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 returns to macroeconomic news announcement (MNA) surprises. When the economy is significantly below trend (output gap is large and negative) and interest rates are not expected to go up, the stock return sensitivity to news is large. On the other hand, stock returns hardly react to news during periods when the economy is near trend (output gap is small) and interest rates are expected to rise. A monetary regime-switching model is shown to have implications consistent with this evidence. Taken together, the phase of the economy and interest rate expectations are key determinants of the cyclicality of the response of the stock market.

JEL Classification: G12, E30, E40, E50.

Keywords: Macroeconomic news announcements, cyclical return variation, interest rate expectations, phase of business cycle, output gap, return decomposition.

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1 Introduction

Recent evidence points to the prominent role the Federal Open Market Committee (FOMC) meetings and other macroeconomic news announcements (MNA) have on financial markets (e.g., Savor and Wilson (2013) and Lucca and Moench (2015) among others). However, predicting the direction of the stock market's response to these news is challenging. For example, stock prices might not react to announcements that suggest improvement in expected future cash flows if market participants expect future interest rate to be elevated 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's ability to lower interest rates in response to negative MNA surprises was limited). This interaction between economic conditions and perceptions about possible response of the Fed 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 from January 1998 to December 2017. We estimate nonparametrically the time-varying sensitivity of stock returns to the MNA surprises by relying on the nonlinear regression method proposed by Swanson and Williams (2014). There are two forms of return sensitivity to announcement surprises: one measures the sample average responses and the other measures deviation from the average responses. We refer to the latter as the time-varying stock return sensitivity throughout the paper. 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.

We establish that although the average response is a muted one, it masks significant time-varying cyclical responses of stock prices to MNA surprises. We show that the stock return sensitivity increases by a factor greater than two coming out of recessions and remains above average for about one to two years. The reaction of stock returns gradually

[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.

attenuates as the economy expands and it takes about four years to move from peak to trough sensitivity with the recovery taking about similar amount of time. At trough sensitivity, stock prices generally do not react to the MNA surprises. We highlight distinctly different responses of the stock market to MNA surprises between the early recovery phase and late expansion phase of the economy, which is unique to the literature. We show that our results survive a variety of robustness tests. Most importantly, our results persist (i) when we measure the responses using daily returns, and (ii) when we extend our analysis to data beginning in 1989 which encompass three recessions. Moreover, and somewhat surprisingly, we find weak evidence for asymmetry in the time variation of the responses to negative and positive MNA surprises. The corresponding return sensitivity estimates for positive and negative MNA surprises are statistically indistinguishable from each other.

We then attempt to identify the economic drivers of the cyclical variation in the stock return sensitivity. We rely on the same nonlinear regression of Swanson and Williams (2014), but modify the specification of the time-varying stock return sensitivity. Specifically, we impose an affine relationship between the stock return sensitivity and lagged macroeconomic variables under the assumption that cyclical return variations are rooted in macroeconomic fundamentals. Lagging the variables is particularly important in our context as it suggests a causal link from the macroeconomic variables to the cyclicality of the response of the stock market. We consider output gap, inflation, interest rates, price-dividend (PD) ratio, VIX, and some media-based measures of uncertainty index as potential predictors of the stock return sensitivity. We show that interest rates and output gap are the most important factors for the observed cyclical variations. Our evidence suggests that stock returns respond more aggresively when there is greater slack in the economy and interest rate has been previously falling. As is well known in the literature, the output gap is a key indicator of business cycle conditions while movements in interest rates reflect the stance of monetary policy. This implies that cyclical return variations are indeed rooted in variables well recognized as affecting monetary policy.

To more explicitly account for expectations regarding monetary policy, we repeat our analysis by including forward-looking measures, i.e., interest rate expectations based on surveys. We investigate whether market participants' interest rate expectations play any role in predicting the stock return sensitivity. We use the mean of the Blue Chip Financial Forecasts survey as a measure of interest rate expectation. We define "easing (tightening)" period as ones in which interest rates are expected to decline (rise). We show that tightening (easing) periods are associated with significantly smaller (larger) return reactions to announcement surprises. Importantly, we also show that when the economy is significantly below trend (output gap is large and negative), and at the same time, interest rate is expected to fall (easing expectation) the stock returns' response to news is about 2.5 times greater than the average response. We find similar results when interest rates are not expected to change during periods below trend. In contrast, when the economy is near trend (output gap is small) in conjunction with tightening expectation, the stock returns' response to news is estimated to be muted (statistically insignificantly different from zero).

These findings are consistent with a view that during periods in which the economy is below trend, the economy has larger capacity to grow. Thus, better-than-expected announcement surprises can lead to rise in growth expectation and expected asset valuation. The effect is larger especially when this takes place during periods in which market participants hold the view that the interest rate is not expected to rise. On the other hand, during periods in which the economy is near trend with smaller growth opportunities, and at the same time, market participants expect interest rate to rise, we find much smaller stock price reactions to news. We show that the response can be even negative upon better-than-expected announcement surprises that in principle would lead to rise in asset valuation. Taken together, the phase of the economy and interest rate expectations are key determinants of the cyclicality of the response of the stock market.

We have highlighted the connection between the state of economy, beliefs about the Fed's reaction, and the cyclical nature of the stock market's response to news. We claim that the evidence of time variation in the stock market's reaction is manifestation of changes in market's beliefs about fundamentals, especially about future interest rate movements. To support our claim, we seek to understand if beliefs about fundamentals embedded in macroeconomic data are also consistent with those in financial data. Specifically, we propose a bivariate regime-switching vector autoregressive model with unemployment rate and interest rate that features two distinct interest rate regimes.[2] One of the regimes is less reactive than the other in the sense that the feedback coefficients between the interest rate and unemployement rate are smaller in absolute magnitude.[3] We assume an

[2]Instead of the output gap, we rely on unemployment rate since it is the empirical proxy for one of the statutory objectives for monetary policy and is available in monthly frequency.

[3]Ideally, we would have three regimes: (1) reactive interest rate with high unemployment rate, (2) reactive interest rate with low unemployment rate, and (3) nonreactive interest rate regimes. We did not pursue this route since it makes the joint learning problem increasingly difficult to solve. Instead,

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

Empirically, we find that the mean probability of nonreactive regime starts to increase in recession and remains near one a few years after the recession. Roughly speaking, the probability starts to come down after the formal NBER announcements of business cycle turning point from contraction to expansion.[4] We emphasize that during periods in which the mean probability of nonreactive regime is high, the level of unemployment rate is also very high. This implies that the nonreactive regime roughly coincides with previously identified periods where the economy is significantly below trend and interest rates are not expected to change. When the mean regime probability is compared with the estimated stock return sensitivity, we find the most interesting co-movement pattern. The estimated stock return sensitivity is above average when the probability of the nonreactive regime is close to one and vice versa. Overall, our learning model suggests that changes in beliefs about future interest rates give rise to cyclical return variations.

Lastly, we decompose the stock market sensitivity to components attributable to news about cash flows, risk-free rate, and risk premium. This is of interest in its own right in terms of understanding which piece of news is affecting the sensitivity at the impact of announcements. Furthermore, such decomposition has a long tradition in the finance literature (e.g., Campbell (1991)) and our analysis provides a new perspective using high-frequency data around announcements. Specifically, we estimate jointly the three equation system in which the stock futures return, Eurodollar futures return, and variance risk premium are included. Eurodollar futures are known to be closely related to market expectations about the federal funds rate and variance risk premium proxies the premium associated with the volatility of volatility. We define the time-varying sensitivity coefficient associated with Eurodollar futures and variance risk premium as risk-free rate sensitivity and risk premium sensitivity, respectively. Consistency than implies that the stock return sensitivity is the sum of the sensitivities associated with cash flows, risk-free rate, and risk premium with the latter two entering with a negative sign. Overall, our decomposition

we estimate a simpler two-regime model, yet one that still allows us to analyse the relationship between beliefs about macroeconomic fundamentals and financial data.

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

shows that during announcement periods, the key drivers for the overall stock market sensitivity are news about cash flows and risk-free rate, while the sensitivity associated with risk premium does not play a big role.

1.1 Literature Review

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

However, the previous literature almost exclusively focused on contrasting the reaction of stock prices to MNA surprises in recessions from those in expansions. We contribute to the literature by providing a more comprehensive, but different characterization of time variation in the stock market's reactions to MNA surprises.[5] By highlighting distinctly different stock market's responses to MNA surprises in the early part of recovery phase to those in late part of expansion periods, we argue that it is not recessions and expansions per se that matter, but rather whether the economy is at trend or below and if future interest rates are expected to rise or fall. Specifically, we identify the degree of slackness in the economy and market's beliefs about the magnitude of movements in future interest rates to be the key drivers of the variations in stock return reactions to MNAs.

Our paper can be linked to a large literature that studies asset market and monetary policy, for example, Pearce and Roley (1985), Thorbecke (1997), Cochrane and Piazzesi (2002), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Gurkaynak, Sack, and Swanson (2005a), and Bekaert, Hoerova, and Lo Duca (2013) among others. Recently, Neuhierl and Weber (2016) document that monetary policy affects stock prices outside of the scheduled FOMC announcements as predicted by Bernanke and Kuttner (2005).

[5] In this regard, our paper extends Goldberg and Grisse (2013) and Swanson and Williams (2014) who provide the full sample characterization of the time variation in the responses of Treasury yield curves to MNA surprises over and above recessions and expansions. However, the focus of these papers is on Treasury bond market.

Cieslak and Vissing-Jorgensen (2017) focus on a related and complementary channel by relating stock market movements to subsequent monetary policy action by the Fed. Nakamura and Steinsson (2017) estimate monetary non-neutrality based on evidence from yield curve and claim Fed announcements affect beliefs not only about monetary policy but also about other economic fundamentals. Paul (2017) estimates the time-varying responses of stock and house prices to changes in monetary policy and finds that asset prices have been less responsive to monetary policy shocks during periods of high and rising asset prices.

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

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

The remainder of this paper is organized as follows. Section 2 describes the data, regression methods, and discusses empirical findings. Section 3 and Section 4 identify the economic drivers and investigate the role of market participants' interest rate expectations on the cyclicality of the response of the stock market. Section 5 intoduces a statistical model in which joint learning of parameters and states is introduced. Section 6 decomposes the announcement surprises into news about cash flows, risk-free rate, and risk premia components. Section 7 provides concluding remarks.

2 The Reaction of Stock Market to News

2.1 Data

Macroeconomic news announcements. MNAs are officially released by government bodies and private institutions at regular prescheduled intervals. In this paper, we use the MNAs from the Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Federal Reserve Board (FRB), Conference Board (CB), Employment and Training Administration (ETA), and Institute for Supply Management (ISM). We use the MNAs as tabulated by Bloomberg Financial Services. Bloomberg also surveys professional economists on their expectations of these macroeconomic announcements. Forecasters can submit or update their predictions up to the night before the official release of the MNAs. Thus, Bloomberg forecasts could in principle reflect all available information until the publication of the MNAs. Most announcements are monthly except Initial Jobless Claims (weekly) and GDP Annualized QoQ (quarterly). All announcements are released at either 8:30am or 10:00am except Industrial Production MoM which is released at 9:15am. We consider all announcements released in between January 1998 to December 2017. Details are provided in the appendix. For robustness, we also consider Money Market Services (MMS) real-time data on expected U.S. macroeconomic fundamentals to measure MNA surprises. None of our results are affected.

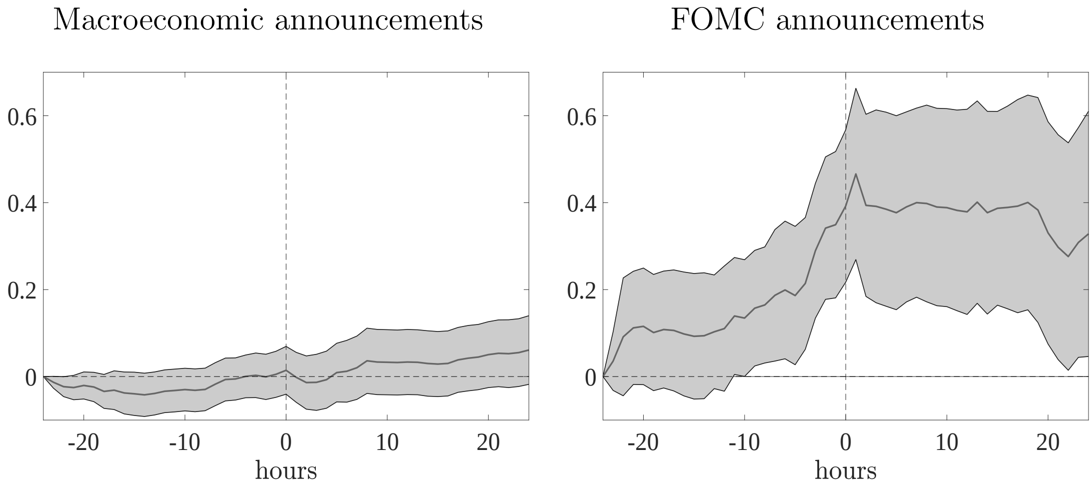
Standardization of the MNA surprises. Denote MNA i at time t by $\mathrm{MNA}_{i,t}$ and let $E_{t-\Delta}(\mathrm{MNA}_{i,t})$ be proxied by median surveyed forecast made at time $t-\Delta$. The individual MNA surprises (after normalization) are collected in a vector X_t whose ith component is

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

The units of measurement differ across macroeconomic indicators. To allow for meaningful comparisons of the estimated surprise response coefficients, we consider two normalizations. The first normalization scales the individual MNA surprise by the cross-sectional standard deviation of the individual forecasters' forecasts for each announcement. 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.[6] The key feature of the second approach is that

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

Figure 1: The 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 1998 through December 2017. The vertical line indicates the time at which announcements are typically released in this sample period.

for each MNA surprise, the normalization constant is identical across time. Thus, this normalization cannot affect the statistical significance of sensitivity coefficient. 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. Details are provided in the appendix.

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), 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.

literature.

2.2 Event study analysis

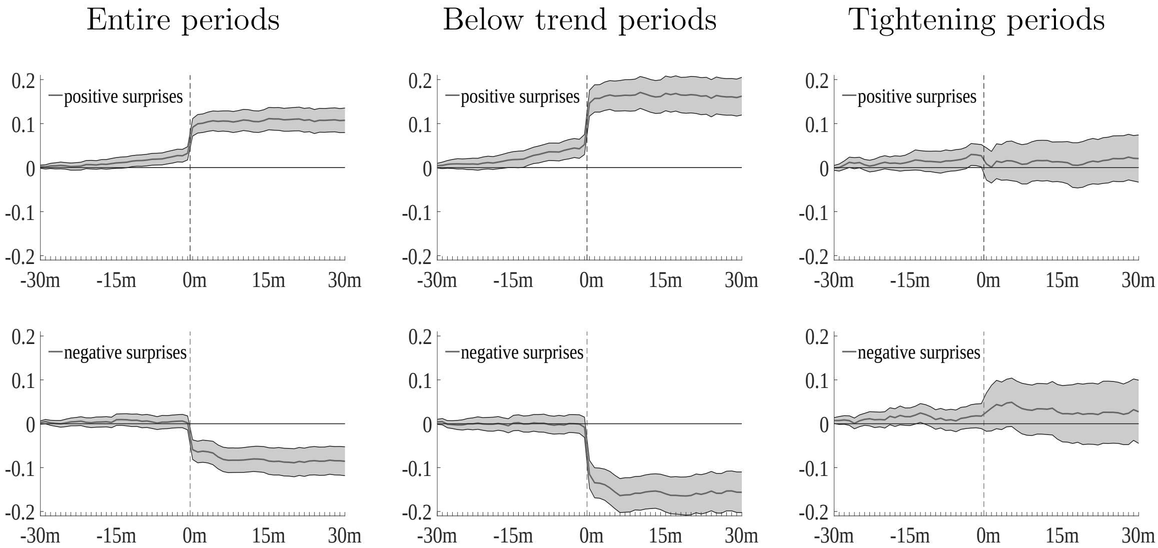
We first show that contrary to the FOMC announcements, the unconditional response of the stock market to macroeconomic announcements is insignificant. We then demonstrate the power of conditioning the stock market response to the MNAs on the business cycle phase and on the nature of the MNAs —when the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

Our analysis focuses on the MNAs but excludes the scheduled FOMC meetings. The latter are known to be associated with a dramatic pre-announcement drift in stock prices as recently shown in Lucca and Moench (2015). They document that the S&P 500 index has on average increased 49 basis points in the 24 hours before the scheduled FOMC announcements.[7] The FOMC pre-announcement drift in Lucca and Moench (2015) is captured in Figure 1 where we plot the cumulative stock returns around the scheduled announcements starting from a day-before to a day-after the announcements. In contrast, when one restricts to macroeconomic news announcements which are different from the scheduled FOMC announcements, this pre-announcement drift disappears. From this result, one might infer that the economic impact of the MNAs is marginal.

However, once the MNA surprises are analyzed at a higher frequency, and conditioned appropriately on the sign of the MNA surprise and the state of the economy, a very significant impact on prices is observed. In Figure 2, we plot the average cumulative stock returns starting from 30 minutes before to 30 minutes after the macroeconomic announcements. Two distinctive patterns emerge. First, the reaction of stock prices can be much more precisely measured when announcements dates are separated into positive and negative announcement surprises dates. The average cumulative stock returns around macroeconomic announcement dates in between 1998 to 2017 is about 10 basis points which is estimated to be statistically significant. Yet the absolute value is still smaller than the measured impact of the pre-announcement drift of the eight regularly scheduled FOMC meetings. However, one has to recall that there are many more MNAs than the typical eight scheduled FOMC meetings, and therefore in an aggregate sense the total impact of the MNA surprises is economically very large.

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

Figure 2: The cumulative stock returns around macroeconomic announcements



Notes: We plot the average cumulative stock returns in percentage points around scheduled announcements. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, ISM Manufacturing, and Initial Jobless Claims. The black solid lines are the average cumulative return on E-mini S&P 500 futures (ES) 30 minutes prior to scheduled announcements to 30 minutes after scheduled announcements. The light-gray shaded areas are ±2-standard-error bands around the average returns. The sample period is from January 1998 through December 2017. The vertical line indicates the time at which announcements are released in this sample period.

Second, there is strong evidence of time variation in the stock market's responses to macroeconomic announcements. We highlight the evidence by comparing the two distinct return responses across different phases of business cycle, which we define as "below trend" and "tightening" periods. For the purpose of capturing the episodes in which the economy is significantly below its potential output, we set the threshold to the one-quarter quantile of output gap and define "below trend" periods whenever output gap is below that threshold. Next, we define "tightening" periods by relying on survey measures of market's expectation on federal funds rate collected from the Blue Chip Financial Forecasts. Whenever the one-quarter-ahead mean forecast exceeds the current quarter federal funds rate over 10 basis points, we claim that it is "tightening periods." We emphasize that the results are not sensitive to the choice of the thresholds. We show that the average impact during "below trend periods" is estimated to be around 15 basis points which is 50% greater then the full sample average impact. In sharp contrast to "below trend periods," the stock return responses to the MNA surprises are statistically indistinguishable from zero during "tightening periods."

This evidence is consistent with a few papers that argue stock market's 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)). However, the findings of the previous literature were concentrated on comparing the stock market's reactions in recession to those in expansion periods. We show that the evidence of time variation in the stock market reactions is manifestation of changes in market's beliefs about fundamentals and not a mere reflection of market's different responses in recessions or expansions. Especially, we argue the importance of relating beliefs about future interest rate movements to the stock market.

Collectively, the evidence suggests the importance of accounting for time variation and highlights the difficulty of measuring the impact of the macroeconomic announcement surprises on stock market. While easy to implement, the event study has significant limitation to understanding the return variation. To gain better econometric power in identifying the stock market responses to the macroeconomic surprises, we proceed with a regression analysis. We then explain how we related output gap and interest rate expectations to the stock market responses.

2.3 Regression analysis

To measure the effect of the MNA surprises on stock prices, we take the intra-day future prices and compute returns r_t in a Δ-minute window around the release time. For our benchmark results, we use the ES contract to measure stock returns because it is most actively traded during the MNA release times. To determine which MNAs impact returns, we estimate the following nonlinear regression over τ-subperiod suggested by Swanson and Williams (2014)

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

where the vector X_t contains various MNA surprises; γ measures the sample average responses; ϵ_t is a residual representing the influence of other factors on stock returns at time t; and α^τ and β^τ are scalars that capture the variation in the return response to announcement during subperiod τ. The underlying assumption is that while the relative magnitude of γ is constant, the return responsiveness to all MNA surprises shifts by a proportionate amount over the τ subperiod. We let τ index the calendar year. The identification assumption is that β^τ is on average equal to one. This implies that the sample average of $\beta^\tau\gamma^\top X_t$ is identical to $\gamma^\top X_t$. When β^τ is always one, then it becomes the OLS regression motivated by Gurkaynak, Sack, and Swanson (2005b) and others. 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. We proceed by first determining the most impactful announcements across various window intervals, selecting the return window, and then focusing on cyclicality of the return response.

As results can depend on the size of the return window, we consider all combinations of Δ_l and Δ_h between 10 minutes and 90 minutes in increments of 10 minutes (81 regressions in total).[8] We examine both cases of multivariate and univariate regressions. Table 1 tabulates the number of regressions in which stock returns significantly respond to a specific MNA at the 1% significance level. For instance, the GDP Annualized QoQ surprise is significant in roughly 80% of these regressions. We use many combinations of the return window precisely because the significance of the MNAs depends on the size of the return window, see for example, Andersen, Bollerslev, Diebold, and Vega (2003) and Bartolini, Goldberg, and Sacarny (2008). This is confirmed in Table 1. This step allows us to select the MNAs while being agnostic over the size of the return window.

Selection of the MNA surprises. We now turn to the selection of the MNAs. Table 1 reveals that only a subset of the MNAs impacts the stock market. We find that Change in Nonfarm Payrolls, Initial Jobless Claims, ISM Manufacturing, Consumer Confidence Index are, broadly speaking, the most influential MNAs. This choice of four announcments is consistent with findings in the literature. For example, Andersen, Bollerslev, Diebold, and Vega (2007) analyze the impact of announcement surprises of 20 monthly macroeconomic announcements on high-frequency S&P 500 futures returns. They argue that Change in Nonfarm Payrolls is among the most significant of the announcements for all of the markets and it is often referred to as the "king" of announcements by market participants. Bartolini, Goldberg, and Sacarny (2008) discuss the significance of Change in Nonfarm Payrolls as well as the other three announcements which are also significant in our regressions.[9] Based on Table 1, we consider the top four most influential MNAs as

[8]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.

[9]This is consistent with Gilbert, Scotti, Strasser, and Vega (2017) who claim that investors care about certain macro announcements more than others based on evidence from Treasury yields.

Table 1: The stock return reaction to the MNA surprises

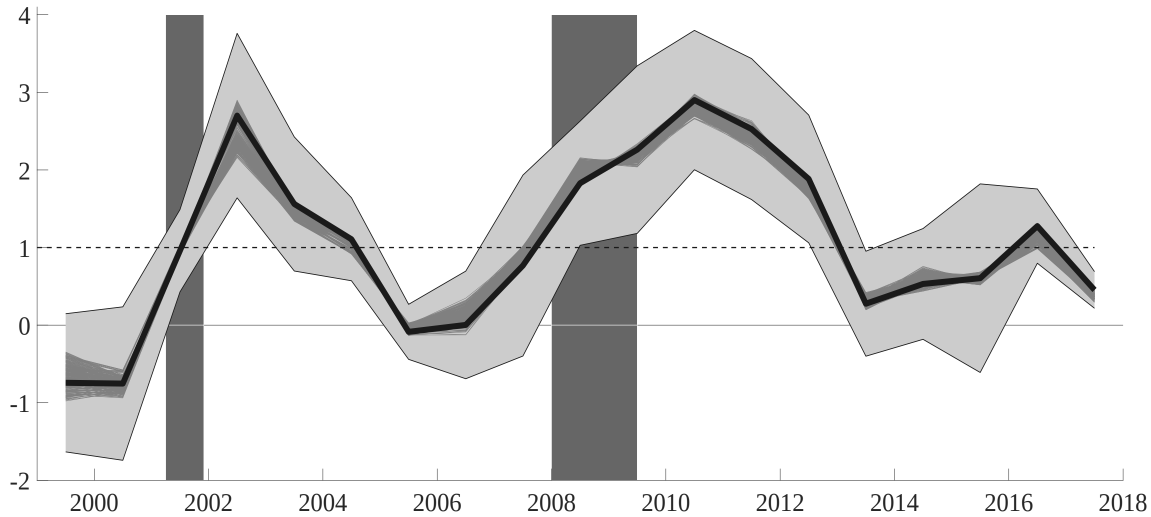
MNAs	Intra-day return						Daily return	
	Percent	p-val	Percent	p-val	Percent	p-val	p-val	p-val
Change in Nonfarm Payrolls	100.0 %	0.00	100.0 %	0.00	100.0 %	0.00	0.50	0.60
Consumer Confidence Index	100.0 %	0.00	100.0 %	0.00	100.0 %	0.00	0.36	0.37
Initial Jobless Claims	100.0 %	0.00	100.0 %	0.00	100.0 %	0.00	0.09	0.06
ISM Manufacturing	100.0 %	0.00	100.0 %	0.00	100.0 %	0.00	0.32	0.43
Retail Sales Advance MoM	100.0 %	0.00	72.8 %	0.01	76.5 %	0.01	0.14	0.12
Durable Goods Orders	100.0 %	0.00	60.5 %	0.01	91.4 %	0.00	0.41	0.40
Construction Spending MoM	96.3 %	0.04	0.0 %	0.12	0.0 %	0.31	0.21	0.26
Unemployment Rate	91.4 %	0.02	14.8 %	0.17	0.0 %	0.43	0.80	0.88
GDP Annualized QoQ	80.2 %	0.05	67.9 %	0.04	75.3 %	0.02	0.33	0.42
ISM Non-Manf. Composite	70.4 %	0.11	49.4 %	0.05	38.3 %	0.11	0.01	0.02
Industrial Production MoM	67.9 %	0.08	28.4 %	0.18	37.0 %	0.04	0.83	0.92
Housing Starts	48.1 %	0.17	0.0 %	0.58	4.9 %	0.43	0.82	0.94
New Home Sales	40.7 %	0.22	1.2 %	0.56	0.0 %	0.59	0.92	0.94
CPI MoM	35.8 %	0.22	93.8 %	0.00	100.0 %	0.00	0.20	0.22
Personal Income	32.1 %	0.22	0.0 %	0.67	0.0 %	0.53	0.51	0.56
Leading Index	8.6 %	0.32	0.0 %	0.70	0.0 %	0.73	0.41	0.50
Factory Orders	2.5 %	0.45	0.0 %	0.28	0.0 %	0.37	0.09	0.09
Trade Balance	2.5 %	0.39	0.0 %	0.19	1.2 %	0.17	0.01	0.01
PPI Final Demand MoM	0.0 %	0.78	0.0 %	0.27	0.0 %	0.29	0.44	0.32
Capacity Utilization	0.0 %	0.67	0.0 %	0.61	11.1 %	0.12	0.76	0.84
Nonlinear regression	✓							
Multivariate regression	✓		✓				✓	
Univariate regression					✓			✓

Notes: The sample is from January 1998 to December 2017 for the 81 regressions described in the main text. "Percent" refers to the percentage (number significant/81) of regressions in which returns significantly responds the MNA at the 99% confidence interval. Average p-value is the average two-sided p-value across all 81 regressions. We consider "multivariate" and "univariate" regressions. Daily return refers to using returns from 8am to 3.30pm. It is important to note that we remove all the days when there are the FOMC related news in construting daily returns. We refer to the non-linear regression when β^{τ} is estimated; all the rest assume β^{τ} is set to one.

the benchmark MNAs for our analysis. We later show that none of our results are affected by the inclusion of the next eight influential MNAs in Table 1.

Selection of the window interval. For the subsequent analysis, we consider regressions with $\Delta = \Delta_l = \Delta_h$ and set $\Delta = 30$min. We emphasize that our results are maintained across all 81 combinations of Δ_l and Δ_h. 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 announcements.

Figure 3: The time-variation in the stock return sensitivity to macroeconomic news



Notes: The top four MNAs from Table 1 are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We flip the sign of Initial Jobless Claims surprises for ease of comparison across other surprises. We impose that β^τ (black-solid line) is on average equal to one. We set $\Delta = 30$min. We provide ± 2-standard-error bands (light-shaded area) around β^τ. The shape is robust to all possible combinations (light-gray-solid lines) of the next eight MNAs listed in Table 1. We provide the individual estimate for γ and its standard error in parenthesis: $\hat{\gamma}_{\mathrm{CNP}} = 0.22(0.04)$, $\hat{\gamma}_{\mathrm{CCI}} = 0.15(0.03)$, $\hat{\gamma}_{\mathrm{IJC}} = 0.04(0.01)$, $\hat{\gamma}_{\mathrm{ISM}} = 0.16(0.03)$. Number of observations is 1699.

Estimating stock return sensitivity to the MNA surprises. The coefficients that measure the average sensitivity, i.e., $\hat{\gamma}$, are positive and significant at 1% level, which are reported in the notes of Figure 3. Figure 3 provides the main focus of our study, that is, the estimate of the time-varying sensitivity coefficient $\hat{\beta}^\tau$ (black-solid line).[10] For robustness, we also plot the results from additionally including every possible combination of the next eight MNAs in Table 1. All these regressions yield the light-gray-solid lines that are very close to each other and hence, appear as a gray band when viewed from a distance.

We find strong evidence of persistent cyclical variation in the stock market's 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 (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

[10] Note that we flip the sign of Initial Jobless Claims surprises for ease of comparison across other surprises. We find that all estimated $\hat{\gamma}$s have the positive sign which are reported in the notes of Figure 3. This enables a cleaner interpretation of the estimated senstivity coefficient $\hat{\beta}^\tau$.

it takes about four 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 news.

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

$$\hat{r}_{t-30m}^{t+30m} = \hat{\alpha}^\tau + \hat{\beta}^\tau(\hat{\gamma}^\top X_t) = \hat{\alpha}^\tau + \hat{\beta}^\tau \hat{X}_t. \tag{2}$$

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

$$r_{t-\Delta_l}^{t+\Delta_h} = \alpha^\tau + \beta^\tau \hat{X}_t + \epsilon_t \tag{3}$$

and obtain estimate of $\hat{\beta}^\tau$ for each combination of $(\Delta_h, \Delta_l) \in \{-5m, 0m, 5m, 30m\}$, which we denote by $\hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$. It follows that $\hat{\beta}^\tau$ in (2) by construction equals

$$\begin{aligned} \hat{\beta}^\tau(t-30m \to t+30m) &= \hat{\beta}^\tau(t-30m \to t-5m) + \hat{\beta}^\tau(t-5m \to t) \\ &+ \hat{\beta}^\tau(t \to t+5m) + \hat{\beta}^\tau(t+5m \to t+30m). \end{aligned} \tag{4}$$

The sensitivity is with respect to the linearly transformed MNA surprises, $\hat{X}_t$. Since $\hat{X}_t$ is a generated regressor from (2), asymptotic standard errors are constructed using generalized methods of moments.

To save space, we refer to Appendix E for details and summarize the results here: We do not find any evidence of pre-announcement phenomenon which is different from Lucca and Moench (2015); stock prices on impact react significantly to the MNA surprises, but there is no statistically significant movement five minutes after the announcements. This is important as it shows there is no immediate mean reversion in the reaction of the stock market. We extend our analysis to daily data and further confirm that the market reactions are not reflecting temporary noise.

Stock return sensitivity with lower-frequency data. To show that the impact of the MNA surprises on the stock market is not short-lived, we estimate the restricted regression (3) 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 $\hat{X}_t$. It is important to note that we remove all the days when there are the FOMC related news in constructing daily returns. We find that the mean estimates are broadly similar across various window intervals. As expected, the standard-error bands increase moving from the case of hourly returns to daily returns. We emphasize that the results from the unrestricted regression are qualitatively similar. We refer to Appendix E for details.

Evidence for asymmetry. We decompose the macroeconomic news announcements into "good" (better-than-expected or positive) and "bad" (worse-than-expected or negative) announcements and examine if the stock return responses to good and bad MNA surprises are different from each other.[11] Here, we flip the sign of Initial Jobless Claim surprises for ease of comparison across other "good" surprises. We then run the following regression

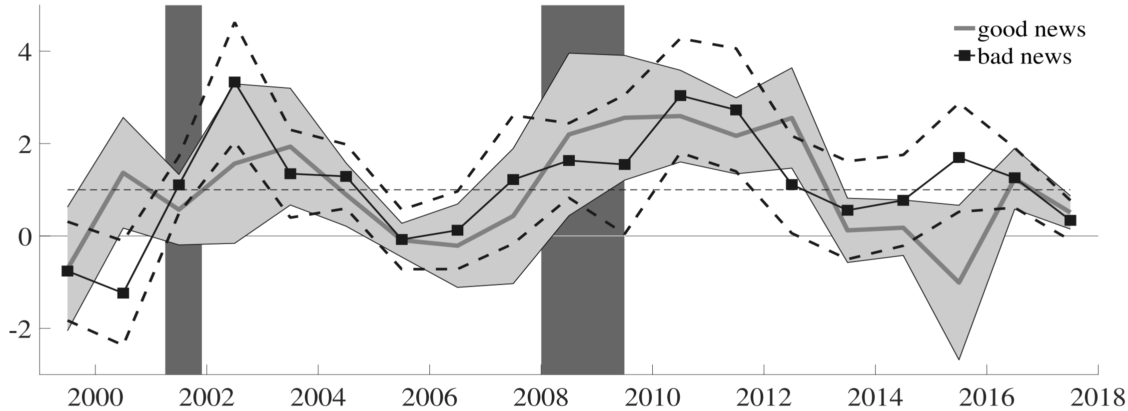
$$r_{t-\Delta}^{t+\Delta} = \alpha^{\tau} + \beta_{\text{good}}^{\tau} \gamma^{\top} X_{\text{good},t} + \beta_{\text{bad}}^{\tau} \gamma^{\top} X_{\text{bad},t} + \epsilon_t. \tag{5}$$

Note that if $\beta_{\text{good}}^{\tau}$ and $\beta_{\text{bad}}^{\tau}$ are identical, this equation becomes (1). Figure 4 displays the corresponding estimates of $\hat{\beta}_{\text{good}}^{\tau}$ and $\hat{\beta}_{\text{bad}}^{\tau}$. Surprisingly, the standard error bands on $\hat{\beta}_{\text{good}}^{\tau}$ and $\hat{\beta}_{\text{bad}}^{\tau}$ overlap almost always, and thus the sensitivity estimates are statistically indifferent from one another. In sum, there is no evidence for asymmetry in the response to good and bad MNA surprises during 1998 to 2017.

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. To test the hypothesis formally, we partition the sample into "recession," "early expansion," "late expansion" and perform the two sample Kolmogorov-Smirnov test. We do this based on Figure 3 since the stock returns' responses are distinctively different across these three subsamples. Recession periods correspond to the NBER recession dates. Broadly defined, early expansion indicates periods within two years after recession and late expansion indicates periods five years after recession. We try to keep the number of samples similar across three different periods. The test results are robust to 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. We refer to Appendix E for detailed discussion.

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

Figure 4: The stock return sensitivity to good and bad surprises



Notes: We decompose the macroeconomic news announcements into "good" (better-than-expected or positive) and "bad" (worse-than-expected or negative) announcements. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We flip the sign of Initial Jobless Claims surprises for ease of comparison across other "good" surprises. We set $\Delta = 30\text{min}$. We impose that β_j^τ is on average equal to one. We provide $\pm$2-standard-error bands around β_j^τ, $j \in \{\text{good,bad}\}$.

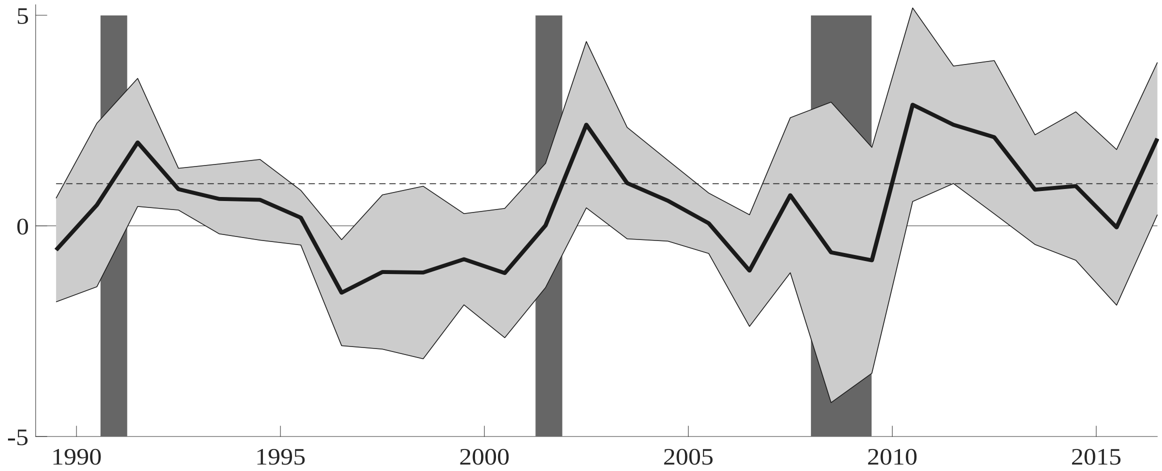
Controlling for possible omitted variable problems. It is possible that our benchmark specification may suffer from omitted variable problems. We augment the regression with other predictor variables $Z_{t-\Delta_z}$ which are known before the announcements

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

We consider three forms of $Z_{t-\Delta_z}$. The first one is spread between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity and the second one is the change in spread both of which are available in daily frequency. The third one is the Aruoba-Diebold-Scotti business conditions index which is designed to track real business conditions at daily frequency.[12] We set Δ_z to be a day to reflect that most up-to-date information is included in the regression. We find that the coefficient loading on change in spread and the ADS index are estimated to be significant at 1% and 5% level of significance, respectively. Nonetheless, the resulting estimates for $\hat{\beta}^\tau$ from these regressions are essentially unchanged and are identical to Figure 3. This evidence highlights that at least at the intra-day frequency the MNAs provide impactful information regarding the stock market above and beyond other well known predictors, such as the slope of the term structure

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

Figure 5: The stock return sensitivity: longer sample evidence with daily returns



Notes: We use S&P 500 futures (SP) which are available from 1988 to 2017. We use daily returns to incorporate the following macroeconomic announcements, which are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, ISM Manufacturing, New Home Sales, Unemployment Rate, GDP Annualized QoQ. We first run (1) with ES from 1998 to 2017 in which the return window is set to $\Delta = 30$ min to obtain the estimate of $\hat{\gamma}$. Then, conditional on $\hat{\gamma}$, we run (1) with daily SP from 1988 to 2017 to obtain the estimates of $\hat{\beta}^{\tau}$. We do this to sharpen the inference on β^{τ}. We impose that β^{τ} (black-solid line) is on average equal to one. We provide $\pm$2-standard-error bands (light-shaded area) around β^{τ}.

(e.g., see Neuhierl and Weber (2016) for weekly evidence). We also tried to control for volatility changes, if any, in stock returns by dividing the return by VIX. Our results are not affected.

Longer-sample evidence. We extend the sample to the 1990s and examine if a similar pattern emerges. Before 2000, the futures market was very illiquid outside the trading hours. This restriction excludes the use of all announcements released at 8:30am. To tackle this issue, we use daily returns to incorporate a wider range of macroeconomic announcements which include Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, ISM Manufacturing, New Home Sales, Unemployment Rate, GDP Annualized QoQ. 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 regression, we aim to provide further robustness to our main finding.

We first run (1) with intra-day returns from 1998 to 2017 in which the return window is set to $\Delta = 30$ min to obtain the estimate of $\hat{\gamma}$. Then, conditional on $\hat{\gamma}$, we work with daily returns from 1988 to 2017 to obtain the estimates of $\hat{\beta}^{\tau}$ by running (3). It is important to note that we remove all the days when there are the FOMC related news in constructing daily returns. We do this to sharpen the inference on $\hat{\beta}^{\tau}$ which is provided in Figure 5. The mean estimates are qualitatively similar, but estimated with larger standard errors. Overall, we conclude that our results are robust across various return measures, surprise measures, and different periods.

Other robustness checks. We improve the econometric power in identifying the cyclical variation in stock return responses by pooling information within τ subperiod, that is, a year. Yet, it requires us to assume that the responses move proportionally within τ period. In the appendix, we show that our results are robust to different smoothing parameter values τ. We also relax the assumption that the stock return responsiveness to all MNA surprises shifts by a roughly proportionate amount. This amounts to removing the common β^{τ} structure in (1) and replacing with individual γ^{τ}. We also show that the stock return responsiveness is qualitatively similar across individual MNAs. We refer to Appendix E for details.

3 The Economic Drivers behind the Time-varying Stock Return Sensitivity

In the previous section, we relied on the benchmark regression of (1) which nonparametrically identifies time variation in the stock return sensitivity. To understand the economic drivers behind the time variation, we re-estimate the benchmark regression with the following parametric assumption

$$\begin{aligned} r_{t-\Delta}^{t+\Delta} &= \alpha^{\tau} + \beta^{\tau}\gamma^{\top}X_t + \epsilon_t \\ \beta^{\tau} &= \beta_0 + \beta_1^{\top}Z_{\tau-1}. \end{aligned} \tag{7}$$

We examine if the time variation in the stock return sensitivity, β^{τ}, can be explained by key economic observables, $Z_{\tau-1}$. We consider output gap, inflation, interest rates, price-dividend (PD) ratio, VIX, and uncertainty index (collected by Scott Baker, Nicholas Bloom and Steven J. Davis) as potential predictors of the stock return sensitivity under the assumption that cyclical return variations are rooted in economic fundamentals. Note that consistent with our previous results, we set τ to index a calendar year. We avoid the endogeneity problem by using the lagged annual economic observables. By standardizing the predictor vector Z_τ and assuming $\beta_0 = 1$, we maintain the identification restriction, i.e., $E(\beta^\tau) = 1$.

The estimation results are provided in Table 2. Consistent with the previous results, all macroeconomic news announcement surprises are significant at 1% level, i.e., $\hat{\gamma}$s are estimated to be significantly positive, which are not reported here to save space. We rather discuss the estimation results regarding the stock return sensitivity which are summarized in Panel (A). We document that an increase in each of output gap, interest rates (both level and change), and PD ratio significantly predicts lower stock return sensitivity. It is only inflation that turns out to be insignificant in this regression. On the other hand, all uncertainty-related indexes, i.e., VIX, the economic policy uncertainty (EPU) index, significantly predict larger stock return sensitivity.

Panel (B) of Table 2 provides the estimation results from the multivariate specification of the stock return sensitivity. We estimate various versions in which empirical approximation of monetary policy rules are considered. Column (1) examines the simplest case where output gap and inflation are included. We find that the coefficient associated with output gap is estimated to be significantly negative while that associated with inflation turns out to be insignificant and changed sign from negative to positive.

Column (2)-(7) provide the estimation results when interest rates in various forms are additionally included. This is because interest rates cannot be fully spanned by output gap and inflation series, for example, due to the presence of monetary policy shocks, and may contain valuable information about the future path of the economy. We consider cases in which a lagged interest rate or an interest rate with a longer maturity is included. The objective is to incorporate interest smoothing motive and/or proxy the market's expectation of the future short rate that is not contained in the short-term interest rate. First, we find that the estimate for output gap coefficient is significantly negative across various permutations. The estimate for inflation, on the other hand, is positive and marginally significant. Second, it is important to emphasize that annual change in the short-term interest rate (percent change from a year ago) plays an important role in predicting stock return sensitivity since it maintains negative sign and is estimated to be significant at 5%-10% level in many permutations. When the level of and change in interest rates for both short- and long-term maturities are included, we find that it is the long-term maturity

Table 2: The economic drivers behind the time-varying stock return sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(A) Univariate regression								
Output gap	-0.65***								
	(0.15)								
Inflation (level)		-0.21							
		(0.16)							
FFR (level)			-0.37***						
			(0.12)						
FFR (change)				-1.35***					
				(0.42)					
5y Treasury YLD (level)					-0.39***				
					(0.10)				
5y Treasury YLD (change)						-0.59***			
						(0.18)			
PD ratio							-0.45**		
							(0.14)		
VIX								0.69***	
								(0.20)	
EPU index									0.63***
									(0.15)
R^2 adjusted	0.12	0.08	0.09	0.11	0.10	0.10	0.10	0.10	0.10
	(B) Multivariate regression								
Output gap	-0.73***	-1.58***	-0.74***	-1.08***	-0.70***	-1.02**	-1.50***	-1.52***	-1.38**
	(0.15)	(0.56)	(0.20)	(0.46)	(0.21)	(0.45)	(0.54)	(0.57)	(0.57)
Inflation (level)	0.23	0.48*	0.50*	0.54*	0.53*	0.56*	0.48*	0.48*	0.57*
	(0.16)	(0.25)	(0.27)	(0.30)	(0.27)	(0.30)	(0.27)	(0.27)	(0.29)
FFR (level)		0.16					0.97	0.97	1.08
		(0.51)					(0.70)	(0.71)	(0.70)
FFR (lagged level)		0.75**					0.67	0.68	0.44
		(0.37)					(0.44)	(0.44)	(0.49)
FFR (change)			-0.89**	-0.84*	-0.79*	-0.73*	-0.22	-0.21	-0.09
			(0.44)	(0.47)	(0.43)	(0.46)	(0.43)	(0.44)	(0.43)
5y Treasury YLD (level)				0.32		0.29	-0.83**	-0.86**	-0.98**
				(0.32)		(0.31)	(0.40)	(0.40)	(0.40)
5y Treasury YLD (change)					-0.30*	-0.31*	0.04	0.04	0.17
					(0.18)	(0.19)	(0.18)	(0.19)	(0.21)
PD ratio								0.03	0.02
								(0.21)	(0.21)
VIX									0.43
									(0.40)
R^2 adjusted	0.09	0.12	0.14	0.13	0.13	0.13	0.14	0.14	0.14

Notes: The estimation sample period is from 1998 to 2017. We only report the estimates associated with β in the regression. Output gap is defined by log difference between the real potential GDP and real GDP. Inflation is GDP deflator and FFR is the effective federal funds rate. We also consider the 5-year Treasury yields. PD ratio is the price to dividend ratio and VIX is CBOE volatility index. Economic Policy Uncertainty (EPU) index is the baseline uncertainty index collected by Scott Baker, Nicholas Bloom and Steven J. Davis at www.PolicyUncertainty.com. All variables are standardized. "Change" refers to the annual change. The sample correlation between output gap and inflation (level) is 0.40; correlation between output gap and interest rate (level) is 0.73; correlation between inflation (level) and interest rate is 0.43. We avoid the endogeneity problem by using the lagged annual macroeconomic observables. We use the benchmark macroeconomic announcements: Change in Nonfarm Payroll; Consumer Confidence Index; Initial Jobless Claims; and ISM Manufacturing. We report the Newey-West adjusted standard errors. Notation: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

yield that plays the major role. In column (8) and (9) we show that PD ratio and VIX turn out to be insignificant after controlling for monetary policy-related variables. Lastly, based on the adjusted R^2 values, we conclude that output gap and interest rates are key drivers of the cyclicality of the response of the stock market to news surprises among the set of regressions that achieve the R^2 value of 0.14. The fact that the short-term interest rate change and the long-term interest rate level play important roles indicates that what really matters could be the market's expectation of the future short rate. We attempt to provide an answer to this conjecture in the next section.

Before we move on, we highlight that the fitted $\hat{\beta}^{\tau}$s based on the estimates in Panel (B) look very similar to our benchmark stock return sensitivity in Figure 3 (see Appendix E for graphs). This indirect evidence suggests that cyclical return variations are indeed rooted in monetary-policy related variables.

4 Interest Rate Expectation and the Reaction of Stock Market to News

The previous results suggest that the stance of monetary policy implied from interest rate and the phase of economic cycle proxied by output gap may play important role in predicting how the stock market reacts to macroeconomic news announcements. This evidence supports the view that stock returns respond more aggresively when there is greater slack in the economy or when interest rate has been falling. Our analysis thus far, however, is limited by a specification that does not explicitly account for forward looking expectations of key variables (e.g., interest rates) and their role on the stock return sensitivity.

A more direct approach is to assess whether when market participants expect rate hike to occur in the near future do we expect to see below average stock market reactions as implied from the previous regression results. Also, do we expect to find differential effects when the output gap is small or large? In this section, we seek to provide answers to these questions by specifying the return sensitivity which can depend on forward-looking interest rate expectations. To this end, we work with direct measures of market's expectation on interest rate collected from the Blue Chip Financial Forecasts survey. Specifically, we estimate the response of stock returns to macroeconomic news announcements in the presence of (no) rate hike expectation during periods in which there is (more) less slack in the economy. We measure the degree of slackness with output gap.[13] We also use VIX to condition on different level of stock market uncertainty.

We let the stock return sensitivity depend on

$$\begin{aligned}\beta^{\tau} &= \beta_0 + \beta_i^{\text{tightening}} \mathbb{I}_{\{E_{\tau-1}(i_\tau)-i_{\tau-1}\geq c_i\}} + \beta_i^{\text{easing}} \mathbb{I}_{\{E_{\tau-1}(i_\tau)-i_{\tau-1}\leq -c_i\}} \\ &\quad + \beta_y^{\text{below trend}} \mathbb{I}_{\{y_{\tau-1}<c_y^b\}} + \beta_y^{\text{near trend}} \mathbb{I}_{\{y_{\tau-1}>c_y^n\}} + \beta_v^{\text{large vix}} \mathbb{I}_{\{v_{\tau-1}>c_v^l\}} + \beta_v^{\text{small vix}} \mathbb{I}_{\{v_{\tau-1}<c_v^s\}}.\end{aligned} \tag{8}$$

We start with a general expression and later estimate various versions of (8) in which a subset of coefficients are restricted to zero. We rely on the dummy variable approach for ease of comparing the estimates for different regimes. We impose the same identification restriction that the sample average of β^τ is equal to one.

We use the mean of the Blue Chip Financial Forecasts survey to proxy the one-step ahead forecast of the federal funds rate $E_{\tau-1}(i_\tau)$. It is important to emphasize that we let τ index a calendar quarter. This is because we want τ to be short enough not to stale expectation about interest rate. The dummy observation, $\mathbb{I}_{\{E_{\tau-1}(i_\tau)-i_{\tau-1}\geq c_i\}}$, is equal to one when the one-step ahead forecast exceeds the current federal funds rate over threshold, c_i. The threshold is set to ten basis point to clearly capture episodes in which market participants expect rising interest rate. We define the easing period by $\mathbb{I}_{\{E_{\tau-1}(i_\tau)-i_{\tau-1}\leq -c_i\}}$. The results are robust to any cutoff point greater than five basis points. For output gap, we set c_y^b (c_y^n) to the one-quarter (three-quarter) quantile for the purpose of capturing the episodes in which the economy is significantly below (near) its potential output. For VIX, we set c_v^l (c_v^s) to the three-quarter (one-quarter) quantile for the purpose of capturing the episodes in which the stock market uncertainty is significantly large (small). We emphasize again that the results are not too sensitive to the choices of the threshold. We show the corresponding economic regimes in the appendix. We take the survey measures collected in the previous quarter and use lagged macroeconomic variables to avoid simulataneity bias, i.e., these variables are predetermined before the release of macroeconomic news announcements.

We start by testing the null hypothesis, H_0: $\beta_i^{\text{tightening}} < 0$, that expectation about a rate increase leads to a fall in the sensitivity of stock returns to MNAs. Column (1) of Table 3

[13] From the time series of the output gap, we find that the economy is furthest below trend at the very end of a recession and the very beginning of an expansion.

shows that the estimated coefficient is significantly negative and thus we cannot reject the null hypothesis. Most importantly, the response of the stock market to macroeconomic news during periods of tightening is close to zero as indicated by $\beta_0 + \beta_i^{\text{tightening}}$. We repeat the analysis with "easing" and "no change" periods in column (2) and (3). We define "no change" periods to be ones in which the difference between interest rate expectation and current level is in between the thresholds for the tightening and easing periods. We find that the estimate associated with "easing" is marginally significant while that for "no change" is significant. Overall the response of the stock market to MNAs during these periods, $\beta_0 + \beta_i^{\text{easing}}$ ($\beta_0 + \beta_i^{\text{no change}}$) are approximately 1.4 (1.3) respectively, representing economically significant responses during these periods relative to average return sensitivity. However, one should be cautious in overinterpreting these results since a substantial fraction of our sample covers the ZLB periods during which both the actual and expected interest rates did not move much.

Second, we examine if interest rate expectation has differential effects on the stock return sensitivity when the economic phase changes. We consider output gap and VIX to capture variation in economic phase. The estimates provided in column (4) of Table 3 indicate that the stock market sensitivity is twice larger than average when the economy is significantly below trend ($\beta_0 + \beta_y^{\text{below trend}}$). Note that the loading on easing expectation (β_i^{easing}) is estimated to be 0.55 which is marginally significant. This implies that when the economy is below trend and the market expects interest rate to fall, the stock return sensitivity is $\beta_0 + \beta_i^{\text{easing}} + \beta_y^{\text{below trend}}$, roughly 2.5 times greater than the average sensitivity. On the other hand, when the economy is near trend, and at the same time, the interest rate is expected to rise, the stock return sensitivity is estimated to be $\beta_0 + \beta_i^{\text{tightening}} + \beta_y^{\text{near trend}}$, roughly -0.80 (see column (5)) but statistically insignificantly different from zero.[14] These analyses confirm the view that stock returns respond more aggresively (passively) when there is greater (less) slack in the economy and interest rate is expected to fall (rise). Third, we find qualitatively similar results when VIX is used instead (see column (6) and (7)) but the estimates associate with VIX are not significant.

[14]Using delta method, we computed the corresponding standard error.

Table 3: Interest rate expectation and the time-varying stock return sensitivity

Periods	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	1.30***	0.91***	0.66***	0.32	1.34***	0.31*	1.25***
	(0.09)	(0.07)	(0.15)	(0.20)	(0.21)	(0.17)	(0.24)
+ Expected tightening	-1.36***				-0.57*		-1.41***
	(0.40)				(0.31)		(0.50)
+ Expected easing		0.51*		0.55*		0.70*	
		(0.31)		(0.33)		(0.37)	
+ Expected no change			0.65**	0.29	0.28	0.86***	0.15
			(0.29)	(0.30)	(0.29)	(0.30)	(0.30)
+ Below trend				1.66***			
				(0.42)			
+ Near trend					-1.56***		
					(0.26)		
+ Large VIX						0.44	
						(0.33)	
+ Small VIX							0.14
							(0.30)
R^2 adjusted	0.10	0.08	0.09	0.13	0.14	0.10	0.10

Notes: The estimation sample period is from 1998 to 2017. We only report the estimates associated with β in the regression. We compute the annualized one-quarter ahead forecast direction $E_{\tau-1}(i_\tau) - i_{\tau-1}$ of the federal funds rate based on the Blue Chip Financial Forecasts survey mean. The threshold for interest rate is set to 10 basis point. For output gap, we set c_y^b (c_y^n) to the one-quarter (three-quarter) quantile for the purpose of capturing the episodes in which the economy is significantly below (near) its potential output. For VIX, we set c_v^l (c_v^s) to the three-quarter (one-quarter) quantile for the purpose of capturing the episodes in which the stock market uncertainty is significantly high (low). The results are not to sensitive to the choices of the cutoff points. We avoid the endogeneity problem by using the lagged quarterly macroeconomic observables. We report the Newey-West adjusted standard errors. Notation: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5 Monetary Policy Beliefs Embedded in Macroeconomic Data

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

5.1 The sequential learning problem

We consider a regime-switching vector autoregressive model

$$\begin{aligned} y_t' &= x_t'\Phi_{S_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_{S_t}) \\ Pr(S_t = j|S_{t-1} = i) &= q_{ij}, \quad \sum_{j=1}^{2} q_{ij} = 1. \end{aligned} \tag{9}$$

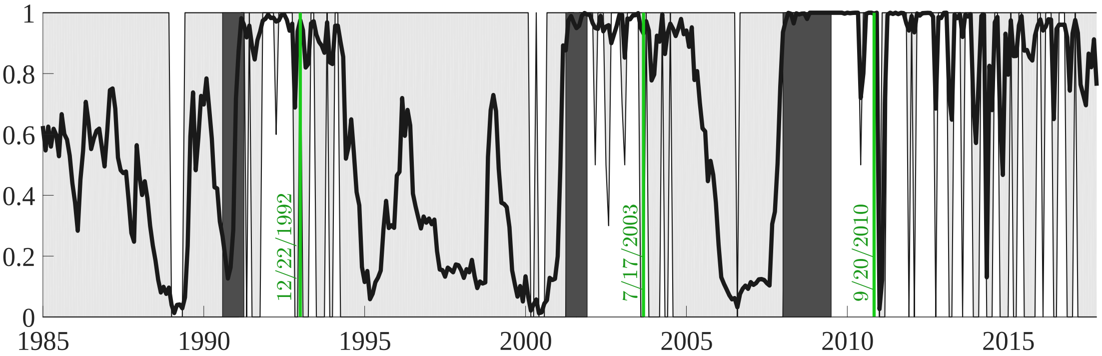
Here, y_t is an $n \times 1$ vector of observables, S_t is a discrete Markov state variable that takes on two values, x_t is a $k \times 1$ vector $x_t' = [y_{t-1}', ..., y_{t-p}', 1]$, and Φ_i is a $k \times n$ parameter matrix that depends on regime i defined by $\Phi_i = [\phi_1(i), ..., \phi_p(i),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

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

$$\begin{aligned} p(\Phi, \Sigma, \Pi, S^{t+1}|y^{t+1}) &= p(\Phi, \Sigma, \Pi|S^{t+1}, y^{t+1})p(S^{t+1}|y^{t+1}) \\ &= \underbrace{p(\Phi|\Sigma, \Pi, y^{t+1}, S^{t+1})p(\Sigma|\Pi, y^{t+1}, S^{t+1})p(\Pi|y^{t+1}, S^{t+1})}_{\text{(i) parameter learning}} \underbrace{p(S^{t+1}|y^{t+1})}_{\text{(ii) state filtering}}. \end{aligned} \tag{10}$$

The joint learning of (i) parameters and (ii) states is a high-dimensional problem which incurs confounding effects arising from multiple sources of uncertainty (see Johannes, Lochstoer, and Mou (2016) for similar problems). To solve for the sequential learning problem, we use the particle learning algorithm developed by Carvalho, Johannes, Lopes,

Figure 6: Probability of the nonreactive interest rate regime



Notes: The black solid line is posterior mean regime probabilities which is overlaid with the 90% credible interval (gray shaded areas). Dark shaded bars indicate the NBER recession dates. Green solid lines represent the dates when the formal announcements of business cycle turning point at which contraction turns into expansion are made by the NBER.

and Polson (2010), which is a generalization of the mixture Kalman filter of Chen and Liu (2000). Roughly speaking, we rely on particle methods to directly sample from the particle approximation to (10). The detailed description of the algorithm is provided in the appendix.

5.2 Empirical illustration

Data, priors, and identification. For the empirical illustration of the model, we use the unemployment rate and the federal funds rate from 1985:M1 to 2017:M12. We use the unemployment rate as the empirical proxy for one of the statutory objectives for monetary policy. To initialize the algorithm, we provide the priors in Table D.3 which summarizes our initial beliefs. We rely on conjugate priors since these prior beliefs coupled with the likelihood function lead to posterior beliefs that are of the same form. To deal with the label switching problem, we impose that the coefficient that governs the feedback from the interest rate to the unemployment rate in the first regime is greater than that in the second regime, that is, $|\Phi_{1,(2,1)}| > |\Phi_{2,(2,1)}|$ and $|\Phi_{1,(1,2)}| > |\Phi_{2,(1,2)}|$.[15]

Parameters and state learning. We provide the evolution of parameter learning in the appendix which visualizes the first part of (10). The credible interval at time 0 correspond

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

to the 90% prior intervals. As more observations are included in the estimation, the 90% credible intervals shrink over time. Posteriors at the end of sample are what one would obtain from the entire time series data. Table D.4 reports 5%, 50%, 95% percentiles of the end of sample posterior distributions. Along with the identification assumption, the fact that the end of sample posterior estimates for $\Phi_{2,(2,1)} \approx \Phi_{2,(1,2)} \approx \Sigma_{2,(2,1)} \approx 0$ provide the natural interpretation that the first regime is the reactive interest rate regime and the second regime is the nonreactive regime.[16] In the second regime, the dynamics of the unemployment rate evolves almost in an autoregressive pattern and the interest rate does not impact the dynamics.

For the sake of saving space, we move to the object of our main interest, that is, the second part of (10). Figure 6 displays the posterior mean probabilities of the second regime, which we define as the nonreactive interest rate regime. It is interesting to observe that the mean probability of nonreactive regime starts to increase in recession and remains near one a few years after the recession. Roughly speaking, the probabilities start to come down after the formal NBER announcements of business cycle turning point from contraction to expansion.[17] In general, significant posterior uncertainty remains regarding the regime probabilities since they are overlaid with large credible intervals (essentially covering from zero to one).

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

6 Decomposing the Stock Return Sensitivity

Having shown the important time variation in return responses to MNAs, we further decompose the stock market sensitivity to components attributable to news about cash flows,

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

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

risk-free rate, and risk premium. This is of interest in its own right in terms of understanding which piece of news is affecting the sensitivity at the impact of the announcement. Furthermore, such decomposition has a long tradition in the finance literature and our analysis provides a new perspective using relatively high-frequency data around announcements.

We follow Campbell (1991) and relate the unexpected stock return to news about cash flows (CF) and news about future returns which can be further decomposed into news about risk-free rate (RF) and risk premium (RP). We use the 12-month Eurodollar futures return and variance risk premium as empirical proxies for news about risk-free rate and risk premium, respectively. Eurodollar futures are known to be closely related to market expectations about the federal funds rate and variance risk premium proxies the premium associated with the volatility of volatility. We refer to the appendix for the construction of variance risk premium. Using the subscripts "ED" and "VP" for eurodollar and variance premium respectively, we jointly estimate the following three equation system:

$$\begin{bmatrix} r_{t-\Delta}^{t+\Delta} \\ r_{t-\Delta,ED}^{t+\Delta} \\ vp_{t+\Delta_v} \end{bmatrix} = \begin{bmatrix} \alpha^{\tau} \\ \alpha_{ED}^{\tau} \\ \alpha_{VP}^{\tau} \end{bmatrix} + \begin{bmatrix} \left(\beta_{CF}^{\tau} - \beta_{RF}^{\tau} - \beta_{RP}^{\tau}\right)(\gamma^{\top} X_t) \\ \beta_{RF}^{\tau}(\gamma_{ED}^{\top} X_t) \\ \beta_{RP}^{\tau}(\gamma_{VP}^{\top} X_t) \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \epsilon_{t,ED} \\ \epsilon_{t,VP} \end{bmatrix} \tag{11}$$

to decompose the stock return sensitivity

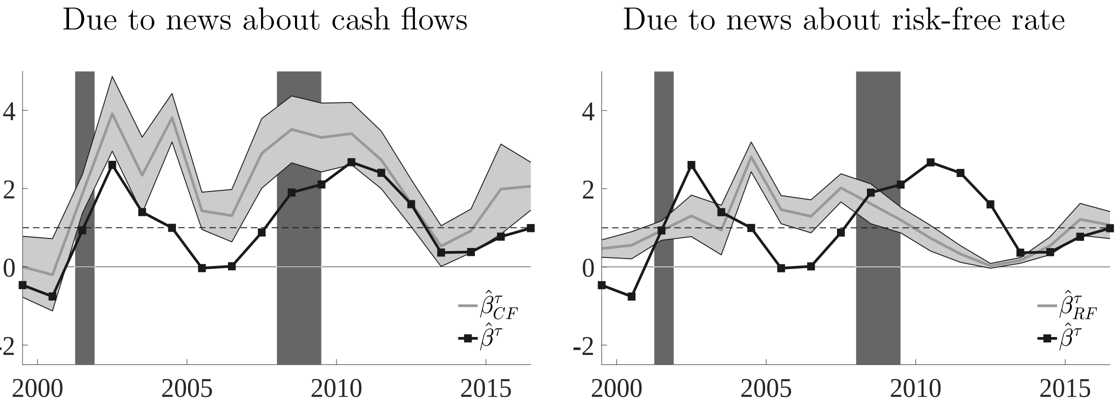
$$\beta^{\tau} = \beta_{CF}^{\tau} - \beta_{RF}^{\tau} - \beta_{RP}^{\tau}. \tag{12}$$

We let $\Delta = 30\text{min}$ and Δ_v be the closing time of a day of macroeconomic announcements. The identification assumption is that the averages of $\beta_{CF}^{\tau} - \beta_{RF}^{\tau} - \beta_{RP}^{\tau}$, β_{RF}^{τ}, and β_{RP}^{τ} are one. Note that the top equation in (11) is identical to our benchmark regression of (1). The purpose of the joint estimation is to separately identify β_{CF}^{τ}, β_{RF}^{τ}, and β_{RP}^{τ} by bringing in more observations.

The estimation results will depend on how valid and informative the empirical proxies are with respect to news about risk-free rate and risk premium. We acknowledge the shortcomings of our proxies since they do not reflect changes in expectations over long-run horizons. For example, VIX only measures the market's expectation of 30-day volatility.[18]

[18]There is also problem with the availability of VIX data as well. First, the intra-day VIX futures and spot data are only available after July 2012 and June 2003, respectively according to our data vendor (www.tickdata.com). The main problem that we are facing is that the access to high-frequency VIX data comes at the cost of shortening the estimation sample. In the subsequent analysis, we decided to rely on the daily VIX spot data to work with longer estimation sample and capture both announcements made

Figure 7: The decomposition of stock return sensitivity



Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We flip the sign of Initial Jobless Claims surprises for ease of comparison against other announcement surprises. The estimate for $\hat{\gamma}$ and $\hat{\gamma}_{ED}$ have the same sign. We estimate (11) by setting $\beta^{\tau} = \beta^{\tau}_{CF} - \beta^{\tau}_{RF}$ to sharpen the inference. The identification assumption is that the averages of $\beta^{\tau}_{CF} - \beta^{\tau}_{RF}$ and β^{τ}_{RF} are equal to one. We can ignore $\hat{\beta}^{\tau}_{RP}$ because of its limited role on the stock return sensitivity. The estimates for $\hat{\beta}^{\tau}_{CF}$ and $\hat{\beta}^{\tau}_{RF}$ are provided in light-gray-solid lines with 2-standard-error bands (light-shaded area) around them. For ease of comparison, we provide the benchmark return sensitivity estimate $\hat{\beta}^{\tau}$ (black-squared lines).

Similarly, while we believe that news about risk-free rate can only be reflected in Eurodollar future contracts with much longer maturity dates, these contracts suffer from liquidity problems and are only available for relatively short period of time. One needs to understand that there is very little fluctuation in short-maturity Eurodollar futures return during the ZLB periods which contrasts starkly with the pre-crisis periods. With these caveats in mind, we move to the discussion of our estimation results.

Our analysis reveals several intersting features. We first show that at high-frequency around the time of our benchmark macroeconomic news announcements, variations in stock prices are hardly accounted for by risk premium news. This is in sharp contrast to a view that discount rate variations, which in turn are primarily driven by risk premium variations, account almost entirely for price fluctuations (e.g., Cochrane (2011)). For brevity, we therefore omit the estimate $\hat{\beta}^{\tau}_{RP}$. To sharpen the inference, we instead estimate (11) by setting $\beta^{\tau} = \beta^{\tau}_{CF} - \beta^{\tau}_{RF}$. We can ignore β^{τ}_{RP} because of its limited role on the stock return sensitivity at the frequencies of our analysis.

We provide the resulting estimates for $\hat{\beta}^{\tau}_{CF}$ and $\hat{\beta}^{\tau}_{RF}$ in Figure 7. For ease of comparison,

at 8:30am and 10:00am.

we plot them against the benchmark stock return sensitivity estimate $\hat{\beta}^{\tau}$ (black-squared line). It is important to understand that the sign of $\hat{\gamma}$ and $\hat{\gamma}_{ED}$ are both positive; therefore, $\hat{\beta}^{\tau}_{CF}$ and $\hat{\beta}^{\tau}_{RF}$ can be interpreted cleanly as measuring variations in cash-flow and risk-free rate news; $\hat{\beta}^{\tau}_{RF}$ is negatively correlated with $\hat{\beta}^{\tau}$ under our assumption and we can reconstruct $\hat{\beta}^{\tau} = \hat{\beta}^{\tau}_{CF} - \hat{\beta}^{\tau}_{RF}$.

As can be seen from Figure 7, time variations in return sensitivity mostly reflects news about cash flows and there is significant comovement between the two measures. This is intuitive because news about cash flows will fluctuate more (less) during periods in which the economy has large (small) capacity to grow. It is also interesting to observe that during times of tightening expectation, say from 2004 to 2007, the role of news about risk-free rate was much elevated.[19] We observe that these are also periods in which the economy had smaller growth opportunities. Consistent with our explanation regarding the interplay between expected cash flow growth and expected interest rate movements, the stock market hardly reacted to MNAs during those periods. Furthermore, and consistent with the findings by Swanson and Williams (2014), we show that news about risk-free rate were small during the ZLB periods and close to zero especially around 2012. From 2013 onward, while small in magnitude, the risk-free rate news have been increasing over time, an effect that has contributed to muting the overall stock market responses to MNAs inspite of increased cashflow growth expectations. Overall, our decomposition shows that during macroeconomic announcement periods, the key drivers for the stock market sensitivity are news about cash flows and risk-free rate, and risk-free rate news can play a big role in determining the return sensitivity.

7 Conclusion

Using high-frequency stock returns, we provide strong evidence of persistent cyclical variation in the sensitivity of stock prices to MNA surprises. We find that during periods in which the economy is below trend, i.e., the output gap is large and negative, the response of the stock market to MNA surprises is quite large. The effect is larger especially when this takes place during periods in which market participants hold the view that the interest rate is not expected to go up. On the other hand, when the economy is near trend,

[19]Note that the Federal Reserve increased the federal funds rate by more than 4 percentage points from mid-2004 until mid-2006.

i.e., the output gap is small, and at the same time, interest rate is expected to rise, we find much smaller stock market's reaction to MNA surprises. The new empirical facts are robust to various measures of stock market returns and combinations of MNAs, and to different sampling periods. Our evidence highlights the importance of understanding the interplay between economic conditions, the expectations about monetary policy given these conditions, and their joint effect on the stock market.

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Online Appendix

Fearing the Fed: How Wall Street Reads Main Street

Tzuo-Hann Law, Dongho Song, Amir Yaron

A High-Frequency Regression

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

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

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

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

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 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 daily VIX index on the day of 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. We square VIX (annualized standard deviation) and divide by 12 to convert to monthly volatility.

C Parameter Learning

The VAR parameters. We assume that

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

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

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

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

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

We can express

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

and

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

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

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

Analogously for Σ_i, we can deduce that

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

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

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

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

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

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

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

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

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

We can deduce that posterior distribution of Π is

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

C.1 Particle Learning

We collect the model parameters in

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

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

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

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

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

Ultimately, we are interested in

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

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

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

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

C.1.1 Algorithm

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

1. **Resample Particles:**

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

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

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

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

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

3. **Propagate Sufficient Statistics:**

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

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

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

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

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

4. **Draw Parameters:**

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

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

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

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

C.2 Priors

To initialize the algorithm, we provide the priors in Table D.3. The length of the prior training sample (prior precision) is set to 200 months.

D Supplemental Tables

Table D.1: Macroeconomic news announcements

Name	Obs.	Release Time	Source	Start Date	End Date
Capacity Utilization	231	9:15	FRB	16-Jun-1998	15-Dec-2017
Change in Nonfarm Payrolls	236	8:30	BLS	05-Jun-1998	08-Dec-2017
Construction Spending MoM	220	10:00	BC	02-Nov-1998	01-Dec-2017
Consumer Confidence Index	233	10:00	CB	30-Jun-1998	27-Dec-2017
CPI MoM	234	8:30	BLS	16-Jun-1998	13-Dec-2017
Durable Goods Orders	255	10:00	BC	24-Jun-1998	22-Dec-2017
Factory Orders	231	10:00	BC	04-Jun-1998	04-Dec-2017
GDP Annualized QoQ	237	8:30	BEA	26-Mar-1998	21-Dec-2017
GDP Price Index	201	8:30	BEA	31-Jul-1998	21-Dec-2017
Housing Starts	231	8:30	BC	16-Jun-1998	19-Dec-2017
Industrial Production MoM	231	9:15	FRB	16-Jun-1998	15-Dec-2017
Initial Jobless Claims	1006	8:30	ETA	04-Jun-1998	28-Dec-2017
ISM Manufacturing	233	10:00	ISM	01-Jun-1998	01-Dec-2017
ISM Non-Manf. Composite	223	10:00	ISM	05-Apr-1999	05-Dec-2017
Leading Index	233	10:00	CB	02-Jun-1998	21-Dec-2017
New Home Sales	232	10:00	BC	02-Jun-1998	22-Dec-2017
Personal Income	235	8:30	BEA	26-Jun-1998	22-Dec-2017
PPI Final Demand MoM	233	8:30	BLS	12-Jun-1998	12-Dec-2017
Retail Sales Advance MoM	231	8:30	BC	14-Jul-1998	14-Dec-2017
Trade Balance	233	8:30	BEA	18-Jun-1998	05-Dec-2017
Unemployment Rate	235	8:30	BLS	02-Jul-1998	08-Dec-2017

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

Table D.2: Descriptive statistics for the standardized MNA surprises

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

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

Table D.3: Priors

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

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

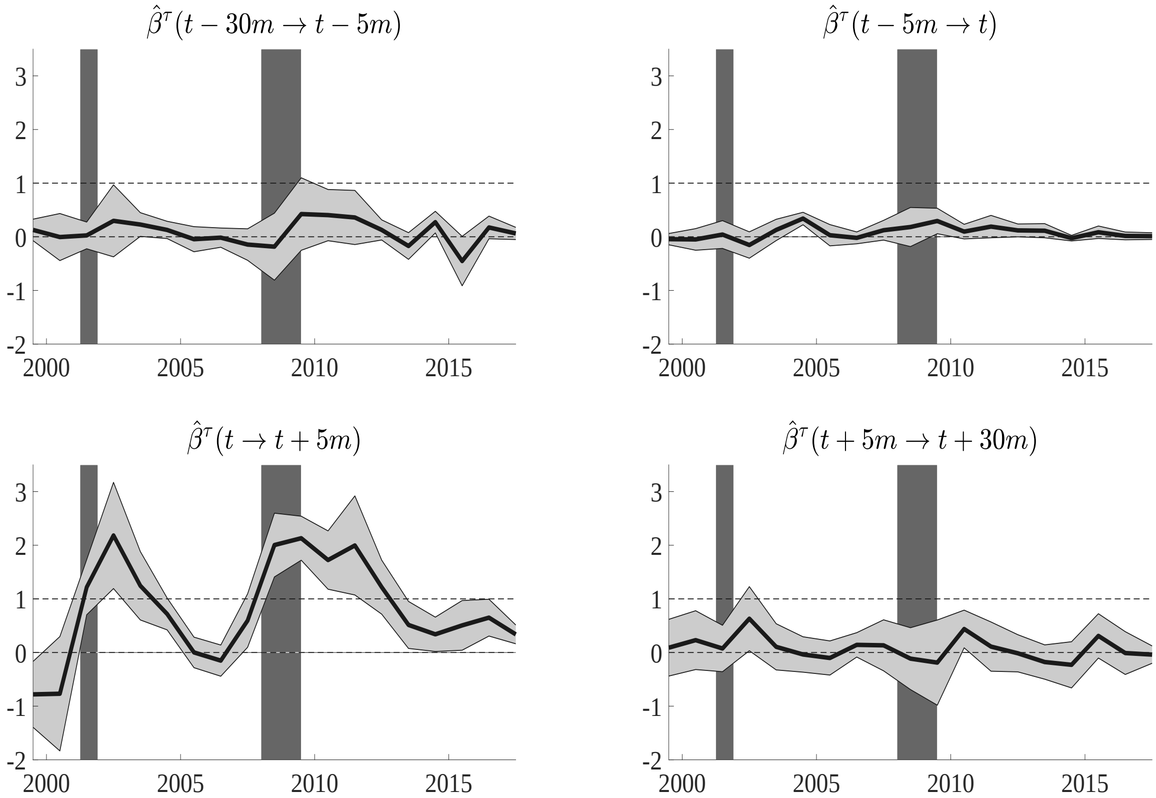
Table D.4: Posteriors (end of sample)

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

Notes: We use the unemployment rate and the federal funds rate from 1985:M1 to 2017:M12 in the estimation. We report the end of sample (2017:M12) posterior distributions. The first subscript identifies the regime and the remaining subscripts which are parenthesized indicate their location in the parameter matrix.

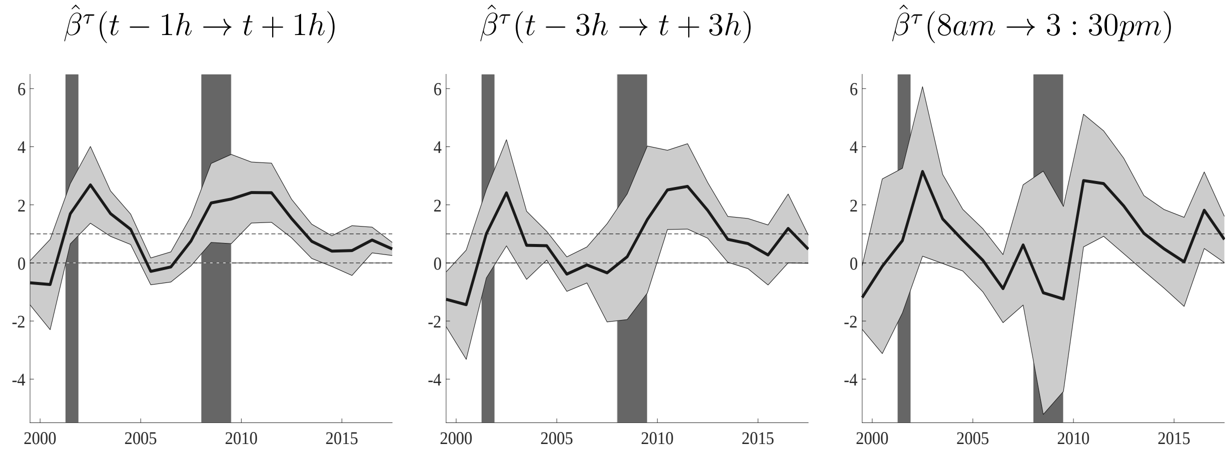
E Supplemental Figures

Figure E.1: The stock return sensitivity before and after the news announcements



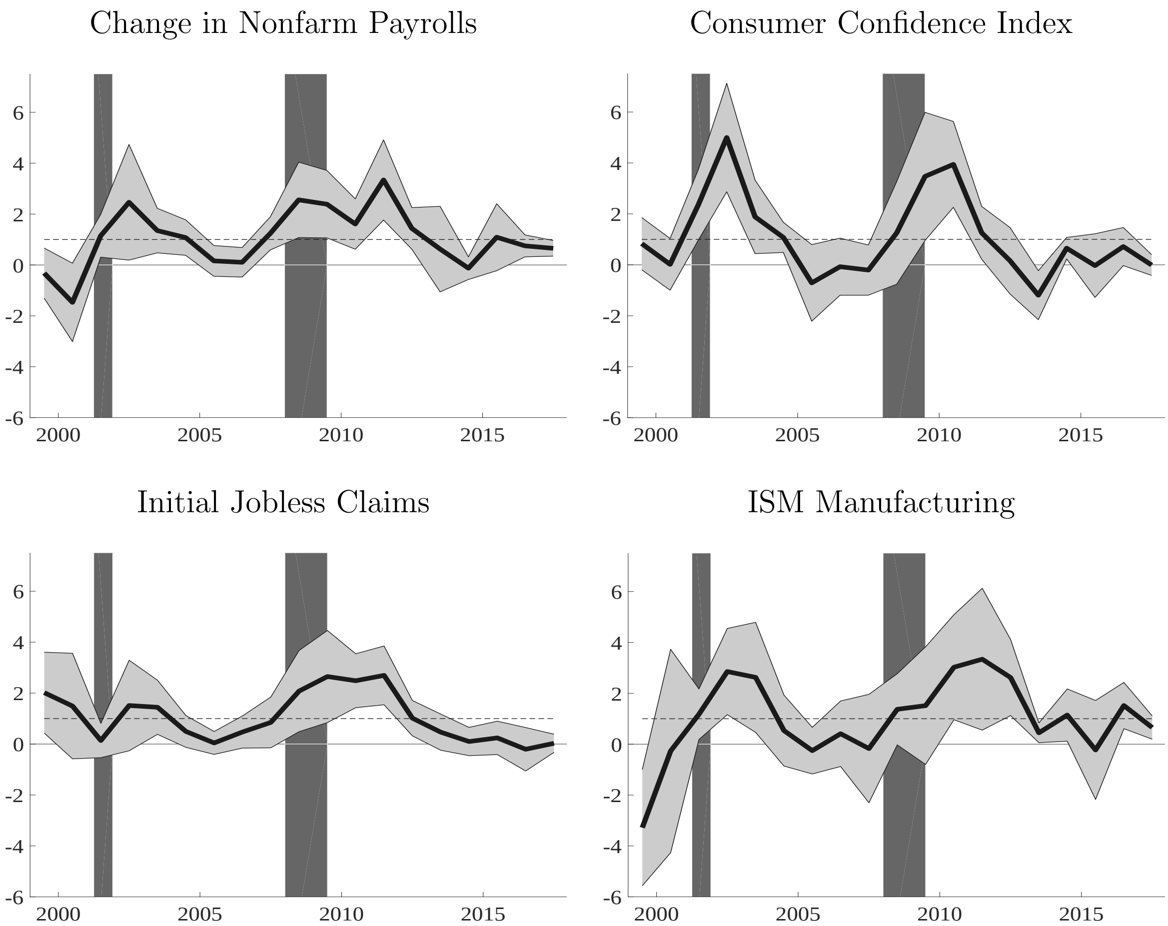
Notes: The individual $\hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$ are shown with ± 2 standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^\tau(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$. By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

Figure E.2: The stock return sensitivity: Evidence from lower-frequency data



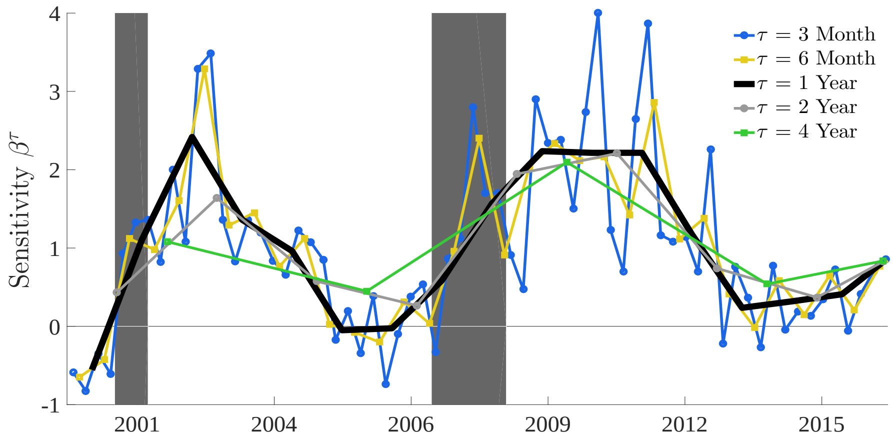
Notes: The individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ are shown with ± 2 standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$.

Figure E.3: The stock return sensitivity: Evidence from individual regression



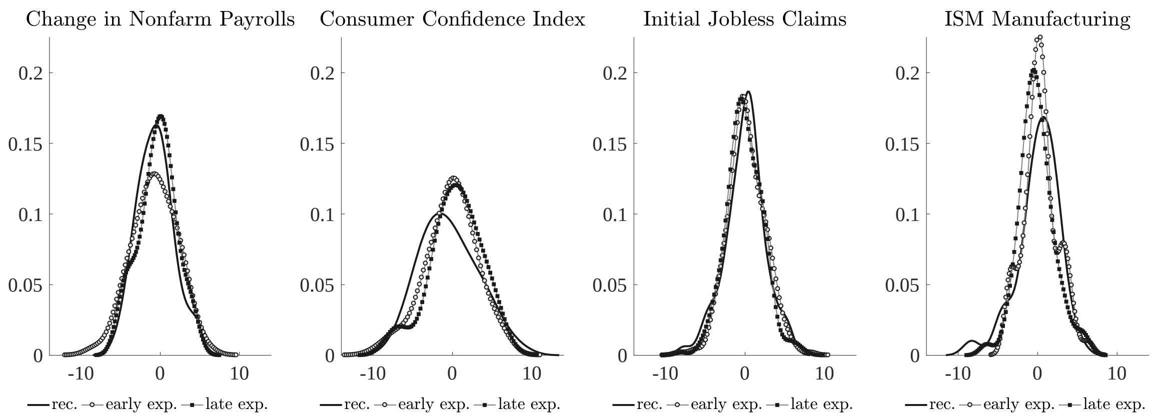
Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30$min. We impose that γ^{τ} (black-solid line) is on average equal to one. We provide ± 2-standard-error bands (light-shaded area)

Figure E.4: The smoothing parameter τ



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

Figure E.5: Distribution of the MNA surprises

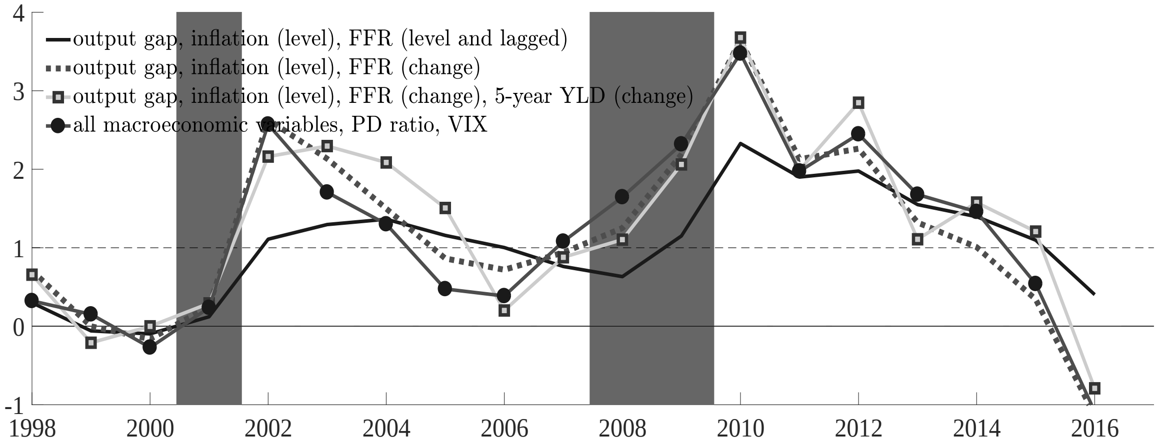


Surprises Pair	NFP	CCI	IJC	ISM
(Recession, Early Expansion)	0.79	0.14	0.61	0.66
(Early Expansion, Late Expansion)	0.78	0.47	0.51	0.24
(Recession, Late Expansion)	0.65	0.23	0.30	0.36

Asympotic p-values from the two-sample Kolmogorov-Smirnov test

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

Figure E.6: The stock return sensitivity: Identifying the economic drivers

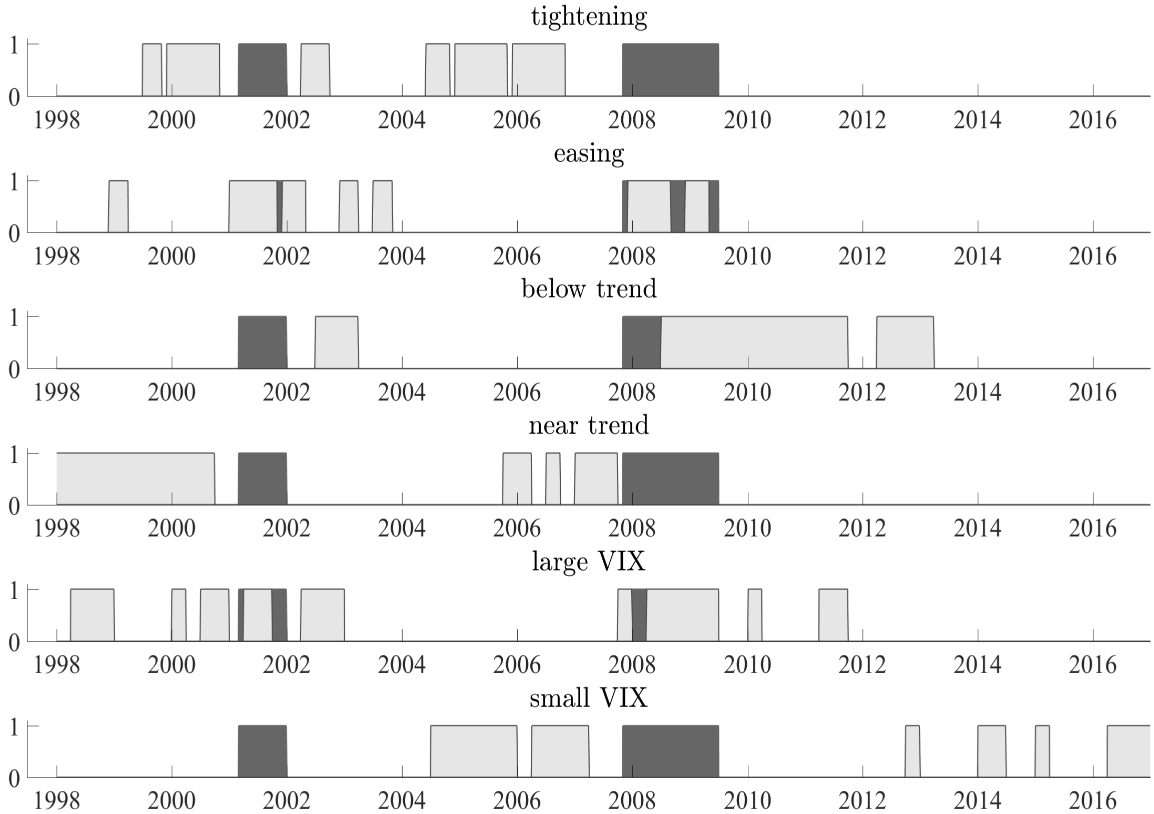


Notes: We re-estimate the benchmark regression with the following parametric assumption

$$r_{t-\Delta}^{t+\Delta} = \alpha^{\tau} + \beta^{\tau}\gamma^{\top}X_t + \epsilon_t, \quad \beta^{\tau} = \beta_0 + \beta_1^{\top}Z_{\tau-1}.$$

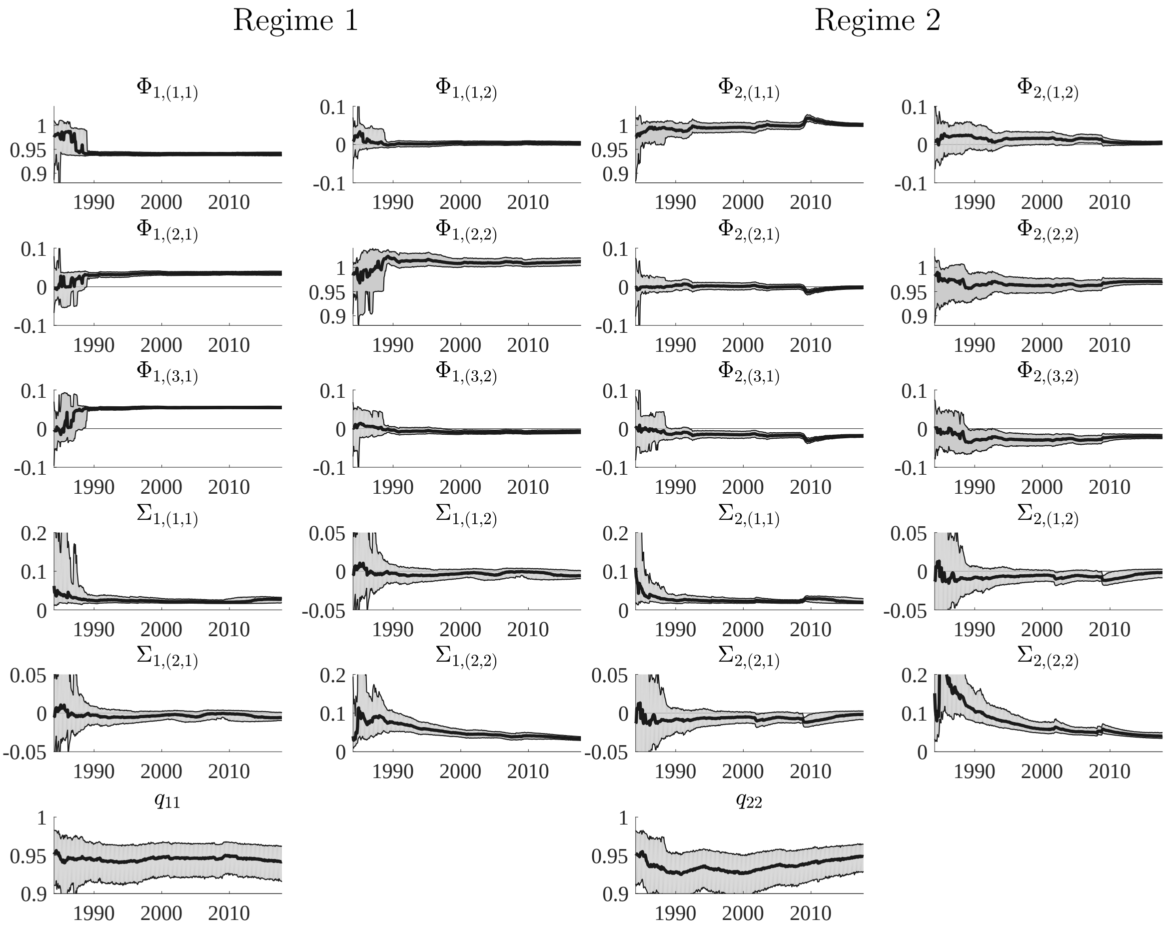
The estimation sample period is from 1998 to 2017. We use the benchmark macroeconomic announcements: Change in Nonfarm Payroll; Consumer Confidence Index; Initial Jobless Claims; and ISM Manufacturing. Output gap is defined by log difference between the real potential GDP and real GDP. Inflation is GDP deflator and interest rate is the effective federal funds rate (FFR). 5-year YLD refers to the 5-year Treasury yields. "Change" refers to percent change from a year ago. PD ratio is the price-dividend ratio. VIX is CBOE volatility index. All variables are standardized. We avoid the endogeneity problem by using the lagged annual macroeconomic observables. The black-solid line corresponds to column (2) in Panel B of Table 2. The black-dashed line corresponds to column (3) in Panel B of Table 2. The squared-line corresponds to column (5) in Panel B of Table 2. The circled-line corresponds to column (9) in Panel B of Table 2.

Figure E.7: Economic regimes



Notes: The dummy observation, $\mathbb{I}_{\{E_{\tau-1}(i_\tau)-i_{\tau-1}\geq c_i\}}$, is equal to one when the one-step ahead forecast exceeds the current federal funds rate over threshold, c_i. The threshold is set to ten basis point to clearly capture episodes in which market participants expect rising interest rate. We define the easing period by $\mathbb{I}_{\{E_{\tau-1}(i_\tau)-i_{\tau-1}\leq -c_i\}}$. The results are robust for any cutoff point greater than five basis points. For output gap, we set c_y^b (c_y^n) to the one-quarter (three-quarter) quantile for the purpose of capturing the episodes in which the economy is significantly below (near) its potential output. For VIX, we set c_v^l (c_v^s) to the three-quarter (one-quarter) quantile for the purpose of capturing the episodes in which the stock market uncertainty is significantly high (low).

Figure E.8: Posteriors



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