Fearing the Fed:
How Wall Street Reads Main Street

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Abstract

We provide strong evidence of persistent cyclical variation in the sensitivity of stock prices to macroeconomic news announcement (MNA) surprises. The stock market sensitivity is muted during the early recession and the late expansion phases of the economy, however, it increases significantly, reaching peak values in the early expansion phase. We show that market expectations and uncertainty about future interest rates are the primary drivers of the cyclical market responses to MNAs – these responses depend on whether the Fed is expected to be reactive. Evidence from survey forecasts and a monetary regime-switching model corroborates the connection between the cyclical stock responses and monetary policy expectations. A decomposition of the stock market responses shows that they primarily reflect news about cash flows and interest rate rather than risk premia news.

Keywords: Macroeconomic news announcements, cyclical return variation, monetary policy expectations, phase of business cycle, return decomposition, learning.
JEL Classification: G12, E30, E40, E50.

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1 Introduction

Recent evidence points to the prominent role the Federal Open Market Committee (FOMC) meetings and other macroeconomic news announcements (MNA) have on financial markets (e.g., Savor and Wilson (2013) and Lucca and Moench (2015) among others). However, predicting the direction of the stock market's response to these news is challenging. For example, increases in stock prices after better-than-expected MNA surprises (improved future expected cash flows), might instead be offset via expected future interest rate hikes as a result of stabilization policy. The perception about stabilization policy, in particular by the Federal Reserve (henceforth Fed), will depend on the phase of the business cycle and economic conditions. Furthermore, market's perception could be asymmetric with respect to negative and positive MNA surprises (e.g., consider the recent zero-lower bound (ZLB) period during which the Fed had limited control over negative MNA surprises). This interaction between market conditions and perceptions about possible Fed response can lead to significant time variation in the stock market's reaction.[1] Motivated by these considerations, this paper examines the cyclical variations in the sensitivity of the stock market to MNA surprises.

We use various measures of high-frequency stock returns and surveys of market expectations of upcoming MNAs. Our benchmark sample spans early 2000 to late 2016. We estimate the time-varying sensitivity of stock returns to the MNA surprises with the nonlinear regression method used in Swanson and Williams (2014). We focus on the MNAs and not on the FOMC meetings as the former allows us to include many more events over the business cycle and measure precisely the impact of surprises on stock market.

First, contrary to the literature on the FOMC meetings, we show that unconditionally it is difficult to detect a significant stock market response to the MNA surprises. Yet, consistent with the motivation above, we establish that this muted unconditional response is masking significant time varying cyclical responses of stock prices to MNA surprises. The sensitivity of stock prices to the MNA surprises starts to increase entering a recession, continues to increase as the recession deepens, and peaks post recession. Peak sensitivity is about twice the average sensitivity. The transition from peak sensitivity to trough sensitivity takes about four to five years with the recovery taking about the same amount of time. At trough sensitivity, stock prices generally do not react to the MNA surprises. We provide many robustness tests: the most important ones being that our results by and large persist (i) when we measure the responses using daily returns, and (ii) when we extend our analysis to data beginning in 1990 which encompass three recessions.

[1] See McQueen and Roley (1993), Flannery and Protopapadakis (2002), Boyd, Hu, and Jagannathan (2005) and Andersen, Bollerslev, Diebold, and Vega (2007) for early explorations relating MNAs and stock market responses.

Second, and somewhat surprisingly, there is weak evidence for asymmetry in the time variation in the responses to negative and positive MNA surprises. The corresponding return sensitivity estimates for positive and negative MNA surprises are statistically indistinguishable from each other in our benchmark estimation sample. Third, we show that the observed cyclical variations of the stock market responses to MNAs are tightly connected to beliefs about monetary policy. Specifically, the sensitivity of short-term interest rate futures to MNA surprises moves in lock-step but in the opposite direction of the stock market's response sensitivity. We further corroborate the connection between the cyclical return responses and the path of future interest rate by examining the Blue Chip Financial Forecasts regarding interest rates. We show that market expectation about the interest rate is more accurate in both early and late expansion periods relative to recessions. In general, interest rate is expected to remain unchanged in the early expansion period, while in the late expansion period expectations are leaned toward a rate increase. Taken together, this evidence suggests that during the recession period uncertainty is large and the ensuing action of the Fed is difficult to predict. In early expansion periods, the market does not fear a rate hike and is relatively certain about the position of the Fed. In contrast, during the late expansion phase, overall uncertainty is relatively low and the remaining uncertainty is primarily about the magnitude of tightening leading to a muted stock response.

To shed light on the mechanism at work, we use a novel state space approach to write the stock return news as the sum of news about cash flows, news about the risk-free rate, and news about risk premium following Campbell (1991). To isolate the role of risk premium news in stock return variation, we use intraday variance premium as an empirical proxy for risk premium news. Interestingly, we find that news concerning cash flows and the risk-free rate explain most of the sensitivity pattern we observe in the data. This important effect of cash flows (and risk-free rate) on stock prices is of interest given the long standing research in analyzing the sources of variation of valuation ratios.[2]

Having shown that the informational content of the MNA surprises can be narrowed down to news about cash flows and risk-free rate, we focus further on the role expectations regarding the future path of interest rate have on the cyclical return sensitivity. Specifically, we examine if beliefs about monetary policy embedded in macroeconomic data are also consistent with those in financial data. To this end, we propose a bivariate regime-switching vector autoregressive model with unemployement rate and interest rate that features two distinct interest rate regimes. One of the regimes is less reactive than the other in the sense that the feedback coefficients between the interest rate and unemployement rate are smaller in absolute magnitude. Most importantly, we

[2] We aimed to discipline the role of risk-free rate news with the Eurodollar futures. The caveat is that there is very little data fluctuation in short-maturity Eurodollar futures during the ZLB period, which contrasts starkly with the pre-crisis periods.

assume an information set similar to that of the stock market participant. The agent here is not endowed with the full structural knowledge of the economy and forms beliefs about parameters and states similar to those of an econometrician. She updates her beliefs using Bayes' rule as new observations arrive.

The joint learning of parameters and states is a high-dimensional problem which incurs confounding effects arising from multiple sources of uncertainty (see Johannes, Lochstoer, and Mou (2016) for similar problems). To solve for the sequential learning problem, we use the particle learning algorithm developed by Carvalho, Johannes, Lopes, and Polson (2010). Empirically, we find that the mean probability of nonreactive regime starts to increase in recession and remains near one a few years after the recession. Roughly speaking, the probability starts to come down after the formal NBER announcements of business cycle turning point from contraction to expansion.[3] When the mean regime probability is compared with the estimated stock return sensitivity, we find the most interesting co-movement pattern. The estimated stock return sensitivity is above average when the probability of the nonreactive regime is close to one and vice versa. What is important to emphasize is that the regime probability is obtained solely based on macroeconomic variables.

Our collective evidence suggests that the stock market response to MNAs is intimately related to the phase of the economy and the likelihood of a monetary response by the Fed. The muted response to MNAs during the early phase of recessions can be attributed to agents being less confident about the regime of the economy and the Fed's actions. On the other hand, the muted response at the late expansion phase seems to be consistent with the fear of a rate hike, while the significant response during the early expansion phase seems to support beliefs that a reactive action by the Fed is unlikely. In totality, our evidence highlights the importance of understanding the interplay between economic conditions, the expectations about monetary policy given these economic conditions, and their combined effect on the stock market.

1.1 Literature Review

Two key steps the literature has identified in measuring the impact of MNA surprises on stock prices are the use of high-frequency returns and the conditioning of the response on the business cycle. McQueen and Roley (1993) first demonstrate that the link between MNA surprises and stock prices is much stronger after accounting for different stages of the business cycle. Boyd, Hu, and Jagannathan (2005) use model-based forecasts of the unemployment rate and Andersen, Bollerslev, Diebold, and Vega (2007) rely on survey forecasts to emphasize the importance of

[3]Importantly, our sequential learning procedure, as well as other regression analysis, do not use any information regarding the NBER dates in the estimation.

measuring the impact of MNA surprises on stock prices over different phases of the business cycle. Goldberg and Grisse (2013) and Swanson and Williams (2014) extend the literature by estimating the time variation in the responses of yield curves to MNA surprises. We add to this literature by characterizing the time varying properties of the stock market's reaction to MNA surprises and its tight relationship with market expectation of monetary policy.

Our paper can be linked to a large literature that studies asset market and monetary policy, for example, Pearce and Roley (1985), Thorbecke (1997), Cochrane and Piazzesi (2002), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Gurkaynak, Rigobon, and Sack (2005), and Bekaert, Hoerova, and Lo Duca (2013) among others. Recently, Neuhierl and Weber (2016) document that monetary policy affects stock prices outside of the scheduled FOMC announcements as predicted by Bernanke and Kuttner (2005). Cieslak and Vissing-Jorgensen (2017) focus on a related and complementary channel by relating stock market movements to subsequent monetary policy action by the Fed. Nakamura and Steinsson (2017) estimate monetary non-neutrality based on evidence from yield curve and claim Fed announcements affect beliefs not only about monetary policy but also about other economic fundamentals. Paul (2017) estimates the time-varying responses of stock and house prices to changes in monetary policy and finds that asset prices have been less responsive to monetary policy shocks during periods of high and rising asset prices.

Broadly speaking, we are related to a literature exploring the relationship between various news announcements including the FOMC announcements and asset prices. Faust and Wright (2009) and Savor and Wilson (2013) find positive risk premia in bond markets for macroeconomic announcements. Lucca and Moench (2015) find the stock market on average does extremely well during the 24 hours before the FOMC announcement. Ai and Bansal (2016) explore the macro announcement premium in the context of generalized risk prefernces.

Our paper also analyzes the relative importance of cash flows versus discount rates, a central discussion in finance. Campbell and Shiller (1988), Campbell (1991), Campbell and Ammer (1993), Cochrane (2011) among others claim variations in discount rate news account for most of the variations in asset prices. Other papers ascribe a significant role to cashflow news in variations of asset prices, such as Bansal and Yaron (2004), Bansal, Dittmar, and Lundblad (2005), Lettau and Ludvigson (2005), Schorfheide, Song, and Yaron (2017) among others. We show that at high frequency around the time of macroeconomic news announcements, variations in stock prices are mostly accounted for by cash flows or risk-free rate news rather than risk premia news.

The remainder of this paper is organized as follows. Section 2 describes the data, unconditional results, regression methods, selection of macroeconomic announcements, and discusses empirical findings. Section 3 corroborates the connection between the cyclical return variation and monetary policy expectation. Section 4 decomposes the announcement surprises into news about cash flows, risk-free rate, and risk premia components. It shows the informational content of the surprises is least related to risk premium news and is mostly explained by news about cash flows and news about risk-free rate. Section 5 intoduces a statistical learning model in which joint learning of parameters and states is introduced. It shows that the beliefs about nonreactive interest rate state embedded in macroeconomic data are consistent with those in financial data. Section 6 provides concluding remarks.

2 The Reaction of Stock Market to Macroeconomic News

2.1 High-frequency data

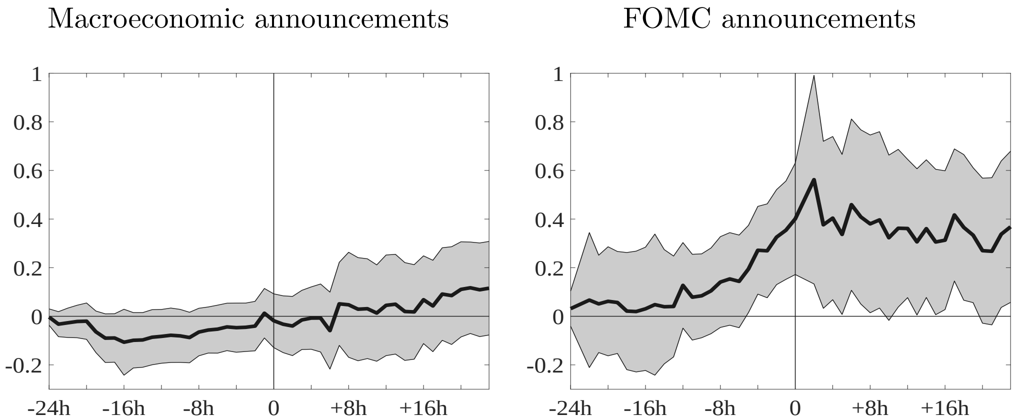
Macroeconomic news announcements. MNAs are officially released by government bodies and private institutions at regular prescheduled intervals. In this paper, we use the MNAs from the Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Federal Reserve Board (FRB), Conference Board (CB), Employment and Training Administration (ETA), and Institute for Supply Management (ISM). We use the MNAs as tabulated by Bloomberg Financial Services. Bloomberg also surveys professional economists on their expectations of these macroeconomic announcements. Forecasters can submit or update their predictions up to the night before the official release of the MNAs. Thus, Bloomberg forecasts could in principle reflect all available information until the publication of the MNAs. Most announcements are monthly except Initial Jobless Claims which is weekly. All announcements are released at either 8:30am or 10:00am except Industrial Production MoM which is released at 9:15am. Announcements released outside of their regular schedule are dropped. We consider announcements where the data span January 2000 to December 2016. Details are provided in Table D.1. For robustness, we also consider Money Market Services (MMS) real-time data on expected U.S. macroeconomic fundamentals. None of our results are affected.

Standardization of the MNA surprises. Denote MNA i at time t by $\text{MNA}_{i,t}$ and let $E_{t-\Delta}(\text{MNA}_{i,t})$ be proxied by median surveyed forecast made at time $t-\Delta$. The individual MNA surprises (after normalization) are collected in a vector X_t whose ith component is

$$X_{i,t} = \frac{\text{MNA}_{i,t} - E_{t-\Delta}(\text{MNA}_{i,t})}{\text{Normalization}}.$$

The units of measurement differ across macroeconomic indicators. To allow for meaningful comparisons of the estimated surprise response coefficients, we consider two normalizations. The first normalization scales the individual MNA surprise by the contemporaneous level of uncertainty

Figure 1: Cumulative stock returns around scheduled announcements.



Notes: We plot the average cumulative stock returns in percentage points around scheduled announcements. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, ISM Manufacturing and Initial Jobless Claims. The black solid lines are the average cumulative return on S&P 500 E-mini futures on a day prior to scheduled announcements to a day after scheduled announcements. The light-gray shaded areas are $\pm$2-standard-error bands around the average returns. The sample period is from January 2000 through December 2016. The vertical line indicates the time at which announcements are typically released in this sample period.

measured by the standard deviation of all survey forecasts. The key feature of this standardization is that the normalization constant differs across time for each MNA surprise. The second normalization scales each MNA surprise by its standard deviation taken over the entire sample period.[4] The key feature of the second approach is that for each MNA surprise, the normalization constant is identical across time. Thus, this normalization cannot affect the statistical significance of sensitivity coefficient. Surprisingly, as reported in Table D.2 we find that the two different approaches yield highly correlated surprise measures. We use the first normalization as our benchmark approach. Our results are robust across both methods.

Financial data. We consider futures contracts for the asset prices in our analysis: S&P 500 E-Mini Futures (ES), S&P 500 Futures (SP), 30-Day Federal Funds Futures (FF), and Eurodollar futures (ED). Futures contracts allow us to capture the effect of announcements that take place at 8:30am Eastern time before the equity market opens. This exercise would not be possible if we relied solely on assets traded during regular trading hours. We use the first transaction in each minute as our measure of price and fill forward if there is no transaction in an entire minute. We also consider SPDR S&P 500 Exchange Traded Funds (SPY) to examine robustness of our findings. To construct measures of risk, we use S&P 500 Volatility (VIX) index from the Chicago Board Options Exchange (CBOE). All our data are obtained from TickData.

[4]This standardization was proposed by Balduzzi, Elton, and Green (2001) and is widely used in the literature.

2.2 Event study analysis

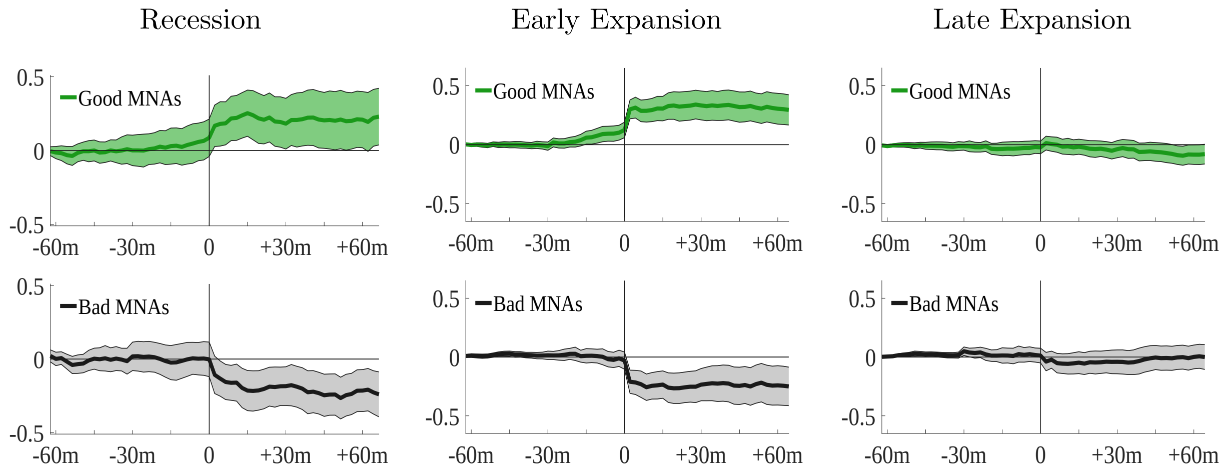
We first show that contrary to the FOMC announcements the unconditional response of the stock market to macroeconomic announcements is insignificant. We then demonstrate the power of conditioning the stock market response to the MNAs on the business cycle phase and on the nature of the MNAs —when the responses become significant and economically important.

Our analysis focuses on the MNAs but excludes the scheduled FOMC meetings. The latter are known to be associated with a dramatic pre-announcement drift in stock prices as recently shown in Lucca and Moench (2015). They document that the S&P 500 index has on average increased 49 basis points in the 24 hours before the scheduled FOMC announcements.[5] The FOMC pre-announcement drift in Lucca and Moench (2015) is captured in Figure 1 where we plot the cumulative stock returns around the scheduled announcements starting from a day-before to a day-after the announcements. In contrast, when one restricts to macroeconomic news announcements which are different from the scheduled FOMC announcements, this pre-announcement drift disappears. From this result, one might infer that there is no economic impact of the MNAs.

However, once the MNA surprises are analyzed at a higher frequency and conditioned appropriately on the state of the economy and the sign of the MNA surprise, a very significant impact on prices is observed. In Figure 2 we plot the cumulative stock returns starting from an hour before macroeconomic announcements to an hour after the announcements. Two distinctive patterns emerge. First, the reaction of stock prices can be much more precisely measured when announcements dates are separated into good (positive) and bad (negative) announcement dates and when we condition on the phase of business cycle. Specifically, we partition the period into "recession," "early expansion," and "late expansion" (discussion on the definition of the phase of the business cycle will follow). For example, the average impact of MNA surprises is about 20 basis points during early expansion periods which is estimated to be statistically significant. Yet the absolute value is still smaller than the measured impact of the pre-announcement drift of the eight regularly scheduled FOMC meetings. However, one has to recall that there are many more MNAs than the typical eight scheduled FOMC meetings, and therefore in an aggregate sense the total impact of the MNA surprises is economically very important. Second, there is strong evidence of time variation in the stock return responses. In contrast to those in recession or early expansion periods, the stock return responses to the MNA surprises are statistically indistinguishable from zero in late expansion periods. This evidence is consistent with a few papers that argue stock market reactions to announcement surprises may depend on the state of the

[5] In related work, Savor and Wilson (2013) also find that average stock returns are significantly higher on days when important macroeconomic news are scheduled. These announcements include inflation indexes, employment figures, and the FOMC decisions.

Figure 2: Cumulative stock returns around macroeconomic announcements



Notes: We plot the average cumulative stock returns in percentage points around scheduled announcements. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, ISM Manufacturing and Initial Jobless Claims. Good (Bad) announcements are positive (negative) surprises. We flip the sign of Initial Jobless Claims for ease of comparison across other "good" surprises. Recession periods correspond to the NBER recession dates. Early expansion periods are upto two years after the recession. Late expansion periods are five years after the recession. The black solid lines are the average cumulative return on S&P 500 futures (SP) on an hour prior to scheduled announcements to an hour after scheduled announcements. The light-gray shaded areas are $\pm$2-standard-error bands around the average returns. The sample period is from January 2000 through December 2016. The vertical line indicates the time at which announcements are released in this sample period.

economy (e.g., McQueen and Roley (1993), Boyd, Hu, and Jagannathan (2005), and Andersen, Bollerslev, Diebold, and Vega (2007)).

Collectively, the evidence suggests the importance of accounting for time variation and highlights the difficulty of measuring the impact of the MNA surprises on stock market. While easy to implement, the event study has significant limitation to understanding the return variation. To gain better econometric power in identifying the stock market responses to the MNA surprises, we proceed with a regression analysis.

2.3 Regression analysis

To measure the effect of the MNA surprises on stock prices, we take the intra-day future prices and compute returns r_t in a Δ-minute window around the release time. For our benchmark results, we use the ES contract to measure stock returns because it is most actively traded during the MNA release times. To determine which MNAs impact returns, we estimate the following regression motivated by Gurkaynak, Sack, and Swanson (2005) and others

$$r_{t-\Delta_l}^{t+\Delta_h} \quad = \quad \alpha + \gamma^\top X_t + \epsilon_t \tag{1}$$

where the vector X_t contains various MNA surprises. We proceed by first determining the most impactful announcements across various window intervals, selecting the return window, and then focusing on the cyclicality of the return response.

As the results can depend on the size of the return window, we consider all combinations of Δ_l and Δ_h between 10 minutes and 90 minutes in increments of 10 minutes (81 regressions in total).[6] Table 1 tabulates the number of regressions in which equity returns significantly respond to a specific MNA at the 1% significance level. For instance, the Unemployment Rate surprise is significant in 16% of these regressions. We use many combinations of the return window precisely because the significance of the MNAs depends on the size of the return window, see for example, Andersen, Bollerslev, Diebold, and Vega (2003) and Bartolini, Goldberg, and Sacarny (2008). This is confirmed in Table 1. This step allows us to select the MNAs while being agnostic over the size of the return window.

Selection of the MNA surprises. We now turn to the selection of the MNAs. Table 1 reveals that only a subset of the MNAs impacts the stock market. We find that Change in Nonfarm Payrolls, Initial Jobless Claims, ISM Manufacturing, Consumer Confidence Index are, broadly speaking, the most influential MNAs. This choice of four announcments is robust to the use of intra-day and daily returns, and is consistent with findings in the literature. For example, Andersen, Bollerslev, Diebold, and Vega (2007) analyze the impact of announcement surprises of 20 monthly macroeconomic announcements on high-frequency S&P 500 futures returns. They argue that Change in Nonfarm Payrolls is among the most significant of the announcements for all of the markets and it is often referred to as the "king" of announcements by market participants. Bartolini, Goldberg, and Sacarny (2008) discuss the significance of Change in Nonfarm Payrolls as well as the other three announcements which are also significant in our regressions. Based on Table 1, we consider the top four most influential MNAs as the benchmark for our analysis. We later show that none of our results are affected by the inclusion of the next eight influential MNAs in Table 1.

Selection of the window interval. Our next step is to select Δ_l and Δ_h. We re-estimate equation (1) using only the top four influential MNAs reported in Table 1 and provide the resulting R^2 values in Figure E.1. We find that the R^2 values are consistent with findings in

[6]Bollerslev, Law, and Tauchen (2008) show that sampling too finely introduces micro-structure noise while sampling too infrequently confounds the effects of the MNA surprise with all other factors aggregated into stock prices over the time interval.

Table 1: Stock return reaction to the MNA surprises

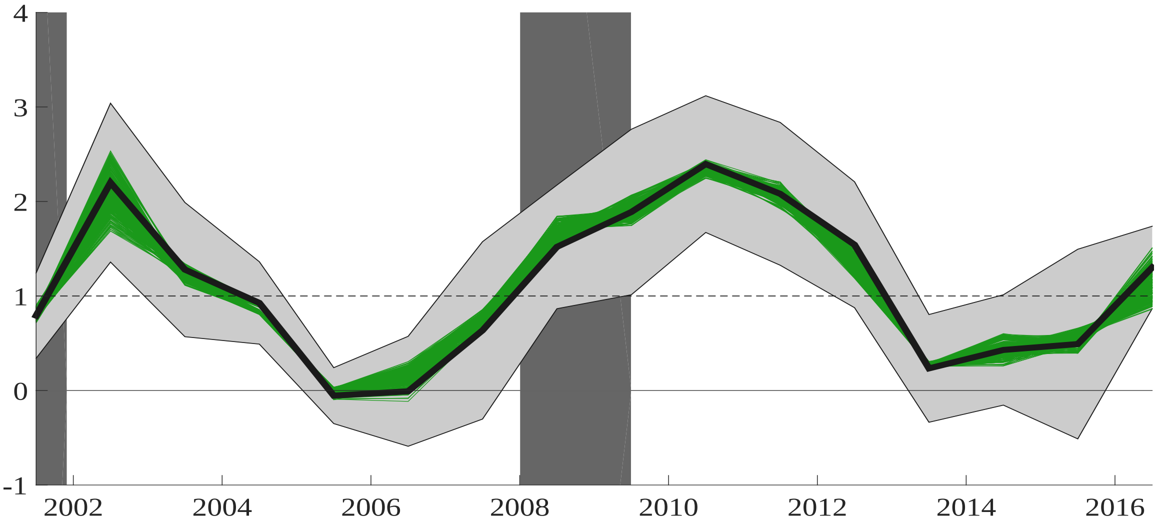
	Intra-day Return				Daily Return	
MNAs	Multivariate		Univariate		Multivariate	Univariate
	Percent	p-val	Percent	p-val	p-val	p-val
Change in Nonfarm Payrolls	100 %	0.00	100 %	0.00	0.23	0.40
Consumer Confidence Index	100 %	0.00	100 %	0.00	0.99	0.99
Initial Jobless Claims	100 %	0.00	100 %	0.00	0.19	0.19
ISM Manufacturing	100 %	0.00	100 %	0.00	0.01	0.02
Durable Goods Orders	88 %	0.00	95 %	0.00	0.49	0.48
CPI MoM	83 %	0.01	89 %	0.01	0.20	0.21
Retail Sales Advance MoM	78 %	0.01	78 %	0.01	0.65	0.60
GDP Annualized QoQ	64 %	0.07	72 %	0.03	0.61	0.57
ISM Non-Manf. Composite	59 %	0.04	42 %	0.09	0.02	0.02
Construction Spending MoM	31 %	0.02	0 %	0.17	0.99	0.90
Industrial Production MoM	19 %	0.20	57 %	0.02	0.47	0.24
Unemployment Rate	16 %	0.18	0 %	0.40	0.30	0.49
New Home Sales	5 %	0.51	4 %	0.46	0.88	0.91
Capacity Utilization	0 %	0.54	33 %	0.03	0.94	0.38
Factory Orders	0 %	0.30	0 %	0.39	0.23	0.27
Housing Starts	0 %	0.54	7 %	0.39	0.87	0.86
Leading Index	0 %	0.46	0 %	0.51	0.73	0.77
PPI Final Demand MoM	0 %	0.47	0 %	0.51	0.82	0.83
Personal Income	0 %	0.73	0 %	0.61	0.74	0.68
Trade Balance	0 %	0.21	1 %	0.23	0.36	0.47

Notes: The sample is from January 2000 to December 2016 for the 81 regressions described in the main text. "Percent" refers to the percentage (number significant/81) of regressions in which returns significantly responds the MNA at the 99% confidence interval. Average p-value is the average two-sided p-value across all 81 regressions. We consider "multivariate" and "univariate" regressions. Daily return refers to using returns from 8am to 3.30pm. It is important to note that we remove all the days when there are the FOMC related news in construting daily returns.

the literature, for example, Andersen, Bollerslev, Diebold, and Vega (2007) and Goldberg and Grisse (2013). For the subsequent analysis, we consider regressions with $\Delta = \Delta_l = \Delta_h$ and set $\Delta = 30$min. This symmetric window yields an R^2 value of 0.13 which is representative of the R^2 distribution in Figure E.1. We emphasize that our results are maintained across all 81 combinations of Δ_l and Δ_h.

Estimating stock return sensitivity to the MNA surprises. Having fixed $\Delta = 30$min and restricted the set of MNAs to the top four most influential MNAs, we now turn our attention to measuring the time-varying sensitivity of the returns to macroeconomic news. To do this, we estimate the following nonlinear regression over τ-period rolling windows as in Swanson and

Figure 3: Time-varying sensitivity coefficient for stock returns



Notes: The top four MNAs from Table 1 are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that β^τ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide ± 2-standard-error bands (light-shaded area) around β^τ. The shape is robust to all possible combinations (green-solid lines) of the next eight MNAs listed in Table 1. Number of observations is 1486.

Williams (2014)

$$r_{t-\Delta}^{t+\Delta} \quad = \quad \alpha^\tau + \beta^\tau \gamma^\top X_t + \epsilon_t \tag{2}$$

where ϵ_t is a residual representing the influence of other news and other factors on stock returns at time t. α^τ and β^τ are scalars that capture the variation in the return response to announcement during period τ. The underlying assumption is that while the relative magnitude of γ is constant, the return responsiveness to all MNA surprises shifts by a proportionate amount over the τ period. We let τ index the calendar year. The identification assumption is that β^τ is on average equal to one. This implies that the sample average of $\beta^\tau \gamma^\top X_t$ is identical to its OLS counterpart $\gamma^\top X_t$ in (1). As discussed in Swanson and Williams (2014), the primary advantage of this approach is that it substantially reduces the small sample problem by bringing more data into the estimation of β^τ.

Figure 3 provides the main focus of our study, that is, the estimate of the time-varying sensitivity coefficient $\hat{\beta}^\tau$ (black-solid line) for the top four MNAs. For robustness, we also plot the results from additionally including every possible combination of the next eight MNAs in Table 1. All these 256 regressions yield the green-solid lines that are very close to each other and hence, appear as a green band when viewed from a distance.[7]

We find strong evidence of persistent cyclical variation in stock market responses to the MNAs. The evidence suggests that the sensitivity of stock returns to the MNAs can increase by a factor greater than two coming out of recessions and remains above average for about one to two years. We find that the stock market's prolonged above-average reaction (about three to four years) is unique to the Great Recession during which the ZLB was binding. The reaction of stock returns gradually attenuates as the economy expands and it takes about four to five years to move from peak to trough sensitivity. There are periods, for example, 2005-2007 and 2013-2015, during which stock market hardly reacted to the MNAs.

Stock return sensitivity before and after the announcements. To better understand how information contained in the MNAs is conveyed in the stock market, we decompose $\hat{\beta}^\tau$ to sensitivity attributable to periods before and after the announcements. To recap, the estimates from the benchmark regression are provided below

$$\hat{r}_{t-30m}^{t+30m} = \hat{\alpha}^\tau + \hat{\beta}^\tau(\hat{\gamma}^\top X_t) = \hat{\alpha}^\tau + \hat{\beta}^\tau \hat{X}_t. \tag{3}$$

We estimate the modified (restricted) regression in which we regress return $r_{t-\Delta_l}^{t+\Delta_h}$ on $\hat{X}_t$

$$r_{t-\Delta_l}^{t+\Delta_h} = \alpha^\tau + \beta^\tau \hat{X}_t + \epsilon_t \tag{4}$$

and obtain estimate of $\hat{\beta}^\tau$ for each combination of $(\Delta_h, \Delta_l) \in \{-5m, 0m, 5m, 30m\}$, which we denote by $\hat{\beta}^\tau(t - \Delta_l \to t + \Delta_h)$. The sensitivity is with respect to the linearly transformed MNA surprises, $\hat{X}_t$. Since $\hat{X}_t$ is a generated regressor from (3), asymptotic standard errors are constructed using generalized methods of moments. Since $r_{t-30m}^{t+30m} = \sum r_{t-\Delta_l}^{t+\Delta_h}$, it follows that $\hat{\beta}^\tau$ in (3) by construction equals $\sum \hat{\beta}^\tau(t - \Delta_l \to t + \Delta_h)$.[8]

Figure E.2 shows that stock prices on impact react significantly to the MNA surprises (bottom left of Figure E.2), but there is no statistically significant movement five minutes after the announcements. This is important as it shows there is no immediate mean reversion in the reaction of the stock market. Below we extend our analysis to daily data and further confirm that the market reactions are not reflecting temporary noise. It is also worth noting that we do not find any evidence of pre-announcement phenomenon (see the top panel of Figure E.2) which is different from Lucca and Moench (2015).

Stock return sensitivity with lower-frequency data. To show that the impact of the MNA surprises on the stock market is not short-lived, we estimate the restricted regression (4) with

[7]The sum of possible combination of eight MNAs is $\sum_{i=0}^{8} \binom{8}{i} = 256$.

[8]Specifically, $\hat{\beta}^\tau = \hat{\beta}^\tau(t - 30m \to t - 5m) + \hat{\beta}^\tau(t - 5m \to t) + \hat{\beta}^\tau(t \to t + 5m) + \hat{\beta}^\tau(t + 5m \to t + 30m)$.

larger window intervals. Since we aim to compare the precision of the sensitivity coefficient estimates when we replace the dependent variable with lower-frequency returns, we fix the unconditional impact of the MNA surprises to be *ex ante* identical across various cases. Thus, the coefficient $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ can only be interpreted with respect to $\hat{X}_t$. Figure E.3 provides three individual sensitivity estimates. It is important to note that we remove all the days when there are the FOMC related news in constructing daily returns. We find that the mean estimates are broadly similar across various window intervals. As expected, the standard-error bands increase moving from the case of hourly returns (first figure) to daily returns (third figure). We emphasize that the results from the unrestricted regression are qualitatively similar.

Evidence for asymmetry. We decompose the macroeconomic news announcements into "good" (better-than-expected or positive) and "bad" (worse-than-expected or negative) announcements and examine if the stock return responses to good and bad MNA surprises are different from each other.[9] Here, we flip the sign of Initial Jobless Claim surprises for ease of comparison across other "good" surprises. We then run the following regression

$$r_{t-\Delta}^{t+\Delta} = \alpha^{\tau} + \beta_{good}^{\tau}\gamma^{\top}X_{good,t} + \beta_{bad}^{\tau}\gamma^{\top}X_{bad,t} + \epsilon_t. \tag{5}$$

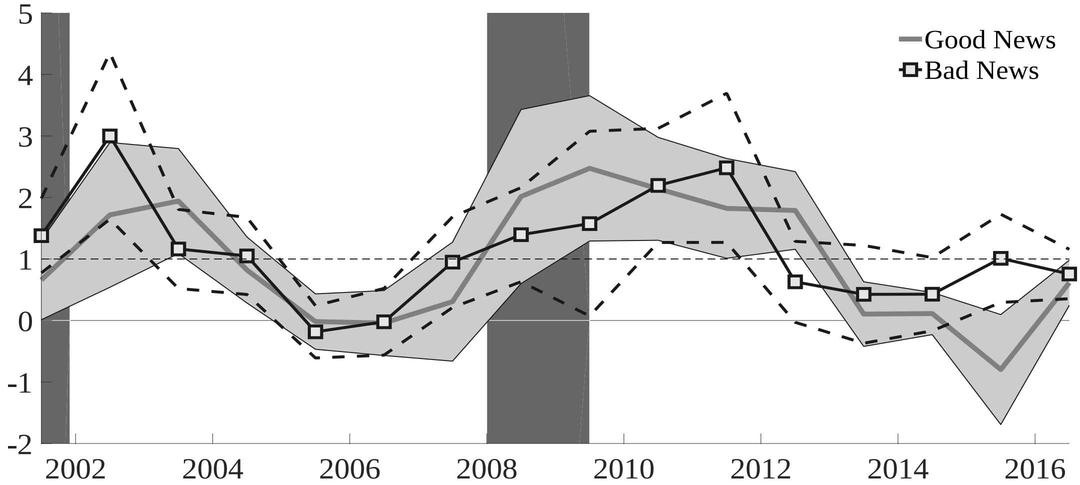
Note that if β_{good}^{τ} and β_{bad}^{τ} are identical, this equation becomes (2). Figure 4 displays the corresponding estimates of $\hat{\beta}_{good}^{\tau}$ and $\hat{\beta}_{bad}^{\tau}$. Surprisingly, the standard error bands on $\hat{\beta}_{good}^{\tau}$ and $\hat{\beta}_{bad}^{\tau}$ overlap most of the time except 2015, and thus the sensitivity estimates are statistically indifferent from one another. In sum, there is no evidence for asymmetry in the response to good and bad MNA surprises.

Distribution of the MNA surprises. One might suspect that time variation in the stock market sensitivity is primarily driven by time variation in MNA surprises. Figure E.4 overlays the normalized annual averages of good and bad MNA surprises with the estimated time-varying sensitivity $\hat{\beta}^{\tau}$ displayed in Figure 3. We plot the negative of bad MNA surprises to make them comparable to good MNA surprises. We do not find any significant co-movement between the stock sensitivity coefficient and MNA surprises. This exercise suggests that time variation in $\hat{\beta}^{\tau}$ cannot be systematically attributable to time variation in the MNA surprises.

To test the hypothesis formally, we partition the sample into "recession," "early expansion," "late expansion" and perform the two sample Kolmogorov-Smirnov test. Recession periods correspond to the NBER recession dates. Broadly defined, early expansion indicates periods within two years after recession and late expansion indicates periods five years after recession. We try to keep the number of samples similar across three different periods. The test results are robust to

[9]We also repeat this exercise using only the better half of good news (the most positive) and the worse half of bad news (the most negative) and find that the results do not change.

Figure 4: Stock return sensitivity to good and bad surprises



Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We flip the sign of Initial Jobless Claims surprises for ease of comparison across other "good" surprises. We set $\Delta = 30$min. We impose that β_j^τ is on average equal to one. We provide ± 2-standard-error bands around β_j^τ, $j \in \{good, bad\}$. $\hat{\gamma}$ estimates and the corresponding standard errors are $0.11(0.01), 0.06(0.01), 0.03(0.00), 0.08(0.01)$, respectively. Number of observations is 1486.

different definition of subsamples. Specifically, for a given MNA i, we generate the surprises for three different subsamples and compute a test decision for the null hypothesis that the surprises in different subsamples are from the same distribution. None of the test reject the null hypothesis at the 5% significance level. This can be seen in Figure E.5 which compares the distribution of the MNA surprises across different subsamples and provides the asymptotic p-values from the two-sample Kolmogorov-Smirnov test.

Controlling for possible omitted variable problems. It is possible that our benchmark specification may suffer from omitted variable problems. We augment the regression with other predictor variables $Z_{t-\Delta_z}$ which are known before the announcements

$$r_{t-\Delta}^{t+\Delta} = \alpha^\tau + \beta^\tau \gamma^\top X_t + \delta^\top Z_{t-\Delta_z} + \epsilon_t. \tag{6}$$

We consider three forms of $Z_{t-\Delta_z}$. The first one is spread between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity and the second one is the change in spread both of which are available in daily frequency. The third one is the Aruoba-Diebold-Scotti business conditions index which is designed to track real business conditions at daily frequency.[10]

[10]Details are provided in `https://fred.stlouisfed.org/series/T10Y3M` and `https://philadelphiafed.org/research-and-data/real-time-center/business-conditions-index`.

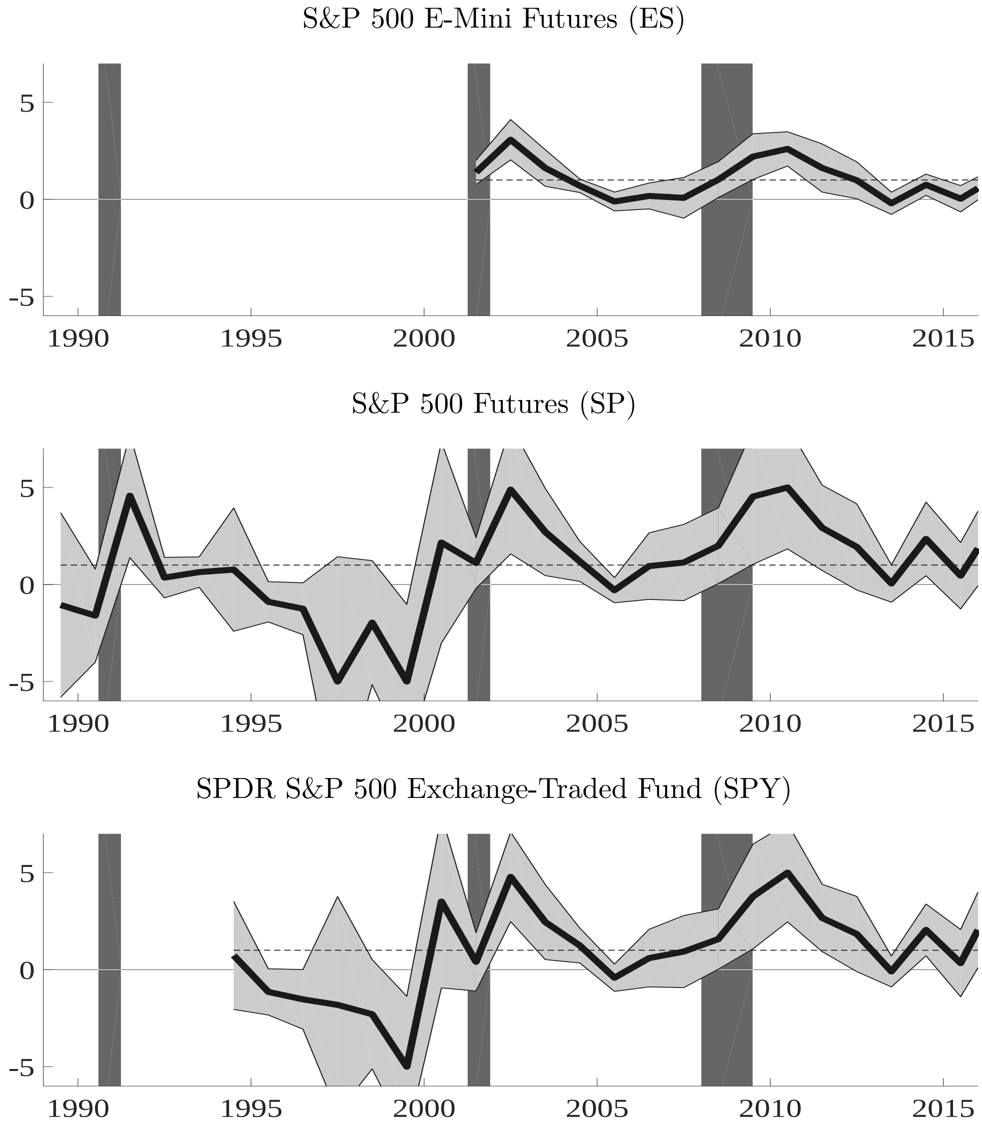
We set Δ_z to be a day to reflect that most up-to-date information is included in the regression. We find that the coefficient loading on change in spread and the ADS index are estimated to be significant at 1% and 5% level of significance, respectively. Nonetheless, the resulting estimates for $\hat{\beta}^\tau$ from these regressions are essentially unchanged and are identical to Figure 3. This evidence highlights that at least at the intra-day frequency the MNAs provide impactful information regarding the stock market above and beyond other well known predictors, such as the slope of the term structure (e.g., see Neuhierl and Weber (2016) for weekly evidence). We also tried to control for volatility changes, if any, in stock returns by dividing the return by VIX. Our results are not affected.

Longer-sample evidence. We extend the sample to the 1990s and examine if a similar pattern emerges. Before 2000, the futures market was very illiquid outside the trading hours. This restriction excludes the use of all announcements released at 8:30am. To extend our analysis, we focus on the MNAs which are released during trading hours, that is, at 10:00am. Thus, the MNAs considered in this exercise are Consumer Confidence Index and ISM Manufacturing. We use the survey data from Money Market Service (MMS) to construct surprises. We do it because survey forecasts are available from early 1980s in MMS while they are only available after 1997 in Bloomberg. By changing both left-hand side and right-hand side variables in the high-frequency regression, we aim to provide further robustness to our main finding. Here, we are estimating the benchmark regression (2) and the corresponding results are provided in Figure 5.

First, observe that exclusion of the MNAs that are released at 8.30am, which are employment-related announcements (Change in Nonfarm Payrolls and Initial Jobless Claims), does not alter our main empirical findings. That is the first panel in Figure 5 is very similar to Figure 3. Second, we find that liquidity and future rolling methods do not affect our findings. Our results are qualitatively preserved whether we use ES or the S&P 500 Future contract (SP) or SPDR S&P 500 Exchange Traded Funds (SPY). Hence, we conclude from Figure 5 that our empirical findings are robust across various return measures, surprise measures, and different periods.

Other robustness checks. We improve the econometric power in identifying the cyclical variation in stock return responses by pooling information within τ period, that is, a year. Yet, it requires us to assume that the responses move proportionally within τ period. Figure E.6 shows that our results are robust to different smoothing parameter values τ. We also relax the assumption that the stock return responsiveness to all MNA surprises shifts by a roughly proportionate amount. This amounts to removing the common β^τ structure in (2) and replacing with individual γ^τ. Figure E.7 shows that the stock return responsiveness is qualitatively similar across individual MNAs.

Figure 5: Stock return sensitivity: longer sample evidence

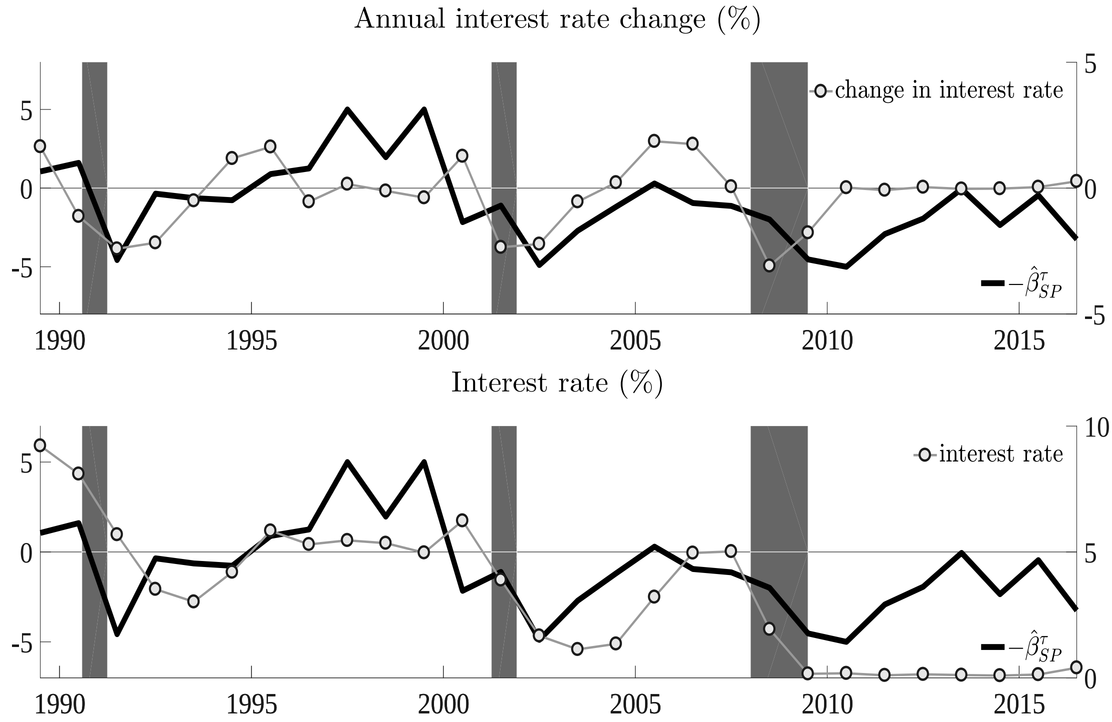


Notes: We restrict the analysis to trading hours. S&P 500 futures (SP) are available from 1988 to 2016, SPDR S&P 500 ETF (SPY) are available from 1994 to 2016, and S&P 500 E-Mini futures (ES) are available from 2000 to 2016. Macroeconomic announcements are Consumer Confidence Index and ISM Manufacturing. We impose that β^{τ} (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide ± 2-standard-error bands (light-shaded area) around β^{τ}.

3 Stock Market and Monetary Policy Expectation

As stated in the outset, we conjecture that the stock market response is intimately related to the economic phase and the perception about possible Fed stabilization policy. To further explore this connection, we first document the relationship between the estimated return sensitivity $\hat{\beta}^{\tau}$

Figure 6: Stock return sensitivity and interest rate



Notes: We overlay the (negative) stock market sensitivity obtained from Figure 5 with the annual change in the federal funds rate and with the level of federal funds rate.

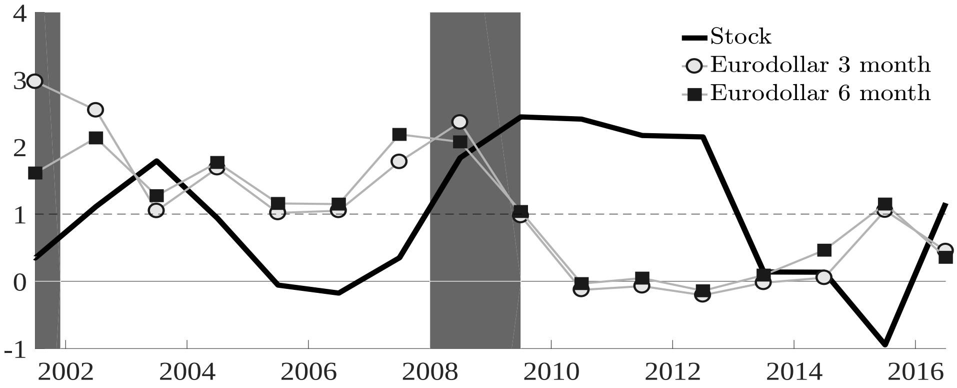
and actual interest rates. To do so, we start by overlaying the (negative) stock market sensitivity with the annual change in the federal funds rate and the level of federal funds rate in Figure 6. As seen in the graph, there is significant co-movement between the two measures. To measure co-movement, we regress $\hat{\beta}^{\tau}$ on the federal funds rate and its annual change. Table D.3 provides the estimation results. Strikingly, we find that the lagged change in federal funds rate and the level of federal funds rate can predict up to 30-50% of the stock market sensitivity $\hat{\beta}^{\tau}$. The associated slope coefficients are significantly negative.[11]

To formally examine whether the cyclical variations in the stock market's response to the MNA surprises reflect the market expectations of monetary policy, we next provide the time-varying sensitivity of Eurodollar futures to the MNAs. Eurodollar futures are known to be closely related to market expectations about the federal funds rate. The dependent variable is either the 3 or 6 month Eurodollar futures. We regress them separately on positive and negative MNA surprises. Figure 7 displays the estimated coefficients. Surprisingly, we find that the interest rate sensitivity moves in lock-step with the stock market sensitivity but in the opposite direction. This pattern

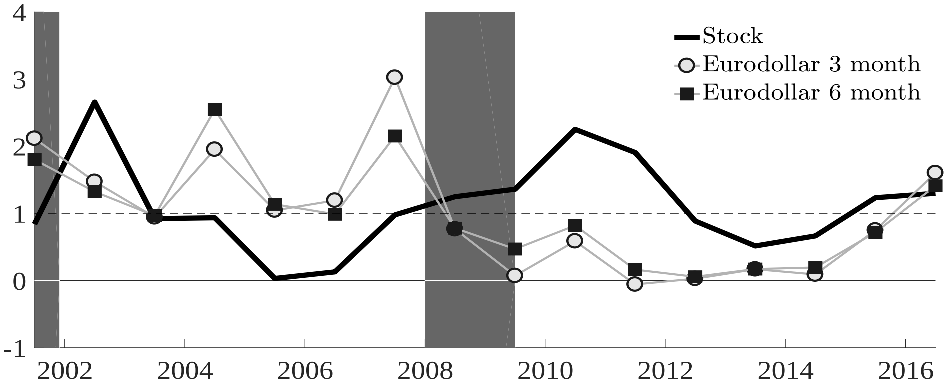
[11]This is related to the findings in Bernanke and Kuttner (2005) where they show reversals in the direction of rate changes have a significantly negative impact on the stock market.

Figure 7: Stock market reaction and expectations about monetary policy

In response to good surprises



In response to bad surprises



Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that β^{τ} (black-solid line) is on average equal to one.

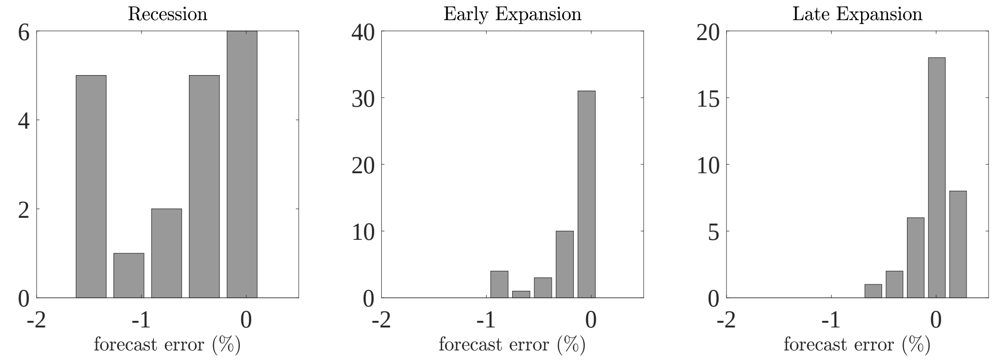
is consistent with the story that, for example, when good MNA surprises have marginal impact on the stock market, it is because the market is worried about a future rate hike.

Several interesting episodes are noteworthy. For example, the stock sensitivity was near zero from mid-2004 to mid-2006. From the minutes of the FOMC meetings we find that the Federal Reserve raised the short-term interest rate in every FOMC meeting during the corresponding periods. This is reflected in above-average interest rate sensitivity coefficients. 2015 was the period in which profound focus was on the possibility of a rate hike by the Federal Reserve.[12] Note that the interest rate sensitivity was above-average for the first time since the ZLB period. The fear about a pending rate hike caused the stock prices to go down in 2015 which is reflected

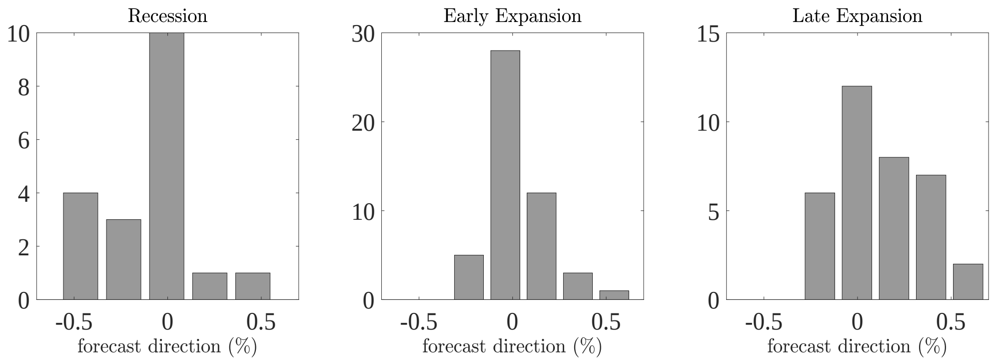
[12] An examination of the minutes of the FOMC from 2014 confirms that a rate hike was impending. We also provide compelling supportive evidence in Figure E.8 and Figure E.9.

Figure 8: Evidence from survey data

(A) Forecast errors in federal funds rate expectation: $i_{t+1} - E_t i_{t+1}$



(B) Direction of federal funds rate expectation: $E_t i_{t+1} - i_t$



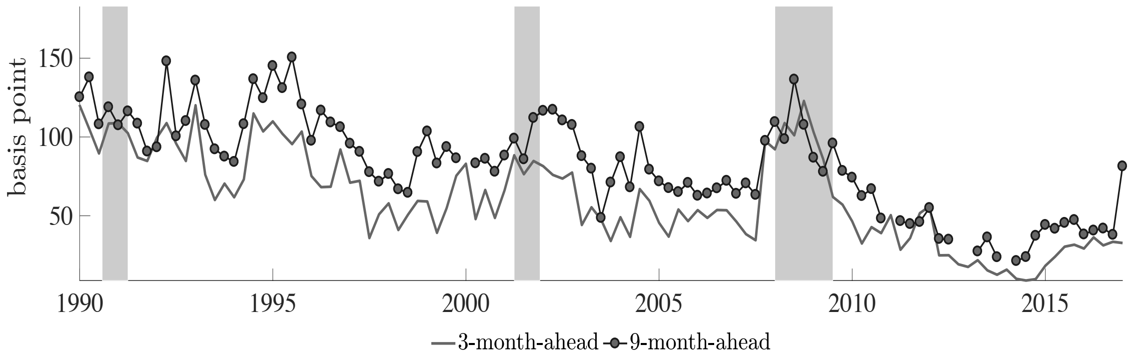
Notes: Recession periods correspond to the NBER recession dates. Early expansion periods are upto two years after the recession. Late expansion periods are five years after the recession. Panel (A): We compute the annualized one-quarter ahead forecast error ($i_{t+1} - E_t i_{t+1}$) of the federal funds rate based on the Blue Chip Financial Forecasts survey mean. The time series plot of the forecast errors is provided in Figure E.11. Panel (B): We compute the annualized one-quarter ahead forecast direction ($E_t i_{t+1} - i_t$) of the federal funds rate based on the Blue Chip Financial Forecasts survey mean.

by the negative black-solid line. The opposite story holds true: when stock market strongly reacts to good MNA surprises, it is because the market assigns a fairly low chance of a rate hike. The entire ZLB periods are good example of the story. Overall, the evidence suggests a tight relationship between the stock market and the expectations about monetary policy.[13] Our findings persist when we extend our analysis to data beginning 1990 which are provided in Figure E.10.

We provide another piece of supporting evidence on the connection between monetary policy expectation and stock reaction. Panel (A) of Figure 8 displays the *ex post* one-quarter ahead

[13] We are restricting our analysis to the conventional monetary policy. The effects of the unconventional monetary policy on financial market are studied in Swanson (2016).

Figure 9: Interest rate forecast uncertainty from Eurodollar options



Notes: Options are on 90-day Eurodollar deposits with expiration 3-month- and 9-month-ahead. We derive the implied volatility from close-to-the-money (within 20% of at-the-money) option assuming a lognormal distribution and multiply the implied volatility by the expected 90-day Eurodollar rate to express in basis point terms. We provide details in Appendix C.

forecast error of the federal funds rate based on the Blue Chip Financial Forecasts survey mean.[14] There are two important messages hidden within the figure. First, the forecast errors during the recession and early expansion periods are more negative than those during late expansion periods. This implies that the extent of the actual easing surprised the market in a positive way. Second, the magnitude of the *ex post* forecast error variance was much larger during the recession periods than those in other periods. The corresponding numbers for recession, early expansion, and late expansion are 0.38, 0.07, and 0.05, respectively.[15] Panel (B) of Figure 8 plots the expectations relative to the current interest rate. It is evident that compared to the early expansion periods, the late expansion periods display a significant lean towards an increase in the interest rate.

Panel (B) of Figure 8 shows the market expectation about the direction of monetary policy going into next quarter. Next, we want to provide a measure of the *ex ante* uncertainty that reflects to what extent market participants were certain about their interest rate forecasts. To this end, we derive the level of *ex ante* market uncertainty about interest rates from 1989 through 2016 derived from 3-month- and 9-month-ahead options on 90-day Eurodollar futures.[16] The first thing to note is that the *ex ante* forecast uncertainty on interest rate (as measured by implied volatility) has trended downward very strongly since 1989.[17] This suggests that the market participants were certain of their interest rate forecasts *ex ante* more in the period after 2000

[14]Roughly 40-50 leading institutions participate in the Blue Chip Financial Forecasts survey. They are published on the first day of each month.

[15]This is consistent with Crump, Eusepi, and Moench (2011) who claim that it is much more difficult to measure the degree of easing than the degree of tightening.

[16]Since the implied volatility constructed from the 6-month-ahead options is very close to the 3-month-ahead one, we do not report in the paper.

[17]Swanson (2006) suggests that increases in transparency by the FOMC have been responsible for the improvements in interest rate forecasts.

than before. It explains why it is cleaner to focus on the relationship between interest rate expectation and the stock sensitivity pattern in the benchmark sample (2000-2016) than in the sample before (1990-2000). Second, we find that the forecast uncertainty is on average much larger during recessions than expansions which is also consistent with the *ex post* uncertainty evidence from the Blue Chip Financial Forecasts survey. We find that the late expansion periods, which are defined as the periods five years after recession, are particularly characterized as ones when market participants are certain about their interest rate forecasts.

Taken together, this evidence suggests that during the recession period uncertainty (both *ex ante* and *ex post*) is large and the ensuing action of the Fed is difficult to predict. In early expansion periods, the market does not fear a rate hike and is relatively certain about the position of the Fed. In contrast, during the late expansion phase, overall uncertainty is relatively low and the remaining uncertainty is primarily about the magnitude of tightening leading to a muted stock response.

4 Return Decomposition

Having shown the important time variation in return responses to MNAs, we further decompose the stock market sensitivity to components attributable to news about cash flows, risk-free rate, and risk premium. This is of interest in its own right in terms of understanding which piece of news is affecting the sensitivity at the impact of the announcement. Furthermore, such decomposition has a long tradition in the finance literature and our analysis provides a new perspective using relatively high-frequency data around announcements.

Our goal is to decompose the return sensitivity β^{τ} to components attributable to cash flows, risk-free rate, and risk premium news, respectively. To do so, we follow Campbell (1991) and relate the unexpected stock return in period $t+1$ to news about cash flows (dividends) and news about future returns

$$r_{t+1} - E_t r_{t+1} \approx (E_{t+1} - E_t)\left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}\right) - (E_{t+1} - E_t)\left(\sum_{j=1}^{\infty} \rho^j r_{t+1+j}\right) \tag{7}$$

where ρ is the approximating constant based on the average of the price dividend ratio. (7) is an accounting identity. An increase in expected future dividend growth (returns) is associated with a capital gain (loss) today. The unexpected stock return can be further decomposed into news about cash flows N_{CF}, news about risk-free rate by N_{RF}, and news about risk premium by

N_{RP}. Put together,

$$r_{t+1} - E_t r_{t+1} \approx N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}. \tag{8}$$

To facilitate the decomposition of (8), we look for empirical proxies for $N_{CF,t}$, $N_{RF,t}$, and $N_{RP,t}$.

To empirically proxy for $N_{RP,t}$ we use the variance risk premium. The variance risk premia can be measured with the VIX index and a measure of the conditional expectations of realized volatility. The Chicago Board Options Exchange's VIX index measures implied volatility using a weighted average of 30-day maturity European-style S&P 500 call and put option prices over a wide range of strikes. This model free approach measures the risk-neutral expectation of S&P 500 return volatility. Subtracting from it the physical measure of expected realized volatility isolates the variance risk premium[18]. The physical measure of expected volatility is proxied by the conditional expectation of realized volatility over the next month $E_t(RV_{t+1}^{t+30days})$, which can be generated by an ARMA model for squared returns. In our implementation, we measure the variance premium using the VIX index observed 60 minutes after the macroeconomic announcement and measure realized volatility over one month using squared daily returns. The variance premium is defined by

$$vp_t = \frac{1}{Scale}\left(\frac{VIX_t^2}{12} - E_t(RV_{t+1}^{t+30days})\right),$$

scaled down appropriately to be comparable to intraday returns.[19]

In equation (9) below, we present a state-space approach to decompose equity returns into news about risk premium and news about cash flows or risk-free rate. Specifically, we assume that the factor, F_t, is comprised of news about risk premium $N_{RP,t}$ and news about the remainder

$$N_{CF,RF,t} = N_{CF,t} - N_{RF,t}.$$

This approach has an important advantage in that we are able to isolate the relative role played by news about risk premium in equity return variation.

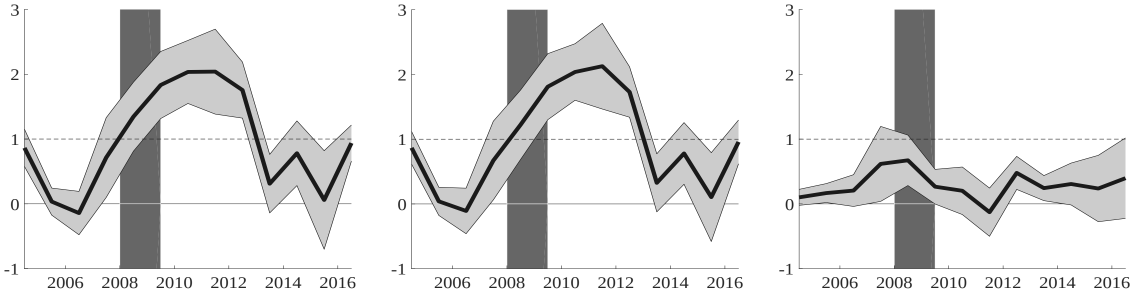
We impose minimal sign restrictions on the factor loadings Λ whereby $N_{RP,t}$ is assumed to increase ($\lambda > 0$) the variance premium and lower equity returns $r_{t-\Delta}^t$ (the differential of log price at time t and log price at time $t - \Delta$). We set $\Delta = 30min$. Time subscript t denotes when new macroeconomic announcement is released. The remainder of equity return variation is explained

[18]See Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011) for theoretical and empirical discussion on the connection between the variance premium and return risk premia

[19]We square VIX (annualized standard deviation) and divide by 12 to convert to monthly volatility.

Figure 10: Return decomposition: The role of news about risk premium

(A) Stock returns, $\hat{\beta}^{\tau}$ (B) Remainder, $\hat{\beta}^{\tau}_{CF,RF}$ (C) Risk premium, $-\hat{\beta}^{\tau}_{RP}$



Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that β^{τ} is on average equal to one. We provide $\pm$2-standard-error bands (light-shaded area) around β^{τ}. However, we do not impose that the average of $\beta^{\tau}_{CF,RF}$ and β^{τ}_{RP} are equal to one. This is because the regressor is already restricted to $\hat{X}_t$.

by $N_{CF,RF,t}$. Put together,

$$\begin{bmatrix} vp_{t+\Delta} \\ r^t_{t-\Delta} \end{bmatrix} = \underbrace{\begin{bmatrix} \lambda & 0 \\ -1 & 1 \end{bmatrix}}_{\Lambda} \underbrace{\begin{bmatrix} N_{RP,t} \\ N_{CF,RF,t} \end{bmatrix}}_{F_t}, \quad var(F_t) = \begin{bmatrix} \sigma^2_{RP} & 0 \\ 0 & \sigma^2_{CF,RF} \end{bmatrix}. \tag{9}$$

The following identity holds

$$\hat{r}^t_{t-\Delta} = -\hat{N}_{RP,t} + \hat{N}_{CF,RF,t}, \tag{10}$$

where "$\wedge$" notation over a variable indicates that this value is the maximum likelihood estimate.

To connect our estimates of $\hat{\beta}^{\tau}$ to the decomposition of cash flow/risk free rate and risk premia news, note that our previous regression analysis implies

$$\hat{r}^t_{t-\Delta} = \hat{\alpha}^{\tau} + \hat{\beta}^{\tau}(\hat{\gamma}^{\top} X_t) = \hat{\alpha}^{\tau} + \hat{\beta}^{\tau}\hat{X}_t. \tag{11}$$

Equipped with the estimated series $\hat{N}_{CF,RF,t}$ and $\hat{N}_{RP,t}$, we run two restricted regressions

$$\begin{aligned} \hat{N}_{RP,t} &= \alpha^{\tau}_{RP} + \beta^{\tau}_{RP}\hat{X}_t + \epsilon_{RP,t} \\ \hat{N}_{CF,RF,t} &= \alpha^{\tau}_{CF,RF} + \beta^{\tau}_{CF,RF}\hat{X}_t + \epsilon_{CF,RF,t} \end{aligned} \tag{12}$$

to obtain $\hat{\beta}^{\tau}_{RP}$ and $\hat{\beta}^{\tau}_{CF,RF}$, respectively. Subtracting the first row from the second row in (12), we achieve the identity shown in (10). This allows us to decompose $\hat{\beta}^{\tau}$ in (11) into $\hat{\beta}^{\tau}_{RP}$ and

$\hat{\beta}^{\tau}_{CF,RF}$

$$\hat{\beta}^{\tau} = -\hat{\beta}^{\tau}_{RP} + \hat{\beta}^{\tau}_{CF,RF}. \tag{13}$$

Figure 10 provides the decomposition of (13). The key takeaway of this analysis is that the informational content of the MNAs is least related to risk premium news and is mostly explained by news about cash flows and news about risk-free rate. The finding is robust across different identification strategies.[20]

5 Monetary Policy Beliefs Embedded in Macroeconomic Data

In previous sections we have established that the stock market response to MNAs is cyclical and is tightly connected to expectations about monetary policy. In this section we explore more formally the connection bewteen beliefs about the state of the economy, the Fed's reaction, and the cyclical nature of the stock market response by explicitly focusing on a simple regime-switching model that features two distinct interest rate regimes. One of the regimes is less reactive than the other in the sense that the feedback coefficients between the interest rate and other macroeconomic variable are smaller in absolute magnitude. We are interested in the extracted beliefs about the reactive (or less reactive) interest rate regime. An important contribution of the analysis here and what differentiate it from previous sections is the fact that in our parsimonious yet realistic setting the information set is similar to that of stock market participants. That is, the agent here is not endowed with the full structural knowledge of the economy, and thus she must form beliefs about parameters and states similar to those of an econometrician. We first describe the environment, discuss the sequential learning problem, and provide an empirical illustration.

5.1 The sequential learning problem

We consider a regime-switching vector autoregressive model

$$\begin{aligned} y_t' &= x_t'\Phi_{S_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_{S_t}) \\ Pr(S_t = j | S_{t-1} = i) &= q_{ij}, \quad \sum_{j=1}^{2} q_{ij} = 1. \end{aligned} \tag{14}$$

[20] For example, we use the difference between the log price at time $t+\Delta$ and log price at time t, that is $r_t^{t+\Delta}$. In this case, we normalize $\lambda = 1$ and freely estimate the coefficient without imposing -1. The estimation leads to positive coefficient loading on $N_{RP,t}$ as theory suggests. This timing difference implies that risk premium on average increases the ex-post equity return. The results for decomposing β^{τ} into cashflow-riskfree and risk premium do not change with this alternative timing and sign restriction.

Here, y_t is an $n \times 1$ vector of observables, S_t is a discrete Markov state variable that takes on two values, x_t is a $k \times 1$ vector $x_t' = [y_{t-1}', ..., y_{t-p}', 1]$, and Φ_i is a $k \times n$ parameter matrix that depends on regime i defined by $\Phi_i = [\phi_1(i), ..., \phi_p(i), \phi_0(i)]'$ where $k = np + 1$. The coefficient matrices without subscript indicate $\Phi = \{\Phi_1, \Phi_2\}$, $\Sigma = \{\Sigma_1, \Sigma_2\}$, and $\Pi = \{q_{11}, q_{22}\}$.

The agent in our analysis is a Bayesian learner. She is uncertain about both model parameters $\{\Phi, \Sigma, \Pi\}$ and states S^{t+1}, learns rationally from current and past observations y^t, and updates her beliefs using Bayes' rule as new data y_{t+1} arrive. The joint posterior distribution $p(\Phi, \Sigma, \Pi, S^{t+1}|y^{t+1})$ summarizes subjective beliefs after observing y^{t+1} which can be factorized into the product of the conditional distributions

$$\begin{aligned} p(\Phi, \Sigma, \Pi, S^{t+1}|y^{t+1}) &= p(\Phi, \Sigma, \Pi|S^{t+1}, y^{t+1})p(S^{t+1}|y^{t+1}) \qquad (15) \\ &= \underbrace{p(\Phi|\Sigma, \Pi, y^{t+1}, S^{t+1})p(\Sigma|\Pi, y^{t+1}, S^{t+1})p(\Pi|y^{t+1}, S^{t+1})}_{\text{(i) parameter learning}} \underbrace{p(S^{t+1}|y^{t+1})}_{\text{(ii) state filtering}}. \end{aligned}$$

The joint learning of (i) parameters and (ii) states is a high-dimensional problem which incurs confounding effects arising from multiple sources of uncertainty (see Johannes, Lochstoer, and Mou (2016) for similar problems). To solve for the sequential learning problem, we use the particle learning algorithm developed by Carvalho, Johannes, Lopes, and Polson (2010), which is a generalization of the mixture Kalman filter of Chen and Liu (2000). Roughly speaking, we rely on particle methods to directly sample from the particle approximation to (15). The detailed description of the algorithm is provided in the appendix.

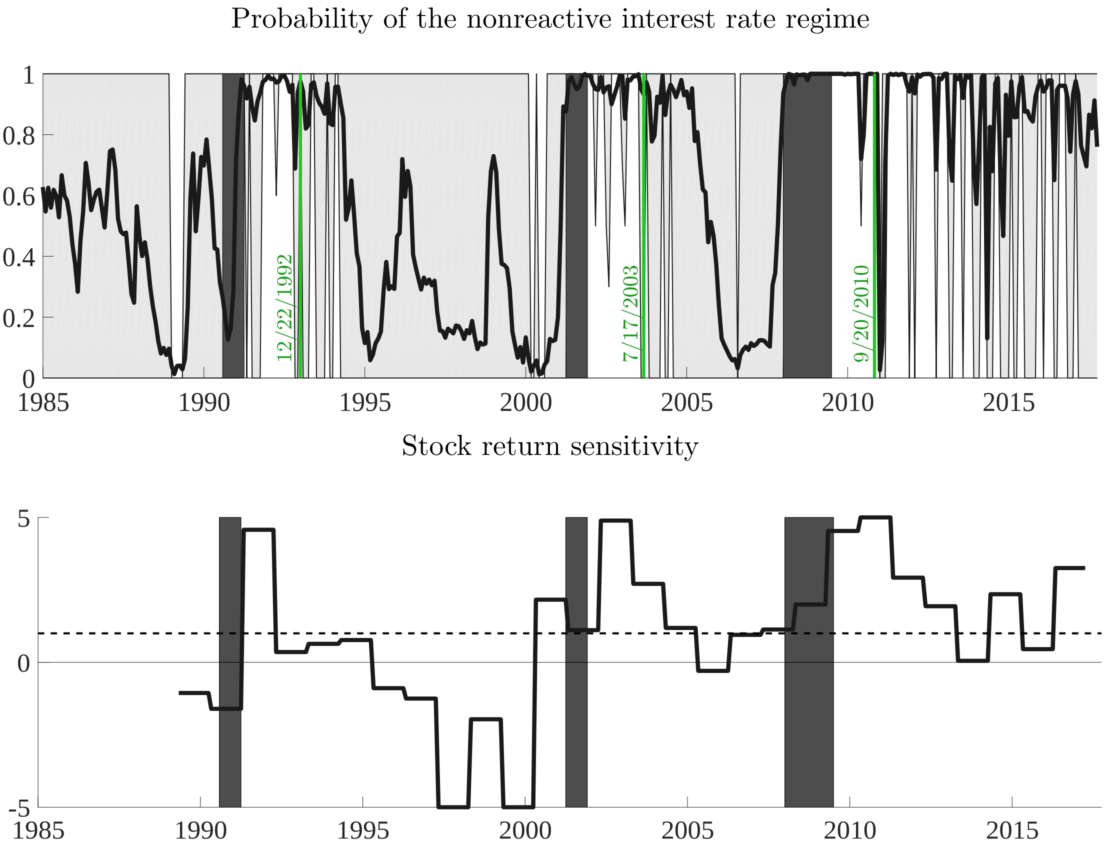
5.2 Empirical illustration

Data, priors, and identification. For the empirical illustration of the model, we use the unemployment rate and the federal funds rate from 1985:M1 to 2016:M12 (the time series plot of data is provided in Figure E.12). We use the unemployment rate as the empirical proxy for one of the statutory objectives for monetary policy. To initialize the algorithm, we provide the priors in Table D.4 which summarizes our initial beliefs. We rely on conjugate priors since these prior beliefs coupled with the likelihood function lead to posterior beliefs that are of the same form. To deal with the label switching problem, we impose that the coefficient that governs the feedback from the interest rate to the unemployment rate in the first regime is greater than that in the second regime, that is, $|\Phi_{1,(2,1)}| > |\Phi_{2,(2,1)}|$ and $|\Phi_{1,(1,2)}| > |\Phi_{2,(1,2)}|$.[21]

Parameters and state learning. We provide the evolution of parameter learning in Figure E.13, which visualizes the first part of (15). The credible interval at time 0 correspond to

[21]The first subscript identifies the regime and the remaining subscripts which are parenthesized indicate their location in the parameter matrix.

Figure 11: Regime probability



Notes: The black solid line in the top panel is posterior mean regime probabilities which is overlaid with the 90% credible interval (gray shaded areas). Dark shaded bars indicate the NBER recession dates. Green solid lines represent the dates when the formal announcements of business cycle turning point at which contraction turns into expansion are made by the NBER. The black solid line in the bottom panel reproduces the stock return sensitivity coefficient estimates (SP) displayed in the middle panel of Figure 5. Since the stock return sensitivity estimates are annual measures, we evenly distribute them over 12 months to make them comparable to the monthly regime probabilities in the top panel. The black dashed-line indicates the value of one which is the average of the stock return sensitivity coefficient estimates.

the 90% prior intervals. As more observations are included in the estimation, the 90% credible intervals shrink over time. Posteriors at the end of sample are what one would obtain from the entire time series data. Table D.5 reports 5%, 50%, 95% percentiles of the end of sample posterior distributions. Along with the identification assumption, the fact that the end of sample posterior estimates for $\Phi_{2,(2,1)} \approx \Phi_{2,(1,2)} \approx \Sigma_{2,(2,1)} \approx 0$ provide the natural interpretation that the first regime is the reactive interest rate regime and the second regime is the nonreactive regime.[22] In the second regime, the dynamics of the unemployment rate evolves almost in an autoregressive

[22]We use the term "reactive interest rate" in the sense that the dynamics of the unemployment rate is intricately linked to the dynamics of the interest rate.

pattern and the interest rate does not impact the dynamics.

For the sake of saving space, we move to the object of our main interest, that is, the second part of (15). Figure 11 displays the posterior mean probabilities of the second regime, which we define as the nonreactive interest rate regime. It is interesting to observe that the mean probability of nonreactive regime starts to increase in recession and remains near one a few years after the recession. Roughly speaking, the probabilities start to come down after the formal NBER announcements of business cycle turning point from contraction to expansion.[23] In general, significant posterior uncertainty remains regarding the regime probabilities since they are overlaid with large credible intervals (essentially covering from zero to one).

When the mean regime probabilities are compared with the estimated stock return sensitivity from the previous section (which is reproduced in the bottom panel of Figure 11), we find the most interesting co-movement pattern. The estimated stock return sensitivity is above average when the probability of the nonreactive regime is close to one and vice versa. What is important to emphasize is that the regime probabilities are obtained solely based on macroeconomic variables. This relationship is particularly visible during periods in which the regime uncertainty is close to zero.

6 Conclusion

Using high-frequency stock returns, we provide strong evidence of persistent cyclical variation in the sensitivity of stock prices to MNA surprises. Starting from a phase where the stock market is insensitive to news, it becomes increasingly sensitive as the economy enters recession with peak sensitivity obtained a year after recession. As the economy expands, the sensitivity comes down to its starting point in four to five years. We then provide evidence that the direction and shape of the market's response reflect the evolution of beliefs about monetary policy proxied by the short-term interest rates. Specifically, we show that the sensitivity of short-term interest rate futures to MNA surprises moves in lock-step with the stock sensitivity but in the opposite direction. Using information from the Blue Chip Financial Forecasts and a regime switching model with learning, we further examine the economic sources for the cyclical stock market responses to MNAs. The analysis shows that the muted stock market response during recession periods is consistent with large uncertainty about the state of the economy and the Fed's actions, while the muted response during late expansion periods is associated with strong beliefs about the Fed's being reactive. The signficant stock market responses during the early expansion period seem to be consistent

[23] The ZLB period was an exception because it remained a few more years after the NBER turning point announcement date.

with a phase in which uncertainty is relatively low, yet expectations are that the Fed actions will not be reactive. Overall, our analysis emphasizes the important interplay between economic conditions, the expectations about monetary policy given these conditions, and their joint effect on the stock market.

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Online Appendix
Fearing the Fed: How Wall Street Reads Main Street

Tzuo-Hann Law, Dongho Song, Amir Yaron

A High-Frequency Regression

For macroeconomic indicator $y_{i,t}$, the standardized news variable at time t is

$$X_{i,t} = \frac{y_{i,t} - E_{t-\Delta}(y_{i,t})}{\sigma(y_{i,t} - E_{t-\Delta}(y_{i,t}))}$$

where $E_{t-\Delta}(y_{i,t})$ is the mean survey expectation which was taken at $t - \Delta$. For illustrative purpose, assume (1) two macroeconomic variables; (2) quarterly announcements (4 per a year); (3) 3 years of announcement data. We represent the quarterly time subscript t as $t = 12(a-1)+q$, where $q = 1, ..., 4$. We consider the following nonlinear least squares specification

$$R_{a,q} \quad = \quad \alpha_a + \beta_a\left(\gamma_1 X_{1,a,q} + \gamma_2 X_{2,a,q}\right) + \epsilon_{a,q},$$

where q is the quarterly time subscript and a the annual time subscript. This nonlinear regression can be expressed as

$$\begin{bmatrix} R_{1,1} \\ R_{1,2} \\ R_{1,3} \\ R_{1,4} \\ R_{2,1} \\ R_{2,2} \\ R_{2,3} \\ R_{2,4} \\ R_{3,1} \\ R_{3,2} \\ R_{3,3} \\ R_{3,4} \end{bmatrix} = \begin{bmatrix} X_{1,1,1} & X_{2,1,1} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ X_{1,1,2} & X_{2,1,2} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ X_{1,1,3} & X_{2,1,3} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ X_{1,1,4} & X_{2,1,4} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & X_{1,2,1} & X_{2,2,1} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & X_{1,2,2} & X_{2,2,2} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & X_{1,2,3} & X_{2,2,3} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & X_{1,2,4} & X_{2,2,4} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & X_{1,3,1} & X_{2,3,1} & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & X_{1,3,2} & X_{2,3,2} & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & X_{1,3,3} & X_{2,3,3} & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & X_{1,3,4} & X_{2,3,4} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_1\gamma_1 \\ \beta_1\gamma_2 \\ \beta_2\gamma_1 \\ \beta_2\gamma_2 \\ \beta_3\gamma_1 \\ \beta_3\gamma_2 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,1} \\ \epsilon_{1,2} \\ \epsilon_{1,3} \\ \epsilon_{1,4} \\ \epsilon_{2,1} \\ \epsilon_{2,2} \\ \epsilon_{2,3} \\ \epsilon_{2,4} \\ \epsilon_{3,1} \\ \epsilon_{3,2} \\ \epsilon_{3,3} \\ \epsilon_{3,4} \end{bmatrix}.$$

B Parameter Learning

The VAR parameters. We assume that

$$y_t' = x_t'\Phi_{S_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_{S_t}). \tag{A.1}$$

Assume further that the joint prior over the VAR coefficients Φ and Σ is Normal-Inverse-Wishart distribution and since they are independent

$$\begin{aligned} p(\Sigma|\Pi, y^t, S^t) &= IW(K_{1,t}, v_{1,t})IW(K_{2,t}, v_{2,t}) \\ p(\Phi|\Sigma, \Pi, y^t, S^t) &= N(m_{1,t}, \Sigma_1 \otimes C_{1,t})N(m_{2,t}, \Sigma_2 \otimes C_{2,t}). \end{aligned} \tag{A.2}$$

These prior beliefs lead to posterior beliefs that are of the same form. The joint posterior distribution of Φ and Σ can be factorized as

$$p(\Phi, \Sigma|y^{t+1}, S^{t+1}, \Pi) = p(\Phi|\Sigma, y^{t+1}, S^{t+1}, \Pi)p(\Sigma|y^{t+1}, S^{t+1}, \Pi). \tag{A.3}$$

We can express

$$\begin{aligned} p(\Phi|\Sigma, y^{t+1}, S^{t+1}, \Pi) &\propto p(y_{t+1}, S_{t+1}|\Phi, \Sigma, y^t, S^t, \Pi)p(\Phi|\Sigma, y^t, S^t, \Pi) \\ &= p(y_{t+1}|S_{t+1}, \Phi, \Sigma, y^t, S^t, \Pi)p(S_{t+1}|\Phi, \Sigma, y^t, S^t, \Pi)p(\Phi|\Sigma, y^t, S^t, \Pi) \\ &\propto p(y_{t+1}|S_{t+1}, \Phi, \Sigma, y^t, S^t, \Pi)p(\Phi|\Sigma, y^t, S^t, \Pi) \\ &\propto \sum_{i=1}^{2} \mathbb{I}_{\{S_{t+1}=i\}}|\Sigma_i|^{-\frac{1}{2}} \exp\Big\{ -\frac{1}{2}tr\big[\Sigma_i^{-1}(y_{t+1}' - x_{t+1}'\Phi_i)'(y_{t+1}' - x_{t+1}'\Phi_i)\big]\Big\} \\ &\quad \times \prod_{i=1}^{2} |\Sigma_i \otimes C_{i,t}|^{-\frac{1}{2}} \exp\Big\{ -\frac{1}{2}tr\big[\Sigma_i^{-1}(\Phi_i - m_{i,t})'C_{i,t}^{-1}(\Phi_i - m_{i,t})\big]\Big\} \end{aligned} \tag{A.4}$$

and

$$\begin{aligned} p(\Sigma|y^{t+1}, S^{t+1}, \Pi) &\propto p(y_{t+1}, S_{t+1}|\Sigma, y^t, S^t, \Pi)p(\Sigma|y^t, S^t, \Pi) \\ &= p(y_{t+1}|S_{t+1}, \Sigma, y^t, S^t, \Pi)p(S_{t+1}|\Sigma, y^t, S^t, \Pi)p(\Sigma|y^t, S^t, \Pi) \\ &\propto p(y_{t+1}|S_{t+1}, \Sigma, y^t, S^t, \Pi)p(\Sigma|y^t, S^t, \Pi) \\ &\propto \sum_{i=1}^{2} \mathbb{I}_{\{S_{t+1}=i\}}|\Sigma_i|^{-\frac{1}{2}}(x_t'C_{i,t}^{-1}x_t)^{-\frac{1}{2}} \exp\Big\{ -\frac{1}{2}tr\big[\Sigma_i^{-1}\frac{(y_t' - x_t'm_{i,t})'(y_t' - x_t'm_{i,t})}{(x_t'C_{i,t}^{-1}x_t)}\big]\Big\} \\ &\quad \times \prod_{i=1}^{2} |K_{i,t}|^{\frac{v_{i,t}}{2}}|\Sigma_i|^{-\frac{v_{i,t}+n+1}{2}} \exp\Big\{ -\frac{1}{2}tr\big[\Sigma_i^{-1}K_{i,t}\big]\Big\}. \end{aligned} \tag{A.5}$$

For illustration, we assume that $S_{t+1} = i$. After tedious calculation, we can deduce that

$$\begin{aligned} p(\Phi_i|\Sigma, y^{t+1}, S^{t+1}, \Pi) &= N(m_{i,t+1}, \Sigma_i \otimes C_{i,t+1}) \\ C_{i,t+1} &= \left(x_{t+1}x'_{t+1}\mathbb{I}_{\{S_{t+1}=i\}} + C_{i,t}^{-1}\right)^{-1} \\ m_{i,t+1} &= C_{i,t+1}\left(x_{t+1}y'_{t+1}\mathbb{I}_{\{S_{t+1}=i\}} + C_{i,t}^{-1}m_{i,t}\right). \end{aligned} \tag{A.6}$$

Analogously for Σ_i, we can deduce that

$$\begin{aligned} p(\Sigma_i|y^{t+1}, S^{t+1}, \Pi) &= IW(K_{i,t+1}, v_{i,t+1}) \\ v_{i,t+1} &= v_{i,t} + \mathbb{I}_{\{S_{t+1}=i\}} \\ K_{i,t+1} &= K_{i,t} + (x'_{t+1}C_{i,t}x_{t+1} + 1)^{-1}(y'_{t+1} - x'_{t+1}m_{i,t})'(y'_{t+1} - x'_{t+1}m_{i,t})\mathbb{I}_{\{S_{t+1}=i\}}. \end{aligned} \tag{A.7}$$

Transition Probabilities. At $t = 0$, the agent is given an initial (potentially truncated) Beta-distributed prior over each of these parameters and thereafter updates beliefs sequentially upon observing the time-series of realized regimes, S_t. The prior Beta-distribution coupled with the realization of regimes leads to a conjugate prior and so posterior beliefs are also Beta-distributed. The probability density function of the Beta-distribution is

$$p(\pi|a, b) = \frac{\pi^{a-1}(1-\pi)^{b-1}}{B(a, b)}, \tag{A.8}$$

where $B(a, b)$ is the Beta function (a normalization constant). The parameters a and b govern the shape of the distribution. The expected value is

$$E(\pi|a, b) = \frac{a}{a+b}. \tag{A.9}$$

The standard Bayes rule shows that the updating equations count the number of times state i has been followed by state i versus the number of times state i has been followed by state j. Given this sequential updating, we let the a and b parameters have a subscript for the relevant state (1 or 2) and a time subscript

$$\begin{aligned} a_{i,t} &= a_{i,0} + \#\text{ (state } i \text{ has been followed by state } i), \\ b_{i,t} &= b_{i,0} + \#\text{ (state } i \text{ has been followed by state } j). \end{aligned} \tag{A.10}$$

The law of motions for $a_{i,t}$ and $b_{i,t}$ are

$$\begin{aligned} a_{i,t+1} &= a_{i,t} + \mathbb{I}_{\{S_{t+1}=i\}}\mathbb{I}_{\{S_t=i\}} \\ b_{i,t+1} &= b_{i,t} + (1 - \mathbb{I}_{\{S_{t+1}=i\}})\mathbb{I}_{\{S_t=i\}}. \end{aligned} \tag{A.11}$$

We can deduce that posterior distribution of Π is

$$p(\Pi|\Phi, \Sigma, y^{t+1}, S^{t+1}) = B(a_{1,t+1}, b_{1,t+1})B(a_{2,t+1}, b_{2,t+1}). \tag{A.12}$$

B.1 Particle Learning

We collect the model parameters in

$$\theta = (\Phi_1, \Phi_2, \Sigma_1, \Sigma_2), \quad \Pi = (q_{11}, q_{22}).$$

Denote sufficient statistics for θ and Π by $F_{\theta,t}$ and $F_{\Pi,t}$ respectively. Specifically,

$$F_{\theta,t} = \{m_{i,t}, C_{i,t}, v_{i,t}, K_{i,t}\}_{i=1}^{2}, \quad F_{\Pi,t} = \{a_{i,t}, b_{i,t}\}_{i=1}^{2}. \tag{A.13}$$

Sufficient statistics imply that the full posterior distribution of the parameters conditional on the entire history of latent states and data takes a known functional form conditional on a vector of sufficient statistics:

$$p(\theta, \Pi|y^t, S^t) = p(\theta, \Pi|F_{\theta,t}, F_{\Pi,t}) = p(\theta|F_{\theta,t})p(\Pi|F_{\Pi,t}). \tag{A.14}$$

Ultimately, we are interested in

$$p(\theta, \Pi, S^t|y^t) = p(\theta, \Pi|S^t, y^t)p(S^t|y^t). \tag{A.15}$$

The idea of particle learning is to sample from $p(\theta, \Pi, F_{\theta,t}, F_{\Pi,t}, S^t|y^t)$ than from $p(\theta, \Pi, S^t|y^t)$.

$$p(\theta, \Pi, F_{\theta,t}, F_{\Pi,t}, S^t|y^t) = \underbrace{p(\theta, \Pi|F_{\theta,t}, F_{\Pi,t})}_{\text{(4) Drawing Parameters}} \times \underbrace{p(F_{\theta,t}, F_{\Pi,t}, S^t|y^t).}_{\text{Propagating (2) State, (3) Sufficient Statistics}} \tag{A.16}$$

The particle learning algorithm can be described through the following steps.

B.1.1 Algorithm

Assume at time t, we have particles $\left\{S_t^{(k)}, \theta^{(k)}, \Pi^{(k)}, F_{\theta,t}^{(k)}, F_{\Pi,t}^{(k)}\right\}_{k=1}^{N}$.

1. **Resample Particles:**

Resample $\left\{S_t^{(k)}, \theta^{(k)}, \Pi^{(k)}, F_{\theta,t}^{(k)}, F_{\Pi,t}^{(k)}\right\}$ with weights $w_t^{(k)}$,

$$
\begin{aligned}
w_{t+1}^{(k)} \quad \propto \quad & \sum_{i=1}^{2} p\left(y_{t+1}|S_{t+1}=i, \left\{S_t^{(k)}, \theta^{(k)}, \Pi^{(k)}, F_{\theta,t}^{(k)}, F_{\Pi,t}^{(k)}\right\}\right) \\
& \times p\left(S_{t+1}=i| \left\{S_t^{(k)}, \theta^{(k)}, \Pi^{(k)}, F_{\theta,t}^{(k)}, F_{\Pi,t}^{(k)}\right\}\right).
\end{aligned} \tag{A.17}
$$

Denote them by $\left\{\tilde{S}_t^{(k)}, \tilde{\theta}^{(k)}, \tilde{\Pi}^{(k)}, \tilde{F}_{\theta,t}^{(k)}, \tilde{F}_{\Pi,t}^{(k)}\right\}_{k=1}^{N}$.

2. **Propagate State:** use the standard Hamilton filter.

$$
S_{t+1}^{(k)} \sim p\left(S_{t+1}|y_{t+1}, \left\{\tilde{S}_t^{(k)}, \tilde{\theta}^{(k)}, \tilde{\Pi}^{(k)}, \tilde{F}_{\theta,t}^{(k)}, \tilde{F}_{\Pi,t}^{(k)}\right\}\right).
$$

3. **Propagate Sufficient Statistics:**

   (a) $F_{\theta,t+1} \sim \mathcal{F}(\tilde{F}_{\theta,t}^{(k)}, S_{t+1}^{(k)}, y_{t+1})$.

$$
\begin{aligned}
C_{i,t+1}^{(k)} &= \left(x_{t+1}x_{t+1}' \mathbb{I}_{\left\{S_{t+1}^{(k)}=i\right\}} + (\tilde{C}_{i,t}^{(k)})^{-1}\right)^{-1} \\
m_{i,t+1}^{(k)} &= C_{i,t+1}^{(k)}\left(x_{t+1}y_{t+1}' \mathbb{I}_{\left\{S_{t+1}^{(k)}=i\right\}} + (\tilde{C}_{i,t}^{(k)})^{-1}\tilde{m}_{i,t}^{(k)}\right).
\end{aligned} \tag{A.18}
$$

   (b) $F_{\Pi,t+1} \sim \mathcal{F}(\tilde{F}_{\Pi,t}^{(k)}, S_{t+1}^{(k)}, y_{t+1})$.

$$
\begin{aligned}
a_{i,t+1}^{(k)} &= \tilde{a}_{i,t}^{(k)} + \mathbb{I}_{\left\{S_{t+1}^{(k)}=i\right\}}\mathbb{I}_{\left\{S_t^{(k)}=i\right\}} \\
b_{i,t+1}^{(k)} &= \tilde{b}_{i,t}^{(k)} + (1-\mathbb{I}_{\left\{S_{t+1}^{(k)}=i\right\}})\mathbb{I}_{\left\{S_t^{(k)}=i\right\}}.
\end{aligned} \tag{A.19}
$$

   Note that $\mathcal{F}$s are analytically known.

4. **Draw Parameters:**

   (a) $\theta^{(k)} \sim p(\theta|F_{\theta,t+1})$.

$$
\begin{aligned}
\Sigma_i^{(k)} &\sim IG(K_{i,t+1}^{(k)}, v_{i,t+1}^{(k)}) \\
\Phi_i^{(k)} &\sim N(m_{i,t+1}^{(k)}, \Sigma_i^{(k)} \otimes C_{i,t+1}^{(k)}).
\end{aligned} \tag{A.20}
$$

   (b) $\Pi^{(k)} \sim p(\Pi|F_{\Pi,t+1})$.

$$
\begin{aligned}
q_{11}^{(k)} &\sim B(a_{1,t+1}^{(k)}, b_{1,t+1}^{(k)}) \\
q_{22}^{(k)} &\sim B(a_{2,t+1}^{(k)}, b_{2,t+1}^{(k)}).
\end{aligned} \tag{A.21}
$$

B.2 Priors

To initialize the algorithm, we provide the priors in Table D.4. The length of the prior training sample (prior precision) is set to 200 months.

C Options Implied Risk Neutral Expectations of Interest Rate Distributions

We use tick level trades of options on Eurodollar future contracts purchased from CME Group to construct market expectations of interest rate distributions. We assume that the risk free rate is the 3-month LIBOR (London Interbank Offered Rate) rate at the time the option was traded. The LIBOR rate is obtained from the Federal Reserve Bank of St. Louis. We also use tick level trades of the Eurodollar futures contracts obtained from TickData.

Eurodollar futures contracts are traded on the Chicago Mercantile Exchange and settle based on the spot 3-month LIBOR rate quoted on the settlement date for a $\$1,000,000$ deposit. These contracts are among the most actively traded futures contracts globally. The most actively traded contracts are the March quarterly contracts which refer to the contracts that expire in March, June, September, and December. These future contracts are the underlying asset of the Eurodollar options which we briefly describe.

Eurodollar options are traded on the Chicago Mercantile Exchange as well. A Eurodollar call option expiring on date T with strike K gives the option holder the right but not the obligation to purchase at price K the aforementioned future contract that expires in the closest quarterly month. For example, an option that expires January, February or March gives the holder the option to buy the future contract that expires in March. Hence, ownership of a call option expiring during the quarterly month gives the right but not the obligation to to replicate a 90-day Eurodollar deposit on date T at an interest rate of $100 - K$.

We do not use all options data. While options expire on 12 (once a month) different calendar dates, they are traded daily. Hence, options implied volatilities are affected by $T_{expiry} - T_{trade}$. We control for this by considering trade dates such that $T_{expiry} - T_{trade} = N$ months ± 3 days. In our results, we consider $N = 3$ and $N = 9$. We only consider option trades that are close to the money. Specifically, we use trades that satisfy $|(100 - K) - (100 - S)|(100 - S) < 0.2$ where K is the strike price and S is the underlying future price. Our $100 - K$ and $100 - S$ notation is the transformation from future and strike prices to interest rates. Our results are not influenced by these selection criteria.

With the trades that meet our moneyness and time-to-maturity filters, we compute the implied volatility for each trade using the commodities options pricing model in Black (1976). In this model, each trade yields a lognormal distribution of interest rates at the maturity date. We average all the lognormal distributions from all trades of options to obtain a single distribution for each maturity-expiration combination. For example, we compute a distribution for March 2016 derived from options that were traded approximately 90 days before the maturity date, and another distribution from options that were traded approximately 360 days before the maturity date. The analysis in the main text is performed using these distributions. Our measures of implied volatility are expressed as basis points following the approximation in Swanson (2006).

D Supplemental Tables

Table D.1: Macroeconomic News Announcements

Name	Obs.	Release Time	Source	Start Date	End Date
Capacity Utilization	220	9:15	FRB	14-Jan-2000	14-Dec-2016
Change in Nonfarm Payrolls	224	8:30	BLS	07-Jan-2000	02-Dec-2016
Construction Spending MoM	208	10:00	BC	04-Jan-2000	01-Dec-2016
Consumer Confidence Index	221	10:00	CB	25-Jan-2000	27-Dec-2016
CPI MoM	222	8:30	BLS	14-Jan-2000	15-Dec-2016
Durable Goods Orders	231	10:00	BC	27-Jan-2000	22-Dec-2016
Factory Orders	219	10:00	BC	05-Jan-2000	06-Dec-2016
GDP Annualized QoQ	225	8:30	BEA	28-Jan-2000	22-Dec-2016
Housing Starts	219	8:30	BC	19-Jan-2000	16-Dec-2016
Industrial Production MoM	220	9:15	FRB	14-Jan-2000	14-Dec-2016
Initial Jobless Claims	954	8:30	ETA	06-Jan-2000	29-Dec-2016
ISM Manufacturing	221	10:00	ISM	03-Jan-2000	01-Dec-2016
ISM Non-Manf. Composite	211	10:00	ISM	05-Jan-2000	05-Dec-2016
Leading Index	221	10:00	CB	02-Feb-2000	22-Dec-2016
New Home Sales	220	10:00	BC	06-Jan-2000	23-Dec-2016
Personal Income	223	8:30	BEA	31-Jan-2000	22-Dec-2016
PPI Final Demand MoM	221	8:30	BLS	13-Jan-2000	14-Dec-2016
Retail Sales Advance MoM	219	8:30	BC	13-Jan-2000	14-Dec-2016
Trade Balance	221	8:30	BEA	20-Jan-2000	06-Dec-2016
Unemployment Rate	223	8:30	BLS	07-Jan-2000	02-Dec-2016

Notes: Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Federal Reserve Board (FRB), Conference Board (CB), Employment and Training Administration (ETA), Institute for Supply Management (ISM), National Association of Realtors (NAR). We use the most up-to-date names for the series, e.g., GDP Price Index was previously known as GDP Price Deflator, Construction Spending MoM was previously labeled as Construction Spending, PPI Final Demand MoM was labeled as PPI MoM, Retail Sales Advance MoM was labeled as Advance Retail Sales, ISM Non-Manf. Composite was labeled as ISM Non-Manufacturing. Observations (across all the MNAs) with nonstandard release times were dropped.

Table D.2: Descriptive Statistics for the Standardized MNA Surprises

	(1) Across Surveys		(2) Across Time		Correlation b/w
MNAs	mean	std.dev.	mean	std.dev.	(1) and (2).
Change in Nonfarm Payrolls	-0.46	2.45	-0.20	0.94	0.95
Consumer Confidence Index	0.00	3.16	0.00	1.04	0.96
Initial Jobless Claims	0.08	2.44	0.04	1.03	0.90
ISM Manufacturing	0.12	2.28	0.06	1.02	0.97

Notes: We divide the individual surprise by a normalization factor. Normalization factor (1,"Across Surveys") is the standard deviation of all analyst forecasts for a particular MNA at a point in time. Normalization factor (2,"Across Time") is the standard deviation of all the raw surprises in the sample for a particular macroeconomic announcement.

Table D.3: Stock Market Sensitivity and Interest Rate

Estimation Sample: 1989-2016

	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)
Constant	0.78	(0.44)	2.41	(0.47)	0.77	(0.43)	1.72	(0.50)	2.27	(0.54)
Change in FFR	-0.57	(0.23)	-0.37	(0.27)						
FFR			-0.48	(0.14)					-0.46	(0.21)
(Lagged) Change in FFR					-0.81	(0.24)	-0.69	(0.26)	-0.45	(0.30)
(Lagged) FFR							-0.27	(0.18)		
adj-R^2	0.06		0.29		0.15		0.20		0.29	

Estimation Sample: 2000-2016

	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)
Constant	0.88	(0.16)	1.20	(0.24)	0.88	(0.18)	0.79	(0.24)	1.13	(0.29)
Change in FFR	-0.44	(0.11)	-0.38	(0.08)						
FFR			-0.16	(0.07)					-0.12	(0.12)
(Lagged) Change in FFR					-0.40	(0.08)	-0.42	(0.08)	-0.31	(0.13)
(Lagged) FFR							-0.04	(0.09)		
adj-R^2	0.41		0.52		0.33		0.30		0.36	

Notes: We perform a regression analysis using federal funds rate and its annual change as regressors. In the top panel, we refer to β^{τ}_{SP} as the stock market sensitivity, while in the bottom panel, we use β^{τ}_{ES}.

Table D.4: Priors

Parameter	Priors		
	5%	50%	95%
$\Phi_{i,(1,1)}$	0.85	0.98	1.02
$\Phi_{i,(2,1)}$	-0.10	0.00	0.10
$\Phi_{i,(3,1)}$	-0.10	0.00	0.10
$\Phi_{i,(1,2)}$	-0.10	0.00	0.10
$\Phi_{i,(2,2)}$	0.85	0.98	1.02
$\Phi_{i,(3,2)}$	-0.10	0.00	0.10
$\Sigma_{i,(1,1)}$	0.02	0.10	1.70
$\Sigma_{i,(2,1)}$	-0.50	0.00	0.55
$\Sigma_{i,(2,2)}$	0.02	0.10	1.70
q_{ii}	0.91	0.95	0.98

Notes: We impose symmetric prior distributions for Φ, Σ, q which are drawn from normal distribution, inverted wishart distribution, multinomial distribution, respectively.

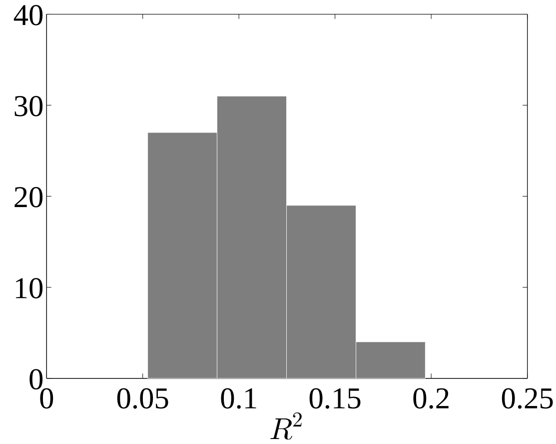
Table D.5: Posteriors (End of Sample)

Parameter	Posteriors			Parameter	Posteriors		
	5%	50%	95%		5%	50%	95%
$\Phi_{1,(1,1)}$	0.93	0.94	0.95	$\Phi_{2,(1,1)}$	1.00	1.00	1.00
$\Phi_{1,(2,1)}$	0.03	0.04	0.04	$\Phi_{2,(2,1)}$	-0.01	0.00	0.00
$\Phi_{1,(3,1)}$	0.05	0.05	0.06	$\Phi_{2,(3,1)}$	-0.02	-0.02	-0.01
$\Phi_{1,(1,2)}$	0.00	0.00	0.01	$\Phi_{2,(1,2)}$	0.00	0.00	0.01
$\Phi_{1,(2,2)}$	1.00	1.01	1.02	$\Phi_{2,(2,2)}$	0.96	0.97	0.98
$\Phi_{1,(3,2)}$	-0.01	-0.01	-0.00	$\Phi_{2,(3,2)}$	-0.02	-0.02	-0.02
$\Sigma_{1,(1,1)}$	0.02	0.03	0.03	$\Sigma_{2,(1,1)}$	0.02	0.02	0.03
$\Sigma_{1,(2,1)}$	-0.01	-0.01	0.00	$\Sigma_{2,(2,1)}$	-0.01	-0.00	0.00
$\Sigma_{1,(2,2)}$	0.03	0.03	0.04	$\Sigma_{2,(2,2)}$	0.03	0.04	0.05
q_{11}	0.92	0.94	0.96	q_{22}	0.93	0.95	0.96

Notes: We use the unemployment rate and the federal funds rate from 1985:M1 to 2016:M12 in the estimation. We report the end of sample (2016:M12) posterior distributions. The first subscript identifies the regime and the remaining subscripts which are parenthesized indicate their location in the parameter matrix.

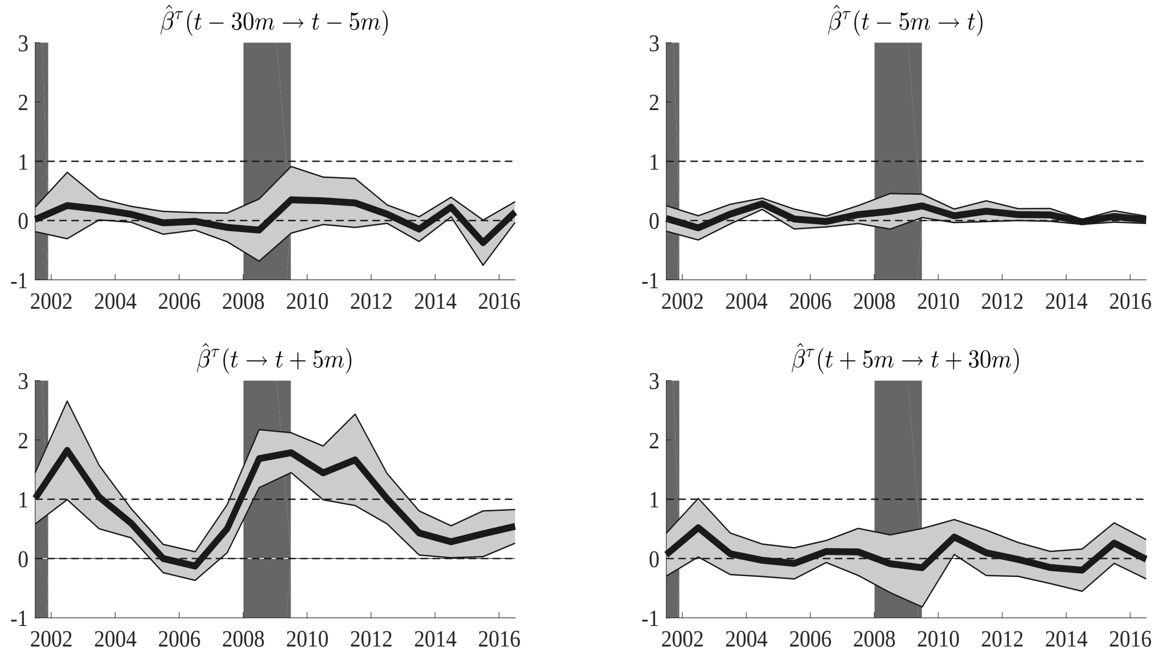
E Supplemental Figures

Figure E.1: R^2 from estimating Eqn. (1) for different values of Δ_l and Δ_h.



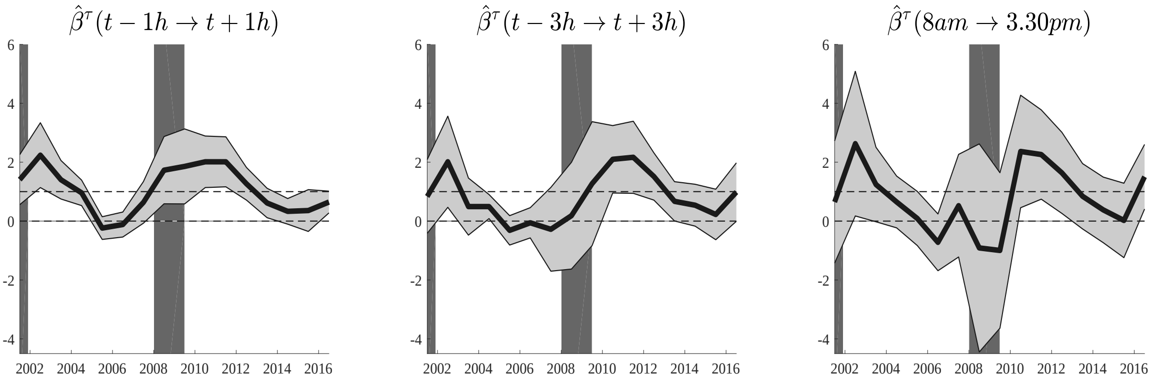
Notes: The sample is from January 2000 to December 2016 for the 81 regressions using the top 4 most influential MNAs reported in the main text.

Figure E.2: Stock Sensitivity Before and After the Announcements



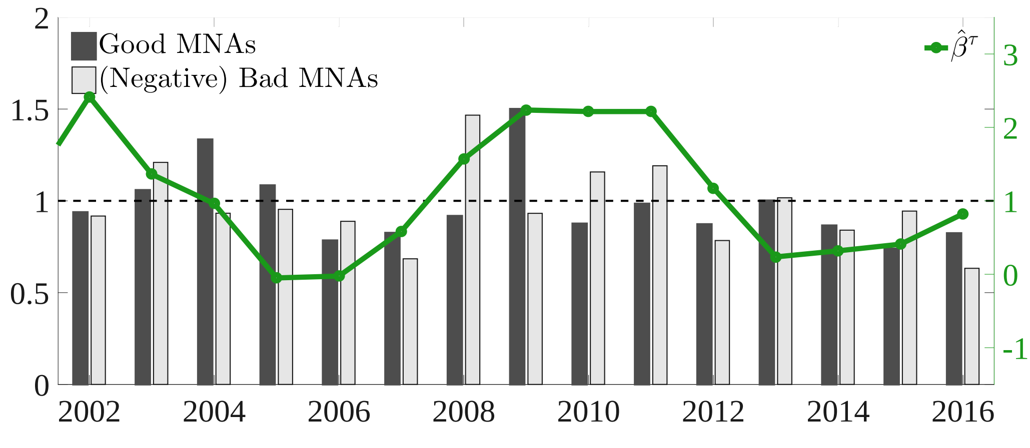
Notes: The individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ are shown with ± 2 standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$. By construction, the sum of individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ equals $\hat{\beta}^{\tau}$ shown in Figure 3.

Figure E.3: Lower-frequency Stock Return Sensitivity



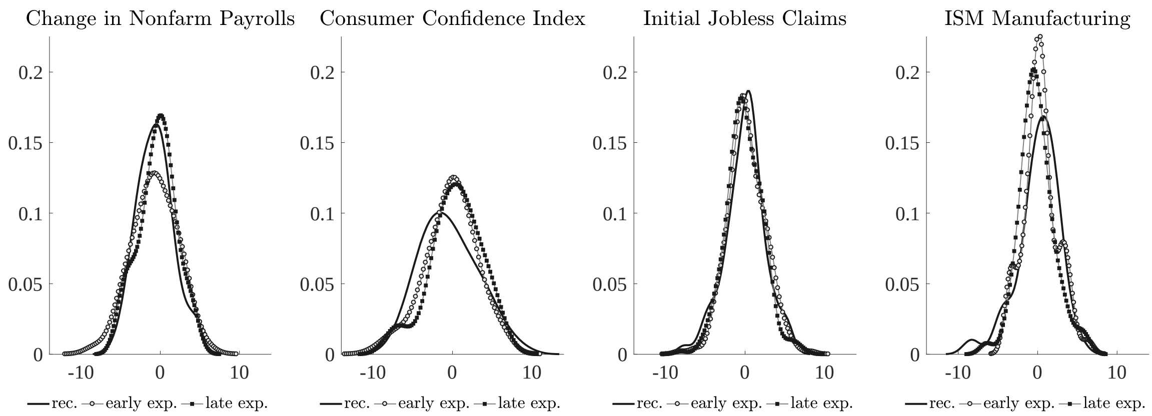
Notes: The individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ are shown with ± 2 standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$.

Figure E.4: Stock Sensitivity and the Average Good and Bad MNA Surprises (Relative to 1)



Notes: We provide the normalized annual averages of good and (negative) bad macroeconomic news announcement surprises. We overlay with the estimated time-varying stock market sensitivity coefficient $\hat{\beta}^{\tau}$ in Figure 3.

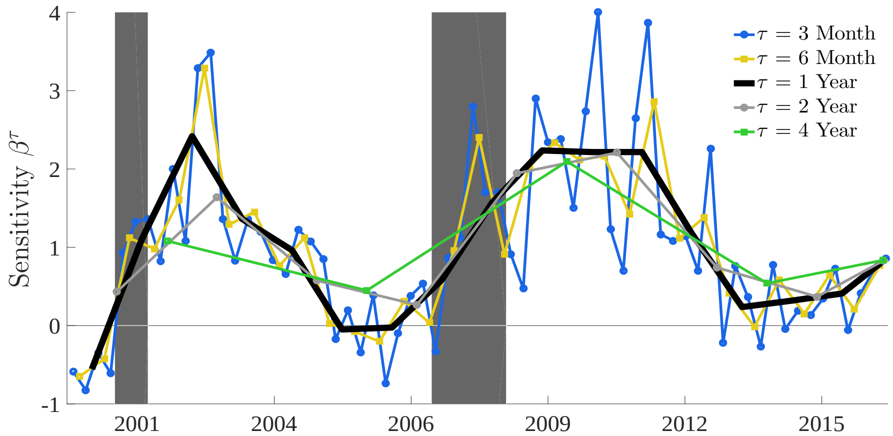
Figure E.5: Distribution of the MNA Surprises



Asympotic p-values from the two-sample Kolmogorov-Smirnov Test				
Surprises Pair	NFP	CCI	IJC	ISM
(Recession, Early Expansion)	0.79	0.14	0.61	0.66
(Early Expansion, Late Expansion)	0.78	0.47	0.51	0.24
(Recession, Late Expansion)	0.65	0.23	0.30	0.36

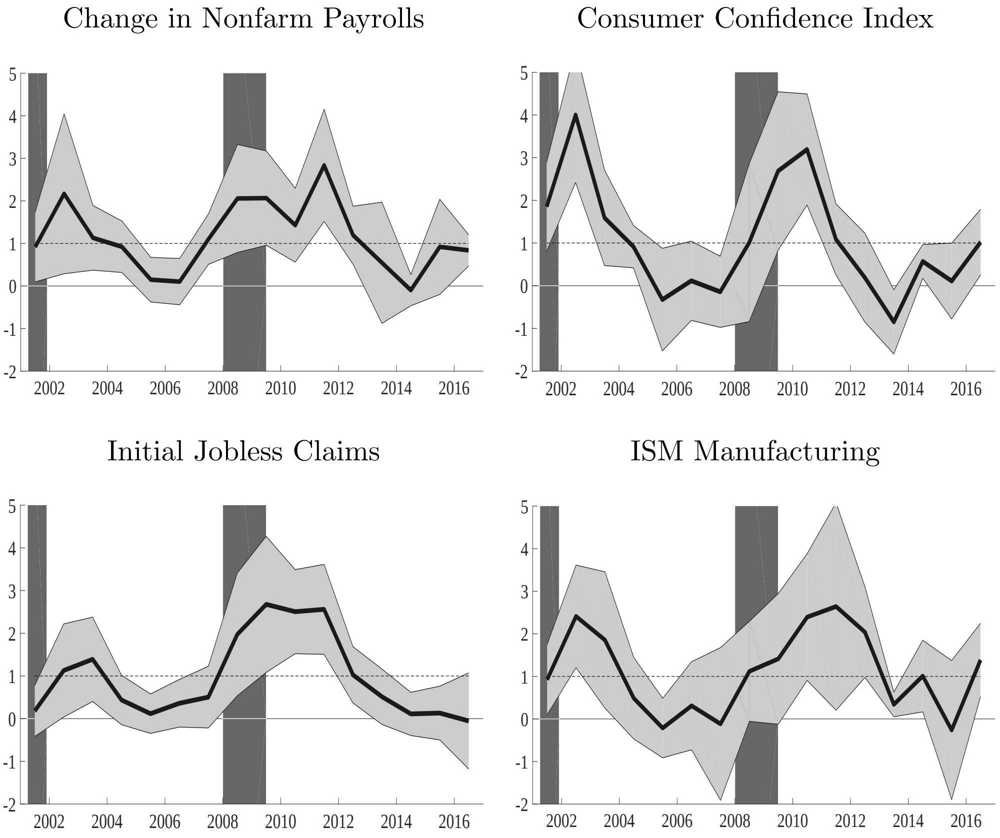
Notes: Macroeconomic announcements are Change in Nonfarm Payrolls (NFP), Consumer Confidence Index (CCI), Initial Jobless Claims (IJC), and ISM Manufacturing (ISM). Recession periods correspond to the NBER recession dates. Early expansion periods are 2002-2004 and 2009-2012. Late expansion periods are 2005-2007 and 2014-2015. For a given MNA i, we generate the surprises for three different subsamples and compute a test decision for the null hypothesis that the surprises in different subsamples are from the same distribution. We report the corresponding asymptotic p-values.

Figure E.6: Smoothing Parameter τ in the Swanson and Williams (2014) Regression



Notes: We repeat the estimation by varying the values of smoothing parameter τ. The highest frequency considered in this picture is 3 months and the lowest is 4 years.

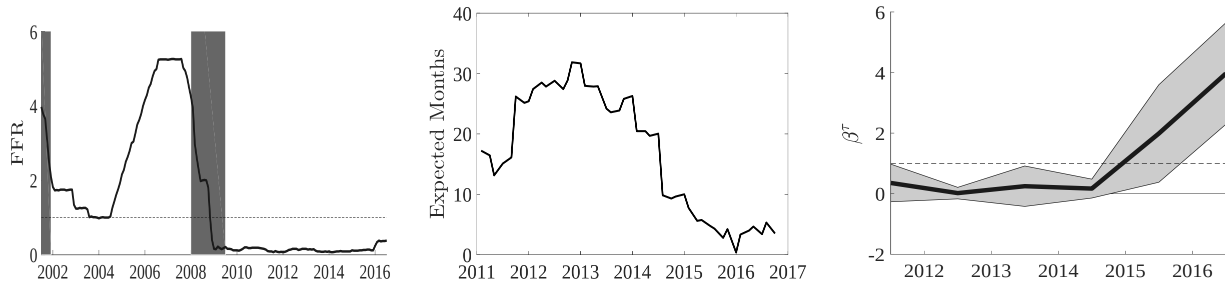
Figure E.7: Individual Responses



Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30$min. We impose that γ^τ (black-solid line) is on average equal to one. We provide ± 2-standard-error bands (light-shaded area)

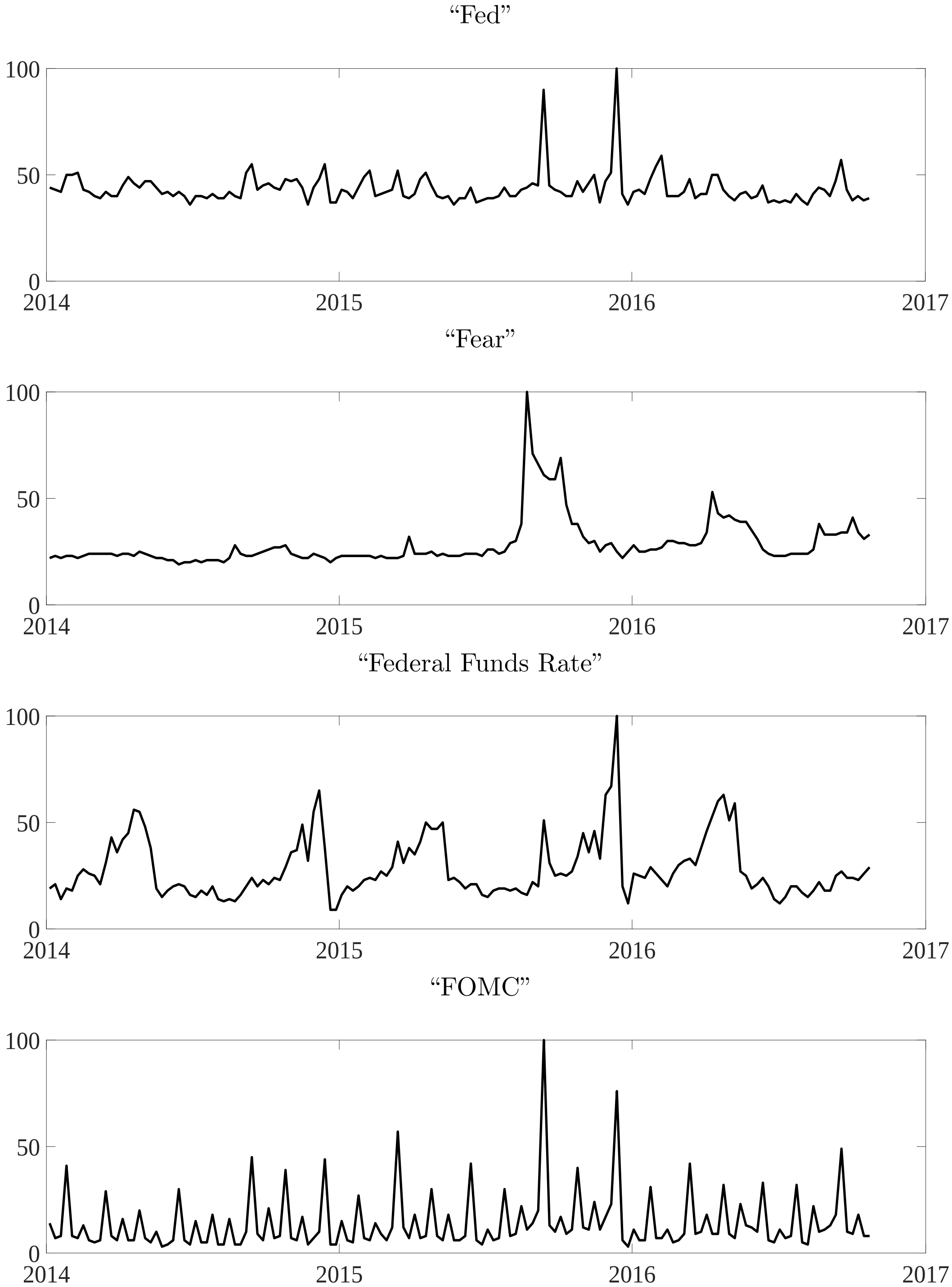
Figure E.8: Monetary Policy

(1) Federal Funds Rate (2) Primary Dealer Surveys (3) Time-Varying Sensitivity 30-Day Fed Funds Futures



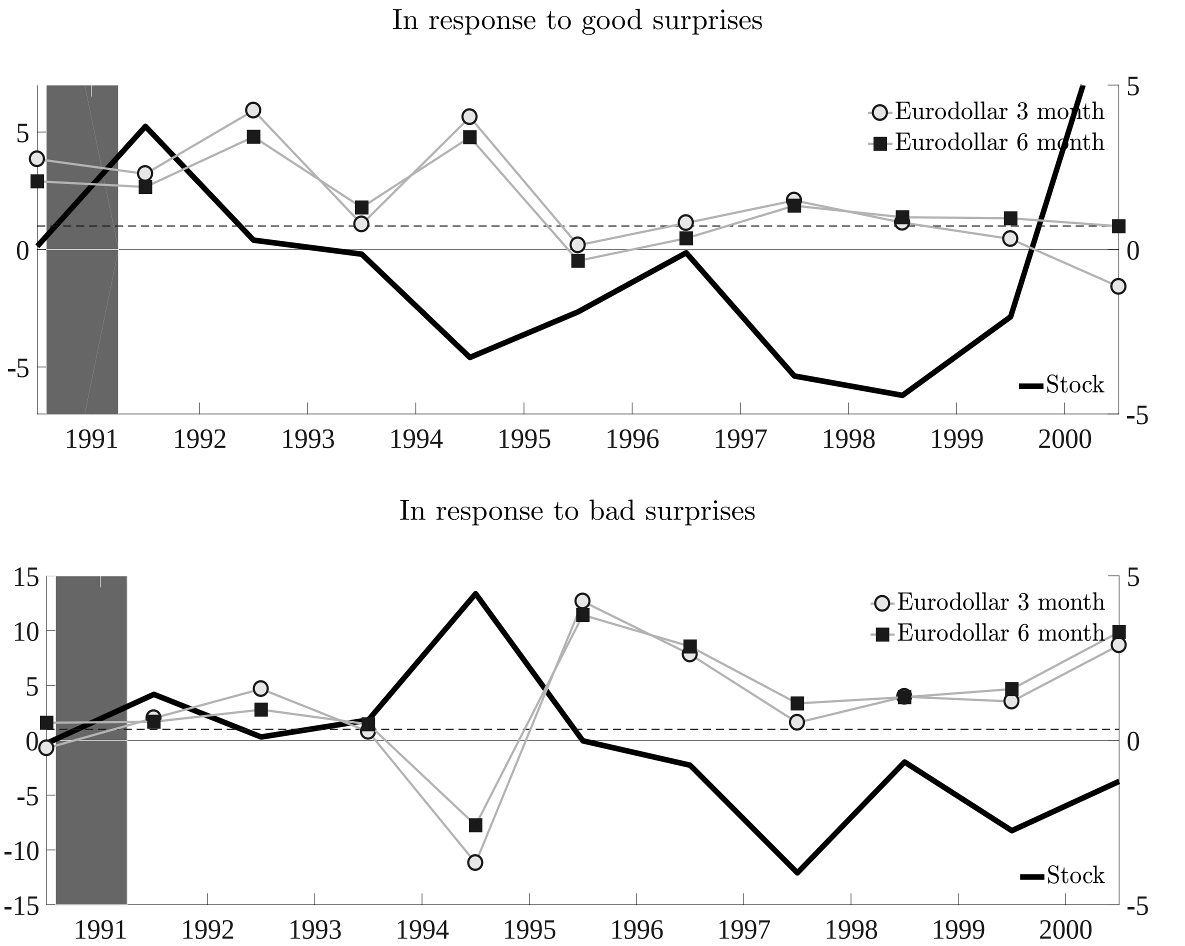
Notes: (1) Effective Federal Funds Rate, retrieved from FRED, Federal Reserve Bank of St. Louis. (2) Primary dealers are surveyed on their expectations for the economy, monetary policy and financial market developments prior to Federal Open Market Committee meetings. The actual survey question is "*provide the percent chance you attach to the timing (of the future FOMC meeting) of the first increase in the federal funds target rate or range.*" (3) Time-varying sensitivity coefficients for interest rate futures. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that β^{τ} (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide ± 2-standard-error bands (light-shaded area) around β^{τ}.

Figure E.9: Google Trend Keyword Search



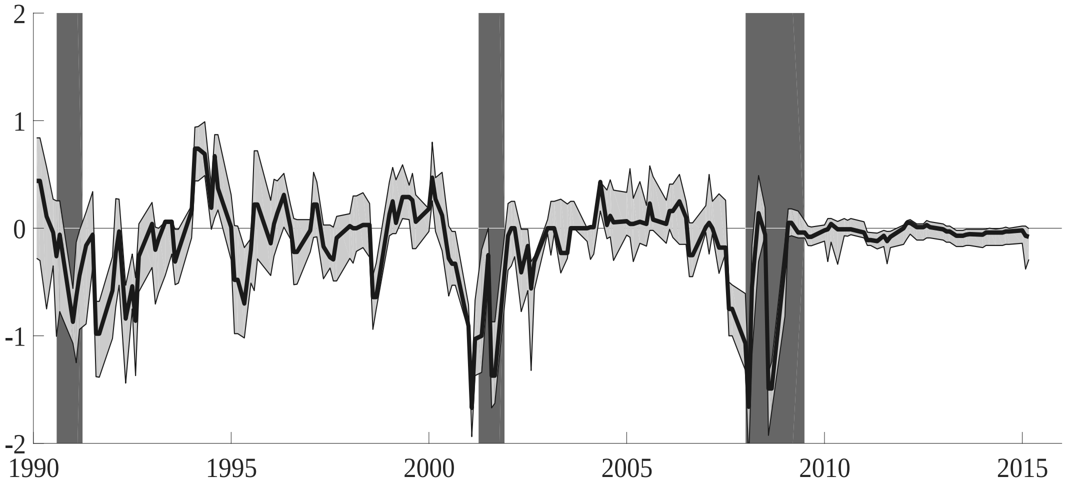
Note: Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise a score of 0 means the term was less than 1% as popular as the peak. Source: `https://www.google.com/trends`.

Figure E.10: Time-Varying Sensitivity Coefficients: Good and Bad Announcements



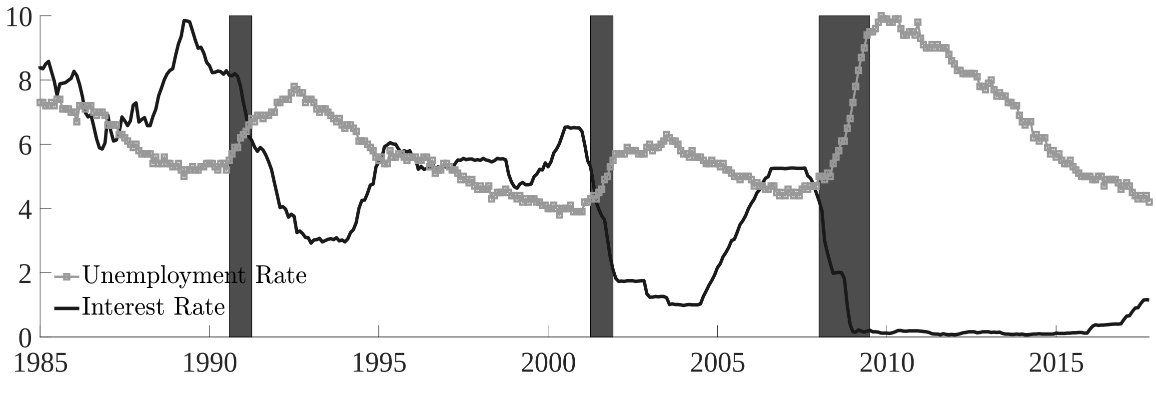
Notes: Macroeconomic announcements are Consumer Confidence Index and ISM Manufacturing. We impose that β^{τ} (black-solid line) is on average equal to one. We set $\Delta = 30\text{min}$.

Figure E.11: Survey forecast of the federal funds rate



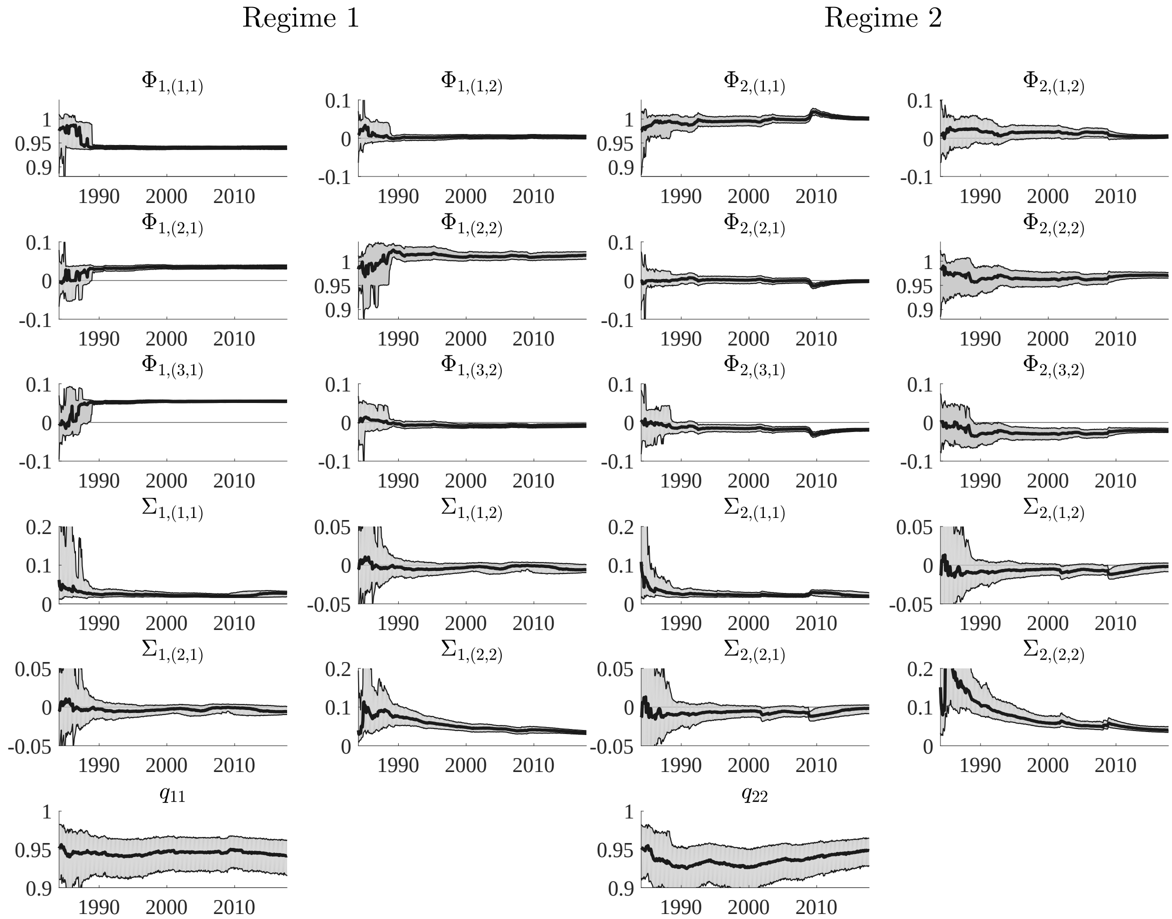
Notes: We compute the annualized one-quarter ahead forecast error of the federal funds rate based on the Blue Chip Financial Forecasts survey. Roughly, 40-50 financial institutions participate in the survey from which we compute the 90% intervals.

Figure E.12: Data



Notes: We provide the time series of the unemployment rate and the federal funds rate from 1985:M1 to 2016:M12. The first-order autocorrelations of both series are greater than 0.99 in our sample. Dark shaded bars indicate the NBER recession dates.

Figure E.13: Posteriors



Notes: Black solid lines are posterior median values which are overlaid with the 90% credible interval (gray shaded areas). To deal with the label switching problem, we impose that the coefficient that governs the feedback from the interest rate to the unemployment rate in the first regime is greater than that in the second regime, that is, $|\Phi_{1,(2,1)}| > |\Phi_{2,(2,1)}|$ and $|\Phi_{1,(1,2)}| > |\Phi_{2,(1,2)}|$