A Market-Level Tug of War: Asset Pricing on ... Days

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A daily tug of war between opposing investor clienteles at the individual stock level has been documented in the asset pricing literature. We measure a market-level tug of war using the cross-sectional intensity of individual tug of war. The Capital Asset Pricing Model (CAPM) tends to perform better and market betas are strongly and positively related to average returns on "quiet days" when the market-level tug of war is less intensive. We further show that the well-established findings of a robust risk-return trade-off on important information days (e.g., FOMC announcement days and influential firms earnings announcement days), and during pessimistic sentiment periods hold only when such days coincide with "quiet days". Overall, we provide a novel explanation for the empirical failure of the CAPM and show that investor disagreement has significant implications on asset pricing.

(*JEL classifications*: G12; G14)

Key words: CAPM; risk; security market line; tug-of-war; beta; investor heterogeneity

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* We thank the feedback collected from Martijn Boons, Philippe Mueller, Xinyao Zhou (Discussant), FMA Asia/Pacific 2022, and CFE 2022. Ran Tao is Assistant Professor at the University of Bristol Business School. Chardin Wese-Simen is Professor at the University of Liverpool Management School. Lei Zhao is Associate Professor at ESCP Business School. The financial support from Bristol Business School, ESCP Business School and Queen's Management School is gratefully acknowledged.

1. Introduction

Starting with the pioneering work of Black (1972), empirical asset pricing studies have shown that the security market line (SML) for the US stocks is either too flat in respect of the Capital Asset Pricing Model (CAPM) prediction or even negative (e.g., high-beta stocks underperform low-beta stocks).[1] Recent studies have made significant progress in understanding such low risk anomalies and show empirical evidence of a conditionally positive relation between betas and average stock returns in a variety of empirical settings. For example, a robust risk-return trade-off exists on macroeconomic (such as Federal Open Markets Committee (FOMC) interest rate decisions) announcement days (Savor and Wilson (2014)), when an aggregate of influential S&P 500 companies disclose corporate earnings (Chan and Marsh (2022)), and when investor sentiment about the stock market's prospects is low (Antoniou et al. (2016)).[2] Why average stock returns are sometimes positively and on other occasions negatively related to market risk? In this paper, we seek to address the question head on.

As the release of important information tends to resolve disagreement (e.g., heterogeneous beliefs on expected stock returns) among different investor clienteles, and high investor sentiment tends to amplify such disagreement or/and its impact on asset prices, the strand of literature on conditional CAPM points to investor heterogeneity as a potential cause of the empirically observed negative risk-return relation. We exploit the recently documented phenomenon of a daily "tug-of-war" between opposing investor clienteles, and propose a novel measure of investor heterogeneity at the market level. An flourishing literature establishes that stocks display systematic return patterns across the daily trading cycle, e.g., positive overnight returns tend to be followed by negative intraday reversals.[3] For example, Berkman et al. (2012) find that the US stocks have a strong tendency of having positive overnight returns followed by intraday reversals, and this tendency is concentrated among stocks recently attracted retail investors' attention. Interestingly, the authors show evidence that individuals tend to place orders outside of normal working hours, to be executed at the start of the next trading day. Consistent with their findings, Lou et al. (2019) also argue that there are two distinct investor clienteles who tend to exercise tradings over different time periods within the day, e.g., the overnight versus the intraday periods. Specifically, sentiment-driven retail investors prefer to trade at or near the morning open while institutional investors dominate the rest of the day, including the market close. The heterogeneous views of the two types of investors

[1] See, for example, Haugen and Heins (1975), Fama and French (1992),Fama and French (2004), and Frazzini and Pedersen (2014).

[2] Other studies that document a conditional positive beta-return relation include Ben-Rephael et al. (2021), and Hendershott et al. (2020).

[3] See, among others, Heston et al. (2010), Branch and Ma (2012), Berkman et al. (2012), Bogousslavsky (2016), Aboody et al. (2018), and Bogousslavsky (2021).

on the fair price of an asset, if any, are manifested in the often distinct patterns of asset price movements during the overnight and the intraday periods. Any back-and-forth across the two periods is referred to as a "tug of war". Recently, Akbas et al. (2022) further show that stocks with a higher frequency of positive overnight returns followed by negative intraday reversals are associated with higher future returns. The authors attribute the underlying economic mechanism behind their findings to daytime arbitrageurs (e.g., institutional investors) overcorrecting the upward overnight price pressure by noise traders (e.g.,retail investors). To the extent that such overcorrection exists and high beta assets are more prone to speculative overpricing by noise traders, one would expect a negative slope of the SML on days when a market level "tug of war" is more intensive.[4]

Following the literature, we design a measure of the intensity of a market-level "tug of war" (ToW_t^m), calculated as the proportion of stocks experiencing a "tug-of-war" return pattern on trading day t. Specifically, ToW_t^m measures how many stocks (as a proportion of the US stock universe) experience positive overnight returns followed by negative intraday reversals, capturing the cross-section intensity of investor heterogeneity on day t. We classify a trading day as a noisy day ($N-day$) if ToW_t^m is higher than the sample median, and as a quiet day ($Q-day$) otherwise.[5] Fig 1 summarizes the key findings that motivate this study. As in Savor and Wilson (2014) and Chan and Marsh (2022), we first estimate stock market betas (from the CAPM) for all stocks using a rolling window of 12 months of daily returns from July 1992 to December 2020. We next group stocks into ten (value-weighted) beta-sorted portfolios and plot the average realized portfolio daily excess returns (over the risk-free rate) against the corresponding full-sample portfolio betas on noisy days (circle-shaped points and a blue line) and quiet days (square-shaped points and a red line), respectively. Noticeably and as expected, the SML in the US market during our sample period has a downward slope on $N-day$, indicating a negative market risk premium. An increase in beta of one is associated with a decrease in an average excess return of about 17.7 basis points, with a t-statistic estimate for the slope coefficient of -10.11. In sharp contrast, this negative beta-return relation is completely reversed on $Q-day$. An increase in beta of one is associated with a statistically significant (t-stat = 9.81) increase in average excess returns of 17.6 basis points. These results suggest that, as indicated by the CAPM, beta is indeed an important risk factor that positively predicts average returns on days when the cross-section intensity of investor disagreement is relatively low (e.g., on quiet days).

——————————— Insert Figure 1 here ———————————

[4] For related theoretical and empirical work that shows noise traders (retail investors) have a preference toward high beta stocks, see Barber and Odean (2000), Barber and Odean (2001), and Hong and Sraer (2016).

[5] In robustness checks, we discuss alternative definitions of noisy and quiet days. See Section 3.3 for details.

In a number of further analyses, we confirm that our results are robust to 1). using different test portfolios or individual stocks; 2). using alternative econometric methods (e.g., Fama-MacBeth or pooled panel regressions); 3). controlling for other return predictors documented in the literature (e.g., ME, BTM, and MOM); and 4).using alternative definitions of noisy and quiet days; 5).using estimators that correct for microstructure noise.

Furthermore, we document evidence that supports the overcorrection hypothesis of Akbas et al. (2022) as the mechanism that is behind our findings: the SML is downward (upward) sloping on noisy (quiet) days. The overcorrection hypothesis, which inspires and guides our main analysis, has four immediate empirical implications. First, while optimistic retail investors can cause overvaluation (positive returns) overnight for some stocks (e.g., high beta stocks with positive overnight news), pessimistic retail investors are less likely to cause undervaluation due to the difficulties in initiating short positions and the relatively high cost associated with short selling. Anticipating such an asymmetric role of overnight noise traders, daytime arbitrageurs are more likely to overcorrect positive overnight returns. In other words, it is less likely that positive intraday reversals (e.g., return patterns with negative overnight returns followed by positive intraday returns) capture investor disagreement and indicate mispricing. To test this implication, we identify noisy days using positive intraday reversals, instead of negative intraday reversals as in our main analysis. As expected, on such newly and differently identified noisy days, the SML slope is no longer negative. Instead, it turns positive.

Second, the overcorrection by daytime arbitrageurs occurs during the trading hours. Therefore, the negative slope of the SML on noisy days should be driven by intraday returns. Consistent with this implication, we find that on noisy days stock returns are positively related to betas overnight, whereas returns and betas are negatively related during the trading hours. The absolute magnitude of the (negative) intraday SML slope is significantly larger than that of the (positive) overnight SML slope, leading to the negative 24h SML slope on $N-day$ shown in Fig 1. These findings further support the overcorrection mechanism and are in line with those in Hendershott et al. (2020).

Third, noise traders tend to increase trading during optimistic periods and their trading activity is disproportionately concentrated among high beta stocks (see Antoniou et al. (2016)). Anticipating this phenomenon, daytime arbitrageurs are more likely to overcorrect positive overnight returns (of high beta stocks) during optimistic sentiment periods. Therefore, the effect of overcorrection on the slope of the SML is expected to be stronger when investor sentiment is optimistic. Consistent with this conjecture, we find that on noisy days the magnitude of the negative SML slope measured during optimistic sentiment periods (when the Baker and Wurgler (2006) index is positive) is over two times that measured during pessimistic sentiment periods.

Lastly, if daytime arbitrageurs indeed overcorrect positive overnight returns, such mispricing should be corrected during the following days when a market-level tug of war is absent, e.g., on the following quiet days. In other words, one would expect that the negative SML slope observed on noisy days will turn positive on the following quiet days. Exploiting a sub-sample in which noisy days are followed by two consecutive quiet days, we find that it takes on average two quiet days in a row to correct the overcorrection. Specifically, the negative noisy-day beta-return relation turns flat (positive) after considering the return of the following one quiet day (two quiet days).

We next conduct a placebo test in which we analyze the alternative sequence of daily reversals that proceed from a negative intraday return to a positive overnight reversal. These alternative intraday-to-overnight positive reversals are unrelated to the overcorrection mechanism, which works through daytime arbitrageurs responding to and overcorrecting positive overnight returns. To implement the analysis, we re-define daily returns as the 24h returns from open to open, instead of from close to close, and identify noisy days using intraday-to-overnight positive reversals, instead of overnight-to-intraday negative reversals. We re-estimate the SML on noisy days according to the new empirical setting. As expected, we find that the slope of the SML turns positive. This placebo test establishes that the sequence of daily reversals matters and only overnight-to-intraday negative reversals capture investor heterogeneity and lead to the downward sloping SML shown in Fig 1.

Our study is closely related to Savor and Wilson (2014) and Chan and Marsh (2022), which document empirical evidence that market risk is properly priced on days when important news (e.g., news about the unemployment rate, inflation, and FOMC interest rate decisions and news about influential S&P500 firms' quarterly earnings) arrives, but not on other days. To the extent that the release of important news washes away some information asymmetry, daytime arbitrageurs are less likely to overcorrect positive overnight returns on news days. In Section 5, we show that our results are robust to excluding the aforementioned important news days from the sample. More importantly, we find that the (investor-disagreement-induced) overcorrection mechanism seems to drive the positive risk-return trade-off on important news days: the SML slope is positive only on a subset of news days that coincide with quiet days, but not on other news days. Interestingly and as expected, the mispricing of high beta stocks on noisy days is weaker, still significant though, when such days overlap with important news days, supporting the hypothesis that news announcements tend to reduce information asymmetry. Furthermore, Antoniou et al. (2016) find that the SML slope depends on investor sentiment. The sentiment hypothesis is related to the overcorrection hypothesis. Specifically, daytime arbitrageurs are more likely to overcorrect positive overnight returns in optimistic periods, anticipating heightened noise trader activity in such periods. We show that our results are not conditional on the status of investor sentiment, but the upward (downward) SML slope reported in Antoniou et al. (2016) is conditional on quiet (noisy) days.

We test and rule out two alternative explanations for our results. First, Pettengill et al. (1995) show that when the SML slope is estimated using realized rather than expected returns, a segmented relationship between realized returns and beta may exist, e.g, the SML slope is positive (negative) during periods when the realized excess market return is positive (negative). Our main finding that the SML is upward (downward) sloping on quiet (noisy) days may be conditional on realized excess market returns. Second, Andrei et al. (2021) show that (investor-disagreement-induced) beta inflation causes flattened SML. Our results might be driven by the distortion in beta estimates, if beta inflation is less (more) severe on quiet (noisy) days. We show in Section 6 that neither realized market return nor beta distortion is likely to serve as an explanation to our results.

2. Data and Methodology

2.1. Data and variables

The stock market data, including daily opening and closing prices, are obtained from the Centre for Research in Security Prices (CRSP), while the firm-level balance sheet data come from Compustat. We obtain daily US market excess returns and returns for the 25 size- and book-to-market-sorted portfolios and the ten industry portfolios from Kenneth French's website [6]. Our sample includes all the US common stocks (with a CRSP share code value of either 10 or 11) trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ). The primary sample period used throughout this study is from July 1992 and December 2020. Stocks' opening prices are available from the CRSP database only from July 1992.

We compute the intraday and overnight returns of stock i on day t as in Lou et al. (2019) :

$$Ret_t^N = (1 + Ret_t^{close-to-close})/(1 + Ret_t^{open-to-close}) - 1 \tag{1}$$

where $Ret_t^{open-to-close} = Ret_t^D = (Close_t - Open_t)/Open_t$. The close-to-close return is the dividend-adjusted holding period return (RET) from the CRSP.

[6] Kenneth French's website can be found in the following `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french`

Following Lou et al. (2019) and Akbas et al. (2022), we identify a tug of war for stock i on day t if a negative intraday reversal (NR_{it}) is observed, e.g., the stock has a positive overnight return followed by a negative intraday reversal:

$$NR_{it} = \begin{cases} 1, & \text{if } Ret_{it}^N > 0 \text{ \& } Ret_{it}^D < 0. \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Our main variable of interest the intensity of a market-level tug of war (ToW_t^m) can then be calculated on each day t as the proportion of stocks with a tug-of-war return pattern:

$$ToW_t^m = \frac{\sum_{i=1}^{N} NR_{it}}{N} \tag{3}$$

where N is the total number of stocks on day t. We next classify each day into one of the two categories: noisy days $N - day$ or quiet days $Q - day$, depending on whether ToW_t^m is above or below its full-sample median. The $N - day$ ($Q - day$) group contains days on which the daily tug-of-war is more (less) intensive. We calculate ToW_t^m for each of the 6,926 trading days in total. The median of ToW_t^m during our sample period is 0.27, with the Min and Max being 0.03 and 0.87, respectively. The average value of ToW_t^m is 0.28, suggesting that there are more than one-quarter of stocks exhibiting a tug-of-war return pattern than the theoretical value of 0.25.[7]

Following Savor and Wilson (2014), we estimate a test asset's market beta in two different ways: in the figures we compute a single full-sample beta, whereas in the tables we compute time-varying betas over rolling estimation windows of 12 months using daily returns. We measure a stock's log market capitalization (ME) and book-to-market (BM) as in Fama and French (1992). As standard in the momentum literature, we define month t momentum (MOM) as the stock return during the 11-month period up to but not including the current month (e.g., months $t - 11$ through $t - 1$, inclusive).

2.2. Methodology

To estimate the SML slope, we follow the classic two-step procedure. In the first step, we estimate betas for test assets, including different stock portfolios and individual stocks, using rolling regressions with 12-month daily excess returns. For the second-stage regressions, we adopt two different approaches. We first apply the standard Fama-MacBeth procedure and compute beta coefficients separately for noisy and quiet days. More specifically, for each day we estimate the following cross-sectional regressions:

$$Ret_{j,t+1}^{24h,N} = \lambda_0^N + \lambda_1^N * \hat{\beta}_{j,t} + \epsilon_{j,t+1}^N \tag{4}$$

[7] In theory, the probability of a stock exhibiting positive overnight return and negative intraday return should be 25% out of the other three combinations.

and

$$Ret^{24h,Q}_{j,t+1} = \lambda^Q_0 + \lambda^Q_1 * \hat{\beta}_{j,t} + \epsilon^Q_{j,t+1} \tag{5}$$

where $Ret^{24h,N}_{j,t}$ is the daily excess return of test asset j over the risk-free rate on noisy days and $Ret^{24h,Q}_{j,t}$ is the daily excess return on quiet days. $\hat{\beta}_{j,t}$ is the asset's market beta at day t (estimated over the previous 12 months using daily returns) from the first-stage regression. We next calculate the SML slope estimate for noisy (quiet) days as the time-series average of λ^N_1 (λ^N_1).

In addition to the Fama-MacBeth regression analysis with two separate regressions, we estimate a single regression and test whether beta coefficients are different on noisy and quiet days:

$$Ret^{24h}_{j,t+1} = \lambda_0 + \lambda_1 * \hat{\beta}_{j,t} + \lambda_2 * N_{t+1} + \lambda_3 * \hat{\beta}_{j,t} * N_{t+1} + \epsilon^{24h}_{j,t+1} \tag{6}$$

where N_{t+1} is a dummy variable that equals one if day $t+1$ is a noisy day and zero otherwise.

3. SML on noisy and quiet days

3.1. Stock portfolios

We construct beta decile portfolios, which are rebalanced each month, as follows. First, for each individual stock i we estimate a time series of betas using a 12-month rolling regression of the stock's daily excess returns on the market excess returns. Specifically, beta of stock i at time t, denoted as $\beta_{i,t}$, is estimated from the following regression:

$$Ret^{24h}_{i,t} = \alpha_{i,t} + \beta_{i,t} * Ret^{24h}_{M,t} + \epsilon^{24h}_{i,t} \tag{7}$$

where $Ret^{24h}_{M,t}$ is the US daily market excess return on day t. We require at least 100 return observations to calculate betas. Next, at the beginning of each month we sort stocks into one of ten portfolios based on their pre-ranking betas $\beta_{i,t}$. Post-ranking portfolio betas are then estimated for each day t using again a 12-month rolling regression of the daily (equal- or value-weighted) portfolio excess returns on the daily market excess returns.

Panel A of Table 1 reports, on the left-hand side, the Fama-MacBeth regression results estimated from Equation 4 and Equation 5 for noisy and quiet days, respectively. Robust t-statistics calculated using Newey-West adjusted standard errors are reported in parentheses. For value-weighted portfolios, the SML slope λ^N_1 is negative and statistically significant on noisy days, with a coefficient estimate of -12.6 bps (t-statistic = -4.8), implying a negative market risk premium. The intercept λ^N_0 is 4.9 bps and significantly different from zero (t-statistic = 2.6). The average R^2 for the cross-sectional regressions is 39.6%. In stark contrast, on quiet days the coefficient estimate of the SML slope λ^Q_1 is 14.3 bps and it is not only statistically significant (t-statistic = 4.6), but also statistically indistinguishable from the average market excess return (e.g., the market risk premium) of 14.4 bps on quiet days. The intercept λ_0^Q, consistent with the CAPM, is insignificant (t-statistic = 0.9). The average R^2 increases to 45.3%.

The results are similar for equal-weighted portfolios (Panel B, left-hand side). The SML slope is significantly negative on noisy days (-24.9 bps, with a t-statistic of -10.7) and significantly positive (and not statistically distinguishable from the average market excess return) on quiet days (15.2 bps, with a t-statistic of 5.1).

On the right-hand side of Panels A and B, we report results from pooled regressions, according to Equation 6. We are mostly interested in the coefficient estimate of the interaction term λ_3, and find consistent results as those from the Fama-MacBeth regressions. For value-weighted portfolios, the results from Panel A show that the SML slope is 12.4 bps (with a t-statistic of 4.2) on quiet days and is significantly lower on noisy days, with a difference of 25.9 bps (t-statistic = -6.7). We obtain similar results for equal-weighted portfolios, see the regression coefficients estimates in Panel B.

Taken together, the results from the 10 beta-sorted portfolios provide the first evidence that the SML displays distinct patterns on noisy and quiet days: traditional beta pricing prevails on quiet days, but not on noisy days.

We next expand the set of test portfolios by adding to the 10 beta-sorted portfolios 25 size- and book-to-market-sorted portfolios and 10 Fama-French industry portfolios to test the robustness of our results and provide a higher hurdle for accepting the CAPM.

Fig 2 presents analogous results to those in Fig 1 for the 45 test portfolios. Clearly and consistently, on noisy days portfolios with higher betas have lower returns. The N-day SML (the blue line with diamond-shaped points) has a downward slope, with an estimated negative risk premium (-24.1 bps, with a t-statistic of -11.4). Furthermore, the intercept is positive and significant, with an estimate of 12.4 bps and a t-statistic of 6.0. In stark contrast, the Q-day SML (the orange line with square-shaped points) has an insignificant intercept of 2.6 (t-statistic = 1.1) and a significant slope of 18.2 (t-statistic = 7.42), showing that on quiet days, market beta commands a positive risk premium and the CAPM holds.

Panel C of Table 1 reports coefficient estimates for Fama-MacBeth (left-hand side) and pooled (right-hand side) regressions for the 45 test portfolios, confirming the results of Fig 2. The implied market risk premium estimated using the Fama-MacBeth regression is negative (-17.3 bps with a t-statistic of -7.7) on noisy days and it is positive (14.1 bps with a t-statistic of 4.8) on quiet days. Consistently, the coefficient estimate of the interaction term from the pooled regression is -24.1 bps (t-statistic = -6.6).

——————————— Insert Figure 2 here ———————————

——————————— Insert Table 1 here ———————————

3.2. Individual stocks

Having shown that on noisy (quiet) days market betas are strongly negatively (positively) related to average returns of various test portfolios, we next investigate the risk-return trade-off for individual stocks. In Table 2, we conduct Fama-MacBeth and pooled regressions of excess returns on market betas of individual stocks. In Panel A, we include only one explanatory variable: market beta. The negative N-day (positive Q-day) slope estimate from Fama-MacBeth regressions and the negative coefficient estimate of the interaction term in Pooled regressions are consistent with the portfolio findings shown in Table 1. In Panel B, we add as controls three independent variables that are identified in the literature as return predictors: firm size (ME), book-to-market ratio (BM), and momentum (MOM). We can see that the risk-return relation remains robust after controlling for these variables. The SML slope is strongly negative (positive) on noisy (quiet) days and the difference in implied market risk premium (-25.5 bps) is statistically significant.

——————————— Insert Table 2 here ———————————

3.3. Robustness checks

Having presented a consistent and positive (negative) relationship between beta and returns on Q-day (N-day), in this section we perform a battery of robustness tests, showing that our results are robust to using alternative definitions of noisy (and quiet) days, and to correcting for noisy security prices.

3.3.1. Alternative definitions of noisy days

In this section, we perform a set of analyses, exploiting different definitions of noisy (and quiet) days. First, we define the two types of day using the sample median of ToW^m as the threshold. The selection of the threshold matters because using a too-low threshold would "mis-classify" Q-day as N-day, whereas using a too-high threshold would do the opposite. Either way, the SML slope estimates would be biased. Although it is not obvious which threshold we should use, one legitimate question is how sensitive our results are to the choice of the threshold. We first use the "natural" threshold of 0.25, which is the proportion of all stocks that experiences negative intraday return reversal patterns if stock prices evolve according to a random walk, to define noisy and quiet days based on ToW^m. Panel A of Table 3 reports the corresponding regression results on noisy and quiet days. We next use the 70th percentile of the ToW^m distribution as the threshold, e.g., a trading day t is identified as a noisy day if ToW^m at t is higher than the 70th percentile of the whole sample, and as a quiet day otherwise. Panel B contains the results. Our main finding that the beta-return relation is negative (positive) on N-day (Q-day) is robust to using these alternative thresholds, as clearly shown in Panels A and B.

Second, we calculate ToW^m as the equal-weighted average of NR of individual stocks, see Equation 3. This approach overweights small stocks. Are our results driven by small stocks? To examine this question, we calculate the value-weighted market-level tug of war ToW^m_{VW} and re-define noisy and quiet days accordingly. The regression results using the newly defined N- and Q-days are reported in Panel C, which shows that our results remain robust.

Lastly, we construct ToW^m by aggregating the return patterns of individual stocks. As discussed at the beginning of this section, one challenge of this approach is that we have to select a (subjective) threshold to define noisy and quiet days. To circumvent this obstacle, we exploit the return patterns of the S&P500 index. Specifically, we classify a trading day t as a noisy day if the index return at t has a pattern of negative intraday reversal, e.g., a positive overnight return followed by a negative intraday reversal, and a quiet day otherwise. With the alternatively defined N- and Q-days, we re-estimate the SML slope for the two types of day and report the results in Panel D of Table 3. The negative (positive) beta coefficient estimate is -0.36 (0.07) on N-day (Q-day).

Overall, we find that results are robust to the alternative definitions of noisy days.

——————————— Insert Table 3 here ———————————

3.3.2. Weighted least squares estimation

It has been well documented in the literature that the market prices of securities contain noise attributable to market imperfections, such as bid-ask spread, discrete price grids, and the temporary price impact of order imbalances. Asparouhova et al. (2010) show that noisy prices lead to biased estimates of intercept and slope coefficients from any ordinary least squares (OLS) regressions using returns as the dependent variable. To correct our empirical estimates for the effect of noisy prices and alleviate the impact of microstructure noise on our main findings, we conduct weighted least squares (WLS) regression analysis on individual stocks. We follow Asparouhova et al. (2013) and use two weighting methods:the value-weighted (VW) method, with the prior-period market value as the weighting variable, and the return-weighted (RW) method, with the prior-period gross return $(1 + Ret_{t-1})$ as the weighting variable.[8] As shown in Table 4, our main finding that the SML slope is positive (negative) on Q-day (N-day) is robust after correcting for noisy security prices, with and without controlling for firm size, book-to-market ratio, and momentum.

[8] Asparouhova et al. (2013) show that the VW method and the RW method are indistinguishably effective in correcting for the effects of noise in prices. Note that the VW method weights large firms more heavily, whereas the RW method places equal weight on each firm.

——————————— Insert Table 4 here ———————————

4. SML on noisy days and the overcorrection hypothesis

Our main finding that the SML slope is negative (positive) on noisy (quiet) days can be explained by the overcorrection hypothesis articulated in Akbas et al. (2022): daytime arbitrageurs respond to the upward price pressure exerted by overnight retail traders and overcorrect positive overnight returns. In this section, we provide empirical evidence that the overcorrection hypothesis is likely to be the mechanism behind our findings.

4.1. Identify noisy days with positive intraday reversals

As pointed out in Akbas et al. (2022), overcorrection occurs more likely on days when positive overnight returns are followed by negative intraday returns. While optimistic retail investors can cause overvaluation (positive returns) overnight for some stocks (e.g., high beta stocks with positive overnight news), pessimistic retail investors are less likely to cause undervaluation due to the difficulties in initiating short positions and the relatively high cost associated with short selling. Anticipating such an asymmetric role of overnight noise traders, daytime arbitrageurs are more likely to overcorrect positive overnight returns. In other words, it is less likely that positive intraday reversals (e.g., return patterns with negative overnight returns followed by positive intraday returns) are associated with overcorrection and capture investor heterogeneity. Therefore, such return patterns should not be informative about the beta-return relation. To test this implication, we identify noisy days using positive intraday reversals, instead of negative intraday reversals, and repeat the asset pricing tests on noisy days for the 45 test portfolios. As shown in Panel A of Table 5, the SML slope is no longer negative on the (differently defined) noisy days. It is instead positive and significant, with a coefficient estimate of 11.2 (t-statistic = 5.3). This asymmetric finding is consistent with the overcorrection hypothesis.

——————————— Insert Table 5 here ———————————

4.2. Overnight SML versus intraday SML on noisy days

The overcorrection of positive overnight returns by daytime arbitrageurs occurs, by definition, during the trading hours. Therefore, the negative slope of the SML on noisy days should be driven by intraday returns. In this section, we split the 24h (close-to-close) of a trading day into two conjunct periods: overnight (close-to-open) and intraday (open-to-close) periods, respectively. We then investigate overnight versus intraday asset pricing on noisy days. Specifically, we re-estimate for the 45 test portfolios the SML slope using close-to-open overnight returns and open-to-close intraday returns, respectively. Panel B of Table 5 contains the Fama-MacBeth regression results. Consistent with the overcorrection hypothesis, we find that on noisy days stock returns are positively related to betas overnight, whereas returns and betas are negatively related during the trading hours. The absolute magnitude of the (negative) intraday SML slope (51.1 bps) is significantly larger than that of the (positive) overnight SML slope (34.3 bps), leading to a negative 24h (close-to-close) SML slope. The sum of the two slope estimates (16.8 bps) is very close to the previously documented 24h SML slope on noisy days (-17.3 bps) as reported in Panel C of Table 1. These findings lend further support to the overcorrection mechanism and are in line with those in Hendershott et al. (2020).

4.3. Investor sentiment and SML on noisy days

As noise traders tend to increase trading during optimistic periods and their trading activity is disproportionately concentrated among high beta stocks (see Antoniou et al. (2016)), one would expect that the effect of overcorrection on the slope of the SML is stronger when investor sentiment is optimistic. We use the Baker and Wurgler (2006) index (BW) to measure investor sentiment, which is orthogonalized with respect to a set of macro variables. As shown in Panel C of Table 5, the (absolute) magnitude of the negative N-day SML slope measured during optimistic sentiment periods (when the BW index is positive) is over two times that measured during pessimistic sentiment periods (when the BW index is negative), and the difference is highly significant (t-statistic = 4.1). Once again, the results are consistent with the overcorrection hypothesis.

4.4. Correction of the overcorrection

If the overcorrection of daytime arbitrageurs indeed drives our results, one would expect that the negative noisy-day SML slope will gradually turn positive on the the following days when a market-level tug of war is less intensive, e.g., the mispricing (caused by arbitrageurs) will be corrected in the absence of further price distortion. To examine this conjecture, we focus on a sub-sample in which noisy days are followed by two consecutive quiet days. We calculate three SML slopes, using one-day returns (the noisy day returns), two-day average returns (the average returns of a noisy day and the following quiet day), and three-day average returns (the average returns of a noisy day and the following two quiet days), respectively. We report the three Fama-MacBeth SML slope estimates and their 95% confidence intervals in Figure 3, for 10 beta-sorted portfolios and 45 portfolios (10 beta-sorted portfolios, 25 size- and BM-sorted portfolios, and 10 Fama-French industry portfolios), respectively. As shown in Figure 3, the N-day (day 1) SML slope estimate confirms a native beta-return relation on noisy days. Interestingly, the negative SML slope turns flat (e.g., close to 0) once the following quiet day return is considered and the risk-return tradeoff prevails after two quiet days in a row. The dynamics of SML slope around noisy days lend further support to the overcorrection mechanism and suggest that it takes on average two quiet days in a row to correct the mispricing caused by daytime arbitrageurs.

——————————— Insert Figure 3 here ———————————

4.5. Placebo test: Identify noisy days with daytime-to-overnight positive reversals

Following Akbas et al. (2022), we next conduct a placebo test in which we analyze the alternative sequence of daily reversals that proceed from a negative intraday return to a positive overnight reversal. These alternative intraday-to-overnight positive reversals are unrelated to the overcorrection mechanism, which works through daytime arbitrageurs responding to and overcorrecting positive overnight returns, and consequently should not predict a negative SML slope. To implement the analysis, we re-define daily returns as 24h open-to-open returns, instead of close-to-close returns, and re-define noisy days using intraday-to-overnight positive reversals, instead of overnight-to-intraday negative reversals. We then re-estimate the SML slope for the 45 test portfolios on the (newly defined) noisy days. As expected, the results in Panel D of Table 5 show that the slope of the N-day SML turns positive with the new definition of noisy days. This placebo test establishes that the sequence of daily reversals matters and only overnight-to-intraday negative reversals capture overcorrection and lead to the downward sloping SML shown in Fig 1.

5. SML, information days and investor sentiment

The extant literature has shown that the SML slope tends to be positive upon the arrival of important information. To the extent that significant information releases (partially) resolve information asymmetry and thus reduce the likelihood of a market-level tug of war, these findings are consistent with our hypothesis. One, however, may wonder whether our results are driven by news. To address this concern, we construct two sets of information days: Macronews days, and Earnings-wave days, respectively. Following the Savor and Wilson (2014), we define Macronews days as trading days on which news about inflation, unemployment, or FOMC interest rate decisions is scheduled to be announced. Following Chan and Marsh (2022), we define Earnings-wave days as the trading days (excluding Monday and Friday) in the first week of (earnings) reporting quarter that has a minimum of 50 (S&P500) announcers (e.g., one-tenth of S&P500 firms). Fig 6 clearly shows that our results are robust to excluding important news days. The SML on N-day (Q-day) has a negative (positive) slope, after removing Macronews (Fig 4b) or Earnings-wave (Fig 4d) days from the sample. These findings are confirmed by the Fama-MacBeth and pooled regression results reported in Table 6. For the 45 test portfolios, as shown on the left-hand side of Panel A the SML slope estimate is -18.6 bps (11.5 bps) on N-day (Q-day) when Macronews days are excluded. Consistently, beta enters into the regression with a negative (positive) sign on N-day (Q-day) when

Earnings-wave days are excluded (see results on the left-hand side of Panel B). Overall, this set of analyses suggests that our results are unlikely to be driven by Macornews and Earnings-wave days.

——————————— Insert Table 6 here ———————————

Next, we zoom in on the news days and examine how SML performs on N-days and Q-days when important news arrives. Specifically, we obtain a sub-sample of Macronews days and a sub-sample of Earnings-wave days. For each sub-sample, we then investigate the slope of the SML on N-day and Q-day, respectively. Interestingly, 4a (4c) shows that on Macronews days (Earnings-wave days) the SML is upward sloping only on Q-day. Reassuring regression results are shown in Table 6. For the 45 test portfolios, the Fama-MacBeth SML slope estimate is -7.6 bps (with a t-statistic of -1.1) on N-day and 33.6 bps (with a t-statistic of 3.8) on Q-day when Macronews days are concerned (Panel A of Table 6). We obtain similar results for Earnings-wave days (see results in Panel B). It is worth noting that upon the arrival of significant news, the SML slope estimate on N-day becomes insignificant from zero, with a t-statistic of -1.06 on Macronews days and -0.19 on Earnings-wave days. This finding is perhaps not surprising as on news days when both types of investors are better informed, asset mispricing is less likely and intraday negative return reversals are less informative about the overcorrection by daytime arbitrageurs. Overall, our results show that the findings documented in previous studies that a positive risk-return trade-off exists on important information days hold only when a market-level tug of war is absent on such days, suggesting that market-level investor heterogeneity might be the true driver of the flat (negative) empirical SML.

Consistent with our hypothesis that unsophisticated trading is more prevalent in optimistic periods and the intensity of a market-level tug of war positively relates to investor sentiment, Antoniou et al. (2016) finds that the CAPM performs better in pessimistic sentiment periods. To what extent our results are driven by investor sentiment? We follow Antoniou et al. (2016) and define optimistic and pessimistic periods using the (one-month) lagged investor sentiment index of Baker and Wurgler (2006). Specifically, a trading day is considered as an optimistic (pessimistic) day if the sentiment score measured at the end of the previous month is positive (negative).[9]

——————————— Insert Table 7 here ———————————

[9] We thank the authors for making this data publicly available, which can be downloaded from `https://pages.stern.nyu.edu/~jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx`.

Table 7 reports the SML slop estimates on N-day and Q-day, for optimistic and pessimistic sentiment periods, respectively. We observe similar patterns of the SML regardless of investor sentiment: the SML slope is negative (positive) on N-day (Q-day). The positive Fama-MacBeth SML slope estimates (0.221 and 0.109) for both optimistic and pessimistic periods suggest that our results are not driven by investor sentiment. Interestingly, during pessimistic sentiment periods, an upward SML slope is only detected on Q-day, indicating that the documented investor sentiment effect on SML might be just an investor heterogeneity effect in disguise.

——————————— Insert Figure 4 here ———————————

——————————— Insert Figure 5 here ———————————

6. Alternative explanations

In this section, we examine two alternative explanations of our main findings. We first show that our results are not likely to be a mechanical reflection of the realized market returns. We next provide evidence that our findings cannot be explained by beta compression on quiet days.

6.1. Security market line and realized market returns

It is important to recognize that the positive relationship between returns and beta predicted by the CAPM is based on expected rather than realized returns. Pettengill et al. (1995) show that the SML slope, estimated using realized returns, may be negative when the realized excess market return is negative. The positive and negative slopes of the SML on Q-Day and N-Day may be conditional on realized excess market returns. In other words, the downward sloping SML on N-Day may simply reflect the negative excess market return on such days. We address the concern with three empirical analyses.[10] First, we conduct a sorting analysis, controlling for excess market return Ret_M. Specifically, we first sort trading days into terciles based on daily Ret_M. We next conduct Fama-MacBeth regression analysis (4 and 5) and pooled regression analysis (6) for each tercile, respectively. The regression coefficient estimates are then averaged across the terciles. We report the average coefficient estimates in Panel A of Table 8. Clearly, our results (e.g., the SML slope is positive on Q-day and negative on N-day) are robust to controlling for Ret_M. To reassure that our results are not driven by Ret_M and complement the sorting analysis, we we perform a further investigation. Specifically, we first extract the portion of ToW^m that is orthogonal to Ret_M, denoted as $ToW^m_\perp Ret_M$, by regressing ToW^m on Ret_M and taking the sum of the intercept and the residual from the time series regression. Subsequently, we define N-day and Q-day using $ToW^m_\perp Ret_M$ and

[10] During our sample period, the average daily excess market return is 0.144% on Q-day and -0.070% on N-day.

re-run Fama-MacBeth (4 and 5) and pooled (6) regressions. We report the regression results in Panel B of Table 8. Once again, the slope estimate is positive (negative) on Q-day (N-day). Since, by construction, $ToW^m_{\perp}Ret_M$ is completely (linearly) independent of Ret_M, the results from this exercise further confirm that the unfit (fit) of the CAPM on N-Day (Q-day) cannot be explained by realized market returns. Third, we directly address the concern that the negative risk-return relationship on N-Day simply reflects the negative excess market return on such days by repeating our analysis with a sub-sample of N-Day: $N-Day^{sub}$. We remove low excess market return days from the N-Day sample so that $N-Day^{sub}$ has an average excess market return (0.086%) that is statistically indistinguishable from that of Q-Day (0.144%). [11] The results in Panel C of Table 8 clearly show distinct patterns of the SML on Q-Day and $N-Day^{sub}$.

——————————— Insert Table 8 here ———————————

6.2. Security market line and beta distortion

With a one-period model, Andrei et al. (2021) show that investor disagreement (e.g., variation in expected returns across investors and over time), which is not observed by empiricist, result in beta inflation, e.g., the empiricist perceives high-beta (low-beta) assets as riskier (safer) than they really are. Hence, the SML appears flat to the empiricist. Despite that investor disagreement plays a central role in both Andrei et al. (2021) and our study, it is, in our paper, the investor-disagreement-induced distortion in expected returns that creates CAPM distortion. Interestingly, Andrei et al. (2021) show evidence of beta compression on days when important public information is released, suggesting that the strong risk-return trade-off on FOMC days might be driven by beta compression, e.g., beta estimates are less distorted, on such days. Could our results be explained by the distortion in beta estimates as modeled in Andrei et al. (2021)? [12] Following the procedure in Andrei et al. (2021), we create ten beta-sorted portfolios (value-weighted), then estimate a regression in which the intercept and the portfolio beta are allowed to vary conditional on the type of day (e.g., Q-day vs N-day):

$$Ret_{j,t} = \alpha_{N-Day,j} + \alpha_{Q-day,j} * Q-day + \beta_{N-day,j} * Ret_{M,t} + \beta_{\Delta Q-day,j} * (Q-day * Ret_{M,t}) + \epsilon_t \tag{8}$$

[11] Specifically, we first sort all N-day into ten groups based on excess market return. We next remove days with the lowest excess market returns (e.g., the 1st percentile) from each group. We keep removing low excess market return days until the average excess market return of the remaining N-day is statistically indistinguishable from 0.144%.

[12] In our analysis, we estimate betas using all days, without distinguishing between N- and Q-days, e.g., the beta estimates are not conditional on the type of day. One potential concern is that the results could be biased by this approach.

where N-day and Q-day are dummies, representing noisy and quiet days, respectively, $Ret_{M,t}$ is the market excess return, $Ret_{j,t}$ is the portfolio excess return, $beta_{N-day,j}$ is the beta on N-day, and $beta_{\Delta Q-day,j}$ measures the change in the beta on Q-day.

We are interested in $beta_{\Delta Q-day,j}$ estimates for low and high beta portfolios. Positive $beta_{\Delta Q-day,j}$ estimates for low beta portfolios and negative $beta_{\Delta Q-day,j}$ estimates for high beta portfolios would suggest beta compression on Q-day. As shown in Table 9, the differences in beta on Q-day for low beta portfolios are insignificant, and for high beta portfolios are either insignificant or positive. In other words, there does not seem to be beta compression on Q-day, suggesting that our results are unlikely driven by beta distortion. In Figure 6, we visualize the regression results by plotting Q-Day beta, which is estimated on Q-day, against N-day beta, which is estimated on N-day, for the ten beta-sorted portfolios (value-weighted).

——————————— Insert Table 9 here ———————————

——————————— Insert Figure 6 here ———————————

7. Conclusion

The asset pricing literature has long documented that the empirical SML is too flat or even downward sloping. Motivated by the findings in the literature that institutional investors (daytime arbitrageurs) tend to overcorrect positive overnight returns (caused by noisy traders), and the trading activity of noisy traders are disproportionately concentrated among high beta stocks, we expect a negative (positive) SML slope on days when such overcorrection is present (absent). Following Lou et al. (2019) and Akbas et al. (2022), we utilize the often distinct overnight and intraday price movements and propose a novel measure (ToW^m) to identify days on which the degree of investor disagreement (thus overcorrection by daytime arbitrageurs) at the market level is relatively low (quiet days) or relatively high (noisy days). We show that the CAPM tends to perform better and market betas are positively related to average returns on quiet days. We further show that the well-established findings that a robust risk-return trade-off exists on important information days (e.g., FOMC announcement days and influential firms earnings announcement days), and during pessimistic sentiment periods hold only when such days coincide with quiet days. Overall, our findings suggest that investor disagreement has significant implications on asset pricing.

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Figure 1 Security Market Line on Noisy and Quiet Days

Figure 1 shows average (value-weighted) daily excess returns (over the risk-free rate) in percent against market betas for ten beta-sorted portfolios of all US publicly listed common stocks. The beta portfolios are formed every month according to market beta, estimated using daily returns over a one-year rolling window. We classify each trading day into either *Noisy* (N-day) or *Quiet* (Q-day) sub-samples, based on the intensity of the market-level tug of war (ToW^m), e.g., day t is classified as a *Noisy* (*Quiet*) day if ToW_t^m is above (below) the full-sample median. For each sub-sample, portfolio returns are averaged, and post ranking portfolio betas are estimated over the whole sample period from July 1992 to December 2020, and then a line (SML) is fitted using ordinary least square estimates.

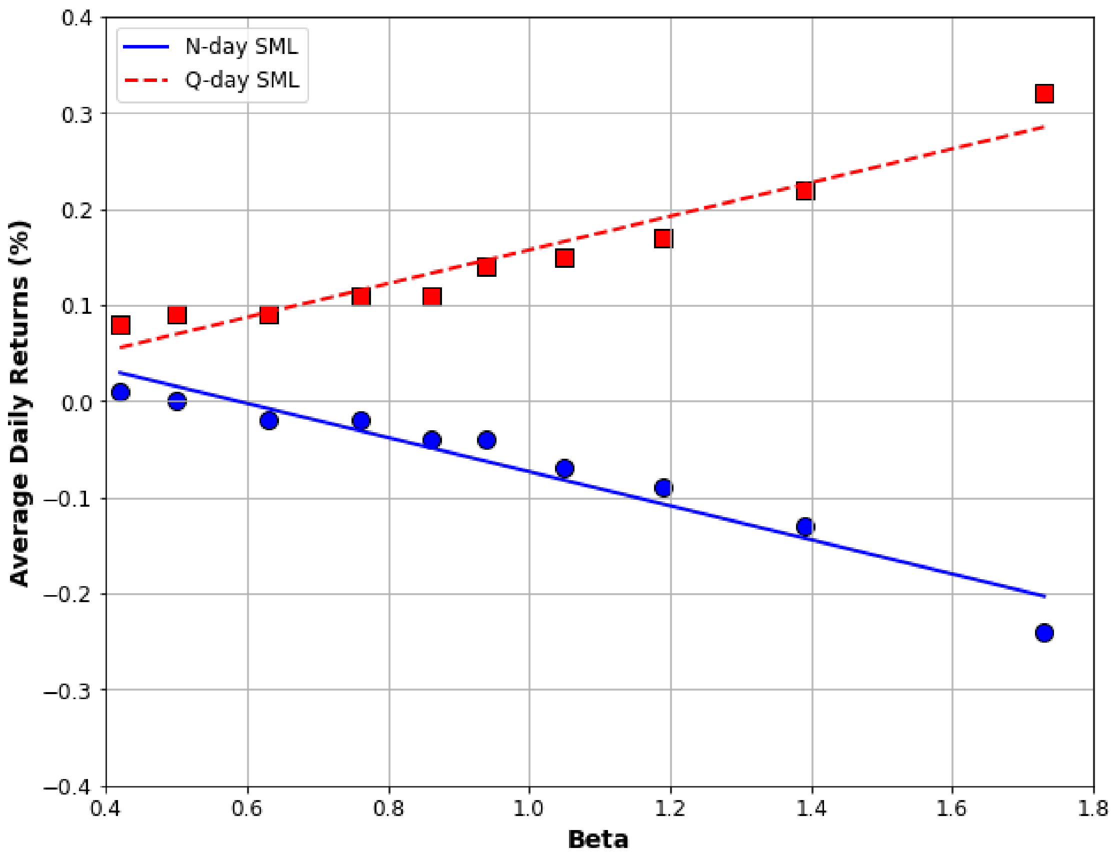


Figure 2 Security Market Line on Noisy and Quiet Days (45 portfolios)

Figure 2 shows average (value-weighted) daily excess returns (over the risk-free rate) in percent against market betas for 45 test portfolios including 10 beta-sorted, 25 size- and book-to-market-sorted, and 10 Fama-French industry portfolios. The beta portfolios are formed every month according to market beta, estimated using daily returns over a one-year rolling window. We classify each trading day into either *Noisy* (N-day) or *Quiet* (Q-day) sub-samples, based on the intensity of the market-level tug of war (ToW^m), e.g., day t is classified as a *Noisy* (*Quiet*) day if ToW_t^m is above (below) the full-sample median. For each sub-sample, portfolio returns are averaged, and post ranking portfolio betas are estimated over the whole sample period from July 1992 to December 2020, and then a line (SML) is fitted using ordinary least square estimates.

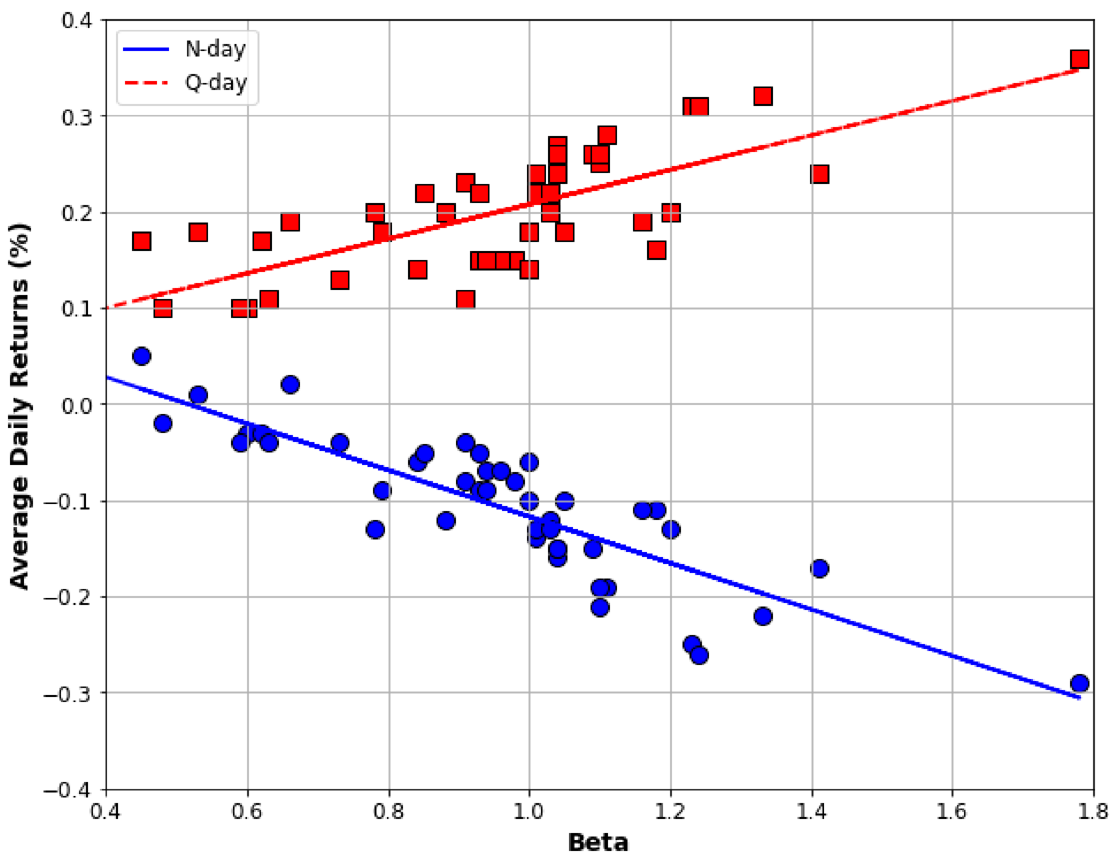
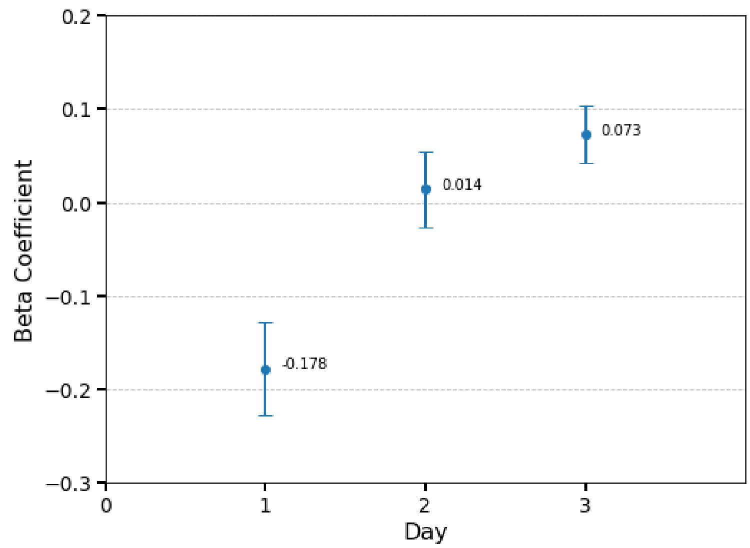
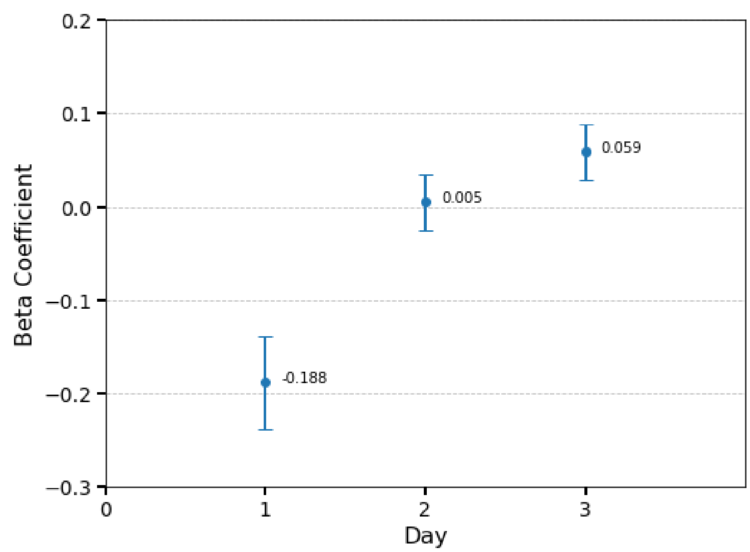


Figure 3 The Dynamics of the SML Slope around Noisy Days

Figure 3 shows the dynamics of the Fama-MacBeth regression SML slope estimes and their 95% confidence intervals around noisy days, for 10 beta-sorted portfolios in Panel (a) and 45 portfolios (10 beta-sorted, 25 size- and book-to-market-sorted, and 10 Fama-French industry portfolios) in Panel (b). The sample includes noisy days that are followed by two consecutive quiet days, and the following quiet days. Three SML slopes are calculated, using one-day returns (the noisy day, Day 1, returns), two-day average returns (the average returns of a noisy day and the following quiet day, Day 2), and three-day average returns (the average returns of a noisy day and the following two quiet days, Day 3), respectively



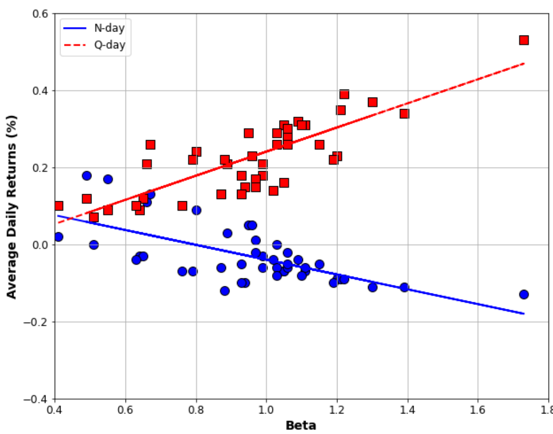
(a) 10 Beta-sorted Portfolios



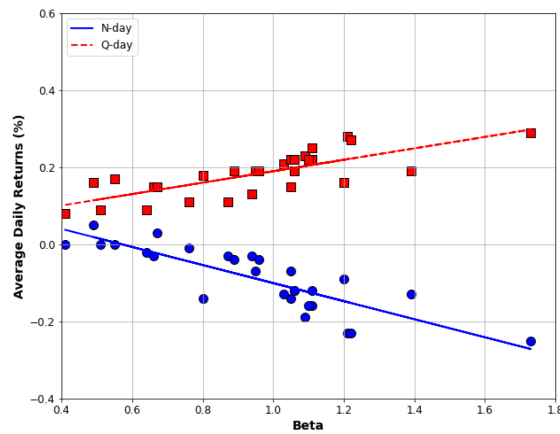
(b) 45 Portfolios (10 beta-sorted, 25 size- and book-to-market-sorted, and 10 Fama-French industry portfolios)

Figure 4 Security Market Line and Information Days

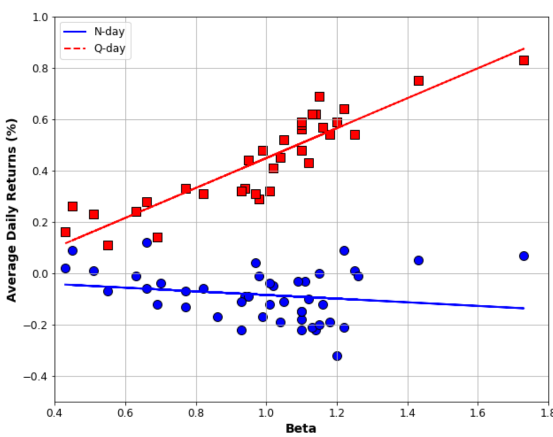
Figure 4 shows security market line (SML) on news and non-news days. Specifically, we draw N-day and Q-day SMLs on macroeconomic news (e.g., unemployment, inflation, and FOMC announcements) days (Fig 4a); on days without nacroeconomic news (Fig 4b); on firms earnings wave (e.g., important S&P500 firms' earnings announcements) days (Fig 4c); and on days without such earnings news (Fig 4d).For each panel, portfolio returns are averaged, and post ranking portfolio betas are estimated over the whole sample period, and then a line (SML) is fit using ordinary least square estimates for *Noisy* (N-day) and *Quiet* (Q-day) days, respectively.



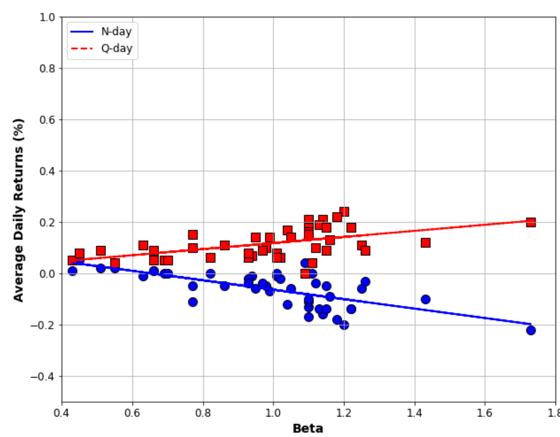
(a) SML on MacroNews Days



(b) SML on non-MacroNews Days



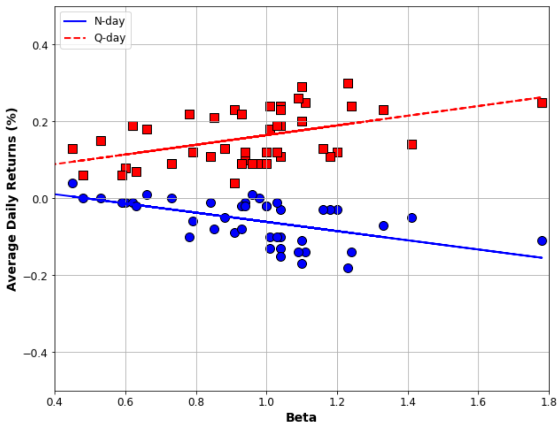
(c) SML on EarningsWave Days



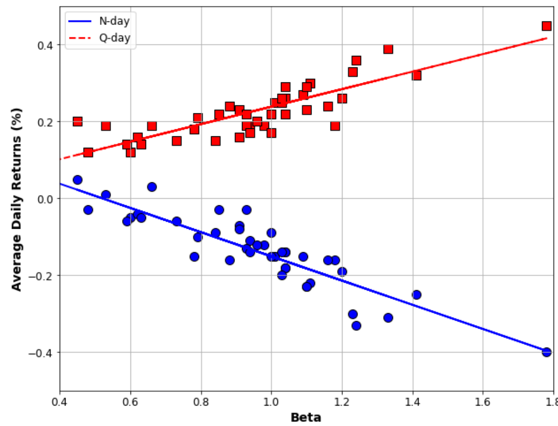
(d) SML on non-EarningsWave Days

Figure 5 Security Market Line and Investor Sentiment

Figure 5 shows security market line (SML) during pessimistic sentiment periods in Fig 5a, and during optimistic sentiment periods in Fig 5b. For each panel, portfolio returns are averaged, and post ranking portfolio betas are estimated over the whole sample period, and then a line (SML) is fit using ordinary least square estimates for *Noisy* (N-day) and *Quiet* (Q-day) days, respectively.



(a) SML during Pessimistic Sentiment Periods



(b) SML during Optimistic Sentiment Periods

Figure 6 Beta on N-day and Q-day

Figure 6 plots betas on Q-day against betas on N-day, along with a 45-degree line.The sample period is from July 1992 to December 2020.

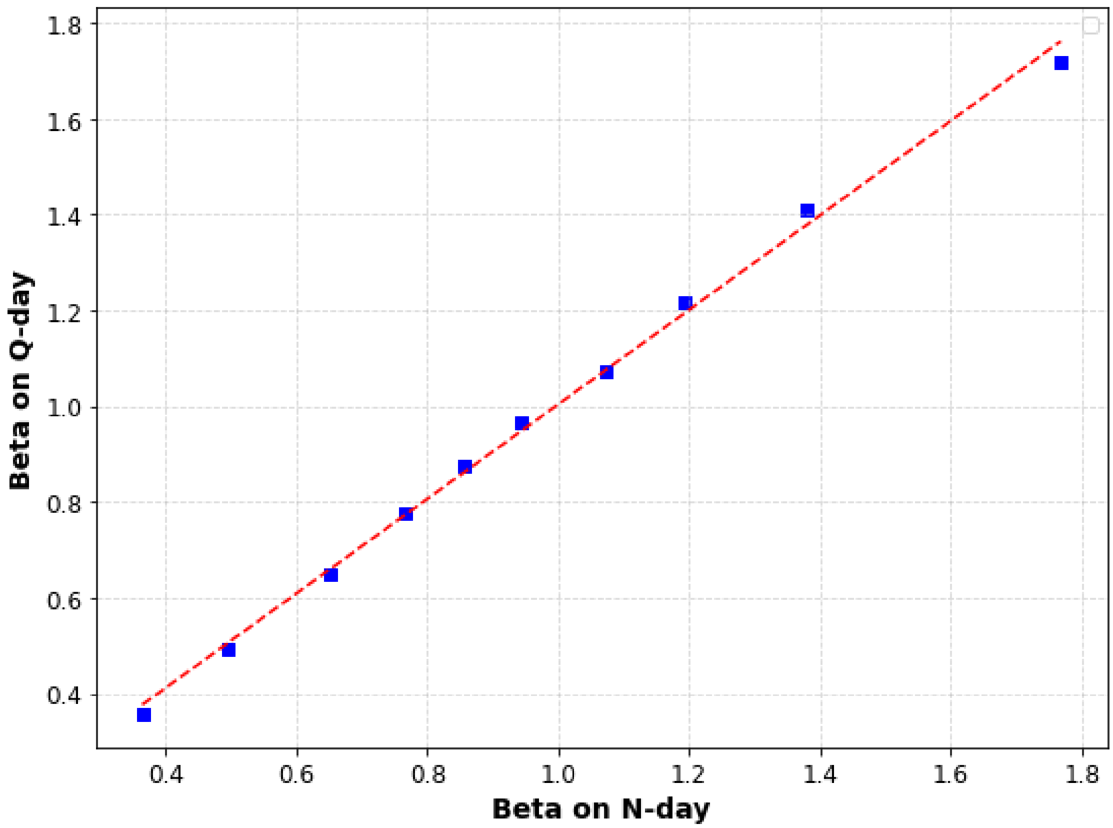


Table 1 Fama-MacBeth and Panel Regression Results for Portfolios

Table 1 reports the estimates from Fama-MacBeth regressions and pooled regressions of daily excess returns (in percent) on betas for various test portfolios. For the Fama-MacBeth regressions, the estimates are computed for the full sample and for *Noisy* and *Quiet* days, respectively. A trading day is classified as a *Noisy* day (N-day) if the intensity of the market-level tug of war (ToW^m) is above the full-sample median, and a *Quiet* day (Q-Day) otherwise. Panels A and B show results for 10 beta-sorted portfolios, value-weighted and equal-weighted, respectively. Panel C shows results for 45 portfolios (10 beta-sorted portfolios, 25 size- and BM-sorted portfolios, and 10 Fama-French industry portfolios). Robust Newey and West (1987) t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions and using clustered (by trading day) standard errors in pooled regressions.

Fama-MacBeth Regressions				**Pooled Regressions**				
Type of Day	Intercept	Beta	*Avg* R^2	Intercept	Beta	N-day	Beta*N-day	*Adj* R^2
Panel A: 10 Beta-sorted Portfolios (Value-weighted)								
Full Sample	0.032	0.009	42%	0.043	0.001			0.000
	(2.46)	(0.45)		(3.09)	(0.04)			
N-day	0.049	-0.126	40%	0.025	0.124	0.045	-0.259	0.007
	(2.59)	(-4.84)		(1.16)	(4.15)	(1.63)	(-6.73)	
Q-day	0.016	0.143	45%					
	(0.86)	(4.57)						
N-day - Q-day	0.033	-0.269						
	(1.27)	(-6.61)						
Panel B: 10 Beta-sorted Portfolios (Equal-weighted)								
Full Sample	0.133	-0.048	50%	0.149	-0.060			0.000
	(14.13)	(-2.50)		(10.22)	(-3.16)			
N-day	0.177	-0.249	47%	0.136	0.089	0.039	-0.318	0.011
	(14.21)	(-10.71)		(5.91)	(3.05)	(1.35)	(-8.50)	
Q-day	0.089	0.152	53%					
	(6.35)	(5.09)						
N-day - Q-day	0.088	-0.401						
	(4.71)	(-10.60)						
Panel C: 10 Beta, 25 Size and BTM, and 10 FFind Portfolios (Value-weighted)								
Full Sample	0.066	-0.022	22%	0.076	-0.029			0.000
	(6.99)	(-1.21)		(4.77)	(-1.54)			
N-day	0.090	-0.173	19%	0.083	0.088	-0.004	-0.241	0.008
	(6.45)	(-7.71)		(3.38)	(3.09)	(-0.14)	(-6.62)	
Q-day	0.035	0.141	24%					
	(2.29)	(4.83)						
N-day - Q-day	0.054	-0.315						
	(2.63)	(-8.53)						

Table 2 Fama-MacBeth and Panel Regression Results for Individual Stocks

Table 2 reports the estimates from Fama-MacBeth and panel regressions (with day fixed effects), for individual stocks, of daily excess returns on market betas (*Beta*) in Panel A; and on *Beta*, *Size*, *BTM*, and *MOM* in Panel B.The Fama-MacBeth regression is estimated for *Noisy* and *Quiet* days, respectively. A trading day is classified as a *Noisy* day (N-day) if the intensity of the market-level tug of war (ToW^m) is above the full-sample median, and a *Quiet* day (Q-Day) otherwise. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions and using clustered (by trading day) standard errors in pooled regressions.

	Fama-MacBeth Regressions						**Pooled Regressions**							
Type of Day	Intercept	Beta	Size	BTM	Mom	*Avg* R^2	Intercept	Beta	N-day	Beta*N-day	Size	BTM	Mom	*Adj* R^2
						Panel A: Beta only								
N-day	0.103	-0.173				0.0106	0.183	0.064	-0.067	-0.255				0.0013
	(10.56)	(-12.20)					(9.75)	(3.20)	(-2.90)	(-10.30)				
Q-day	0.148	0.092				0.0164								
	(10.81)	(4.71)												
N-day - Q-day	-0.045	-0.265												
	(-2.66)	(-10.98)												
					Panel B: Firm characteristics as controls									
N-day	0.428	-0.137	-0.027	0.026	0.000	0.0185	0.550	0.101	-0.068	-0.255	-0.030	0.009	0.000	0.0014
	(11.78)	(-9.88)	(-9.79)	(7.75)	(-4.77)		(14.20)	(5.09)	(-2.95)	(-10.29)	(-10.77)	(1.73)	(-1.87)	
Q-day	0.440	0.114	-0.026	-0.008	0.000	0.0247								
	(11.46)	(5.96)	(-9.07)	(-2.45)	(-0.91)									
N-day - Q-day	-0.012	-0.251												
	(-0.23)	(-10.62)												

Table 3 Alternative Definitions of Noisy and Quiet Days

Table 3 reports estimates from Fama-MacBeth regressions and pooled regressions of daily excess returns (in percent) on betas for *Noisy* and *Quiet* days, respectively. In Panels A through C, a trading day is classified as a *Noisy* (*Quiet*) day if the intensity of the market-level tug of war is above (below) a certain threshold. In Panels A and B, the market-level tug of war (ToW^m) is calculated according to Equation 2 and Equation 3, and 0.25 and the full-sample 70th percentile of the ToW^m distribution are used as the threshold, respectively. In Panel C, the market-level tug of war is calculated as the value-weighted counterpart of ToW^m (ToW^m_{VW}), and the full-sample median of the ToW^m_{VW} distribution are used as the threshold. In Panel D, a trading day t is classified as a noisy day if the S&P500 index return at t has a pattern of negative intraday reversal, e.g., a positive overnight return followed by a negative intraday reversal, and a quiet day otherwise. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions and using clustered (by trading day) standard errors in pooled regressions.

Fama-MacBeth Regressions				**Pooled Regressions**				
Type of Day	Intercept	Beta	*Avg* R^2	Intercept	Beta	N-day	Beta*N-day	*Adj* R^2
Panel A: 0.25 as the threshold								
N-day	0.098	-0.123	20%	0.044	0.101	0.060	-0.222	0.0037
	(7.59)	(-5.79)		(1.52)	(3.12)	(1.76)	(-5.77)	
Q-day	0.011	0.141	20%					
	(0.62)	(4.24)						
N-day - Q-day	0.087	-0.264						
	(4.06)	(-6.68)						
Panel B: 70th percentile as the threshold								
N-day	0.074	-0.294	19%	0.111	0.053	-0.133	-0.236	0.0148
	(3.97)	(-10.14)		(5.76)	(2.28)	(-4.24)	(-6.48)	
Q-day	0.057	0.107	23%					
	(4.58)	(4.62)						
N-day - Q-day	0.016	-0.402						
	(0.72)	(-10.80)						
Panel C: value-weighed ToW^m								
N-day	0.091	-0.126	19%	0.072	0.049	0.006	-0.148	0.0027
	(6.51)	(-5.56)		(2.92)	(1.67)	(0.18)	(-4.02)	
Q-day	0.034	0.094	24%					
	(2.20)	(3.21)						
N-day - Q-day	0.058	-0.220						
	(2.79)	(-5.94)						
Panel D: SPY-based ToW^m								
N-day	0.063	-0.360	20%	0.091	0.039	-0.070	-0.342	0.0136
	(2.88)	(-10.16)		(5.06)	(1.85)	(-1.98)	(-8.29)	
Q-day	0.062	0.068	22%					
	(5.31)	(3.18)						
N-day - Q-day	0.001	-0.428						
	(0.04)	(-10.35)						

Table 4 Weighted-Least-Squares Regressions

Table 4 reports the estimates from Weighted-Least-Squares Fama-MacBeth regresions for individual stocks, of daily excess returns on market betas (*Beta*) and on *Beta*, *Size*, *BTM*, and *MOM*, respectively. In Panel A and B, the weighting variable is the prior-period firm market value (VW). In Panel C and D, the weighting variable is the prior-period gross return (RW). A trading day is classified as a *Noisy* day (N-day) if the intensity of the market-level tug of war (ToW^m) is above the full-sample median, and a *Quiet* day (Q-Day) otherwise. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions.

Type of Day	Intercept	Beta	Size	BTM	Mom	Avg. R^2
Panel A: Beta only (VW)						
N-day	0.090	-0.167				0.0120
	(9.45)	(-11.49)				
Q-day	0.132	0.101				0.0183
	(9.87)	(5.09)				
N-day - Q-day	-0.043	-0.268				
	(-2.61)	(-10.89)				
Panel B: Firm characteristics as controls (VW)						
N-day	0.335	-0.140	-0.020	0.024	0.000	0.0207
	(9.62)	(-9.80)	(-7.56)	(7.26)	(-4.16)	
Q-day	0.418	0.120	-0.025	-0.010	0.000	0.0274
	(11.24)	(6.09)	(-9.03)	(-2.99)	(-0.43)	
N-day - Q-day	-0.083	-0.260				
	(-1.63)	(-10.69)				
Panel C: Beta only (RW)						
N-day	0.083	-0.162				0.0106
	(8.40)	(-11.37)				
Q-day	0.125	0.103				0.0165
	(9.18)	(5.25)				
N-day - Q-day	-0.042	-0.265				
	(-2.51)	(-10.94)				
Panel D: Firm characteristics as controls (RW)						
N-day	0.318	-0.135	-0.020	0.026	0.000	0.0185
	(8.69)	(-9.71)	(-7.05)	(7.38)	(-3.50)	
Q-day	0.329	0.117	-0.018	-0.007	0.000	0.0248
	(8.52)	(6.10)	(-6.38)	(-2.02)	(0.36)	
N-day - Q-day	-0.011	-0.252				
	(-0.21)	(-10.64)				

Table 5 Security Market Line on Noisy Days and Overcorrection

Table 5 reports estimates from Fama-MacBeth regressions of daily excess returns (in percent) on betas for 45 value-weighted portfolios (10 beta-sorted portfolios, 25 size- and BM-sorted portfolios, and 10 Fama-French industry portfolios) on noisy days (N-day). A trading day is defined as a N-day if the intensity of the market-level tug of war (ToW^m) is above the full-sample median. In Panels B and C, we calculate ToW^m based on the measure of a tug of war between opposing investor clienteles: negative intraday reversals (NP) as defined in Equation 2. In panel A, we calculate ToW^m based on positive intraday reversals (PIR). In panel D, we re-define N-day based on positive daytime-to-overnight return reversals ($PDOR$). In panel B, we split the 24h of a trading day into overnight (close-to-open) and intraday (open-to-close) periods, and estimate the SML slope for the two periods, respectively. In panel C, we divide N-day into optimistic (Opt) and pessimistic (Pess) periods, based on the Baker and Wurgler (2006) index, and estimate the SML slope for the two periods, respectively. Robust Newey and West (1987) t-statistics, allowing for six lags of serial correlation, are reported in brackets.

Panel A: Positive Intraday Reversals

	Intercept	Beta	$Avg\, R^2$
N-day (PIR)	0.104 (7.72)	0.112 (5.29)	18%

Panel B: Overnight and Intraday SML

		Intercept	Beta	$Avg\, R^2$
N-day	Overnight	-0.017 (-3.47)	0.343 (32.90)	20%
	Intraday	0.141 (12.80)	-0.511 (-31.13)	20%

Panel C: Investor Sentiment and SML

		Intercept	Beta	$Avg\, R^2$
N-day	Opt	0.128 (8.12)	-0.293 (-10.89)	21%
	Pess	0.065 (3.41)	-0.113 (-3.30)	18%

Panel D: Placebo Test

	Intercept	Beta	$Avg\, R^2$
N-day ($PDOR$)	0.203 (3.17)	0.001 (1.20)	16%

Table 6 Security Market Line and Information Days

Table 6 reports estimates from Fama-MacBeth regressions and pooled regressions of daily excess returns (in percent) on betas for 45 value-weighted portfolios (10 beta-sorted portfolios, 25 size- and BM-sorted portfolios, and 10 Fama-French industry portfolios), on news days and non-news days. For the Fama-MacBeth regressions, the estimates are computed for *Noisy* and *Quiet* days, respectively. A trading day is classified as a *Noisy* (*Quiet*) day if the intensity of the market-level tug of war (ToW^m) is above (below) the full-sample median. ToW^m is calculated according to Equation 2 and Equation 3. Panels A and B show results for Macronews and Earnings-wave days, respectively. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions and using clustered (by trading day) standard errors in pooled regressions.

Fama-MacBeth Regressions					**Pooled Regressions**				
Type of Day		Intercept	Beta	*Avg* R^2	Intercept	Beta	N-day	Beta*N-day	*Adj* R^2
Panel A: Macronews Days and SML									
MacroNews Days	N-day	0.046	-0.076	22%	0.115	0.117	0.035	-0.293	0.0084
		(1.10)	(-1.06)		(1.68)	(1.43)	(0.41)	(-2.81)	
	Q-day	-0.080	0.336	25%					
		(-1.64)	(3.78)						
	N-day - Q-day	0.126	-0.412						
		(1.96)	(-3.61)						
Non MacroNews Days	N-day	0.096	-0.186	19%	0.078	0.084	-0.009	-0.234	0.0079
		(6.48)	(-7.89)		(2.98)	(2.77)	(-0.26)	(-6.05)	
	Q-day	0.051	0.115	24%					
		(3.17)	(3.71)						
	N-day - Q-day	0.045	-0.301						
		(2.04)	(-7.74)						
Panel B: EarningsWave Days and SML									
EarningsWave Days	N-day	-0.061	-0.021	19%	-0.122	0.540	0.079	-0.580	0.0339
		(-0.92)	(-0.19)		(-0.89)	(3.71)	(0.46)	(-3.18)	
	Q-day	-0.075	0.492	28%					
		(-0.91)	(2.75)						
	N-day - Q-day	0.014	-0.513						
		(0.13)	(-2.43)						
Non EarningsWave Days	N-day	0.077	-0.148	21%	0.040	0.076	0.029	-0.205	0.0042
		(4.44)	(-5.31)		(1.47)	(2.48)	(0.82)	(-5.22)	
	Q-day	0.025	0.094	20%					
		(1.46)	(2.79)						
	N-day - Q-day	0.052	-0.241						
		(2.12)	(-5.53)						

Table 7 Security Market Line and Investor Sentiment

Table 7 reports the estimates from Fama-MacBeth regressions and pooled regressions of daily excess returns (in percent) on betas duirng optimistic sentiment periods (*Opt*) and pessimistic sentiment periods (*Pess*), for 45 value-weighted portfolios (10 beta-sorted portfolios, 25 size- and BM-sorted portfolios, and 10 Fama-French industry portfolios). For the Fama-MacBeth regressions, the estimates are computed for *Noisy* (N-day) and *Quiet* (Q-day) days, respectively. A trading day is classified as a *Noisy* (*Quiet*) day if the intensity of the market-level tug of war (ToW^m) is above (below) the full-sample median. ToW^m is calculated according to Equation 2 and Equation 3. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions and using clustered (by trading day) standard errors in pooled regressions.

	Fama-MacBeth Regressions				**Pooled Regressions**				
	Type of Day	Intercept	Beta	*Avg* R^2	Intercept	Beta	N-day	Beta*N-day	*Adj* R^2
Opt	N-day	0.117	-0.268	21%	0.075	0.148	0.036	-0.400	0.0214
		(7.40)	(-9.83)		(2.35)	(3.81)	(0.87)	(-8.13)	
	Q-day	0.012	0.221	24%					
		(0.65)	(6.35)						
	N-day - Q-day	0.104	-0.490						
		(4.27)	(-11.06)						
Pess	N-day	0.082	-0.142	19%	0.139	0.020	-0.140	-0.073	0.0055
		(4.27)	(-4.20)		(3.62)	(0.47)	(-2.89)	(-1.33)	
	Q-day	0.052	0.109	25%					
		(2.32)	(2.36)						
	N-day - Q-day	0.030	-0.251						
		(1.03)	(-4.38)						

Table 8 Security Market Line and Realized Market Returns

Table 8 reports estimates from Fama-MacBeth regressions and pooled regressions of daily excess returns (in percent) on betas for $Noisy$ and $Quiet$ days, respectively. In Panel A, trading days are first sorted into terciles based on Ret_M. Fama-MacBeth and pooled regressions are then conducted for each tercile, respectively. The regression coefficient estimates are averaged across the terciles and reported. In Panel B, N-day and Q-day are defined using $ToW^m_\perp Ret_M$, the portion of ToW^m that is orthogonal to Ret_M. $ToW^m_\perp Ret_M$ is calculated by regressing ToW^m on Ret_M and taking the sum of the intercept and the residual from the time series regression. In Panel C, we analyze a sub-sample of N-Day, which has an average excess market return that is statistically indifferent from that of Q-day. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation in Fama-MacBeth regressions and using clustered (by trading day) standard errors in pooled regressions.

Fama-MacBeth Regressions				**Pooled Regressions**				
Type of Day	Intercept	Beta	$Avg\,R^2$	Intercept	Beta	N-day	Beta*N-day	$Adj\,R^2$
Panel A: Controlling for realized market return								
N-day	0.109	-0.178	12%	0.323	-0.060	-0.084	-0.279	0.0191
	(8.48)	(-9.31)		(14.43)	(-3.22)	(-2.97)	(-10.99)	
Q-day	0.197	0.110	19%					
	(14.00)	(4.01)						
N-day - Q-day	-0.089	-0.288						
	(-4.65)	(-8.61)						
Panel B: Noisy and quiet days defined using $ToW^m_\perp Ret_M$								
N-day	0.084	-0.095	19%	0.064	0.041	0.028	-0.140	0.0018
	(5.93)	(-4.05)		(2.63)	(1.47)	(0.89)	(-3.82)	
Q-day	0.041	0.064	24%					
	(2.69)	(2.25)						
N-day - Q-day	0.044	-0.160						
	(2.10)	(-4.31)						
Panel C: An analysis on a sub-smaple of N-Day								
$N-Day^{sub}$	0.102	-0.034	18%	0.096	0.074	0.026	-0.124	0.0011
	(5.17)	(-1.03)		(3.82)	(2.50)	(0.71)	(-2.79)	
Q-day	0.032	0.144	23%					
	(2.07)	(4.89)						
$N-Day^{sub}$ - Q-day	0.069	-0.178						
	(2.75)	(-4.05)						

Table 9 Beta Compression

Table 9 reports the slope estimates of regression Eq.8 for the 10 beta-sorted portfolios. $beta_{N-day}$ is the beta on N-day, and $beta_{\Delta Q-day}$ measures the change in the beta on Q-day. t-statistics, reported in parentheses, are calculated using robust Newey and West (1987) standard errors, allowing for six lags of serial correlation.

Beta	Low	2	3	4	5	6	7	8	9	High
$beta_{N-day}$	0.4063	0.4927	0.6094	0.7212	0.8182	0.9001	1.0189	1.1541	1.3380	1.7260
	(13.83)	(24.95)	(35.89)	(51.15)	(55.55)	(68.56)	(75.23)	(86.74)	(71.77)	(49.30)
$beta_{\Delta Q-day}$	0.0139	0.0169	0.0259	0.0564	0.0624	0.0602	0.0475	0.0550	0.0689	-0.0098
	(0.37)	(0.66)	(1.13)	(2.77)	(3.15)	(3.60)	(2.69)	(3.18)	(2.50)	(-0.20)

Table A1 Variable Definition

Variable	Description
ToW^m	Market-level tug of war, measured as the percentage of stocks with a tug-of-war return pattern on each trading day, e.g., a positive overnight return followed by a negative trading day reversal
Q-day/N-day	A trading day is classified as a "quiet day" or "noisy day" if the intensity of the market-level tug of war is below or above a certain threshold
$Size$	The natural log of the market capitalization from CRSP updated in each July
BTM	The natural log of the book value of equity at each fiscal year-end divided by the market capitalization from CRSP at the nearest calendar year-end
MOM	Momentum defined as the stock return during the 11-month period up to but not including the current month (months $t-11$ through $t-1$, inclusive)
ToW^m_{VW}	The value-weighted counterpart of ToW^m
$ToW^m_{\perp}Ret_M$	Regressing ToW^m on Ret_M and taking the sum of the intercept and the residual from the time series regression
PIR	Calculate ToW^m based on positive intraday reversals
$PDOR$	Re-define N-day based on positive daytime-to-overnight return reversals
MacroNews Days	Trading days on which news about inflation, unemployment, or FOMC interest rate decisions is scheduled to be announced following the Savor and Wilson (2014)
EarningsWave Days	Trading days (excluding Monday and Friday) in the first week of (earnings) reporting quarter that has a minimum of 50 (S&P500) announcers (e.g., one-tenth of S&P500 firms) following Chan and Marsh (2022)
Opt/Pess	Optimistic and pessimistic periods are defined using the (one-month) lagged investor sentiment index of Baker and Wurgler (2006). A trading day is considered as an optimistic or pessimistic day if the sentiment score measured at the end of the previous month is positive or negative following Antoniou et al. (2016)