

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 recession. 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 returns. The 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

Interpreting the tone of macroeconomic news announcements (MNAs) and the direction of the stock market's response is challenging. Depending on the state of the economy, better-than-expected MNA surprises that push prices up through higher expected future cash flows might instead bring them down via expected future interest rate hikes as a result of stabilization policy. More generally, how stock prices respond to news can change with risk conditions, economic phase, and, policy reaction (e.g., McQueen and Roley (1993), Flannery and Protopapadakis (2002), Boyd, Hu, and Jagannathan (2005) and Andersen, Bollerslev, Diebold, and Vega (2007)). We follow this line of research by characterizing the time-varying response of stock prices to MNA surprises and relating the stock response to expectations about monetary policy.

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 MNA surprises with the nonlinear regression method used in Swanson and Williams (2014). First, we establish that the sensitivity of stock prices to MNA surprises is cyclical and time varying. The sensitivity of stock prices to 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 4 to 5 years with the recovery taking about the same amount of time. At trough sensitivity, stock prices generally do not react to MNA surprises. Second, the sensitivity of short-term interest rate futures to MNA surprises moves in lock-step but in the opposite direction as that of stock prices'. These two robust facts persist when we extend our analysis to data beginning 1990 which encompass three recessions.

To shed light on the mechanism at work, we first present a novel state space approach to examine the informational content of MNA surprises. Following Campbell (1991), we write unexpected stock returns as the sum of news about cash flows, news about the risk-free rate, and news about risk premium. 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. By directly measuring the contribution of variance premium news, we find that news concerning cash flows and the risk-free rate mostly explain the sensitivity pattern we observe in the data.

After narrowing down the informational content of MNA surprises to news about cash flows and/or news about risk-free rates, we propose a simple regime-switching dividend growth model to 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

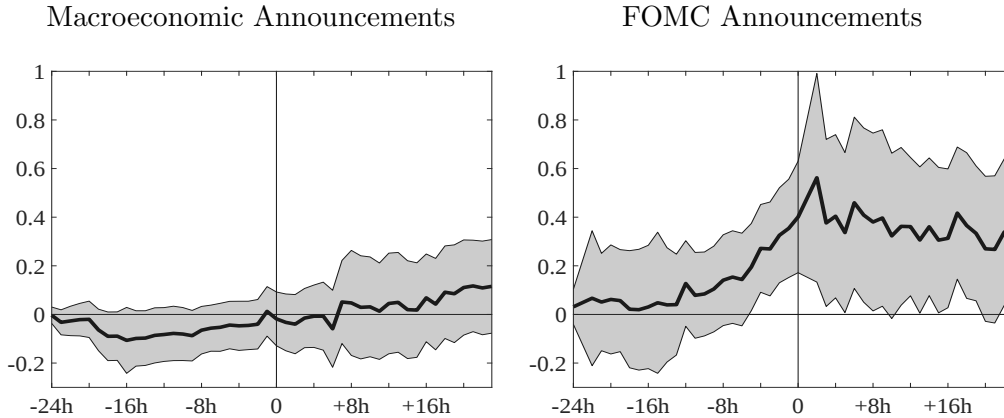
features two distinct economic regimes. In the “Reactive Monetary Policy (R-MP)” regime, positive dividend growth shocks can increase both future dividend growth and future interest rates. In this regime, high interest rates slow down future dividend growth. In the “Non-Reactive Monetary Policy (NR-MP)” 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 incurring an interest rate hike. Finally, we assume that time varying Markov transition probabilities governs 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 we observe in the data. We interpret these transition probabilities to reflect beliefs about the duration of the economic regimes at each point in time. We interpret the underlying mechanism through the lens of this simple model. 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., we stay 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 response observed in the data.

1.1 Literature Review

Earlier literature, such as Chen, Roll, and Ross (1986) and Chan, Karceski, and Lakonishok (1998), highlight a glaring disconnect between the stock market and macroeconomic conditions. Since then, 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.

Figure 1: Cumulative Stock Returns Around Scheduled Announcements.



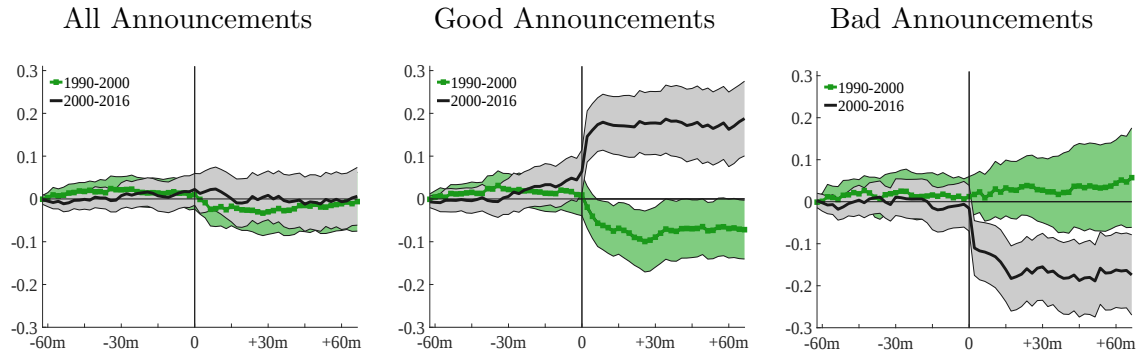
Notes: We plot the average cumulative stock returns in percentage points around scheduled announcements. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, ISM Manufacturing and Initial Jobless Claims. The black solid lines are the average cumulative return on S&P 500 E-mini futures on a day prior to scheduled announcements to a day after scheduled announcements. The light-gray shaded areas are ± 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.

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

However, once the MNA surprises are analyzed at a higher frequency and are conditioned on whether they are positive or negative, a very significant impact on prices is observed. In Figure 2, we plot the cumulative stock returns starting from an hour before macroeconomic announcements to an hour after the announcements. Three distinctive patterns emerge. First, even at an hourly interval, it is hard to find any statistically significant pattern for stock returns (first panel of Figure 2) when positive and negative announcements are grouped. Second, the reaction of stock prices, on the other hand, can be much more precisely measured when announcements are separated into positive and negative announcements (second and third panels of Figure 2).

¹In 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 Federal Open Market Committee (FOMC) decisions.

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 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 ± 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.

The average impact of MNA surprises is about 20 basis points which is 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. Third, there is strong evidence of time variation in the reaction of stock prices for example, when the sample is split into pre- and post-2000. 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 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 emphasizes the importance of accounting for time variation in understanding the relationships between MNA surprises and stock prices, which cannot be addressed in the context of event study analyses.

More generally, our paper can be linked to a large literature that studies asset price responses to monetary policy rate decisions, for example, Cochrane and Piazzesi (2002), Rigobon and Sack (2004), Bernanke and Kuttner (2005), and Bekaert, Hoerova, and Lo Duca (2013) among others. Neuhierl and Weber (2016) document that monetary policy affects stock prices outside of the scheduled FOMC announcements as predicted by Bernanke and Kuttner (2005).

The remainder of this paper is organized as follows. Section 2 describes the data, regression methods, selection of macroeconomic announcements, and discusses empirical findings. Section 3 illustrates the mechanism. Section 4 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 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 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 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 allows us to capture the effect of announcements that takes 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 Regression Analysis

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

$$r_{t-\Delta_l}^{t+\Delta_h} = \alpha + \gamma X_t + \epsilon_t. \quad (1)$$

The results depends on the size of the return window interval.³ We consider all combinations of Δ_l and Δ_h between 10 minutes and 90 minutes in increments of 10 minutes (81 regressions in total). Table 1 tabulates the number of regressions in which equity returns significantly respond to a specific MNAs at the 99% confidence interval. For instance, the Unemployment Rate surprise is significant in 23.46% (19 of 81) of these regressions. We use many combinations of the return window precisely because the significance of MNAs depends on the size of the return window, see for example, Andersen, Bollerslev, Diebold, and Vega (2003) and Bartolini, Goldberg, and

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

³Bollerslev, 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

MNAs	Count	Percent	Average p-value
Change in Nonfarm Payrolls	81	100.00 %	0.00
Consumer Confidence Index	81	100.00 %	0.00
Initial Jobless Claims	81	100.00 %	0.00
ISM Manufacturing	81	100.00 %	0.00
Durable Goods Orders	72	88.89 %	0.00
CPI MoM	70	86.42 %	0.01
Retail Sales Advance MoM	63	77.78 %	0.01
GDP Annualized QoQ	51	62.96 %	0.07
ISM Non-Manf. Composite	43	53.09 %	0.05
Construction Spending MoM	22	27.16 %	0.03
Unemployment Rate	19	23.46 %	0.18
Industrial Production MoM	17	20.99 %	0.21
New Home Sales	5	6.17 %	0.50
Leading Index	1	1.23 %	0.45
Capacity Utilization	0	0.00 %	0.52
Factory Orders	0	0.00 %	0.31
Housing Starts	0	0.00 %	0.50
PPI Final Demand MoM	0	0.00 %	0.47
Personal Income	0	0.00 %	0.73
Trade Balance	0	0.00 %	0.25

Notes: The sample is from January 2000 to December 2016 for the 81 regressions described in the main text. “Count” refers to the number of regressions in which returns significantly responds the MNA at the 99% confidence interval. Percent is Count/81. Average p-value is the average two-sided p-value across all 81 regressions.

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 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 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 Δ_l and Δ_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 $\Delta = 30\text{min}$. This symmetric window yields an R^2 value of 0.13 which is representative of the distribution in Figure C.1. We emphasize that our results are maintained across all 81 combinations of Δ_l and Δ_h .

Time-Varying Sensitivity of the Stock Returns to Macroeconomic News. Having fixed $\Delta = 30\text{min}$ and restricted the set of MNAs to the top four most influential MNAs, we now turn our attention to measuring the time-varying sensitivity of the returns to macroeconomic news. To do this, we estimate the following nonlinear regression over τ -period rolling windows as in Swanson and Williams (2014)

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

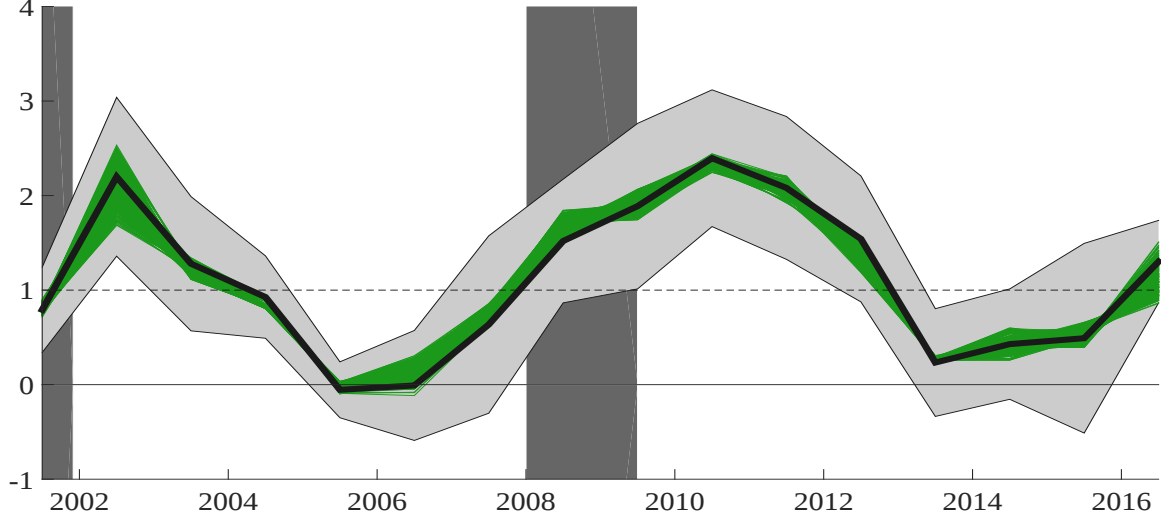
where ϵ_t is a residual representing the influence of other news and other factors on stock returns at time t . α^τ and β^τ are scalars that are allowed to change over the τ period. The underlying assumption is that while the relative magnitude of γ is constant, the magnitude of β^τ varies as the stock returns become more or less affected over time. Put differently, we expect that the stock return responsiveness to all MNAs to shift by a roughly proportionate amount. We let τ index the calendar year. The identification assumption is that β^τ is on average equal to one. This implies that $\beta^\tau \gamma X_t$ is identical to its OLS counterpart γX_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 β^τ .

Figure 3 provides the estimates of the time-varying sensitivity coefficient β^τ (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.⁴

We find strong evidence of persistent cyclical variation in stock market responses to MNAs. The evidence suggests that the sensitivity of stock returns to MNAs can increase by a factor

⁴The sum of possible combination of eight MNAs is $\sum_{i=0}^8 \binom{8}{i} = 256$.

Figure 3: Time-Varying Sensitivity Coefficient for Stock Returns

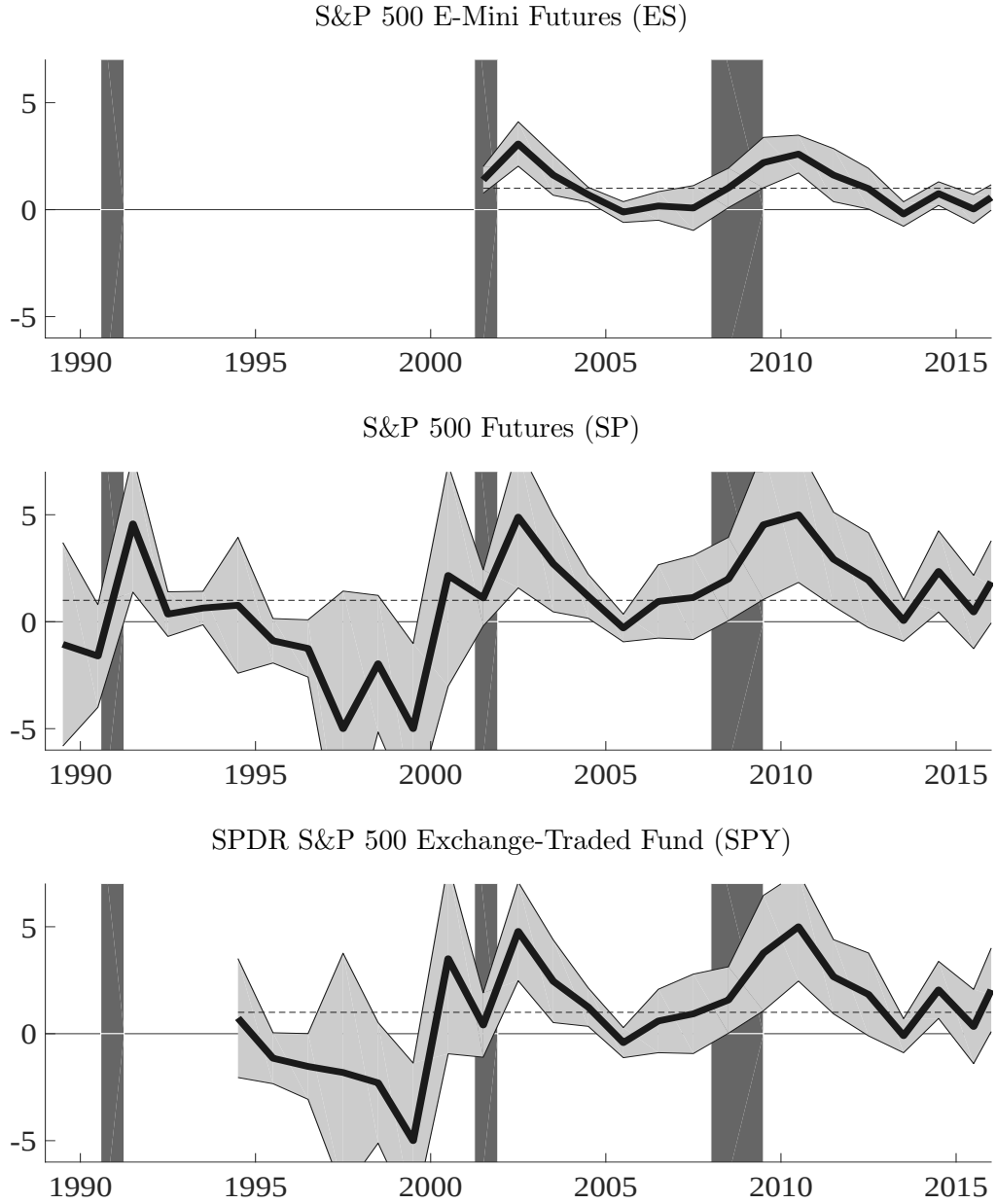


Notes: The top four MNAs from Table 1 are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that β^τ (black-solid line) is on average equal to one. We set $\Delta = 30\text{min}$. We provide ± 2 -standard-error bands (light-shaded area) around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

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 zero lower bound (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 MNAs.

Robustness Checks. Figure C.2 shows that our results are robust to different smoothing parameter values τ . We also relax the assumption that the stock return responsiveness to all MNA surprises to shift by a roughly proportionate amount. This amounts to removing the common β^τ structure in (2) and replacing with individual γ^τ . Figure C.3 shows that the stock return responsiveness is qualitatively similar across individual MNAs. One might suspect that time variation in the stock market sensitivity is primarily driven by time variation in MNA surprises. Figure C.4 overlays the normalized annual averages of good and bad MNA surprises with the estimated time-varying sensitivity coefficient β^τ in Figure 3. We provide 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 confirms that time variation in β^τ cannot be fully attributable to time variation in MNA surprises.

Figure 4: Time-Varying Sensitivity Coefficient for Stock Returns: 10am Announcements



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

We extend the sample to the 1990s and examine if 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. MNAs considered in this exercise are Consumer Confidence Index and ISM Manufacturing. We use the survey data from Money Market Service (MMS) to construct surprises. We do it because survey forecasts are available from early 1980s in MMS while they are only available after 1997 in Bloomberg. By changing both left-hand side and right-hand side variables in the high-frequency regression, we aim to further provide robustness to our main finding.

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. 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 4 that our empirical findings are robust across various return measures, surprise measures, and different periods.⁵

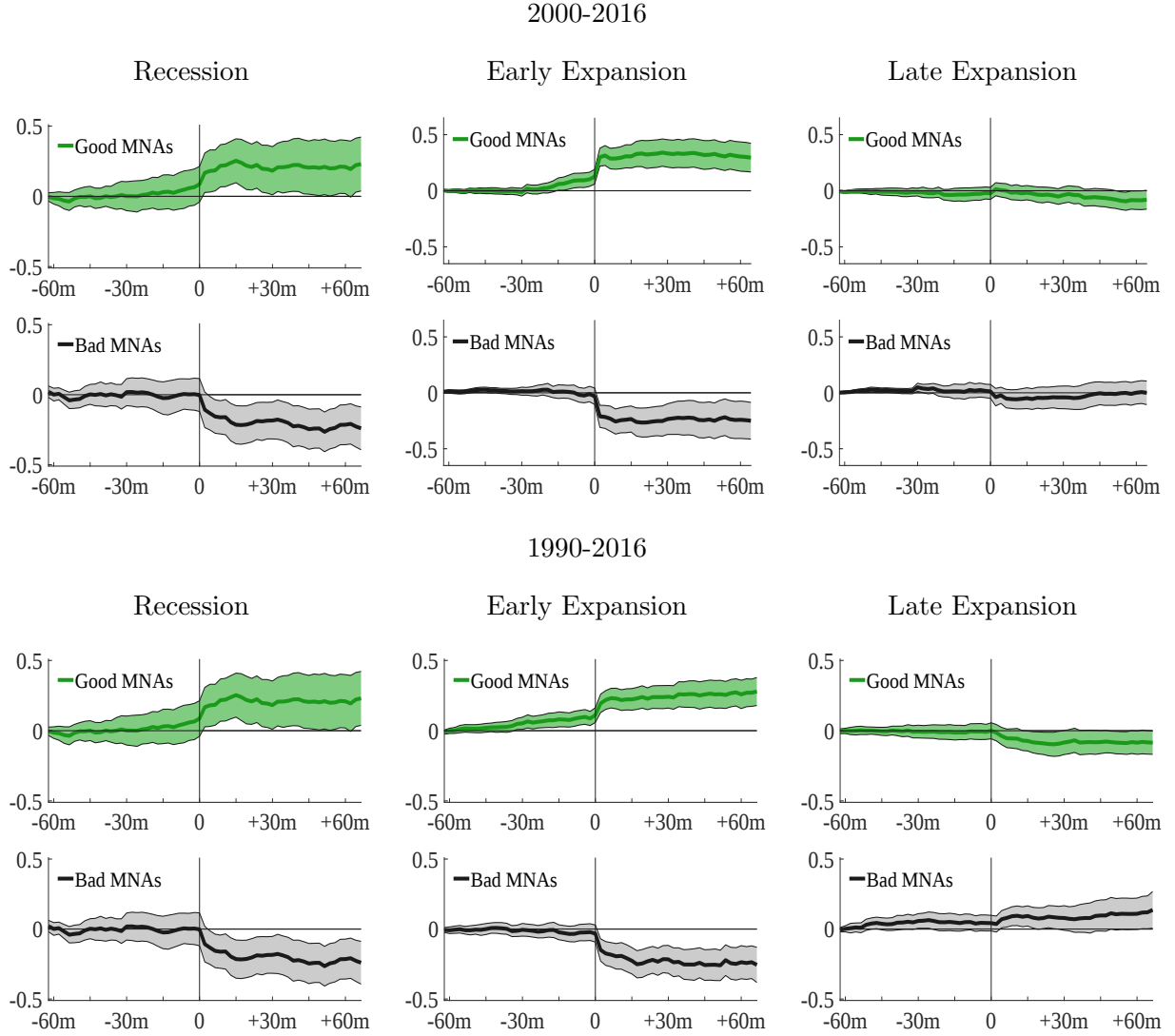
Decomposition into Good and Bad Macroeconomic News Announcements. We have shown that the stock market response to MNAs varies over the business cycle. Especially, the stock price responses in the early part of expansion (including recession) and the late part of expansion are remarkably different. Based on Figure 3 and Figure 4, 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 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.⁶ To use the long sample, we use Consumer Confidence Index and ISM Manufacturing in our analysis.

Figure 5 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. 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 expansions. Yet, during late expansions, we find that stock prices actually went up in response to bad MNAs in the 1990s. This pattern disappears when we restrict to post-2000 sample, that is, bad MNAs in general drive down stock prices. By decomposing economic phases into recessions, early expansions, and late

⁵We can infer from Figure 4 that the sign-switching pattern in Figure 2 is mostly caused by mid- to late-1990s samples.

⁶We 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 5: Cumulative Stock Returns Around Macroeconomic Announcements

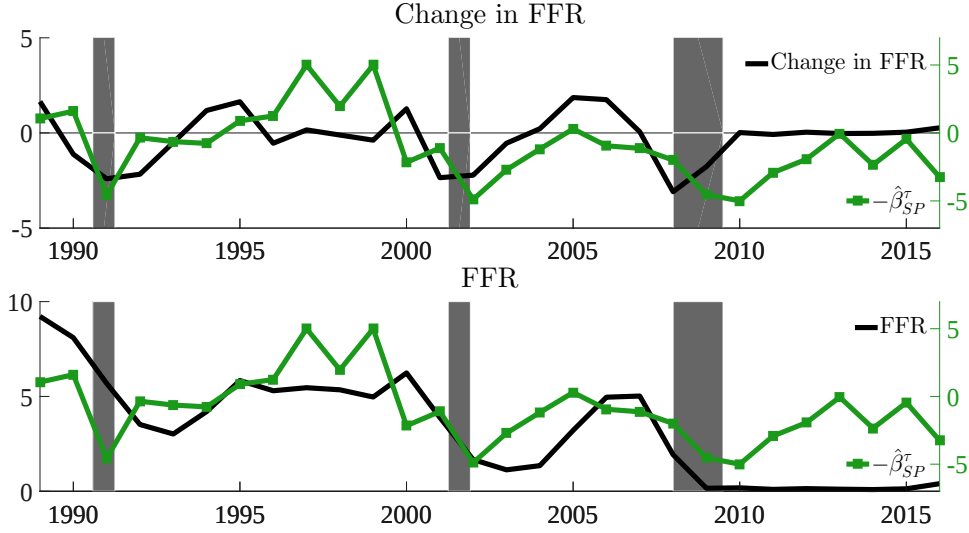


Notes: We plot the average cumulative stock returns around scheduled announcements (Consumer Confidence Index and ISM Manufacturing). We pick macroeconomic announcements that are available from early 1990s. Good (Bad) announcements are positive (negative) surprises. Recession periods correspond to NBER 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, we are able to systematically characterize the return responses.

Stock Market Reaction and Interest Rate. The estimated β^τ s in Figure 3 and Figure 4 provide the empirical measure of stock market sensitivity to MNAs. To better understand the

Figure 6: Stock Market Sensitivity and Interest Rate

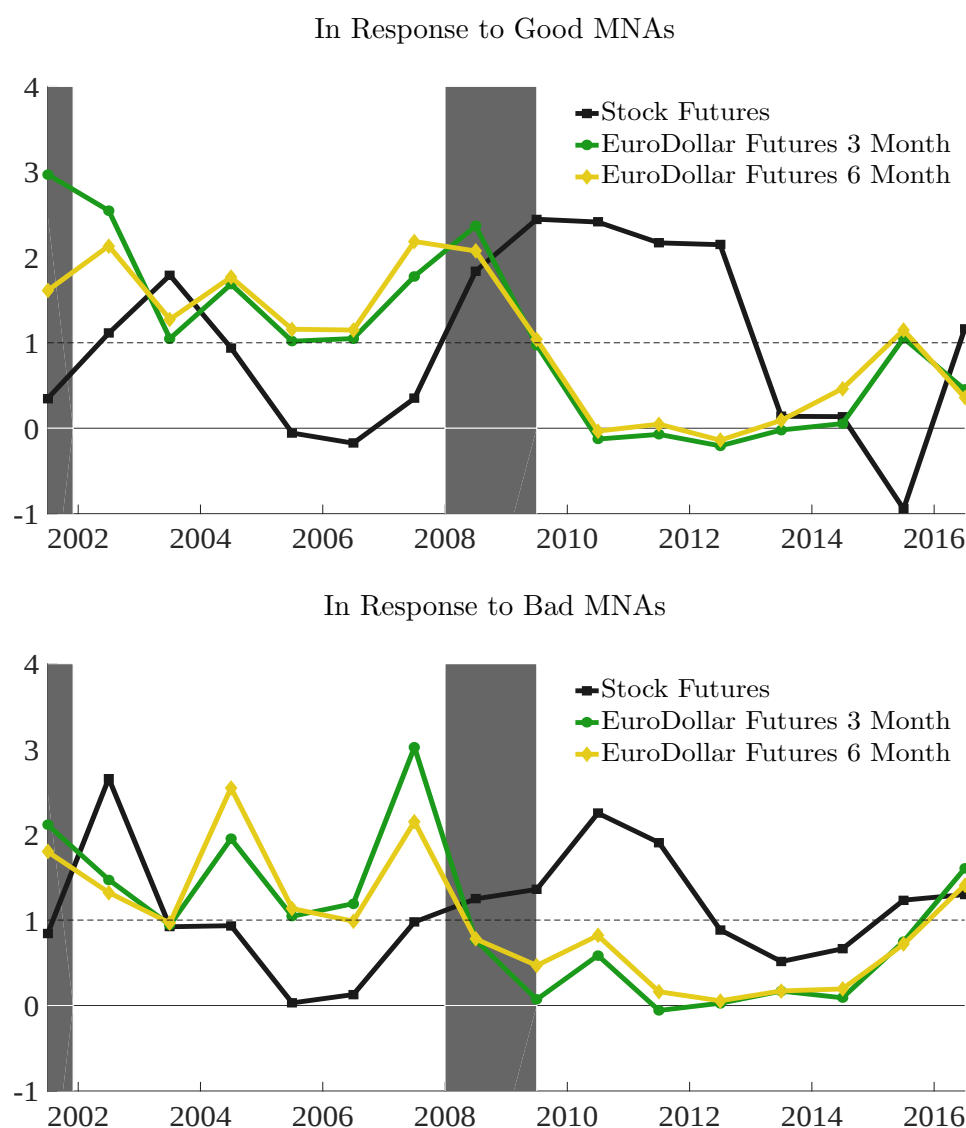


Notes: We overlay the (negative) stock market sensitivity obtained from Figure 4 with the annual change in the federal funds rate and with the level of federal funds rate.

relationship between stock market sensitivity and monetary policy, we overlay the (negative) stock market sensitivity with the annual change in the federal funds rate and with the level of federal funds rate in Figure 6. We then perform a regression analysis using federal funds rate and its annual change as regressors. 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 stock market sensitivity. The associated slope coefficients are significantly negative. This is consistent with 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.

Stock Market Reaction and the Expectations of Monetary Policy. We believe that the cyclical variations in the stock market's response to MNA surprises reflect the market expectations of monetary policy. As external validity check, we provide the time-varying sensitivity of Eurodollar futures to MNAs in Figure 7. Eurodollar futures are known to be closely related to market expectations about the federal funds rate. 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 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 7. 2015 was the period in which there was profound

Figure 7: Stock Market Reaction and Expectations about Monetary Policy



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

interest in the possibility of a rate hike by the Federal Reserve.⁷ Note that the interest rate sensitivity was above-average for the first time since the zero-lower-bound (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

⁷An examination of the minutes of FOMC from 2014 confirms that a rate hike was impending. We also provide compelling supportive evidence in Figure C.5 and Figure C.6.

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. Our findings persist when we extend our analysis to data beginning 1990 which are provided in Figure C.12.

3 Return Decomposition

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

Return Decomposition. Following Campbell (1991), we relate the unexpected stock return in period $t + 1$ to news about cash flows (dividends) and news about future returns

$$r_{t+1} - E_t r_{t+1} \approx (E_{t+1} - E_t) \left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \right) - (E_{t+1} - E_t) \left(\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \right) \quad (3)$$

where ρ is the approximating constant based on the average of the price dividend ratio. (3) is an accounting identity. An increase in expected future dividend growth (returns) is associated with a capital gain (loss) today. We assume that the unexpected stock return can be further decomposed into news about cash flows by N_{CF} , news about risk-free rate by N_{RF} , and news about risk premium by N_{RP} . Put together,

$$r_{t+1} - E_t r_{t+1} \approx N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}. \quad (4)$$

To facilitate the decomposition of (4), we look for empirical proxies for $N_{CF,t}$, $N_{RF,t}$, and $N_{RP,t}$.

Variance Risk Premium. $N_{RP,t}$ can be proxied empirically by variance risk premium. This can be measured with the VIX index and the conditional expectations of realized volatility. The Chicago Board of 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)). 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. We square VIX (annualized standard deviation) and divide by 12 to convert to monthly volatility. 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.

News Decomposition. We present a state-space approach to decomposition of 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 an empirical proxy for either news about cash flows or news about risk-free rate.⁸ 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 minimalistic sign restrictions on the factor loadings Λ that $N_{RP,t}$ is assumed to increase variance premium and lowers ($\lambda < 0$) equity returns $r_{t-\Delta}^t$, that is, the differential of log price at time t and log price at time $t - \Delta$. The remainder of equity return variation is explained by $N_{CF,RF,t}$. Put together,

$$\begin{bmatrix} vp_{t+\Delta} \\ r_{t-\Delta}^t \end{bmatrix} = \begin{bmatrix} \alpha_v \\ \alpha_r \end{bmatrix} + \underbrace{\begin{bmatrix} 1 & 0 \\ \lambda & 1 \end{bmatrix}}_{\Lambda} \underbrace{\begin{bmatrix} N_{RP,t} \\ N_{CF,RF,t} \end{bmatrix}}_{F_t}, \quad var(F_t) = \begin{bmatrix} \sigma_{RP}^2 & 0 \\ 0 & \sigma_{CF,RF}^2 \end{bmatrix}. \quad (5)$$

We normalize the magnitude of $N_{RP,t}$ and $N_{CF,RF,t}$ by setting the diagonal element in Λ to 1. Time subscript t denotes when new macroeconomic announcement is released. The maximum likelihood estimates (with standard errors) are provided below.

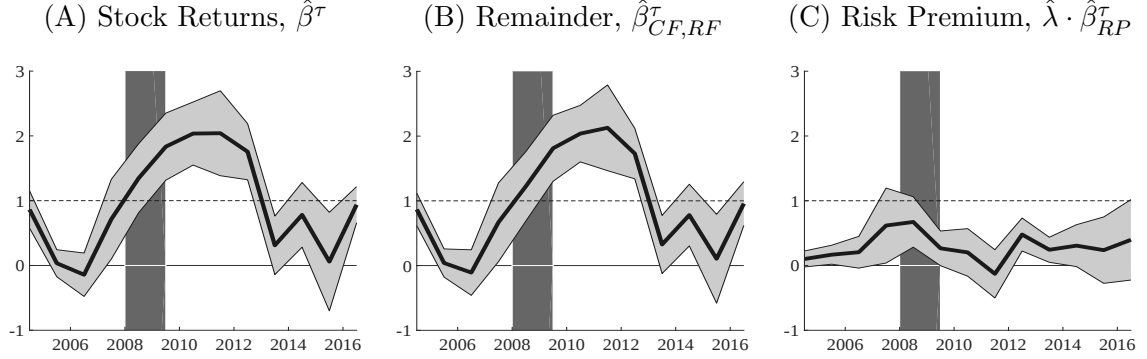
$$\begin{bmatrix} vp_{t+\Delta} \\ r_{t-\Delta}^t \end{bmatrix} = \begin{bmatrix} 3.09 \\ [2.78, 3.38] \\ 0.00 \\ [-0.59, 0.59] \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ -0.31 & 1 \\ [-0.63, -0.01] \end{bmatrix} \begin{bmatrix} N_{RP,t} \\ N_{CF,RF,t} \end{bmatrix}, \quad std(F_t) = \begin{bmatrix} 0.10 & 0 \\ [0.00, 0.20] & \\ 0 & 0.40 \\ & [0.27, 0.52] \end{bmatrix}.$$

The following identity holds from (5),

$$r_{t-\Delta}^t = \hat{\lambda} \cdot \hat{N}_{RP,t} + \hat{N}_{CF,RF,t}, \quad (6)$$

⁸In principle, we could use Eurodollar futures return as an empirical proxy for news about risk-free rate. However, as we observe in Figure C.9, 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.

Figure 8: Time-Varying Sensitivity Coefficients for Stock Returns: Decomposition



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

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

We obtain time-varying estimates of $\hat{\beta}^\tau$ which is of genuine interest to our paper.

$$r_{t-\Delta}^t = \alpha^\tau + \beta^\tau \gamma X_t + \epsilon_t. \quad (7)$$

We take the estimates $\hat{\gamma}$ from (7) and run two individual regressions

$$\begin{aligned} \hat{N}_{RP,t} &= \alpha_{RP}^\tau + \beta_{RP}^\tau \hat{\gamma} X_t + \epsilon_{RP,t} \\ \hat{N}_{CF,RF,t} &= \alpha_{CF,RF}^\tau + \beta_{CF,RF}^\tau \hat{\gamma} X_t + \epsilon_{CF,RF,t} \end{aligned} \quad (8)$$

to obtain $\hat{\beta}_{RP}^\tau$ and $\hat{\beta}_{CF,RF}^\tau$, respectively. It is important to note that we are fixing $\hat{\gamma}$. We can combine (6) and (8) to achieve

$$\hat{\lambda} \cdot \hat{N}_{RP,t} + \hat{N}_{CF,RF,t} = \left(\hat{\lambda} \cdot \alpha_{RP}^\tau + \alpha_{CF,RF}^\tau \right) + \left(\hat{\lambda} \cdot \beta_{RP}^\tau + \beta_{CF,RF}^\tau \right) \hat{\gamma} X_t + \left(\hat{\lambda} \cdot \epsilon_{RP,t} + \epsilon_{CF,RF,t} \right).$$

We just decomposed $\hat{\beta}^\tau$ in (7) into $\hat{\beta}_{RP}^\tau$ and $\hat{\beta}_{CF,RF}^\tau$.

$$\hat{\beta}^\tau = \hat{\lambda} \cdot \hat{\beta}_{RP}^\tau + \hat{\beta}_{CF,RF}^\tau. \quad (9)$$

Figure 8 provides the decomposition of (9). The key takeaway of the exercise 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. For example, we use the differential of log price at time $t + \Delta$ and log price at time t , $r_t^{t+\Delta}$, and apply sign restriction $\lambda > 0$. The assumption is that risk premium

increases the ex-post equity return. The results do not change with this sign restriction.

The Regime-Switching Dividend Growth Model. After narrowing the informational content of MNAs down to news about cash flows and/or news about risk-free rate, we propose a simple regime-switching dividend growth model to 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. We propose a VAR(1) dynamics in which the non-neutrality of interest rate is presumed.

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

$$\begin{aligned}\Delta d_{t+1} &= \Lambda_0 + \Lambda_1 Z_{t+1}, \\ Z_{t+1} &= \Phi(S_{t+1})Z_t + \Omega(S_{t+1})x_{t+1}, \quad x_{t+1} \sim N(0, 1),\end{aligned}\tag{10}$$

in which the joint dynamics of (de-measured) dividend growth and (de-measured) risk-free rate, $Z_t = [\Delta d_t, i_t]'$, follow a regime-switching VAR. The VAR coefficients are subject to regime switches. Λ_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 Π

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

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 ϵ_{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 ϵ_{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 by

$$\begin{aligned} N_{CF,RF,t+1}|(S_{t+1} = j) &= E_{t+1}\left(\sum_{i=1}^{\infty} \rho^{i-1} \Delta d_{t+i}\right) - E_t\left(\sum_{i=1}^{\infty} \rho^{i-1} \Delta d_{t+i}\right) \\ &\approx \underbrace{\left(\rho^0 \Lambda_1^{(1)}(j) + \dots + \rho^{k-1} \Lambda_1^{(k)}(j) + \dots + \rho^{\infty} \Lambda_1^{(\infty)}(j)\right)}_{\Gamma(S_{t+1}, \Pi_{t+1})} \Omega(j) x_{t+1}, \end{aligned} \quad (11)$$

where

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

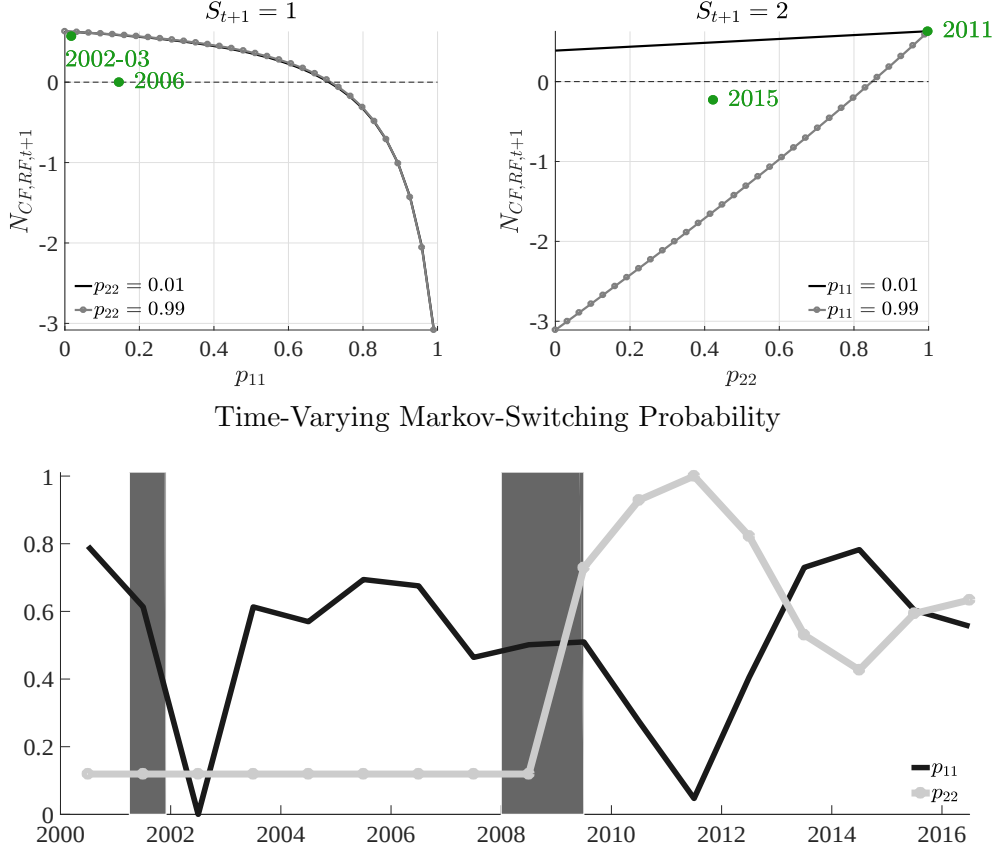
The underlying assumption is that dividend growth dynamics is dependent on risk-free rate dynamics. Thus, it is not possible to separately identify news about future cash flows from news about risk-free rate.

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

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

For illustrative purpose, we treat Change in Nonfarm Payrolls surprise as the only shock to dividend growth.⁹ Under the regime-switching model, news about cash flows and news about risk-free rate at time t can be derived analytically conditional on information about the state S_t

⁹This particular MNA is the literature consensus single most influential MNA.

Figure 9: News about Cash flows and Risk-Free Rate, $N_{CF,RF,t+1}$ 

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

and the Markov transition probability Π_t :

$$N_{CF,RF,t} = \Gamma(S_t, \Pi_t)x_t.$$

We assume that the time-varying Markov transition probability reflects changing beliefs about the state each point in time. The top panel of Figure 9 computes (11) as functions of the Markov transition probabilities.

To build intuition, we attempt to extract the Markov transition coefficients, $\hat{\Pi}_t$. We impose S_t is 1 until 2008 and S_t is 2 afterward. We split x_t into good (positive) and bad (negative) components and match $\beta_g^\tau \gamma^g$ and $\beta_b^\tau \gamma^b$ in Figure C.7 with $\Gamma(S_t, \Pi_t)$ by varying Π_t . The extracted $\hat{\Pi}_t$ in the second panel of Figure 9 reveal 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.5. Consistent with the survey evidence, we find that the probability of staying in the NR-MP regime was below half in 2015. Third, we show that 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, like in the data (highlighted by green dot 2015).¹⁰ In contrast, during the post recession years of 2002-03 and 2011 where the extracted $\hat{p}_{22,t}$ is close to one, we observe that returns respond positively to good dividend growth shocks. From this exercise, we conclude that the direction and duration of the market response reflect the evolution of market beliefs about monetary policy.

4 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 recession. As the economy expands, the sensitivity comes down to its starting point in four to five years. We then provide evidence that the direction and shape of the market's response reflect the evolution of beliefs about monetary policy proxied by the short-term interest rates. Specifically, we show that the sensitivity of short-term interest rate futures to MNA surprises moves in lock-step with the stock sensitivity but in the opposite direction. The new empirical facts are robust to various measures of stock market returns and combinations of MNAs. We utilize the standard cash flow, risk-free rate, and risk premium news decomposition of returns and 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 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.

¹⁰The pattern is symmetric to negative dividend growth shocks, which implies that the current model cannot simultaneously explain good news being bad news and bad news being bad news for stock market. The reason is that as long as the coefficient ρ_{di} in our VAR dynamic is negative, the interest rate can ease cash flow problems and turns bad news into good news by the same logic. We could resolve the problem by having a third regime in which ρ_{di} is assumed to be positive.

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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 $q = 1, \dots, 4$. We consider the following nonlinear least squares specification

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

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

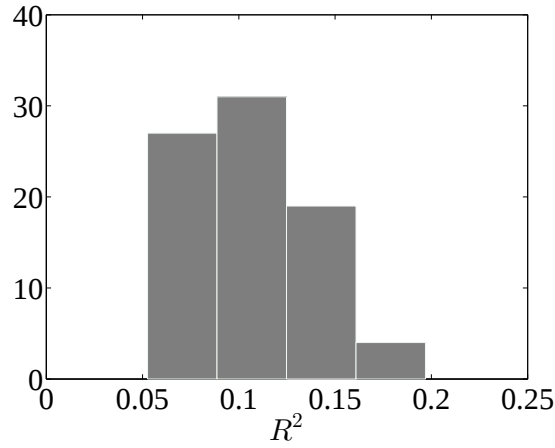
Estimation Sample: 1989-2016										
	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)
Constant	0.78	(0.44)	2.41	(0.47)	0.77	(0.43)	1.72	(0.50)	2.27	(0.54)
Change in FFR	-0.57	(0.23)	-0.37	(0.27)						
FFR			-0.48	(0.14)					-0.46	(0.21)
(Lagged) Change in FFR					-0.81	(0.24)	-0.69	(0.26)	-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 β_{SP}^r as the stock market sensitivity, while in the bottom panel, we use β_{ES}^r .

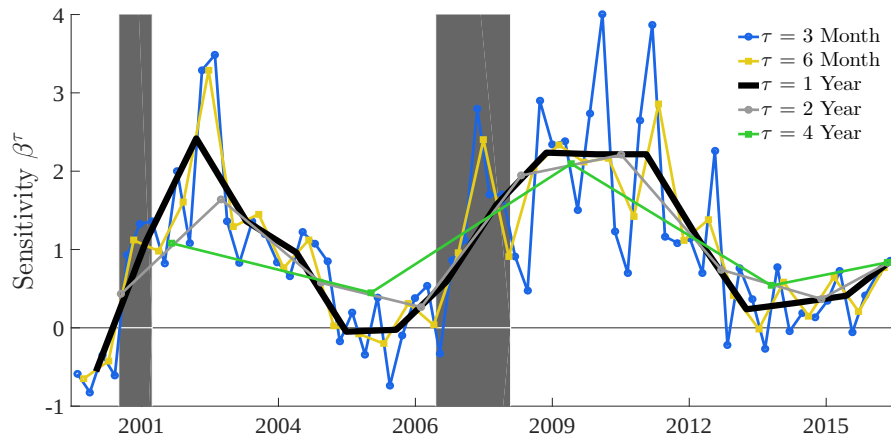
C Appendix Figures

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



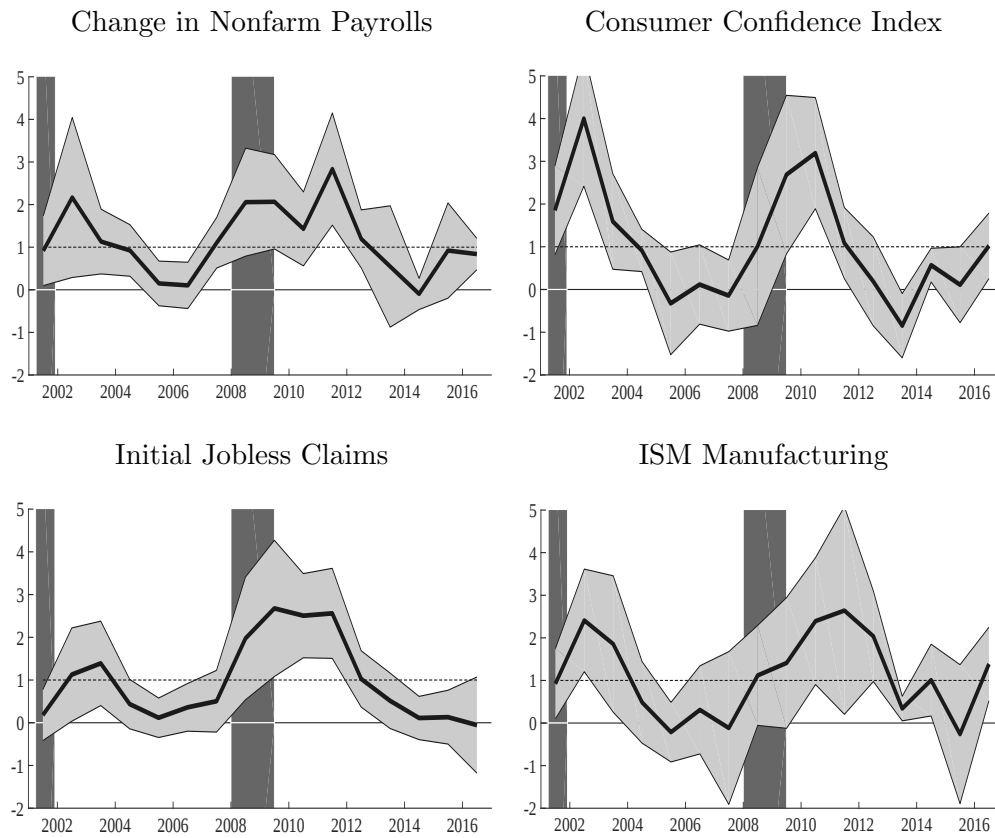
Notes: The sample is from January 2000 to December 2016 for the 81 regressions using the top 4 most influential MNAs reported in the main text.

Figure C.2: Smoothing Parameter τ in the Swanson and Williams (2014) Regression



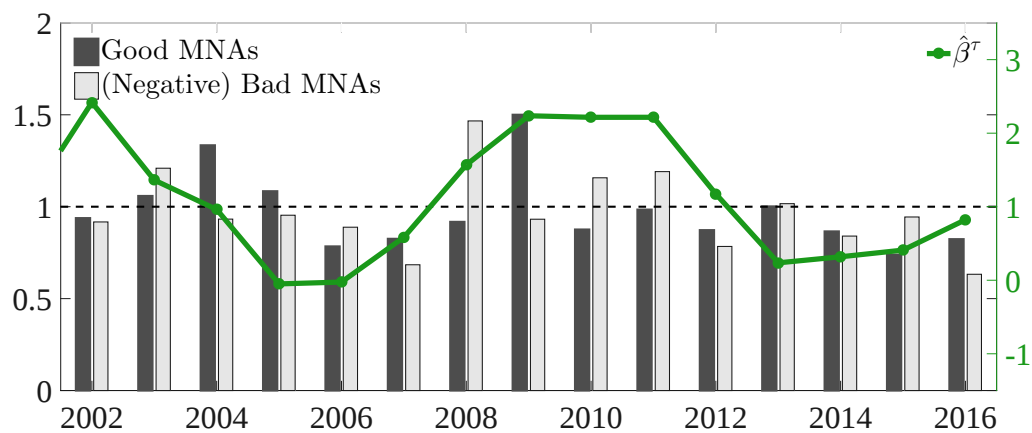
Notes: We repeat the estimation by varying the values of smoothing parameter τ . The highest frequency considered in this picture is 3 months and the lowest is 4 years.

Figure C.3: Individual Responses



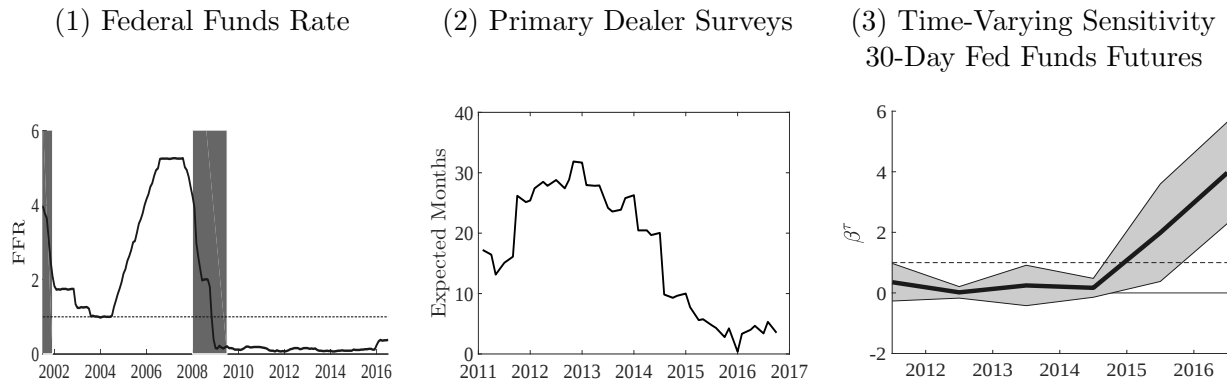
Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30\text{min}$. We impose that γ^τ (black-solid line) is on average equal to one. We provide ± 2 -standard-error bands (light-shaded area)

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



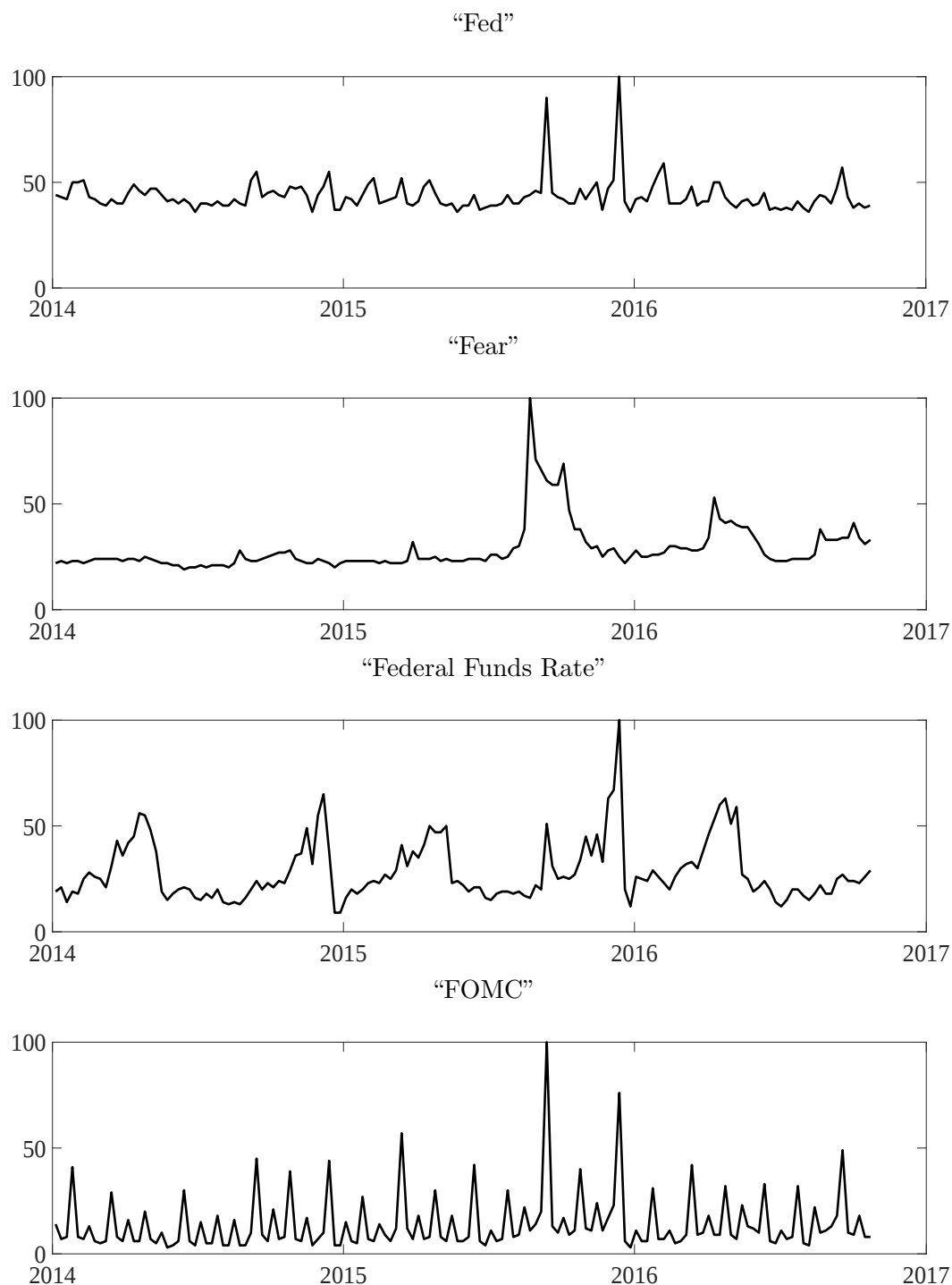
Notes: We provide the normalized annual averages of good and (negative) bad macroeconomic news announcement surprises. We overlay with the estimated time-varying stock market sensitivity coefficient $\hat{\beta}^\tau$ in Figure 3.

Figure C.5: Monetary Policy



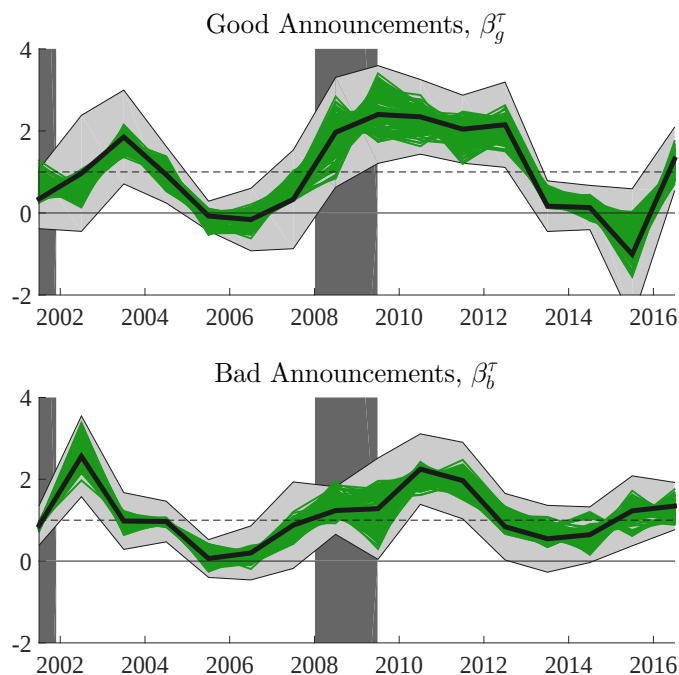
Notes: (1) Effective Federal Funds Rate, retrieved from FRED, Federal Reserve Bank of St. Louis. (2) Primary dealers are surveyed on their expectations for the economy, monetary policy and financial market developments prior to Federal Open Market Committee meetings. The actual survey question is “provide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

Figure C.6: 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>.

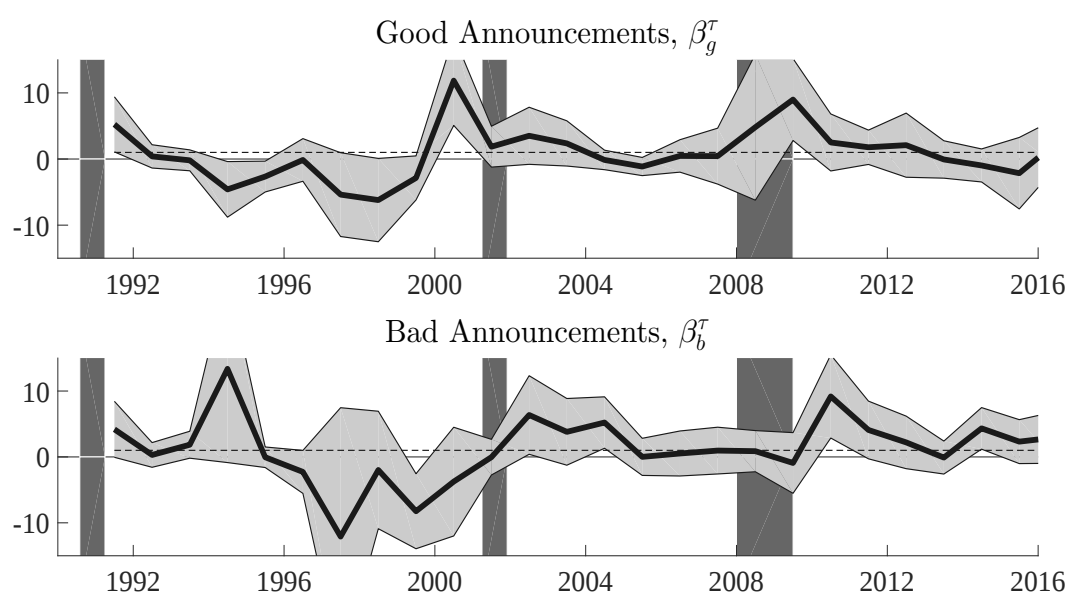
Figure C.7: Time-Varying Sensitivity Coefficients for Stock Returns: Good and Bad Announcements



MNAs	Good Announcements		Bad Announcements	
	$\hat{\gamma}^g$	p-value	$\hat{\gamma}^b$	p-value
Change in Nonfarm Payrolls	0.22	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

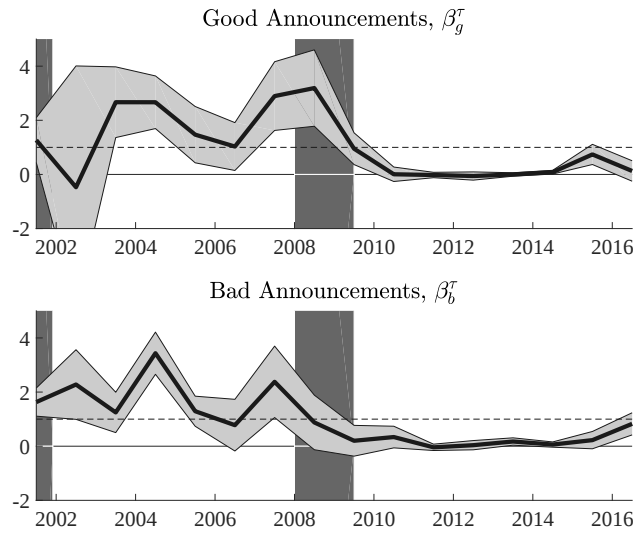
Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30\text{min}$. We impose that β_j^τ (black-solid line) is on average equal to one. We provide ± 2 -standard-error bands (light-shaded area) around β_j^τ , $j \in \{g, b\}$. The shape is robust to all possible permutations (green-solid lines) of the window intervals, $\Delta^{l,h} \in \{10\text{min}, \dots, 90\text{min}\}$. 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 $\Delta=30\text{min}$. 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.8: 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 β^τ (black-solid line) is on average equal to one. We set $\Delta = 30\text{min}$. We provide ± 2 -standard-error bands (light-shaded area) around β^τ .

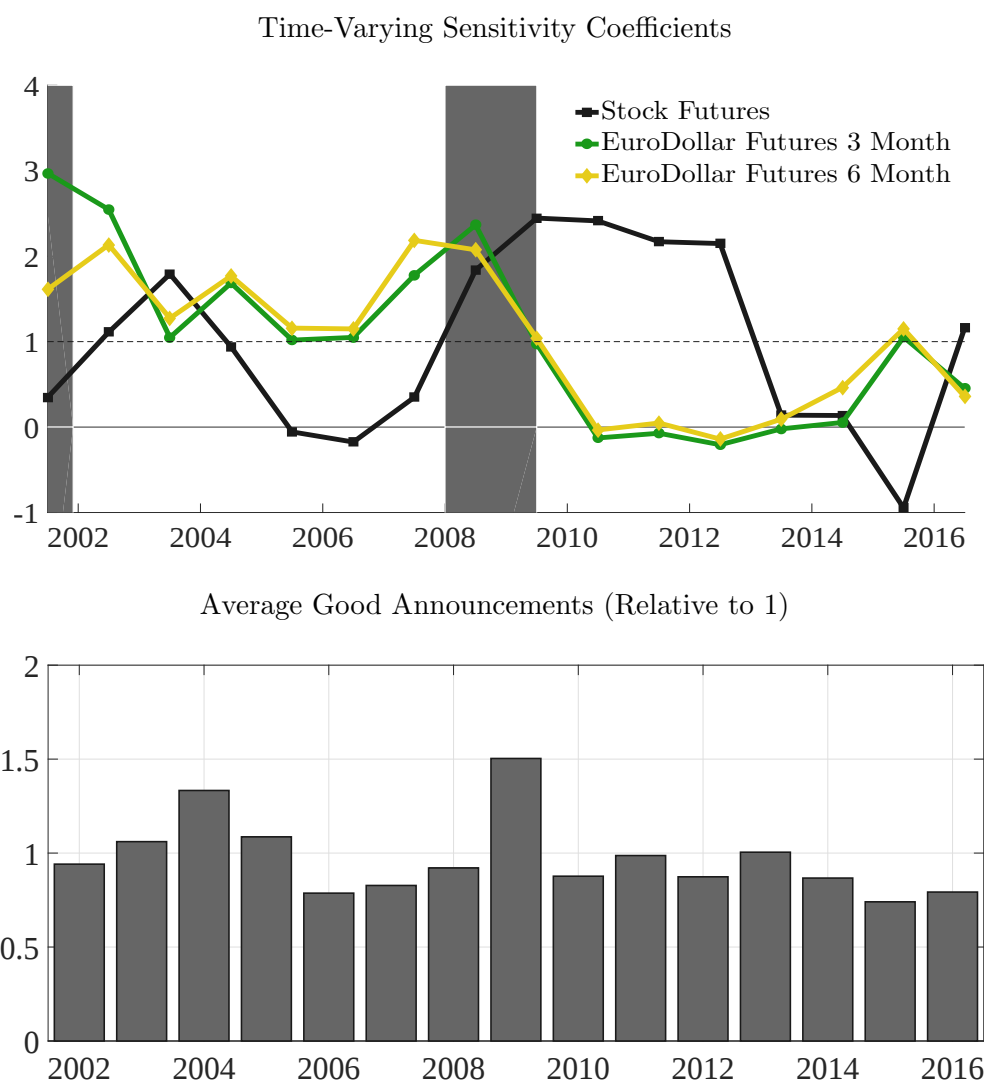
Figure C.9: Time-Varying Sensitivity Coefficient for Eurodollar Futures Returns: Good and Bad Announcements



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

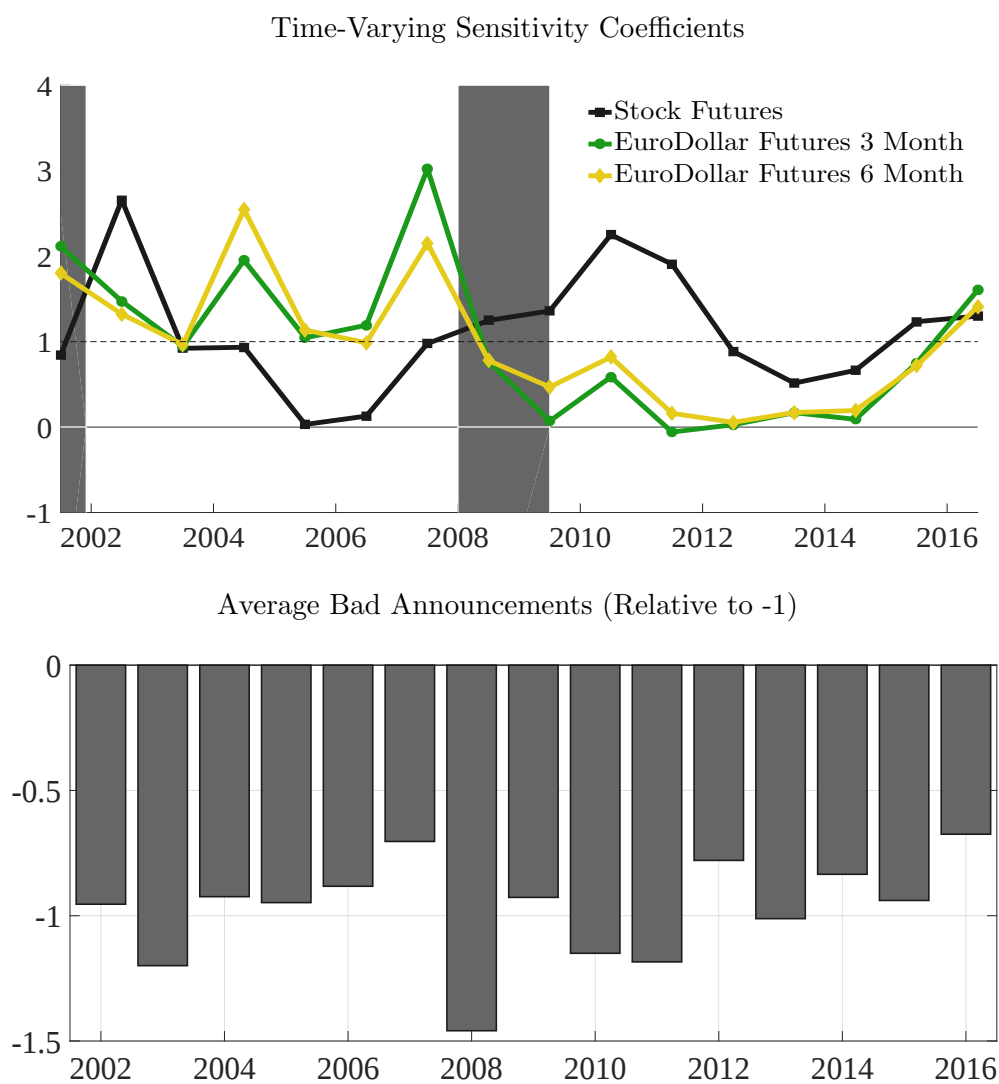
Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We impose that β^τ (black-solid line) is on average equal to one. We set $\Delta = 30\text{min}$. We provide ± 2 -standard-error bands (light-shaded area) around β^τ . 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 $\Delta=30\text{min}$. 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.10: 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 β^T (black-solid line) is on average equal to one. We set $\Delta = 30\text{min}$.

Figure C.11: 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 β^T (black-solid line) is on average equal to one. We set $\Delta = 30\text{min}$.

Figure C.12: Time-Varying Sensitivity Coefficients: Good and Bad Announcements



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

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 Π

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

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

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

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

$$\begin{aligned} \sum_{i=0}^{k-1} E(K_{t+i}|S_t = j) &= \left(\Lambda_0^{(0)}(j) + \Lambda_0^{(1)}(j) + \dots + \Lambda_0^{(k-1)}(j) \right) \\ &\quad + \left(\Lambda_1^{(0)}(j) + \Lambda_1^{(1)}(j) + \dots + \Lambda_1^{(k-1)}(j) \right) X_t. \end{aligned} \quad (\text{A.2})$$

D.2 News and Shock Decomposition

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

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

denotes the news.

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

denotes the shocks.

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

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