# 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. Starting from a phase in which the stock market is insensitive to news, it becomes increasingly sensitive as the economy enters a recession with peak sensitivity obtained a year after the recession started. As the economy expands, the sensitivity comes down to its starting point in four to five years. We then show that market expectation about the future interest rate path is one of the primary drivers of the cyclical variations in stock price responsiveness to news surprises. These new empirical facts are robust to various measures of stock returns and MNA surprises. We introduce a simple regime-switching dividend growth model in which beliefs over the duration of monetary regimes drive the sensitivity of returns to news surprises. The model analysis illustrates that the evolution of market expectations about monetary policy can generate the time-varying return responses observed in the data.


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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., Lucca and Moench (2015) and Savor and Wilson (2013)). However, predicting the direction of the stock market's response to these news is challenging. For example, better-than-expected MNA surprises that push prices up through higher expected future 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 response of the stock market to the MNA surprises. Yet, consistent with the motivation above, we establish that this muted unconditional response is masking significant and time varying cyclical responses of stock prices to the 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 interpret these findings as reflecting the overall informativeness of the announcements given economic conditions. The relatively muted responses during early recession and late expansion periods are a result of the MNAs that are

[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.

perceived as (i) carrying temporary shocks and/or (ii) ones for which (uncertainty about) the Fed stabilization policy makes them effectively uninformative.

Second, and somewhat surprisingly, there is no evidence for asymmetry in the responses to negative and positive MNA surprises. Third, the sensitivity of short-term interest rate futures to the MNA surprises moves in lock-step but in the opposite direction as that of stock prices'. 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.

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 cashflows (and risk-free rate) on stock prices is of interest given the long standing research in analyzing the sources of variation of valuation ratios.

After narrowing down the informational content of the MNA surprises to news about cash flows and/or news about risk-free rates, we propose a simple regime-switching dividend growth model to further understand the role of beliefs about future dividend growth and interest rate path in accounting for stock return variation. In our simple framework, the nominal short rate is the monetary policy instrument and is thought to vary jointly with dividend growth. The regime-switching model features two distinct economic regimes. In the "Reactive Monetary Policy (R-MP)" regime, positive dividend growth shocks can increase both future dividend growth and future interest rates. In this regime, high interest rates slow down future dividend growth. In the "Non-Reactive Monetary Policy (NR-MP)" regime, dividend growth evolves in an autoregressive pattern and the interest rate does not impact the dividend growth. The key feature in the NR-MP regime is that dividend growth shock is entirely transmitted to future dividend growth without a countervailing rise in the interest rate. Finally, we assume that the time varying Markov transition probabilities govern transitions between the two states.

Given plausible VAR dynamics and Markov transition probabilities, this simple model yields time-varying reaction of stock prices to shocks that are qualitatively similar to what is observed in the data. We interpret these transition probabilities as reflecting beliefs about the duration of the economic regimes at each point in time to help clarify the underlying response mechanism. First, beliefs about the duration of the "R-MP" regime inversely track the time-varying sensitivity coefficient for stock returns. This is intuitive because in the "R-MP" regime by construction the interest rate diminishes the pure cash flow effects. In contrast, in the "NR-MP" regime, the cash flow effects dominate if the beliefs that no interest rate change will take place persist (i.e., staying in the "NR-MP" regime). Second, under the extracted transition probabilities, we show that the risks of an interest rate hike (transition from the "NR-MP" to the "R-MP" regime) could entirely mitigate the positive cash flow shock. This model analysis illustrates that the evolution of market beliefs about monetary policy can generate the time varying return response observed in the data. We close our analysis by showing that such qualitative results can be reconciled in a modern dynamic (consumption-based) asset pricing model that incorporates regime-switching (aggressive and loose) monetary policy.

### 1.1 Literature Review

The literature has identified accommodating time variation and using high-frequency returns as key steps in measuring the impact of MNA surprises on stock prices. 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 measuring the impact of MNA surprises on stock prices over different phases of the business cycle. 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 expectations of monetary policy.

More generally, 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 (2003), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Gurkaynak, Rigobon, and Sack (2005), and Bekaert, Hoerova, and Lo Duca (2013) among others. More 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 regarding the relationship between stock market movements and subsequent monetary policy by the Fed.

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 decomposes the announcments into cashflow and risk premia components and illustrates the key role beliefs regarding interest rate play in the return reponse. Section 4 illustrates the mechanism within a calibrated dynamic asset-pricing model. Section 5 provides concluding remarks.

# 2 Empirical Analysis

## 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 should 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 B.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.

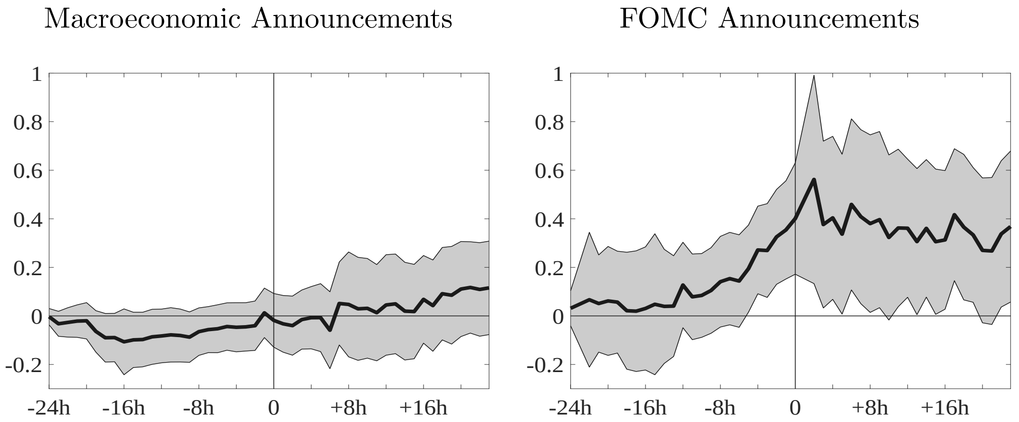
**Standardization of the MNA Surprises.** Denote MNA $i$ at time $t$ by $\text{MNA}_{i,t}$ and let $E_{t-\Delta}(\text{MNA}_{i,t})$ be median surveyed forecast made at time $t-\Delta$. The individual MNA surprises (after normalization) are collected in $X$ whose $i$th component is

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

The units of measurement differ across the 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 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. It includes future announcements that have yet to occur from the perspective of the economic agent.[2] 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 B.2

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

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.

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.

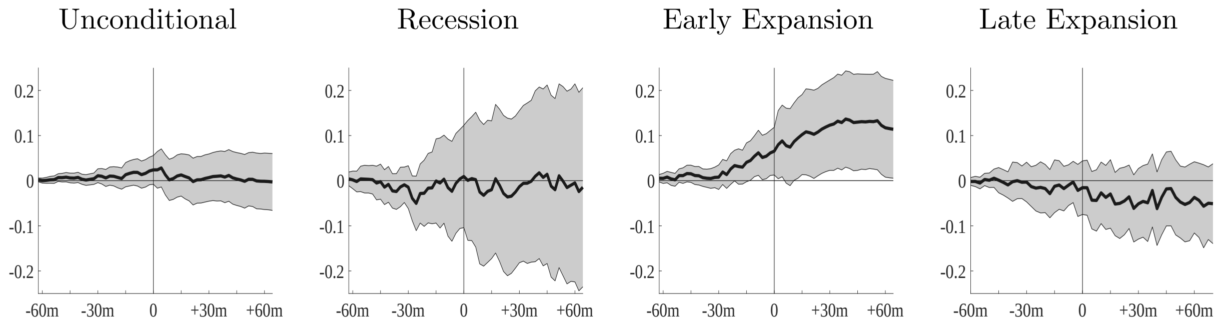
**Financial Data.** We consider futures contracts for the asset prices in our analysis: S&P 500 E-Mini Futures (ES), S&P 500 Futures (SP), 30-Day Federal Funds Futures (FF), and Eurodollar futures (ED). Futures contracts allow us to capture the effect of announcements that take place at 8:30am Eastern 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.

## 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

Figure 2: Cumulative Stock Returns Around Macroeconomic Announcements



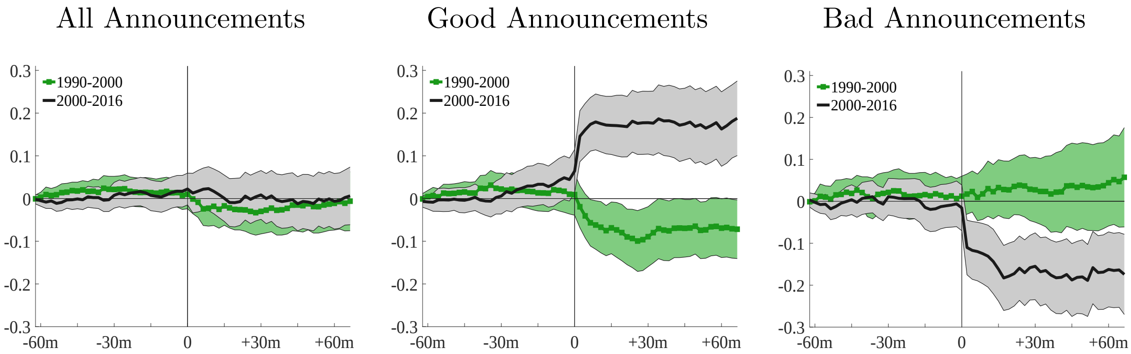

*Notes:* We plot the average cumulative stock returns in percentage points around major scheduled announcements: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, ISM Manufacturing and Initial Jobless Claims. We pick macroeconomic announcements that are available from 2000 to 2016. Recession periods correspond to NBER recession dates. Early expansion periods are 2002-2004 and 2009-2012. Late expansion periods are 2005-2007 and 2014-2015. Good (bad) announcements are positive (negative) surprises. The black solid lines are the average cumulative return on S&P 500 futures (ES) 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 vertical line indicates the time at which announcements are typically released in this sample period.

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.[3] The FOMC pre-announcement drift in Lucca and Moench (2015) is captured in Figure 1 where we plot the cumulative stock returns around 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 and Figure 3 we plot the cumulative stock returns starting from an hour before macroeconomic announcements to an hour after the announcements. Four distinctive patterns emerge. First, even at an hourly interval it is hard to find unconditionally any statistically significant pattern for stock returns (first panel of Figure 2). Second, after we condition on the phase of business cycle, that is, we partition the period into "recession," "early expansion," and "late expansion" (discussion on the definition of the phase of the business cy-

[3]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 3: Cumulative Stock Returns Around Macroeconomic Announcements




*Notes:* We plot the average cumulative stock returns in percentage points around major scheduled announcements: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, ISM Manufacturing and Initial Jobless Claims. We pick macroeconomic announcements that are available from early 1990s. Good (bad) announcements are positive (negative) surprises. 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 1990 through December 2016. The vertical line indicates the time at which announcements are typically released in this sample period.

cle will follow), we find evidence for time variation in stock return responses to the MNAs. In particular, during the early expansion period we document a statistically significant cumulative average impact of 10 basis points (third panel of Figure 2).[4] The stock return responses to the MNAs are statistically indistinguishable from zero in recession or late expansion periods.

Third, even without conditioning on the phase of the business cycle, the reaction of stock prices can be much more precisely measured when announcements dates are separated into positive and negative announcements dates (second and third panels of Figure 3). Within the benchmark sample from 2000 to 2016, the average impact of MNA surprises is about 20 basis points which 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.

Fourth, there is another piece of evidence of strong time variation in the reaction of stock prices for example, when the sample is split into pre- and post-2000 periods that are broadly viewed as distinct in terms of economic performance. This evidence is consistent with a few papers that argue stock market reactions to announcement surprises may depend on the state of the economy (e.g., McQueen and Roley (1993), Boyd, Hu, and Jagannathan (2005), and Andersen, Bollerslev, Diebold, and Vega (2007)). Further, we see that after 2000, good announcements are usually

[4] Albeit marginally statistically significant one can in fact detect a pre-announcement drift during this early expansion period of about 5 basis points.

good for the stock market and bad announcements are usually bad. This is markedly different from the 1990s where good (bad) announcements are usually bad (good) as emphasized in the earlier literature.

Collectively, Figure 2 and Figure 3 emphasize the importance of accounting for time variation and highlight the difficulty of measuring the impact of the MNA surprises on stock market. To gain better econometric power in identifying the stock market responses, we proceed with a regression analysis.

### 2.3 Main 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 $\Delta$-minute window around the surprises. 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

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

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

As the results can depend on the size of the return window, we consider all combinations of $\Delta_l$ and $\Delta_h$ between 10 minutes and 90 minutes in increments of 10 minutes (81 regressions in total).[5] Table 1 tabulates the number of regressions in which equity returns significantly respond to a specific MNA at the 99% confidence interval. 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 Macroeconomic News Announcement 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 Consistent are, broadly speaking, the most influential MNAs. This is consistent

[5] 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 Macroeconomic News Announcement 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.

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 and 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 significant in all our regressions. Based on Table 1 we consider the top four most influential MNAs in the remainder of 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 $\Delta_l$ and $\Delta_h$. We re-estimate equation (1) using only the top four influential MNAs reported in Table 1 and provide the $R^2$ values from these regressions in Figure C.1. We find that the $R^2$ values are consistent with findings in 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 C.1. We emphasize that our results are maintained across all 81 combinations of $\Delta_l$ and $\Delta_h$.

**Cyclical Stock Return Sensitivity to News.** 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 $\tau$-period rolling windows as in Swanson and Williams (2014)

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

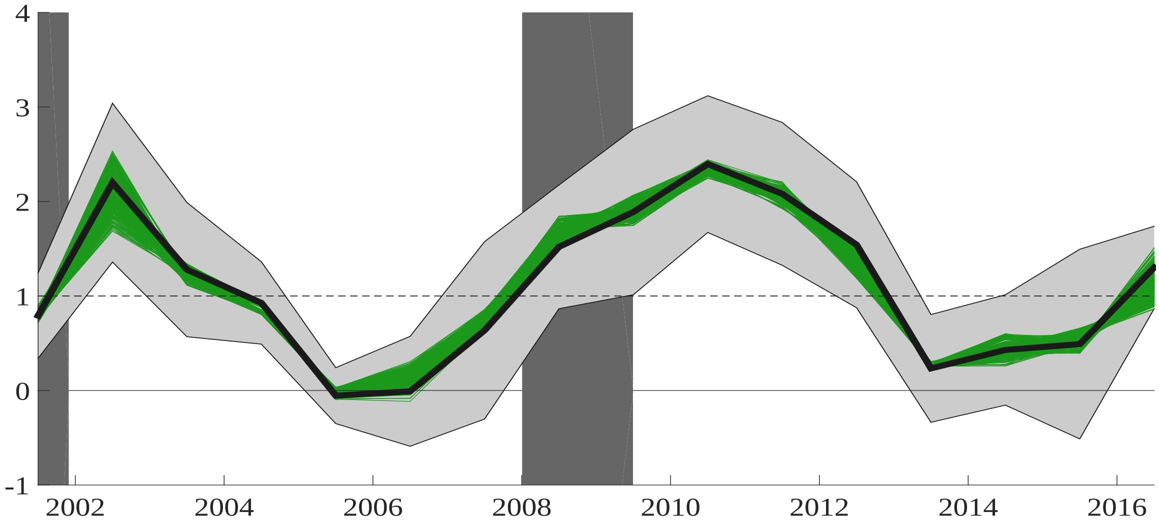
where $\epsilon_t$ is a residual representing the influence of other news and other factors on stock returns at time $t$. $\alpha^\tau$ and $\beta^\tau$ are scalars that capture the variation in the return response to announcement during period $\tau$. The underlying assumption is that while the relative magnitude of $\gamma$ is constant, the magnitude of $\beta^\tau$ varies as the stock returns become more or less affected over time in a proportional way across all announcement during period $\tau$. We let $\tau$ index the calendar year. The identification assumption is that $\beta^\tau$ is on average equal to one. This implies that $\beta^\tau \gamma^\top X_t$ is identical to its OLS counterpart $\gamma^\top X_t$ in (1) on average. 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 $\beta^\tau$.

Figure 4 provides the main focus of our study, that is, the estimates of the time-varying sensitivity coefficient $\beta^\tau$ (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.[6]

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.

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

Figure 4: 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 $\beta^\tau$ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide $\pm$2-standard-error bands (light-shaded area) around $\beta^\tau$. The shape is robust to all possible combinations (green-solid lines) of the next eight MNAs listed in Table 1.

**Pre- and Post-announcement Stock Return Sensitivity.** 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

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

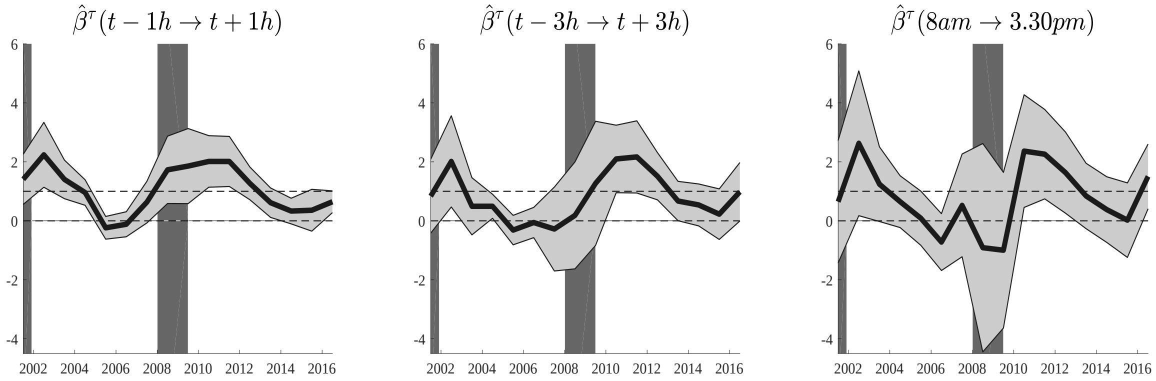
We estimate the modified (restricted) regression in which we regress return $r_{t-\Delta_l}^{t+\Delta_h}$ on $\hat{X}_t$

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

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, $\hat{X}_t$. We emphasize that we accounted for the two-stage sampling uncertainty when constructing standard error bands. Since $r_{t-30m}^{t+30m} = \sum r_{t-\Delta_l}^{t+\Delta_h}$, it follows that $\sum \hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$ in Figure C.2 equals $\hat{\beta}^\tau$ shown in Figure 4.

Figure C.2 shows that stock prices on impact react significantly to the MNA surprises (bottom left of Figure C.2), but there is no statistically significant movement five minutes after the

Figure 5: Lower-frequency Stock Return Sensitivity




*Notes:* The individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ are shown with $\pm 2$ 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 $\hat{X}_t$.

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 C.2) which is different from Lucca and Moench (2015).

**Lower-frequency Stock Return Sensitivity.** To show that the impact of the MNA surprises on the stock market is not short-lived, we estimate the restricted regression (4) with 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 5 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 frequencies. 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.

**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 C.5 overlays the normalized annual averages of good and bad MNA surprises with the estimated time-varying sensitivity coefficient in Figure 4. We plot the negative of bad MNA surprises to make them comparable to good MNA surprises. We do not find any significant comovement between the stock sensitivity coefficient and MNA surprises. This exercise suggests that time variation in $\hat{\beta}^{\tau}$

cannot be systematically attributable to a time-varying pattern 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. The test results are robust to 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 C.6 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

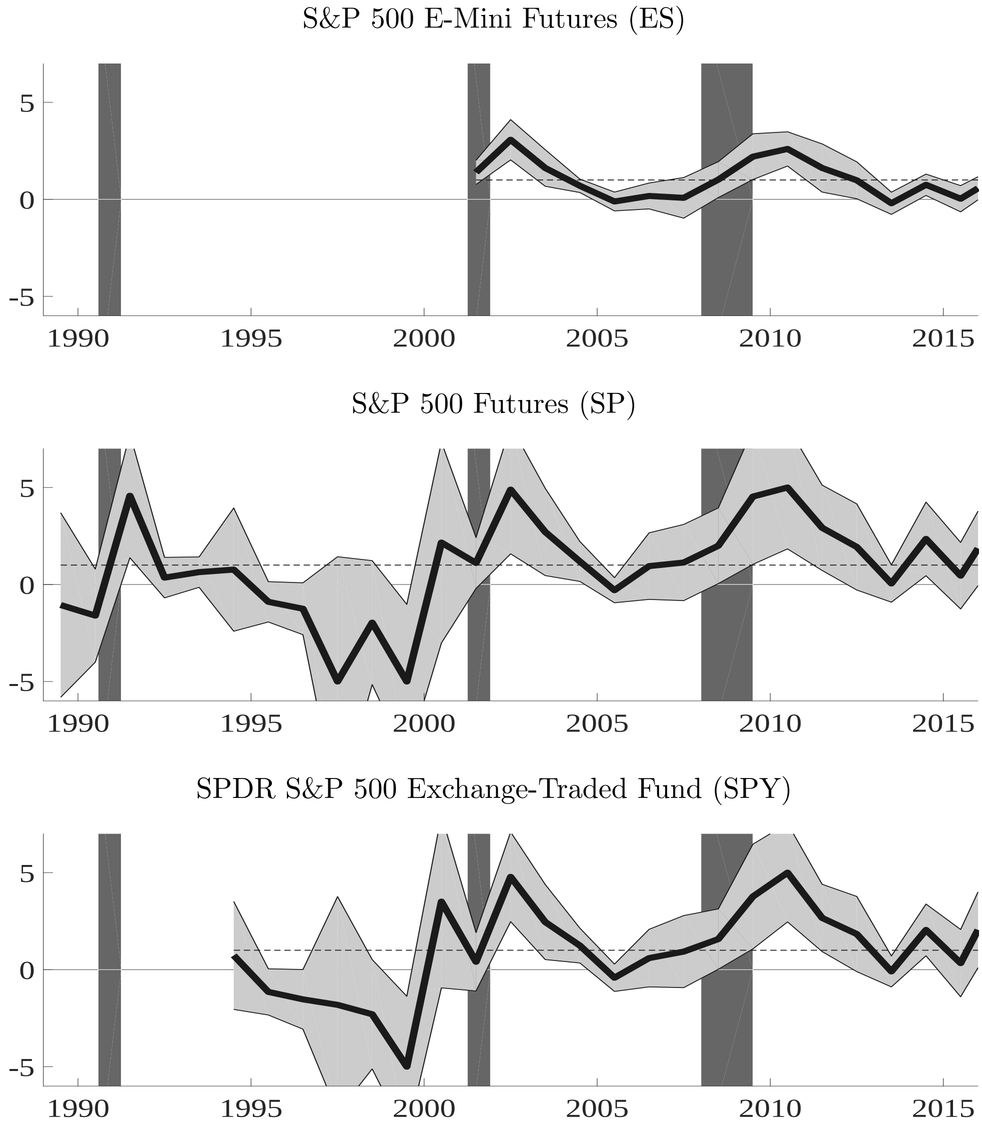
$$r_{t-\Delta}^{t+\Delta} \;=\; \alpha^\tau + \beta^\tau \gamma^\top X_t + \delta^\top Z_{t-\Delta_z} + \epsilon_t. \tag{5}$$

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.[7] We set $\Delta_z$ 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 4. This information 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 and in particular financial variables such as the slope of the term structure (e.g., see Neuhierl and Weber (2016) for weekly evidence).

**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 after 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

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

Figure 6: 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 $\beta^{\tau}$ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide $\pm 2$-standard-error bands (light-shaded area) around $\beta^{\tau}$.

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 unrestricted regression (2) with the results given in Figure 6.

First, observe that exclusion of 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 6 is very similar to Figure 4. 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 6 that our empirical findings are robust across various return measures, surprise measures, and different periods.[8]

**Other Robustness Checks.** We improve the econometric power in identifying the cyclical variation in stock return responses by pooling information within $\tau$ period, i.e., a year. Yet, it requires us to assume that the responses move proportionally within $\tau$ period. Figure C.3 shows that our results are robust to different smoothing parameter values $\tau$. 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 $\beta^{\tau}$ structure in (2) and replacing with individual $\gamma^{\tau}$. Figure C.4 shows that the stock return responsiveness is qualitatively similar across individual MNAs.

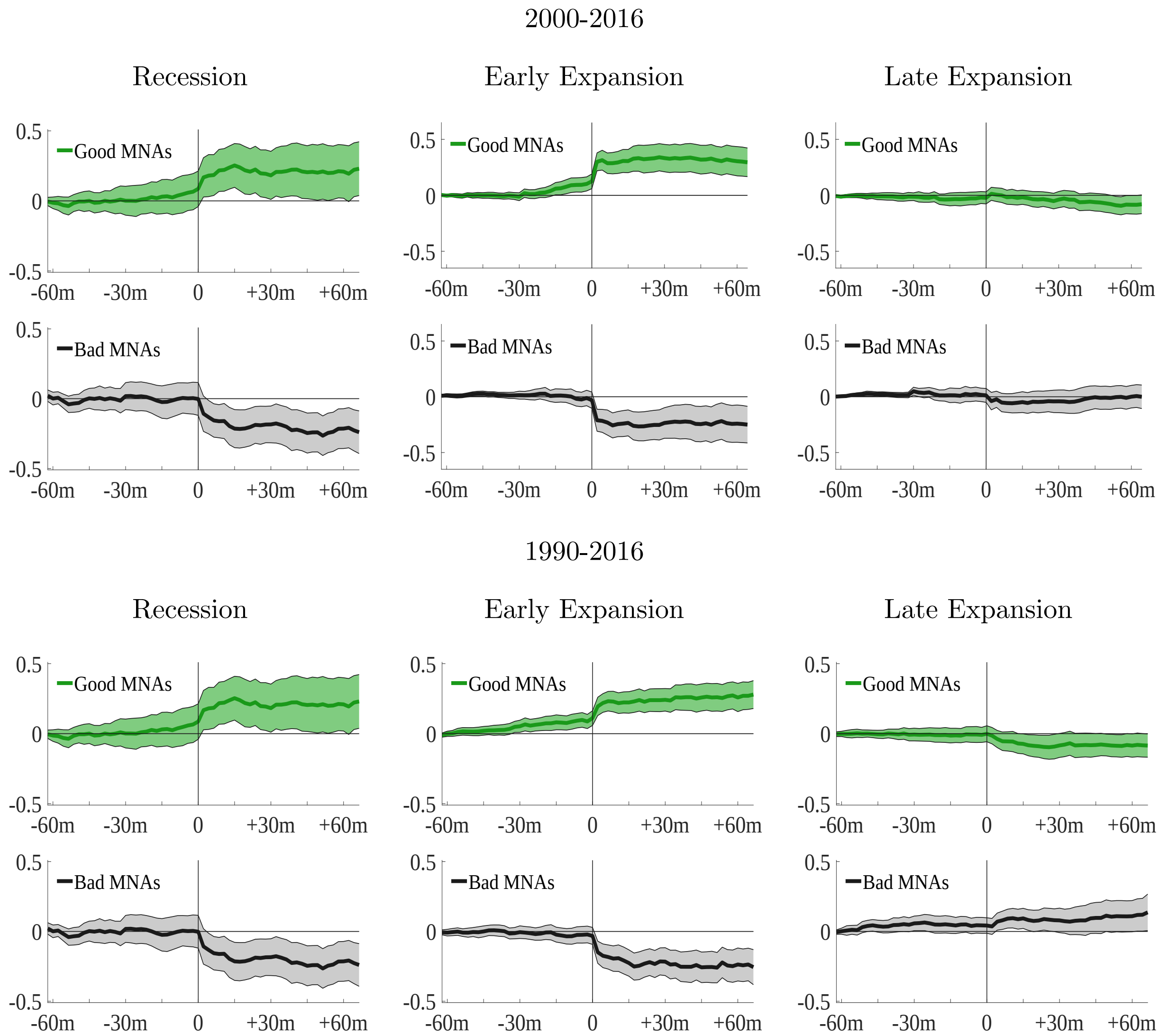
**Decomposition into Good and Bad Macroeconomic News Announcements.** We have shown that the stock market response to the MNAs varies over the business cycle. In particular, the stock price responses in the early part of expansion (including recession) and the late part of expansion are remarkably different. Based on Figure 4 and Figure 6, we define early expansion periods by 1991-1992, 2002-2004, 2009-2012, and late expansion periods by 1996-2000, 2005-2007, 2014-2015. We decompose the macroeconomic news announcements into "good" (better-than-expected or positive) and "bad" (worse-than-expected or negative ) announcements and plot the average cumulative stock returns around scheduled announcements.[9] To use the long sample, we use Consumer Confidence Index and ISM Manufacturing in our analysis.

Figure 7 provides the average cumulative stock returns around scheduled announcements. It is interesting to see that the stock market reactions are fairly consistent across the sample periods. Our results suggest that good news is generally good for the stock market during recessions and early expansions. In fact, stock prices react significantly positively to good MNAs during early expansions while during recession their point estimates are economically large but are only marginally statistically significant. On the contrary, during late expansions, stock prices barely respond or even respond negatively to good MNAs. Stock price reactions to bad MNAs are both qualitatively and quantitatively similar to those of good MNAs during recessions and early

[8] We can infer from Figure 6 that the sign-switching pattern in Figure 3 is mostly caused by mid- to late-1990s samples.

[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 7: Cumulative Stock Returns Around Macroeconomic Announcements




*Notes:* We plot the average cumulative stock returns around scheduled announcements (Consumer Confidence Index and ISM Manufacturing). We pick macroeconomic announcements that are available from early 1990s. Good (Bad) announcements are positive (negative) surprises. Recession periods correspond to NBER recession dates. Early expansion periods are 1991-1992, 2002-2004, 2009-2012. Late expansion periods are 1996-2000, 2005-2007, 2014-2015. 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 ±2-standard-error bands around the average returns. The sample period is from January 1990 through December 2016. The vertical line indicates the time at which announcements are released in this sample period.

expansions. Overall, it seems the responses to good and bad MNAs do not display asymmetry.[10]

[10]This is also confirmed in Figure C.10. Except 2015, the evidence for asymmetry is weak.

## 2.4 Stock Market Response to the MNAs and Monetary Policy

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 that the relationship between the estimated response $\hat{\beta}^{\tau}$ 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 with the level of federal funds rate in Figure C.7. We then regress $\beta^{\tau}$ onto the federal funds rate and its annual change. Table B.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 $\beta^{\tau}$. The associated slope coefficients are significantly negative.[11]

**Stock Market Reaction and the Expectations of Monetary Policy.** To further 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. The dependent variable is either the 3 or 6 month Euro-dollar futures. Eurodollar futures are known to be closely related to market expectations about the federal funds rate. We regress them on the positive and negative MNA surprises. Figure 8 display the estimated coefficients. Surprisingly, we find that the interest rate sensitivity moves in lock-step with the stock sensitivity but in the opposite direction. This pattern is consistent with the story that 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 in Figure 8. 2015 was the period in which there was profound interest in 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 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]

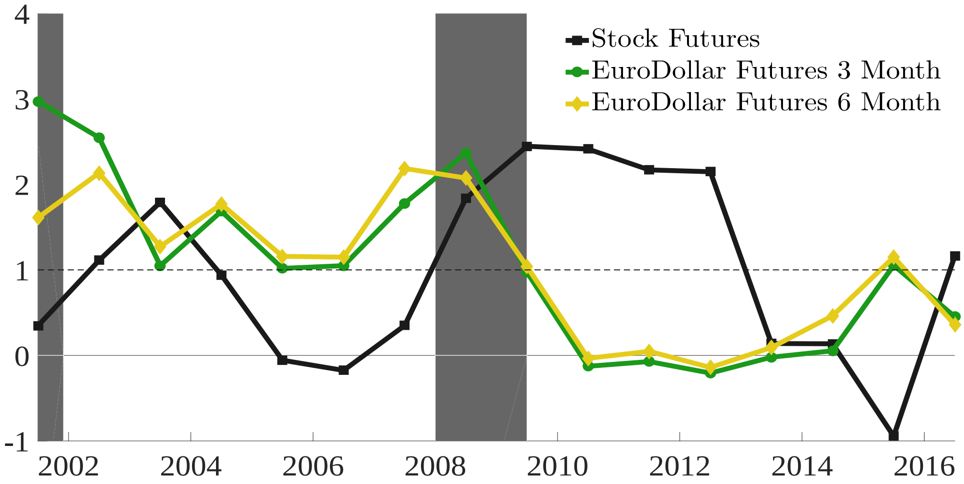
[11] This is related to the findings in Bernanke and Kuttner (2005) where they show reversals in the direction of rate changes have a significantly negative impact on the stock market.

[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 C.8 and Figure C.9.

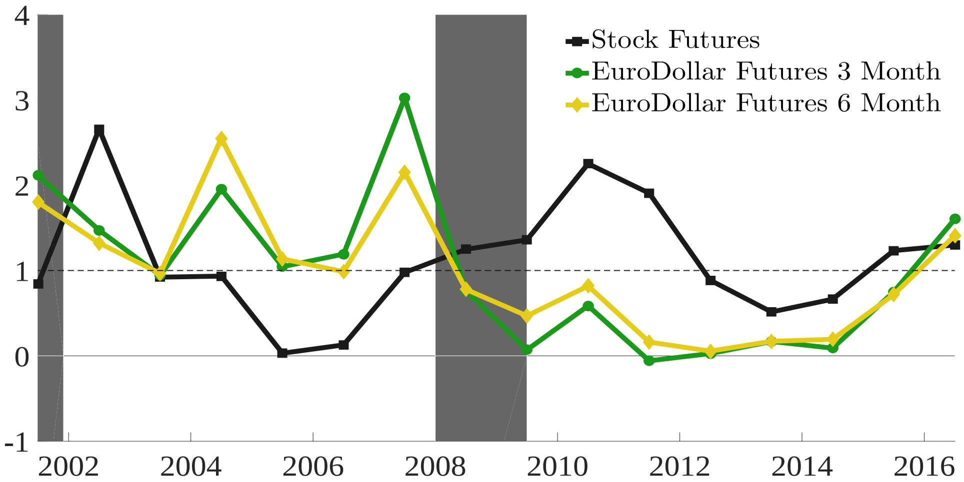
[13] We are restricting our analysis to the conventional monetary policy. The effects of the unconventional monetary policy on financial market are studied in Swanson (2016).

Figure 8: Stock Market Reaction and Expectations about Monetary Policy

In Response to Good MNAs




In Response to Bad MNAs




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

Our findings persist when we extend our analysis to data beginning 1990 which are provided in Figure C.15.

## 3 Return Decomposition

Having shown the important time variation in return responses to MNAs, we further investigate the mechanism that drives the variation in these responses. To do so, we utilize the standard cash flow, risk-free rate, and risk premium news decomposition of returns and combine it with a dividend growth model that illustrates the role of market participants perceptions on monetary policy and its interaction with evolving economic conditions.

## 3.1 Return Decomposition

Our goal is to decompose the return sensitivity $\beta^{\tau}$ to components attributable to cash flows, risk-free rate, and risk premium, 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

$$r_{t+1} - E_t r_{t+1} \approx (E_{t+1} - E_t)\left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}\right) - (E_{t+1} - E_t)\left(\sum_{j=1}^{\infty} \rho^j r_{t+1+j}\right) \tag{6}$$

where $\rho$ is the approximating constant based on the average of the price dividend ratio. (6) 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,

$$r_{t+1} - E_t r_{t+1} \approx N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}. \tag{7}$$

To facilitate the decomposition of (7), we look for empirical proxies for $N_{CF,t}$, $N_{RF,t}$, and $N_{RP,t}$.

**Variance Risk Premium.** 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 (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). 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.[14]

**News Decomposition.** In equation (8) 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 is because we do not have a useful empirical proxy for either news about cash flows or news about risk-free rate.[15] Nevertheless, 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 $\Lambda$ whereby $N_{RP,t}$ is assumed to increase ($\lambda > 0$) the variance premium and lower equity returns $r_{t-\Delta}^t$, that is, the differential of log price at time $t$ and log price at time $t-\Delta$. Time subscript $t$ denotes when new macroeconomic announcement is released. The remainder of equity return variation is explained by $N_{CF,RF,t}$. Put together,

$$\begin{bmatrix} vp_{t+\Delta} \\ r_{t-\Delta}^t \end{bmatrix} = \underbrace{\begin{bmatrix} \lambda & 0 \\ -1 & 1 \end{bmatrix}}_{\Lambda} \underbrace{\begin{bmatrix} N_{RP,t} \\ N_{CF,RF,t} \end{bmatrix}}_{F_t}, \quad var(F_t) = \begin{bmatrix} \sigma_{RP}^2 & 0 \\ 0 & \sigma_{CF,RF}^2 \end{bmatrix}. \tag{8}$$

The following identity holds

$$\hat{r}_{t-\Delta}^t = -\hat{N}_{RP,t} + \hat{N}_{CF,RF,t}, \tag{9}$$

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 cashflow/risk free rate and risk premia news, note that our previous regression analysis imply

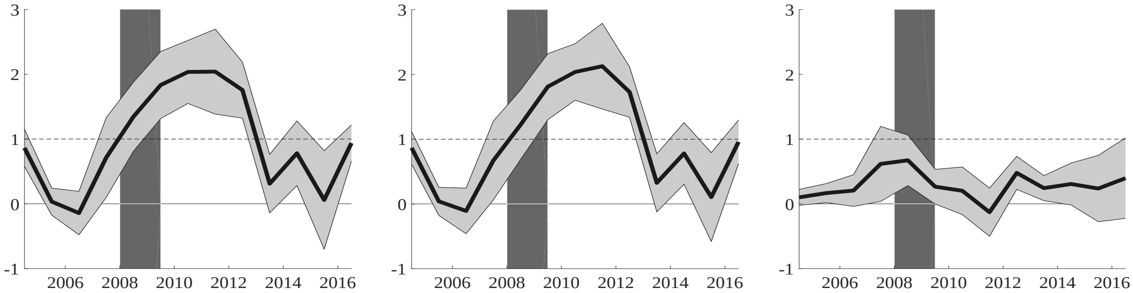
$$\hat{r}_{t-\Delta}^t = \hat{\alpha}^\tau + \hat{\beta}^\tau(\hat{\gamma}^\top X_t) = \hat{\alpha}^\tau + \hat{\beta}^\tau \hat{X}_t. \tag{10}$$

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

[15] In principle, we could use Eurodollar futures return as an empirical proxy for news about risk-free rate. However, as we observe in Figure C.12, there is almost zero fluctuation in one-quarter ahead Eurodollar futures return during 2009-2014 which contrasts starkly with the pre-crisis periods. We believe that news about risk-free rate can only be reflected in Eurodollar future contracts with much longer maturity dates, which suffer from liquidity problems.

Figure 9: Time-Varying Sensitivity Coefficients for Stock Returns: Decomposition

(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 $\beta^{\tau}$ (black-solid line) is on average equal to one. We provide $\pm$2-standard-error bands (light-shaded area) around $\beta^{\tau}$.

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

$$\begin{aligned} \hat{N}_{RP,t} &= \alpha^{\tau}_{RP} + \beta^{\tau}_{RP}\hat{X}_t + \epsilon_{RP,t} \\ \hat{N}_{CF,RF,t} &= \alpha^{\tau}_{CF,RF} + \beta^{\tau}_{CF,RF}\hat{X}_t + \epsilon_{CF,RF,t} \end{aligned} \tag{11}$$

to obtain $\hat{\beta}^{\tau}_{RP}$ and $\hat{\beta}^{\tau}_{CF,RF}$, respectively. Subtracting the first row from the second row in (11), we achieve the identity shown in (9). This allows us to decompose $\hat{\beta}^{\tau}$ in (10) into $\hat{\beta}^{\tau}_{RP}$ and $\hat{\beta}^{\tau}_{CF,RF}$

$$\hat{\beta}^{\tau} = -\hat{\beta}^{\tau}_{RP} + \hat{\beta}^{\tau}_{CF,RF}. \tag{12}$$

Figure 9 provides the decomposition of (12). 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.[16]

## 3.2 The Regime-Switching Dividend Growth Model.

**Framework.** After narrowing the informational content of the MNAs down to news about cash flows and/or news about risk-free rate, we propose a simple regime-switching dividend growth model designed to highlight the role of beliefs about future dividend growth and interest rate

[16] 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 $\beta^{\tau}$ into cashflow-riskfree and risk premium do not change with this alternative timing and sign restriction.

path in accounting for stock return variation. In our simple framework, the nominal short-rate is the monetary policy instrument and is thought to vary jointly with dividend growth. We propose a VAR(1) dynamics in which non-neutrality of interest rate is presumed.

Dividend growth dynamics is characterized by the following state-space form

$$\begin{aligned} \Delta d_{t+1} &= \Lambda_0 + \Lambda_1 Z_{t+1}, \\ Z_{t+1} &= \Phi(S_{t+1}) Z_t + \Omega(S_{t+1}) x_{t+1}, \quad x_{t+1} \sim N(0,1), \end{aligned} \tag{13}$$

in which the joint dynamics of (de-meaned) dividend growth and (de-meaned) risk-free rate, $Z_t = [\Delta d_t, i_t]'$, follow a regime-switching VAR. The VAR coefficients are subject to regime switches. $\Lambda_0$ is the mean of dividend growth. $\Lambda_1 = [1, 0]$ is a simple selection vector. For simplicity, we assume that there is a single shock $x_t$ that drives both dividend growth and risk-free rate.

We consider two regimes $S_t \in \{1, 2\}$ where $S_t$ denotes the regime indicator variable. The corresponding Markov transition probability matrix is provided by $\Pi$

$$\Pi = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}$$

which characterizes all $2^2$ transition probabilities. We label the first regime as the "Reactive Monetary Policy" regime and the second regime as the "Non-Reactive Monetary Policy" regime.

1. $S_t = 1$: "Reactive Monetary Policy (R-MP)" regime ($\rho_{di} < 0$, $\rho_{id} > 0$, $\phi > 0$).

$$\Phi(1) = \begin{bmatrix} \rho_{dd} & \rho_{di} \\ \rho_{id} & \rho_{ii} \end{bmatrix}, \quad \Omega(1) = \begin{bmatrix} 1 \\ \phi \end{bmatrix}.$$

2. $S_t = 2$: "Non-Reactive Monetary Policy (NR-MP)" regime.

$$\Phi(2) = \begin{bmatrix} \rho_{dd} & 0 \\ 0 & 0 \end{bmatrix}, \quad \Omega(2) = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

The sign restrictions in the R-MP regime capture the idea that a high risk-free rate hampers future dividend growth $\rho_{di} < 0$ and the risk-free rate responds positively to lagged dividend growth $\rho_{id} > 0$ and to contemporaneous dividend growth shock $\phi > 0$. We aim to incorporate two things in the R-MP regime: non-neutrality of monetary policy ($\rho_{di} < 0$) and description of monetary policy rule ($\rho_{id} > 0$ and $\phi > 0$ provide the dynamics of the risk-free rate with the interpretation of monetary policy rule). In the R-MP regime, dividend growth shock $\epsilon_{t+1}$ raises current dividend growth and also risk-free rate which can offset the future dividend growth. The NR-MP regime is simply a regime in which risk-free rate is set to zero and dividend growth evolves in an autoregressive pattern. The key feature in the NR-MP regime is that dividend growth shock $\epsilon_{t+1}$ is entirely transmitted to current and future dividend growth. The shifts across R-MP and NR-MP regimes occur exogenously.

We can characterize the news about future cash flows and risk-free rate, which we denote with $N_{CF,RF,t+1}$, by

$$\begin{aligned} N_{CF,RF,t+1}|(S_{t+1}=j) &\approx E_{t+1}\left(\sum_{i=1}^{\infty}\rho^{i-1}\Delta d_{t+i}\right) - E_t\left(\sum_{i=1}^{\infty}\rho^{i-1}\Delta d_{t+i}\right) \\ &\approx \underbrace{\left(\rho^0\Lambda_1^{(1)}(j)+\ldots+\rho^{k-1}\Lambda_1^{(k)}(j)+\ldots+\rho^{\infty}\Lambda_1^{(\infty)}(j)\right)\Omega(j)}_{\Gamma(S_{t+1},\Pi_{t+1})}\, x_{t+1}, \end{aligned} \tag{14}$$

where

$$\Lambda_1^{(k)}(j) = \begin{bmatrix} \Lambda_1(1) & \Lambda_1(2) \end{bmatrix} \begin{bmatrix} p_{11,t+1}\Phi(1) & p_{12,t+1}\Phi(1) \\ p_{21,t+1}\Phi(2) & p_{22,t+1}\Phi(2) \end{bmatrix}^{(k-1)} \begin{bmatrix} \Phi(1) & 0 \\ 0 & \Phi(2) \end{bmatrix} \begin{bmatrix} p_{1j}\mathbf{I}_2 \\ p_{2j}\mathbf{I}_2 \end{bmatrix}.$$

The underlying assumption is that dividend growth dynamics depends on the risk-free rate dynamics. Thus, it is not possible to separately identify news about future cash flows from news about risk-free rate. Under the regime-switching model (i.e., equation (14)), news about cash flows and news about risk-free rate can be derived analytically conditional on information about the state $S_t$ and the Markov transition probability $\Pi_t$. We are assuming that the current state $S_t$ is known when forming beliefs. The time-varying Markov transition probability $\Pi_t$ reflects changing beliefs about the state at each point in time.

In what follows we use the model setup to illustrate the impact of beliefs about monetary policy on returns. We treat Change in Nonfarm Payrolls surprise as the only shock to dividend growth.[17] We run the following regression to obtain the measure of left-side of equation (14)

$$r_{t-\Delta}^{t+\Delta} = \alpha^{\tau} + \beta_g^{\tau}\gamma^g x_t^g + \beta_b^{\tau}\gamma^b x_t^b + \epsilon_t$$

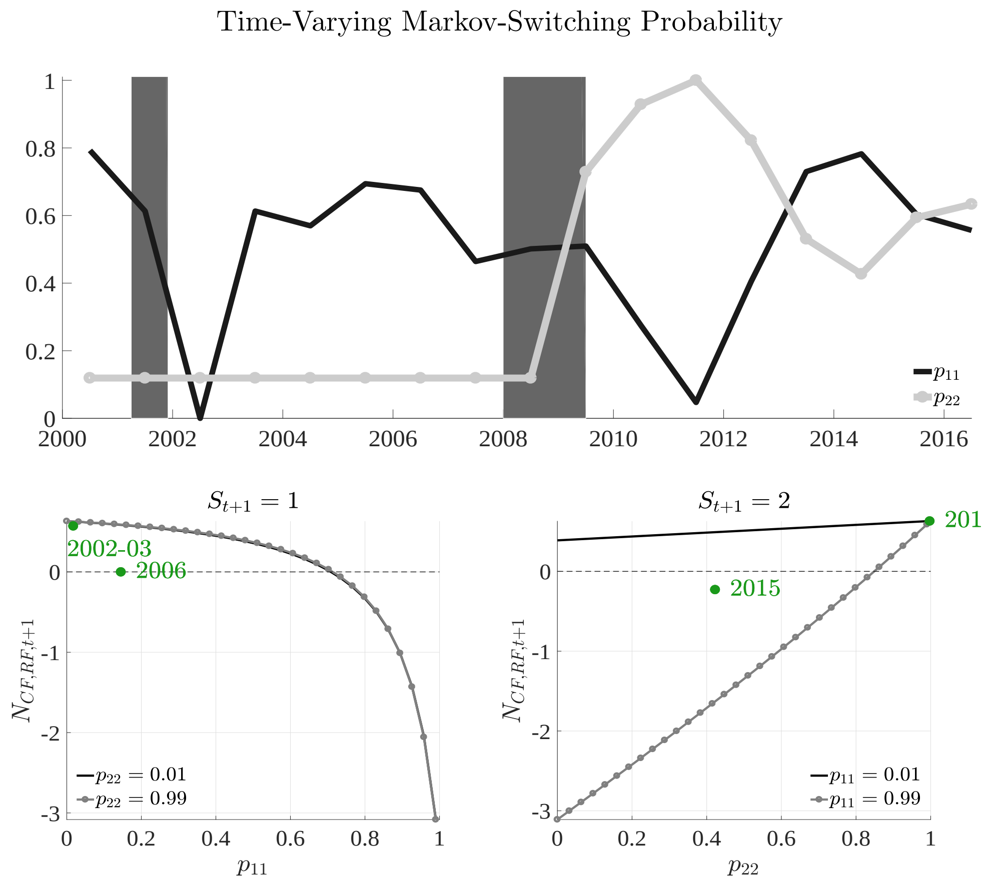
where $x_t$ is split into positive $x_t^g$ and negative $x_t^b$ surprises. We assume that

$$\hat{N}_{CF,RF,t} \approx \hat{\beta}_g^{\tau}\hat{\gamma}^g x_t^g + \hat{\beta}_b^{\tau}\hat{\gamma}^b x_t^b.$$

To compute the right-side of equation (14), we impose $S_t$ is 1 until 2008 and $S_t$ is 2 afterward.

[17]This particular MNA is the literature consensus single most influential MNA.

Figure 10: News about Cash flows and Risk-Free Rate, $N_{CF,RF,t+1}$




*Notes:* In the top panel, the lower bound of $p_{22}$ is set to 0.1. The bottom panel assumes that the system is shocked by a positive one-standard-deviation shock. There is symmetry with respect to positive and negative shocks.

We calibrate the VAR dynamics such that the model-implied annual moments of dividend growth and interest rate is consistent with the actual data.

$$\Phi(1) = \begin{bmatrix} 0.40 & -0.30 \\ 0.10 & 0.99 \end{bmatrix}, \quad \Omega(1) = \begin{bmatrix} 1 \\ 0.5 \end{bmatrix}.$$

Within a year there are 12 realizations of $x_t^g + x_t^b$ surprises whose average responses are measured as $\hat{N}_{CF,RF,t}$. We choose the pair $p_{11,t}$ and $p_{22,t}$ that minimizes the distance between $\hat{N}_{CF,RF,t}$ and $\Gamma(S_t, \Pi_t)x_t$.

The extracted $\hat{\Pi}_t$ in the top panel of Figure 10 reveals the underlying mechanism. First, beliefs about the duration of the R-MP regime, $\hat{p}_{11,t}$, inversely track the time-varying sensitivity coefficient for stock returns. This is intuitive because conditional on same magnitude of dividend growth shock lowering the probability of staying in the R-MP regime would increase future dividend growth and, consequently, lead to higher stock returns. Second, the beliefs about the NR-MP regime, $\hat{p}_{22,t}$, after 2009 closely match the New York Fed's Survey of Primary Dealers in Figure C.8. Consistent with the survey evidence, we find that the probability of staying in the NR-MP regime was below half in 2015.

The bottom panel of Figure 10 computes (14) as functions of the Markov transition probabilities. We want to use this illustrative model to show that, as in the data, the risks of an interest rate hike (drop in $\hat{p}_{22,t}$ or increase in transition probability from the NR-MP to the R-MP regime) could entirely mitigate the effect of good dividend growth shocks (actual data is highlighted by green dots). On the left-hand-side, when the state is R-MP it is evident that $N_{CF,RF,t}$ will be positive (i.e., positive return) only when the probability of remaining in this R-MP state is sufficiently low. Indeed consistent with this intuition, during the post recession years in 2002-03, $N_{CF,RF,t}$ is positive as the extracted $\hat{p}_{11,t}$ is close to zero during those year (top panel). The right hand side in the bottom panel illustrates that for large $\hat{p}_{11,t}$ values $N_{CF,RF}$ can turn negative even for relatively large $\hat{p}_{22,t}$. Loosely speaking, reasonable chances of moving from the NR-MP to R-MP are enough to generate a negative effect. During the post recession year of 2011 when the extracted $\hat{p}_{22,t}$ is close to one and $\hat{p}_{11,t}$ is close to zero, we observe that returns respond positively to good dividend growth shocks. On the other hand, in 2015 when the market perception of a reactive monetary policy substantially increase (that is, the extracted $\hat{p}_{11,t}$ increase immensely) the resulting reaction is negative.

# 4 Asset Pricing Model

The previous section highlights the interaction of cashflow news, monetary policy, and return innovation within a reduced form model. In this section we demonstrate that similar intuition can be extended to a modern dynamic (regime-switching) asset-pricing model, which we calibrate to consumption and interest rate dynamics.

**Real Endowments and Monetary Policy.** We assume that the Federal Reserve can directly control the real rate, $r_t$. The monetary policy rule responds to expected consumption growth and the strength with which the Federal Reserve tries to pursue its goal—a stabilization policy—changes over time. Stabilization policy is "aggressive" or "loose" depending on its responsiveness to consumption fluctuations. We capture this time variation with a regime-switching policy coefficient, $\phi(S_t)$. To generate monetary non-neutrality, we assume that the dynamics of expected consumption growth resembles the standard New Keynesian IS curve:

$$\begin{aligned} x_t &= E_t x_{t+1} - \lambda(S_t) r_t + u_{x,t} \\ r_t &= \phi(S_t) x_t + u_{r,t}. \end{aligned} \tag{15}$$

We impose that $\lambda(S_t) \geq 0$ governs the extent to which the real rate affects expected consumption growth. There are two shocks (both serially correlated) in this economy. One is real endowment (consumption) shock, $u_{x,t}$, and the other is monetary policy shock, $u_{r,t}$. While the individual series follows an AR(1) process, we use a VAR(1) notation to describe the dynamics of

$$\begin{bmatrix} u_{x,t} \\ u_{r,t} \end{bmatrix} = \begin{bmatrix} \rho_x & 0 \\ 0 & \rho_r \end{bmatrix} \begin{bmatrix} u_{x,t-1} \\ u_{r,t-1} \end{bmatrix} + \begin{bmatrix} \sigma_x & 0 \\ 0 & \sigma_r \end{bmatrix} \begin{bmatrix} \eta_{x,t} \\ \eta_{r,t} \end{bmatrix}. \tag{16}$$

The persistence coefficient $\Phi(S_t)$ and standard deviation matrix $\Sigma(S_t)$ may depend on regime. We define Markov transition probability matrix by

$$\Pi = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}.$$

Here, $p_{ji}$ is the probability of changing from regime $i$ to regime $j$, $\forall i, j \in \{1, 2\}$.

By plugging the second equation in (15) to the first equation in (15), the system reduces to a single regime-dependent equation

$$\chi(S_t) x_t = E_t x_{t+1} + \Lambda(S_t) u_t \tag{17}$$

where

$$\chi(S_t) = 1 + \lambda(S_t)\phi(S_t), \quad \Lambda(S_t) = \begin{bmatrix} 1, & -\lambda(S_t) \end{bmatrix}, \quad u_t = \begin{bmatrix} u_{x,t} & u_{r,t} \end{bmatrix}'.$$

**Solution.** There exists a unique bounded regime-dependent linear solutions of the form

$$x_t = \Psi(S_t) u_t \tag{18}$$

for $p_{11} \in [0, 1]$ and $p_{22} \in [0, 1)$ (see Davig and Leeper (2007) for a detailed discussion). The expressions for $\Psi(S_t)$ are given in Appendix E. It suffices to emphasize that $\Psi(S_t)$ depends on the current regime and expectations of monetary policy aggressiveness throughout the future path of the economy.

Table 2: Calibration

| Preference | | Shocks | | Consumption | | Policy | |
|---|---|---|---|---|---|---|---|
| $\delta$ | 0.999 | $\rho_x$ | 0.4 | $\mu_c$ | 0.0016 | $\lambda(1)$ | 0.1 |
| $\psi$ | 1.5 | $\rho_r$ | 0.9 | $\sigma$ | 0.0020 | $\lambda(2)$ | 0.0 |
| $\gamma$ | 8.0 | $\sigma_x$ | 0.0020 | | | $\phi(1)$ | 0.2 |
| | | $\sigma_r$ | 0.0015 | | | $\phi(2)$ | 0.0 |

*Notes:* The model frequency is monthly. The model is calibrated to match the first three moments of annual consumption growth.

**Asset Pricing.** Assume that agents have recursive preferences

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1) r_{c,t+1} \tag{19}$$

where $r_{c,t+1}$ is the return on all invested wealth, $\gamma$ is risk aversion, $\psi$ is intertemporal elasticity of substitution, $\theta = \frac{1-\gamma}{1-1/\psi}$. Suppose that realized consumption growth follows

$$\Delta c_{t+1} = \mu + x_t + \sigma \eta_{t+1} \tag{20}$$

where $x_t$ is defined in (18). Combining (16), (18), (19), and (20), the return on all invested wealth can be expressed by

$$r_{c,t+1} - E_t r_{c,t+1} \approx \kappa_1 A_1(S_{t+1}) \Sigma(S_{t+1}) \eta_{t+1} \tag{21}$$

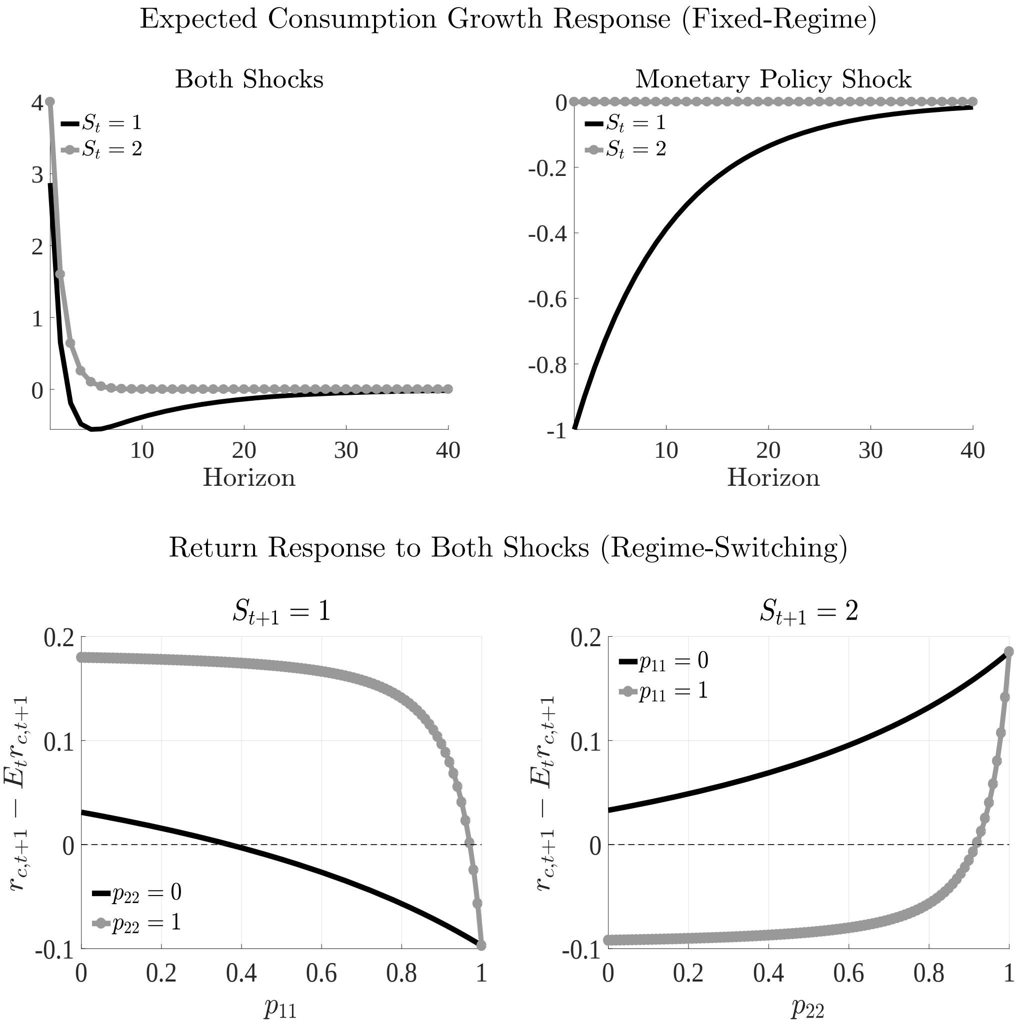
where $\kappa_1$ is the Campbell and Shiller (1988) log linearization constant. The equilibrium solution coefficient $A_1(S_{t+1})$, which describes the dynamics of the price-consumption ratio, is determined by the preference, consumption, and monetary policy parameters and is obtained from

$$E_t(m_{t+1} + r_{c,t+1}) + \frac{1}{2} Var_t(m_{t+1} + r_{c,t+1}).$$

**Model Implication.** The calibrated parameter values are reported in Table 2 and are chosen to broadly capture key moments of consumption growth data and joint interest rate dynamics.[18]. In the second regime, real rate has no bearing on expected consumption growth as indicated by $\lambda(2) = 0$. The monetary policy rule does not respond to expected consumption growth in this regime, $\phi(2) = 0$. To build intuition, we show the impulse responses of expected consumption growth to real endowment $u_{x,t}$ and monetary policy $u_{r,t}$ shocks when regimes are fixed in the first panel of Figure 11. As expected, impulse responses of expected consumption growth to monetary

[18]Note that in the model the autocorrelation of $u_x$ is not the autocorrelation of $x_t$

Figure 11: Response of Returns and Consumption Growth




*Notes:* The first panel provides impulse responses of consumption growth to real endowment and monetary policy shocks. We provide the return response to both real endowment and monetary policy shocks in the second panel. The model has symmetric implications for negative shocks.

policy shock are zero in regime 2. When both shocks are present, they are uniformly higher in regime 1 than in regime 2. The second panel of Figure 11 reveals return responses when both shocks are present. It is interesting to see that the sign of return response depends on agents' beliefs about economic regimes.

## 5 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 a recession with peak sensitivity obtained a year after the recession ensued. 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. The new empirical facts are robust to various measures of stock market returns and combinations of MNAs. Using standard return decomposition into cash flow, risk-free rate, and risk premium news, we show that in fact, the news about future cash flows and risk-free rates are the primary drivers of the cyclical variations. We provide a simple regime-switching model, which is then also extended to a dynamic asset-pricing framework, in which beliefs over the duration of monetary regimes drive the sensitivity of returns to news surprises. The model's qualitative fit to the data highlights that market's beliefs over monetary policy regimes can explain the empirical facts we present in this paper.

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# Appendix

## 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 Appendix Tables

Table B.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 B.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 B.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 | |

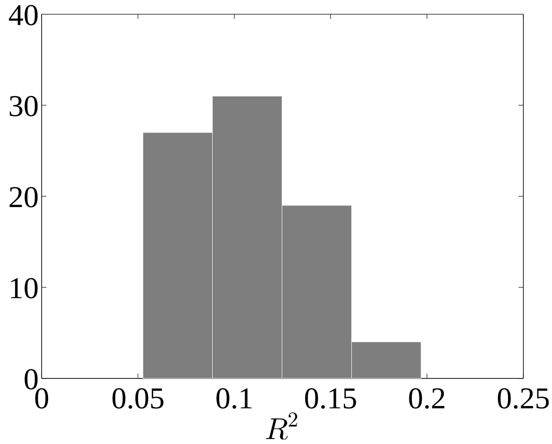
Estimation Sample: 2000-2016

| | 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 $\beta^{\tau}_{SP}$ as the stock market sensitivity, while in the bottom panel, we use $\beta^{\tau}_{ES}$.

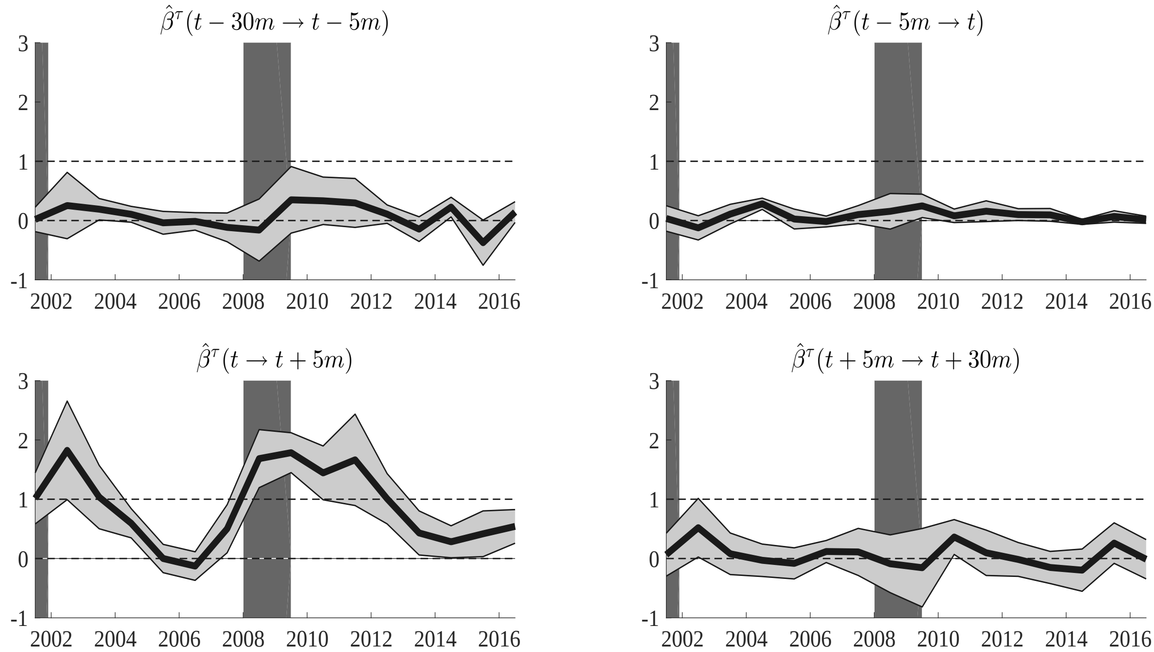
# C Appendix Figures

Figure C.1: $R^2$ from estimating Eqn. (1) for different values of $\Delta_l$ and $\Delta_h$.



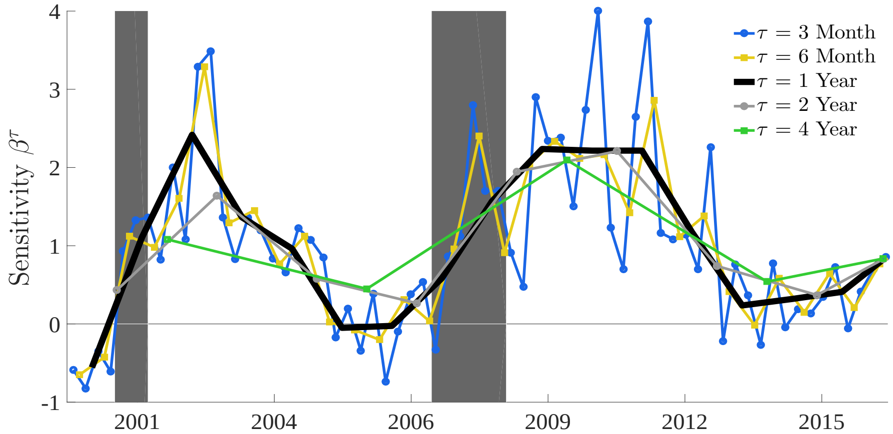

*Notes:* The sample is from January 2000 to December 2016 for the 81 regressions using the top 4 most influential MNAs reported in the main text.

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



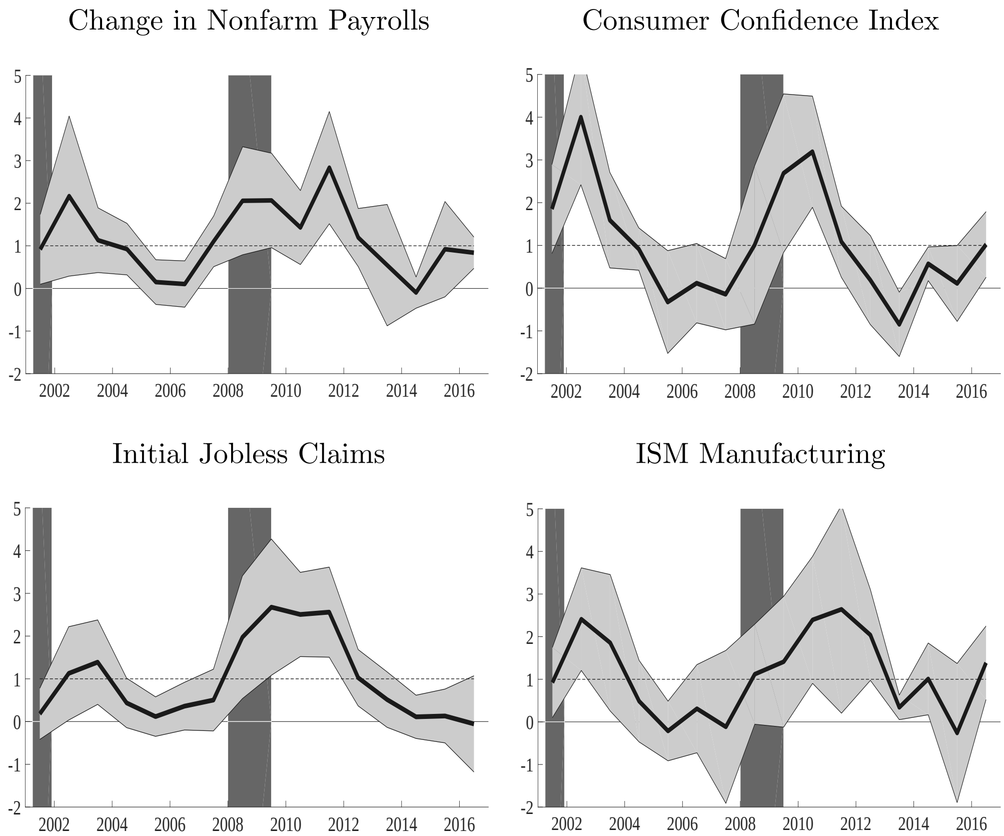

*Notes:* The individual $\hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$ are shown with $\pm 2$ standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$. By construction, the sum of individual $\hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$ equals $\hat{\beta}^\tau$ shown in Figure 4.

Figure C.3: Smoothing Parameter $\tau$ in the Swanson and Williams (2014) Regression



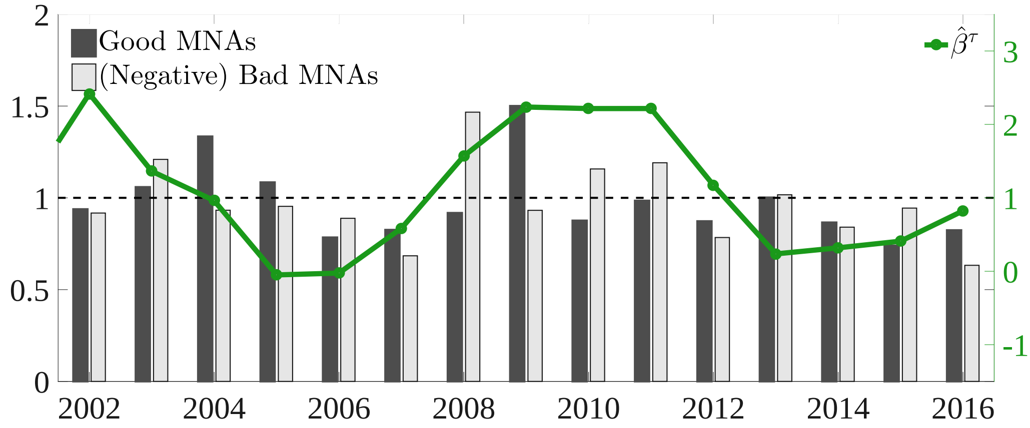

*Notes:* We repeat the estimation by varying the values of smoothing parameter $\tau$. The highest frequency considered in this picture is 3 months and the lowest is 4 years.

Figure C.4: Individual Responses



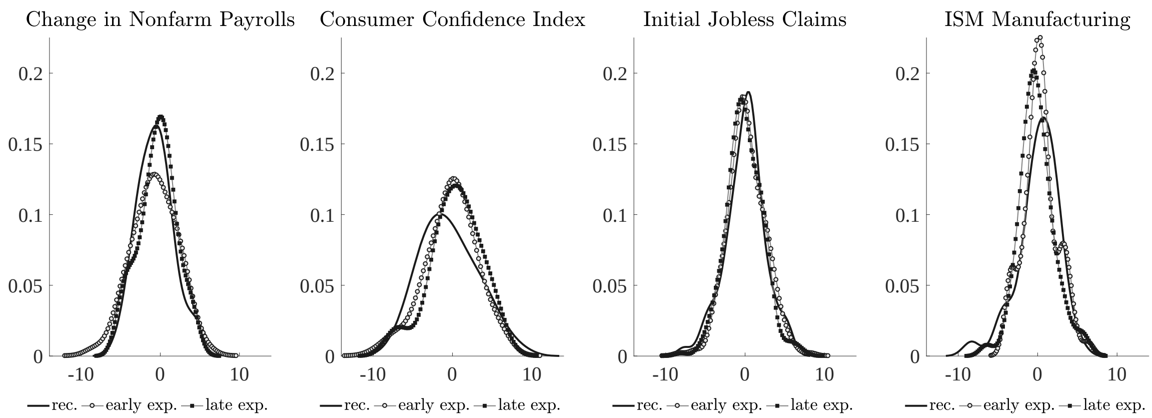

*Notes:* Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30$min. We impose that $\gamma^\tau$ (black-solid line) is on average equal to one. We provide $\pm 2$-standard-error bands (light-shaded area)

Figure C.5: 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 4.

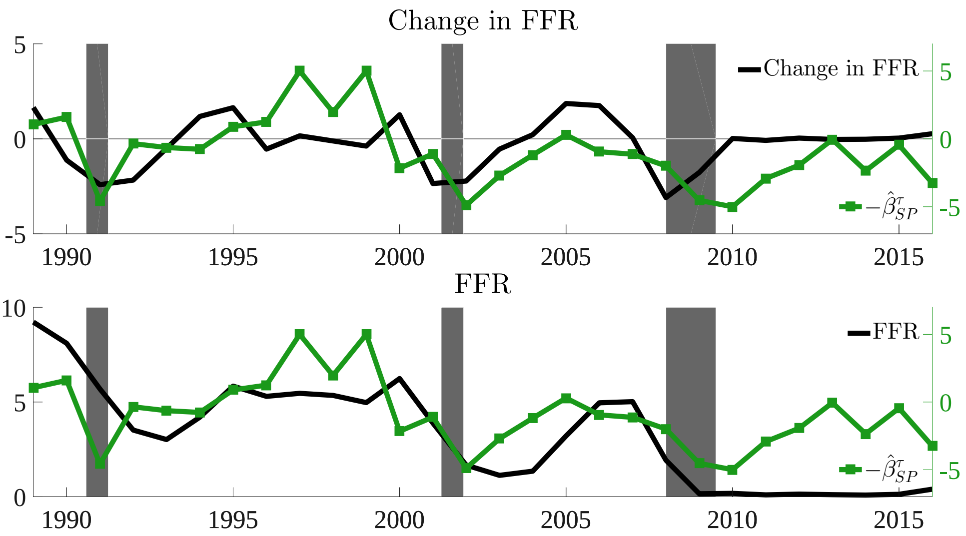
Figure C.6: Distribution of the MNA Surprises




| 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 |

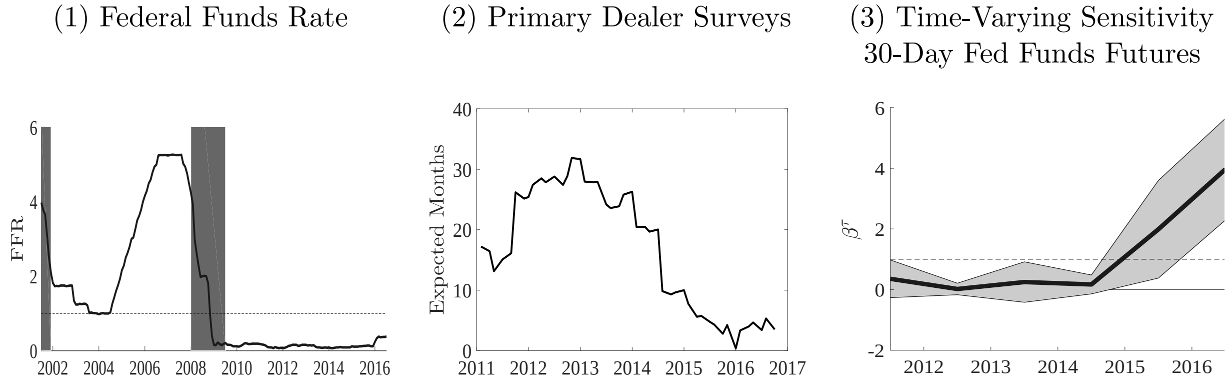
*Notes:* Macroeconomic announcements are Change in Nonfarm Payrolls (NFP), Consumer Confidence Index (CCI), Initial Jobless Claims (IJC), and ISM Manufacturing (ISM). Recession periods correspond to the NBER recession dates. Early expansion periods are 2002-2004 and 2009-2012. Late expansion periods 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 C.7: Stock Market Sensitivity and Interest Rate



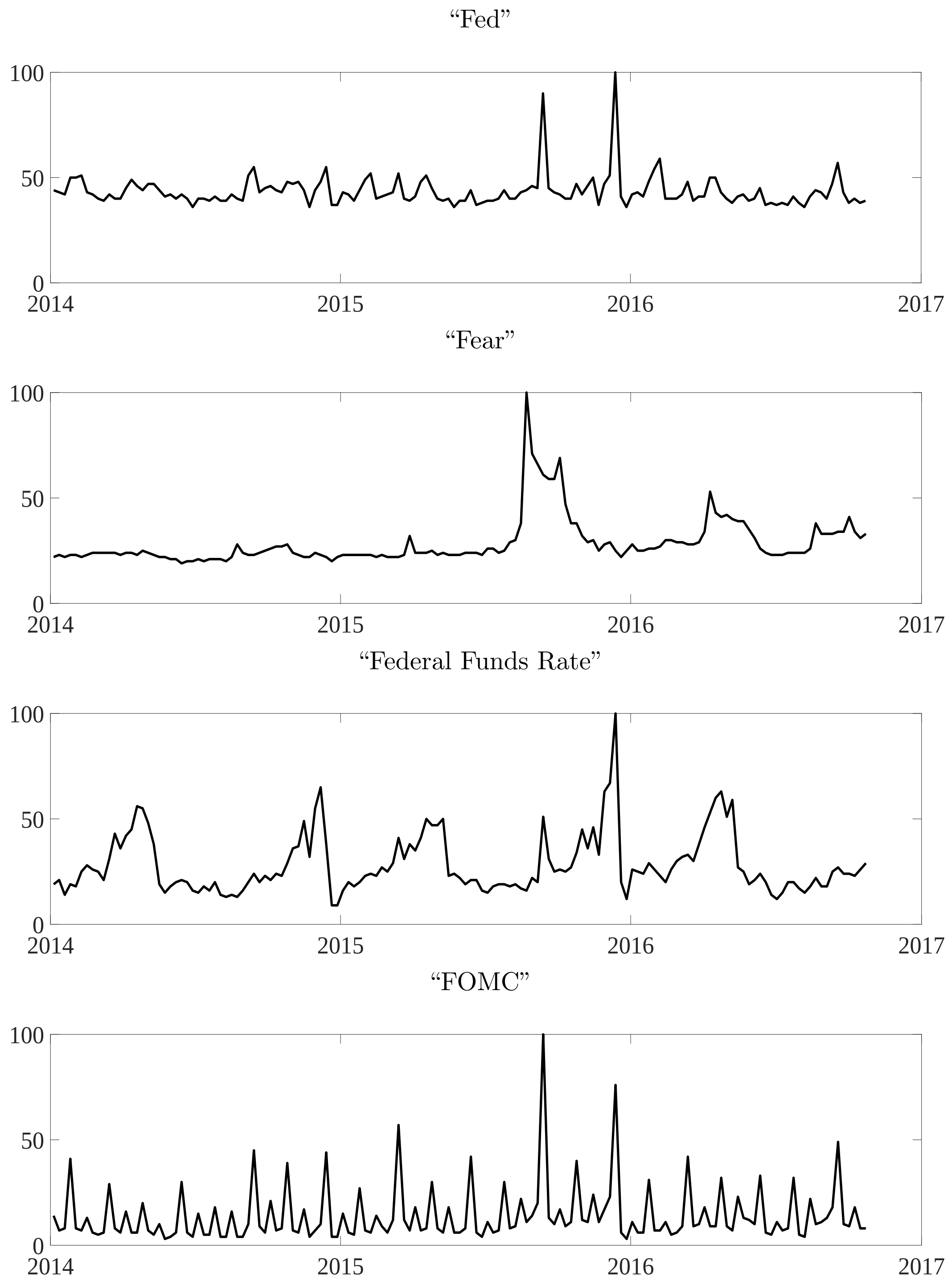

*Notes:* We overlay the (negative) stock market sensitivity obtained from Figure 6 with the annual change in the federal funds rate and with the level of federal funds rate.

Figure C.8: Monetary Policy



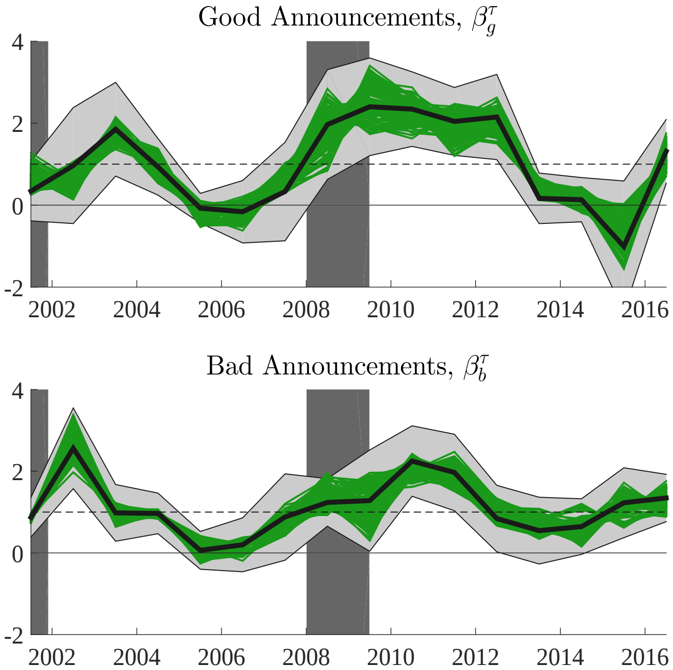

*Notes:* (1) Effective Federal Funds Rate, retrieved from FRED, Federal Reserve Bank of St. Louis. (2) Primary dealers are surveyed on their expectations for the economy, monetary policy and financial market developments prior to Federal Open Market Committee meetings. The actual survey question is "*provide 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 $\beta^{\tau}$ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide $\pm 2$-standard-error bands (light-shaded area) around $\beta^{\tau}$.

Figure C.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`.

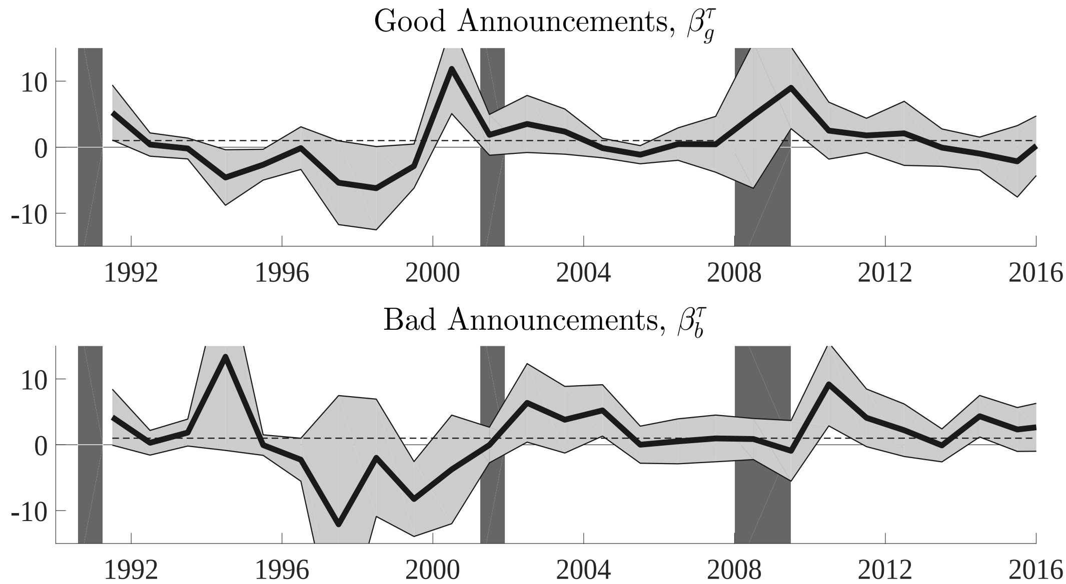
Figure C.10: Time-Varying Sensitivity Coefficients for Stock Returns: Good and Bad Announcements




| MNAs | Good Announcements $\hat{\gamma}^g$ | p-value | Bad Announcements $\hat{\gamma}^b$ | p-value |
|---|---|---|---|---|
| Change in Nonfarm Payrolls | 0.22 | 0.00 | 0.33 | 0.00 |
| Consumer Confidence Index | 0.13 | 0.01 | 0.22 | 0.00 |
| (Negative) Initial Jobless Claims | 0.08 | 0.00 | 0.02 | 0.06 |
| ISM Manufacturing | 0.15 | 0.00 | 0.24 | 0.00 |

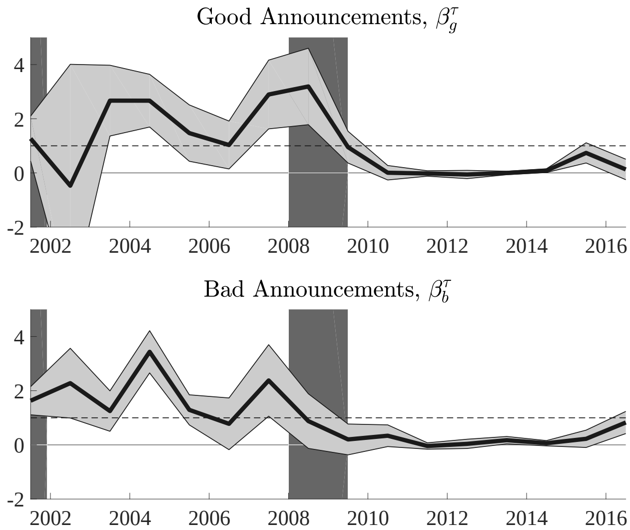
*Notes:* Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30$min. We impose that $\beta_j^\tau$ (black-solid line) is on average equal to one. We provide $\pm$2-standard-error bands (light-shaded area) around $\beta_j^\tau$, $j \in \{g, b\}$. The shape is robust to all possible permutations (green-solid lines) of the window intervals, $\Delta^{l,h} \in \{10min, ..., 90min\}$. In the table, we report the estimates $\hat{\gamma}^g$ and $\hat{\gamma}^b$ from $r_{t-\Delta}^{t+\Delta} = \alpha^\tau + \beta_g^\tau \gamma^g X_t^g + \beta_b^\tau \gamma^b X_t^b + \epsilon_t$ where $\Delta$=30min. We flip the sign of Initial Jobless Claims surprises for ease of comparison across other "good" surprises. Number of observations is 1456. The $R^2$ value is 0.13.

Figure C.11: Time-Varying Sensitivity Coefficients for Stock Returns: Good and Bad Announcements




*Notes:* We restrict the analysis to trading hours. S&P 500 futures (SP) are available from 1991 to 2016. Macroeconomic announcements are Consumer Confidence Index and ISM Manufacturing. We impose that $\beta^\tau$ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide $\pm 2$-standard-error bands (light-shaded area) around $\beta^\tau$.

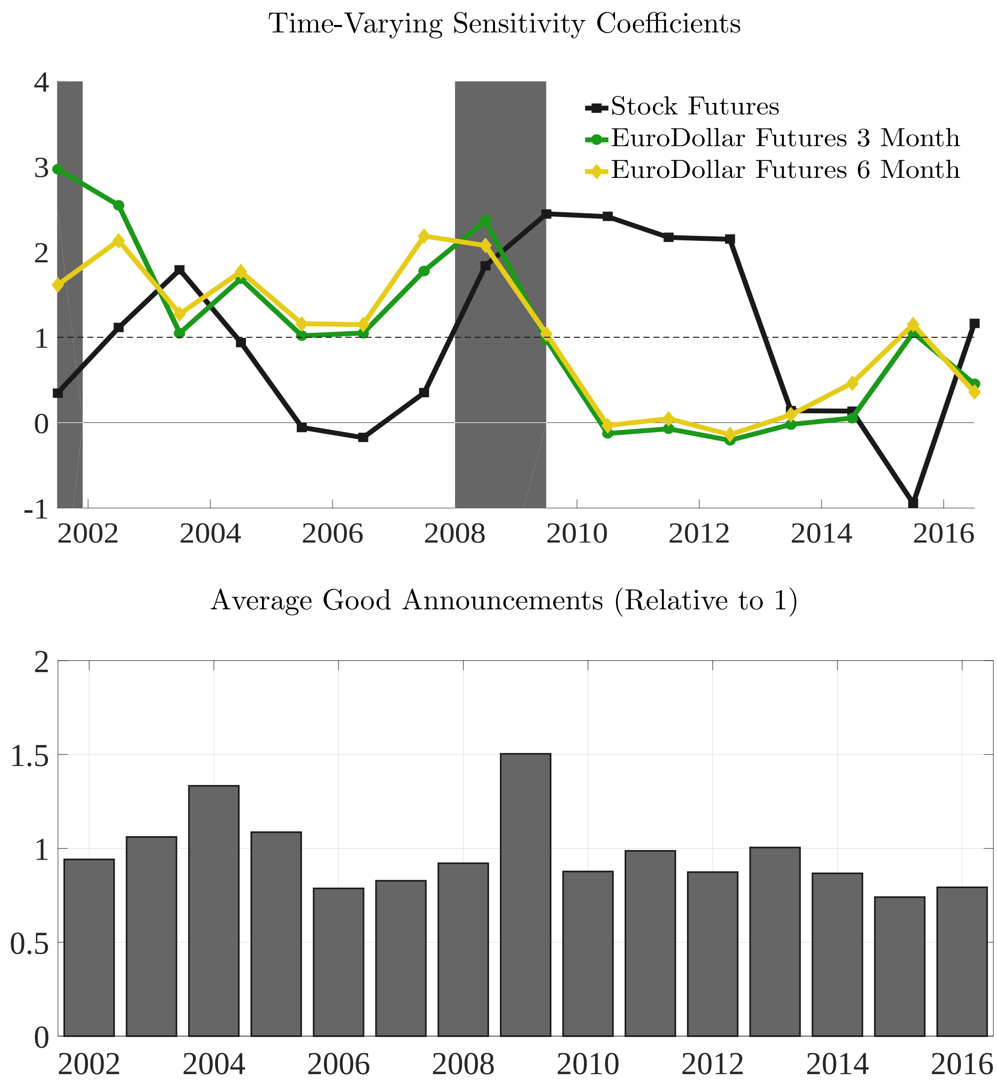
Figure C.12: Time-Varying Sensitivity Coefficient for Eurodollar Futures Returns: Good and Bad Announcements




| MNAs | Good Announcements | | Bad Announcements | |
|---|---|---|---|---|
| | $\hat{\gamma}^g$ | p-value | $\hat{\gamma}^b$ | p-value |
| Change in Nonfarm Payrolls | -0.046 | 0.008 | -0.040 | 0.005 |
| Consumer Confidence Index | -0.004 | 0.003 | -0.016 | 0.003 |
| (Negative) Initial Jobless Claims | -0.008 | 0.002 | -0.006 | 0.002 |
| ISM Manufacturing | -0.010 | 0.003 | -0.022 | 0.005 |

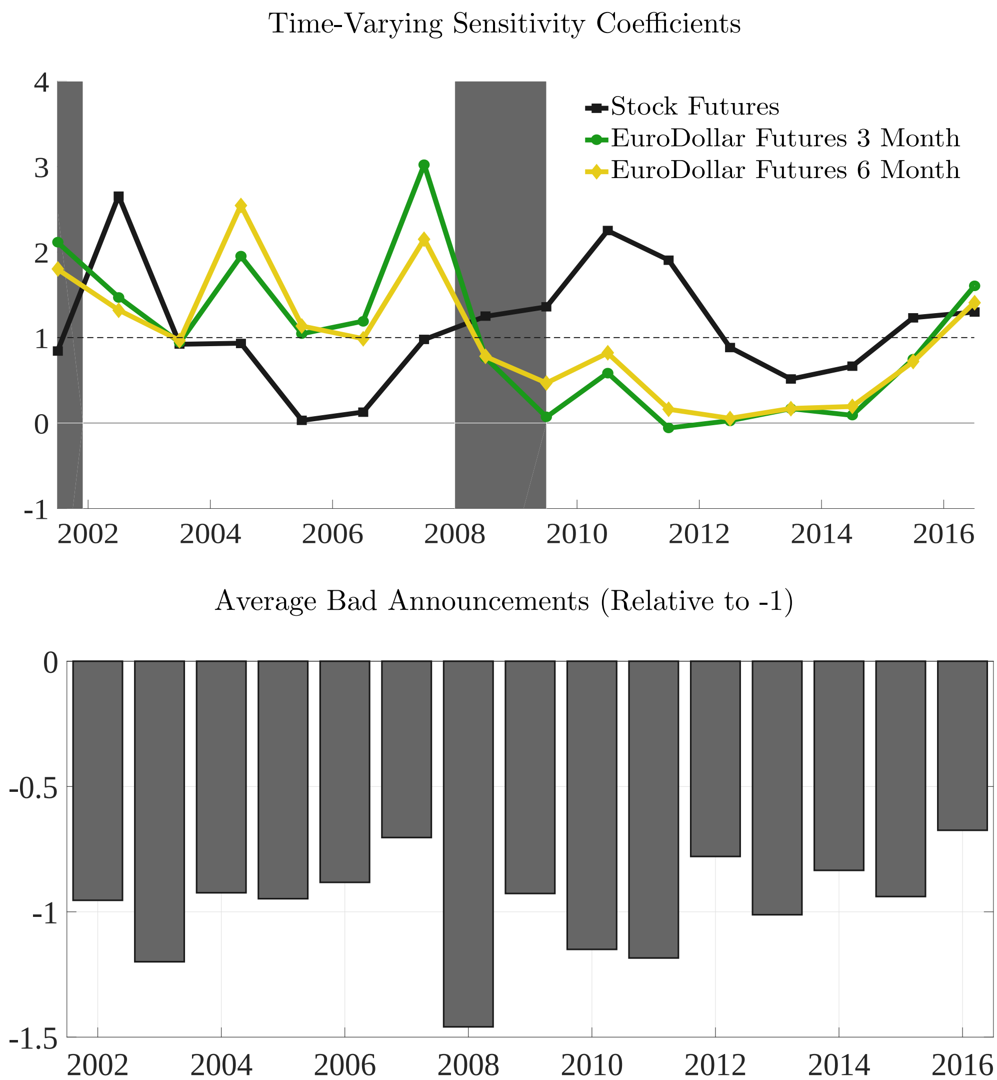
*Notes:* Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that $\beta^\tau$ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide $\pm$2-standard-error bands (light-shaded area) around $\beta^\tau$. In the table, we report the estimates $\hat{\gamma}^g$ and $\hat{\gamma}^b$ from $r_{t-\Delta}^{t+\Delta} = \alpha^\tau + \beta_g^\tau \gamma^g X_t^g + \beta_b^\tau \gamma^b X_t^b + \epsilon_t$ where $\Delta$=30min. We flip the sign of Initial Jobless Claims surprises for ease of comparison across other "good" surprises. Number of observations is 1456. The $R^2$ value is 0.13.

Figure C.13: Time-Varying Sensitivity Coefficients: Good Announcements




*Notes:* Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that $\beta^{\tau}$ (black-solid line) is on average equal to one. We set $\Delta = 30$min.

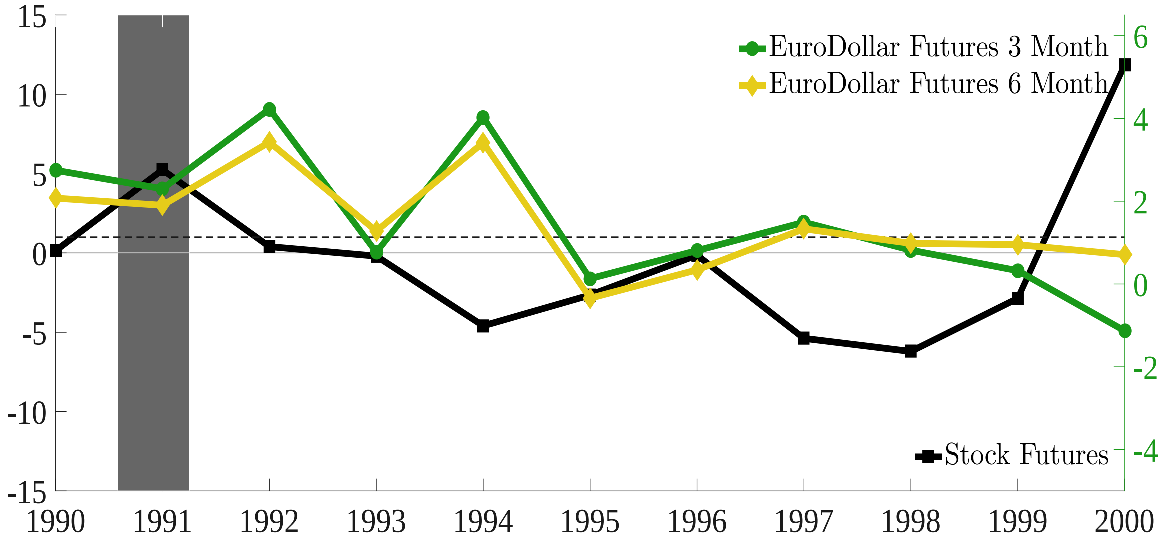
Figure C.14: Time-Varying Sensitivity Coefficients: Bad Announcements



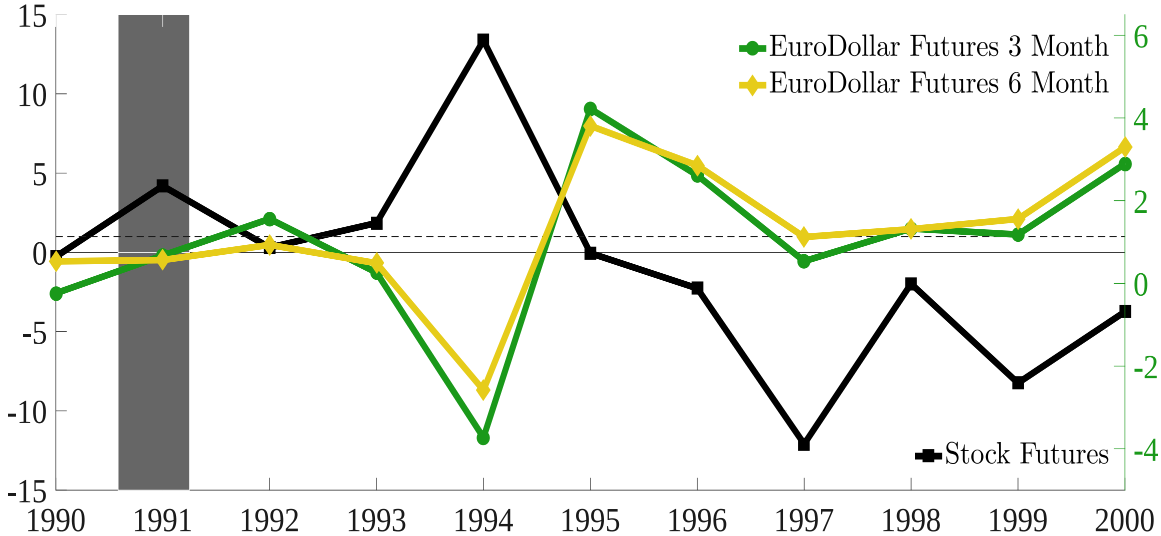

*Notes:* Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that $\beta^{\tau}$ (black-solid line) is on average equal to one. We set $\Delta = 30$min.

Figure C.15: Time-Varying Sensitivity Coefficients: Good and Bad Announcements

In Response to Good MNAs




In Response to Bad MNAs




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

# D News Decomposition under the Regime-Switching Model

Let $S_t$ denote the regime indicator variable, $S_t \in \{1, 2\}$. Define a Markov transition probability matrix by $\Pi$

$$\Pi = \begin{bmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{bmatrix}$$

which summarizes all $2^2$ transition probabilities.

## D.1 $k$ Step ahead Expectations

Any variable $K_{t+1}$ that can be expressed as

$$\begin{aligned} K_{t+1} &= \Lambda_0(S_{t+1}) + \Lambda_1(S_{t+1})X_{t+1} \\ X_{t+1} &= \Phi(S_{t+1})X_t + \Omega(S_{t+1})\Sigma_x(S_{t+1})\eta_{x,t+1}, \quad \eta_{x,t} \sim N(0, I) \end{aligned}$$

has the following k-step-ahead expectation form of

$$\begin{aligned} E(K_{t+k}|S_t) &= \underbrace{E(\Lambda_0(S_{t+k})|S_t)}_{\Lambda_0^{(k)}} + \underbrace{E(\Lambda_1(S_{t+k})\Phi(S_{t+k})\Phi(S_{t+k-1})\ldots\Phi(S_{t+1})|S_t)}_{\Lambda_1^{(k)}} X_t \qquad \text{(A.1)} \\ K_{t+k} &= \Lambda_0(S_{t+k}) + \Lambda_1(S_{t+k})\Phi(S_{t+k})\Phi(S_{t+k-1})\ldots\Phi(S_{t+1})X_t \\ &+ \Lambda_1(S_{t+k})\Omega(S_{t+1})\Sigma_x(S_{t+1})\eta_{x,t+k} \\ &+ \sum_{i=0}^{k-2}\Lambda_1(S_{t+k})\prod_{j=0}^{i}\Phi(S_{t+k-j})\Omega(S_{t+k-i-1})\Sigma_x(S_{t+k-i-1})\eta_{x,t+k-i-1}. \end{aligned}$$

We can characterize the constant and the slope coefficients as

$$\begin{aligned} \Lambda_0^{(k)}(j) &= \begin{bmatrix} \Lambda_0(1) & \Lambda_0(2) \end{bmatrix} \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}^{(k-1)} \times \begin{bmatrix} p_{1j} \\ p_{2j} \end{bmatrix}, \\ \Lambda_1^{(k)}(j) &= \begin{bmatrix} \Lambda_1(1) & \Lambda_1(2) \end{bmatrix} \begin{bmatrix} p_{11}\Phi(1) & p_{12}\Phi(1) \\ p_{21}\Phi(2) & p_{22}\Phi(2) \end{bmatrix}^{(k-1)} \\ &\times \begin{bmatrix} \Phi(1) & 0 \\ 0 & \Phi(2) \end{bmatrix} \begin{bmatrix} p_{1j}\mathbf{I}_2 \\ p_{2j}\mathbf{I}_2 \end{bmatrix}. \end{aligned}$$

The cumulative k-step-ahead expectation is

$$\sum_{i=0}^{k-1} E(K_{t+i}|S_t = j) = \Big(\Lambda_0^{(0)}(j) + \Lambda_0^{(1)}(j) + \ldots + \Lambda_0^{(k-1)}(j)\Big) + \Big(\Lambda_1^{(0)}(j) + \Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k-1)}(j)\Big) X_t. \tag{A.2}$$

## D.2 News and Shock Decomposition

For illustrative purposes, we assume that $S_{t-1} = m$ and $S_t = j$.

$$\begin{aligned}
N_{K,t}^{(k)} &= E_t\Big(\sum_{i=1}^{k} K_{t+i}\Big) - E_{t-1}\Big(\sum_{i=1}^{k} K_{t+i}\Big) \qquad \text{(A.3)}\\
&= E\Big(\sum_{i=1}^{k} K_{t+i}|S_t = j\Big) - E\Big(\sum_{i=1}^{k} K_{t+i}|S_{t-1} = m\Big)\\
&= \Big(\Lambda_0^{(1)}(j) + \ldots + \Lambda_0^{(k)}(j)\Big) + \Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big) X_t\\
&\quad -\Big(\Lambda_0^{(2)}(m) + \ldots + \Lambda_0^{(k+1)}(m)\Big) - \Big(\Lambda_1^{(2)}(m) + \ldots + \Lambda_1^{(k+1)}(m)\Big) X_{t-1}\\
&= \Big(\Lambda_0^{(1)}(j) + \ldots + \Lambda_0^{(k)}(j)\Big) + \Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big)\Big(\Phi(j)X_{t-1} + \Omega(j)\Sigma_x(j)\eta_{x,t}\Big)\\
&\quad -\Big(\Lambda_0^{(2)}(m) + \ldots + \Lambda_0^{(k+1)}(m)\Big) - \Big(\Lambda_1^{(2)}(m) + \ldots + \Lambda_1^{(k+1)}(m)\Big) X_{t-1}\\
&= \Big(\Lambda_0^{(1)}(j) + \ldots + \Lambda_0^{(k)}(j)\Big) - \Big(\Lambda_0^{(2)}(m) + \ldots + \Lambda_0^{(k+1)}(m)\Big)\\
&\quad +\Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big)\Phi(j)X_{t-1} - \Big(\Lambda_1^{(2)}(m) + \ldots + \Lambda_1^{(k+1)}(m)\Big) X_{t-1}\\
&\quad +\Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big)\Omega(j)\Sigma_x(j)\eta_{x,t}\\
&= \Big(\Big\{\Lambda_0^{(1)}(j) - \Lambda_0^{(2)}(m)\Big\} + \ldots + \Big\{\Lambda_0^{(k)}(j) - \Lambda_0^{(k+1)}(m)\Big\}\Big)\\
&\quad +\Big(\Big\{\Lambda_1^{(1)}(j)\Phi(j) - \Lambda_1^{(2)}(m)\Big\} + \ldots + \Big\{\Lambda_1^{(k)}(j)\Phi(j) - \Lambda_1^{(k+1)}(m)\Big\}\Big) X_{t-1}\\
&\quad +\Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big)\Omega(j)\Sigma_x(j)\eta_{x,t}
\end{aligned}$$

denotes the news.

$$\begin{aligned}
\varepsilon_{K,t} &= K_t - E\big(K_t|S_{t-1}\big) \qquad \text{(A.4)}\\
&= \Lambda_0(j) + \Lambda_1(j)X_t - \Lambda_0^{(1)}(m) - \Lambda_1^{(1)}(m)X_{t-1}\\
&= \Lambda_0(j) + \Lambda_1(j)\Big(\Phi(j)X_{t-1} + \Omega(j)\Sigma_x(j)\eta_{x,t}\Big) - \Lambda_0^{(1)}(m) - \Lambda_1^{(1)}(m)X_{t-1}\\
&= \Big(\Lambda_0(j) - \Lambda_0^{(1)}(m)\Big) + \Big(\Lambda_1(j)\Phi(j) - \Lambda_1^{(1)}(m)\Big)X_{t-1} + \Lambda_1(j)\Omega(j)\Sigma_x(j)\eta_{x,t}
\end{aligned}$$

denotes the shocks.

If $S_{t-1} = j$ and $S_t = j$, we can express $N_{K,t}^{(k)}$ and $\varepsilon_{K,t}$ by

$$\begin{aligned}
N_{K,t}^{(k)} &= \Big(\Big\{\Lambda_0^{(1)}(j) - \Lambda_0^{(2)}(j)\Big\} + \ldots + \Big\{\Lambda_0^{(k)}(j) - \Lambda_0^{(k+1)}(j)\Big\}\Big) \qquad \text{(A.5)}\\
&\quad + \Big(\Big\{\Lambda_1^{(1)}(j)\Phi(j) - \Lambda_1^{(2)}(j)\Big\} + \ldots + \Big\{\Lambda_1^{(k)}(j)\Phi(j) - \Lambda_1^{(k+1)}(j)\Big\}\Big)X_{t-1}\\
&\quad + \Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big)\Omega(j)\Sigma_x(j)\eta_{x,t}\\
&\approx \Big(\Lambda_1^{(1)}(j) + \ldots + \Lambda_1^{(k)}(j)\Big)\Omega(j)\Sigma_x(j)\eta_{x,t},\\
\varepsilon_{K,t} &= \Big(\Lambda_0(j) - \Lambda_0^{(1)}(j)\Big) + \Big(\Lambda_1(j)\Phi(j) - \Lambda_1^{(1)}(j)\Big)X_{t-1} + \Lambda_1(j)\Omega(j)\Sigma_x(j)\eta_{x,t}\\
&\approx \Lambda_1(j)\Omega(j)\Sigma_x(j)\eta_{x,t}.
\end{aligned}$$

# E Solution of the Asset Pricing Model

The solutions are

$$\Psi_k(i) = \Psi_k^F(i)\Bigg(\frac{\Lambda_k(j) + \Phi_{kk}(j)p_{ji}\Psi_k^F(j)}{\Lambda_k(i)\Lambda_k(j) - p_{ij}p_{ji}\Phi_{kk}(i)\Phi_{kk}(j)\Psi_k^F(i)\Psi_k^F(j)}\Bigg), \quad i,j,k \in \{1,2\}.$$

For ease of understanding, we express the regime-switching coefficient, $\Psi_k(i)$, as function of the fixed-regime coefficient,

$$\Psi_1^F(i) = \frac{1}{(1+\lambda(i)\phi(i)) - p_{ii}\Phi_{11}(i)}, \quad \Psi_2^F(i) = \frac{-\lambda(i)}{(1+\lambda(i)\phi(i)) - p_{ii}\Phi_{22}(i)}.$$

For illustration, we focus on the first coefficient. Aggressive monetary policy raises $\phi$ and decreases the impact of real endowment shocks on expected consumption growth. Greater persistence amplifies the impact of real endowment shocks on expected consumption growth. When the real endowment shock is serially uncorrelated $\Phi_{11} = 0$, the solution collapses to its fixed-regime counterpart, $\Psi_1(i) = \Psi_1^F(i)$. The interpretation of the second coefficient, loading on monetary policy shock, is analogous to the first case except that its sign is negative.

The key feature is that expectations of policy behavior in regime 2 affect the equilibrium in regime 1 and vice versa. Denote the denominator

$$D_k = \Lambda_k(i)\Lambda_k(j) - p_{ij}p_{ji}\Phi_{kk}(i)\Phi_{kk}(j)\Psi_k^F(i)\Psi_k^F(j).$$

$D_k$ reaches its upper bound whenever regimes are absorbing states $p_{ij} = 0$. For all values of $p_{ij} \neq 0$, $D_k$ scales up the coefficients relative to their fixed-regime counterparts. In the limiting case $p_{ij} = 1$, $D_k$ raises the variability of expected consumption growth to its maximum amount. There are two distinct effects that real endowment shock has on expected consumption growth, which are highlighted in the numerator. The first is the fixed-regime effect and real endowment shock directly raises expected consumption growth by an amount inversely related to monetary policy coefficient $\phi$. The second effect is the expectations formation effect. The term $p_{ji}\Psi_k^F(j)$ arises from the expectation that regime switch can happen, with $p_{ji}$ the probability of changing from regime $i$ to regime $j$.[19]

[19] The intuition is from Davig and Leeper (2007).