the FRED-MD factors by using only the FRED-MD factors as controls. Table 1.8 plots these IRFs. The first thing we note is the much larger error bands around every estimate. We take this as evidence that the Greenbook forecasts do in fact contain information in predicting future economic conditions above and beyond what is available in the macroeconomic factors. Next looking at the estimated path of the Federal Funds rate, we observe a much quicker decline back to zero total effect a year after the impact of the shock. Inflation, on the other hand, increases on impact and stays elevated for the entire horizon, returning to zero only at the very end of the estimation horizion. Output exhibits a much larger peak decline of almost 3% four years after the impact of the shock while unemployment exhibits a similiar path, peaking around a 0.8% increase. Overall, we take the larger standard errors and inconsistent inflation response as evidence that the Greenbook factors do contain additional information about the future path of the economy and that the FOMC does use this information when setting monetary policy.

1.5 Conclusion

In this paper we have utilized a new method of estimating narrative based estimates of the effect of monetary policy and show that traditional methods perform poorly in estimating exogenous movements in monetary policy. Our method is easy to implement and is able to provide robust proxies for exogenous monetary policy. We also explore the role of the Financial Assumptions process and show that while this process can theoretically cause misidentification in narrative methods, in practice this effect is negligible.

To summarize our empirical findings, the Greenbook forecasts do contain information that is useful for predicting the path of economic variables, and the FOMC utilizes this information when setting monetary policy; however, standard methods of including many variables from the Greenbook forecasts can over fit the measure of the stance of monetary policy and create unreliable estimates of exogenous monetary policy. By using a factor model, we are able to exploit the information sparsity behind the Greenbook forecasts and robustly remove the endogenous component of monetary policy explainable by the FOMC's forecasts of output and inflation.

We also showed that even after controlling for the information in the Greenbook forecasts, the eight common factors estimated from the FRED-MD dataset contain additional but different information which further removes remaining endogeneity in monetary policy actions. This is possibly because the FRED-MD factors contain information about financial condtions that the FOMC responds to. Overall we find effects of monetary policy that are similar in magnitude as to the traditional VAR literature [4] but with later peak effects around four years similar to traditional narrative methods.

1.6 Chapter 1 Figures

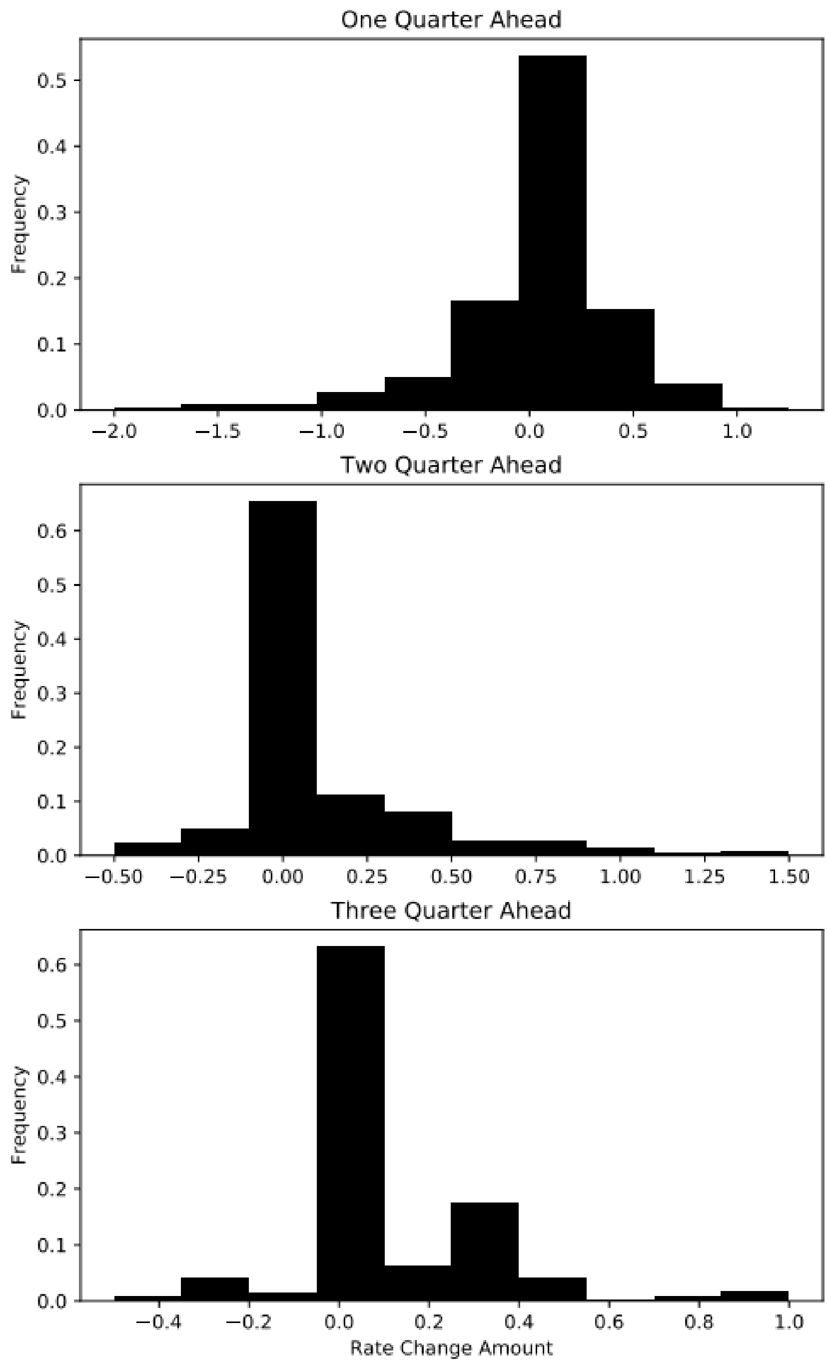

Figure 1.1: Distribution of Rate changes in the Financial Assumptions

Notes: This figure presents the distribution of implied rate changes at different horizons within the Financial Assumptions.

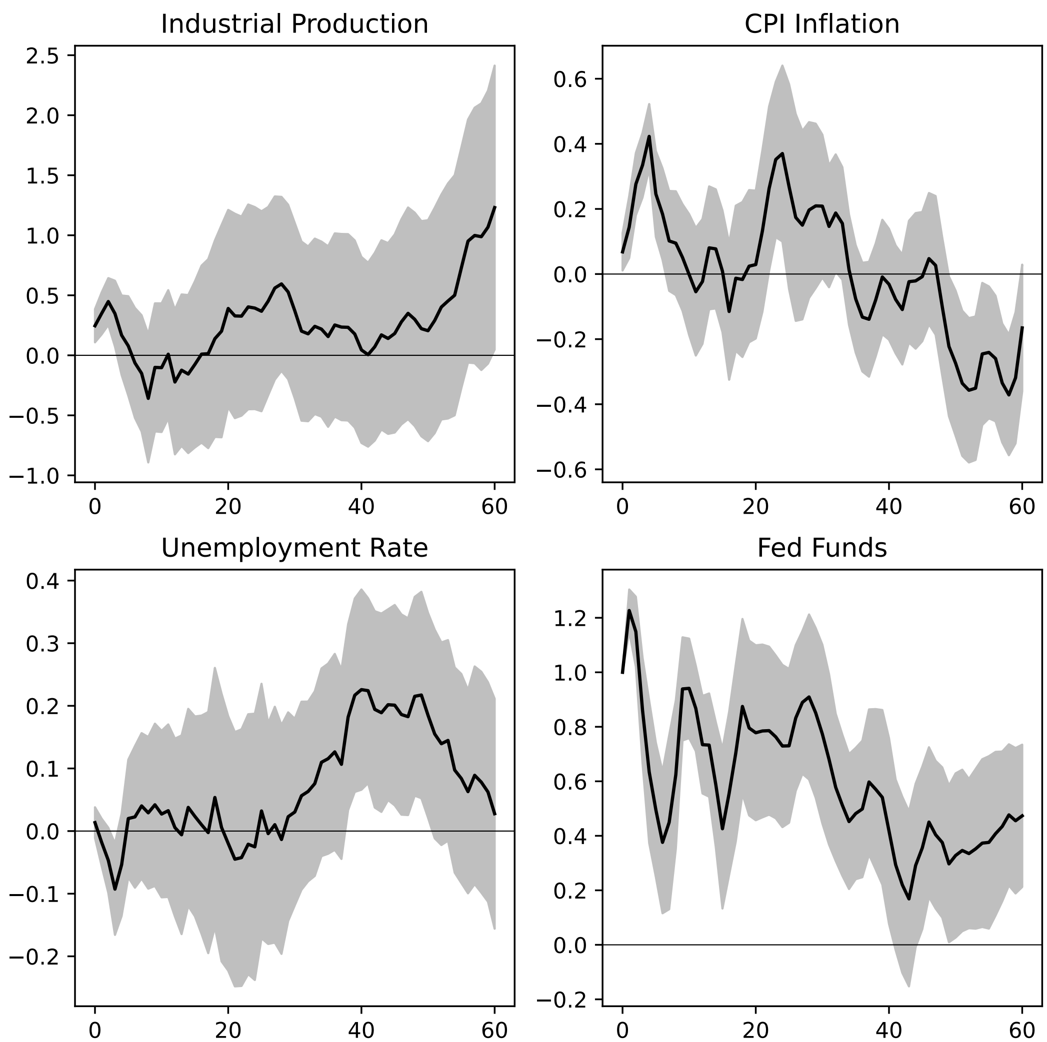

Figure 1.2: Impulse Response Functions using Greenbook Variables

Notes: This figure presents the estimated IRF for four macroeconomic variables for equation 1.6. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

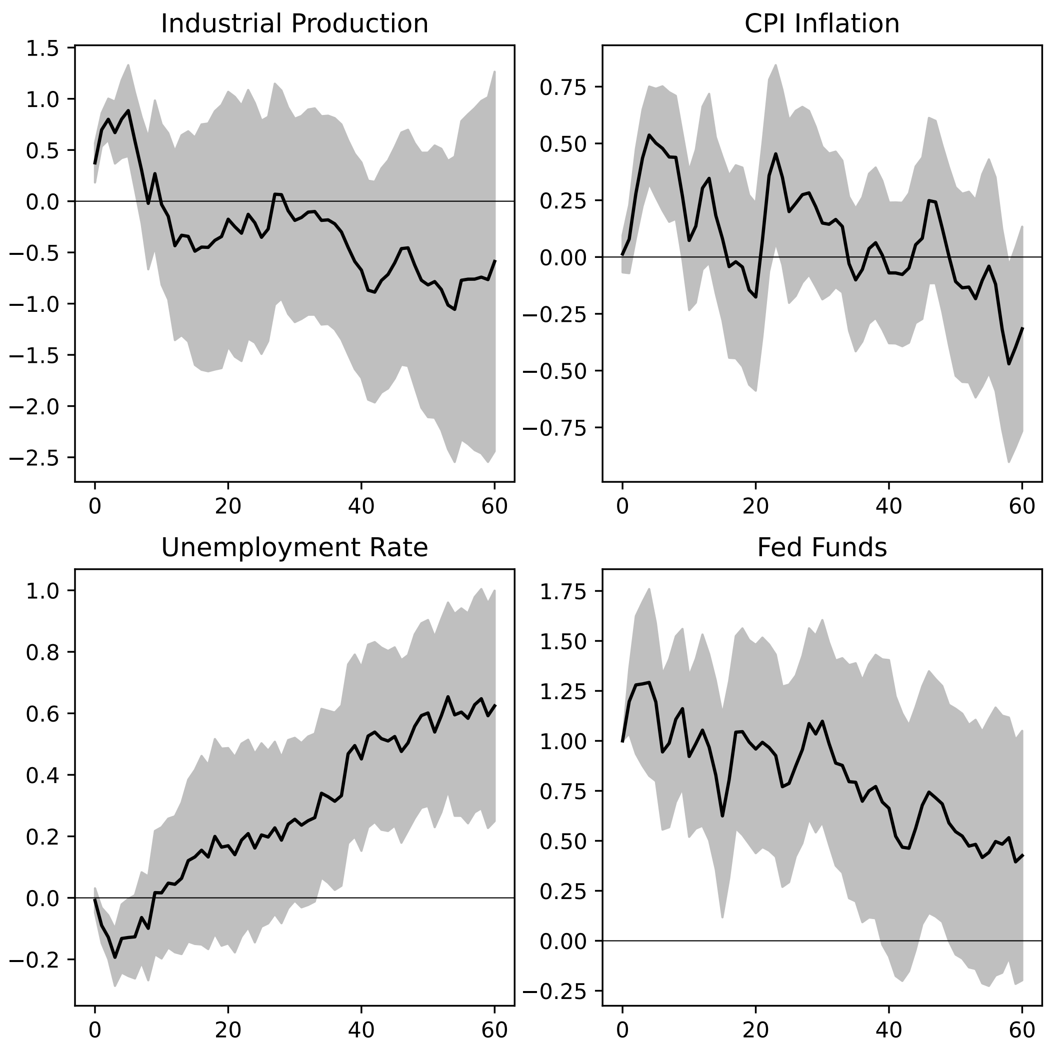

Figure 1.3: Impulse Response Functions with Macroeconomic Controls

Notes: This figure presents the estimated IRF for four macroeconomic variables to changes in Federal Funds rate controlling for 12 lags of industrial production growth and changes in Unemployment and inflation. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

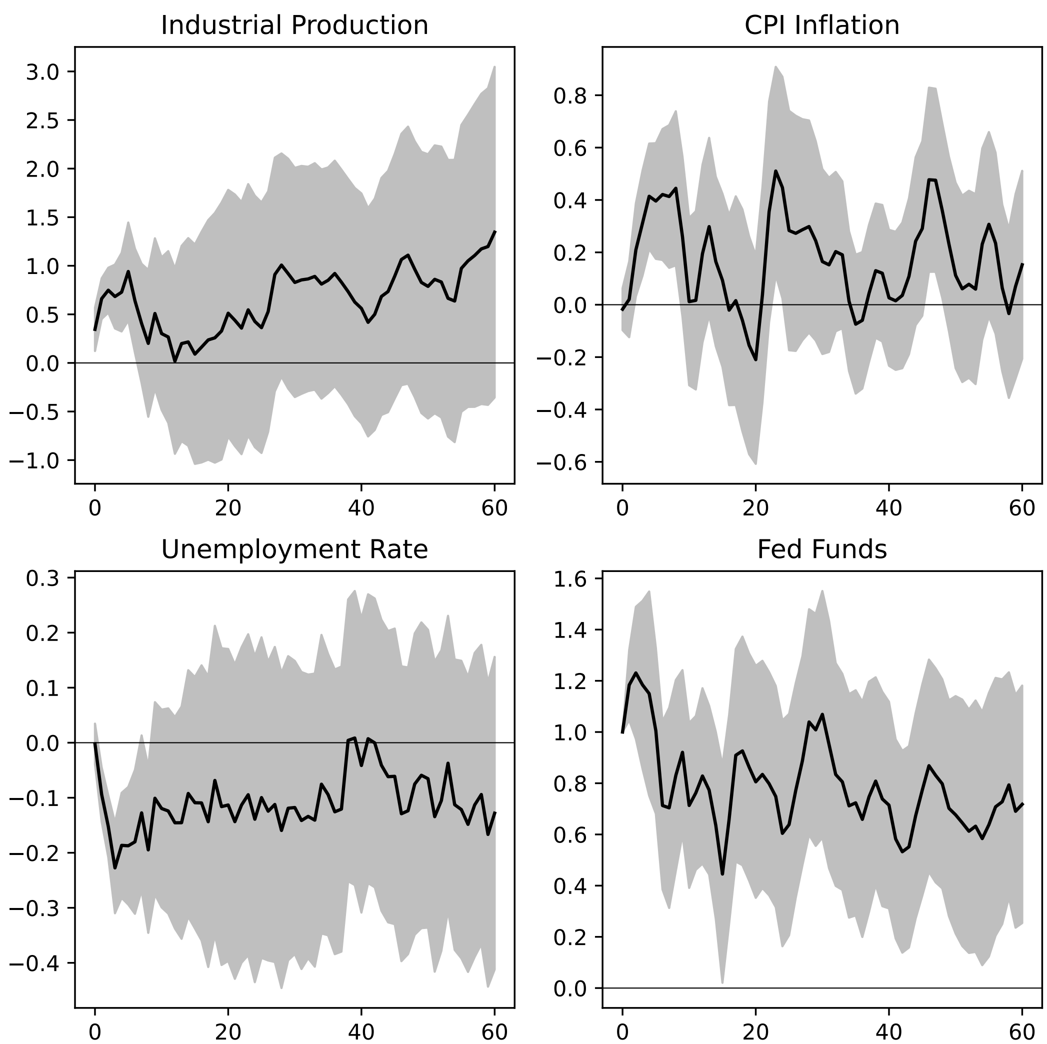

Figure 1.4: Impulse Response Functions using Greenbook Variables and Financial Assumptions
Notes: This figure presents the estimated IRF for four macroeconomic variables for equation 1.6 including the change in the 1-quarter ahead Financial Assumptions Federal Funds Rate. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

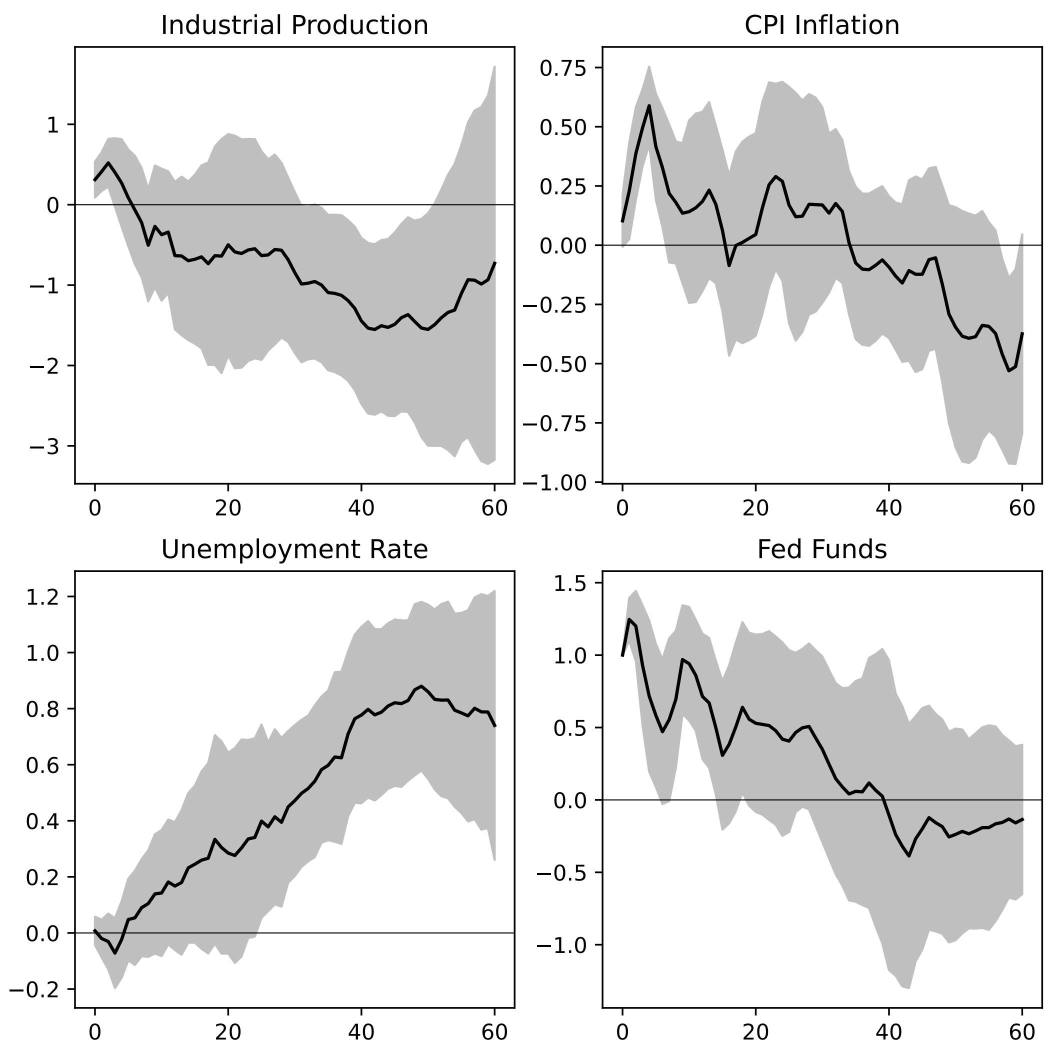

Figure 1.5: Impulse Response Functions using Greenbook Factors

Notes: This figure presents the estimated IRF for four macroeconomic variables using the first 6 PCA factors estimated from the Greenbook forecast variables as controls. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

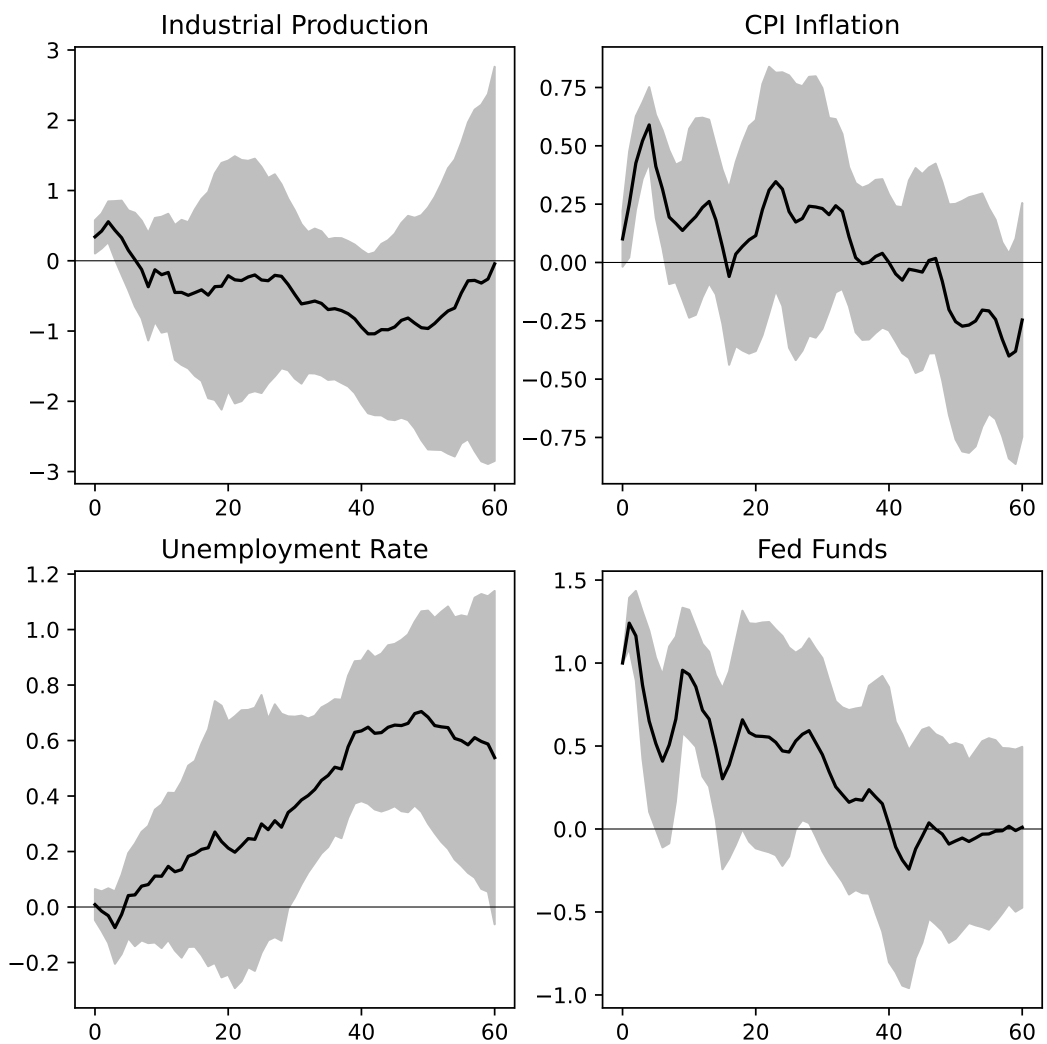

Figure 1.6: Impulse Response Functions using Greenbook Factors, Alternative Specification
Notes: This figure presents the estimated IRF for four macroeconomic variables using the first 4 PCA factors estimated from the Greenbook forecast variables as controls. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

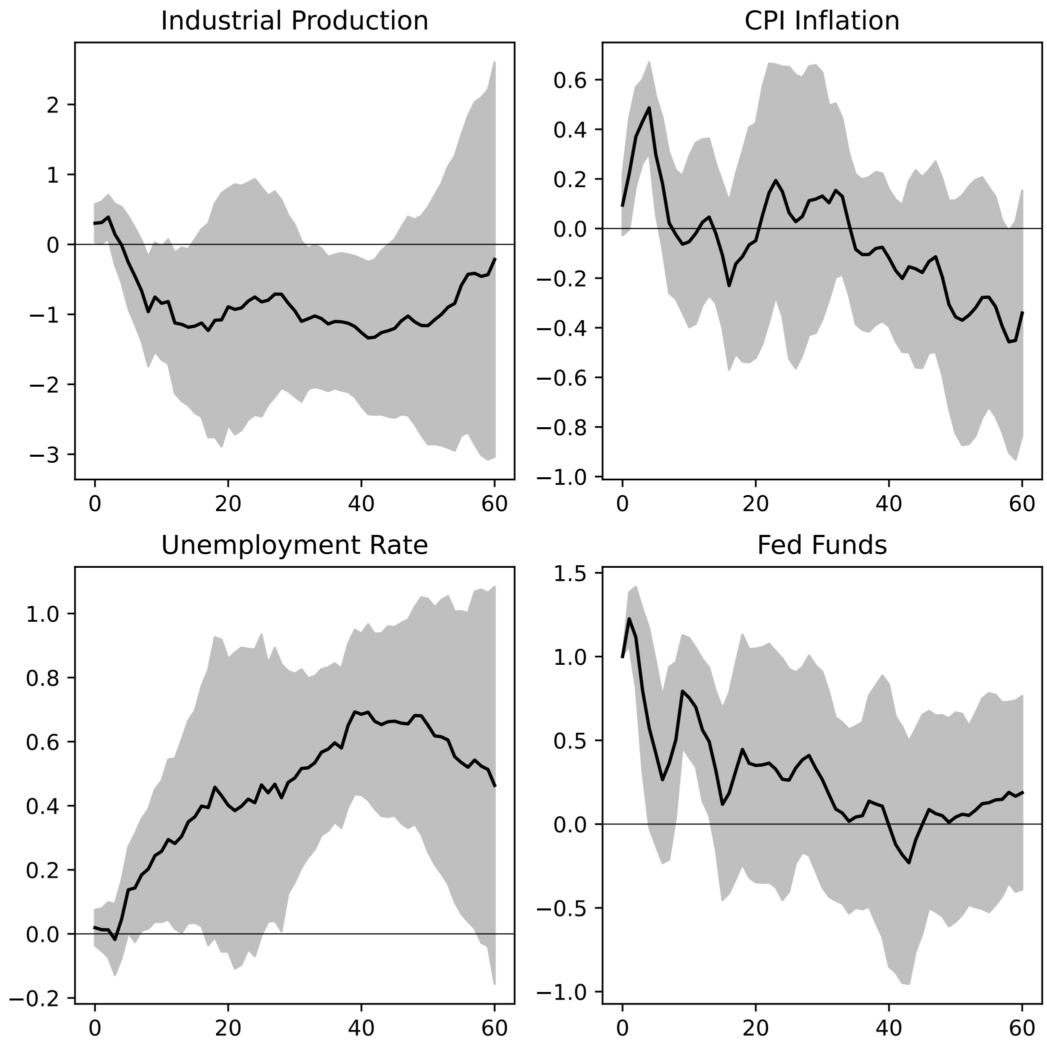

Figure 1.7: Impulse Response Functions using Greenbook and FRED-MD Factors

Notes: This figure presents the estimated IRF for four macroeconomic variables using the first 4 PCA factors estimated from the Greenbook forecast variables and as controls. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

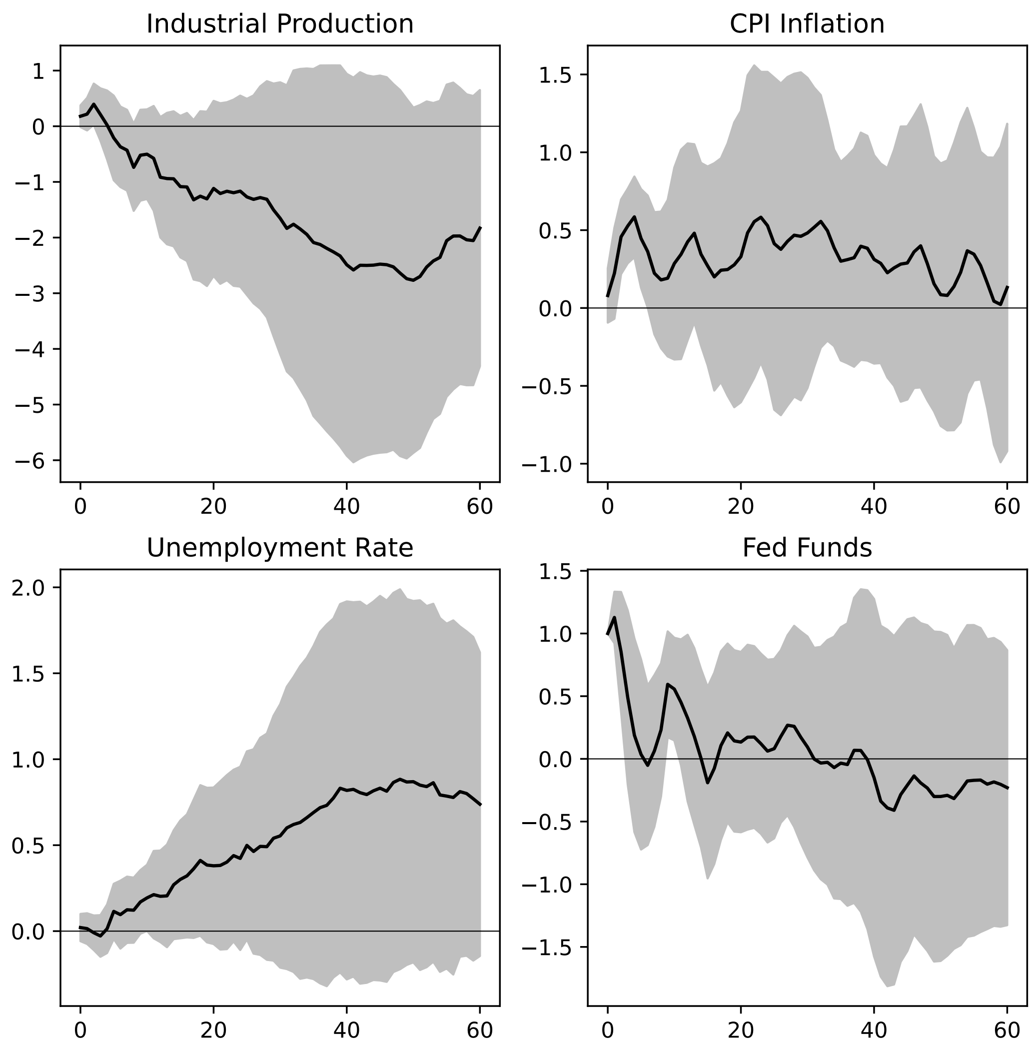

Figure 1.8: Impulse Response Functions using FRED-MD Factors

Notes: This figure presents the estimated IRF for four macroeconomic variables using the first 8 PCA factors estimated from the FRED-MD dataset as controls. Industrial Production is the log growth of the industrial production index, CPI Inflation is the change in the 12-month inflation rate, Unemployment Rate is the change in the unemployment rate, and Fed Funds is the change in the Federal Funds rate. Shaded areas indicate 95% confidence intervals.

Chapter 2: Robust Tests for Monetary Information Effects

Obtaining exogenous measures of monetary policy is one of the central challenges in empirical macroeconomics. One strand of the literature, starting with [6] attempts to control the information set of monetary policy makers by using the internal forecasts used by these policy makers. In particular, Romer and Romer use the Greenbook forecasts, which are prepared by Federal Reserve economic staff for each FOMC meeting. They present narrative evidence that the FOMC's views on the economy are heavily influenced by the Greenbook forecasts, and argue that they serve as good proxies for the FOMC's information set. By regressing policy rate changes on these forecasts, they argue that one can obtain measures of monetary policy that are uncorrelated with economic conditions at the time of the policy action.

A second strand, pioneered by [15] and later refined by [8], and [16], has attempted to control for the information set of asset market participants. These papers use the high frequency returns of interest rate futures around monetary policy announcements as measures of exogenous monetary policy. If asset prices fully incorporate all available information, then these high frequency shocks will be exogenous to the state of the economy.

[10] and [1] highlight that the macroeconomic response to both narrative and high frequency shocks often run contrary to standard economic theory and this is especially true for the high frequency measures. [17] explain these findings by their being information transfer from the FOMC to markets during FOMC announcements due to the FOMC having superior information sets to asset markets at the time of the FOMC announcements.

Miranda-Agrippino and Ricco extend this thought by considering a model where monetary policy makers and asset market participants have incomplete, but different information about the state of the economy. They show that a such a model predicts that high frequency shocks will be autocorrelated, predictable by past economic conditions and predictable by the Greenbook forecasts, even if agents are fully rational. They proceed to show that commonly used high frequency measures of monetary policy have these three properties.

[18] propose that counterintuitive macroeconomic responses to high frequency monetary policy shocks can be explained by risk-premium effects. These risk premium effects can cause the high frequency returns to be correlated with the state of the economy which makes them invalid measures of exogenous monetary policy.

In this paper we look at the high frequency asset returns themselves, and extend the analysis to equity prices and asset returns around economic news announcements. Our results show that information effects plat at most, a small role in the behavior of high frequency asset returns around economic and monetary news events.

We find that these raw high frequency returns are not autocorrelated around either news event. These returns are also find only weak evidence that these returns are predicted by the set of Greenbook forecasts traditionally used in the literature; however, when using the Greenbook forecast for CPI instead of the GDP deflator and controlling for a single lag of the level of economic activity, these results completely disappear. Finally, we do that the high frequency returns are predicted by lags of economic data, but that this pattern also holds around economic news releases, not just monetary news releases. Together this evidence points to risk premium effects being the source of the counterintuitive macroeconomic responses to monetary policy and not information effects specific to monetary policy.

In Section 2.1 we describe a simple model linking diffuse information and its testable predictions on asset returns around news events. In Section 2.2 we describe the high frequency shocks that we test and detail their construction. We also describe the different economic and monetary news events that we analyze. In Section 2.3 we proceeded to test the predictions from Section 2.1.

The paper makes the following primary contributions. First, it extends recent analysis by [9] to primitive asset shocks commonly used in the literature to construct monetary policy shocks and to the S&P 500 Index which has recently become a common auxiliary measure for monetary policy shocks, e.g. [19] and [20].

Secondly, we refine the analysis to only use correctly sized hypothesis tests by using joint hypothesis tests and a bootstrap method that is robust in small sample inference. Finally we also analyze economic news releases as well as monetary news release which allows us to separate monetary specific information effects from other possibilities. Existing papers have explored the role of information frictions around monetary events e.g. [1], [17], [19] but none have expanded their analysis to non-monetary news events.

2.1 A Simple Model of Information Frictions

We begin by describing the link between asset prices and information, borrowing the model in [9] [1]. To begin assume we have a state variable x_t which follows an AR(1) process governed by the parameter ρ with innovations ξ_t:

$$x_t = \rho x_{t-1} + \xi_t$$

Next assume that there are a continuum of agents in the economy who each receive a signal s_{it} with i.i.d. noise ν_{it}:

$$s_{it} = x_t + \nu_{it}$$

After receiving their signal agents update their forecasts of the state variable as

$$F_{it}[x_t] = Ks_{it} + (1 - K)F_{it-\Delta}[x_t]$$

We denote the aggregate forecast, $F_t[x_t]$ as the average of the individual agent forecasts. [22] highlight that even when the individual forecasts are fully rational, the aggregate forecasts errors are predictable.

To link this information to asset markets, assume that agents trade securities whose price at maturity is determined by the policy rate at time $t + h$. The current period price is based on the

[1] See [21] for additional details.

aggregate forecast for the state variable:

$$p_t(i_t + h) = F_t[x_{t+h}] + \mu_t$$

μ_t represents a stochastic component which may be due to risk premium [16] or changes in asset supply [23]. If the stochastic component is constant around news events, then changes in the aggregate forecast drive changes in prices.

The central bank also receives an idiosyncratic signal and sets the policy according to a policy rule of the form:

$$i_t = \phi F_{cb,t}[x_t] + u_t$$

When the central bank announces their policy rule for period t, agents extract information about $F_{cb,t}[x_t]$ and thus x_t itself. Miranda-Agrippino and Ricco show that these aggregate forecast revisions, and therefore the asset returns, will be autocorrelated, predictable by past information and predictable by the central bank's information set. Importantly, even if agents have a common information set, but one that is different from the central bank's, then the central bank information set will continue to be informative about asset price returns around central bank releases.

2.2 Data

In this section we describe our four asset returns which we test for information effects. Next we describe the economic and monetary events around which we test for information effects. Finally we describe the Greenbook and macroeconomic data used.

2.2.1 Measures of Forecast Revisions

We test four measures of monetary policy. The first three are interest rate derivatives, the near month Federal Funds Rate futures along with the three and 12-month Eurodollar futures. The last measure is the S&P 500 Index.

Federal Funds Rate Future

The Federal Funds Rate future price is pegged to the average of the effective Federal Funds rate in the month in which it expires, specifically

$$p_m = 100 - \frac{1}{T_m} \sum_{t=1}^{T_m} r_t$$

where T_m is the number of days in the expiration month and r_t is the daily effective Federal Funds rate with days indexed by t. It is a monthly future with an expiring contract for every month. This future is useful for measuring the expected and unexpected component of monetary policy because it is pegged directly to the policy rate.

The unexpected component of monetary policy for a given announcement can be calculated from the scaled changes in the futures price

$$\epsilon_m^{ff} = \frac{T_m}{T_m - t} \left(p_{t-\Delta} - p_{t+\Delta} \right) \tag{2.1}$$

This is the formula that we use when constructing our Federal Funds Rate future shocks with the modifications that if the policy change occurs in the final 5 days of the month, we use the next month's futures price instead to avoid dividing by a number close to zero. We use this same formula to calculate high frequency shocks around economic news announcements with t equal to the day of the announcement, not the next FOMC meeting. Therefore our measure cannot be interpreted as a direct measure of the change in expected policy at the next FOMC meeting arising from the economic news announcement.

We use tick level from the CME group to measure $p_{t-\Delta}$ and $p_{t+\Delta}$ around announcements. We use a standard thirty minute window beginning five minutes before the announcement and ending 25 minutes after the announcement. $p_{t-\Delta}$ is taken to be the outstanding price from the last trade before the start of the thirty minute window and $p_{t+\Delta}$ is the last trade before the end of the thirty minute window. If no trades occur within the thirty minute window, this produces a value of zero for the shock. We have CME data on the Federal Funds Rate futures starting in January 1995 through December 2019.

Eurodollar Futures

The Eurodollar futures price is pegged to the outstanding level of the three-month Libor rate at the expiration of each contract, specifically

$$p_m = 100 - r_t$$

. It is a monthly future with expiring contract for each month. These futures contracts are commonly used because they have much higher liquidity, especially at longer horizons than the Federal Funds futures which allows one to measure market expectations about changes in the future path on monetary policy beyond the immediate future [16]. Interpreting price changes is also straightforward because the final settlement price is based only on the 3-month Libor rate at expiration, unlike the Federal Funds Futures which is priced based on a monthly average of rates. This is especially relevant for economic news days.

We construct our shocks as the simple difference in futures prices:

$$\epsilon_m^{ed} = p_{t-\Delta} - p_{t+\Delta} \tag{2.2}$$

We measure $p_{t-\Delta}$ and $p_{t+\Delta}$ identically to the Federal Funds futures using the same 30 minute window. We have CME data on Eurodollar futures starting in January 1982 through December 2019.

One complication is that the liquidity of contracts that fall on the end of a quarter are much higher than other contracts. The liquidity difference can sometimes be substantial, especially at longer horizons, with the quarter end contracts sometimes exhibiting 1,000 times more activity than adjacent non-quarter end contracts around news announcements. Following the existing literature, we restrict ourselves to using only quarter end contracts. To measure the 3-month ahead and 12-

month ahead Eurodollar future price we linearly interpolate the opening and closing prices using the quarter end contracts' opening and closing prices and then use the interpolated 3-month and 12-month prices to calculate the 3-month and 12-month surprise. Some authors (e.g. [17]) use the nearest quarter end contract for each horizon of interest instead of interpolating, but the resulting shocks are very similar because the entire Eurodollar futures yield curve tends to move together, especially at horizons less than 12 months.

S&P 500

Our final asset is the S&P 500 Index. Empirical researchers recently begun to incorporate equity prices in their analysis as a potential way to measure information effects of monetary policy, e.g. [19] and [24], but there has been little research on wether equity prices also show signs of information effects. Because the S&P 500 Index only trades during limited times we use three different measures. The first is the SPY ETF to measure changes in the S&P 500 Index during regular trading hours. The SPY ETF was introduced in 1993 and tracks the S&P 500 Index by purchasing the underlying stocks in the S&P 500 Index. Any differences in the value between the SPY ETF and S&P 500 Index are easily arbitraged away which makes the SPY ETF an easy way to track the value of the S&P 500 Index. Outside of regular market hours we use two futures whose value is pegged to the S&P 500 Index. The first is the original CME S&P 500 futures contract. The final settlement price of this future is equal to 250 times the closing price of the S&P 500 index on the day of contract expiration. The second contract is the E-mini S&P 500 futures contract, which is identical to the original S&P 500 futures contract except that its final settlement price is equal to 50 times the closing price of the S&P 500.

We construct our shocks as the simple log difference in ETF or futures prices:

$$\epsilon_m^{sp} = \log p_{t-\Delta} - \log p_{t+\Delta} \tag{2.3}$$

We measure $p_{t-\Delta}$ and $p_{t+\Delta}$ identically to the Federal Funds futures using the same 30 minute window. We have data on the SPY ETF starting in January 1993 through December 2019. We have CME data on S&P 500 futures starting in April 1982 through December 2019 and E-mini S&P 500 futures starting in September 1997 through December 2019. We use S&P 500 futures before 2000 and E-mini futures after, with the switch over determined by when liquidity on the E-mini contract surpassed liquidity on the original contract.

2.2.2 Monetary and Economic Events

We analyze shocks around three different news releases, FOMC policy decisions, the "Employment Situation Report" (commonly referred to as the "Jobs Report") and the CPI release. We begin by discussing the economic news releases.

Our two economic news events are the CPI and jobs report. Both reports are watched closely by market participants as monthly leading indicators of the economy. The jobs report is typically released at 8:30 AM on the first Friday of each month and contains estimates for the unemployment rate, newly created jobs, information about flows into and out of the labor market, and information on wages. The CPI report is typically released on the second Tuesday or Wednesday of each month and contains information on the estimated CPI and its subcomponents. We obtain the release date and times for each report by combing data from Bloomberg and the BLS website. The dates and times account for disruptions in regularly scheduled releases due to national emergencies or Federal Government shutdowns. Our sample of release times for the CPI release runs from December 1996 through November 2019 and our sample of jobs report release times runs from February 1994 through October 2020.

Our monetary news releases are the FOMC policy decisions. We have four types of policy decision releases, scheduled and unscheduled Open Market Operations and scheduled and unscheduled FOMC policy statements. Before 1994, the FOMC did not publicly announce its monetary actions so markets needed to infer them from the New York Reserve Bank's open market operations, usually on the following morning. We classify such windows that follow a scheduled FOMC meeting as scheduled open market operations. Often times the FOMC or the Chairman of the FOMC would instruct the New York Reserve Bank to conduct open market operations to alter the levels of monetary reserves outside of scheduled FOMC meetings. We classify such operations as unscheduled. Between January 1990 and December 1993 we observe 31 scheduled open market operations and 15 unscheduled open market operations. After December 1993, there are no unannounced open market operations.

In 1994 the FOMC started to publicly announce their policy changes after the FOMC meeting. The announcements almost exclusively contained only the policy action with very little, if any, explanation about why any given policy action was taken. We classify statements that come out after scheduled FOMC meetings as scheduled statements and those that come out after unscheduled meetings as unscheduled announcements. There were eight scheduled announcements and one unscheduled announcement in 1994.

Beginning in 1995, the FOMC expanded its policy statement to include information about about its view on the forecast of the economy and an explanation of why it was conducting its policy actions. The length and detail of the statements has generally increased over time. Between January 1995 and December 2019 there were a total of 199 scheduled FOMC statements and 6 unscheduled statements.

Table 2.1 shows summary statistics for each of our four shocks around each event type. Unscheduled open market operations are excluded from the table for space and due to the fact that there are no Federal Funds futures observations for that period and only a few S&P 500 observations. We report the count, mean, min, max and the average of the absolute value of each shock as a measure of their typical magnitude. The interest rate returns are expressed in basis points, while the S&P 500 is expressed in percentage points.

We first note that the asset returns around scheduled events are about zero on average, while interest rates on average decrease around unscheduled FOMC statements and equity prices increase. The average magnitude of the returns is also much higher with the three-month Eurodollar and S&P 500 showing movements about four times larger. This is easily explained by the fact that unscheduled statements usually carry news about large changes in policy at time when markets

Table 2.1: Summary Statistics for Asset Returns

Release	Statistic	ED12	ED3	FF	SP500
FOMC Stmt.	count	207	207	199	207
	mean	-0.01	-0.01	-0	-0.03
	min	-0.25	-0.25	-0.20	-1.62
	max	0.25	0.18	0.11	1.75
	abs. mean	0.04	0.03	0.02	0.37
FOMC Unschd.	count	7	7	6	7
	mean	-0.04	-0.10	-0.20	1.49
	min	-0.20	-0.30	-0.44	-0.38
	max	0.08	0.08	0.00	4.76
	abs. mean	0.07	0.12	0.20	1.65
FOMC OMO	count	31	31	—	8
	mean	-0	-0	—	0.05
	min	-0.09	-0.10	—	-0.14
	max	0.02	0.02	—	0.56
	abs. mean	0.01	0.01	—	0.14
Jobs Report	count	311	311	300	311
	mean	-0.00	-0.00	-0.00	0.02
	min	-0.35	-0.23	-0.07	-1.64
	max	0.40	0.26	0.04	1.99
	abs. mean	0.06	0.03	0.00	0.38
CPI Release	count	276	276	276	276
	mean	-0.00	-0.00	-0.00	0.01
	min	-0.24	-0.23	-0.29	-1.85
	max	0.16	0.08	0.05	1.78
	abs. mean	0.03	0.01	0.00	0.19

Notes: This table presents summary statistics for asset returns around different announcements. “FOMC Stmt.” includes only scheduled FOMC statements. “FOMC Unschd. Stmt.” includes only unscheduled FOMC statements. “ED12” is the 12-month Eurodollar Future, “ED3” is the 3-month Eurodollar Future, “FF” is the near month Federal Funds Future, “SP500” is the S&P 500 index or future. “absolute mean” is the average value of the absolute value of each series.

did not expect any possibility of policy changes. Comparing FOMC statements to the open market operations, we see that the open market operations have much smaller asset price movements associated with them. This can be explained by the more frequent open market operations leading to smaller policy changes at each one, combined with the fact that markets needed to infer the FOMC policy change from the open market operations leading to slower price reaction. Next we can see that the asset price responses around the Jobs Report are similar in magnitude to the responses around FOMC Statements and that the responses around the CPI release are about on average about half as large in magnitude.

2.2.3 Auxiliary Data

We use the first factor estimated off of the FRED-MD dataset as a robust measure of economic activity. The FRED-MD dataset contains 156 monthly economic series available on FRED. These series were chosen to capture the majority of variation across the economy. The first factor is strongly correlated with the growth rate of real activity across the economy and explains about 16% of the total variation in all 156 series, and about 70% of the variation in industrial production and employment according to [14]. Information criteria test select eight factors as the optimal number of factors to explain the joint variation across the FRED-MD dataset. We only use the first factor to be conservative in our predictability regressions and to minimize the number of regressors used. The FRED-MD factor is estimated using the entire FRED-MD dataset from 1960 through 2019.

We also use the realtime Greenbook forecasts collected by the Philadelphia Federal Reserve Bank. The Greenbook forecasts contain the Federal Reserve Board of Governors's staff forecast for the U.S. economy and is produced for each scheduled FOMC meeting. [6] present evidence from FOMC meeting transcriptions that the FOMC closely reads the Greenbook forecasts and these Greenbook forecasts are very important when FOMC participants form their own forecasts. In particular we follow Romer and Romer and [9] and use the forecast for quarterly real GDP growth, unemployment and the GDP deflator. In robustness checks, we also use forecasts for CPI inflation and the PCE deflator. Because the Greenbook forecasts are released with a five year lag, we have forecasts up to December 2015.

2.3 Testing Predictability of Returns

In this section we formally test for information effects in high frequency returns around monetary and economic news releases. Specifically we test if the lags of each shock, general economic conditions and information in the Greenbook can predict each of our shocks. We show that economic conditions, as measured by the first FRED-MD factor, predict returns around FOMC statements and economic news releases, but that the lags of past shocks and information in the Greenbook do not predict current shocks after controlling for economic conditions.

Our definition of predictability is the same as [9]. We say that the return r_t is predictable by the covariates z_t if $\mathbb{E}[r_t z_{t-1}] \neq 0$. We test this hypothesis with the following regression:

$$r_t = \theta' z_{t-1} + \gamma' w_t + e_t \tag{2.4}$$

with w_t being a vector of controls, including a constant term, which is excluded from the hypothesis test. We test the joint hypothesis that $\theta = 0$ with a Wald statistic.

We use a joint hypothesis test for each element of θ in order to deliver an appropriately sized test for predictability. As is well known within the context of testing for a time series break, the distribution of the extremum of several test statistics does not follow the same distribution as the individual test statistics; therefore, individual t-tests on the elements on θ will be incorrectly sized for testing the null hypothesis that $\theta = 0$ for all elements in θ and will tend to over reject the null hypothesis. We calculate p-values for our test statistic with a residual bootstrap under the null hypothesis that $\theta = 0$.

Our primary sample for FOMC statements runs from January 1995 through June 2008. We choose January 1995 as our start date because it aligns with the start of current FOMC policy of announcing its rate decisions with a written statement accompanied by an explanation of its policy decisions. It also allows us to have balanced panel of shocks and events. In robustness checks, we also use a sample beginning in 1990. We choose our end date to avoid the ZLB period, the introduction of explicit forward guidance and the 2008–2009 financial crises. We also only include monthly observations that contain a scheduled FOMC statement.

We do not include unscheduled FOMC meetings because these meetings are systematically different than scheduled meetings, with average returns far from zero and extremely large variances. As noted by Miranda-Agrippino and Ricco, dropping unscheduled events should strengthen signs of information effects. In the base series, we do not include months with no FOMC statements and do not impute any missing values as zeros. We also test a second series which imputes a zero for months with no scheduled FOMC statement release. As standard in the literature, we also drop September 2001 from the sample. Our sample of CPI releases runs from April 1997 through June 2008 and our Employment Situation Report sample runs from February 1995 through June 2008. The start of each economic news samples is limited by data availability and the end date is chosen to match the FOMC sample. We also drop September 2001 from these samples.

Our first test is for the presence of autocorrelation in the shocks within each sample. Autocorrelation in aggregate forecast revisions is an indicator of diffuse information. For each asset we regress the current return on its own first four lags for each event. For economic news events, these lags are taken at a monthly frequency. For FOMC statements, these lags are taken at the meeting frequency, i.e. the first lag corresponds to the shock at the previous meeting, the second lag to the shock from two meetings previously, etc.

for Table 2.2 shows the results for the joint test that all four coefficients on the lags are zero for each model. For each asset and event type, the joint test robustly fails to reject the null hypothesis that shocks are predicted by their own lags. This result holds across each event type analyzed, indicating that it is a robust feature of the data. The "FOMC Monthly" model, interpolates a zero for months with no FOMC meeting and uses monthly lags. It too fails to show evidence of autocorrelation. [9] provides evidence of autocorrelation in shocks that are built from aggregating shocks around the irregularly scheduled FOMC meetings into monthly series. This paper's results suggest that these earlier results were in fact due to the aggregation method used by previous authors and are not due to autocorrelation in the primitive returns nor due to interpolating missing values.

Table 2.2: F-test for Autocorrelation

Model	Ticker	F-Stat	p-Value
FOMC	FF	0.81	0.503
	ED3	1.55	0.175
	ED12	0.90	0.471
	SP500	0.36	0.834
FOMC Monthly	FF	0.60	0.680
	ED3	1.53	0.156
	ED12	0.62	0.658
	SP500	0.78	0.547
Jobs	FF	1.46	0.173
	ED3	0.66	0.624
	ED12	0.36	0.837
	SP500	0.28	0.889
CPI	FF	0.53	0.242
	ED3	1.56	0.152
	ED12	2.04	0.099
	SP500	0.36	0.843

Notes: This table presents the F-stat and p-values for a joint test of model significance for different models around monetary announcements and economic releases. The ‘model tested is an AR(4) model. The FOMC release are scheduled FOMC releases, FOMC Monthly is scheduled FOMC releases with imputed zeros for months with no scheduled statement. “Jobs” is the Employment Situation Report and CPI is the CPI release. The asset “FF” is Federal Funds futures, “ED3” and “ED12” are three/twelve-month Eurodollar futures, and “SP500” is the S&P 500 index. The p-values are calculated with a residual bootstrap. *, ** and *** denotes 5%, 1% and 0.1% statistical significance.

Our second test analyzes the predictive power of the first lag of the first FRED-MD factor. This series contains publicly available at the time of each news release. If information frictions are present, then this series should be able to predict returns. However, time varying risk premium effects can also lead this series to predict returns. For this test, we regress each shock on a constant and the first lag of the first FRED-MD factor. Table 2.3 shows our results. Unlike the test for autocorrelation, we find evidence that the first FRED-MD factor is predictive of returns in the interest rate futures, especially the Eurodollar futures, with only the tests around the CPI release failing to reject the null hypothesis. Shocks around the CPI release are about half as large on average as around the FOMC statements and Employment Situation Report, lowering the statistical power of our test which may explain the lower F-statistics. Around the scheduled FOMC statements and the Employment Situation Report we can reject the null hypothesis at either the 1% or 0.1% level for both the three and twelve-month Eurodollar futures. These results mirror those in Miranda-Agrippino and Ricco who find that the first FRED-MD factor has predictive power for their set of monetary shocks.

The fact that economic conditions can predict asset returns around news events is consistent with several mechanisms. Mechanisms like risk premium effects should manifest themselves similarly between economic and monetary news events, while information effects driven by private information of the central bank can potentially look different. Figures 2.1 and 2.2 plot each shock against the first lag of the FRED-MD factor. The shocks and factors have been standardized to be mean zero and have unit variance within each figure. The solid line is the OLS line of best fit and its slope is reported in the legend of each panel. From these two figures we can see a very similar relationship between the FRED-MD factor and the Eurodollar futures and the S&P 500 Index. The relationship between the FRED-MD factor and the Federal Funds futures is positive around both events, but with different slopes, but this can be explained by the mechanical differences in the construction of the Federal Funds futures shocks.

In order to investigate the difference in behavior in returns around the Employment Situation

Table 2.3: F-test for FRED-MD Factor

Model	Ticker	F-Stat	p-Value
FOMC	FF	1.07	0.309
	ED3	9.00	0.003**
	ED12	12.92	0.000***
	SP500	0.27	0.610
FOMC Monthly	FF	1.06	0.308
	ED3	7.99	0.004**
	ED12	11.30	0.001***
	SP500	0.26	0.611
Jobs	FF	7.59	0.004**
	ED3	12.66	0.000***
	ED12	8.06	0.005**
	SP500	2.25	0.136
CPI	FF	1.09	0.310
	ED3	1.27	0.271
	ED12	1.45	0.232
	SP500	0.04	0.853

Notes: This table presents the F-stat and p-values testing for the significance of the coefficient on the first lag of the first FRED-MD factor around monetary announcements and economic releases. The FOMC release are scheduled FOMC releases, FOMC Monthly is scheduled FOMC releases with imputed zeros for months with no scheduled statement. "Jobs" is the Employment Situation Report and CPI is the CPI release. The asset "FF" is Federal Funds futures, "ED3" and "ED12" are three/twelve-month Eurodollar futures, and "SP500" is the S&P 500 Index. The p-values are calculated with a residual bootstrap. *, ** and *** denotes 5%, 1% and 0.1% statistical significance.

Table 2.4: Event Discontinuity Analysis

	ED3	ED12	FF	SP500
F_1	0.267***	0.217***	0.192	0.054
	(0.087)	(0.059)	(0.181)	(0.101)
F_1*jobsday	0.001	0.042	-0.061	0.079
	(0.114)	(0.107)	(0.187)	(0.133)
Observations	269	269	269	269

Notes: This table presents regression results for the high frequency return on the first lag of the first FRED-MD factor, an indicator for the event type and an interaction term. Heteroskedastic robust standard errors in parenthesis. The asset "FF" is Federal Funds futures, "ED3" and "ED12" are three/twelve-month Eurodollar futures, and "SP500" is the S&P 500 index. *, ** and *** denotes 5%, 1% and 0.1% statistical significance.

Report and FOMC statements, we estimate the following pooled regression

$$r_t = \alpha + \delta I_t[\text{Jobs Release}] + \beta F_{t-1} + \gamma F_{t-1} I_t[\text{Jobs Release}] + e_t \tag{2.5}$$

where r_r is the return around a FOMC or Employment Situation Report release, I_t[Jobs Release] is an indicator variable equal to 1 if the event at time t is an Employment Situation Report release or 0 if the event is a FOMC event. The coefficient, γ, on the interaction term measures the difference in the return response to the FRED-MD factor across event types. Table 2.4 contains these regression results. We can see that the estimated coefficient on the interaction term across all four coefficients are not significant. This null result points to the source of the predictability being common across news events, which is consistent with risk premium effects and not information transfer around FOMC announcements.

Now we turn to testing for information transfer from the FOMC to the markets around scheduled FOMC statements. If market participants extract information about the FOMC's forecasts around FOMC announcements, then these forecasts themselves, and in particular, the Greenbook forecast revisions should predict the forecast revisions and asset returns. Following Miranda-Agrippino and Ricco we use forecasts and forecast revisions for real GDP, the GDP Deflator, and unemployment. We include forecasts and revisions for the first lag though 3 quarters ahead relative to the date of the FOMC meeting, with the exception of the level of unemployment which only includes the current quarter. Because of the large number of coefficients relative to observations in our sample, we test three models. The first model, denoted as "GB" in Table 2.5 contains all the forecasts and revisions considered. The second model, denoted as "GB Forecasts" includes only the forecasts, and the third model, "GB Revisions" includes only the forecast revisions. Each model is then also tested with and without the first lag of the first FMD factor included as a control that is excluded from the F-statistic.

The first panel in Table 2.5 reports that the twelve-month Eurodollar future and S&P 500 Index return is predicated by the information within the Greenbook forecasts. A natural concern is that

Table 2.5: F-test for Greenbook Information

Model	Ticker	F-Stat	p-Value
GB No Controls	FF	0.92	0.295
	ED3	0.58	0.889
	ED12	1.78	0.050
	SP500	1.96	0.049*
GB with FMD Control	FF	1.08	0.176
	ED3	0.59	0.875
	ED12	1.27	0.227
	SP500	1.95	0.044*
GB Forecasts, No FMD Control	FF	1.26	0.171
	ED3	1.27	0.227
	ED12	2.79	0.007**
	SP500	1.85	0.085
GB Forecasts, FMD Control	FF	1.31	0.151
	ED3	1.04	0.383
	ED12	1.28	0.253
	SP500	1.84	0.079
GB Revisions, No FMD Control	FF	0.82	0.504
	ED3	0.44	0.956
	ED12	0.79	0.670
	SP500	3.01	0.004**
GB Revisions, FMD Control	FF	1.10	0.218
	ED3	0.62	0.811
	ED12	0.61	0.844
	SP500	2.75	0.006**

Notes: This table presents the F-stat and p-values testing for the significance of the coefficients on Greenbook information around scheduled FOMC statements. The asset "FF" is Federal Funds futures, "ED3" and "ED12" are three/twelve-month Eurodollar futures, and "SP500" is the S&P 500 index. The p-values are calculated with a residual bootstrap. *, ** and *** denotes 5%, 1% and 0.1% statistical significance.

the private information of the FOMC is correlated with public information about the state of the economy which we have shown has predictive power. The second panel address this concern by controlling for the first lag of the first FRED-MD factor. After including this control we see that the F-statistic on the twelve-month Eurodollar falls and becomes insignificant, while the F-statistic for the S&P 500 remains almost unchanged. Next we focus just on the level of the forecasts and drop the forecast innovations. We see that without the FRED-MD factor, the level of the forecasts predicts the twelve-month Eurodollar return but when the factor is included as a control, the forecast levels lose their predictive power. Finally, looking at just the Greenbook forecast revisions in the final two panels, we see that none of the interest rate futures are predicated by the forecast revisions but that the S&P 500 returns are, even after controlling for the first FRED-MD factor.

These results suggest that the Greenbook forecast may have predictive for the asset returns but these results are sensitive to the exact model tested. We explore the robustness of these results by expanding the sample period and changing the inflation measured used. We switch from using the inflation forecast for the GDP Deflator to CPI inflation. The CPI more closely matches the inflation measure targeted by the FOMC during this period, so the information transfer around this measure should be greater than around the GDP Deflator.

Table 2.6 reports results from our alternative specifications. The first panel expands our sample to begin in 1990 for the Eurodollar futures and 1993 for the S&P 500 while still using the FRED-MD factor as a control. In this expanded sample, we continue to see weak evidence that the return on the S&P 500 Index is predictable by information in the Greenbook Forecasts. The second panel uses the same sample but drops the FRED-MD factor, again we see weak evidence for predictability.

In the third panel of Table 2.6 we replace the GDP Deflator forecasts with the CPI forecasts. When switching to this more accurate measure of the FOMC inflation objective, the predictive power of the Greenbook forecasts disappear. The fourth and fifth panels add the first lag of the first FRED-MD factor as a control and shorten the sample to the original 1995–2008 sample period to align with the tests in Table 2.5. These results indicate that earlier findings of information transfer are sensitive to the exact inflation measure used, with inflation measures that align more closely with the FOMC's inflation target showing weaker evidence for predictability.

2.4 Conclusion

Distinguishing information from risk premium effects in high frequency returns around monetary news events is important when interpreting their effects. In this paper we present statistical tests on actual asset returns around monetary and economic news events and use robust statistics to test for information effects arising from diffuse information both within financial market participants and between the FOMC and market participants. We test both equity returns and interest rate changes for information effects.

Table 2.6: F-test for Greenbook Information, Alternative Specifications

Model	Ticker	F-Stat	p-Value
GB 1990-2008	FF	1.08	0.171
	ED3	0.68	0.796
	ED12	1.29	0.196
	SP500	2.16	0.022*
GB 1990-2008, No Control	FF	0.92	0.290
	ED3	0.68	0.794
	ED12	1.77	0.043*
	SP500	2.23	0.020*
GB CPI No Control, 1990-2008	FF	0.60	0.762
	ED3	0.67	0.802
	ED12	1.60	0.077
	SP500	1.54	0.147
GB CPI 1990-2008	FF	0.71	0.609
	ED3	0.62	0.865
	ED12	1.20	0.258
	SP500	1.44	0.178
GB CPI	FF	0.71	0.604
	ED3	0.43	0.981
	ED12	1.21	0.266
	SP500	1.48	0.166

Notes: This table presents the F-stat and p-values testing for the significance of the coefficients on Greenbook information around monetary announcements. The FOMC release are scheduled FOMC releases, FOMC Monthly is scheduled FOMC releases with imputed zeros for months with no scheduled statement. "Jobs" is the Employment Situation Report and CPI is the CPI release. The asset "FF" is Federal Funds futures, "ED3" and "ED12" are three/twelve-month Eurodollar futures, and "SP500" is the S&P 500 index. The p-values are calculated with a residual bootstrap. *, ** and *** denotes 5%, 1% and 0.1% statistical significance.

Diffuse information within financial markets should lead to autocorrelation in the high frequency returns around news events but we find no evidence for this autocorrelation. Diffuse information between the FOMC and financial markets also predicts that the FOMC information set should predict asset returns around FOMC announcements. We show that evidence for this effect is weak, is sensitive to the inflation forecast used and wether a single control for lagged economic conditions is included.

Finally we show that lagged economic conditions can predict asset returns around news events but this result is consistent with risk premium effects. Importantly, this effects is similar in both direction and magnitude around economic and monetary news announcements, pointing to an effect that is not specific to monetary news announcements.

2.5 Chapter 2 Figures

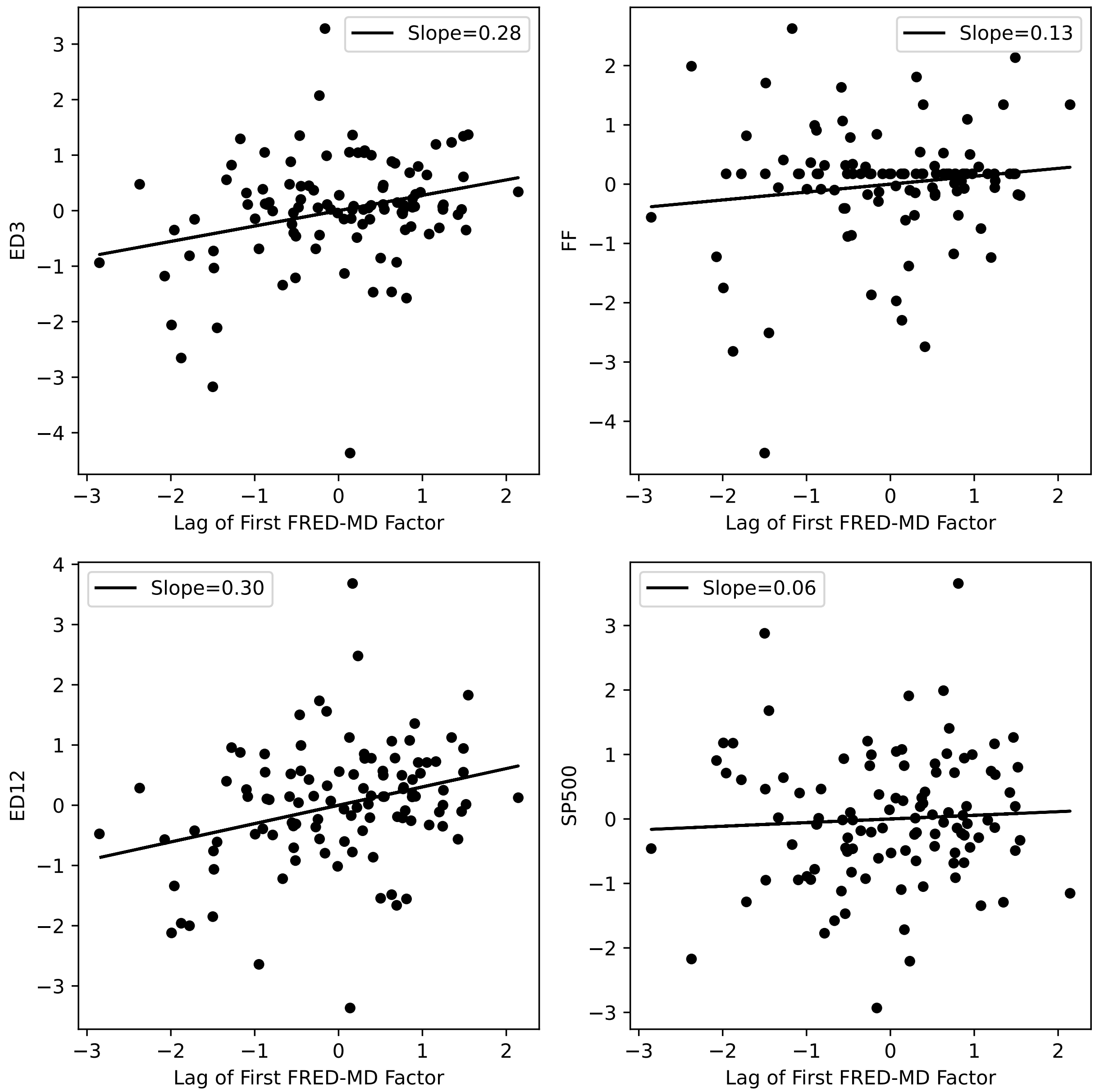

Figure 2.1: Returns and FRED-MD Factor, FOMC Statements

Notes: Each subfigure plots the 30-minute return around the release of each scheduled FOMC Statement for each asset against the first lag of the first factor estimated off of the FRED-MD dataset. Variables are standardized to be mean zero and have unit variance. Solid lines represent the line of best fit. Sample is Jan. 1995 — June 2008.

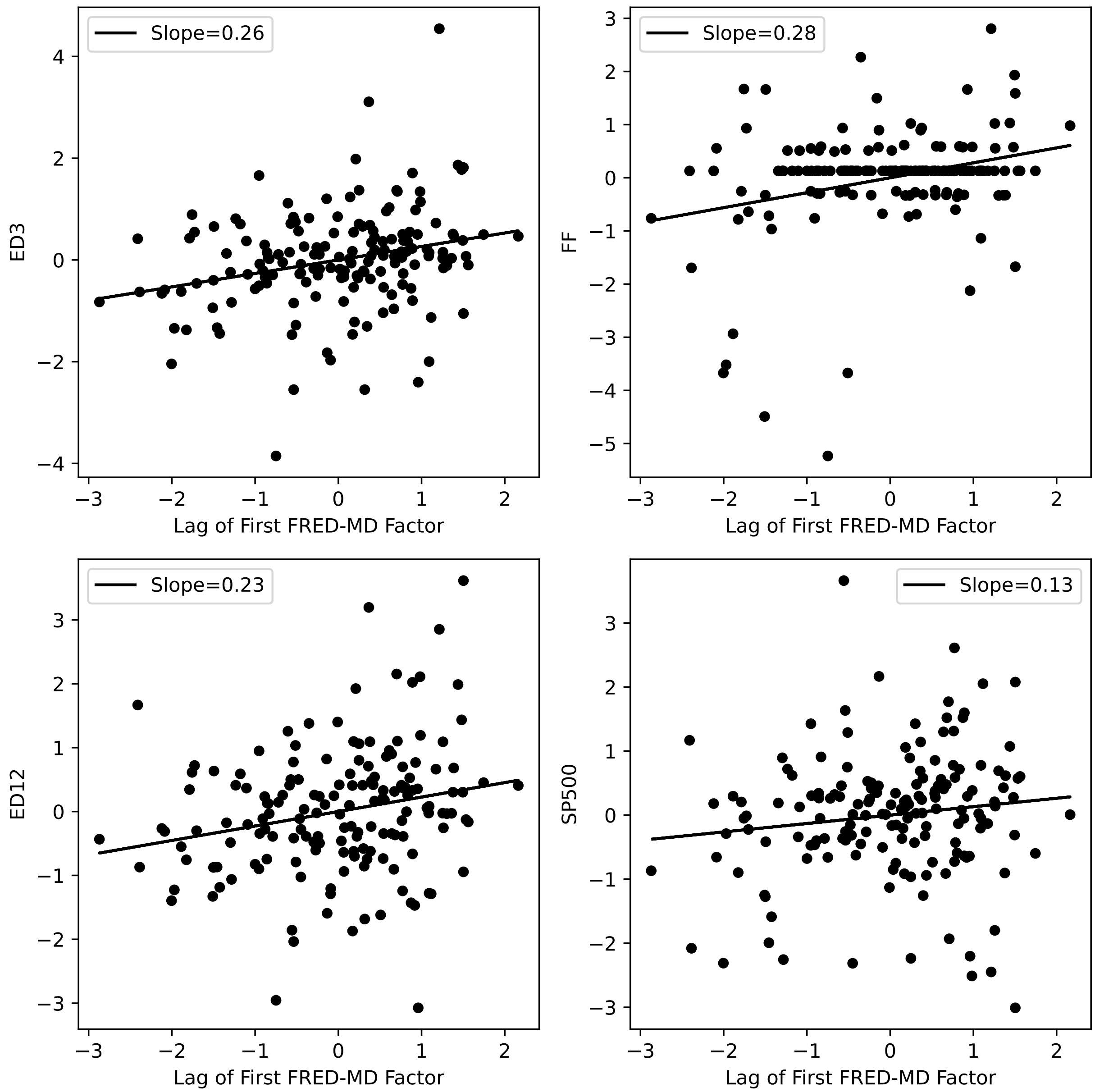

Figure 2.2: Returns and FRED-MD Factor, Employment Situation Report

Notes: Each subfigure plots the 30-minute return around the release of the Employment Situation Report for each asset against the first lag of the first factor estimated off of the FRED-MD dataset. Variables are standardized to be mean zero and have unit variance. Solid lines represent the line of best fit. Sample is Jan. 1995 — June 2008.

Chapter 3: Estimating Information Robust Monetary Policy Shocks

The use of high frequency asset price returns around monetary news releases has become a standard tool in the empirical macroeconomic toolkit. This approach allows for researchers to indirectly measure information released within small windows by measuring changes in asset prices which respond to this information. Traditionally, researchers have assumed that the only systematic information released around monetary policy announcements is information about exogenous monetary policy. However, these announcements can potentially affect market participants' expectations about the economy in ways that are distinct from the exogenous interest rate policy actions taken by the central bank. This mechanism means that univariate high-frequency measures will contain multiple kinds of information in them which can make them poor measures of exogenous monetary policy.

This paper provides estimates of two, point-identified, exogenous shocks around monetary policy announcements. The first is a traditional monetary policy shock capturing exogenous movements in interest rates. The second is a shock measuring changes in forecasts of the economy orthogonal to the traditional monetary policy shock. To identify these shocks we analyze differences in how interest rates futures and stock prices co-move between the release of the Employment Situation Report and FOMC announcements. We then use these shocks as instruments in a proxy VAR and recover estimates for the effect of monetary policy which are consistent with theory.

Using high frequency changes in interest rate futures as measures of monetary policy was first proposed by [15] and later refined by [25], [8], and [26]. [10] and [1] showed that these traditional univariate high frequency measures of monetary policy based only on interest rate futures consistently predict macroeconomic responses to monetary policy which are contrary to standard economic theory. [27] and [17] provide further puzzling evidence: these high-frequency measures also lead financial market participants to update their beliefs about the economy in ways that contradict standard macroeconomic theory.

Recently, the literature has proposed several methods to control for this non-monetary information flow around monetary policy announcements. [28] propose a methodology for categorizing monetary policy announcements into announcements dominated by exogenous monetary policy shocks or informational shocks about the state of the economy by looking at the comovement of interest rate changes and equity returns. Their method is intuitive, but imposes the restriction that only one type of shock can be present around a given announcement. [19] propose a similar classification scheme, but use it to impose sign restrictions on these structural shocks within a Bayesian SVAR. This method relaxes the restriction that only one shock can be present at a time, but must be estimated with Bayesian methods which do not easily provide point estimates for individual shocks. Finally, [9] propose purging non-monetary information from the high frequency measures by orthogonalizing them with respect to Greenbook forecasts. These forecasts are produced by the Federal Reserve for each FOMC meeting and serve as a good proxy for the FOMC's private forecasts. By orthogonalizing the high frequency responses to the Greenbook forecasts, they hope to remove the effects of any direct information flow from the FOMC to asset markets. However, [29] shows that the Greenbook forecasts do not systematically predict high frequency asset returns, indicating that the direct provision of private information by the FOMC is unlikely to be a major factor around monetary announcements.

Our proposed procedure for point-identifying monetary and information shocks starts by analyzing how interest rates and equity prices co-move in high-frequency windows around the release of the Employment Situation Report (a.k.a. the "jobs report") which is usually released the first Friday of every month. Because monetary shocks cannot be present around these economic news releases, the co-movement in yields and stocks is driven by other macroeconomic shocks—what we call "information shocks." Thus, around FOMC announcements, we posit that any changes in yields and stocks that do not fit the pattern observed around economic news releases arise instead from exogenous monetary policy shocks. The assumptions that monetary shocks are not emitted during economic news releases is an assumption of heteroskedasticity, and we therefore leverage the existing methodology proposed by [30] to identify the relationship between the high frequency asset returns and the structural shocks. This allows us to back out estimates of the structural shocks from asset returns. Because the joint movement of interest rates and equity prices differs significantly after monetary and economic news shocks, we can precisely estimate the structural shocks. We then proceed to use our identified shocks as instruments in a proxy VAR and estimate responses to monetary policy that are consistent with standard macroeconomic theory.

This paper is organized as follows. First, we detail the assets and news announcements that we analyze in Section 3.1. In Section 3.2 we show that the joint reaction of interest rates and equity prices varies significantly between economic and monetary news releases. In Section 3.3 we detail our econometric model to estimate each structural shock along with estimation results. Finally, in Section 3.4 we use our shocks as instruments in a proxy VAR to measure the effect of monetary policy on macroeconomic variables. Section 3.5 concludes.

3.1 Data and Events

To separately identify monetary and information shocks around FOMC announcements we exploit the fact that these shocks affect interest rates and equity prices differently. Therefore the joint reaction of interest rates and equity prices can be used to recover each of the underlying shocks. We begin by describing the assets that we use in our estimation and then describe our news events.

3.1.1 Assets

Eurodollar Futures

The Eurodollar futures price at time t (p_t) is pegged to the outstanding level of the three-month Libor rate at the expiration of each contract (i_τ), specifically

$$p_t^r = 100 - \mathbb{E}_t \, i_\tau$$

It is a monthly future with contracts expiring each month. These futures contracts are commonly used because they have much higher liquidity, especially at longer horizons than the Federal Funds futures which allows one to measure market expectations about changes in the future path of monetary policy beyond the immediate future [26]. We use the 12-month Eurodollar Future as our measure of monetary policy because is is almost perfectly correlated with the path factor estimated by [26] which explains the majority of the movement in interest rates around monetary policy announcements.

We construct our shocks as the simple difference in futures prices such that they represent the change in expected interest rates:

$$\Delta\,\mathbb{E}_t\, i_\tau = p^i_{t-\underline{\Delta}} - p^i_{t+\overline{\Delta}} \tag{3.1}$$

We use tick level from the CME group to measure $p^i_{t-\underline{\Delta}}$ and $p^i_{t+\overline{\Delta}}$ around announcements and a standard thirty minute window beginning five minutes before the announcement and ending 25 minutes after the announcement. The pre-announcement price $p^i_{t-\underline{\Delta}}$ is taken to be the outstanding price from the last trade before the start of the thirty minute window, and $p^i_{t+\overline{\Delta}}$ is the last trade before the end of the thirty minute window. If no trades occur within the thirty minute window, this produces a value of zero for the shock.

One complication is that the liquidity of contracts which fall on the end of a quarter (i.e., the March, June, September, and December contracts) are much higher than other contracts. The liquidity difference can sometimes be substantial, especially at longer horizons, with the quarter-end contracts sometimes exhibiting 1,000 times more activity than adjacent non-quarter-end contracts around news announcements. Following the existing literature, we restrict ourselves to using only quarter-end contracts. To measure the 12-month ahead Eurodollar future price we linearly interpolate the opening and closing prices of the quarter-end contract which expires between 9 and 12 months ahead and the quarter-end contract which expires between 12 and 14 months ahead.[1] Some

[1] Concretely, if the contract twelve months ahead is a quarter-end contract then no interpolation is involved. If the contract twelve months ahead expires in, e.g., November, we average the prices for the September and December contracts. We take the closing price of each contract used for interpolation at the minutely frequency, and use the most-recent closing price for interpolation. In practice, this amounts to using the average closing price within each minute because Eurodollar futures are heavily traded.

authors use the nearest quarter-end contract for each horizon of interest instead of interpolating, but the resulting shocks are very similar because the entire Eurodollar futures yield curve tends to move together.

S&P 500

Our second asset is the S&P 500 Index. Because the S&P 500 Index only trades during limited times we use three different measures. The first is the SPY ETF to measure changes in the S&P 500 Index during regular trading hours. The SPY ETF was introduced in 1993 and tracks the S&P 500 Index by purchasing the underlying stocks in the S&P 500 Index. Any differences in the value between the SPY ETF and S&P 500 Index are easily arbitraged away which makes the SPY ETF an easy way to track the value of the S&P 500 Index. Outside of regular market hours we use two futures whose values are pegged to the S&P 500 Index. The first is the original CME S&P 500 futures contract. The final settlement price of this future is equal to 250 times the closing price of the S&P 500 Index on the day of contract expiration. The second contract is the E-mini S&P 500 futures contract, which is identical to the original S&P 500 futures contract except that its final settlement price is equal to 50 times the closing price of the S&P 500 Index.

We construct our shocks as the simple log difference in ETF or futures prices:

$$\Delta \log(p_t^{\text{equity}}) = \log p_{t+\overline{\Delta}}^{\text{sp}} - \log p_{t-\underline{\Delta}}^{\text{sp}} \tag{3.2}$$

For announcements that take place during trading hours, we set $\log p_t^{\text{sp}}$ to the SPY ETF (which we have from January 1993 through December 2019). We have CME data on S&P 500 futures starting in April 1982 through December 2019 and E-mini S&P 500 futures starting in September 1997 through December 2019. We use S&P 500 futures for $\log p_t^{\text{sp}}$ before 2000 and E-mini futures after, with the switch over determined by when liquidity on the E-mini contract surpassed liquidity on the original contract. The window for measuring $p_{t-\underline{\Delta}}^{\text{sp}}$ and $p_{t+\overline{\Delta}}^{\text{sp}}$ is identical to the one we used for constructing Eurodollar futures.

3.1.2 Events

We analyze returns around monetary announcements and economic news releases which we describe here.

Our monetary news releases are the FOMC policy decisions. We use FOMC policy announcements between January 1995 and June 2008. Beginning in 1995, the FOMC began to announce every policy change along with a short statement explaining why this policy change was taken. During this period, no announcement after a FOMC meeting was easily inferred as no policy change. Before 1995, the exact time of FOMC meetings were not (as) regularly scheduled and not every policy was publicly announced. This resulted in markets learning about monetary policy decisions slowly—over the course of multiple days as they observed Federal Reserve open market operations. This makes applying the high frequency event study framework impossible. We end our sample in June 2008 to avoid complicating factors arising from the Financial Crisis and the extended Zero Lower Bound period after the Great Recession.[2] Finally, we drop September 2001 from the sample as is standard practice. The timing of FOMC announcements and scheduled non-announcements is taken from [26]. We supplement this with dates and times of monetary announcements from Bloomberg for the latter portion of our sample.[3]

Our economic news events are the releases of the Employment Situation Report, commonly refereed to as the "Jobs Report". The Employment Situation Report is closely watched by market participants as a leading indicator of state of the economy and the magnitude of asset returns is similar to around FOMC announcements. We obtain the release date and times for each report by combining data from Bloomberg and the BLS website.[4]

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[2] As highlighted by [31], even longer-term interest rates were mechanically constrained by the ZLB.

[3] Starting in 2005, we use the calendar of FOMC releases from Bloomberg (ECO <GO> then "Central Banks"), keeping all releases with the ticker FDTR Index. We verify that these releases coincide with those of [26] for the years in which they overlap (1997–2004). The extension of the dataset beyond 2004 through 2019 introduces two unscheduled meetings with interest rate decisions—January 21 and October 7, 2008.

[4] We collect the times of macroeconomic data releases from three sources; Bloomberg, the BLS's economic release calendar and the BLS's "Employment Situation Reports" themselves. The data from Bloomberg comes from the "Economic Releases" calendar (ECO <GO>). When available, this is our authoritative source of release times as it contains the actual release times, not the scheduled release times. For most releases these overlap perfectly, but there are several observations where the actual and scheduled releases times differ by several minutes. This data starts in 1997. Earlier data on the "Employment Situation Report" release dates comes from the URLs on the BLS website for

3.2 Joint Asset Responses to News

In this section we describe a simple semi-structural model to theoretically analyze the joint reaction of interest rates and equity prices to monetary and economic news shocks and show that these assets can be used to measure the two separate components of monetary policy.

3.2.1 Stylized Model

We begin by assuming that we observe log equity returns and changes in interest rates around monetary and economic news announcements. We stack these returns into a vector x_t with the elements $x_t^i \equiv \Delta\,\mathbb{E}_t[i_\tau]$ and $x_t^e \equiv \Delta \log p_t^{\text{equity}}$. Around these announcements there are two distinct structural shocks. The first is a non-monetary shock, denoted ν_t and the second is a monetary shock denoted ϵ_t.

Following [32], log equity returns can be decomposed into a component arising from changes in expected dividends, and a component arising from changes in the discount rate, which is captured by changes in the interest rates. This gives us the following:

$$x_t^e = \alpha\Delta\,\mathbb{E}_t[d_{t+1}] + \beta x_t^i. \tag{3.3}$$

We can model the reduced form effect of each of the structural shocks on interest rates and dividends as:

$$x_t^i = \phi_\nu \nu_t + \phi_\epsilon \epsilon_t \tag{3.4}$$

$$\Delta\,\mathbb{E}_t[d_{t+1}] = \gamma_\nu \nu_t + \gamma_\epsilon \epsilon_t. \tag{3.5}$$

Combining these equations we can write the log return of equity prices and changes in interest

each report. The release times for these are set to 8:30 AM which is the embargo time for each report as manually verified. The dates and times account for disruptions in regularly scheduled releases due to national emergencies or Federal Government shutdowns.

rates as linear combinations of the structural shocks:

$$x_t^i = \phi_\nu \nu_t + \phi_\epsilon \epsilon_t \tag{3.6}$$

$$x_t^e = (\alpha\gamma_\nu + \beta\phi_\nu)\nu_t + (\alpha\gamma_\epsilon + \beta\phi_\epsilon)\epsilon_t. \tag{3.7}$$

If we interpret ϵ_t as a monetary policy shock and ν_t as an information shock about the economy, then equation 3.6 specifies the monetary policy reaction function in the spirit [33], with ϕ_ν capturing the monetary response to economic news and ϕ_ϵ measuring the magnitude of monetary policy shocks—thus, we conceive of "theoretical monetary shocks" ϵ_t as Taylor rule innovations. Without loss of generality, we normalize the sign of $\phi_\nu > 0$ by the fact that "good" news about the economy leads the central bank to raise interest rates and discount rates to increase. We can also (without loss) normalize $\phi_\epsilon > 0$, consistent with positive (negative) values of ϵ_t capturing contractionary (expansionary) changes in the interest rate. Equity prices are increasing in expected dividends and decreasing with respect to changes in the interest rate, i.e. $\alpha > 0$ and $\beta < 0$. Finally conventional theory states that expected dividends should increase with positive economic news and decrease in response to a monetary policy shock giving us $\gamma_\nu > 0$ and $\gamma_\epsilon > 0$.

Applying the signs implied by theory to the structural parameters, we can sign the reaction of interest rates and equity prices as follows:

$$\begin{bmatrix} x_t^i \\ x_t^e \end{bmatrix} = \begin{bmatrix} + & + \\ ?/+ & - \end{bmatrix} \begin{bmatrix} \nu_t \\ \epsilon_t \end{bmatrix} \tag{3.8}$$

Interest rates unambiguously increase in response to positive economic news and monetary policy shocks. Equity prices unambiguously decrease after a monetary policy shock but their reaction to positive economic news is ambiguous, depending on the relative reactions of dividends and discount rates to the economic news, but is usually assumed to be positive.

Equations 3.6 and 3.7 imply that if we knew the structural parameters then we could recover the structural shocks from asset returns, as long as $\alpha\frac{\gamma_\nu}{\phi_\nu} \neq \alpha\frac{\gamma_\epsilon}{\phi_\epsilon}$.[5] This implies the intuitive result that we require the relative responses of equities and interest rates to vary across different structural shocks.

To investigate the plausibility of this invertibility assumption we plot the joint distribution of equity returns and interest rate changes, along with a line of best fit in Figure 3.1. We split the returns in two dimensions, the top two panels plot the joint returns around monetary announcements and the bottom two panels plot the joint returns around economic announcements. The left pair of panels plot the returns in the subsample from 1995 through 2000, while the right pair of panels plot the returns from 2001 through June 2008. As a temporary approximation, we can assume that economic news shocks dominate economic news releases but monetary shocks dominate monetary announcements. If our invertibility condition holds, this should lead to differing correlations between equity returns and interest rate changes around our two types of announcements.

Looking at the returns around monetary announcements we see that interest rate changes and equity returns are consistently negatively correlated in both samples, consistent with equation (3.8). Looking at the joint returns around economic news announcements in the bottom two panels, we see a very different pattern. In the earlier sample, interest rate changes and equity returns are again negatively correlated, which runs against conventional assumptions. In the later sample, the correlation flips and the returns become positively correlated, as previously noted by [28].

To investigate this trend break, we formally test for a structural break in the correlation between interest rate changes and equity returns around monetary and economic announcements with an Andrews test. We regress log returns on equity prices (x_t^e) on changes in interest rates (x_t^i) interacted with a dummy variable that is one if the month $t > \tau$ as shown in equation 3.9. We run a series of regressions each with a different value of τ spanning the central 80% of our sample. Our test statistic is the largest t-statistic for the coefficient on this interaction across our regressions.

[5] That is, the determinant of the matrix mapping x_t^i and x_t^e to the shocks ν_t and ϵ_t is not null.

Critical values for this test-statistic come from [34].

$$x_t^e = \beta_0 + \delta_0 I_{[t>\tau]} + \beta x_t^i + \delta I_{[t>\tau]} x_t^i + \text{error}_t. \tag{3.9}$$

The top panel of Figure 3.2 plots the test statistics from a break test for each proposed break date for the sample of returns around Employment Situation Reports releases and the bottom panel plots the same test statistic for the sample of returns around FOMC policy announcements. The largest t-statistic for the break tests around Employment Situation Reports releases is 52.5 in April 2001, which far exceeds the 1% critical value of 12.7 for the Andrews test. Around this date, the break test statistics plateaus, justifying our choice of January 2001 as the date to split the sample. Turning to the sample of returns around monetary announcements, the largest individual break-test statistic is just under 4, which is far below the 10% Andrews test critical value of 7.6, indicating that there is no structural break in the correlation of returns around monetary policy announcements.

We hypothesize that this economic news shock contains different information around economic news releases over the course of the business cycle. In particular, when the output gap is large then economic news contains information about persistent changes in aggregate demand while at the height of economic expansions, it contains news about aggregate supply. A positive aggregate demand shock leads to an increase in both equity prices and interest rates, while a positive aggregate supply shock leads to an increase in equity prices, but a decrease in interest rates.

To test if this time variation in the correlation between equity returns and interest rate changes around economic announcements is plausibly explained by the state of the economy we run a twelve month rolling regression of equity returns on interest rate changes. Figure 3.3 plots these coefficients as a time series along with the unemployment rate and the Federal Reserve's Staff estimate of the output gap. Figure 3.3 shows that when the unemployment rate is high or output gap is large, equity returns and interest rate changes are positively correlated and when the unemployment rate is low or output gap is small equity returns and interest rate changes are negatively correlated.

Because the time series break in the correlation between equity returns and interest rate changes only occurs around economic news releases, we take this as evidence for a structural break in the information content of the economic news shock. Before 2001, when the output gap was low, the Employment Situation Report contained information about the potential output of the economy while after 2001 the report contained information useful for measuring aggregate demand. The lack of a structural break in the joint asset reaction around monetary policy announcements is indicative that monetary policy announcements only contain information about aggregate demand and monetary policy, but never contain information about aggregate supply, even at times of full employment.

3.3 Estimating Monetary Policy Shocks

In this section we describe our methodology for estimating two orthogonal shocks around FOMC monetary announcements by exploiting heteroskedasticity in monetary policy shocks across FOMC announcements and economic news releases using the estimation method proposed by [30]. In particular, we exploit the fact that monetary shocks can only arrive around monetary announcements or actions, which never occur at the same time as the release of the Employment Situation Report within our sample. We assume that there is a common shock across economic and monetary news announcements and that this common shock is the only shock present around the Employment Situation Report, while there is also a monetary policy shock present around FOMC statements. With this setup, we can then use GMM to estimate the mapping between structural shocks and asset returns, along with the variance of these structural shocks across events days. Our approach is related to [17], who use a similar approach as a robustness check to their standard regression techniques. They model two sources of information around monetary announcements, a monetary policy shock and a general "background noise" shock. They then use returns during the same window the week after the FOMC announcements to control for the impact of the background noise. We model the information flow around monetary policy announcements in a similar way, except our second regime are windows around economic news announcements. Importantly, the fact that our second regime consists of periods when we know that meaningful economic information is released (*not* background noise) we can interpret the second shock around monetary policy announcements as an information shock.

3.3.1 Model

Our goal is to estimate two distinct shocks around monetary policy announcements that drive the responses of interest rate futures and equity prices. We stack the interest rate future return and equity price log return into the vector $x_t = \Delta p_t$. We denote the monetary policy shock as ϵ_t and the other structural shock as ν_t and stack them in the vector s_t. The two-by-two matrix A maps the structural shocks to the observed asset returns:

$$x_t = As_t. \tag{3.10}$$

To estimate the mapping matrix A, we exploit the fact that the variance of the structural shocks varies across announcement types. In particular, the variance of monetary shocks is zero around non-monetary data releases. The covariance matrix of the observed asset returns around an event type $j \in \{econ, mon\}$ is given by:

$$\Omega_j \equiv \mathbb{E}\left[x_t x_t' | t \in j\right] = \begin{bmatrix} A_{11}^2 \sigma_{\nu,j}^2 + A_{12}^2 \sigma_{\epsilon,j}^2 & A_{11}A_{21}\sigma_{\nu,j}^2 + A_{22}A_{12}\sigma_{\epsilon,j}^2 \\ \cdot & A_{21}^2 \sigma_{\nu,j}^2 + A_{22}^2 \sigma_{\epsilon,j}^2 \end{bmatrix}$$

We have the standard heteroskedasticity identifying restriction that $\sigma_{\epsilon,econ}^2 = 0$, $\sigma_{\nu,econ}^2 > 0$, and $\sigma_{\epsilon,mon}^2 > 0$. Without loss of generality, we normalize the variance of the structural shocks to unity around monetary announcements and the sign of the elements A_{11} and A_{12} to be greater than zero. The estimation challenge then becomes estimating the four elements of A and $\sigma_{\nu,econ}^2$.

The first two moment conditions come from the covariance matrix around economic news announcements. Because the monetary shock has a variance of zero, the covariance matrix has a rank of 1, giving us only two linearly independent moment conditions.

$$\Omega_{econ} = \begin{bmatrix} A_{11}^2 \sigma_{v,econ}^2 & A_{11}A_{21}\sigma_{v,econ}^2 \\ \cdot & A_{21}^2 \sigma_{v,econ}^2 \end{bmatrix}$$

The final three moment conditions come from the covariance matrix around monetary policy announcements which has three linearly independent moments:

$$\Omega_{mon} = \begin{bmatrix} A_{11}^2 + A_{12}^2 & A_{11}A_{21} + A_{22}A_{12} \\ \cdot & A_{21}^2 + A_{22}^2 \end{bmatrix}$$

We estimate these model parameters using GMM. We stack our moment conditions into the vector $f(\theta)$

$$f(\theta) \equiv [\text{vech}(\hat{\Omega}_{econ} - \Omega_{econ}(\theta))', \text{vech}(\hat{\Omega}_{mon} - \Omega_{mon}(\theta))']'$$

where $\hat{\Omega}_j$ is the empirical estimate of the covariance matrix of the observables around event j, $\Omega_{econ}(\theta)$ is the model covariance matrix as function of our parameters, and the vech$(\cdot)$ operator stacks the upper trigonal elements of its input matrix into a one dimensional column vector. Our objective function is

$$L(\theta) = f(\theta)' W f(\theta)$$

We use the identity matrix as our weight matrix, $W = I_6$, and all three moment conditions from the economic news periods because they are not linearly dependent in finite samples. Once we have estimated the elements of A we can invert this mapping and calculate the structural shocks from the asset returns.

3.3.2 Estimation Details

We estimate monetary policy and information news shocks around monetary policy announcements between January 1995 and June 2008. We begin analyzing monetary announcements in 1995 because this is when the FOMC switched to its current communications policy of announcing each monetary action, along with an explanation after FOMC meetings. We end our sample in June 2008 to avoid complications arising from the financial crisis and the zero lower bound period. Before calculating the sample covariance matrix for each news event, we standardize equity returns and interest rate changes to have unit variance across the entire joint sample.

In Section 3.2 we showed that there is a structural break in the behavior of equity prices around economic news announcements which occurs in 2001. We interpret this break as a break in the information content contained the Employment Situation Report, with the report containing information about the supply side of the economy before 2001 and about the demand side of the economy after 2001. Because monetary policy announcements appear to contain information about monetary policy and aggregate demand, we only use economic news events between 2001 and 2008 to control for information about aggregate demand. In addition to our baseline sample, we also analyze three other subsamples with economic news and monetary announcements from 1995–2000, 2001–2008, and 1995–2008. Table 3.3 shows the estimation results for four different subsamples with stratified empirical bootstrap standard errors in parentheses below each parameter estimate.

Across all four samples the information news and monetary shocks are normalized to increase interest rates. In our baseline sample, we see that a one standard deviation information news shock around monetary policy announcements leads to a 0.61 standard deviation increase in interest rates and that a one standard deviation monetary policy shock leads to a 0.45 standard deviation increase in interest rates. For equities, a one standard deviation news shock leads to 0.29 standard deviation return and a one standard deviation monetary policy shock leads to a negative 1.15 standard deviation return. Finally, we estimate that the variance of the information news shock is 3.56 times higher around Employment Situation Report releases than FOMC statements. When we restrict our sample to only looking at monetary and economic announcements post 2001, the results are similar to our base sample.

Looking at the last two subsamples, we see that including economic news announcements between 1995 and 2000 significantly alters our results. The estimated effect of monetary policy shocks on interest rates decreases to nearly zero in both samples while the estimated return of equity prices to information news shocks becomes negative. This second result is consistent with the idea that the information news shock around Employment Situation Report releases contains information about aggregate supply in the earlier sample. Because the joint return of interest rates and equity prices is similar around economic and monetary news announcements, we have no identifying power and thus the model estimates that monetary shocks are unimportant for explaining interest rate changes around monetary announcements.

3.3.3 Identified Shock Details

Now we turn to analyzing our identified information news and monetary policy shocks. Table 3.2 contains summary statistics for each identified shock. Each shock is mean zero and has unit variance by construction. The largest positive and negative information shocks are balanced in magnitude, but the monetary shock shows a large amount of skew with a minimum value of nearly negative 6 standard deviations and a maximum of around 2.5 standard deviations.

Figure 3.4 plots the S&P 500 returns and twelve-month Eurodollar price changes against the identified information and monetary shocks. We see the positive relationship between the information shock and S&P 500 returns around FOMC announcements in the top left panel, although this relationship is noisy. The other three relationships also have the expected sign and feature very little dispersion. Table 3.4 quantifies these relationships. The twelve-month Eurodollar price changes have correlation coefficients of 0.8 and 0.6 with the information and monetary policy shocks. The S&P 500 returns have a low correlation of 0.24 with the information news shock, but are nearly perfectly negatively correlated with the monetary shocks with a correlation coefficient of -0.97.

Next we analyze the time series of the identified shocks. Figure 3.5 plots the two identified shocks over the entire sample for each scheduled FOMC announcement. The largest monetary shocks both occur in 2001, the first on January 3, and the second on April 18 with values of -6.0 and -3.5 respectfully. On each of these two days, the FOMC released unscheduled policy statements stating that they were easing monetary policy significantly. The largest information shock also occurs on January 3, 2001. Market commentary around this announcement states that financial markets viewed this policy action as a sign that the FOMC had changed its view on the state of the business cycle and that monetary policy had become more aggressive which eliminated the risk of a serious recession. On the other hand, April 18 featured a small and negative information news shock along with a large expansionary monetary policy shock. Market commentary at the time indicated that investors were surprised by this action, which is captured by the large monetary shock, but that it did not change their views on likely FOMC policy in the future or how aggressively they thought the FOMC would respond to a weakening economy.

3.4 Estimating the Macroeconomic Response to Monetary Policy

In this section we estimate the response of macroeconomic variables to monetary policy using our identified monetary shocks as external instruments in a structural VAR as proposed by [18]. Using our identified monetary policy shocks, we estimate macroeconomic responses to monetary policy that are aligned with traditional theory.

3.4.1 SVAR Estimation Details

In order to estimate the effect of monetary policy, we estimate a proxy VAR whose reduced form structure mirrors [35]. We first estimate a reduced form monthly VAR with the one-year Treasury rate, S&P 500 index, Industrial Production, unemployment, CPI inflation and CPI commodity inflation. The one-year Treasury rate and S&P 500 are included to capture monetary policy actions and any forward looking information contained in financial markets. Industrial Production and unemployment capture the real state of the economy, while our two inflation measures capture the nominal side of the economy, with the commodity inflation capturing forward looking and transient elements of inflation. Our sample for the reduced form VAR is 1983–2019.

We follow [14] and first make each macroeconomic series stationary by applying the following differencing scheme to each series before estimating our VAR. The one-year Treasury and unemployment rate enter the VAR in first differences, the S&P 500 and Industrial Production enter in the first difference of their logs, and the two inflation measures enter in the second difference of their logs, i.e. the first difference of inflation.

After estimating our reduced form VAR, we regress each residual on our identified shocks for each monthly observation for which we have a measure of our identified shocks. From these regressions, we can recover the contemporaneous impact of monetary policy on each variable in our VAR, which combined with our reduced form estimates, allows us to construct impulse response functions for each variable. For any month that has two identified proxy shocks, we sum the identified proxy shocks within the month. We do not include any months for which we do not observe an identified proxy shock. Our sample for this regression is Jan. 1995 — June 2008.

3.4.2 Macroeconomic Effects

Figure 3.6 plots the estimated impulse response functions to each variable in the VAR using our identified monetary policy proxy shock, information proxy shock and the high frequency return on the twelve-month Eurodollar future around FOMC announcements. The gray bands plot the asymmetric 68% and 90% confidence intervals for the impulse response to a monetary shock which are calculated with a Wild bootstrap that accounts for sampling uncertainty in the first and second stage regressions. The confidence intervals are calculated from the relevant percentile of bootstrap distribution.

Looking first at our monetary policy shock, we see that across each response variable the shock has the expected that standard theory would predict. A contractionary shock (which raises interest rates and lowers the S&P 500 index on impact) lowers the Industrial Production growth rate and increases the unemployment rate. It also lowers the growth rate of inflation for both our inflation measures. For each variable, nearly all of the 90% confidence interval has the correct sign. Our monetary shock is also estimated to have near-zero effects on impact on the growth rates of Industrial Production and unemployment unlike the monetary shock in [9] which shows large effects on impact. Across our four macroeconomic variables, the peak effect on the growth rates of these variables is two to three months after impact, with growth rates returning to positive values approximately one year out, indicating a peak response horizon of about one year.

Turning to our information shock we see that it increases both interest rates and equity prices on impact. It's effects on the growth rates of Industrial Production and unemployment mirror that of the monetary shock, except that the effects are much larger on impact. Looking at inflation, the information shock has almost no impact at any horizon. Finally, examining the response of a monetary shock measured by changes in the twelve-month Eurodollar future, we see that these impulse response functions lay between the monetary and information shock for each response variable, indicating the simple univariate measure of monetary policy is capturing information in both of the identified proxy shocks.

Returning to information shocks, the impulse responses are in conflict with the notion that these information effects represent a flow of information from the FOMC to asset markets about the state of the economy—"expansionary" information shocks are followed by sharp and immediate economic contractions. Our alternative explanation is that the information shock is capturing changes in the markets perception of the FOMC's reaction function, often around the start of recessions. For example, in January 2001 we estimate a large positive information shock which corresponds to first rate cut by the FOMC in response to the budding recession. Market commentary indicates that market participants interpreted this unexpected rate cut as evidence that the FOMC would respond aggressively to the recession. Later rate cuts, even ones that were larger than expected, during this recession did not elicit as large of a response because market participates did not change their overall view of how the FOMC would respond to economic conditions. Because the information shock is capturing turning points in FOMC policy, which occur more frequently at the start of recessions, they are mechanically followed by economic contractions. Because we only observe large expansionary turning points at the start of recessions, and never observe large expansionary turning points at other points in the business cycle within our sample the estimated effect of these information shocks is contractionary.

3.5 Conclusion

We propose a novel approach to identifying exogenous monetary policy shocks within the high frequency framework. In order to control for potential confounding economic information released during monetary policy announcements we estimate how asset prices respond to economic news releases. We can then control for asset price co-movements around monetary policy announcements which have the same form as around the economic news announcements and recover pure monetary policy shocks.

Our identified monetary shock has estimated macroeconomic effects that are consistent with standard macroeconomic theory. The estimated effects are substantial, but more transitory than previous estimates. Using traditional high-frequency measures of monetary shocks—i.e., without our decomposition—we would estimate much weaker effects, since those measures only noisily measure truly exogenous policy.

The macroeconomic responses to the information shock we identify call into question the traditional interpretation of the shock confounding the interpretation of traditional estimates of monetary shocks. That view holds that private information transfer from the central bank to the public is the primary confounding factor. The analysis here suggests that the Fed "setting the tone" for its actions over the course of a recession can cause asset prices to react counter to how they respond to monetary policy shocks. Concretely, signaling a strong reaction to negative shocks early in a recession (i.e. lowering interest rates quickly) can cause market participants to revise up expectations about future economic outcomes—including longer-term interest rates. Further theoretical work on this question could help elucidate the role for this channel.

3.6 Tables

Table 3.1: Summary Statistics Around News Releases

	Employment Situation Report		Monetary Announcements	
	ED12	S&P 500	ED12	S&P 500
Mean	−0.01	−0.02	−0.01	−0.07
Std.	0.11	0.47	0.07	0.74
Min	−0.35	−1.22	−0.25	−1.62
Max	0.35	0.98	0.25	4.94

Notes: This table presents summary statistics for the the twelve-month Eurodollar return and S&P 500 return around the Employment Situation Report releases between January 2001 and June 2008, and FOMC Statements between January 1995 and June 2008.

Table 3.2: Summary Statistics for Identified Shocks around Monetary Announcements

	Information	Monetary
Mean	0.00	0.00
Std.	1.00	1.00
Min	−3.83	−6.25
Max	5.54	3.09

Notes: This table presents summary statistics for the identified shocks around FOMC announcements between January 1995 and June 2008.

Table 3.3: Reduced Form Estimates by Sample Period

Sample Period	$A_{p_i,\nu}$	$A_{p_i,\epsilon}$	$A_{p_e,\nu}$	$A_{p_e,\epsilon}$	$\sigma^2_{\nu,econ}$
FOMC:1995–2008	0.61	0.45	0.29	-1.15	3.56
Econ:2001–2008	(0.06)	(0.09)	(0.05)	(0.25)	(1.11)
2001–2008	0.72	0.45	0.36	-1.37	2.52
	(0.08)	(0.14)	(0.06)	(0.39)	(0.87)
1995–2000	0.6	0.03	-0.48	-0.66	3.53
	(0.13)	(0.16)	(0.12)	(0.16)	(2.85)
1995–2008	0.74	0.1	-0.31	-1.14	2.28
	(0.13)	(0.16)	(0.12)	(0.36)	(2.81)

Notes: This table presents the reduced form parameter estimates for each sample period. Parameters are estimated with GMM with stratified empirical bootstrap standard errors in parenthesis below each estimate.

Table 3.4: Correlation Matrix of Identified Shocks and Asset Returns

	ED12	S&P 500	Economic	Monetary
ED12	1.0	-0.38	0.8	0.6
S&P 500	-0.38	1.0	0.24	-0.97
Economic	0.8	0.24	1.0	0.0
Monetary	0.6	-0.97	0.0	1.0

Notes: This table presents the correlations between the identified monetary policy and economic news shocks, and the returns on the 12-month Eurodollar and S&P 500.

3.7 Chapter 3 Figures

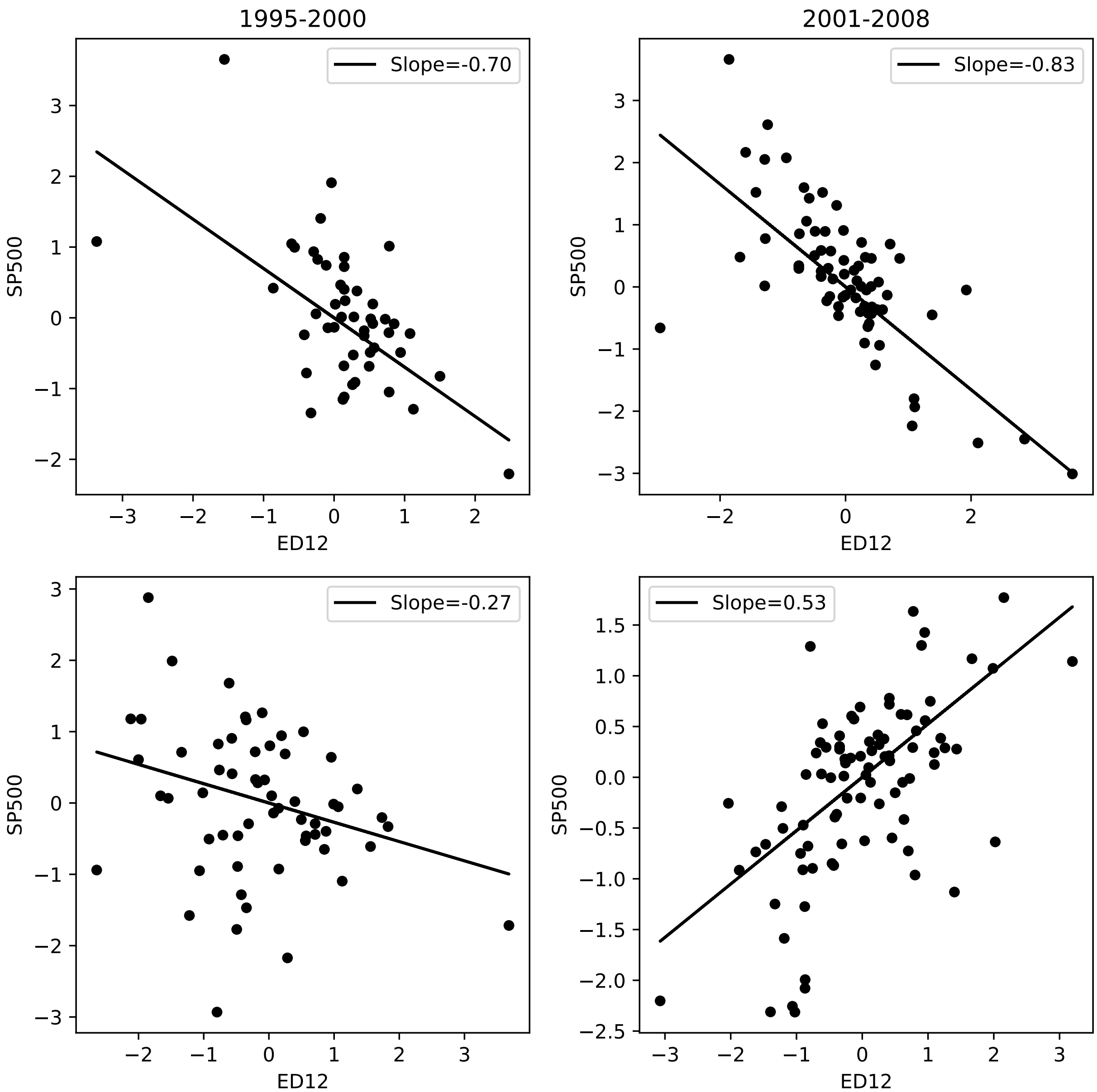

Figure 3.1: Returns by Sample Period

Notes: Each subfigure plots the 30-minute return of the S&P 500 against the 12-month Eurodollar return around the release of each scheduled FOMC Statement in the top row and Employment Situation Report in the bottom row between 1995–2000 or 2001–2008. Variables are standardized to be mean zero and have unit variance within the entire sample. Solid lines represent the line of best fit. Sample is January 1995–June 2008.

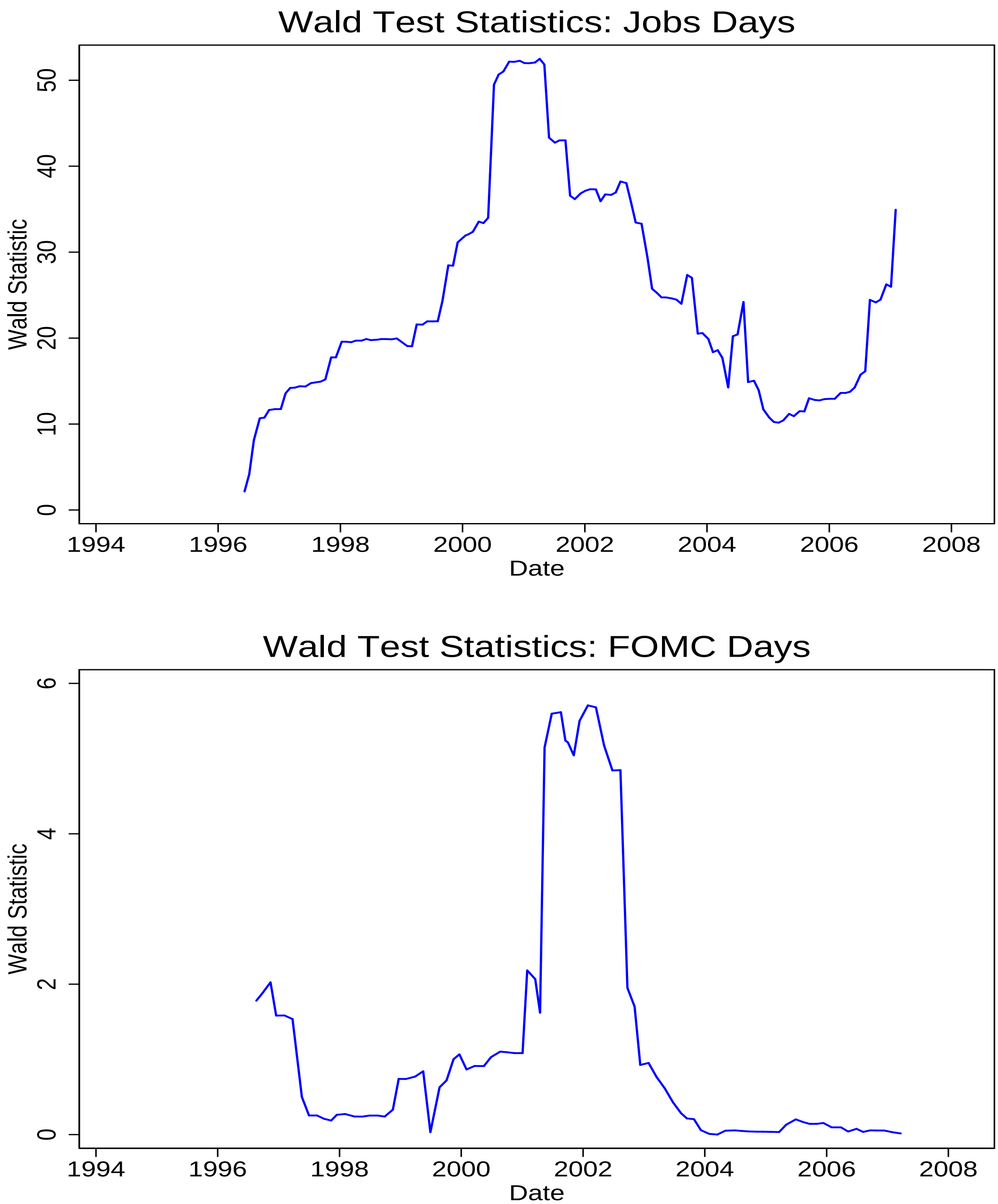

Figure 3.2: Test for structural Breaks in Interest Rate and Equity Return Correlations

Notes: Each subfigure plots the Wald test statistics from a test for a structural break in the relationship between S&P 500 returns and 12-month Eurodollar changes around the release of the Employment Situation Report (top panel) and FOMC announcements (bottom panel) at the given date. 10 and 1% critical values are 7.6 and 12.7 respectfully, as calculated in [34].

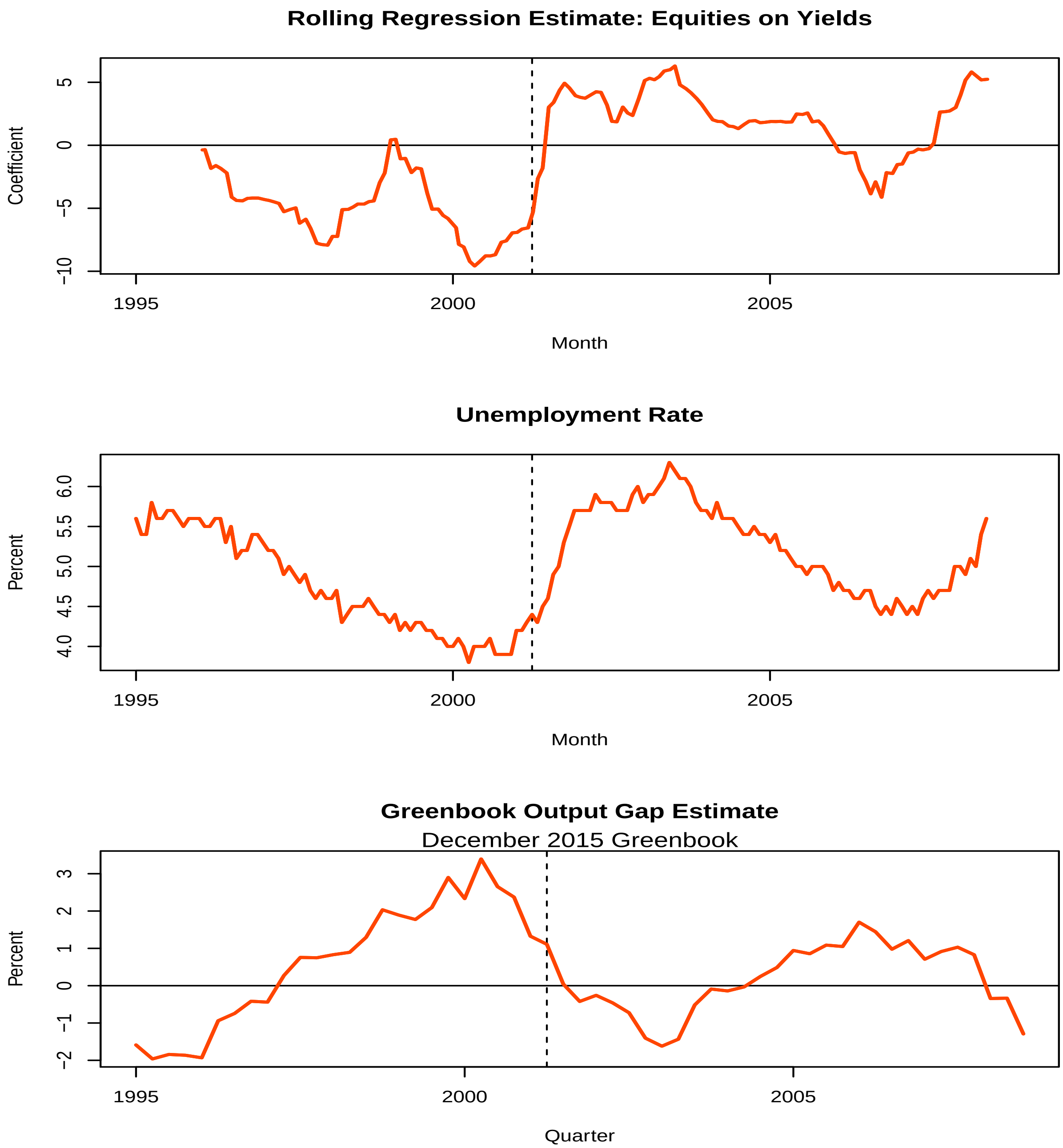

Figure 3.3: Explaining Equity-Yield Covariance Instability around Employment Situation Releases
Notes: The top panel plots the coefficient β from 12-month rolling regressions of the form $\Delta\log(p_t^{\text{equity}}) = \alpha + \beta\Delta\mathbb{E}_t[i_\tau] + \text{error}_t$, where $\mathbb{E}_t[i_\tau]$ and $\Delta\log(p_t^{\text{equity}})$ are the high-frequency changes in the 12-month Eurodollar future and S&P 500 described in the text, taken around the release of the Employment Situation report. The second panel plots the civilian unemployment rate (`UNRATE` in the Federal Reserve Bank of St. Louis' FRED portal) and the third panel plots the most-recently available Greenbook estimate of the output gap, available from the Philadelphia Fed here. The dashed vertical line is drawn in April 2001, where we find evidence for a structural break in the top panel.

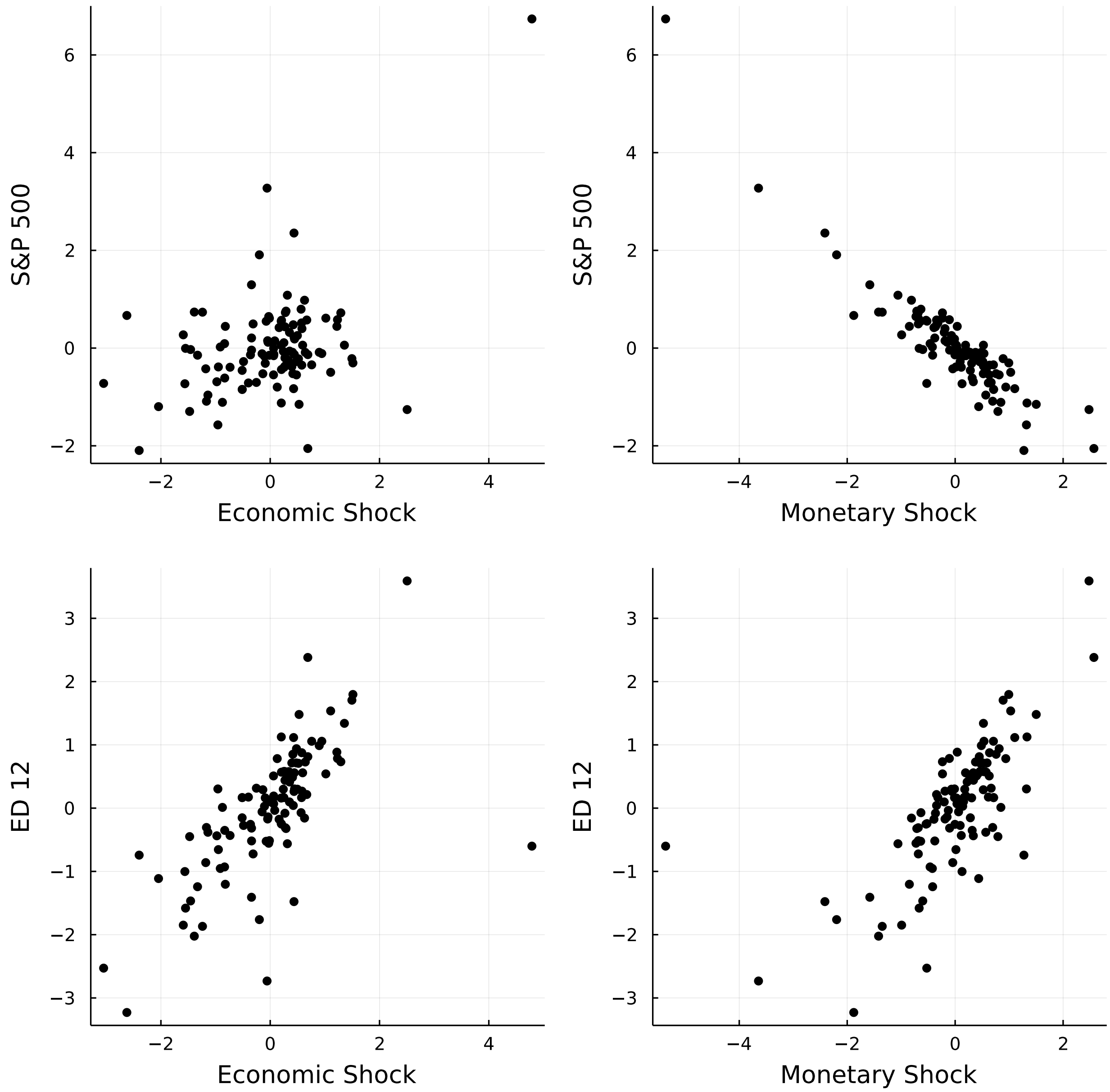

Figure 3.4: Returns and Identified Shocks Series

Notes: Each subfigure plots the observed asset return against the estimated structural shock for scheduled FOMC meetings between January 1995 and June 2008. Each series is standardized to be mean zero and have unit variance.

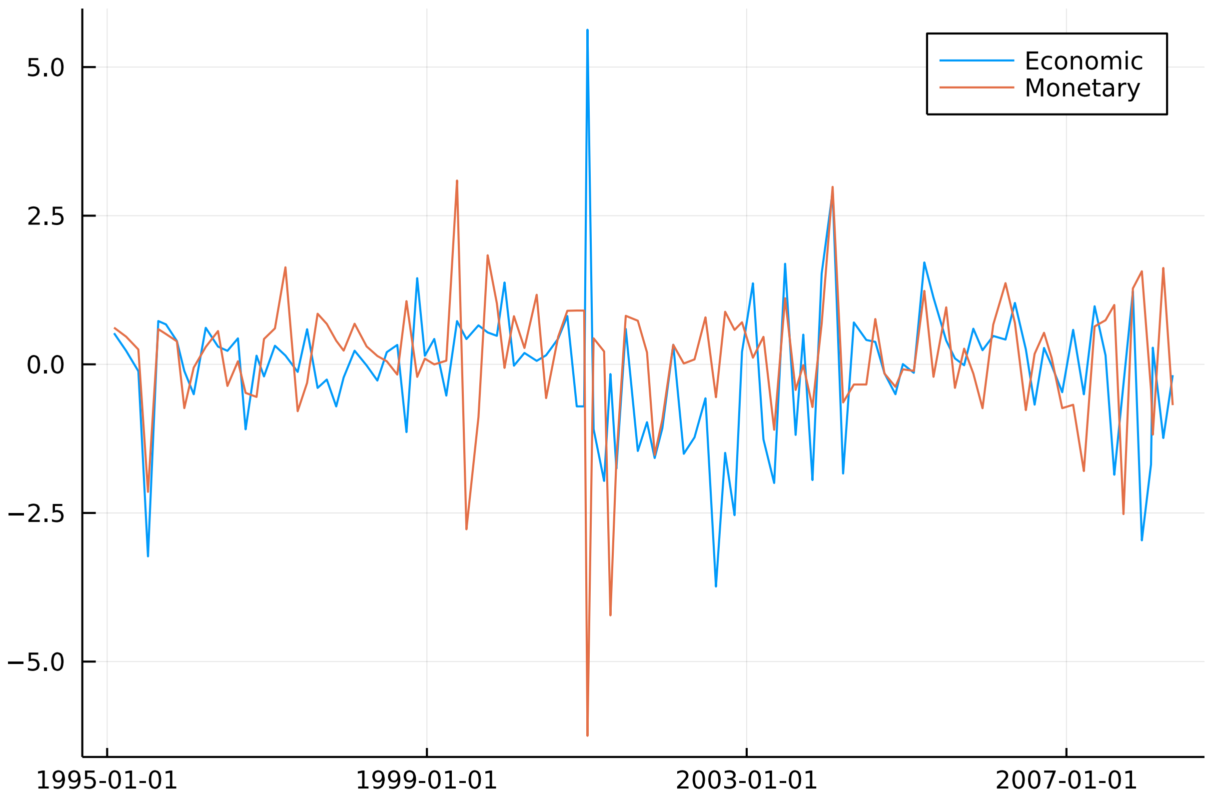

Figure 3.5: Identified Shocks over Time

Notes: This figure plots the times series of the identified Economic news shock and Monetary shock for scheduled FOMC meetings between January 1995 and June 2008. Each series is standardized to be mean zero and have unit variance.

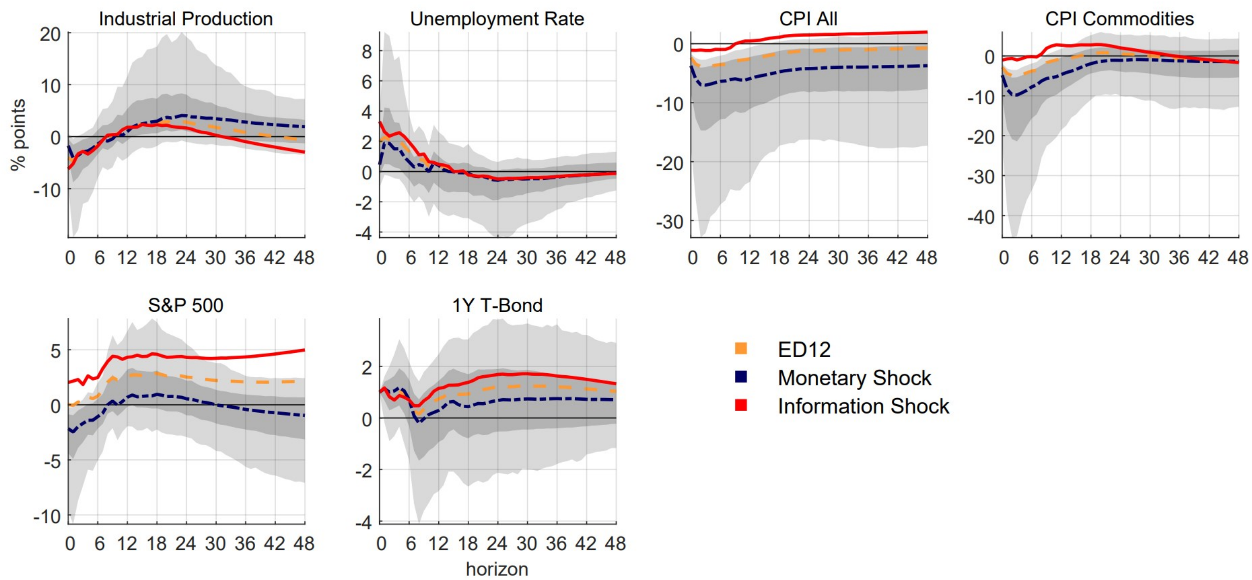

Figure 3.6: Macroeconomic Effects from a Proxy-SVAR

Notes: This figure plots the impulse responses to our identified monetary and information shocks, as well as the high-frequency change in the 12-month Eurodollar future around FOMC announcements. Details of the VAR are described in the text. We include 12 lags in the VAR. Confidence intervals are reported at the 68% and 90% levels using 999 wild bootstrap draws. The VAR parameters are estimated on the sample from January 1969–October 2019, and our first stage is estimated on the sample of months with an FOMC meeting from January 1995–June 2008.

Conclusion

This dissertation has explored how to identify the information sets of central banks and financial markets and the ways in which they interact. In particular, I have shown how to exploit the information sparsity in the forecasts of the FOMC to efficiently identify the underling information in these forecasts. Next I have shown that the FOMC does not have private information that is not available to financial markets, ruling out a possible confounding path for the identification strategy of high frequency methods. I also show that there are other confounding effects around monetary policy releases, but that these effects are also present around non-monetary news releases. Finally I exploited the high frequency returns around non-monetary economic news releases to control for these confounding effects in order to produce a robust high-frequency shock series.

In total, I have shown two new methods for estimating monetary policy shocks whose effects align closely with traditional economic theory and VAR methods estimated on earlier sample periods of data. Both methods produce series that can be used to directly measure the effect of monetary policy on macroeconomic variables, or can be used in other situations, such as panel data settings.

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