Underreaction to Macroeconomic News Announcements and the Downward-Sloping Security Market Line

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Abstract

The relationship between betas and expected returns is positive on days with pre-scheduled macroeconomic news announcements (MNAs), but negative on the other days. This paper shows that stock price underreaction to MNAs explains the negative relation on non-MNA days. First, I use high-frequency S&P 500 futures data to identify positive (good) and negative (bad) news from macro announcements. Stocks with low sensitivities to bad macro news perform poorly on the following non-announcement days. Moreover, the under-performance of low sensitivity stocks is most pronounced when investor disagreement is high and short-selling constraints are binding. Subsequently, I show that the security market line on non-announcement days is particularly downward-sloping among stocks with low sensitivities to bad macro news. The results are consistent with stocks, especially those with high market betas, underreact to bad news on MNA days when high shorting costs prevent prices from reflecting pessimists' beliefs, and experience low returns on the following non-announcement days.

Keywords: Security Market Line, Underreaction, Macroeconomic News Announcement

JEL Classification : G12, G14

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1 Introduction

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) implies that stocks with high market betas should deliver higher expected returns than stocks with low market betas. However, empirical asset pricing studies have presented an abundance of evidence suggesting a flat or even downward-sloping security market line (see Black et al. (1972), Baker et al. (2011), and Frazzini and Pedersen (2014)). Recently, Savor and Wilson (2014) document a significantly positive relationship between market beta and average returns on days when pre-scheduled macroeconomic news announcements (MNAs) are released. Meanwhile, the combination of the strongly positive slope of the security market line on MNA days and the overall flatness mechanically implies a strongly negative slope on non-MNA days. This paper confirms the negative relationship between market beta and non-MNA day returns using a comprehensive set of MNAs. More importantly, I present an explanation for the downward-sloping security market line: underreaction to negative macroeconomic news announcements.

I first document strong and robust evidence of firm-level stock price underreaction to negative macro news. To quantify the news, I use five-minute returns on E-mini S&P 500 futures immediately after the release time of announcements. I distinguish between good and bad news based on the signs of returns: the news is defined to be bad (good) when the announcement return is negative (positive). I show that firms with tight short-selling constraints and high investor disagreement have low sensitivity to bad macro news. In other words, these firms perform relatively well on days when the market plunges following a bad macro announcement. Moreover, stocks less sensitive to bad news experience much lower returns than high-sensitivity stocks in the following month, especially on days without announcements. The relation is particularly strong for stocks with high investor disagreement and high short-selling constraints.

Following the argument of Miller (1977), the results are consistent with underreaction to bad macro news due to tight short-selling constraints and investor disagreement on firm value. Specifically, following a bad announcement, stocks with high cost of short-selling will be slower in incorporating the negative macro news, especially when investors have diverse beliefs on the valuation of the firm. The combination of short-sales constraints and investor disagreement leads to overvaluation, or under-reaction to the bad news, as stock prices reflect more of the beliefs of optimistic investors. Therefore, these stocks will have lower sensitivities to bad macro news compared to less constrained stocks with lower investor disagreement, and experience lower returns in the future as the mispricing is gradually corrected.

The results have strong implications for the negative relationship between market beta and returns on non-MNA days. Since stocks with high market betas tend to have high exposures to macroeconomic risk, they should be more affected by bad macro news. Meanwhile, investors of high-beta stocks may also have high disagreement and face high short-sales constraints, so underreaction to bad news will be more pervasive among those stocks. Thus, low sensitivities to bad macro news should lead to low returns on the non-MNA days particularly for high-beta stocks. I therefore hypothesize that the relationship between market beta and non-MNA day returns will be most negative among stocks that have low sensitivity to bad macro news.

This paper confirms the hypothesis by first showing that, consistent with Diether et al. (2002) and Hong and Sraer (2016), high-beta stocks tend to have high disagreement and high short-sales constraints. More importantly, the slope of the security market line on non-announcement days is the most negative for stocks with low bad news sensitivity. Meanwhile, the relation between returns and market beta is much more flattened among stocks with high sensitivity, with the magnitude reduced by 60% and not significant anymore. Therefore, high-market-beta stocks' underreaction to bad news on MNA days plays an important role in explaining the downward-sloping security market line on non-MNA days. The results are robust to controlling for a battery of firm characteristics and alternative estimations of the sensitivity.

My empirical analysis begins with identifying and quantifying macro news. I collect the prescheduled release dates and times of a comprehensive set of 18 macro news announcements which trigger significant stock market reactions (see Kurov et al. (2017) and Law et al. (2018)). Many of the announcements are made at 8:30 a.m. Eastern Time when the US stock market is still closed. I therefore use E-mini S&P 500 futures, which trade almost around the clock and allow me to use five-minute returns immediately after announcements to measure market reaction to the news. The tight window isolates the impact of MNAs from other significant events which may influence stock prices. Based on the sign, I split returns into good (positive returns) and bad (negative returns) macro news. Furthermore, I compare the five-minute announcement returns with a trailing jump-robust volatility of returns over the time period of five trading days. Only the returns with an absolute value higher than one unit of volatility are included in my further analysis, although my results are robust to alternative thresholds.

To measure underreaction to the negative news, I then estimate firm-level sensitivity to bad announcement returns, hereafter also referred to as bad MNA beta. At the end of each month, I regress daily stock returns on good and bad announcement returns over the past 24 months, controlling for the market factor. I document a wide dispersion of both good and bad MNA beta. More importantly, stocks with high short-selling constraints and high investor disagreement have low sensitivities to bad news, indicating that these market frictions lead to stock price underreaction to negative macro announcements.

Sorting stocks into deciles based on the bad MNA beta, I find a statistically and economically significant relationship between bad MNA beta and future returns. On the days without MNAs, the highest decile portfolio outperforms the lowest decile portfolio by 0.59% per month, with a *t*-stat of 1.8. The difference mainly comes from the increase in returns from -0.60% for the lowest decile portfolio to 0.03% for the sixth decile portfolio. The top four deciles, however, have average returns close to zero. On days with MNAs, average returns across all deciles are close to 0.7% per month, except for the top decile with 1% per month. At the same time, sorting stocks into deciles based on good MNA beta does not generate much spread in monthly returns on both MNA days and non-MNA days.

To test the robustness of the relation to well-known firm characteristics that predict cross-sectional stock returns, I next perform stock-level Fama-Macbeth regressions. The coefficients on bad MNA beta for full month returns and non-MNA day returns are positive and significant after controlling for firm and risk characteristics including size, book-to-market, illiquidity, and idiosyncratic volatility. On MNA days, however, there is no significant explanatory power of bad MNA betas. Moreover, I expect that underreaction will be more dominant for stocks with negative sensitivity to bad macro news. The stocks in the long leg could underreact, but it should contain the least degree of underreaction. This hypothesis is confirmed. I find that the positive relationship between bad MNA beta and non-MNA day returns concentrates on stocks with lower-than-median bad MNA betas.

In order to test the channel of underreaction, I exploit cross-sectional variations in investor disagreement and short-selling constraints. I posit that short-sale constraints are tighter for stocks with lower residual institutional ownership following Nagel (2005), Asquith et al. (2005), Boehme et al. (2006), and Weber (2018). I also assume that differences in opinion among investors are higher for stocks with higher analysts forecast dispersion on earnings, higher turnover or higher idiosyncratic volatility following Diether et al. (2002) and Boehme et al. (2006). The testable empirical implication is that stocks with low sensitivity to bad macro news will experience low returns especially when they have low institutional ownership as well as high analysts' forecast dispersion, high turnover, or high idiosyncratic volatility. Firm-level Fama-Macbeth regressions where bad MNA betas interact with these firm characteristics confirm the hypothesis, indicating that the underreaction is caused by short-selling constraints preventing stock prices from reflecting the views of pessimistic investors.

Finally, I examine how stock price underreaction to bad macro news explains the negative relationship between market beta and expected returns on non-MNA days. First, firm-level regressions show that high-disagreement and high-constraint stocks also tend to have high market betas. This result suggests that underreaction is more pervasive among high-beta stocks. To show the role played by underreaction in the negative relation between market beta and stock returns, I then conduct portfolio double-sorting where stocks are first sorted into quintiles based on bad MNA beta and subsequently into quintiles based on market beta. The slope of the security market line on non-MNA days is the most negative for stocks within the lowest quintile of bad MNA beta, which are the stocks that are most likely to underreact to negative macro news. On the other hand, among stocks within the highest quintile of sensitivity to the bad news, which are the stocks that are least likely to underreact, the security market line is only insignificantly negative, with the magnitude shrunk by 60%. Firm-level Fama-Macbeth regressions show that the result is robust to a battery of firm characteristic and alternative estimations of bad MNA beta. Underreaction to bad macro new, therefore, is a primary driver for the negative beta-return relationship on the non-MNA days.

A risk-based explanation for the positive relationship between bad MNA beta and returns on non-MNA days is faced with many challenges. First, the bad MNA beta may serve as a direct measure of MNA risk for individual stocks. However, it is difficult to explain why investors, knowing the dates of pre-scheduled announcements, ask for a premium on MNA risk during days without announcements. Second, my analysis shows that the bad MNA beta is insignificantly related to a list of well-known risk characteristics, such as downside risk from Ang et al. (2006a). Moreover, a risk-based explanation is inconsistent with the observation that, among stocks with higher-than-median bad MNA beta, investors are not compensated for bearing more risk by higher returns on non-MNA days.

The paper is mostly related to the recent literature on stock returns on macroeconomic news announcement days and non-announcement days. Savor and Wilson (2013) document high stock market returns and Sharpe ratios on MNA days. Savor and Wilson (2014) show that the relation between market beta and average returns is positive on MNA days but negative on non-MNA days. Ai and Bansal (2018) and Wachter and Zhu (2018) show that under certain assumptions about utility function or consumption process, investors ask for announcement premium around macro news announcement. In particular, Wachter and Zhu (2018) present a model with rare events that explain the positive relation between market beta and returns on MNA days. However, the model also results in a slightly upward-sloping, instead of downward-sloping, security market line on non-MNA days. In contrast, this study confirms the negative slope of the security market line on non-MNA days and provides evidence for an explanation based on underreaction to macroeconomic announcements.

This work also contributes to the literature investigating the potential factors behind the flat or downward-sloping security market line. Cohen et al. (2005) examine the effect of inflation on the security market line. Huang et al. (2016) study the impact of speculative capital committed to betting against beta. Antoniou et al. (2015) examine the relation between the pricing of beta and variations in investor sentiment. Jylhä (2018) shows that tighter leverage constraints result in a flatter relation between beta and expected returns. Hong and Sraer (2016) show that disagreement on aggregate variables affects the slope of market security line as higher-beta stocks are more likely to be overvalued in the presence of limits to arbitrage and disagreement about aggregate growth. Although they do not model public information announcements, their model should lead to lower (higher) returns on high-beta stocks during MNA (non-MNA) days. The reason is that the overvaluation of high-beta stocks should occur on non-MNA days and be corrected on MNA days, as announcements will reduce disagreement on aggregate variables. In contrast, my paper focuses on firm-level disagreement and shows evidence that overvaluation occurs on announcement days in the form of underreaction to bad news.

This study also relates to the literature on the impact of MNA surprises on asset prices. McQueen and Roley (1993), Boyd et al. (2005), Andersen et al. (2007), and Law et al. (2018) show that there is a strong relationship between stock prices and news which varies across the business cycle. Gilbert et al. (2017) show that timeliness and relation to economic fundamentals explain the variation in the response of U.S. Treasury yields to macroeconomic news announcements. De Goeij et al. (2016) find fixed results for the pricing of macroeconomic announcements in the cross-section of stock returns. A major difference of this paper is the usage of five-minute announcement returns to measure MNA shocks rather than the difference between surveyed professional forecast and actual values. Therefore, the MNA shocks in this study measure the "surprise" from the perspective of investors revealed in prices. Similarly, Gürkaynak et al. (2005) and Gertler and Karadi (2015) use 30-minute returns on federal fund futures to measure monetary policy surprises. Furthermore, my firm-level analysis contributes to this literature by showing evidence that stocks underreact to bad MNA news although the aggregate market immediately respond to announcements.

This study also contributes to the empirical literature on mispricing due to investor disagreement and short-sales constraints. Diether et al. (2002) find that stocks with higher dispersion in analysts' earnings forecasts earn lower returns in the future. Asquith et al. (2005) consider institutional ownership as a proxy for short-selling supply and find under-performance of constrained stocks on an equal-weight basis. Boehme et al. (2006) find evidence of significant overvaluation for stocks that have both short-selling constraints and investor disagreement. They emphasize that either condition alone is not sufficient to produce overpricing. Studies such as Nagel (2005), Phalippou (2008), Hirshleifer et al. (2011), and Weber (2018) use institutional ownership as a proxy for the ease of short-selling and show that short-sale constraints explain many cross-sectional return anomalies. This paper adds to the literature by showing evidence that a significant amount of overpricing occurs on days with MNAs which explains the downward-sloping security market line on non-MNA days.

2 Data and Methodology

2.1 Macroeconomic news announcements

Following Andersen et al. (2007), Kurov et al. (2017) and Law et al. (2018), I focus on 18 macroeconomic news announcements, all listed in Table 1. I do not include announcements of PPI, GDP final, housing sales, government budgets, trade balance, personal income, leading indicators and factory orders, as surprises of these announcements are not followed by significant stock market movements (Table B3 in Kurov et al. (2017) and Table 1 in Law et al. (2018)). The dates and times of announcements are mainly obtained from the related agency websites. For those of which the release dates are not available from websites, I use Factiva to identify historical release dates. On average, there are 21 trading days in a month, 12 trading days with one or more macro announcements, and 9 trading days without announcement. According to Kurov et al. (2017), two of these announcements, ISM Manufacturing Index and ISM Non-Manufacturing Index, have pre-announcement price drift in the same direction of the announcement surprise, indicating information leakage before announcement. However, both of the announcements are released at 10:00 a.m, so an alternative explanation could be that informed investors trade on their private information after the stock market is open on 9:30 a.m. for liquidity and transaction cost issues. I do not include FOMC announcements for the main results. Lucca and Moench (2015) report unconditional excess returns in equity index futures during 24 hours prior to the FOMC announcements. Ai and Bansal (2018) also point out that most of the premiums for FOMC announcements are realized in several hours prior to the announcements. It seems that, instead of receiving information on announcement time, investors obtain signals and update their beliefs on monetary policy before FOMC announcements. Therefore, my methodology to quantify the news using a tight window of equity index future returns does not apply to FOMC announcements. That being said, including FOMC announcements in the sample have little impact on the results of this paper.

2.2 High-Frequency data on E-mini S&P 500 futures

I obtain high-frequency data from Thomson Reuters Tick History for E-mini S&P 500 futures (ES). Each observation is time-stamped to the millisecond. I obtain futures returns over a narrow time window of five minutes immediately following the set of macroeconomic news announcements. If an announcement is made on 8:30 EST, then the five-minute interval is 8:29:999 EST to 8:34:999 EST. As investors of the futures bear market-wide risk instead of firm-specific risk, the announcement returns measure the impact of announcements on the market. I clean the data by first dropping observations outside trading hours. High-frequency price observations that are higher (lower) than the daily high (low) price of futures from Datastream. I construct a new liquidity-maximum continuous series for E-mini S&P 500 futures using front-month contracts and the next closest future contracts by rolling over from front-month contract to the next contract on the day when there are more trades in next contract than front month contract. Prices are sampled every five minutes starting from 7:55 EST until 16:00 EST, using the last recorded trading price within each five-minute interval, e.g., 7:55:00:000 to 7:59:59:999. The choice of frequency strikes a balance between test power and potential contamination caused by microstructure noise. There are at most 97 price observations during a day. A trading day is dropped if it has fewer than 80 sampled price observations.

I obtain five-minute log-returns as the difference between two adjacent logged prices. If there is no price in a five-minute interval, the return is set to zero. Following this procedure, there are 96 five-minute returns for each trading day.

Figure 1 motivates the choice of window size of five minutes. I plot the standard deviation of returns over each one-minute interval around announcements. The figure shows that the standard deviation increases immediately after the announcements and gradually decreases to the pre-announcement level over the first five minutes. The pattern indicates that surprises of the announcements are mostly incorporated into futures price within five minutes. Therefore, five-minute returns suit my need to capture market reaction to macro announcements.

An alternative measure is the difference between announcement realizations and their forecast values from a survey of professionals (MNA surprises). However, announcement returns are more suitable in this paper for the following reasons. First, the same amount of surprise (the scaled difference between actual and forecast value) from different announcements have different market relevance. Returns on equity index futures provide a uniform measure which is comparable among MNAs. Second, big MNA surprises may not always have a substantial market impact. Announcement returns serve as a natural proxy for surprises of announcements from the perspective of investors. Third, good economic surprises (better-than-expected) are not necessarily good news to the stock market. Using returns allows me to have a clear separation of good and bad MNA shocks.

However, not all announcements necessarily convey unexpected and important information that will move the stock market. Following Jiang and Zhu (2017), I restrict my sample of announcement returns to those presumably dominated by information surprises. Specifically, I compare the announcement returns with local volatility. Consider an MNA released on 8:30 E.T. on a given day. The return from 8:30 to 8:35 is denoted as r_j where j indexes five-minute intervals. I first estimate integrated variance over a window of 5 "days", or in total $K = 96 \times 5$ observations of five-minute returns before r_j, using the MedRV estimator from Andersen et al. (2012),

$$MedRV = \frac{\pi}{6-4\sqrt{3}+\pi} \times \frac{K}{K-2} \sum_{i=j-K+2}^{j-1} med(|r_i|, |r_{i-1}|, |r_{i-2}|)^2.$$

Based on the estimated integrated variance, I get "instantaneous volatility" with respect to five-minute, $\widehat{\sigma(t_j)}$, and compare it to the five-minute returns following MNAs. Lee and Mykland (2007) use a similar methodology to obtain jump test statistics. Only the announcement returns satisfying $|r_j| > \kappa\widehat{\sigma(t_j)}$ are considered as MNA shocks. I set the threshold $\kappa = 1$ for my main analysis, but the results are robust to alternative thresholds. Dropping returns with small magnitudes has two other benefits. First, different kinds of announcements have various economic relevance and market impact. The threshold mechanically restricts the sample of MNA shocks to the announcements with significant market impact. Second, including announcement returns with small magnitudes blur the distinction between positive MNA shocks and bad MNA shocks.

Previous studies show that trading volumes and volatility on stocks and equity index futures tend to be high after stock market opens and before stock market closes, which may compound my estimation of volatility. I take care of volatility periodicity following the details shown in Appendix 1.

2.3 Stock returns and firm characteristics

I obtain daily and monthly returns on US NYSE/Amex/Nasdaq stocks from CRSP. I drop stocks with prices lower than \$5 dollar and market valuations lower than the bottom 20 percentile of the NYSE monthly market capitalization distribution to ensure that small and illiquid stocks do not drive my results. This procedure is also used by Nagel (2005), Hong and Sraer (2016), and Weber (2018). The breakpoints as well as risk-free rate, factor mimicking portfolio returns for size, book-to-market, momentum factors are all obtained from Kenneth French's online data library.

I use residual institutional ownership as a proxy for short-sales constraints. I obtain institutional ownership data from the Thomson Reuters 13F database (TR-13F). If a common stock is on CRSP but not in the TR-13, I set the institutional ownership as zero. Following Nagel (2005) and Weber (2018), I perform a logit transformation

$$logit(INST) = log(\tfrac{INST}{1-INST}),$$

where institutional ownership INST is winsorized at 0.0001 and 0.9999. To control for size effect, I obtain residual institutional ownership using the following quarterly Fama-Macbeth regression,

$$logit(INST_{i,t}) = \alpha + \beta_1 log(ME_{i,t}) + \beta_2 log(ME_{i,t})^2 + RI_{i,t} + \varepsilon_{i,t}$$

where $log(ME)$ is the natural logarithm of size.

Analysts' forecast dispersion of earnings is an important measure of investor disagreement. Data on analyst forecasts of fiscal-year-end earnings is from Institutional Broker's Estimate System (IBES). The summary file unadjusted for stock splits is used to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002). The dispersion is calculated as the standard deviation of forecast scaled by the average forecast.

To save space, the detailed definitions of other firm characteristics and risk measures are listed in Appendix A2, constructed following the convention of the literature.

3 MNA betas and stock returns on non-MNA days

In this section, I first present summary statistics on announcement returns and stock sensitivity to macro news. Subsequently, I investigate firm characteristics that are related to the sensitivity. Furthermore, using uni-variate portfolio sorting and Fama-Macbeth regressions, I show that stocks with low sensitivity to bad macro news have low expected stock returns on non-MNA days, and the relationship concentrate on stocks with lower-than-median sensitivity to bad macro news.

3.1 Summary statistics

Panel A of Table 2 reports the average and standard deviation of announcement returns following good or bad macro news, as well as the number of days on which good or bad macro news are released. It shows that good and bad MNA returns have similar magnitude and frequency. On average, there are around 37 good and bad announcements during a one-year period, and a typical announcement move the market by about 0.3%.

To measure underreaction to bad news, I estimate sensitivities of individual stocks to bad and good announcement returns over a rolling window of 24 months using the following time-series regression

$$r_{i,t} - r_{f,t} = \alpha_i + \alpha_{i,good} I_t^{good} + \alpha_{i,bad} I_t^{bad} + \beta_{i,good} MNA_t^{good} + \beta_{i,bad} MNA_t^{bad} + \beta_{i,MKT} MKT_t + \varepsilon_{i,t}. \quad (1)$$

MNA_t^{bad} (MNA_t^{good}) is the sum of bad (good) MNA returns on day t, that is, if there are multiple announcements and multiple bad MNA returns on day t, I use the sum of them as the MNA_t^{bad}. However, multiple MNA returns on the same day is rare in my sample. The rolling window of two years on average contains about 70 bad MNA returns and 70 good MNA returns.

I control for the market factor in the estimation of the MNA betas. As a result, instead of measuring absolute exposures to announcement returns, MNA betas capture the sensitivity to macro announcements over and above what is captured by the market beta. Note that I allow the intercept to be different on trading days without announcements, with good announcements or with bad announcements. Therefore the estimation of MNA betas is not compounded by the change in α_i on announcement days. Table 2 Panels B present descriptive statistics of MNA betas. While good and bad MNA betas are close to zero on average, they exhibit considerable cross-sectional variation. In particular, the standard deviations of MNA betas are four times larger than that of the market beta. Moreover, as I will show in Table 4, the decile portfolios sorted on bad MNA betas also exhibit increasing bad MNA betas from the bottom portfolio to the top. The pattern addresses the concern that MNA betas are driven by noise.

3.2 MNA betas and firm characteristics

If market frictions prevent stock prices from reflecting bad news, stocks with greater short-selling constraints and investor disagreement will be less sensitive to bad macro announcements. The intuition follows the argument by Miller (1977). Consider a firm whose investors face tight short-selling constraints and disagree on the value of the firm. Following a bad macro announcement, stocks with high cost of short-selling will be slower in incorporating the bad news, especially when investors have diverse beliefs on firm-specific valuation. The short-sales constraints and investor disagreement will lead to over-valuation, or under-reaction to the bad news, as stock prices reflect more of the beliefs of optimistic investors. As a result, underreaction stocks will perform relatively well on announcement days and have low bad MNA betas.

To investigate the cross-sectional determinants of bad news sensitivity at the individual stock level, I use Fama-Macbeth regressions of realized MNA betas on firm and risk characteristics that are known ex ante. For example, the model specification for bad MNA beta is as follows

$$\widehat{\beta}_{i,bad,t} = \alpha + \gamma_1 Firm\ Characteristics_{i,t-24} + \gamma_2 Risk\ Characteristics_{i,t-24} + \varepsilon_{i,t}. \quad (2)$$

Specifically, the bad MNA beta estimated at the end of month t is regressed on explanatory variables known at month t-24. I use Newey-West standard error with 24 lags.

I use residual institutional ownership (RIO) to proxy for short-selling constraints following Weber (2018) and Nagel (2005). As short sellers have to borrow shares from a stock lender, and higher institutional ownership indicates higher stock loan supply (see D'avolio (2002)), low institutional ownership suggests tight short-selling constraints. I use three proxies for investor disagreement following Boehme et al. (2006): dispersion of analysts' forecast of earnings (DISP), idiosyncratic volatility of stock returns (IVOL), and trading volume as a proportion of shares outstanding (TURN). Therefore, I assume stocks with high values of the three measures have large investor disagreement on firm-specific valuation.

Panel A of Table 3 reports the estimation results for bad MNA betas. To facilitate comparison across different variables, I standardize all independent variables to have zero mean and unit variance. Regression (1) to (3) show that stocks with higher residual institutional ownership, lower analysts' forecast dispersion, lower turnover, and lower idiosyncratic volatility are more sensitive to bad macro news, suggesting that short-selling constraints and investor disagreement prevent stock prices from incorporating the beliefs of pessimistic investors on days of announcements. The effect is significant except for idiosyncratic volatility. Value stocks exhibit higher sensitivity to bad news, suggesting that they are more affected by an economic downturn. Downside beta, co-skewness, co-kurtosis, and O-score are insignificantly related to bad MNA beta, addressing the concern that stocks that are less sensitive to bad news have significantly lower default risk, downside risk, or co-skewness.

Panel B of Table 3 reports the result of Fama-Macbeth regression for good MNA betas. Both the downside and upside beta have a consistently positive relationship with good MNA beta, indicating that the asymmetry captured by downside and upside betas is different from the asymmetry between good and bad MNA betas. Interestingly, residual institutional ownership, analysts' forecast dispersion, and idiosyncratic volatility have little predictive power for stocks' sensitivity to good news. It suggests that market friction plays a minor role in how stock prices respond to good news.

3.3 Portfolio-level analysis

If stocks with low bad MNA beta underreact to bad macro news, they should have low returns in the future as the mispricing is corrected, especially on days without announcements. To investigate the relation between MNA beta and stock returns, I first use uni-variate portfolio sorts. Each month, stocks are sorted into decile portfolios according to their estimated bad MNA beta or good MNA beta. I obtain value-weighted and equal-weighted decile portfolio returns during the one-month period after the portfolio formation. Moreover, monthly returns are decomposed into two parts: returns over days with MNAs and returns over days without MNAs. I weigh each stock by its market value at the end of the beta estimation period. Portfolio returns are out-of-sample in the sense that there is no overlap between the time period used for beta estimation and for post-formation returns. Rolling the beta estimation window forward one month at a time, I repeat the procedure and obtain time series of monthly returns for all decile portfolios. I report the average full monthly return, average monthly return over MNA days and over non-MNA days, as well as corresponding Jensen alphas and t-stats concerning the Carhart four-factor model. This section presents results for value-weighted portfolios. Appendix A.2 shows similar results for equal-weighted portfolios.

Table 4 Panel A reports value-weighted returns for the ten portfolios sorted by bad MNA beta. Portfolio 1 consists of stocks with the lowest bad MNA betas during the past 24 months, and portfolio 10 consists of stocks with the highest bad MNA betas. The columns labeled "Full month" in Panel A shows that there is a positive and almost monotonic relation between bad MNA beta and value-weighted monthly returns. However, the next column shows that the relationship is virtually flat on days with MNAs. The returns across decile portfolios are very similar except for portfolio 10. The difference in average excess return between decile 10 and decile 1 portfolios over MNA days is 0.34, with an insignificant alpha of 0.24. In contrast, on non-MNA days the average returns exhibit a strong and monotonic increase from portfolio 1 to 6. From portfolio 6 to 10 the relation is almost flat. The value-weighted monthly return difference between decile 10 and decile 1 is 0.59% per month, with an alpha concerning Carhart four-factor model of 0.39% per month with a *t*-stat of 1.8.

Panel B reports the pre- and post-formation loadings of decile portfolios on MNA returns and Carhart four factors. Sorting on bad MNA beta leads to a wide spread in pre-formation bad MNA betas across deciles, as shown in the first column. The post-formation bad MNA beta is estimated using unconditional full-sample daily returns for each portfolio and shows a virtually monotonic increasing pattern across deciles. In other words, the sorting generates portfolios that unconditionally vary in their exposures to bad news, confirming the existence of firm-level variation in sensitivity to bad macro news. Moreover, sorting on sensitivities to bad MNA beta is very different from sorting on good beta. In particular, sorting on bad MNA beta generates a spread in post-formation good MNA beta between the top decile and the bottom decile portfolio of only 0.14. For comparison, the corresponding spread in bad MNA beta is 0.44.

Panel C documents a negative relationship between good MNA beta and expected returns. The long-short value-weighted strategy produces an average monthly return of -0.36%, with a Carhart four-factor alpha of -0.14% per month. Most of the difference realizes over days without MNAs, but the alpha is small in magnitude and insignificant. Therefore, in the following analysis, I put emphasis on the relationship between returns and bad MNA beta, though good MNA beta is also included in most results.

In summary, the portfolio-level analysis shows that stocks with low bad MNA beta earn economically and statistically low returns in the following month. The pattern is consistent with the hypothesis that stocks underreact to bad macro news have low bad MNA beta and low returns in the future days without announcements. However, these results do not take into account other known cross-sectional determinants of expected returns, which I investigate in the following section.

3.4 Fama-Macbeth regressions of individual stock returns

In this section, I estimate firm-level Fama-Macbeth (1973) cross-sectional regressions of monthly excess stock returns over MNA days and non-MNA days. The independent variable of interest is the bad MNA beta. The firm-level analysis allows me to control for other firm and risk characteristics, including market beta, firm size, book-to-market, momentum, illiquidity, and idiosyncratic volatility. Specifically, I regress excess stock returns over MNA days or non-MNA days in month $t+1$ on MNA betas and control variables measured at the end of month t. To facilitate the interpretation of economic significance, I standardize all independent variables to have a zero mean and unit variance.

Table 5 reports the results of the Fama-Macbeth regressions. Consistent with the results of portfolio sorting, Panel A Column (1) and (2) show that bad and good MNA betas are significantly related to full monthly returns. After including control variables, however, the magnitude of both coefficients become smaller, and the good MNA beta becomes insignificant. Column (3) and (4) show that on MNA days, there is a weak and insignificant connection between MNA betas and returns. In contrast, on days without MNAs, bad MNA beta positively predicts returns, as shown in Column (5). The coefficient on bad MNA beta is 0.098, meaning a one-standard-deviation increase in bad MNA beta predicting an increase in next month's stock return on non-MNA days of 0.098%. The inclusion of control variables makes the coefficient smaller but still significant, as reported in Column (6). Note that the intercept is consistently around 1% and highly significant in Column (1)-(4), but is close to zero and insignificant in Column (5) and (6). The results are consistent with the observations from Savor and Wilson (2013) that equity premium and stock market returns are higher on MNA days yet close to zero on non-MNA days. Also, the coefficients on market β

change from positive to negative from MNA days to non-MNA days, consistent with Savor and Wilson (2014).

Underreaction should be more dominant for stocks with negative sensitivity to bad MNA returns. The stocks in the long leg could underreact, but it should contain the least degree of underreaction. Panel B of Table 6 confirms the hypothesis, showing that the positive relation between bad MNA beta and non-MNA day returns concentrates on stocks with lower-than-median bad MNA betas. I construct dummy variable Low_{bad} ($High_{bad}$) equal to 1 if a stock's bad MNA beta is lower (higher) than the median at the end of a month and 0 otherwise. I interact Low_{bad} and $High_{bad}$ with bad MNA beta and repeat the regressions in Panel A with control variable included. Column (3) in Panel B of Table 6 shows that the insignificant relation between bad MNA beta and MNA-day returns holds for stocks with both higher- or lower-than-median sensitivities to bad news. However, Column (5) shows that the higher bad MNA beta predicts higher returns on non-MNA days only among the stocks with lower-than-median bad MNA betas.

For completeness, I also construct Low_{good} ($High_{good}$) equal to 1 if a stock's good MNA beta is higher than the median at the end of a month and 0 otherwise. Column (4) and (6) show that for stocks with higher- or lower-than-median good MNA betas, the relation between good MNA beta and returns are both insignificant.

One explanation for the positive relation between bad MNA beta and non-MNA day returns is that the bad MNA beta is a proxy for some risk characteristics which bear a positive risk premium on non-MNA days. However, the concentration of the relation on stocks with lower-than-median bad MNA beta is a challenge to the risk-based channel. Specifically, it is not clear why among stocks with higher-than-median beta MNA betas, investors are not rewarded by higher returns for bearing more risk. Moreover, the sensitivity to bad MNA shocks may serve as a direct measure of MNA risk for individual stocks. However, the risk premium should exist primarily on days with MNAs, instead of days when investors know in advance no announcements are scheduled.

4 Short-sales constraints and investor disagreement

The results in the previous section show that stocks with low bad MNA betas underperform in the future, especially on non-MNA days, and the effect concentrates on stocks with lower-than-median bad MNA betas, consistent with underreaction to negative macro news. In this section, I present further evidence that the channel of underreaction is through high investor disagreement and short-selling constraints.

As I use three measures of disagreement, there are three pairs of constraints-disagreement combinations. I test the prediction for each combination separately. For example, using analyst forecast dispersion, I estimate the following Fama-Macbeth regression on monthly returns over non-MNA days,

$$R_{i,t}^{non-MNA} = \beta_{i,t-1}^{bad} \times Low_{i,t-1} \times (\gamma_1 + \gamma_2 RIO_{i,t-1} + \gamma_3 DISP_{i,t-1} + \gamma_4 RIO_{i,t-1} DISP_{i,t-1})$$
$$+\beta_{i,t-1}^{bad} \times High_{i,t-1} \times (\eta_1 + \eta_2 RIO_{i,t-1} + \eta_3 DISP_{i,t-1} + \eta_4 RIO_{i,t-1} DISP_{i,t-1}) + controls_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where the indicator variable $Low_{i,t-1}$ ($High_{i,t-1}$) is equal to 1 if a stock i's bad MNA beta is lower (higher) than the median at month $t-1$ and 0 otherwise. I interact RIO and DISP with lower- and higher-than-median beta MNA beta separately. My hypothesis predicts that the positive relation between bad MNA beta and returns focus on stocks with lower-than-median bad MNA betas, lower RIO, and larger DISP. Therefore, γ_4 should be significantly negative. At the same time, the combination of tight constraints and high disagreement should not lead to a positive relation between bad beta and returns among higher-than-median stocks if they are less likely to be affected by underreaction in the first place. As a result, η_4 should be insignificant.

Panel A of Table 6 presents the regressions where DISP serves as the measure of disagreement. Column 1 reports the regression result where the dependent variable is full month returns while in Column 2 and 3 the dependent variables are returns over MNA days and non-MNA days, respectively. The results from Column 1 and 2 show that full monthly returns and returns on MNA days have little relation with bad MNA betas. The small and insignificant coefficients on interaction terms suggest that neither full month returns nor returns on MNA days exhibit underreaction through short-selling constraints and investor disagreement.

For returns on non-MNA days in Column 3, the positive and significant coefficient on the interaction between bad MNA beta and Low shows that lower bad MNA beta predicts lower returns among stocks with lower-than-median bad MNA betas. The coefficient on the further interaction with DISP is positive, indicating that the prediction is stronger among stocks with higher dispersion in how investors interpret the bad news. Furthermore, the negative and significant coefficient on the four-term interaction, with the addition of RIO, points out that the effect is much stronger on stocks with lower institutional ownership and therefore greater short-selling constraints. The economic significance is also substantial. Among stocks with average RIO and DISP, a one unit decrease in bad beta leads to a lower return of 0.07% per month on non-MNA days. However, as short-selling constraints RIO decreases by one unit and investor disagreement DISP increases by one unit, the same decrease in bad beta leads to lower returns of 0.17%, with the magnitude amplified by more than two times. Meanwhile, the coefficients on interaction terms for stocks with higher-than-median bad betas are insignificant and have the opposite sign, suggesting that those stocks do not experience market-friction driven underreaction.

In Panel B and C, I check the robustness of the results using idiosyncratic volatility and turnover as measures of investor disagreement. The findings are consistent with Panel A. The interaction term with constraints on short-sales and investor belief dispersion is both statistically and economically significant for returns on non-MNA days.

As pointed out by Hanson and Sunderam (2013), Frazzini and Pedersen (2014), and Drechsler and Drechsler (2014), the amount of arbitrage capital that are involved in short-selling may be limited due to funding constraints. I use the TED spread, which is the difference between the three-month Eurodollar deposit yield (LIBOR) and three-month US T-Bills, as a proxy for funding constraints following Cohen et al. (2005) and Frazzini and Pedersen (2014). Table 7 shows that the relationship between returns on non-MNA days and sensitivity to negative macro news is stronger on periods when the TED spread is higher than sample average. The magnitude of the coefficient on the four-term interaction almost doubles during high TED period compared to low period. The results suggest that short-selling constraints are more binding and leading to stronger underreaction when arbitrage capital is scarce.

On July 2008, SEC issued an emergency order restricting naked shorting in financial stocks. SEC then issued a permanent ban on naked shorting in all U.S. stocks on September 2008. The ban supposedly increase short-selling constraints, and the results in previous tables may mainly come from post-crisis sample. To address the concern, Table 8 conducts the Fama-Macbeth regression for pre- and post-ban sample separately. The results show that indeed after 2008 July, the coefficient on the interaction term of interest becomes more negative, but still comparable with pre-ban level of the coefficient.

In summary, I show that the positive relation between non-MNA day returns and bad MNA beta is particularly strong among stocks with high constraints of short-selling and high investor disagreement. The results are robust to various measures of investor disagreement. Moreover, the effect is stronger during time periods when funding constraints are tighter and arbitrage capital is scarce. The overall results show that the underreaction is caused by short-selling constraints keep price from reflecting the views of pessimistic investors on days when bad macro news hits the market.

5 The security market line on non-MNA days

Savor and Wilson (2014) show that there is a negative relation between market beta and returns on non-MNA days. In this section, I first show that the non-MNA days based on my sample of announcements also exhibit the same pattern. Next, I provide evidence that it is driven by stocks with high market beta but low bad MNA beta. Specifically, the slope of the security market line on non-announcement days is much more negative among stocks less sensitive to bad news. The results suggest that high-market-beta stocks experience low returns on non-MNA days because they underreact to bad news on MNA days.

5.1 The robustness of Savor and Wilson (2014)

The MNAs investigated by Savor and Wilson (2014) include only inflation, employment, and Federal Open Market Committee interest rate decision. I cover a more comprehensive set of 18 macroeconomic news announcements and confirm the downward-sloping security market line on the corresponding non-MNA days.

Specifically, I estimate each stock's market beta using daily returns in a rolling window of 12 months. Stocks are sorted into decile portfolios based on the market beta. I calculate the value-weighted and equal-weighted returns for each portfolio on days with and without MNAs. Moreover, I estimate each portfolio's market beta using daily returns also within a rolling window of 12 months, although using the whole sample leads to similar results. Figure 2 plots average monthly excess returns on days with and without macro news announcements against market betas for the ten market beta-sorted portfolios. On days with announcements there exists a positive relationship between returns and market betas for both value-weighted and equal-weighted returns. The non-MNA days, however, show a negative relation between returns and market betas. Furthermore, compared to Figure 1 from Savor and Wilson (2014), the negative relation in Figure 2 is much stronger. A potential explanation is that Savor and Wilson (2014) report results of daily returns and they identify most trading days as non-MNA days. As a result, their monthly returns on non-MNA days are scaled by a larger number of days than monthly returns on MNA days.

Savor and Wilson (2014) also shows that there is little difference in beta conditional on announcement days or on non-announcement days. Figure 3 presents similar result. For each of the portfolios sorted by market beta, I estimate the post-formation announcement (non-announcement) beta using only the returns on announcement (non-announcement) days. It shows that the upward-sloping security market line on announcement days and the downward-sloping security market line on non-announcement days holds equally for market betas estimated with either set of trading days.

5.2 Security market line in quintiles of bad MAN beta

So far I have shown that stocks with high investor disagreement and tight short-selling constraints are more likely to underreact to bad macro news, have low bad MNA betas, and experience low returns in the future. These findings provide a potential explanation for the downward-sloping security market line on non-MNA days. As stocks with high market beta tend to have a high exposure to the economy, they should react more strongly to bad macro news compared with low-market-beta stocks. However, investors of high-market-beta stocks may also have more diverse beliefs and face tighter short-sales constraints. As a result of such market frictions, underreaction to bad MNA will be more pervasive for high-market-beta stocks. The underreaction channel leads to a testable hypothesis that the relationship between market beta and non-MNA day returns will be most negative among stocks with low bad MNA betas.

Using Fama-Macbeth regressions of market beta, Table 9 shows that the high-market-beta stocks indeed tend to have high investor disagreement and high constraints of short-sales. In particular, higher analysts forecast dispersion, turnover, and idiosyncratic volatility are all positively and significantly related to higher market beta. Moreover, the coefficients on residual institutional ownership are significantly negative across all regressions except for the regression where IVOL is used as a proxy for disagreement. Diether et al. (2002) and Liu et al. (2018) document similar result that market beta is positively related to analysts' forecast dispersion and IVOL.

Next, Table 10 confirms the underreaction hypothesis of the downward-sloping security market line using double-sorted portfolios. At the end of each month, I sort stocks into quintiles based on bad MNA betas. Subsequently, I further sort stocks into quintiles based on market betas. Panel A of Table 10 reports the value-weighted average returns on non-MNA days for each portfolio. In the first column where stocks have bad MNA betas in the bottom quintile, there is a pronounced downward-sloping security market line: low-market-beta stocks earn an excess return of -0.02% per month on days without MNAs, while high-market-beta stocks earn an excess return of –1.33% per month, with returns decreasing monotonically in market beta. The difference in average excess returns between the two extreme market beta portfolios is -1.31% per month and highly statistically significant (t-stat equal to -2.59). However, moving to the top quintile of bad MNA betas, the return difference between high and low market beta portfolios shrinks by around 60% and becomes statistically insignificant.

One potential explanation for the smaller return spread in the top bad-MNA-beta quintile is less variation in the market beta. Panel B reports the market beta for each of the 25 portfolios. Portfolio market betas are estimated using daily returns within a rolling window of 12 months. The market-beta spread in the highest quintile of bad MNA beta is actually similar to the lowest bad-MNA-beta quintile and larger than the middle quintiles. The results are also summarized in Figure 4.

The results so far show that the security market line is especially downward-sloping in stocks with low bad MNA betas. Next, I show the result is robust to controlling for other risk and firm characteristics.

5.3 Fama-Macbeth regression

Table 11 reports the Fama-Macbeth estimation on firm-level where the dependent variable is monthly non-MNA day returns. To facilitate the interpretation of economic significance, I standardize all firm characteristics as well as market beta to have zero mean and unit variance. Column (1) shows that the coefficient on market beta is -0.22 on average. Column (2) and (3) run the following Fama-Macbeth regression:

$$R_{i,t+1}^{n-MNA} = \sum_{j=1}^{5} \gamma_j Q_{i,t}^{j} \times \beta_{i,t}^{CAPM} + controls_{i,t} + \varepsilon_{i,t+1}. \quad (4)$$

Specifically, I separate the coefficient on market beta for stocks from different quintiles of bad MNA betas. $Q_{i,t}^{j}$ is equal to 1 if a stock i is in the j'th bad beta quintile at month t and zero otherwise. The coefficient on the interaction between market beta and Q^j is the slope of security market line for the stocks from the j'th bad beta quintile. In both regressions, the coefficient on market beta's interaction with Q^5, where stocks have high sensitivity to bad news, is around -0.13 and insignificant, meaning the slope is still negative but insignificant and the magnitude is 40% smaller than the whole sample slope of -0.22. In contrast, the coefficient on market beta's interaction with

Q^1 is highly significant and as high as -0.28 in Column (3) where firm characteristics are controlled. The magnitude is 30% larger than the whole sample average and two times the slope from the fifth quintile. Overall, the results support the hypothesis that the negative security market line is driven by high-market-beta stocks that underreact to bad MNA shocks and consequently experience low returns in the following non-MNA days.

Campbell et al. (2018) document that high-beta stocks hedge time variation in the aggregate market's return volatility, offering a potential neoclassical explanation for the low-beta anomaly. It is possible that my results are spurious if stocks that underreact to bad news and have low bad MNA beta also hedge against increases in aggregate volatility. Therefore I control for individual stocks' exposure to daily changes in VIX, which is estimated as $\beta_{i,VIX}$ in

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,VIX}\Delta VIX_t + \beta_{i,MKT}MKT_t + \varepsilon_{i,t}.$$

Column (4) shows the results for controlling for exposures to VIX. The coefficient on market beta among stocks in the bottom 20% stocks of bad MNA beta is barely affected and remain highly significant.

5.4 Conditional market beta

Stocks that underreact to negative macro news will by definition have low conditional market beta on bad days. Therefore, it is probable that the security market line is most downward-sloping among stocks that experience sharp decrease in market beta on bad days. Therefore, I estimate for each stock the change in market beta on days when there are bad MNA shocks using the following model:

$$r_{i,t} - r_{f,t} = \alpha_i + \alpha_{i,good}I_t^{good} + \alpha_{i,bad}I_t^{bad} + \beta_{i,MKT}MKT_t + \Delta\beta_{i,good,MKT}MKT_t \times I_t^{good} + \Delta\beta_{i,bad,MKT}MKT_t \times I_t^{bad} + \varepsilon_{i,t} \quad (5)$$

where I_t^{bad} (I_t^{good}) is an indicator variable equal to 1 if on day t there exists bad (good) macro news. $\Delta\beta_{i,bad,MKT}$ ($\Delta\beta_{i,good,MKT}$) captures the change in market beta on bad (good) days. Similar to previous section, I assume $Q^j_{i,t}$ to be equal to 1 if a stock i is in the j'th quintile of $\Delta\beta_{i,bad,MKT}$ at month t and zero otherwise. With the new quintile dummy I re-estimate model (4) and the results are reported in Table 12. The coefficient on market beta is significantly negative but similar across different quintiles. The lack of disparity suggests that change in market beta on bad days is different from bad MNA beta.

6 Robustness Tests

In this section, I show that the main results of the paper are robust to alternative estimations of MNA betas. I also extend Equation (1) to take into account potential changes in market betas on days with good or bad MNAs. Specifically, I re-estimate firm-level bad and good MNA betas as in the following time-series regression

$$r_{i,t} - r_{f,t} = \alpha_i + \alpha_{i,good} I_t^{good} + \alpha_{i,bad} I_t^{bad} + \beta_{i,good} MNA_t^{good} + \beta_{i,bad} MNA_t^{bad}$$
$$+ \beta_{i,MKT} MKT_t + \Delta\beta_{i,good,MKT} MKT_t \times I_t^{good} + \Delta\beta_{i,bad,MKT} MKT_t \times I_t^{bad} + \varepsilon_{i,t} \quad (6)$$

where I_t^{good} or I_t^{bad} is equal to 1 if there is a good or bad shock on day t. I also use alternative thresholds to restrict my sample of announcement returns. Specifically, I use $\kappa = 0.5$ as in $|r_j| > \widehat{\kappa\sigma(t_j)}$ to determine MNA shocks.

Table 13 presents the robustness of the relation between bad MNA betas and stock returns. Panel A of Table 13 shows the relation still holds when bad MNA betas are estimated using equation (6) to control for the conditional market beta. In particular, across different proxies of investor disagreement, there still exists a positive relationship between bad MNA betas and non-MNA returns, particularly for stocks with lower-than-median bad MNA betas, higher investor disagreement, and tighter short-selling constraints. Panel B confirms that using $\kappa = 0.5$ results in a similar conclusion across three proxies of investor disagreement.

Table 14 presents the robustness of my finding that the slope of security market line is more negative among stocks with lower bad MNA betas. Column 1 reports the result when $\kappa = 0.5$. In

Column 2 the bad MNA betas are estimated as in equation (6) with $\kappa = 1$. Across both specifications, there is no change in the main conclusion: the coefficient on market beta is most negative among stocks within the lowest quintile of bad MNA betas. For stocks in the highest quintile, the coefficient is largely insignificant, and the magnitude is reduced by around 60%.

7 Conclusion

This paper examines the relationship between individual stocks' sensitivities to macroeconomic news announcements (MNAs) and the cross-section of equity returns on days with and without MNAs. Stocks with low sensitivities to bad MNA shocks tend to underperform relative to other stocks in the future, especially during days without announcements. The effect is concentrated in stocks with high investor disagreement and tight short-selling constraints. The results are consistent with the hypothesis that stocks with high shorting costs underreact to bad macroeconomic news on announcement days as pessimists' beliefs are not reflected in prices. As a result, these stocks tend to underperform in the following non-announcement day as the overpricing gradually gets corrected.

These findings provide valuable insights into the documented negative relationship between market beta and stock returns on non-MNA days. Savor and Wilson (2014) argue it is challenging for risk-based models to explain why market betas do not change on the two type of days, while return patterns look very different. In this paper, I provide a market friction explanation. I show that the downward-sloping security market line on non-MNA days is driven by high-market-beta stocks which have low sensitivities to bad MNA shocks. The results are robust to various firm characteristics and alternative estimations of bad MNA betas. It suggests that high-market-beta stocks experience low returns on non-MNA days because they underreact to bad MNA news on announcement days. Overall, this study provides strong empirical evidence that underreaction to macroeconomic news announcements results in a downward-sloping security market line on days without announcements.

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Table 1: **Overview of U.S. macroeconomic announcements**

This table lists the macroeconomic announcements covered in this paper. The release time is stated in Eastern Time (ET). The dates of these announcements are obtained from official websites of Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Conference Board (CB),Federal Reserve Board (FRB), Thomson Reuters/University of Michigan (TR/UM), Institute of Supply Management (ISM) and Archival Federal Reserve Economic Data (ALFRED). For those of which the release dates are not available from official websites, I use Factiva to identify historical release dates.

Category	Announcement	Frequency	Time	Source
Income	GDP Advance	Quarterly	8:30	BEA
	GDP Preliminary	Quarterly	8:30	BEA
Employment	Initial Jobless Claims	Monthly	8:30	ETA
	Employment Situations	Monthly	8:30	BLS
Industrial Activity	Industrial Production	Monthly	9:15	FRB
	Construction Spending	Monthly	10:00	BC
	Durable Goods Orders	Monthly	8:30	BC
	Business Inventory	Monthly	8:30	BC
Consumption	Advance Retail Sales	Monthly	8:30	BC
	Consumer Credit	Monthly	15:00	FRB
Housing Sector	Building Permits & Housing Starts	Monthly	8:30	BC
Inflation	CPI	Monthly	8:30	BLS
Forward-looking Index	UM Consumer Sentiment Pre	Monthly	9:55	TR/UM
	UM Consumer Sentiment Final	Monthly	9:55	TR/UM
	Consumer Confidence Index	Monthly	10:00	CB
	ISM Manufacturing Index	Monthly	10:00	ISM
	ISM Non-manufacturing Index	Monthly	10:00	ISM

Table 2: **Summary statistics of MNA shocks and MNA betas**

This table reports summary statistics of macroeconomic news announcement shocks and MNA betas. Panel A reports the sample mean and standard deviation of bad and good MNA shocks in percentage. I also report the total number of MNA shocks and annual average number of shocks. Panel B reports times-series means of cross-sectional statistics of firm-level MNA betas. At the end of each month, MNA betas are estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months.

Panel A: Summary Statistics of MNA shocks

	Mean	Sd	Total Num	Num per year
Bad MNA	-0.27	0.25	730	37
Good MNA	0.26	0.22	752	38

Panel B: Descriptive Statistics of MNA betas

Betas	Mean	SD	Skewness	Kurtosis	P25	P75
Bad MNA β	0.02	1.71	0.34	16.58	-0.81	0.89
Good MNA β	-0.07	1.73	-0.11	9.77	-0.96	0.82
MKT β	1.11	0.46	0.75	3.95	0.78	1.36

Table 3: MNA betas and firm characteristics

This table reports the results of monthly Fama-Macbeth regressions of bad and good MNA betas on firm characteristics. At the end of each month, MNA betas are estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. I match MNA betas with firm characteristics and risk measures known 24 months ago. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Panel A reports the regression results for bad MNA beta, and Panel B reports the results for good MNA beta. The *t*-statistics are calculated using Newey-West *t*-statistic with 24 lags and reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3: Continued

Panel A: Bad MNA beta

	(1)	(2)	(3)
RIO	0.0423**	0.0405**	0.0406**
	(2.35)	(2.34)	(2.44)
DISP	-0.0817**		
	(-2.41)		
TURN		-0.0771*	
		(-1.84)	
IVOL			-0.0146
			(-0.41)
Size	-0.0811	-0.0620	-0.0630
	(-1.60)	(-1.26)	(-1.35)
BM	0.107	0.115*	0.113*
	(1.48)	(1.83)	(1.76)
Downside β	0.0458	0.0498	0.0445
	(0.62)	(0.83)	(0.78)
Upside β	0.00925	0.0107	0.0129
	(0.22)	(0.24)	(0.29)
Coskew	-0.00419	-0.00518	-0.00657
	(-0.51)	(-0.70)	(-0.88)
Cokurt	0.00602	0.00380	0.00388
	(0.57)	(0.38)	(0.38)
O-score	-0.325*	-0.318	-0.325
	(-1.67)	(-1.57)	(-1.58)
ILLIQ	-0.181	-0.112	-0.0167
	(-0.62)	(-1.48)	(-0.19)
r2	0.0696	0.0637	0.0641
N	255609	291004	291004

Table 3: Continued

Panel B: Good MNA beta

	(1)	(2)	(3)
RIO	-0.00171	0.00594	0.00517
	(-0.13)	(0.60)	(0.48)
DISP	0.00189		
	(0.07)		
TURN		0.106*	
		(1.84)	
IVOL			-0.0188
			(-0.89)
Size	0.0696	0.0714	0.0658
	(0.88)	(0.81)	(0.76)
BM	-0.0190	-0.00600	-0.00912
	(-0.26)	(-0.10)	(-0.16)
ILLIQ	-0.152	0.236***	0.146
	(-0.58)	(3.73)	(1.50)
Coskew	0.0138	0.0142	0.0146
	(1.52)	(1.57)	(1.58)
Cokurt	-0.00767	-0.00817	-0.00802
	(-1.32)	(-1.53)	(-1.44)
Downside β	0.107*	0.0779	0.0949*
	(1.92)	(1.51)	(1.85)
Upside β	0.0982*	0.0990*	0.0950*
	(1.79)	(1.80)	(1.71)
O-score	-0.0330	-0.0640	-0.0529
	(-0.14)	(-0.30)	(-0.24)
r2	0.0730	0.0683	0.0664
N	255609	291004	291004

Table 4: MNA betas and expected stock returns

This table reports average value-weighted full monthly returns, monthly returns on MNA days and on non-MNA days, as well as alphas of ten portfolios sorted by bad and good MNA betas. I also report for each portfolio the pre-formation average MNA betas, post-formation MNA betas and factor loadings on Carhart four factors. At the end of each month, I estimate MNA betas using daily excess returns over the preceding 24 months. Stocks are then sorted into deciles (1-10) based on bad or good MNA beta. I obtain value-weighted portfolio returns during the one-month period after the portfolio formation. Jensen alpha and the corresponding *t*-stat of each decile portfolio are estimated with respect to Carhart four-factor model.

Panel A: Performance of value-weighted portfolios sorted by bad MNA β

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.09	-0.32	-1.46	0.69	-0.07	-0.40	-0.60	-0.25	-1.79
2	0.35	-0.10	-0.66	0.75	0.09	0.76	-0.40	-0.19	-2.06
3	0.27	-0.15	-1.13	0.56	-0.04	-0.41	-0.29	-0.11	-1.24
4	0.33	-0.10	-0.85	0.44	-0.14	-1.42	-0.10	0.03	0.47
5	0.61	0.18	1.57	0.71	0.13	1.50	-0.10	0.05	0.65
6	0.69	0.23	1.98	0.66	0.07	0.76	0.03	0.16	2.23
7	0.66	0.21	1.72	0.66	0.05	0.50	0.01	0.16	2.17
8	0.65	0.12	0.92	0.54	-0.11	-1.10	0.11	0.23	2.87
9	0.84	0.26	1.67	0.71	-0.00	-0.03	0.13	0.27	2.65
10	1.02	0.31	1.53	1.03	0.17	1.07	-0.01	0.14	1.12
High-Low	0.93	0.63	1.82	0.34	0.24	0.89	0.59	0.39	1.80
9-2	0.48	0.36	1.40	-0.04	-0.10	-0.47	0.53	0.46	2.82

Panel B: Characteristics of value-weighted portfolios sorted by bad MNA β

	pre-formation			post-formation					
Portfolio	β_{bad}	β_{good}	β_{MKT}	β_{bad}	β_{good}	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-2.70	-0.14	1.32	-0.24	-0.13	1.14	0.19	-0.27	-0.29
2	-1.16	-0.14	1.09	-0.06	-0.04	1.01	0.04	-0.02	-0.06
3	-0.69	-0.15	1.03	-0.12	0.09	0.96	-0.05	-0.04	0.01
4	-0.36	-0.11	1.01	-0.02	-0.06	0.91	-0.08	0.06	0.06
5	-0.08	-0.07	1.00	-0.08	-0.03	0.91	-0.08	0.07	0.03
6	0.20	-0.07	1.01	-0.00	-0.02	0.91	-0.08	0.12	0.06
7	0.49	-0.00	1.03	0.05	-0.01	0.95	-0.10	0.10	0.02
8	0.84	-0.03	1.07	0.08	-0.13	1.00	-0.07	0.16	0.09
9	1.32	-0.05	1.13	0.16	-0.24	1.05	-0.03	0.26	0.02
10	2.80	0.01	1.28	0.20	0.01	1.22	0.19	0.21	0.08

Table 4: Continued

Panel C: Performance of value-weighted portfolios, sorted by good MNA β

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.56	-0.18	-0.88	0.76	-0.14	-0.88	-0.20	-0.04	-0.32
2	0.68	0.03	0.18	0.77	-0.01	-0.05	-0.09	0.03	0.34
3	0.59	0.08	0.68	0.73	0.05	0.57	-0.14	0.03	0.37
4	0.55	0.13	1.07	0.74	0.13	1.44	-0.19	-0.01	-0.08
5	0.58	0.20	1.67	0.73	0.14	1.47	-0.15	0.06	0.84
6	0.55	0.14	1.25	0.66	0.08	0.89	-0.11	0.06	0.89
7	0.52	0.12	0.99	0.61	0.02	0.24	-0.08	0.09	1.27
8	0.45	0.04	0.32	0.70	0.08	0.88	-0.25	-0.04	-0.61
9	0.42	-0.01	-0.05	0.67	0.03	0.34	-0.25	-0.04	-0.48
10	0.19	-0.31	-1.58	0.66	-0.13	-0.85	-0.47	-0.18	-1.46
High-Low	-0.36	-0.14	-0.46	-0.10	0.01	0.02	-0.27	-0.14	-0.76
9-2	-0.26	-0.03	-0.14	-0.10	0.04	0.22	-0.16	-0.07	-0.50

Panel D: Characteristics of value-weighted portfolios, sorted by good MNA β

	pre-formation			post-formation					
Portfolio	β_{good}	β_{bad}	β_{MKT}	β_{good}	β_{bad}	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-3.15	-0.13	1.27	0.00	-0.11	1.17	0.33	0.34	-0.05
2	-1.53	-0.04	1.14	-0.12	-0.19	1.07	0.11	0.36	0.02
3	-0.96	0.01	1.07	-0.12	-0.10	1.02	-0.01	0.11	-0.01
4	-0.57	0.01	1.03	-0.05	-0.07	0.97	-0.04	-0.03	-0.01
5	-0.24	0.04	1.02	0.05	-0.14	0.96	-0.09	-0.09	-0.06
6	0.08	0.05	1.02	-0.09	-0.07	0.94	-0.11	-0.01	0.02
7	0.42	0.06	1.03	-0.12	0.02	0.95	-0.11	-0.02	-0.00
8	0.82	0.07	1.07	0.07	0.17	1.01	-0.07	-0.12	0.01
9	1.38	0.07	1.14	0.11	0.17	1.05	-0.01	-0.18	0.04
10	2.98	0.05	1.34	0.24	0.23	1.22	0.25	-0.33	-0.04

Table 5: Stock-level Fama-MacBeth regressions

This table reports results from stock-level Fama-MacBeth regressions of full monthly returns, monthly returns on MNA days and on non-MNA days. MNA betas are estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months. Control variables include size, book-to-Market, momentum, illiquidity, return reversal, maximum and minimum daily return over the past month, co-skewness, co-kurtosis. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. to have a zero mean and unit variance. Low^{bad} (Low^{good}) is equal to one if a stock's bad (good) MNA beta is lower than the cross-sectional median at the end of a month. $High^{bad}$ ($high^{good}$) is equal to one if a stock's bad (good) MNA beta is higher than the cross-sectional median at the end of a month. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5: Continued

Panel A: Fama-Macbeth regressions of monthly returns

	Full month		MNA days		non-MNA days	
	(1)	(2)	(3)	(4)	(5)	(6)
Bad MNA β	0.14*	0.074**	0.041	0.010	0.098**	0.060**
	(1.96)	(1.98)	(0.71)	(0.29)	(2.23)	(2.38)
Good MNA β	-0.13**	-0.032	-0.024	0.0081	-0.097***	-0.037
	(-2.47)	(-0.94)	(-0.56)	(0.27)	(-2.79)	(-1.63)
MKT β		-0.17		0.071		-0.22**
		(-1.09)		(0.56)		(-2.21)
Size		-0.18**		-0.11*		-0.059
		(-2.47)		(-1.81)		(-1.30)
BM		0.013		0.0072		0.0086
		(0.27)		(0.20)		(0.28)
MOM		-0.061		-0.066		0.019
		(-0.56)		(-0.81)		(0.30)
ILLIQ		0.42		0.36		0.19
		(1.18)		(0.91)		(1.29)
IVOL		0.050		0.011		0.026
		(0.99)		(0.28)		(0.88)
REV		-0.31***		-0.32***		0.010
		(-3.13)		(-4.17)		(0.21)
Max		0.096*		0.13***		-0.011
		(1.86)		(2.86)		(-0.33)
Min		0.083*		0.056		0.0067
		(1.74)		(1.50)		(0.21)
Coskew		0.090		0.021		0.061
		(0.81)		(0.27)		(1.36)
Cokurt		0.071		0.047		0.020
		(0.66)		(0.61)		(0.44)
Constant	0.97***	1.01***	1.03***	1.07***	0.0064	0.011
	(2.74)	(2.86)	(3.35)	(3.47)	(0.03)	(0.04)
r2	0.012	0.10	0.011	0.098	0.012	0.100
N	374602	352520	374602	352520	374602	352520

Table 5: Continued

Panel B: Piecewise Fama-Macbeth regressions of monthly returns

	Full month		MNA days		non-MNA days	
	(1)	(2)	(3)	(4)	(5)	(6)
Bad MNA $\beta \times Low^{bad}$	0.077		-0.033		0.10**	
	(1.39)		(-0.61)		(2.52)	
Bad MNA $\beta \times High^{bad}$	0.019		0.0088		0.016	
	(0.27)		(0.15)		(0.38)	
Good MNA $\beta \times Low^{good}$		0.0065		0.062		-0.048
		(0.10)		(1.26)		(-1.24)
Good MNA $\beta \times High^{good}$		-0.063		-0.0093		-0.049
		(-1.03)		(-0.18)		(-1.17)
Bad MNA β		0.073**		0.011		0.059**
		(1.97)		(0.31)		(2.33)
Good MNA β	-0.033		0.0074		-0.037	
	(-0.97)		(0.25)		(-1.63)	
MKT β	-0.17	-0.16	0.068	0.073	-0.22**	-0.22**
	(-1.09)	(-1.07)	(0.54)	(0.58)	(-2.18)	(-2.19)
Size	-0.18**	-0.18**	-0.11*	-0.11*	-0.062	-0.061
	(-2.52)	(-2.51)	(-1.82)	(-1.82)	(-1.35)	(-1.33)
BM	0.012	0.013	0.0066	0.0064	0.0076	0.0087
	(0.25)	(0.27)	(0.18)	(0.18)	(0.25)	(0.28)
MOM	-0.060	-0.056	-0.067	-0.062	0.020	0.019
	(-0.56)	(-0.51)	(-0.83)	(-0.76)	(0.32)	(0.31)
ILLIQ	0.40	0.44	0.35	0.36	0.17	0.19
	(1.16)	(1.19)	(0.91)	(0.94)	(1.18)	(1.34)
IVOL	0.052	0.051	0.0099	0.013	0.028	0.025
	(1.06)	(1.03)	(0.26)	(0.35)	(0.99)	(0.88)
$High^{bad}$	0.063		0.049		0.0072	
	(1.13)		(1.03)		(0.22)	
$High^{good}$		-0.011		-0.043		0.024
		(-0.21)		(-0.95)		(0.74)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.10	0.10	0.10	0.10	0.10	0.10
N	352520	352520	352520	352520	352520	352520

Table 6: Stock-level Fama-MacBeth regressions: Disagreement and short-selling constraints

This table reports results from stock-level Fama-MacBeth regressions of full monthly returns, monthly returns on MNA days and non-MNA days. MNA betas are estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months. High (Low) is equal to one if a stock's bad MNA beta is higher (lower) than the cross-sectional median at the end of a month and zero otherwise. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Other controls include size, book-to-market, momentum, illiquidity, return reversal, maximum and minimum daily return over the past month, co-skewness, co-kurtosis, as well as interactions of High (Low) with RIO, DISP, IVOL, and TURN. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6: Continued

Panel A: Interaction with RIO and DISP

	(1) Whole month	(2) MNA days	(3) non-MNA days
Bad MNA β $\times$ Low	0.034	-0.044	0.074**
	(0.80)	(-1.16)	(2.39)
Bad MNA β $\times$ Low $\times$ RIO	-0.023	0.0036	-0.013
	(-0.45)	(0.09)	(-0.38)
Bad MNA β $\times$ Low $\times$ DISP	-0.029	-0.059	0.038
	(-0.54)	(-1.46)	(1.05)
Bad MNA β $\times$ Low $\times$ RIO $\times$ DISP	-0.049	0.039	-0.094***
	(-0.75)	(0.74)	(-2.60)
Bad MNA β $\times$ High	0.023	0.0021	0.024
	(0.46)	(0.05)	(0.86)
Bad MNA β $\times$ High $\times$ RIO	0.056	0.026	0.023
	(1.08)	(0.56)	(0.72)
Bad MNA β $\times$ High $\times$ DISP	-0.053	0.018	-0.074*
	(-0.75)	(0.32)	(-1.91)
Bad MNA β $\times$ High $\times$ RIO $\times$ DISP	0.035	-0.0094	0.052
	(0.50)	(-0.15)	(1.29)
MKT β	-0.17	0.068	-0.22**
	(-1.11)	(0.55)	(-2.21)
Size	-0.18***	-0.12**	-0.045
	(-2.64)	(-2.21)	(-1.06)
BM	0.015	0.00067	0.016
	(0.31)	(0.02)	(0.47)
MOM	-0.040	-0.043	0.024
	(-0.38)	(-0.51)	(0.39)
ILLIQ	0.66	-3.69	4.40
	(0.12)	(-0.73)	(0.88)
IVOL	0.013	-0.025	0.025
	(0.24)	(-0.61)	(0.80)
Controls	Yes	Yes	Yes
r2	0.12	0.12	0.12
N	310031	310031	310031

Table 6: Continued

Panel B: Interaction with RIO and IVOL

	(1) Whole month	(2) MNA days	(3) non-MNA days
Bad MNA β $\times$ Low	0.021	-0.042	0.061*
	(0.46)	(-1.03)	(1.93)
Bad MNA β $\times$ Low $\times$ RIO	0.018	0.026	0.0096
	(0.35)	(0.62)	(0.31)
Bad MNA β $\times$ Low $\times$ IVOL	0.060	0.039	0.013
	(1.20)	(0.88)	(0.47)
Bad MNA β $\times$ Low $\times$ RIO $\times$ IVOL	-0.045	-0.0017	-0.048**
	(-1.03)	(-0.05)	(-2.01)
Bad MNA β $\times$ High	0.021	-0.0061	0.023
	(0.44)	(-0.15)	(0.83)
Bad MNA β $\times$ High $\times$ RIO	0.012	-0.017	0.025
	(0.24)	(-0.37)	(0.73)
Bad MNA β $\times$ High $\times$ IVOL	-0.052	-0.039	-0.0099
	(-1.03)	(-1.00)	(-0.31)
Bad MNA β $\times$ High $\times$ RIO $\times$ IVOL	0.041	0.056	-0.014
	(0.80)	(1.32)	(-0.41)
MKT β	-0.17	0.067	-0.21**
	(-1.12)	(0.55)	(-2.21)
Size	-0.18**	-0.11*	-0.062
	(-2.50)	(-1.82)	(-1.35)
BM	0.013	0.0054	0.0087
	(0.27)	(0.15)	(0.29)
MOM	-0.053	-0.061	0.021
	(-0.50)	(-0.75)	(0.36)
ILLIQ	0.38	0.37	0.13
	(1.19)	(0.98)	(0.86)
Controls	Yes	Yes	Yes
r2	0.12	0.11	0.11
N	351349	351349	351349

Table 6: Continued

Panel C: Interaction with RIO and TURN

	(1) Whole month	(2) MNA days	(3) non-MNA days
Bad MNA β $\times$ Low	0.024	-0.053	0.070***
	(0.57)	(-1.52)	(2.65)
Bad MNA β $\times$ Low $\times$ RIO	-0.021	0.0017	-0.0094
	(-0.42)	(0.04)	(-0.31)
Bad MNA β $\times$ Low $\times$ TURN	0.052	0.038	0.014
	(1.05)	(1.06)	(0.40)
Bad MNA β $\times$ Low $\times$ RIO $\times$ TURN	-0.025	0.031	-0.055*
	(-0.56)	(0.97)	(-1.78)
Bad MNA β $\times$ High	0.012	0.0015	0.0071
	(0.27)	(0.04)	(0.27)
Bad MNA β $\times$ High $\times$ RIO	0.068	0.022	0.038
	(1.30)	(0.54)	(1.13)
Bad MNA β $\times$ High $\times$ TURN	0.070	0.044	0.028
	(1.21)	(0.90)	(0.72)
Bad MNA β $\times$ High $\times$ RIO $\times$ TURN	0.024	0.0061	0.032
	(0.43)	(0.15)	(0.83)
MKT β	-0.16	0.057	-0.19**
	(-1.11)	(0.47)	(-2.03)
Size	-0.18**	-0.11*	-0.056
	(-2.46)	(-1.85)	(-1.26)
BM	0.0078	0.0052	0.0050
	(0.17)	(0.15)	(0.17)
MOM	-0.054	-0.063	0.023
	(-0.51)	(-0.79)	(0.39)
ILLIQ	0.10	0.24	-0.045
	(0.31)	(0.61)	(-0.40)
IVOL	0.038	-0.013	0.036
	(0.76)	(-0.33)	(1.24)
Controls	Yes	Yes	Yes
r2	0.12	0.12	0.12
N	351349	351349	351349

Table 7: Stock-level Fama-MacBeth regressions: Time variation with TED spread

This table reports results from stock-level Fama-MacBeth regressions of monthly returns on non-MNA days during periods of high and low TED spread. MNA betas are estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months. High (Low) is equal to one if a stock's bad MNA beta is higher (lower) than the cross-sectional median at the end of a month and zero otherwise. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Other controls include size, book-to-market, momentum, illiquidity, return reversal, maximum and minimum daily return over the past month, co-skewness, co-kurtosis, as well as interactions of High (Low) with RIO, DISP, IVOL, and TURN. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 7: Continued

	(1) High TED	(2) Low TED
Bad MNA β $\times$ Low	0.083	0.073*
	(1.57)	(1.90)
Bad MNA β $\times$ Low $\times$ RIO	0.038	-0.039
	(0.53)	(-1.13)
Bad MNA β $\times$ Low $\times$ DISP	0.0063	0.053
	(0.09)	(1.29)
Bad MNA β $\times$ Low $\times$ RIO $\times$ DISP	-0.13*	-0.079*
	(-1.80)	(-1.89)
Bad MNA β $\times$ High	0.094	-0.0071
	(1.45)	(-0.26)
Bad MNA β $\times$ High $\times$ RIO	0.015	0.027
	(0.21)	(0.87)
Bad MNA β $\times$ High $\times$ DISP	0.014	-0.11**
	(0.22)	(-2.40)
Bad MNA β $\times$ High $\times$ RIO $\times$ DISP	0.14	0.0093
	(1.62)	(0.22)
MKT β	-0.39*	-0.14
	(-1.73)	(-1.41)
Size	0.12	-0.13***
	(1.25)	(-2.97)
BM	0.019	0.016
	(0.27)	(0.43)
MOM	-0.075	0.071
	(-0.46)	(1.59)
ILLIQ	4.58	4.18
	(0.99)	(0.59)
IVOL	0.046	0.016
	(0.66)	(0.52)
Controls	Yes	Yes
r2	0.14	0.11
N	101040	208991

Table 8: Stock-level Fama-MacBeth regressions: Before and after short-selling bans

This table reports results from stock-level Fama-MacBeth regressions of monthly returns on non-MNA days before and after 2008 July. MNA betas are estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months. High (Low) is equal to one if a stock's bad MNA beta is higher (lower) than the cross-sectional median at the end of a month and zero otherwise. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Other controls include size, book-to-market, momentum, illiquidity, return reversal, maximum and minimum daily return over the past month, co-skewness, co-kurtosis, as well as interactions of High (Low) with RIO, DISP, IVOL, and TURN. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 8: Continued

	(1) Before 2008 July	(2) From 2008 July
Bad MNA β × Low	0.031	0.12***
	(0.63)	(3.22)
Bad MNA β × Low × RIO	-0.0080	-0.018
	(-0.17)	(-0.37)
Bad MNA β × Low × DISP	0.039	0.036
	(0.83)	(0.66)
Bad MNA β × Low × RIO × DISP	-0.083*	-0.11*
	(-1.79)	(-1.89)
Bad MNA β × High	0.015	0.034
	(0.32)	(1.10)
Bad MNA β × High × RIO	0.036	0.0080
	(0.87)	(0.17)
Bad MNA β × High × DISP	-0.089	-0.058
	(-1.58)	(-1.10)
Bad MNA β × High × RIO × DISP	-0.00017	0.11*
	(-0.00)	(1.71)
MKT β	-0.060	-0.38**
	(-0.50)	(-2.46)
Size	-0.023	-0.068
	(-0.41)	(-1.06)
BM	-0.053	0.089*
	(-1.21)	(1.80)
MOM	0.069	-0.025
	(1.27)	(-0.22)
ILLIQ	8.62	-0.12
	(0.89)	(-0.30)
IVOL	0.038	0.011
	(0.92)	(0.23)
Controls	Yes	Yes
r2	0.12	0.12
N	155796	154235

Table 9: Market beta and firm characteristics

This table reports the results of monthly Fama-Macbeth regressions of market beta on firm characteristics. At the end of each month, market beta is estimated using daily returns over previous 12 months. I match market beta with firm characteristics known 12 months ago. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. The t-statistics are calculated using Newey-West t-statistic with 12 lags and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
RIO	-0.0109*	-0.0143**	-0.00638
	(-1.77)	(-2.50)	(-1.11)
DISP	0.0523***		
	(6.83)		
TURN		0.176***	
		(8.97)	
IVOL			0.141***
			(7.24)
Size	-0.123***	-0.0795***	-0.0849***
	(-7.28)	(-4.01)	(-4.30)
BM	-0.0392*	-0.0209	-0.0149
	(-1.94)	(-1.47)	(-1.25)
ILLIQ	-0.0235	0.140***	-0.105***
	(-0.34)	(3.66)	(-3.39)
r2	0.110	0.199	0.165
N	274823	311413	311303

Table 10: Double-sorted portfolios: Security market line in quintiles of bad MNA betas

This table reports value-weighted monthly returns and market betas of 25 double-sorted portfolios on non-MNA days. At the end of each month stocks are first sorted into quintiles based on bad MNA beta and subsequently into quintiles based on market beta. Portfolios are rebalanced monthly. Panel A reports the average value-weighted monthly returns on non-MNA days of the 25 portfolios as well as the long-short strategy within each quintile of bad MNA beta, long the highest market beta portfolio and short the lowest market beta portfolio. The *t*-statistics are also reported. Panel B reports average market beta for each portfolio estimated at the end of each month using portfolio daily returns over the past 12 months.

Panel A: non-MNA day returns of 25 portfolios

	Low β_{bad}	2	3	4	High β_{bad}
Low β_{MKT}	-0.02	0.08	0.20	0.16	0.21
2	-0.22	-0.02	0.13	-0.06	-0.24
3	-0.36	0.01	0.06	0.18	0.11
4	-0.88	-0.33	-0.06	-0.12	-0.29
High β_{MKT}	-1.33	-0.76	-0.68	-0.26	-0.38
High-Low	-1.31	-0.84	-0.88	-0.42	-0.59
t-stat	-2.59	-2.27	-2.73	-1.37	-1.49

Panel B: Market betas of 25 portfolios

	Low β_{bad}	2	3	4	High β_{bad}
Low β_{MKT}	0.64	0.58	0.57	0.61	0.74
2	0.93	0.79	0.79	0.83	0.96
3	1.14	0.92	0.95	0.95	1.15
4	1.40	1.14	1.10	1.15	1.37
High β_{MKT}	1.82	1.53	1.47	1.46	1.70

Table 11: Stock-level Fama-MacBeth regressions on market beta

This table reports results from Fama-MacBeth regressions of monthly returns during non-MNA days on market beta. $Q^j_{i,t}$ is equal to 1 if a stock i is in the j'th quintile at month t and zero otherwise. Market β is estimated by a regression of daily excess returns on market factor over a 12-months window. Control variables include exposure to daily changes in VIX, firm size (Size), book-to-market ratio (BM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), momentum (MOM), return reversal, maximum and minimum daily return over the past month, co-skewness, and co-kurtosis. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
MKT β	-0.22**			
	(-2.24)			
MKT $\beta \times Q^1$		-0.28**	-0.28***	-0.26**
		(-2.24)	(-2.67)	(-2.55)
MKT $\beta \times Q^2$		-0.23*	-0.21**	-0.19*
		(-1.88)	(-2.07)	(-1.97)
MKT $\beta \times Q^3$		-0.23*	-0.23**	-0.22**
		(-1.93)	(-2.34)	(-2.31)
MKT $\beta \times Q^4$		-0.20*	-0.19*	-0.18*
		(-1.66)	(-1.87)	(-1.87)
MKT $\beta \times Q^5$		-0.14	-0.12	-0.13
		(-1.12)	(-1.14)	(-1.27)
VIX β				-0.039
				(-1.05)
Size	-0.059		-0.060	-0.070
	(-1.28)		(-1.31)	(-1.59)
BM	0.0063		0.0086	0.015
	(0.20)		(0.28)	(0.51)
MOM	0.023		0.014	0.016
	(0.37)		(0.24)	(0.28)
ILLIQ	0.17		0.11	0.11
	(1.21)		(0.90)	(0.90)
IVOL	0.022		0.023	0.018
	(0.75)		(0.78)	(0.63)
Q^1		-0.11	-0.12**	-0.12**
		(-1.45)	(-2.04)	(-2.15)
Q^2		-0.048	-0.054	-0.056
		(-0.65)	(-1.03)	(-1.11)
Q^3		-0.012	-0.027	-0.025
		(-0.17)	(-0.54)	(-0.52)
Q^4		0.0056	-0.016	-0.017
		(0.09)	(-0.36)	(-0.41)
Controls	Yes	No	Yes	Yes
r2	0.095	0.059	0.10	0.11
N	351349	362272	351349	351349

Table 12: Stock-level Fama-MacBeth regressions on market beta: Conditional beta

This table reports results from Fama-MacBeth regressions of monthly returns during non-MNA days on market beta. $Q^{j}_{i,t}$ is equal to 1 if a stock i is in the j'th quintile of $\Delta\beta_{i,bad,MKT}$ at month t and zero otherwise. Market β is estimated by a regression of daily excess returns on market factor over a 12-months window. Control variables include exposure to daily changes in VIX, firm size (Size), book-to-market ratio (BM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), momentum (MOM), return reversal, maximum and minimum daily return over the past month, co-skewness, and co-kurtosis. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)
MKT $\beta \times Q^1$	-0.21*	-0.19*
	(-1.75)	(-1.90)
MKT $\beta \times Q^2$	-0.20*	-0.20**
	(-1.72)	(-2.08)
MKT $\beta \times Q^3$	-0.20*	-0.19*
	(-1.68)	(-1.97)
MKT $\beta \times Q^4$	-0.23*	-0.22**
	(-1.96)	(-2.27)
MKT $\beta \times Q^5$	-0.26**	-0.24**
	(-2.14)	(-2.44)
Size		-0.061
		(-1.34)
BM		0.0067
		(0.22)
MOM		0.0072
		(0.11)
ILLIQ		0.20
		(1.33)
IVOL		0.029
		(1.03)
Q^1	-0.00037	-0.025
	(-0.00)	(-0.41)
Q^2	0.031	0.017
	(0.34)	(0.35)
Q^3	0.016	0.0089
	(0.20)	(0.22)
Q^4	-0.049	-0.054
	(-0.67)	(-1.37)
Controls	No	Yes
r2	0.054	0.10
N	362272	351349

Table 13: Robustness test: Stock-level Fama-Macbeth regressions on bad MNA beta

This table reports results from Fama-MacBeth regressions of monthly returns over non-MNA days. Panel A uses bad MNA beta estimated by equation (5) where market beta conditional on days with MNA shocks are allow to be different from other days. Panel B uses threshold $\kappa = 0.5$ to restrict the sample of announcement returns. High (Low) is equal to one if a stock's bad MNA beta is higher (lower) than the cross-sectional median at the end of a month and zero otherwise. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Other controls include firm size (Size), Book-to-Market (BM), momentum (MOM), illiquidity (ILLIQ), reversal, maximum daily return, minimum daily return, coskewness, cokurtosis, as well as interactions of High (Low) with RIO, DISP, IVOL, and TURN. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 13: Continued

Panel A: Conditional market beta

	(1) DISP	(2) IVOL	(3) TURN
Bad MNA β × Low	0.053*	0.046	0.055**
	(1.78)	(1.52)	(2.20)
Bad MNA β × Low × RIO	-0.019	0.0037	-0.018
	(-0.59)	(0.12)	(-0.56)
Bad MNA β × Low × Disagreement	0.018	0.0099	0.026
	(0.51)	(0.35)	(0.77)
Bad MNA β × Low × RIO × Disagreement	-0.096***	-0.049**	-0.067**
	(-2.63)	(-2.08)	(-2.12)
Bad MNA β × High	-0.0020	-0.0046	-0.018
	(-0.08)	(-0.17)	(-0.72)
Bad MNA β × High × RIO	0.052	0.058*	0.062*
	(1.64)	(1.79)	(1.96)
Bad MNA β × High × Disagreement	-0.074*	-0.021	0.027
	(-1.81)	(-0.66)	(0.70)
Bad MNA β × High × RIO × Disagreement	0.025	0.018	0.035
	(0.57)	(0.54)	(0.98)
MKT β	-0.21**	-0.21**	-0.19**
	(-2.21)	(-2.17)	(-1.99)
Size	-0.047	-0.064	-0.058
	(-1.12)	(-1.40)	(-1.30)
BM	0.016	0.0088	0.0061
	(0.48)	(0.29)	(0.21)
MOM	0.027	0.021	0.025
	(0.44)	(0.36)	(0.42)
ILLIQ	4.59	0.14	-0.059
	(0.94)	(0.94)	(-0.49)
IVOL	0.024		0.035
	(0.77)		(1.20)
Rev	0.019	0.0067	0.012
	(0.38)	(0.14)	(0.24)
Coskew	0.055	0.062	0.069
	(1.26)	(1.39)	(1.57)
Controls	Yes	Yes	Yes
r2	0.12	0.11	0.12
N	310031	351349	351349

Table 13: Continued

Panel B: Threshold $\kappa = 0.5$

	(1) DISP	(2) IVOL	(3) TURN
Bad MNA β $\times$ Low	0.049	0.053	0.045
	(1.38)	(1.49)	(1.54)
Bad MNA β $\times$ Low $\times$ RIO	-0.055*	-0.031	-0.054*
	(-1.84)	(-1.11)	(-1.89)
Bad MNA β $\times$ Low $\times$ Disagreement	0.0078	-0.031	0.0052
	(0.24)	(-1.02)	(0.16)
Bad MNA β $\times$ Low $\times$ RIO $\times$ Disagreement	-0.085**	-0.057**	-0.026
	(-2.41)	(-2.30)	(-0.92)
Bad MNA β $\times$ High	-0.0042	-0.0078	-0.019
	(-0.12)	(-0.24)	(-0.61)
Bad MNA β $\times$ High $\times$ RIO	0.0046	0.031	0.029
	(0.15)	(0.99)	(0.90)
Bad MNA β $\times$ High $\times$ Disagreement	-0.058	-0.030	0.0049
	(-1.38)	(-0.88)	(0.14)
Bad MNA β $\times$ High $\times$ RIO $\times$ Disagreement	-0.0081	-0.035	0.047
	(-0.18)	(-1.06)	(1.57)
MKT β	-0.21**	-0.21**	-0.19**
	(-2.17)	(-2.15)	(-2.00)
Size	-0.044	-0.061	-0.056
	(-1.05)	(-1.34)	(-1.26)
BM	0.017	0.0083	0.0076
	(0.50)	(0.27)	(0.26)
MOM	0.023	0.018	0.018
	(0.37)	(0.30)	(0.31)
ILLIQ	4.42	0.16	0.051
	(0.88)	(1.01)	(0.39)
IVOL	0.024		0.037
	(0.77)		(1.25)
Controls	Yes	Yes	Yes
r2	0.12	0.11	0.12
N	310031	351349	351349

Table 14: Robustness test: Stock-level Fama-Macbeth regressions on market beta

This table reports results from Fama-MacBeth regressions of monthly returns over non-MNA days on market beta. Column (1) use bad MNA beta estimations based on threshold $\kappa = 0.5$ to restrict the sample of announcement returns. The bad MNA beta in Panel A Column (2) is estimated by equation (5) where market beta conditional on days with MNA shocks are allow to be different from other days. At the end of each month, market beta is estimated using daily returns over previous 12 months. $Q^j_{i,t}$ is equal to 1 if a stock i is in the j'th quintile at month t and zero otherwise. Control variables include firm size (Size), book-to-market ratio (BM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), momentum (MOM), reversal return, maximum daily return, minimum daily return, co-skewness, and co-kurtosis. Firm characteristics are standardized, i.e. demeaned and divided by standard deviation, cross-sectionally within each month. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1) $\kappa = 0.5$	(2) $\kappa = 1$, cond. beta
MKT $\beta \times Q^1$	-0.28***	-0.29***
	(-2.62)	(-2.80)
MKT $\beta \times Q^2$	-0.21**	-0.18*
	(-2.08)	(-1.80)
MKT $\beta \times Q^3$	-0.19*	-0.23**
	(-1.88)	(-2.30)
MKT $\beta \times Q^4$	-0.20**	-0.20**
	(-1.99)	(-1.99)
MKT $\beta \times Q^5$	-0.12	-0.13
	(-1.21)	(-1.21)
Size	-0.057	-0.060
	(-1.26)	(-1.32)
BM	0.0099	0.0100
	(0.32)	(0.33)
MOM	0.0083	0.014
	(0.14)	(0.23)
ILLIQ	0.099	0.091
	(0.85)	(0.78)
VOL	0.026	0.022
	(0.88)	(0.75)
Q^1	-0.061	-0.11*
	(-0.97)	(-1.90)
Q^2	-0.022	-0.050
	(-0.40)	(-0.96)
Q^3	0.018	-0.014
	(0.42)	(-0.29)
Q^4	0.059	-0.0059
	(1.49)	(-0.14)
Controls	Yes	Yes
r2	0.10	0.10
N	351349	351349

Figure 1: Volatility of one-minute returns around macro announcements

This figure plots the standard deviation of one-minute returns on E-mini S&P 500 futures around MNA shocks for the period of 1997-2017. Returns are expressed as percentages. The horizontal axis marks the ordinal number of the one-minute intervals around announcement time point. Specifically, number t from -6 to 6 is defined as the t'th one-minute interval after (positive t) or before (negative t) announcement time.

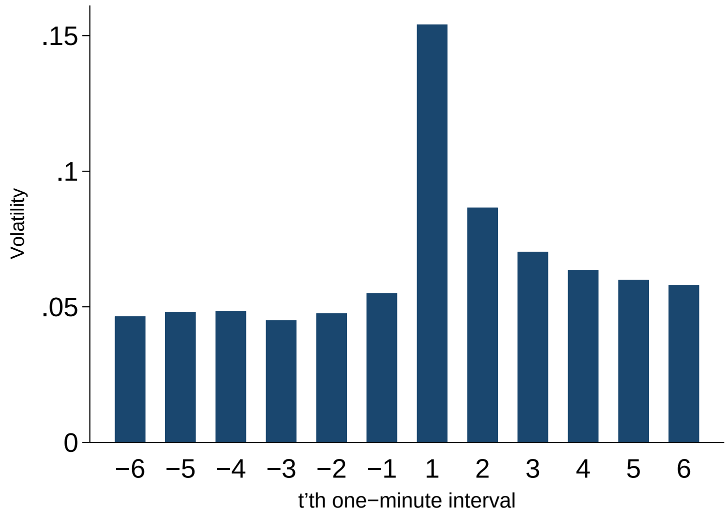


Figure 2: Average excess returns for 10 market beta-sorted portfolios

This figure plots average monthly excess returns on days with and without macro news announcements against market betas for 10 market beta-sorted portfolios. Individual stock market betas are estimated at the end of each month using daily returns in a rolling window of 12 months. Stocks are then sorted into decile portfolios based on the market beta. Portfolios are rebalanced monthly. Value-weighted and equal-weighted returns are calculated for each portfolio on days with and without MNAs. Portfolio market betas are estimated at the end of each month using daily returns over the past 12 months. Returns are expressed as percentages.

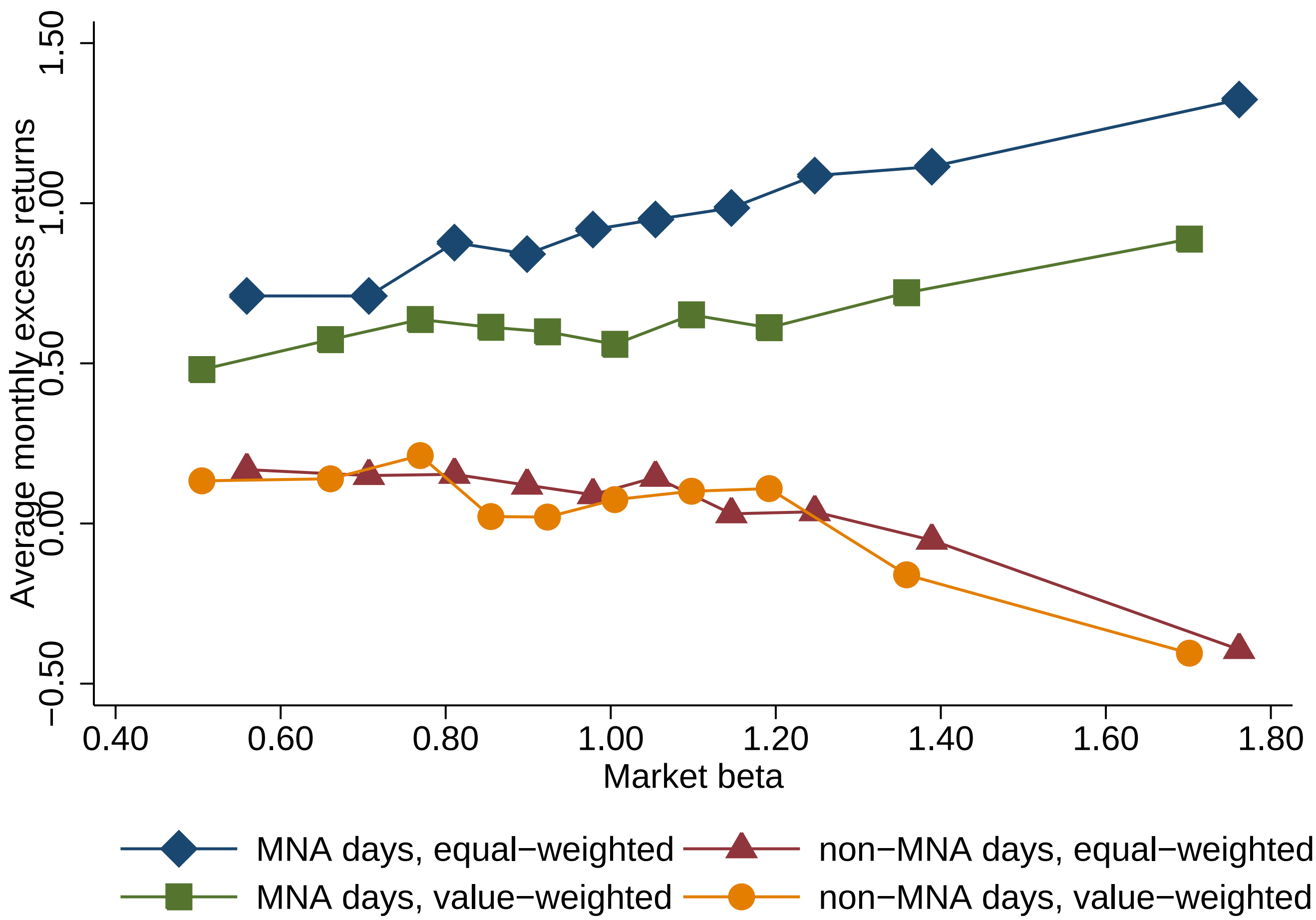


Figure 3: Average excess returns for 10 market beta-sorted portfolios: Announcement-day and non-announcement-day beta

This figure plots average monthly excess returns on days with and without macro news announcements against market betas for 10 market beta-sorted portfolios. Individual stock announcement-day (non-announcement-day) market betas are estimated at the end of each month using daily returns on announcement (non-announcement) days in a rolling window of 12 months. Stocks are then sorted into decile portfolios based on the market beta. Portfolios are rebalanced monthly. Value-weighted and equal-weighted returns are calculated for each portfolio on days with and without MNAs. Portfolio market betas are estimated at the end of each month using daily returns over the past 12 months. Returns are expressed as percentages.

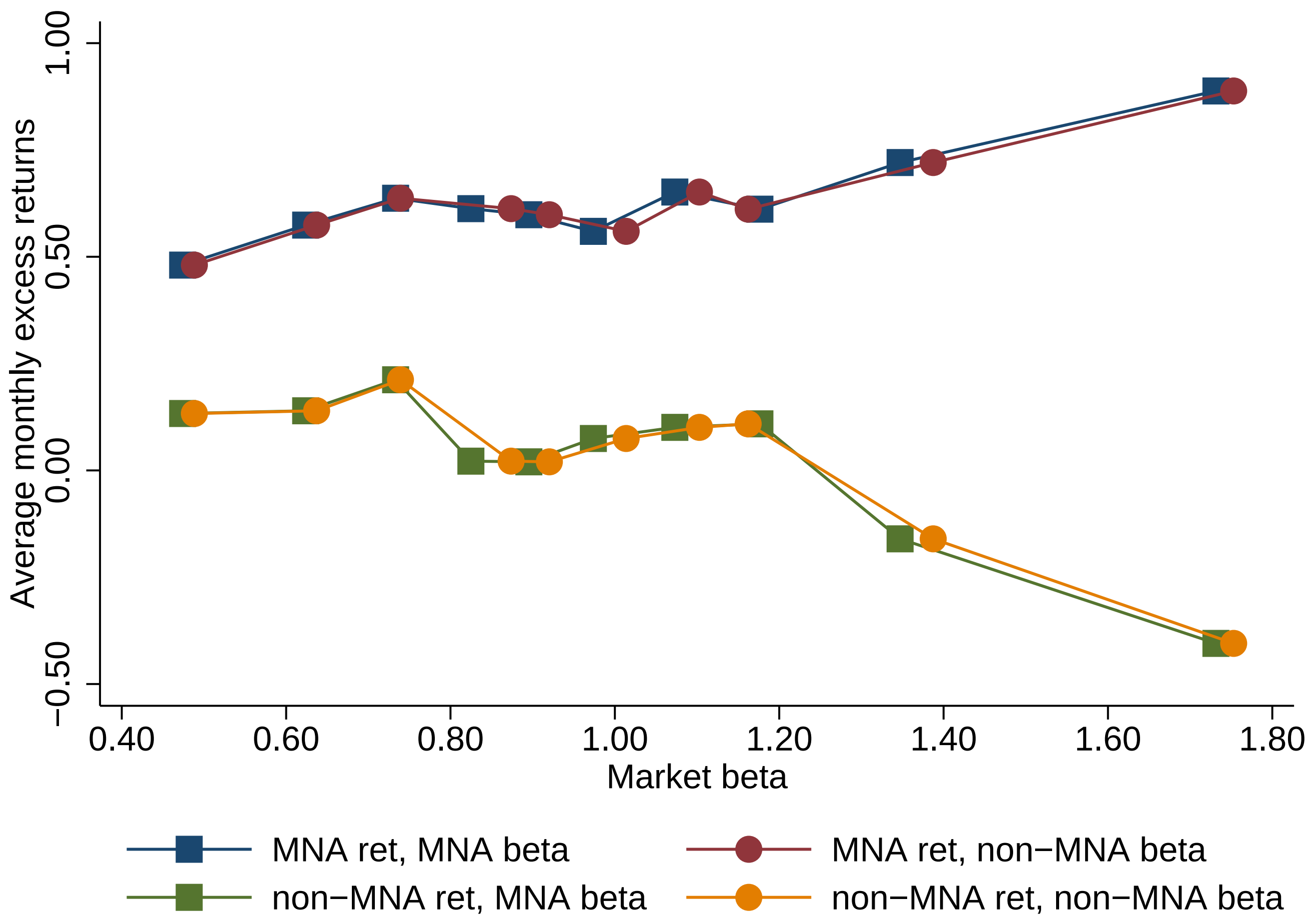
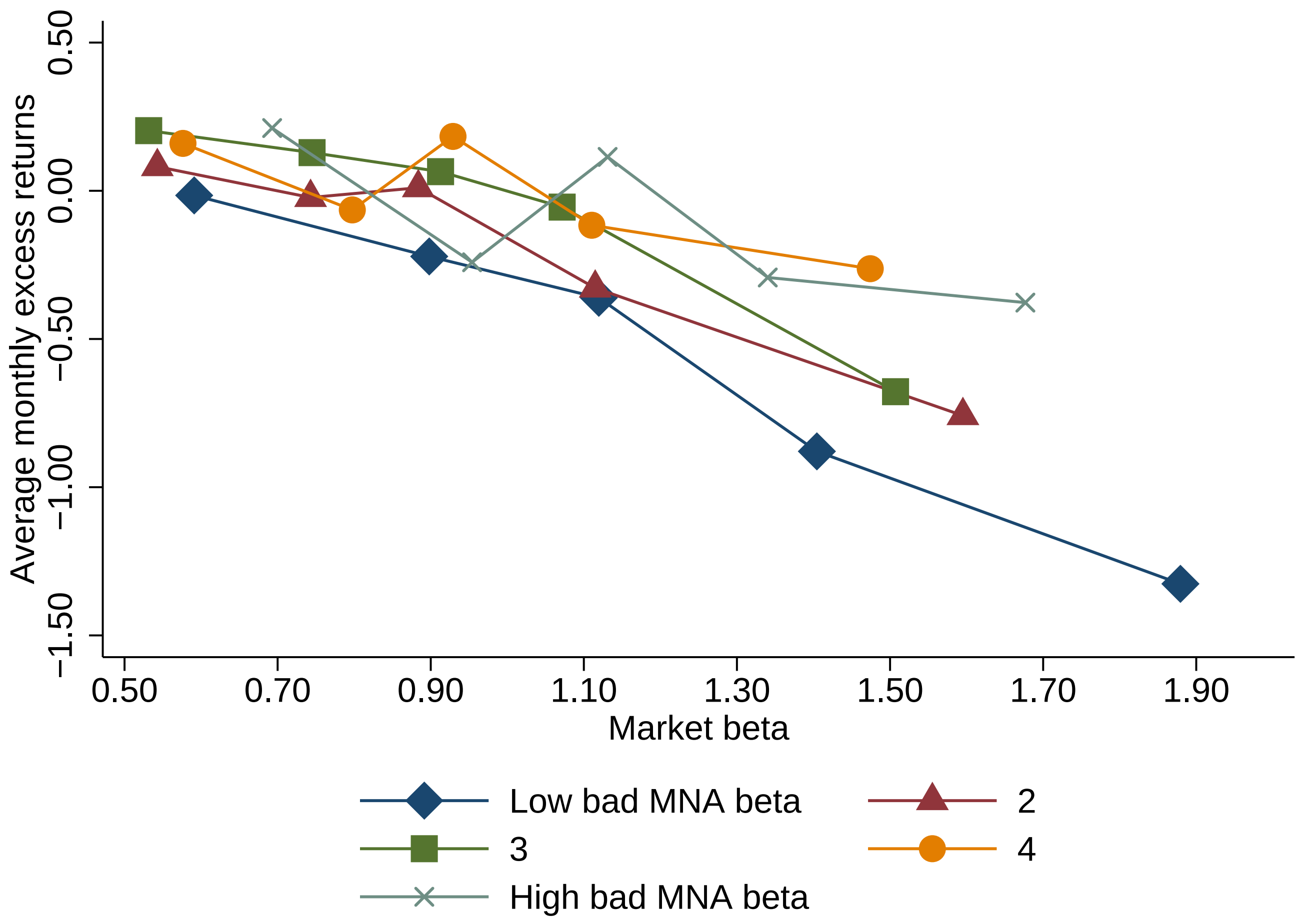


Figure 4: Average excess returns on non-MNA days for 25 double-sorted portfolios

This figure plots average value-weighted monthly returns on days without macro news announcements against market betas for 25 double-sorted portfolios. At the end of each month stocks are first sorted into quintiles based on bad MNA beta and subsequently into quintiles based on market beta. Portfolios are rebalanced monthly. Portfolio market betas are estimated at the end of each month using portfolio daily returns over the past 12 months. Returns are expressed as percentages.



Appendix

A.1 Periodicity

I control volatility periodicity following the non-parametric weighted standard deviation (WSD) estimator in Boudt et al. (2011) which is built on shortest half estimator. For each year I estimate the periodicity factor which varies across the day of the week and the $j'th$ interval during the day. Suppose $r_j = \{r_{(1),j}, r_{(2),j}, r_{(3),j}, ..., r_{(T),j}\}$ is the vector of returns observed on the the time j of the day and a certain day of the week (e.g. Friday), such that $r_{(1),j} \leq r_{(2),j} \leq r_{(3),j} \leq, ... \leq r_{(T),j}$. The shortest half scale is

$$ShortH_j = 0.741 \times min\{r_{(h_i),j} - r_{(1),j}, ..., r_{(T_i),j} - r_{(T-h+1),j}\}, \; where \; h = [T/2] + 1.$$

Suppose there are L observations during a day, the shortest half scale estimator for periodicity at time j on that day of the week is then defined as $f_j^{ShortH} = \frac{ShortH_j}{\sqrt{\frac{1}{L}\sum_{l=1}^{L} ShortH_l^2}}$. The WSD periodicity factor related to timing j is defined as $f_j^{WSD} = \frac{WSD_j}{\sqrt{\frac{1}{L}\sum_{l=1}^{L} WSD_l^2}}$, where $WSD_j = \sqrt{1.081 \frac{\sum_{t=1}^{T} w_{t,j} \times r_{t,j}^2}{\sum_{t=1}^{T} w_{t,j}}}$ and $w_{t,j} = 1$ if $r_{t,j}/f_j^{ShortH} <= 6.635$ and 0 otherwise.

I scale five-minute returns with WSD periodicity factor and use the scaled returns to estimate instantaneous volatility. Specifically, suppose $r_{t,j}$ on day t over the $j'th$ interval of five-minute during the day as an WSD-scaled announcement return , I estimate the local "instantaneous volatility" with respect to five-minute as

$$\widehat{\sigma_{t,j}}^2 = \frac{\pi}{6 - 4\sqrt{3} + \pi} \times \frac{1}{K-2} \sum_{i=j-K+2}^{j-1} med(|r_{t,i}|, |r_{t,i-1}|, |r_{t,i-2}|)^2,$$

with $K = 5 \times 96$.

A2.Variable Definition

- **Size**: The natural logarithm of the market value of equity (the product of closing price and the number of shares outstanding) at the end of each month.

- **Book-to-Market (BM)**: I following Novy-Marx (2013) and measure book equity as shareholder equity, plus deferred taxes, minus preferred stock, when available, for the fiscal year ending in the calendar year t-1. If shareholder equity is missing, I calculate it as the sum of the book value of common and preferred equity. If all of these are missing, we calculate shareholder equity as total assets minus total liabilities. Market value of equity is stock price times shares outstanding at the end of December of year t − 1.

- **Momentum (MOM)**: The cumulative return over the past 12 months, skipping the return in the last month.

- **Idiosyncratic volatility (IVOL)**: Following Ang et al. (2006b), idiosyncratic volatility at the end of month t as $ivol_{i,t} = \sqrt{var(\varepsilon_{i,t})}$, where $\varepsilon_{i,t}$ is the error term of the Fama and French (1993) three-factor regression. The regression is estimated using daily returns over month t.

- **Illiquidity (ILLIQ)**: Following Amihud (2002), I calculate illiquidity of stock i at the end of month tas the average daily ratio of the absolute stock return to the dollar trading volume of that month:

$$ILLQ_{i,t} = \frac{1}{N}\sum_d\left(\frac{|r_{i,d}|}{volume_{i,d} \times price_{i,d}}\right),$$

where N is the number of trading days in month t, $r_{i,d}$ is the daily return, $volume_{i,d}$ is the daily trading volume, and $price_{i,d}$ is the daily price on day d.

- **Reversal (REV)**: REV in month t is defined as the monthly stock return over the month.

- **Maximum daily return (MAX)**: MAX of month t is defined as the maximum daily return of that month, following Bali et al. (2011).

- **MKT beta**: The regular market β at the end of month t is estimated using the following model of daily returns over the past 12 months,

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_i \times MKT_d + \varepsilon_{i,d},$$

where $r_{i,d}$ is the return on stock i, MKT is the market factor, and $r_{f,d}$ is the risk-free rate.

- **Downside beta** β_i^-: The downside beta at the end of month t is estimated using the following model of daily returns over the past 12 months, $r_{i,d} - r_{f,d} = \alpha_{i,d} + \beta_i^- \times MKT_d + \varepsilon_{i,d}$ on the condition that $MKT_d < \mu_m$, where μ_m is the average market excess return.

- **Upside beta** β_i^+: The upside beta at the end of month t is estimated using the following model of daily returns over the past 12 months, $r_{i,d} - r_{f,d} = \alpha_{i,d} + \beta_i^+ \times MKT_d + \varepsilon_{i,d}$ on the condition that $MKT_d > \mu_m$, where μ_m is the average market excess return.

- **Turnover (TURN)**: The turnover in month t is measured as the ratio of the number of shares traded during the month divided by the number of shares outstanding at the end of the month.

- **Analysts' forecast dispersion of earnings (DISP)**: Data on analyst forecasts of fiscal-year-end earnings is from Institutional Broker's Estimate System (IBES). The summary file unadjusted for stock splits is used to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002). The dispersion is calculated as the standard deviation of forecast scaled by the average forecast.

- **Residual institutional ownership (RIO)**: I obtain institutional ownership data from the Thomson Reuters 13F database (TR-13F). If a common stock is on CRSP but not in the TR-13, I set the institutional ownership as zero. Following Nagel (2005) and Weber (2018), I perform a logit transformation

$$logit(INST) = log(\frac{INST}{1-INST}),$$

where institutional ownership INST is winsorized at 0.0001 and 0.9999. To control for size effect, I obtain residual institutional ownership using the following quarterly Fama-Macbeth regression,

$$logit(INST_{i,t}) = \alpha + \beta_1 log(ME_{i,t}) + \beta_2 log(ME_{i,t})^2 + RI_{i,t} + \varepsilon_{i,t}$$

where $log(ME)$ is the natural logarithm of size.

A3. Additional Tables

Table 15: MNA Betas and expected stock returns

This table reports average equal-weighted full monthly returns, monthly returns on MNA days and non-MNA days, as well as alphas of ten portfolios sorted by bad and good MNA betas. I also report for each portfolio the pre-formation average MNA betas, post-formation MNA betas and factor loadings on Carhart four factors. At the end of each month, I estimate MNA betas using daily excess returns over the preceding 24 months. Stocks are then sorted into deciles (1-10) based on bad or good MNA beta. I obtain equal-weighted portfolio returns during the one-month period after the portfolio formation. Jensen alpha and the corresponding t-stat of each decile portfolio are estimated with respect to Carhart four-factor model.

Panel A: Performance of equally-weighted,sorted by bad MNA β

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.66	0.04	0.27	1.01	0.10	0.85	-0.35	-0.06	-0.59
2	0.80	0.17	1.88	0.94	0.14	1.96	-0.14	0.03	0.55
3	0.82	0.22	2.65	0.90	0.15	2.20	-0.07	0.07	1.49
4	0.90	0.31	3.67	0.86	0.13	2.02	0.04	0.17	3.40
5	0.87	0.27	3.26	0.83	0.10	1.59	0.04	0.17	3.25
6	1.00	0.40	4.53	0.93	0.21	2.97	0.07	0.19	3.56
7	0.94	0.32	3.58	0.93	0.18	2.56	0.01	0.14	2.54
8	1.02	0.35	3.78	0.95	0.14	1.99	0.07	0.20	3.62
9	1.05	0.32	3.03	0.96	0.10	1.15	0.09	0.23	3.43
10	1.04	0.24	1.63	1.09	0.10	0.88	-0.05	0.13	1.52
High-Low	0.37	0.20	0.88	0.07	0.00	0.02	0.30	0.19	1.38
9-2	0.25	0.15	1.07	0.02	-0.04	-0.38	0.23	0.20	2.22

Panel B: Characteristics of equally-weighted portfolios sorted by bad MNA β

	pre-formation			post-formation					
Portfolio	β_{bad}	β_{good}	β_{MKT}	β_{bad}	β_{good}	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-2.70	-0.14	1.32	-0.15	0.09	1.13	0.78	-0.08	-0.25
2	-1.16	-0.14	1.09	-0.09	-0.02	0.98	0.55	0.18	-0.10
3	-0.69	-0.15	1.03	-0.09	-0.10	0.94	0.45	0.18	-0.05
4	-0.36	-0.11	1.01	-0.08	-0.09	0.93	0.43	0.19	-0.02
5	-0.08	-0.07	1.00	-0.07	-0.09	0.92	0.42	0.20	-0.00
6	0.20	-0.07	1.01	-0.04	-0.07	0.93	0.39	0.22	-0.01
7	0.49	-0.00	1.03	-0.03	-0.06	0.95	0.41	0.24	-0.00
8	0.84	-0.03	1.07	0.00	-0.02	1.01	0.46	0.28	-0.01
9	1.32	-0.05	1.13	0.08	-0.11	1.07	0.51	0.30	-0.02
10	2.80	0.01	1.28	0.14	0.15	1.22	0.75	0.16	-0.02

Table 15: Continued

Panel C: Performance of equally-weighted portfolios sorted by good MNA β

Portfolio	Full month			MNA days			Non-MNA days		
	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.98	0.21	1.59	0.99	0.04	0.39	-0.01	0.17	2.05
2	0.97	0.27	3.08	0.99	0.14	1.97	-0.02	0.13	2.51
3	0.99	0.33	4.19	1.00	0.19	3.16	-0.01	0.13	2.77
4	1.02	0.41	5.36	0.99	0.23	3.85	0.03	0.17	3.81
5	1.02	0.42	5.32	0.98	0.25	4.03	0.04	0.17	3.48
6	0.90	0.31	3.90	0.93	0.19	3.05	-0.02	0.12	2.44
7	0.90	0.30	3.62	0.94	0.19	2.97	-0.04	0.10	2.09
8	0.78	0.18	2.20	0.86	0.08	1.27	-0.08	0.09	1.96
9	0.81	0.19	2.03	0.87	0.05	0.65	-0.06	0.14	2.48
10	0.53	-0.11	-0.73	0.94	0.01	0.06	-0.41	-0.12	-1.26
High-Low	-0.45	-0.32	-1.66	-0.05	-0.03	-0.22	-0.40	-0.29	-2.37
9-2	-0.16	-0.09	-0.70	-0.12	-0.09	-0.95	-0.04	0.01	0.07

Panel D: Characteristics of equally-weighted portfolios sorted by good MNA β

Portfolio	pre-formation			post-formation					
	β_{good}	β_{bad}	β_{MKT}	β_{good}	β_{bad}	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-3.15	-0.13	1.27	0.15	-0.04	1.14	0.79	0.19	-0.09
2	-1.53	-0.04	1.14	-0.05	-0.07	1.04	0.58	0.25	-0.06
3	-0.96	0.01	1.07	-0.06	-0.09	0.99	0.50	0.26	-0.06
4	-0.57	0.01	1.03	-0.05	-0.02	0.95	0.45	0.21	-0.04
5	-0.24	0.04	1.02	-0.04	-0.14	0.93	0.43	0.20	-0.03
6	0.08	0.05	1.02	-0.09	-0.10	0.94	0.42	0.19	-0.03
7	0.42	0.06	1.03	-0.04	0.03	0.96	0.43	0.17	-0.04
8	0.82	0.07	1.07	-0.02	-0.00	1.00	0.46	0.11	-0.05
9	1.38	0.07	1.14	-0.01	0.06	1.07	0.55	0.03	-0.07
10	2.98	0.05	1.34	0.23	0.10	1.21	0.77	-0.20	-0.16