Monetary Uncertainty and the Response of Stock Market to Macroeconomic News

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Abstract

This paper examines the effect of macroeconomic news announcements (MNA) on the stock market. Stocks exhibit a strong positive response to major MNA: 1 standard deviation of MNA surprise causes 11-25 bps higher returns. This response is highly time-varying and is weaker during periods of high monetary uncertainty. I decompose this response into cash flow and risk-free rate channels. 1 standard deviation of good MNA surprise leads to plus 30 bps returns from the cash flow channel and minus 23 bps per 1% of monetary uncertainty from the risk-free rate channel. Risk-free rate channel is time-varying and is stronger when monetary uncertainty is high. High levels of monetary uncertainty mask the strong positive response of stocks to MNA, which explains why past research failed to detect this relation.

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1 Introduction

Price of an asset is a function of the information set of investors. Any movement in price must be driven by the arrival of new information. One example of such information is news about the state of the economy, i.e., macroeconomic news announcements (MNA). Counterintuitively, an extensive body of research over the recent decades failed to find large directional response of stock prices to MNA. The lack of this evidence is puzzling since it raises questions about the relevance of macroeconomic conditions to stock prices and contradicts the intuition of practitioners and academics.

The aim of this paper is to establish a set of stylized facts on the response of financial assets to MNA and to use this evidence to refine our thinking about asset prices. Utilizing crisper identification and high-frequency data allows detecting patterns of price response to MNA, which eluded researchers for decades. My results suggest a large positive response of both stocks and risk-free rates to MNA surprise and reaffirm the strong link between macroeconomic conditions and prices of financial assets.

First, I document that several types of MNA have a large effect on both volatility and direction of aggregate stock returns. In a tight window around these announcements, 9-20% of movement in stock prices is explained by MNA surprises. Response to these MNA alone is as large as 35%-70% of price variation during periods without MNA. Stocks exhibit a strong positive reaction to major MNA: 1 standard deviation of good surprise causes 11-25 bps higher returns. Unsurprisingly, these are MNA, closely followed by the financial press: non-farm payroll, PMI, retail sales, and consumer confidence.

Second, I report that the response of stocks to MNA crucially depends on the level of uncertainty about monetary policy. This allows me to reinterpret puzzling findings that stocks tend to react somewhat negatively to positive growth news (Boyd, Hu, Jagannathan 2005). Good growth news implies both higher expected dividends and a higher future risk-free rate. Therefore, these two channels affect stock prices in opposite directions. Intuitively, the implied volatility of T-notes can instrument for the strength of the monetary channel. When such implied volatility is low, risk-free rate is not expected to vary a lot, making risk-free rate less sensitive to changes in the economic environment.

I show that the positive reaction of stocks to good (i.e., higher growth) MNA surprise is much stronger when monetary uncertainty is low. A high level of monetary uncertainty makes the positive response of stocks to MNA weaker. At a high enough level of monetary uncertainty, the relation between stock returns and MNA surprise may even reverse due to the larger strength of the monetary channel. Very high monetary uncertainty during the 1970s-1980s is likely to be the reason previous research failed to find a positive response of stocks to MNA surprise. A simple theoretical framework allows me to quantitatively assess the contribution of these two channels to the reaction of aggregate stock prices to most types of MNA. After controlling for the monetary channel, 1 standard deviation surprise in major MNA causes 30 bps higher returns, i.e., price movement, equal to 90% of the standard deviation of returns during similar 30-minute periods on days without MNA.

Third, I document that none of the major MNA surprises is priced in the cross-section of expected stock returns. I use MNA surprise as a proxy for macroeconomic shock, associated with each MNA type and estimate the sensitivities of individual stocks to these shocks. None of the 4 major MNA shocks produces a significant return spread. This finding is consistent with the idea that risk premium is not significantly affected by MNA, implying that most changes in discount rate come from the risk-free rate. The whole yield curve appears to shift up or down in response to MNA surprise. The effect is larger for short maturities and slowly declines at the long end of the term structure.

The literature on the behavior of stock prices during periods of MNA dates back at least to Schwert (1981). Pearce and Roley (1985) find that money supply is the only MNA, which affects stock returns. Cutler, Poterba, and Summers (1989) use vector autoregression on monthly data to quantify the fraction of returns, driven by macroeconomic news. McQueen and Roley (1993) suggest that response of the stock market to MNA may depend on the business cycle. They find a positive reaction to good news during periods of low growth and a negative reaction during a boom. Flannery and Protopapadakis (2002) argue that the nonlinearity and time dependence of effects of MNA makes them hard to detect. They focus on the response of market volatility to MNA and find that money supply and inflation are the most important MNA. Boyd, Hu, and Jagannathan (2005) study market response to unemployment news and find that on average bad unemployment news have a positive effect on stocks. They explain this result by the hypothesis that during expansions market perceives unemployment news as news about interest rate rather than economic growth. Law, Song, and Yaron (2020) use the New Keynesian model to argue that the stock response to MNA surprise is the strongest during periods of the low output gap. My paper reinterprets the results in the papers above by showing that monetary uncertainty is the driver of state dependence of stock response to MNA. Since monetary uncertainty is the lowest during early recovery, previous research misattributed time variation in this response to business cycles rather than monetary uncertainty. I show that the stage of the business cycle has little explanatory power after controlling for monetary uncertainty.

By uncovering and quantifying the large monetary channel of the stock response to major MNA, this paper contributes to monetary economics. The last two decades saw increased interest in asset pricing effects of monetary policy. Bernanke and Kuttner (2005) used high-frequency identification to argue that stocks react negatively to Fed Funds rate surprises. There is a growing body of research on the implications of zero lower bound (ZLB) for monetary transmission and asset prices. Swanson and Williams (2013, 2014) and Zhou (2014) focus on the response of forward rates to monetary news at ZLB. My results suggest that ZLB is an extreme case of low monetary uncertainty and is useful to isolate out cash flow channel of MNA response.

The paper is organized as follows. Section 2 explains the advantages of event studies for identifying the relation between asset prices and macroeconomic conditions. Section 3 contains a simple signal extraction model to motivate decomposition. Section 4 discusses data sources, identifies types of MNA and discusses the construction of monetary uncertainty proxy. Section 5 focuses on the response of stocks to major MNA and decomposes this response into cash flow and monetary channels using a simple statistical framework. Section 6 explores the cross-section of stocks by their response to major MNA. Section 7 concludes.

2 Estimation of the response using event study

Asset pricing has a long tradition of estimating exposures of financial assets to macroeconomic variables. Most studies use low-frequency regressions to perform such estimation. For example, to estimate the exposure of a stock to consumption growth, we usually regress its returns on contemporaneous consumption growth at monthly (quarterly) frequency. While the simplicity of this approach makes it very appealing, it suffers from some drawbacks. Examples of such limitations are a lack of causal interpretation of estimates, low statistical power and inability to distinguish between similar macroeconomic variables. Another problem of this approach is its inability to account for market expectations in a reasonably precise way. As emphasized by Brunnermeier et al. (2021), since returns of financial assets should be driven by changes in expectations, controlling for the expectations is critically important. The traditional approach usually uses either first differences or residuals from some time-series model, such as VAR, in order to measure innovations in macroeconomic variables. Multiple studies (Ang et al., 2007, Rossi and Sekhposyan, 2015) suggest that investors‘ surveys provide a better proxy for expectations, compared to time series models. To the best of my knowledge, there are no investors' forecasts, made during the last days of the month t-1 for macroeconomic variables in month t. Thus controlling for investors‘ expectations is not feasible within the traditional framework.

High-frequency event studies provide a somewhat overlooked alternative to the traditional approach for estimating exposures of financial assets to macroeconomic variables. Event studies in finance date back at least to Fama, Fisher, Jensen, and Roll (1969) and Ball and Brown (1968). As intraday data and investors‘ surveys became available during the last 25 years, we can use event study methodology to estimate responses of asset prices to macroeconomic variables in a way, which mitigates most of the limitations of the traditional approach. Such high-frequency event study involves regressing asset returns during a short intraday window, centered on news announcement, on announcement surprise. An announcement surprise is a difference between the announced value of the macroeconomic variable and a mean value from the investors‘ survey.

Such high-frequency event studies have a number of advantages over traditional low-frequency analysis:

1. Higher signal-to-noise ratio.
2. Controlling for market expectations.
3. Ability to distinguish between the effects of highly correlated macroeconomic variables.
4. Higher statistical power from combining multiple MNA of the same type.
5. More causal interpretation of results.

Measuring the response of asset prices to MNA over a short intraday window allows us to isolate the shock, associated with MNA surprise. This leads to higher statistical power and enables us to detect asset price responses, previously obscured by noise in asset returns.

Brunnermeier et al. (2021) emphasize the importance of accounting for market expectations when analyzing asset price movements. Since multiple entities (Bloomberg, Reuters) conduct investors‘ surveys immediately before the release of MNA, it is possible to measure the response of asset prices to actual change in market expectations.

Most macroeconomic variables are measured at a monthly or quarterly frequency. Since many assets do not have long time series of their returns, this often results in a small sample size. Hence estimating the exposure of financial assets to macroeconomic variables often suffers from low statistical power. Combining multiple MNAs of a similar type (e.g., economic growth) allows to effectively increase the sample size by a factor of 2-10 and achieve higher statistical power.

One of the problems with low-frequency analysis, commonly used to estimate loadings of an asset on macroeconomic variables, is the high correlation between most macroeconomic variables. This makes it difficult to distinguish between the effects of correlated macroeconomic variables. Since most of MNA releases do not coincide in time, an event study can easily identify the most relevant MNA. By definition, irrelevant MNA do not induce any market reaction upon release.

Finally, estimates of the exposure of financial assets to macroeconomic variables using traditional analysis are just correlations. Since at low frequency many macroeconomic variables may be affected by financial market movements, such estimates suffer from reverse causality. Furthermore, as explained above, these estimates may be hard to attribute to a specific macroeconomic variable. Using high-frequency event studies allows to mitigate these endogeneity concerns and gives causal flavor to such estimates.

3 Theoretical Framework

This section describes a simple signal-extraction model, which allows me to decompose the response of stocks to MNA shocks into cash flow channel and monetary channel.

Consider a problem, in which market tries to learn the value of unobserved short-term interest rate $\hat{i}_t$. To do so, it relies on its prior knowledge as well as on the signal m_t, contained in MNA. Thus, the problem is to dynamically use noisy signal m_t to extract useful information about unobserved state $\hat{i}_t$. Suppose the law of motion of $\hat{i}_t$ and its relation to m_t are as follows:

$$\hat{i}_t = \hat{i}_{t-1} + w_t, \qquad w_t \sim N(0, \sigma_w^2). \tag{1}$$

$$m_t = \hat{i}_t + v_t, \qquad v_t \sim N(0, \sigma_m^2). \tag{2}$$

We can solve this problem by using recursive updating and Kalman filter. Let $\hat{i}_{t,t}$ be an estimate of unobserved rate i_t for the period t, based on all observables, known at the time t. Put differently,

$$\hat{i}_{t,t} = \mathbb{E}[\hat{i}_t | m_t, m_{t-1}, m_{t-2}, ...]. \tag{3}$$

Similarly, define $p_{t,t}$ as the variance of our guess of unobserved rate $\hat{i}_t$, based on all observables, known at the time t:

$$p_{t,t} = Var(\hat{i}_t | m_t, m_{t-1}, m_{t-2}, ...). \tag{4}$$

The idea of the Kalman filter is to update the estimate of unknown rate $\hat{i}_{t,t}$ at every step as the weighted average of a prior estimate $\hat{i}_{t,t-1}$ and the noisy signal m_t. Kalman filter consists of 5 equations:

$$K_t = \frac{p_{t,t-1}}{p_{t,t-1} + \sigma_m^2}. \tag{5, Kalman Gain}$$

$$\hat{i}_{t,t} = \hat{i}_{t,t-1} + K_t(m_t - \hat{i}_{t,t-1}), \tag{6, State update}$$

$$p_{t,t} = (1 - K_t)p_{t,t-1}, . \tag{7, Variance update}$$

$$\hat{i}_{t+1,t} = \hat{i}_{t,t}, . \tag{8, State extrapolation}$$

$$p_{t+1,t} = p_{t,t} + \sigma_w^2, . \qquad \text{(9, Variance extrapolation)}$$

State update equation implies that Kalman gain is the weight of the signal. Intuitively, Kalman gain is a ratio of prior uncertainty to prior uncertainty plus noise in a signal. Thus, when signal m_t is very noisy, Kalman gain is small and we mostly use prior knowledge $p_{t,t-1}$ to estimate $\hat{i}_{t,t}$. Alternatively, a precise signal leads to high Kalman gain and we mostly rely on the signal m_t to update our estimate of i_t.

In general, Kalman filter at time t works as follows:

1. Measure signal m_t.
2. Update interest rate $\hat{i}_{t,t}$ and estimate uncertainty $p_{t,t}$ using (5), (6) and (7).
3. Predict for the next period using (8) and (9).

We can rewrite state update equation as

$$\begin{aligned} \hat{i}_t - \hat{i}_{t-1} &= K_t(m_t - \hat{i}_{t-1}). \\ \Delta\hat{i}_t &= \frac{p_{t,t-1}}{p_{t,t-1} + \sigma_m^2}(m_t - \hat{i}_{t-1}). \\ \Delta\hat{i}_t &= MU_{t-1}\epsilon_t. \end{aligned} \tag{10}$$

We can think of estimate uncertainty $p_{t,t-1}$ as uncertainty about short-term interest rate. Then the whole Kalman Gain can be used as a proxy for monetary uncertainty MU. Difference between news and prior expectations $(m_t - \hat{i}_{t-1})$ is simply MNA shock ϵ_t.

Now consider the response of the aggregate stock market to MNA shock. According to (11), stock price is a function of expected dividends, risk-free rate, and risk premium.

$$P_t = \frac{\mathbb{E}_t[D]}{i_t + RP_t}. \tag{11}$$

Thus any price movement must come from one or more of these three channels. Most MNA in my sample have a natural interpretation as shocks to expected growth, i.e., cash flows. However, due to the dual mandate of the Fed, it is supposed to use monetary policy to offset cyclical fluctuations. Therefore, any changes in macroeconomic expectations are likely to affect future monetary policy. Hence each MNA affects stocks through at least 2 channels: the growth channel and the monetary channel. Furthermore, if MNA is related to risk premium, it could reflect a combination of all 3 channels.

Consider growth news ϵ_t, which does not affect risk premium. Then, according to log-linearized (11), it should move the price through expected cash flow and risk-free rate (Δi_t) channels:

$$R_t = a_1 * \epsilon_t + a_2 * \Delta i_t + e_{1,t}. \tag{12}$$

Risk-free rate channel reflects changes in expected monetary policy due to growth news ϵ. As we know from (10), such response should depend on monetary uncertainty MU_t:

$$\Delta i_t = (\gamma_0 + \gamma_1 * MU_{t-1}) * \epsilon_t + e_{2,t}. \tag{13}$$

Plugging (13) into (12) and rearranging the terms yields (14):

$$R_t = [a_1 + a_2 * \gamma_0] * \epsilon_t + [a_2\gamma_1] * MU_{t-1} * \epsilon_t + e_{3,t}. \tag{14}$$

Equation (10) from Kalman filter suggests that $\gamma_0 = 0$, which allows me to simplify (14):

$$R_t = [a_1] * \epsilon_t + [a_2\gamma_1] * MU_{t-1} * \epsilon_t + e_{3,t}. \tag{15}$$

The equation above provides intuitive decomposition of stock response into two components. a_1 shows the strength of the reaction to growth shock ϵ_t. $a_2\gamma_1$ shows sensitivity of stock response to the change in short-term interest rates. In some sense, this decomposition relies on using monetary uncertainty MU_{t-1} to instrument for exogenous component of risk-free rate. I can estimate equation (15) by regressing stock returns on MNA surprise ϵ_t, monetary uncertainty MU_{t-1} and their interaction term. Before running this regression, I will estimate (13) and verify that $\gamma_0 = 0$.

This decomposition is based on two assumptions. First, I assume that MNA surprise does not affect the risk premium. Section 6 will show that this assumption holds for all 4 major MNA in cross-section. Section 5 will show that the response of interest rates to MNA surprise decreases at longer maturities, suggesting a little effect on risk premium. Second, I assume that the cash flow channel of the response of stocks to growth shock ϵ_t does not depend on the level of monetary uncertainty. In unreported results, I show that MNA surprise has similar predictive power for future earnings during periods of low and high monetary uncertainty. Thus, it does not seem that the cash flow channel varies according to the level of monetary uncertainty.

4 Data and News Types

I obtain MNA data from Bloomberg. Over 1997-2019 I download all MNA for variables, which are collected at a monthly frequency. Together with Federal Open Market Committee (FOMC) meetings, there are 20 such announcement types. Table 1 describes the types and exact times when these MNA are released. In a few cases macroeconomic variables were not released for some month, so there is a small variation in the number of announcements for each MNA. For most MNA, my sample includes 272-278 news releases.

Since asset prices reflect beliefs about the future, to capture their forward-looking nature, I need some proxy for expectations. I use Bloomberg survey data to proxy for expected values of these macroeconomic variables before the MNA release. Bloomberg collects these data for 2 weeks before a news release, with most forecasts made within 5 days before the announcement. This allows me to compute news surprise as a difference between the announced variable and its survey median.

Table 1 shows that many MNA are released at 8:30 am when stock exchanges are closed. Therefore, to estimate the reaction of financial assets to such announcements, I use futures, which are traded around the clock. To proxy for the aggregate stock market, I use E-Mini S&P 500 futures. To gauge the reaction of the risk-free rate, I use Fed Funds futures as well as Treasury rates at maturities of 2, 5, and 10 years. My sample of Fed Fund futures and Treasury rates starts in 1997.

I use S&P 500 futures, Fed Funds futures, and Treasury rates data at a 1-minute frequency. As I show in Section 5, using high-frequency data is critically important to identify the response of asset prices to MNA. In addition to aggregate data, I download prices of constituents of SP500 from TAQ. These data span 1997-2019 and are aggregated at a 5-minute frequency. One potential drawback of using TAQ is that trades data starts at 9:30 am, making it somewhat difficult to estimate stock response to early-morning MNA.

I use Bloomberg data on Black implied volatilities of US LIBOR rate swaptions to proxy for implied volatilities of Treasury rates. For example, to proxy for implied volatility of 2-year Treasury rate, I use Black implied volatility of swaptions with a 1-year maturity and 2-year tenor. Then I multiply this implied volatility by the level of the 2-year Treasury rate. This paper uses the implied volatility of the 2-year Treasury as a proxy for monetary uncertainty. Figure 1 describes the time variation of monetary uncertainty.

5 Stock Market Response to MNA

Ernst et al. (2020) show that any study which explores a large set of MNA could suffer from a data mining problem. To avoid multiple hypothesis testing concerns, I first identify a set of MNA, which have a significant effect on the market, and then study only those MNA.

To be relevant for financial markets, MNA must lead to increased volatility immediately after the announcement. To measure such an increase, I look at the absolute value of market returns during the 30-minutes window around news release. Unless stated otherwise, all analysis in this paper uses the window, starting 10 minutes before the announcement and ending 20 minutes after it. Then I compare average absolute returns within this window to average absolute returns during the same time of day over days without MNA. Relevant MNA should produce a significantly higher absolute value of returns compared to the no-news baseline.

Table 2 describes this volatility. To test whether MNA generates increased variation in returns, I run both T-test and Mann-Whitney-Wilcoxon tests between MNA and no-news periods. In order to be considered relevant, MNA must have p-value below 0.05 in T-test. According to this metric, there are 7 relevant MNA:

- Non-farm payroll (NFP).
- ISM Manufacturing (PMI).
- Retail Sales.
- Construction Spending.
- Consumer Price Index (CPI).
- Producer Price Index (PPI).
- Conference Board Consumer Confidence.

After identifying 7 types of MNA to explore, I report their summary statistics in Table 3. It documents the distribution of aggregate stock returns during MNA, news surprises as well as levels of several macroeconomic variables, which will be used in subsequent analysis. For each MNA, I normalize its news surprise by its full-sample standard deviation. All results are robust to using a rolling or expanding window to estimate standard deviation for scaling.

Then I explore the reaction of the market to these MNA. Since NFP and unemployment news are announced as a part of a single release, Table 4 contains 8 types of MNA. To assess this response, I run a simple OLS:

$$R_t = a + b * Surprise_t + \epsilon_t. \tag{16}$$

Table 4 reports coefficient b and adjusted R^2 for each type of MNA. There are 5 types of MNA, which have a large directional effect on the stocks: NFP, PMI, Retail Sales, Consumer Confidence and CPI. Their coefficient estimates are highly statistically significant with t-statistics above 4. More importantly, economic magnitudes are large: 1 standard deviation of good news leads to 11-25 bps higher returns. R^2 from these regressions imply that these 5 MNA surprises can explain 9-20% of return variation during announcement windows.

Another way to see the large economic importance of these responses is to compare the magnitude of returns, caused by news surprise, to average price movement during similar periods without MNA. 1 standard deviation of S&P 500 returns over the no-news window at 8:30 (10:00) is 34(37)bps. In other words, 1 standard deviation of MNA news surprise creates price movement, equal to 35-75% of price movement on comparable periods without MNA. Since inflation news releases contain information, conceptually different from the news about future growth (NFP, PMI, Retail), to facilitate interpretation of my results I focus on news about growth in the remainder of the paper.

The direction of stock response is another interesting result. While, intuitively, good (i.e., higher growth) macroeconomic news should lead to higher stock prices, past research (McQueen, Roley 1993, Flannery, Protopapadakis 2002, Boyd, Hu, Jagannathan 2005) failed to detect such a relation. These papers do not find significant unconditional relation between stock returns and news surprises. Thus they focus on more complex relations such as the effect of the news on market volatility or the differential effect of MNA surprises over a business cycle. For example, Boyd, Hu, and Jagannathan (2005) argue that, on average, good unemployment news is bad news for stocks, since such news is seen as bad news during expansions due to a larger effect on interest rates than expected growth. But even when considering more complex relations, these papers struggle to find patterns with high statistical and economic significance.

My identification approach has 2 main advantages over these papers, which allows me to estimate the response more accurately.

First, using intraday data dramatically improves the signal-to-noise ratio. Given the high liquidity of the stock market over the recent decades, it is reasonable to expect that most of the important and widely followed news will be incorporated into prices within minutes. This is especially true for macroeconomic news due to its standardized and repetitive nature. While using a 30-minutes or 1-hour window to measure the effect of monetary policy changes on financial markets has been standard for more than 15 years (Gurkaynak, Sack, and Swanson 2005), for some reason this approach is not yet dominant in the analysis of the connection between asset prices and macroeconomic variables.

Table 5 illustrates the benefits of using a 30-minutes window to identify the effect of MNA on the example of PMI news. While moving from daily frequency to a 30-minutes window (i.e., column 1 versus column 4) has little effect on the coefficient estimate, it dramatically reduces standard error. Using a daily window, we would find a barely significant positive response with R^2 of 1%. So it would appear that this pattern is too small to be worth studying. But using a 30-minutes window allows us to uncover a highly significant response with a t-statistic of 5 and R^2 of 9%.

The second methodological improvement is in using surveys of market participants to proxy for their expectations. Most papers, studying MNA, use either time-series models or low-frequency surveys to construct expectations, needed to compute news surprises. I use Bloomberg surveys, which are continuously updated up to 2 hours before MNA. A better proxy for market expectations leads to a more accurate measure of news surprise.

Results in Table 4 suggest that unemployment, PPI, and construction news do not have a highly significant effect on aggregate stock returns. This evidence suggests that the market views NFP as a more important indicator of the state of the labor market than unemployment. This result is consistent with the Congress Testimony of Alan Greenspan on Feb 11, 2004, when he suggested investors pay closer attention to NFP rather than unemployment. Unlike unemployment, NFP accounts for both the labor force participation rate and the number of job-seekers. Thus focus on unemployment as opposed to NFP may be another reason why past research failed to uncover a strong response of stocks to labor market news.

In the remainder of the paper, I restrict my analysis to 3 types of MNA, which induce large market response: NFP, PMI, and Retail. Not surprisingly, these types of news are among the most closely-followed news by the financial press.

After documenting the large response of stocks to MNA surprises, I explore its dependence on the economic environment. McQueen, Roley (1993), Flannery, Protopapadakis (2002), Boyd, Hu, Jagannathan (2005), and Law, Song and Yaron(2021) suggest that this reaction may vary across stages of the business cycle. To test this hypothesis, I divide the sample into 2 parts by the rates of economic growth, proxied by the Chicago Fed National Activity Indicator. Additionally, I look at this response across samples with low and high interest rates.

Table 6 contains the results for the 4 most important types of MNA (NFP, PMI, Retail, and Consumer Confidence). This table reports estimates from regression (1) in subsamples, divided by growth and interest rates. For every MNA, we observe the following pattern. Unconditionally, news surprises have a positive effect on stocks. This effect appears stronger during recessions, though this difference is not very large (6 bps). So far, the results are consistent with the past research.

The last two columns in Table 6 show that stock response to MNA surprise differs dramatically across periods of low monetary uncertainty versus high monetary uncertainty. While positive growth news is still good news for the market, the response is much weaker during periods of high monetary uncertainty. The magnitude of this response is almost 3 times stronger during the period of low monetary uncertainty. In other words, when interest rates are not supposed to change, good macroeconomic news is interpreted very optimistically by the market. For example, in the low monetary uncertainty subsample, NFP surprise explains 37% of variation in announcement-period return as opposed to mere 1% during the period of high monetary uncertainty. When monetary uncertainty is low, 1 standard deviation of good NFP surprise leads to 42 bps higher announcement returns.

Whereas these results are different from McQueen, Roley (1993), Flannery, Protopapadakis (2002), and Boyd, Hu, Jagannathan (2005), it is not hard to reconcile them. Dependence of stock response on the stage of the business cycle appears to be a manifestation of the monetary uncertainty effect. Post-recession recovery coincides with the periods of low rates and low monetary uncertainty. Thus previous findings of strong positive response during recession and recovery were likely driven by low interest rates uncertainty. Failure of these papers to find a positive response of stocks to MNA surprise in their full sample was mostly due to very high interest rates in the 1980s. My sample, starting in 1997, does not contain periods of monetary uncertainty, high enough to reverse the sign of the response.

Intuitively, MNA should affect stocks through 3 channels: expected cash flows, risk-free rate, and risk premium. A good growth shock will raise expectations of dividends but is likely to increase the discount rate through its risk-free component. The next subsection discusses the decomposition of these effects using the theoretical framework from Section 3.

5.1 Decomposition of the response

I decompose stock response to MNA into channels using (17), an empirical counterpart to (15). Table 7 reports the estimates of the coefficients in the regression with an interaction term between MNA surprise and monetary uncertainty (MU):

$$R_t = a + b * Surprise_t + c * \mathrm{MU}_{t-1} + d * Surprise_t * \mathrm{MU}_{t-1} + \epsilon_t. \tag{17}$$

I proxy for monetary uncertainty using implied volatility of 2-year interest rate 1 day before MNA. Controlling for interaction between monetary uncertainty and MNA surprise doubles the coefficient on MNA surprise. The coefficient on the interaction term is negative (-23 bps) and highly significant (t-statistic above 4). Consistent with the results in Table 6, adding the interaction term of surprise with a proxy for the stage of the business cycle (Chicago Fed Index) does not affect results.

One standard deviation of news surprise leads to 30 bps positive returns when the level of monetary uncertainty is zero. As monetary uncertainty increases, this positive response becomes weaker. When implied volatility of Treasury rate is equal to 1.3%, interaction term perfectly offsets positive channel and surprise does not affect stock prices. At levels of the implied volatility of the Treasury rate above 1.3%, we are likely to see a negative response: stocks will fall in response to good growth news.

These results imply that the interaction term proxies for the strength of the monetary channel, while the coefficient on MNA surprise captures the cash-flow channel. Intuitively, at zero lower bound (ZLB), changes in macroeconomic conditions will have a smaller effect on a possible change in monetary policy, and monetary uncertainty will be close to zero. This argument applies not only to downward movement in risk-free rate (it is unlikely to become negative), but to rate increases too. Experience of the past decade shows that whenever the interest rate reaches zero, it is likely to stay at zero for some time. We can view zero interest rate as the time when Fed's desired rate is negative, but they are unable to decrease it due to ZLB. So even when good news arrives, it means that Fed's preferred rate becomes less negative and this does not cause a rate hike. Thus it is natural to expect that the level of interest rates and monetary uncertainty could instrument for the strength of the risk-free rate channel.

The last two columns in Table 7 show the response of the 2-year Treasury rate to the MNA surprise. Following the literature (Hanson and Stein 2015), I use 2-year Treasury rate futures to proxy for changes in expectations. Results in column 4 mean that the risk-free rate increases in response to good news. Risk-free rate changes by 2.2 bps in response to 1 standard deviation MNA surprise. 5-year and 10-year Treasury rates exhibit a similarly strong response to MNA surprise (1.7-2.3 bps), suggesting that positive MNA surprise shifts the whole yield curve up. The positive interaction term in the last column implies that the interest rate is more sensitive to MNA surprise when monetary uncertainty is farther from zero. Overall, these results are consistent with the hypothesis that the monetary channel is stronger when the monetary uncertainty is higher.

Column 5 of Table 7 implies that $\hat{\gamma_0} = 0$, so the estimates of coefficients on the MNA surprise in column 2 are a_1 and $a_2 * \gamma_1$, i.e., cash flow channel and risk-free rate channel respectively. 1 standard deviation of positive MNA surprise raises stock prices by 30 bps due to higher expected cash flows. At the same time, 1 standard deviation of good MNA surprise decreases stock prices by 23 bps per each 1% of monetary uncertainty MU_{t-1}. This is an estimate of the strength of the monetary channel.

The decomposition provides a possible answer to why many papers (McQueen, Roley 1993, Flannery, Protopapadakis 2002, Boyd, Hu and Jagannathan 2005), analyzing MNA, failed to uncover the large effect of MNA on the stock market. The direction and magnitude of the response of stocks to MNA critically depend on the relative strength of cash flow and monetary channels. When interest rate and monetary uncertainty are high, the monetary channel becomes stronger and can offset the cash flow channel. When monetary uncertainty exceeds 1.3%, the direction of the response may even reverse. Since the papers above use a sample, starting in the 1970s, the average risk-free rates in their sample exceed 6% and monetary uncertainty is likely to be above 1.3%. Hence my results can explain the finding of Boyd, Hu, and Jagannathan (2005) that, on average, stocks react negatively to good unemployment news. It is driven by the fact that in most of their sample risk-free rate channel dominates. But when interest rates are constrained by zero lower bound and monetary uncertainty is low, the cash flow channel becomes a dominant channel, so we observe a large positive response to good news. My results for 4 major MNA suggest that 1 standard deviation of good surprise leads to 30 bps positive returns from the cash flow channel. When monetary uncertainty is equal to 1.3%, this good growth shock will additionally lead to the negative returns of a similar magnitude (-23*1.3=-30bps) from the monetary channel. Hence, simple OLS will fail to detect any response, while the total absolute response from these two channels will amount to 60 bps.

Another contribution of this framework is its implications for the effects of monetary policy. While a_1 and γ_1 are MNA-specific, a_2 should be the same for any MNA. I estimate a_2 equal to -8. This estimate is broadly consistent with the results in Bernanke and Kuttner (2005), as well as related papers, which estimate the sensitivity of the stock market to interest rate news around the monetary announcement. These papers obtain estimates between -5 and -10, consistent with my findings.

While I use 2-year Treasury yield to measure news about monetary policy, the strength of the monetary channel implies that it should affect yield at longer maturities. To answer this question, I estimate the sensitivity of interest rates to MNA surprise using Treasuries with maturities from 1 year to 30 years. Due to a lack of intraday data for most of these rates, I use daily data to estimate such sensitivities. Table 8 and Figure 2 describe the results. Consistent with the idea that MNA surprise contains important news about future monetary policy, the strongest response is at the maturities from 2 to 5 years. As maturity increases, the response of interest rates to MNA surprise weakens and falls to 1.26 bps, 57% decrease from 2.91 bps response at 3-year maturity. These results are broadly consistent with the idea that if there is a risk premium channel in MNA shock, it is much smaller than the monetary channel. Since time-varying term premium, similarly to equity premium, reflects risk premium, we should expect a large comovement between term premium and the equity premium. Thus if the MNA surprise contained a large equity premium shock, we would observe a stronger response of long-term yields than short-term yields.

6 MNA surprise in the cross-section

This section uses surprises for 4 types of MNA to test whether these surprises are priced in the cross-section of expected returns. For each type of MNA, I use the same methodology. After estimating the covariance of stock returns with MNA surprise, I divide stocks into quintile portfolios on this covariance and test whether there is a significant return spread.

As mentioned in Section 3, accurate identification of stock response to MNA requires using intraday data. Since individual stocks are less liquid than S&P 500 and require more time to react to the news, I decide to use the window from 10 minutes before the news release to 2 hours after the announcement. Since small stocks are likely to respond to news slower due to low liquidity and resulting lags, I focus on constituents of the S&P 500. In order to avoid effects due to inclusion/exclusion to S&P 500 in the year t, I consider all stocks, which were constituents on S&P500 at the end of year t-1.

I estimate covariances of individual stock returns and MNA surprises using a rolling window over 4 years. For each MNA and for each stock I run regression (7):

$$R_t = \alpha + \beta^{MNA} * Surprise_t + \beta * R_t^{SP500} + e_t. \tag{18}$$

Each month I sort stocks into quintile portfolios, based on their β^{MNA}. I compute the returns of these decile portfolios and report them in Table 9. Tables 9 and 10 suggest that none of the 3 types of MNA are priced in the cross-section of expected stock returns. Long-short portfolios have returns between -10 and +21 bps with all t-statistics below 1. Abnormal return spreads of long-short portfolios are statistically and economically insignificant (-16 to + 3 bps).

One possible concern with this methodology is that I may be unable to get precise estimates of the sensitivities of individual stocks to MNA surprises. Figure 3 explores whether investors could implement these trading strategies in the real time. To implement them, investors must be able to use their ex ante estimates of β^{MNA} to predict its realized values. In other words, pre-ranking β^{MNA} must predict post-ranking β^{MNA}. I calculate post-ranking β^{MNA} as a coefficient from regression (16) over a full sample for each quintile portfolio. Figure 1 shows that pre-ranking β^{NFP} is a strong predictor of post-ranking β^{NFP} with an almost perfectly linear relation between these variables. Results are similar for predictability of post-ranking β^{PMI}.

These results imply that risk premium is not affected by MNA and are consistent with time-series evidence, showing that response to MNA decreases at longer maturities. The concentration of the response to MNA in short-term and medium-term yields can mean that this news contains little information about risk premium. Similarly, the lack of the spread in the cross section seems to imply that changes in key macroeconomic variables do not have a significant effect on risk premium. While theoretically puzzling, they are consistent with empirical research, which documents similar findings using a lower-frequency methodology (e.g., Herskovic, Moreira, and Muir, 2019). These results are consistent with asset pricing models, in which risk premium is not strongly correlated with the business cycle.

7 Conclusion

This paper explores a large set of macroeconomic news announcements (MNA). Availability of new data enables improvements in identification, which allows me to obtain three important results. First, stocks exhibit a strong positive response to major MNA: 1 standard deviation of good surprise causes 11-25 bps higher returns. This response is the strongest for 4 commonly reported MNA: Non-farm payroll, PMI, Retail Sales, and Consumer Confidence.

Second, I use monetary uncertainty to proxy for the strength of the monetary channel and decompose this response into cash flow and monetary components. 1 standard deviation of good MNA surprise leads to 30 bps returns from the cash flow channel and minus 23 bps per 1% of monetary uncertainty from the monetary channel. The positive response of stocks to MNA via the cash flow channel is very large and amounts to 60%-180% of return variation during comparable no-news periods. Large monetary channel during periods of high monetary uncertainty masks a strong positive response of stocks to MNA, which explains why past research failed to detect this relation.

Third, I explore the response to major MNA in the cross-section of stock returns. Differential exposure to MNA shocks does not produce a spread in the cross-section of expected returns. This result is consistent with previous findings and suggests that the cash-flow channel and risk-free rate channel are the main channels through which MNA affect stocks.

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9 Appendix

Figure 1: Implied volatility of 2-year Treasuries

The figure describes implied volatility of the rate on 2-year Treasury notes in percentage points. To proxy for this implied volatility I use Black implied volatility of swaptions with 1-year maturity and 2-year tenor. I rescale this implied volatility by the level of 2-year Treasury rate. For example, implied volatility of 100 bps in July 2002 is a product of swaption implied volatility of 42% and 2.4% level of 2-year Treasury rate.

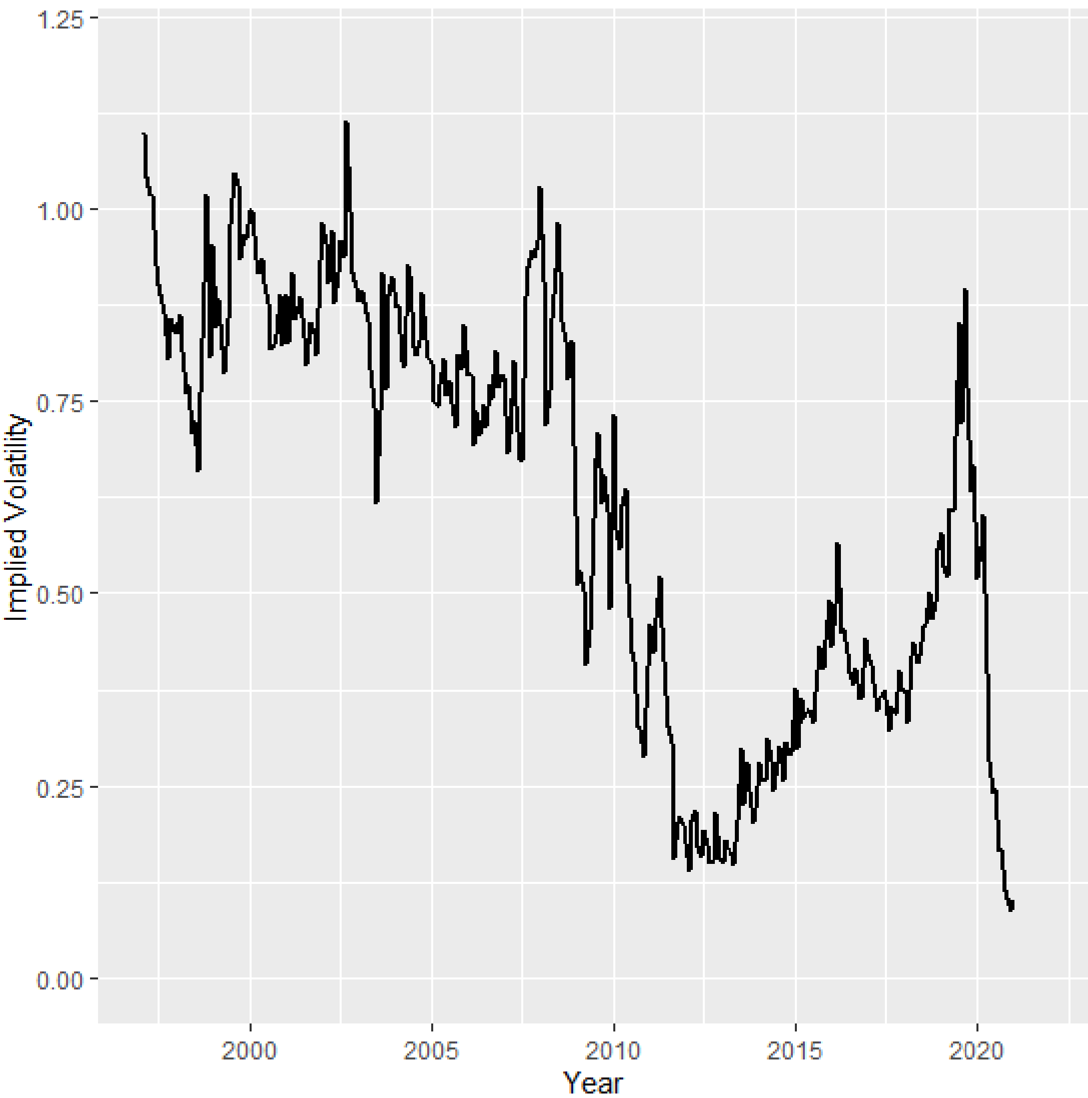

Figure 2: Term structure response to MNA surprise

The figure describes response of interest rates to MNA surprise across maturities. Y-axis depicts coefficient estimate b from daily-frequency regression $\Delta i_t = a + bSurprise_t + \epsilon_t$. The sample includes most important MNA: Non-farm payrolls, PMI, Retail sales and Consumer sentiment.

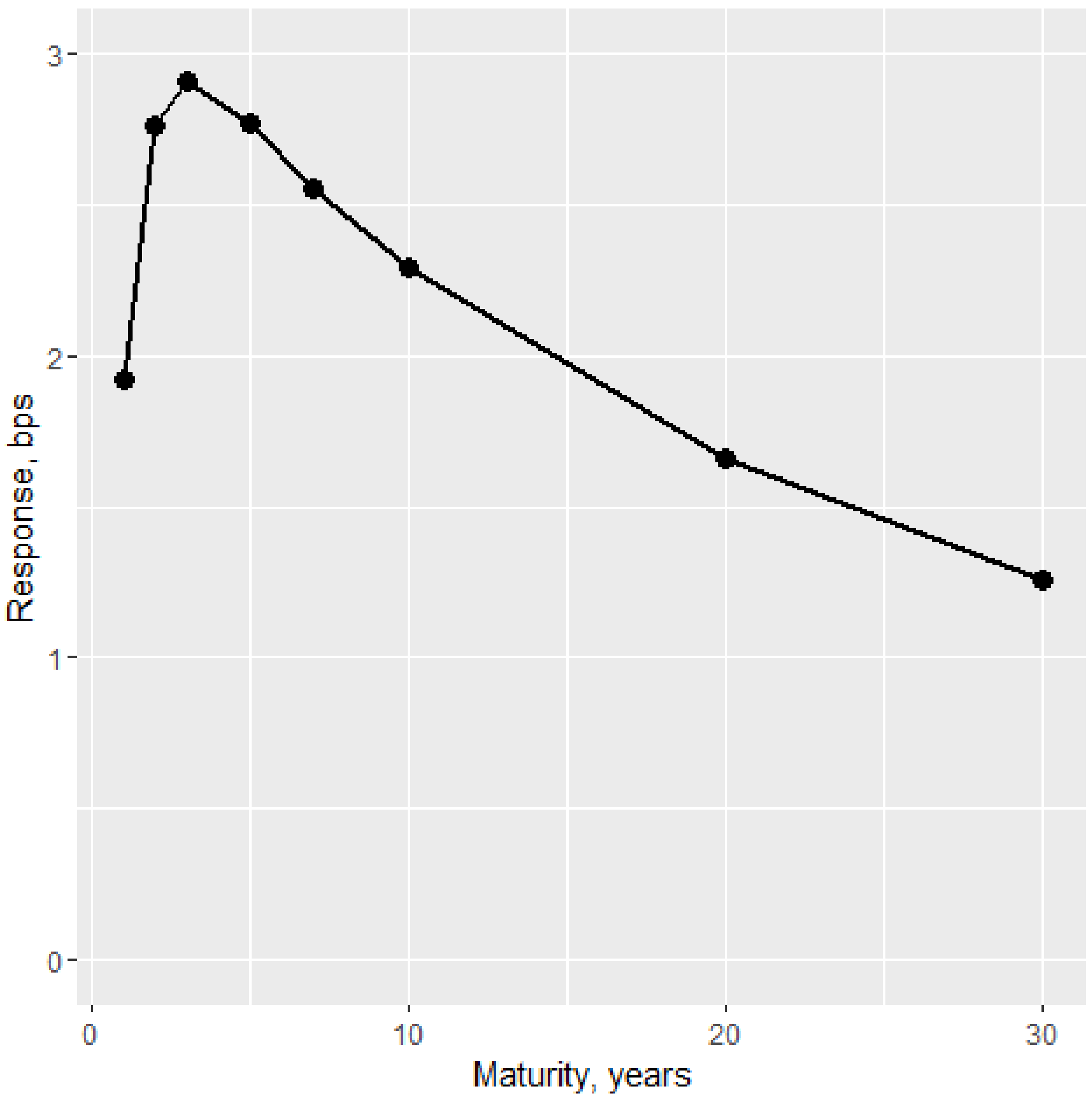

Figure 3: Pre-ranking and postranking betas

The figure describes pre-ranking and post-ranking betas of quintile portfolios, sorted on pre-ranking beta. For each panel, β_{MNA} is a coefficient from the regression of stock returns on MNA surprise for a certain type of MNA. I estimate post-ranking β_{MNA} using full sample for each quintile value-weighted portfolio, formed on pre-ranking β_{MNA}.

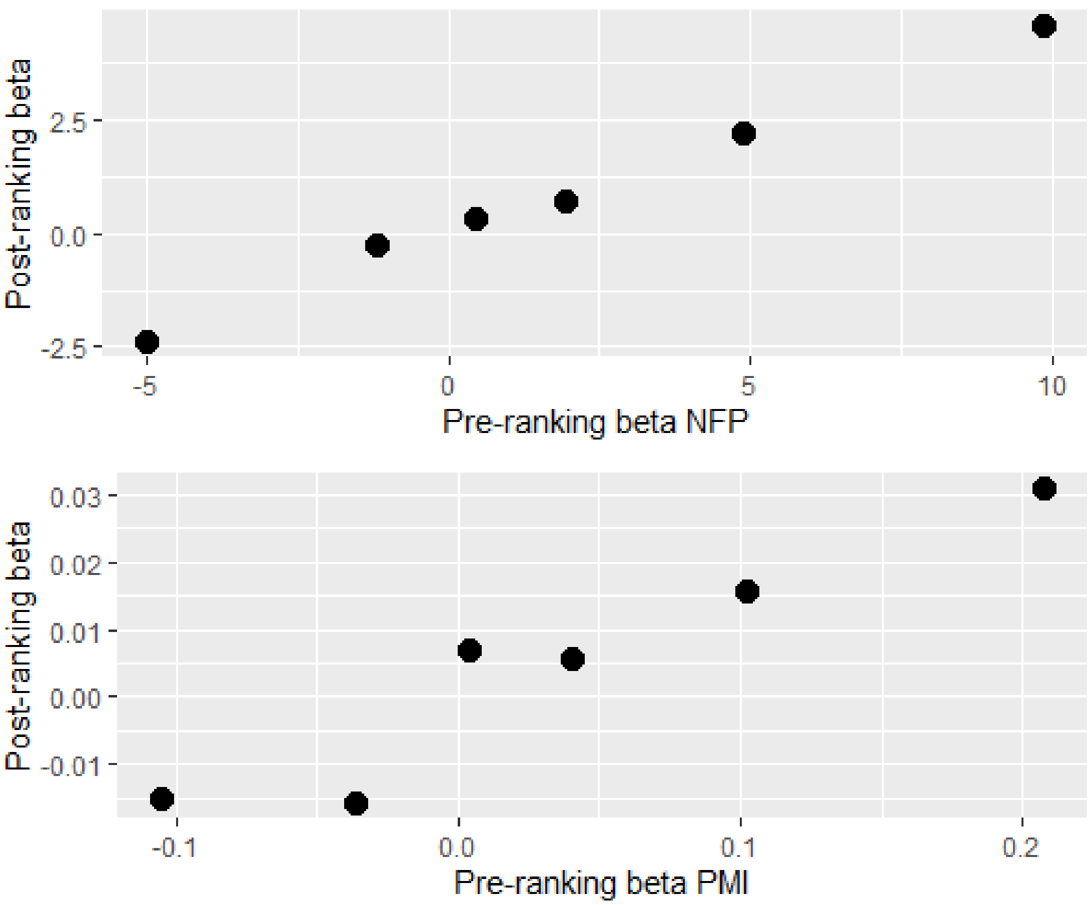

Table 1: **Macroeconomic News Announcements**

The table reports main details about all MNA at monthly frequency. N stands for the number of observations in the sample, while Day means business day of the month, when the news is released.

News	N	Time	Day
Non-Farm Payroll	276	8:30	1-5
ISM Manufacturing	278	10:00	1-2
Retail Sales Advance MoM	277	08:30	9-12
Construction Spending MoM	272	10:00	1-2
CPI MoM	278	08:30	7-12
PPI MoM	264	08:30	9-13
Conf. Board Consumer Confidence	275	10:00	18-21
Capacity Utilization	276	09:15	10-13
U. of Mich. Sentiment F	248	10:00	1-2, 16-21
Trade Balance	277	08:30	3-15
Business Inventories	270	10:00	9-12
Housing Starts	263	08:30	10-14
Factory Orders	279	10:00	2-4
Leading Index	274	10:00	1-3, 10-16
U. of Mich. Sentiment P	247	10:00	8-13
Monthly Budget Statement	278	14:00	8-17
New Home Sales	268	10:00	16-21
Durable Goods Orders	258	08:30	16-20
Consumer Credit	278	15:00	5

Table 2: **Absolute returns during MNA**

The table reports absolute value of returns of S&P 500 futures over 30-minutes window around MNA. I test hypothesis that absolute value of returns is higher during MNA window than during similar window on days without MNA. Mean absolute returns on non-MNA days range between 14 and 24 bps depending on the time. The last two columns report p-values from the two tests: T-test and Mann-Whitney-Wilcoxon test. Null hypothesis is that mean absolute returns during MNA periods are equal to mean absolute returns over comparable periods without MNA.

News	Mean	Median	p-value (t)	p-value (MWW)
Non-Farm Payroll	0.41	0.29	0	0
ISM Manufacturing	0.36	0.27	0.0000	0
Retail Sales Advance MoM	0.21	0.13	0.0000	0
Construction Spending MoM	0.34	0.23	0.0000	0
CPI MoM	0.21	0.13	0.0001	0
PPI MoM	0.19	0.12	0.0002	0
Conf. Board Consumer Confidence	0.29	0.18	0.03	0.12
Capacity Utilization	0.17	0.10	0.14	0.37
U. of Mich. Sentiment F	0.27	0.18	0.28	0.17
Trade Balance	0.16	0.10	0.31	0.03
Business Inventories	0.23	0.16	0.40	0.53
Housing Starts	0.15	0.09	0.40	0.07
Factory Orders	0.24	0.17	0.46	0.97
Leading Index	0.26	0.19	0.47	0.29
U. of Mich. Sentiment P	0.26	0.16	0.76	0.66
Monthly Budget Statement	0.17	0.11	0.78	0.33
New Home Sales	0.25	0.16	0.79	0.86
Durable Goods Orders	0.14	0.09	0.84	0.17
Consumer Credit	0.20	0.12	0.91	0.66

Table 3: **Summary statistics of returns and announcement surprises**

The table reports summary statistics of macroeconomic variables, announcement surprises and announcement returns for each major MNA. px stands for x^{th} percentile. Returns are reported in percentage points, surprises are normalized to have standard deviation of 1.

News	Variable	Min	p1	p10	p25	Median	p75	p90	p99	Max	Mean	SD
All	CFNAI	-3.35	-2.68	-0.61	-0.31	0.02	0.28	0.50	0.94	1.21	-0.07	0.60
All	USREC	0	0	0	0	0	0	0	1	1	0.09	0.29
All	FFR_{t-1}	0.12	0.12	0.12	0.12	1.62	4.75	5.50	6.50	6.50	2.25	2.14
All	drate	-0.09	-0.05	-0.01	0	0	0	0.01	0.04	0.09	0	0.01
NFP	spx_ret	-2.03	-1.46	-0.66	-0.20	0.10	0.31	0.72	1.41	1.97	0.04	0.56
NFP	surprise	-3.93	-2.90	-1.31	-0.68	-0.06	0.44	1.02	2.19	3.22	-0.13	1
PMI	spx_ret	-3.26	-1.34	-0.57	-0.29	0.01	0.23	0.50	1.47	2.17	0	0.52
PMI	surprise	-3.23	-2.45	-1.13	-0.59	0	0.66	1.32	2.37	3.98	0.06	1
Retail	spx_ret	-1.49	-0.93	-0.30	-0.08	0.02	0.16	0.33	0.93	1.04	0.02	0.32
Retail	surprise	-3	-2.62	-0.94	-0.56	0	0.37	0.94	2.68	8.62	-0.02	1
Constr	spx_ret	-3.26	-1.23	-0.47	-0.24	0.03	0.22	0.50	1.45	2.17	0.02	0.50
Constr	surprise	-7.71	-2.18	-1.09	-0.51	0	0.45	0.86	2.17	4.20	-0.06	1
Unempl	spx_ret	-2.03	-1.46	-0.66	-0.20	0.10	0.31	0.72	1.41	1.97	0.04	0.56
Unempl	surprise	-3.52	-2.34	-1.41	-0.70	0	0.70	0.70	2.11	2.81	-0.18	1
CPI	spx_ret	-1.87	-0.95	-0.31	-0.11	0.02	0.13	0.35	0.80	2.47	0.01	0.35
CPI	surprise	-3.35	-2.52	-0.84	-0.84	0	0.84	0.84	2.52	3.35	-0.06	1.01
PPI	spx_ret	-1.43	-0.80	-0.30	-0.12	-0.01	0.12	0.27	0.84	0.97	-0.01	0.29
PPI	surprise	-2.91	-2.91	-0.97	-0.48	0	0.48	1.19	2.76	4.12	0.02	1

Table 4: **Response of S&P500 to MNA,** $R_t = a + bSurprise_t + \epsilon_t$.

The table reports response of S&P 500 futures to MNA surprises over 30-minutes announcement window. Each row reports results for different MNA. R^2 is adjusted R^2 from this regression.

Event	b	T-statistic(b)	R^2
Change in Nonfarm Payrolls	0.25	7.82	0.20
ISM Manufacturing	0.16	5.20	0.09
CPI MoM	-0.11	-5.84	0.12
Conf. Board Consumer Confidence	0.11	4.87	0.09
Retail Sales Advance MoM	0.11	5.87	0.12
Construction Spending MoM	0.07	2.44	0.02
Unemployment Rate	0.06	1.60	0.01
PPI MoM	-0.01	-0.71	-0.002

Table 5: **Response of SP500 to PMI news announcement**

The table documents response of S&P 500 futures to PMI news surprises. Each column reports estimates from the regression $R_t = a + bSurprise_t + \epsilon_t$. for different window width over which returns are measured. The first column reports regression, where dependent variable is daily return of CRSP value-weighted index. The dependent variable in the second column is S&P 500 futures at daily frequency. The third column uses S&P 500 futures returns between previous day 4pm and 20 minutes after news release. The last column reports estimates from the main specification with 30-minutes window and S&P 500 futures.

	Dependent variable:			
	vwretd	SP500	SP500	SP500
	(1)	(2)	(3)	(4)
PMI surprise	0.160^{**}	0.169^{**}	0.193^{***}	0.156^{***}
	[1.994]	[2.027]	[3.142]	[5.135]
Constant	0.163^{**}	0.165^{*}	0.105^{*}	-0.008
	[2.018]	[1.961]	[1.696]	[-0.260]
Announcement window	Day	Day	Half-day	30 minutes
Observations	276	266	266	266
Adjusted R^2	0.011	0.012	0.032	0.087
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: **Stock response to major MNA**

The table documents response of S&P 500 futures to news surprises among 4 most important MNA: NFP, PMI, Consumer Confidence and Retail. Each column reports estimates from the regression $R_t = a + bSurprise_t + \epsilon_t$. for different subsamples: periods of recession or expansion, half-samples with low/high level of monetary uncertainty.

	Dependent variable:			
	SPX			
	(1)	(2)	(3)	(4)
Surprise	0.203***	0.141***	0.244***	0.094***
	[4.552]	[9.998]	[12.869]	[4.987]
Constant	−0.030	0.013	0.006	0.004
	[−0.444]	[1.014]	[0.384]	[0.206]
Subsample	Recession	Expansion	Low mon. uncert.	High mon. uncert.
Observations	96	891	514	473
Adjusted R^2	0.172	0.100	0.243	0.048
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: **Response to major MNA with interaction terms**

The table documents response of stocks and 2-year Treasury rates to 4 major MNA surprises: $R_t = a + bSurprise_t + cMU_{t-1} + dSurprise_t MU_{t-1} + \epsilon_t$. The first three columns document response of S&P 500, the last two report the response of 2-year Treasury rates. All responses are measured over 30-minutes window around announcement. MU stands for monetary uncertainty, i.e., implied volatility of 2-year Treasury rate.

	Dependent variable:				
	SPX			$\Delta rate$	
	(1)	(2)	(3)	(4)	(5)
Surprise	0.15***	0.30***	0.29***	2.16***	0.17
	[11.29]	[7.82]	[7.35]	[17.35]	[0.47]
MU		−0.01	−0.02		0.46
		[−0.29]	[−0.29]		[0.98]
CFNAI			−0.02		
			[−0.66]		
Surprise:MU		−0.23***	−0.22***		2.93***
		[−4.18]	[−4.08]		[5.86]
Surprise:CFNAI			−0.05***		
			[−2.96]		
Constant	0.01	0.02	0.02	−0.01	−0.28
	[0.96]	[0.59]	[0.63]	[−0.08]	[−0.90]
Observations	978	978	978	1,008	1,005
Adjusted R^2	0.11	0.13	0.13	0.23	0.25
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 8: **Interest rate response to major MNA**

The table documents response of interest rates at various maturities to MNA surprise. The table report results from the following regression at daily frequency: $\Delta i_t = a + bSurprise_t + \epsilon_t$. Dependent variables are changes in daily treasury yields at maturities from 1 year to 30 years.

	Dependent variable:							
	Δi_1	Δi_2	Δi_3	Δi_5	Δi_7	Δi_{10}	Δi_{20}	Δi_{30}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Surprise	1.92***	2.77***	2.91***	2.77***	2.56***	2.29***	1.66***	1.26***
	[9.42]	[9.85]	[9.92]	[9.16]	[8.78]	[8.47]	[7.62]	[7.09]
Constant	−0.07	−0.07	0.10	0.31	0.39	0.37	0.25	0.19
	[−0.30]	[−0.24]	[0.31]	[0.91]	[1.20]	[1.24]	[1.05]	[0.94]
Observations	491	491	491	491	491	491	491	491
Adjusted R^2	0.15	0.16	0.17	0.14	0.13	0.13	0.10	0.09
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 9: **Average returns of quintile portfolios, sorted on β_{MNA}**

The table reports equal-weighted and value-weighted returns of quintile portfolios, formed on β_{MNA}. Each panel corresponds to different type of MNA. I estimate β_{MNA} using rolling-window regression of stocks returns on MNA surprises. Long-short portfolio buys stocks with the highest beta (i.e., fifth quintile) and sells stocks with the lowest beta (first quintile)

Panel A: Non-Farm Payroll

	Q1	Q2	Q3	Q4	Q5	L/S
Mean ew	0.90**	0.84***	0.82***	0.83***	0.91**	0.01
T-stat ew	[2.47]	[2.74]	[2.73]	[2.71]	[2.40]	[0.03]
Mean vw	0.57*	0.77***	0.70***	0.74***	0.78**	0.21
T-stat vw	[1.65]	[2.85]	[2.78]	[2.74]	[2.39]	[0.82]

Panel B: PMI

	Q1	Q2	Q3	Q4	Q5	L/S
Mean ew	0.84**	0.86***	0.96***	0.85**	0.79**	-0.04
T-stat ew	[2.33]	[2.92]	[3.15]	[2.55]	[2.00]	[-0.24]
Mean vw	0.78**	0.80***	0.73***	0.59*	0.68**	-0.10
T-stat vw	[2.51]	[3.10]	[2.82]	[1.85]	[1.98]	[-0.51]

Panel C: Retail Sales

	Q1	Q2	Q3	Q4	Q5	L/S
Mean ew	0.96***	0.76**	0.89***	1.05***	1.03***	0.07
T-stat ew	[2.69]	[2.48]	[2.87]	[3.25]	[2.94]	[0.43]
Mean vw	0.86***	0.61**	0.52*	0.92***	0.98***	0.12
T-stat vw	[2.75]	[2.16]	[1.80]	[3.47]	[3.31]	[0.60]

Table 10: **Abnormal returns of quintile portfolios, sorted on β_{MNA}**

The table reports abnormal returns of long-short quintile portfolios, formed on β_{MNA}. Long-short portfolio buys stocks with the highest beta (i.e., fifth quintile) and sells stocks with the lowest beta (first quintile). Each panel corresponds to different type of MNA. MOM is momentum factor and STR is short-term reversal factor.

Panel A: Non-Farm Payroll

Statistic	Ret	α_{CAPM}	α_{FF3}	$\alpha_{Carhart}$	α_{FF5}	$\alpha_{FF5+UMD+STR}$
L/S	0.21	0.21	0.15	0.11	0.07	0.03
	[0.82]	[0.81]	[0.58]	[0.43]	[0.27]	[0.13]

Panel B: PMI

Statistic	Ret	α_{CAPM}	α_{FF3}	$\alpha_{Carhart}$	α_{FF5}	$\alpha_{FF5+UMD+STR}$
L/S	-0.10	-0.20	-0.15	-0.12	-0.19	-0.16
	[-0.51]	[-1.00]	[-0.79]	[-0.63]	[-0.95]	[-0.83]

Panel C: Retail Sales

Statistic	Ret	α_{CAPM}	α_{FF3}	$\alpha_{Carhart}$	α_{FF5}	$\alpha_{FF5+UMD+STR}$
L/S	0.12	0.15	0.16	0.15	0.03	0.02
	[0.60]	[0.74]	[0.80]	[0.75]	[0.13]	[0.09]

Table 11: **Announcement premium and the drift before MNA**

The table presents average returns before and during major MNA. The first 4 columns report pre-announcement drift and announcement returns. Pre-announcement window runs fom 4pm of the previous trading day up to 10 minutes before announcement. Announcement window is 30-minutes window around MNA release. The last column reports correlation between pre-announcement drift and announcement returns.

News	$Return^{Annc}$	T-stat	$Return^{Pre-Annc}$	T-stat	Correlation
NFP	0.03	0.92	0.10	3.51	0.05
PMI	0.0001	0.004	-0.01	-0.17	0.10
Construction	0.02	0.53	0.03	0.61	0.08
Retail	0.02	1.06	-0.01	-0.19	-0.09
CPI	0.02	0.71	-0.02	-0.58	0.05
PPI	-0.01	-0.61	-0.001	-0.03	-0.08
FOMC	-0.01	-0.29	0.29	5.25	-0.20