Market-Level Tug of War and Asset Pricing *

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Abstract

We propose a simple indicator function based on the aggregate tug-of-war between overnight and intraday traders, and use it to classify trading days as either *quiet* or *noisy* days. Analyzing these two types of days, we find that the Capital Asset Pricing Model (CAPM) holds on quiet days but fails on noisy days. This result is robust after controlling for major information events, such as macroeconomic and earnings news releases, thereby challenging existing findings in the literature. To rationalize the results, we present and test a mechanism based on over-correction.

JEL classification: G11, G12, G41

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I Introduction

The Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Mossin, 1966) is a foundational framework in financial economics, yet its empirical relevance remains the subject of intense scrutiny. A large literature documents that the model fails to explain the cross-section of expected returns, with estimated betas often unrelated, or even negatively related, to expected returns (Fama and French, 1992; Frazzini and Pedersen, 2014). At the same time, the CAPM continues to play a central role in practice: both corporate managers and investors appear to rely on it to guide capital allocation decisions (Graham and Harvey, 2001; Berk and Van Binsbergen, 2016). Recent work attempts to reconcile this apparent disconnect by showing that the CAPM performs well on some high information days, such as those with macroeconomic news (Savor and Wilson, 2014) or earnings announcements (Chan and Marsh, 2022).

We contribute to this literature by documenting that the CAPM holds on a broader set of days than previously documented. Specifically, we classify trading days as quiet (q) or noisy (n), based on a novel measure of aggregate tug-of-war. We show that the CAPM holds reliably on q-days but breaks down on n-days. Our study yields three main contributions.

First, we propose a simple, bottom-up measure of aggregate tug-of-war to identify n- and q-days. For each stock and each day, we define a tug-of-war episode as a positive overnight return, defined as in Lou et al. (2019), followed by a negative intraday return (Akbas et al., 2022). We then compute the aggregate tug-of-war as the fraction of stocks experiencing such negative intraday reversals on a given day. We classify days with above-median aggregate tug-of-war–i.e, aggregate tug-of-war greater than 28%–as n-days, and the remainder as q-

days.

Second, we use daily data on U.S. stocks from July 1992 through December 2022 to implement our methodology. We divide our sample of 7,694 trading days into two halves consisting of n- and q-days. We characterize the properties of the n- and q-days. We show that the average daily market excess return is positive (0.12) on q-days and negative (-0.05) on n-days.[1] Both types of days are equally likely to occur on any given day of the week, suggesting that extended periods of market closure, such as weekends, have very little effect on the classification. In addition, we find no evidence of a month-of-the-year effect. Furthermore, we analyze the extent to which the days may overlap with the release of important news, including (i) the 3 macroeconomic series analyzed in Savor and Wilson (2014), namely the federal fund rate, the producer price index, and the unemployment rate, and (ii) the leading earnings announcement (LEAD) days as defined in Chan and Marsh (2022). We find that both n- and q-days are equally likely to occur on news and other days. Moreover, we document that the TED spread, the volatility index (VIX), and the risk aversion index (Bekaert et al., 2022) are comparable on n- and q-days. These findings suggest that q- and n-days cannot be easily distinguished by standard risk or information measures.

Third, we show that the CAPM holds on q-days but fails on n-days. Our baseline tests use decile (value-weighted) portfolios sorted on full-sample beta as test assets. On q-days, average excess returns increase with beta, and the monotonicity test of Patton and Timmermann (2010) confirms that the positive risk-return relationship is monotonic (test statistic = 6.33). In contrast, n-days exhibit a negative relationship between beta and excess

[1] Throughout this paper, we express all returns in percentage points.

returns. We further implement the Fama and MacBeth (1973) methodology. Specifically, for each month and test asset, we use a trailing window of 252 daily excess returns to estimate the conditional beta. For each day in the month, we regress the cross-section of excess returns on a constant and the conditional beta estimates. The average price of risk is significantly positive (0.15, t-stat $= 5.15$) on q-days and significantly negative (-0.13, t-stat $= -4.23$) on n-days. We assess the performance of the CAPM by testing the joint hypothesis that the average price of risk equals the average market excess return and that the mean of the regression intercept is zero. The CAPM restrictions are not rejected on q-days (p-value $=$ 0.41), but are strongly rejected on n-days (p-value $= 0.00$), underscoring the distinct pricing dynamics across the day types.

A natural concern is that our empirical results may simply reflect the differences in the sign of the average market excess returns between n- and q-days. To address this concern, we implement a three-pronged strategy. First, we sort all trading days in our sample into terciles based on daily market excess returns and conduct the Fama and MacBeth (1973) analysis separately within each tercile. We then average the resulting estimates across terciles. The securities market line (SML) continues to exhibit a positive slope on q-days and a negative slope on n-days. Second, we perform a bootstrap exercise in which we construct pseudo-samples of n-days. Specifically, we draw 1,000 pseudo-samples of n-days such that the average market excess return in each sample is positive. Even under this restriction, we find a consistently negative market price of risk on n-days, with a mean estimate of -0.12. Third, we orthogonalize our aggregate tug-of-war measure with respect to market excess returns and use the resulting residual to classify n- and q-days. Repeating our main empirical tests, we again observe an upward-sloping SML on q-days and a downward-sloping SML on n-days.

We conduct a range of additional robustness checks. First, we obtain similar results using pooled regressions. Second, we use equal-weighted, rather than value-weighted, beta-sorted portfolios as test assets; the main findings remain unchanged. Third, we replicate our analysis at the individual stock level, again finding qualitatively similar patterns. Fourth, we expand the test asset universe to address the critique of Lewellen et al. (2010). Specifically, we augment the beta-sorted portfolios with 25 size- and book-to-market-sorted portfolios and 10 Fama–French industry portfolios. Our key conclusions hold across this broader asset menu. Fifth, we test the sensitivity of our results to alternative definitions of n-days. Across a wide range of thresholds we use to identify n-days, the main finding remains robust. Sixth, instead of aggregating tug-of-war bottom-up from individual stocks, we compute it directly at the market level. The results obtained using this alternative measure are qualitatively similar. Seventh, we examine the potential impact of microstructure frictions and find no evidence to suggest that microstructure noise materially affects our conclusions. Eighth, we compare the conditional beta estimates on q- and n-days. The average betas across the two sets of days are remarkably similar, and we find no evidence of beta compression on q-days. Thus, our findings are not driven by the "information gap" mechanism proposed in Andrei et al. (2023). Taken together, these extensive robustness checks support the conclusion that the differential performance of the CAPM across q- and n-days is not an artefact of sample construction or measurement error.

To rationalize our results, we build on the over-correction hypothesis recently proposed by Akbas et al. (2022). To fix the ideas, suppose that there are two trading periods each day, overnight and intraday. The overnight period is characterized by high short-selling fees and is typically dominated by noise traders, who are leverage constrained. The intraday period is usually dominated by arbitrageurs, e.g., institutional investors.[2] When the arbitrageur observes a positive overnight return, she analyzes the extent to which it may be driven by noise trading or by a positive fundamental signal, e.g., earnings news released overnight. If the arbitrageur concludes that the positive overnight return is due to noise trading, she will correct the effect of the noise traders during the day, resulting in a negative intraday return and a tug-of-war. Akbas et al. (2022) argue that, if the arbitrageur implements a correction on the same stock for several days within a month, it is likely that an over-correction occurs. Intuitively, over time, the arbitrageur underestimates the possibility that the positive overnight returns are due to news. We posit that if the arbitrageur observes positive overnight returns on several stocks on a given day, she may wrongly discount the possibility that the positive overnight returns are due to news and therefore over-correct. Since noise traders are constrained by leverage, they are very active in high-beta stocks, resulting in a more pronounced over-correction effect for high-beta stocks.[3] We present and test several implications of this mechanism.

First, the over-correction hypothesis suggests that the downward sloping SML on n-days is driven by intraday returns, since this is the period when arbitrageurs are active. To test this, in the Fama and MacBeth (1973) analysis, we separately examine the cross-sections of intraday and overnight returns observed on n-days. Consistent with the prediction, we find that the slope of the SML is positive (negative) overnight (during the day).

Second, the arbitrageur is more likely to over-correct when she believes that noise traders are more active. We proxy the trading activity of noise traders with the sentiment index of

[2] Lou et al. (2019) and Lou et al. (2024) document that household investors are the primary drivers of overnight trading, whereas institutional investors dominate trading during the intraday period.

[3] We empirically verify that the difference in the slopes of the SMLs on n- and q-days is mostly driven by high-beta stocks (see Figure 1).

Baker and Wurgler (2006). Specifically, we divide our sample into optimistic and pessimistic periods, and identify n- and q-days within each of these groups. We find that the n-day SML slope is approximately twice as negative during optimistic periods as during pessimistic periods. This finding is consistent with the over-correction mechanism.

Third, we expect the arbitrageur to be more cautious on news days compared to other days. This is because the positive overnight return may reflect favourable overnight news, rather than noise trading. As such, the n-day SML slope should be more negative on non-news days than on news days. We separately use the macroeconomic series analyzed in Savor and Wilson (2014) and the LEAD days of Chan and Marsh (2022) to identify news days. We find that our prediction is borne out by the data.

Given that our explanation is based on the over-correction hypothesis, one might ask: how long does it take to correct the over-correction? We analyze a subsample of n-days followed by consecutive q-days. We find that the over-correction effect is transitory, and that it generally takes 2 q-days to disappear.

Our paper contributes to the literature examining the slope of the security market line. This literature dates back to Fama and French (1992) who document that the SML is empirically flat. Subsequent research documents time variation in the slope of the SML. Bernanke and Kuttner (2005), Savor and Wilson (2014), and Lucca and Moench (2015) find a positive SML only on macroeconomic announcement days. Antoniou et al. (2016) document an upward sloping SML during periods of pessimistic sentiment and a downward sloping SML during optimistic periods. Jylhä (2018) establishes a negative relationship between the slope of the SML and the prevailing margin requirement. Chan and Marsh (2022) and Cui and Li (2024) document a positive SML only on leading earnings announcement days and balanced trading days, respectively. Abolghasemi et al. (2024) relate the slope of the SML to changes in the granularity of the economy. Several studies attempt to rationalize the time variation in the slope of the SML using arguments based on the sign of the average realized market excess return (Ernst et al., 2021), the information gap between investors and the econometrician (Andrei et al., 2023), and small-sample problems (Ghaderi and Seo, 2024). Our paper documents that the CAPM holds over a large sample of several thousand q-days, spanning both (i) months of optimistic and pessimistic sentiment and (ii) news and non-news days. Thus, our results challenge the findings documented so far in the literature and call for a fundamentally different explanation of the time variation of the SML.

Our work adds to the growing asset pricing literature that exploits intraday and overnight information. Lou et al. (2019) decompose the close-to-close returns into overnight and intraday returns and document a tug-of-war between the overnight and intraday traders. Hendershott et al. (2020) compare the performance of the CAPM during the overnight and intraday trading periods. Bogousslavsky (2021) analyzes the cross-section of intraday and overnight expected returns. Akbas et al. (2022) examine the impact of the firm-level tug-of-war on the cross-section of expected returns. Our research brings together the literature on (i) the tug-of-war and (ii) the time-varying slope of the SML. To the best of our knowledge, we are the first to propose a simple indicator variable of the tug-of-war at the market level that identifies two types of trading days and test its impact on the SML.

The remainder of the paper proceeds as follows. Section II presents our data and methodology. Section III documents our main results and performs various robustness checks. Section IV discusses the mechanism underlying our main results. Finally, Section V concludes the paper.

II Data and Methodology

A Data

We obtain the stock data, including the opening and closing prices of each trading day, from the Centre for Research in Security Prices (CRSP). Since CRSP only reports the opening price from 1992 (Akbas et al., 2022), our sample period starts in July 1992 and ends in December 2022. Our dataset consists of all the U.S.-based common stocks (with a CRSP share code value equal to 10 or 11) traded on the American Stock Exchange (AMEX), the National Association of Securities Dealers Automated Quotations (NASDAQ), and the New York Stock Exchange (NYSE). We discard any observation with a missing opening or closing price, a zero intraday or overnight return.[4]

We calculate the overnight return of each stock as follows (Lou et al., 2019):

$$R_{i,t,night} = \frac{1 + R_{i,t}}{1 + R_{i,t,day}} - 1 \tag{1}$$

where $R_{i,t,night}$ is the overnight return associated with firm i on day t. $R_{i,t}$ is the close-to-close return of firm i on day t. We obtain this return directly from the CRSP database. Finally, $R_{i,t,day}$ is the intraday, i.e., open-to-close, return of firm i on day t. We compute it as follows: $R_{i,t,day} = \frac{P_{i,t,close}}{P_{i,t,open}} - 1$, where $P_{i,t,close}$ and $P_{i,t,open}$ denote the closing and opening prices of stock i, on day t, respectively.

[4]The filter is applied during both the computation of the tug-of-war measure and the construction of the test assets. Untabulated results demonstrate that our main conclusions are quantitatively robust to applying the filter exclusively in computing the tug-of-war measure.

B Methodology

Tug-of-War Our identification of noisy and quiet days involves three steps. First, we build on the insights of Lou et al. (2019) and Akbas et al. (2022), who identify a tug-of-war for a given stock i on day t when the stock has a positive overnight return followed by a negative intraday return:[5]

$$ToW_t^{(i)} = \begin{cases} 1 & \text{if } R_{i,t,night} > 0 \ \& \ R_{i,t,day} < 0 \\ 0 & \text{Otherwise} \end{cases} \tag{2}$$

where $ToW_t^{(i)}$ is a dummy variable that takes the value 1 if there is a tug-of-war associated with stock i on day t.

Second, we compute the market-level tug-of-war by averaging the firm-level tug-of-war indicators:[6]

$$ToW_t^m = \frac{\sum_{i=1}^{N_t} ToW_t^{(i)}}{N_t} \tag{3}$$

where ToW_t^m denotes the tug-of-war measure at time t aggregated at the market level. N_t is the total number of stocks observed on day t.

Third, we classify a day as noisy (n) or quiet (q) if the ToW^m observed on that day is

[5]The reader may ask: why do we focus on the positive overnight return followed by an intraday reversal and not the opposite, i.e., a negative overnight return followed by a positive intraday return? Our choice is motivated by several findings in the literature. First, retail traders are mostly active overnight, while institutional investors trade mostly during the day. Second, short selling fees/constraints make it difficult for market participants, especially retail traders, to open short positions. In turn, this observation implies that retail investors are unlikely to open short positions if they have a negative view of the company. Section IV.D presents empirical results consistent with this intuition.

[6]We also implement a "direct approach" by computing the tug-of-war directly on the SPY ETF, which tracks the S&P 500 index, and find that the main result is very similar. See Section III.D.3 for further details.

higher or lower than the full-sample median estimate of 0.28, respectively.[7]

It is useful to characterize the n- and q- days. Figure A1 of the Online Appendix shows the share of n-days over time. We can see that in the earlier part of the sample period, the fraction of n-days was typically higher than 50%, whereas it is lower in the more recent sample, with the minimum value around 40%. Panel A of Table 1 shows the key moments of the aggregate tug-of-war time-series. We can see that the mean and median estimates are the same. The table also shows that there is very little persistence in the series. Panels B and C of the same table show that both types of days are equally likely to occur on a given (i) day of the week or (ii) month of the year. Given this finding, we conclude that the seasonal effects documented in Tinic and West (1984) and Birru (2018) do not drive our main results. We also compare the values of key state variables on n- and q-days. Specifically, we look at the (i) TED spread, (ii) VIX, and (iii) risk aversion index (Bekaert et al., 2022).[8] Panel D of Table 1 shows that there is very little to distinguish between the two types of days.

The last four rows of that panel examine the relationship between news days and each day type. Following Savor and Wilson (2014), we define macroeconomic news days as those associated with the releases of the federal funds rate, producer price index, and unemployment rate. All other days are classified as non-macroeconomic. Consistent with Chan and Marsh (2022), LEAD days are defined as those falling between Tuesday and Thursday of the first week of the earnings reporting quarter, provided that at least 50 S&P 500 firms

[7]One might ask to what extent the results depend on the use of the median estimate instead of the average estimate. Our untabulated analysis shows that there is very little to distinguish between these two choices. In the data, the median ToW^m computed over the sample is equal to 0.28. This estimate is the same as the mean estimate (see Panel A of Table 1). Section III.D.3 discusses alternative cut-offs, including that of 0.25, and shows that the results are robust.

[8]We obtain our time-series of the TED spread from the website of the Federal Reserve Bank of St Louis. This dataset ends on 28 January 2022. The VIX data come from Bloomberg. The risk aversion index is available on the following website: `https://www.nancyxu.net/risk-aversion-index`.

announce earnings during that week. All other days are classified as non-LEAD. The results show that n- and q-days are equally likely to occur on news and non-news days, a pattern that holds for both macroeconomic and LEAD announcements

Test Assets Our main objective is to assess the performance of the CAPM on n- and q-days, respectively. To achieve this goal, we use 10 beta-sorted portfolios as test assets. We construct these portfolios as follows. For each security and month-end date, we use a trailing window of 252 daily close-to-close returns to estimate the (pre-ranking) beta of the security:[9]

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \epsilon_{i,t} \tag{4}$$

where $R_{f,t}$ denotes the risk-free rate, proxied by the 1-month Treasury bill rate, observed on day t. α_i and β_i are the intercept and slope parameters associated with security i, respectively. $R_{m,t}$ is the return of the market portfolio at time t, proxied by the value-weighted CRSP index. The data for both the risk-free rate and the market portfolio come from Kenneth French's website.[10] $\epsilon_{i,t}$ is the residual associated with stock i at time t.

We then use the (pre-ranking) beta estimates to sort the stocks into 10 beta portfolios to hold for the next month. This allows us to calculate the daily value-weighted returns of each beta portfolio over the month.[11] By repeating the above steps for each calendar month, we

[9]Our interest in this trailing window is motivated by the work of Hollstein et al. (2019), which documents that this estimation window performs well empirically. Throughout this paper, we require the availability of at least 126 observations in order to use the trailing window.

[10]The website is available at the following address: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french.

[11]As a robustness check, we also consider an equal-weighting scheme. This alternative does not materially affect our main conclusions. See Section III.D.1 for further details.

obtain the daily time-series of returns for each decile portfolio, where individual portfolios are rebalanced on a monthly basis.

III Main Results

This section presents our main results. We begin by visually examining the results based on the cross-sectional regression. We then focus on the Fama and MacBeth (1973) analysis. Next, we implement a pooled estimation. Finally, we perform several robustness checks and show that they do not alter our main findings.

A Cross-Sectional Regression

All Days We use the daily time-series of the close-to-close excess returns of (i) each test asset and (ii) the market to estimate the test asset's full-sample (post-ranking) beta:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \epsilon_{i,t} \tag{5}$$

Next, we cross-sectionally regress the average daily (close-to-close) excess returns of the test assets on a constant and the full-sample (post-ranking) beta estimates:[12]

$$\bar{R}_i - \bar{R}_f = \alpha + \lambda \hat{\beta}_i + \epsilon_i \tag{6}$$

[12]An alternative approach is to use a trailing window of 252 days to estimate the (post-ranking) beta each month (Chan and Marsh, 2022). We can then compute the sample average of these conditional beta estimates and use them as explanatory variables instead of the full-sample post-ranking beta. We also consider this alternative and find that our main results are unchanged. For brevity, the results are not tabulated.

where $\bar{R}_i - \bar{R}_f$ is the full-sample average daily (close-to-close) excess return of asset i. λ is the daily market risk premium. $\hat{\beta}_i$ is the estimated full-sample (post-ranking) beta of asset i (see Equation (5)). ϵ_i is the residual associated with asset i.

The CAPM posits a positive relationship between the beta of an asset and its average excess return. To visualize this, we plot the average daily excess return of each test asset as a function of its full-sample beta. Contrary to the prediction of the theory, Figure A2 of the Online Appendix shows a flat, rather than a positive, relationship. This result confirms and updates the empirical results of Black (1972) and Fama and French (1992), among others.

n- vs. q-Days The previous analysis is unconditional in the sense that it aggregates information across all days, regardless of whether they are n- or q-days. However, it is interesting to analyze to what extent the results depend on the type of day. To shed some light on this, we proceed as follows. For each day type, i.e., n or q, we compute the corresponding average excess return of each portfolio. We then estimate a cross-sectional regression of the average portfolio excess return observed on the day type of interest, i.e., n or q, on a constant and the full-sample beta estimate:[13]

$$\bar{R}_i^{(n-day)} - \bar{R}_f^{(n-day)} = \alpha^{(n-day)} + \lambda^{(n-day)}\hat{\beta}_i + \epsilon_i^{(n-day)} \tag{7}$$

$$\bar{R}_i^{(q-day)} - \bar{R}_f^{(q-day)} = \alpha^{(q-day)} + \lambda^{(q-day)}\hat{\beta}_i + \epsilon_i^{(q-day)} \tag{8}$$

where the superscripts $n - day$ and $q - day$ indicate that the data relate to the sample of days classified as n- and q-days, respectively.

[13] As a robustness check, we replace the full-sample beta estimate with the average of the conditional beta estimated at the monthly frequency and repeat our main analysis (Chan and Marsh, 2022). Figure A3 of the Online Appendix shows that this alternative approach leads to similar findings.

Figure 1 depicts the SML for each day-type. Starting with the n-days, we observe a downward sloping SML. The slope estimate is negative and highly significant ($\lambda^{(n-day)}$=−0.18, t-stat=−8.75). Furthermore, the intercept estimate is positive and highly significant ($\alpha^{(n-day)}$=0.12, t-stat=5.39).

Turning to the q-days, we observe very different results. First, the SML slopes upwards, as evidenced by the positive and statistically significant slope estimate ($\lambda^{(q-day)}$=0.18, t-stat=8.69). Second, the intercept estimate is economically small and statistically indistinguishable from 0 ($\alpha^{(q-day)}$=−0.03, t-stat=−1.54). Pursuing our analysis, we implement the monotonicity test of Patton and Timmermann (2010) to investigate the extent to which the relationship between beta and average excess returns is monotonic. To do this, we sort the portfolios based on their (post-ranking) betas and compute the average daily excess returns of each portfolio on q-days. We then compute the test statistic of the monotonicity test and obtain a value of 6.33, which leads us to reject the null hypothesis and conclude that there is a monotonically increasing relationship. Overall, these results are consistent with the predictions of the CAPM.

Taken together, our findings suggest that the performance of the CAPM differs markedly across the samples of n and q-days. For q-days, we observe a positive and monotonic risk-return trade-off. We also find an insignificant intercept. In contrast, the empirical performance of the CAPM on n-days is diametrically opposed to its theoretical predictions.

B Fama and MacBeth (1973) Regression

All Days We implement the empirical procedure of Fama and MacBeth (1973) as follows. For each test asset i and month m, we estimate the conditional (post-ranking) beta, denoted

$\hat{\beta}_{i,m}$, using the most recent 252 daily observations (see Equation (4)). Subsequently, for each trading day t in the following month $m+1$, we run the cross-sectional regression of portfolio excess returns on a constant and the conditional portfolio betas estimated at the end of month m:

$$R_{i,t} - R_{f,t} = \alpha_t + \lambda_t \hat{\beta}_{i,m} + \epsilon_{i,t}, \tag{9}$$

where $R_{i,t} - R_{f,t}$ denotes the excess return of asset i on day t of month $m+1$. The parameters α_t and λ_t represent the intercept and the risk premium for day t, respectively, while $\epsilon_{i,t}$ is the residual term.

Repeating this cross-sectional regression for each day yields a daily time series of parameter estimates (α_t and λ_t) within month $m+1$. We then iterate this procedure across all months in the sample to construct the full time series of estimated parameters, which we use for statistical inference. Throughout this paper, we compute the standard errors following Newey and West (1987), with the bandwidth of the Bartlett kernel set to 10.[14]

The CAPM makes several testable predictions. First, the mean of the intercept is not statistically different from 0. Second, the average slope estimate is positive. Furthermore, it should be equal to the sample average excess return of the market.

Panel A of Table 2 reports the results. We observe a positive and statistically significant average intercept ($\bar{\alpha} = 0.03$, $t-$stat=2.28). Furthermore, the relationship between risk and return is flat, as evidenced by the insignificant average slope estimate ($\bar{\lambda} = 0.01$, t-stat=0.56). While these results are consistent with those of the cross-sectional analysis, they are difficult

[14]This choice is based on the observation-based criterion of the Newey and West (1987) estimator: $4(T/100)^{2/9}$, where T is the total number of observations. We round the estimate to the nearest integer.

to reconcile with the key predictions of the CAPM.

n- vs. q-Days Next, we examine the empirical results obtained when restricting the analysis to n-days and q-days. We employ a two-step procedure. First, we compute the conditional (post-ranking) betas ($\hat{\beta}_{i,m}$) as described previously. Second, for each month $m+1$, we estimate the cross-sectional regression using only the daily returns corresponding to the day-type of interest—either n- or q-days—as the dependent variable. Specifically, we estimate:

$$R_{i,t}^{(n\text{-day})} - R_{f,t}^{(n\text{-day})} = \alpha_t^{(n\text{-day})} + \lambda_t^{(n\text{-day})} \hat{\beta}_{i,m} + \epsilon_{i,t}^{(n\text{-day})}, \tag{10}$$

$$R_{i,t}^{(q\text{-day})} - R_{f,t}^{(q\text{-day})} = \alpha_t^{(q\text{-day})} + \lambda_t^{(q\text{-day})} \hat{\beta}_{i,m} + \epsilon_{i,t}^{(q\text{-day})}, \tag{11}$$

where α_t and λ_t denote the intercept and the conditional market risk premium on day t of month $m+1$, respectively. The superscripts n-day and q-day indicate that the estimation is performed using observations from days classified as n- and q-days, respectively.[15]

Starting with n-days, Panel A of Table 2 shows that the time-series average of the intercept is positive and highly significant on n-days ($\bar{\alpha}^{(n-day)} = 0.06$, t-stat=3.15). Moreover, the average estimated market risk premium is significantly negative ($\bar{\lambda}^{(n-day)} = -0.13$, t-stat=-4.23) and differs significantly from the average realized market excess return computed over n-days ($\bar{R}_{m,t}^{(n-day)} - \bar{R}_{f,t}^{(n-day)} = -0.05$).

Turning to q-days, we see that the average intercept is small and statistically indis-

[15]Since the analysis employs the conditional beta of each portfolio (estimated at the end of the preceding month) as the explanatory variable, an alternative approach would be to estimate post-ranking betas separately using only n- or q-day observations. Figure A5 in the Online Appendix plots the betas estimated on q-days against those estimated on n-days and shows that the two sets of estimates are highly similar.

tinguishable from 0 ($\bar{\alpha}^{(q-day)} = -0.00$, t-stat$=-0.25$). Furthermore, the average estimated market risk premium is positive and statistically significant ($\bar{\lambda}^{(q-day)} = 0.15$, t-stat$=5.15$). Consistent with the CAPM, this average estimated risk premium is statistically indistinguishable from the average realized market excess return computed over q-days ($\bar{R}_{m,t}^{(q-day)} - \bar{R}_{f,t}^{(q-day)}$=0.12). We separately test the null hypotheses that the average intercept and slope estimates are equal across the two day types. As the last row of Panel A of Table 2 shows, we can formally reject each of these hypotheses.

To rigorously assess the validity of the CAPM, we test—separately for each day-type—the joint restriction that the average estimated market price of risk equals the average market excess return observed on days of that type, and that the regression intercept is zero. This joint restriction is not rejected on q-days (p-value $= 0.41$), but is strongly rejected on n-days (p-value $= 0.00$), underscoring the contrasting performance of the CAPM across day types.

Overall, the results suggest that the empirical performance of the asset pricing model depends on the type of days analyzed. On n-days, the empirical performance of the CAPM is at odds with its predictions. On q-days, however, the CAPM provides a good description of the empirical data.

C Pooled Regression

All Days We now perform a pooled estimation:

$$R_{i,t} - R_{f,t} = \alpha + \lambda\hat{\beta}_{i,m} + \epsilon_{i,t} \tag{12}$$

where all variables are as described above. Throughout this paper, our pooled estimation includes day fixed effects and standard errors are clustered by trading day.

Panel B of Table 2 documents a significantly positive intercept ($\alpha = 0.05$, $t-$stat=3.25). Furthermore, the relationship between beta and excess returns is not significant ($\lambda = -0.01$, t-stat=-0.33).

n- vs. q-Days Next, we consider an extended model where the main explanatory variable is interacted with a dummy variable that takes value 1 if the excess return of the portfolio is observed on an n day:

$$R_{i,t} - R_{f,t} = \alpha + \lambda\hat{\beta}_{i,m} + \psi\mathbb{1}_t^{n-day} + \phi\hat{\beta}_{i,m} \times \mathbb{1}_t^{n-day} + \epsilon_{i,t} \tag{13}$$

where α and λ are the intercept and market risk premium associated with q-days, respectively. ψ and ϕ are parameters of interest. Economically, they capture the differences between the intercepts and risk premia associated with n- and q-days, respectively. $\mathbb{1}_t^{n-day}$ is a dummy variable that takes value 1 if the excess return of the test asset is observed on an n-day and 0 otherwise. All other variables are as defined above.

Panel B of Table 2 highlights a number of important results. First, the intercept estimated on q-days ($\alpha = -0.00$, t-stat=-0.01) is small and statistically indistinguishable from 0. This result is consistent with the CAPM. Second, the estimated market price of risk is positive and highly significant ($\lambda = 0.14$, t-stat=4.48). Given these results, we conclude that there is a positive risk-return trade-off on q-days, as predicted by the CAPM. These estimates are statistically indistinguishable from those based on the Fama and MacBeth (1973) methodology (see Panel A of Table 2).

If there is no difference between the estimates linked to n- and q-days, we should observe that $\psi = 0$ and $\phi = 0$. The regression results strongly reject this hypothesis. We note that the market risk premium estimate is significantly lower on n-days compared to q-days ($\phi = -0.30$, t-stat$=-7.65$). This estimate is very comparable both in magnitude and sign to the spread between the risk premium estimates of q- and n-days based on the Fama and MacBeth (1973) methodology (see Panel A of Table 2).

In summary, our findings highlight the contrasting performance of the CAPM across n- and q-days. While the predictions of the model are rejected by the data on n-days, the results based on q-days are consistent with the theory. The conclusions hold whether we use the cross-sectional regression, the Fama and MacBeth (1973) methodology, or the pooled regression framework.

D What About...

Having established our main findings, we now proceed to assess their robustness to alternative research design specifications. To begin with, we examine the extent to which the portfolio-level weighting scheme may affect our main results. We then assess the sensitivity of the results to the menu of test assets. We also consider different methodological choices for the identification of n- and q-days. In addition, we assess the impact of microstructure noise on the results. Finally, we evaluate the impact of the sign of realized market excess returns on the analysis and test an explanation of our main findings based on the information gap theory of Andrei et al. (2023).

1 The Portfolio Weights?

As is common in the asset pricing literature, our main analysis is based on value-weighted returns. As a robustness check, we implement the equal-weighting scheme and assess the impact on our main results. Table A1 of the Online Appendix presents the results. The new results show a sharper contrast in the performance of the CAPM between n- and q-days.

2 Menu of Assets?

Up to this point, our asset pricing tests have been based on 10 beta-sorted portfolios. One might wonder about the robustness of the results to the choice of test assets. To shed some light on this, we follow a two-pronged strategy. First, we use individual stocks as test assets. Second, we extend the set of 10 beta-sorted portfolios to 45 portfolios.

Individual Equities Table A2 of the Online Appendix shows the main results when using individual equities as test assets. Panel A focuses on the Fama and MacBeth (1973) results. We observe a positive market risk premium estimate on q-days ($\bar{\lambda}^{(q-day)}$=0.10, t-stat=5.68), which contrasts sharply with the negative market risk premium estimate on n-days ($\bar{\lambda}^{(n-day)} = -0.16$, t-stat=-9.23). The difference between the n- and q-day estimates is highly significant (-0.26, t-stat=-11.16).

We next control for size ($Size$), book-to-market (BTM), and momentum (MOM). We measure the size of a firm as the logarithm of its market capitalization. Our calculation of BTM follows Fama and French (1992). We compute a firm's MOM of month t as the cumulative stock return over the last 11 months, skipping the most recent month (Daniel and Moskowitz, 2016). Panel B shows that the inclusion of control variables in the implementation of the Fama and MacBeth (1973) analysis does not materially affect the main results. Panel C of Table A2 of the Online Appendix further presents similar results, in terms of both magnitude and statistical significance, in a pooled regression setting.

A Broader Menu of Assets Mindful of the Lewellen et al. (2010) critique, we expand the menu of test assets in our baseline analysis. Specifically, we augment the 10 beta-sorted portfolios with (i) 25 size- and book-to-market-sorted portfolios and (ii) 10 Fama–French industry portfolios.

Table A3 of the Online Appendix reports coefficient estimates for the Fama and MacBeth (1973) and pooled regressions for the 45 test portfolios. The implied market risk premium estimated from the Fama and MacBeth (1973) regression is negative on noisy days ($\bar{\lambda}^{(n-day)} = -0.17$, t-statistic$=-5.71$) and positive on q-days ($\bar{\lambda}^{(q-day)} = 0.15$, t-statistic=5.06). The difference between the two sets of estimates is highly significant. We also obtain qualitatively similar results with the pooled regression. As Panel B of Table A3 of the Online Appendix shows, the SML slopes up and down on q- and n-days, respectively. For the remainder of the paper, we use the 45 portfolios as test assets.

3 Alternative Ways of Identifying n- and q-Days?

Alternative Thresholds Our baseline identification of the n- and q-days depends on whether or not the aggregate tug-of-war measure is higher than its sample median. Clearly, this threshold is somewhat arbitrary and may introduce misclassification errors into our analysis. Given this, it is prudent to consider alternative thresholds. We consider two alternative thresholds. First, we use a threshold of 0.25. Our interest in this value is motivated by the intuition that, under standard assumptions, there is a 25% probability of observing a positive overnight return followed by a negative intraday return for a given day and firm in our cleaned dataset.[16] Second, we set the threshold equal to the 70^{th} percentile of the full-sample distribution of the aggregate tug-of-war. For each of these two cases, we classify a day as n-day if the daily aggregate tug-of-war variable exceeds the specified threshold.

Tables A4 and A5 of the Online Appendix present the results of the Fama and MacBeth (1973) and pooled regression analyses. We find that the coefficient estimates are comparable, both in terms of sign and magnitude, to the baseline estimates (see Table 2). We therefore conclude that our main results are robust to potential classification errors.

Direct Approach Our calculation of the aggregate tug-of-war follows a bottom-up approach, in the sense that we identify the tug-of-war at the firm level and then aggregate the firm-level estimates to the market level. An alternative approach is to calculate the market-level tug-of-war by using the returns of the stock market index directly. Specifically, we estimate the market-level tug-of-war as follows:

$$ToW_t^{(SPY)} = \begin{cases} 1 & \text{if } R_{SPY,t,night} > 0 \ \& \ R_{SPY,t,day} < 0 \\ 0 & \text{Otherwise} \end{cases} \tag{14}$$

where $ToW_t^{(SPY)}$ is a dummy variable that takes the value 1 if there is a tug-of-war associated with the SPY ETF on day t. $R_{SPY,t,day}$ and $R_{SPY,t,night}$ denote the intraday and overnight

[16] Recall that we discard observations associated with a missing opening or closing price, a zero intraday or overnight return (see Section II.A).

returns associated with the SPY ETF on day t, respectively. We focus on this asset because it is very liquid, which mitigates concerns about microstructure noise.

Armed with this measure, we identify n- and q-days as days on which the daily estimate is 1 and 0, respectively.[17] We then repeat our main empirical tests. Table A6 of the Online Appendix shows that this methodological change leads to qualitatively similar conclusions.

4 Potential Microstructure Noise?

One concern relates to the potential impact of microstructure noise, which may arise from frictions such as the discreteness of price changes and the bid–ask bounce. Theoretically, microstructure noise could affect our baseline analysis in at least two ways. First, it may affect the firm-level estimates of the tug-of-war. Second, it could directly affect the asset pricing tests.

Starting with the tug-of-war estimates, we expect the noise to have a minimal impact, if any. As the previous analysis shows, our main results are robust to using the SPY-based aggregate tug-of-war (see Table A6 of the Online Appendix).

Turning to the asset pricing tests, Asparouhova et al. (2010) document that the microstructure noise may bias the ordinary least squares (OLS) parameter estimates. Since our analysis focuses primarily on value-weighted portfolios as test assets, this is not a significant concern. However, it is possible that the microstructure noise may bias our estimates based on individual stocks as test assets. To address this concern, we implement the weighted least squares (WLS) estimation recommended by the authors. Specifically, we weigh each observation by 1 plus the lagged daily return of asset i, i.e., $1 + R_{i,t-1}$. Table A7 of the

[17] Empirically, we find that 85.95% of the n-days based on this "direct" aggregate tug-of-war correspond to the n-days based on the bottom-up approach used in our baseline estimation.

Online Appendix summarizes the findings. Comparing these estimates with those in Table A2 of the Online Appendix, we find that there is very little difference between the two sets of results, suggesting that potential microstructure noise does not materially affect our results.

5 The Sign of the Average Market Excess Return?

The CAPM's risk–return tradeoff pertains to expected, rather than realized, returns. Following standard practice, we treat realized market excess returns as proxies for expected returns, which is reasonable when evaluating the unconditional CAPM over long horizons. However, Pettengill et al. (1995) show that a negative average realized market excess return can induce a negative observed relationship between beta and excess returns. Consequently, the regression-based estimate of the risk premium may mechanically reflect the sign of the average realized market excess return (Ernst et al., 2021). This raises the possibility that our results partly reflect the negative and positive average market excess returns over the n-day and q-day samples, respectively. Indeed, Panel D of Table 1 shows average market excess returns of -0.05 on n-days and 0.12 on q-days. To ensure our findings are not driven by the sign of the average market return, we implement a three-pronged robustness strategy.

Portfolio Sorts We sort all the trading days in our sample into terciles based on the daily market excess return. We run the Fama and MacBeth (1973) estimation for the n- and q-days associated with each tercile. We then average the parameter estimates across all terciles. We report the results in Panel A of Table A8 of the Online Appendix. Overall, we observe patterns that are similar to our baseline results. The SML slopes up and down on q- and n-days, respectively.

Simulation Analysis We perform a bootstrap exercise. The aim is to create a pseudo-sample with the same number of n-days as our original sample. We randomly select 3,720 days (with replacement) from the n-day sample. If the average market excess return of this pseudo-sample is negative, we discard it and repeat the procedure until we obtain a pseudo-sample with a positive average market excess return. We then perform the estimation outlined in Fama and MacBeth (1973) and compute the average risk premium estimate. We repeat these steps 1,000 times.

Figure A4 in the Online Appendix shows the histogram of the estimated SML slope coefficients from the 1,000 pseudo samples. The slope estimates are negative, averaging -0.12, despite the fact that the average realized market excess returns of the pseudo samples are all positive. This result suggests that our finding of a negatively sloped SML on n-days is not a mechanical result due to the sign of the average market excess return.

Orthogonalization It is possible that our aggregate measure of tug-of-war measure (ToW^m) is correlated with the market excess returns, thereby introducing a mechanical link into our results. To address this concern, we first regress ToW^m on a constant and the market excess return. We save the residual, which is essentially the component of ToW^m that is orthogonal to the market excess return. We call it orthogonal aggregate tug-of-war: $ToW^m_\perp$. We identify n-days as the days with an above-median $ToW^m_\perp$ and q-days as the remaining days. We then estimate Fama and MacBeth (1973) regressions on each of the newly identified day types. We report the regression results in Panel B of Table A8 of the Online Appendix. Consistent with the baseline results, the SML has a positive slope for q-days and a negative slope for n-days.

6 Beta Compression?

Andrei et al. (2023) recently show that the information gap between the empiricist and investors can affect the performance of the CAPM. Specifically, they find that when investors disagree about expected returns, beta estimates are biased. On disagreement days, the econometrician overestimates the beta of high-beta assets and underestimates the beta of low-beta securities. As a result, the SML rotates clockwise. When the disagreement is resolved, beta compression occurs: the beta estimate of the high-beta asset decreases and that of the low-beta asset increases. They validate their results by comparing beta estimates on FOMC press conference days and other days. One might wonder if this mechanism could explain the difference between the SML slopes on n- and q- days.

There are several reasons to be skeptical about this mechanism. First, Panel D of Table 1 shows that n- and q- days are equally likely to occur on macro and non-macro days. Second, we compare the averages of the conditional beta estimates estimated separately on n- and q- days, following the approach of Andrei et al. (2023). Figure A5 in the Online Appendix shows that the estimates are very similar, casting doubt on the beta compression mechanism. If the beta compression argument were valid, the 45-degree line would not provide an accurate description of the data.

IV What Explains the Results?

Our main intuition builds on the over-correction hypothesis recently proposed by Akbas et al. (2022). For ease of exposition, assume that the close-to-close trading period can be decomposed into two periods: overnight and intraday. The overnight period is characterized by high short-selling fees (Bogousslavsky, 2021), which make it difficult for market participants to short stocks. Overnight traders are mostly noise traders with limited leverage, while intraday investors are typically daytime arbitrageurs (Berkman et al., 2012; Lou et al., 2019). A positive overnight return may reflect positive overnight news, noise trading activity, or a combination of both.

During the day, the arbitrageur trades based on her assessment of whether the overnight return is mostly noise or news. If she concludes that the noise component dominates, the arbitrageur will correct the upward price pressure of the noise traders, leading to a negative intraday return and a tug-of-war. Akbas et al. (2022) show that if the tug-of-war occurs on several days in a month, the arbitrageur may underestimate the likelihood that the positive overnight returns are due to news and therefore over-correct. In this paper, we argue that the over-correction also occurs when there is a tug-of-war over many stocks on the same day. In other words, if the arbitrageur observes a positive overnight return on several stocks on a given day, she may infer that the noise traders are overly optimistic and therefore over-correct. Since noise traders tend to be optimistic and are constrained by leverage, they prefer to trade high-beta stocks overnight (Barber and Odean, 2007; Hong and Sraer, 2016). As a result, the intraday overcorrection occurs more likely in the high-beta stocks, which is consistent with our empirical evidence (see Figure 1). The over-correction hypothesis provides an explanation for why the n-days exhibit distinctive behavior. More importantly, it predicts a negatively sloped SML on n-days. In the remainder of this section, we present and test several implications of this hypothesis.

A Dissecting the SML on n-days

The hypothesis suggests that the over-correction occurs during the intraday trading period when arbitrageurs are most active. A testable prediction is that the negative slope of the SML observed on n-days is due to intraday, as opposed to overnight, trading activity. To shed light on this, we focus our empirical tests on the n-days. We conduct the test separately for the cross-section of (i) intraday and (ii) overnight excess returns.[18] The hypothesis predicts a positively (negatively) sloped overnight (intraday) SML.

Table 3 presents the results. We see that the overnight SML is upward sloping, as evidenced by a positive and highly significant average estimate of the market price of risk (0.36, t-stat=19.10). However, the analysis based on the cross-section of intraday returns paints a different picture. Specifically, we observe a negative and highly significant average slope estimate (-0.55, t-stat=-20.45). Taken together, these results are consistent with the intuition of the over-correction hypothesis and echo the findings of Hendershott et al. (2020).[19]

B The Impact of Sentiment

Another testable prediction is that, when the trading activity of noise traders increases, the arbitrageur might over-correct even more. To test this hypothesis, we build on the Baker and Wurgler (2006) sentiment index.[20] Specifically, we follow Antoniou et al. (2016) and

[18]Following Lou et al. (2024), we compute intraday and overnight excess returns by subtracting the corresponding fraction of the daily risk-free rate from raw returns—6.5/24 for the intraday trading window and 17.5/24 for the overnight period.

[19]Untabulated analysis shows that the positive (negative) SML slope observed during the overnight (intraday) periods, as documented in Hendershott et al. (2020), is largely driven by the n-days.

[20]We obtain the monthly index from https://pages.stern.nyu.edu/~jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx.

define optimistic and pessimistic periods using the lagged investor sentiment index. We identify a trading month as optimistic (pessimistic) if the sentiment score measured at the end of the previous month is positive (negative). For each sentiment period, i.e., optimistic or pessimistic, we repeat our main asset pricing tests.

Several key findings emerge from Table 4. First, the SML exhibits a positive slope on q-days and a negative slope on n-days. This result holds regardless of the prevailing sentiment, suggesting that the positively sloped SML during pessimistic periods documented by Antoniou et al. (2016) is mostly driven by the q-days. Focusing on the n-days associated with this subsample (pessimistic periods), we find a negatively sloped SML. Second, the slope on n-days is more negative when investor sentiment, and thus the likelihood of noise trading, is high. Specifically, the n-day average market price of risk during the optimistic period (-0.26) is twice the magnitude estimated during the pessimistic period (-0.13). The more negatively sloped SML observed on n-days during the optimistic period is consistent with the over-correction hypothesis: arbitrageurs are more likely to over-correct when they believe that the positive overnight return is due to noise trading.

C News Days

The over-correction hypothesis depends crucially on the extent to which the arbitrageur believes that the positive overnight return is due to news or noise trading. If the arbitrageur believes that the news channel dominates, she is less likely to over-correct. Since our tug-of-war variable is at the market level, we focus on news that may affect the broader economy.

Macroeconomic News Days Building on the work of Savor and Wilson (2014), we split our sample of trading days into news days and other days. The news days are associated with announcements of the (i) producer price index, (ii) unemployment, and (iii) federal fund rate.[21] We refer to the remaining days as other days. For each of these two subsamples, we repeat our main tests separately for q- and n-days.[22]

Table 5 presents several noteworthy results. First, the SML slopes up (down) on q- (n-) days. This result holds on both macroeconomic announcement days and other days. This finding suggests that the upward sloping SML on macroeconomic announcement days documented in the literature, e.g., Bernanke and Kuttner (2005) and Savor and Wilson (2014), is likely due to the q-days. When we focus on the n-days associated with macroeconomic news, the SML has a negative but insignificant slope. Thus, the upward sloping SML on macroeconomic news days documented in the literature is unlikely to be a function of macroeconomic announcements. Rather, it depends on whether the day is a q-day or not.

Second, we note that the n-days SML has a significantly negative slope estimate (-0.18, t-stat=-5.74) on other days, while it is flat (-0.08, t-stat=-0.98) on news days. This finding is consistent with the over-correction hypothesis. If arbitrageurs expect the positive overnight returns to be driven by a signal about the economy, they are less likely to over-correct.

[21] Savor and Wilson (2014) explain that for the period after 1972, the announcement of the producer price index typically takes place a few days before that of the consumer price index. Since our sample period starts in 1992, we therefore focus on the producer price index.

[22] Panel D of Table 1 shows that macroeconomic news and other days are equally likely to be characterized as q- or n-days.

Leading Earnings Announcement Days Since several companies announce their earnings on LEADs, we posit that arbitrageurs are likely to conclude that the positive overnight returns on these days are due to news, rather than noise trading. Therefore, we expect to find weaker evidence of over-correction on n-days that are LEADs relative to other n-days.

The results in Table 6 support this prediction. We can see that the SML is quite flat on the n-days associated with LEADs, while it has a significantly negative slope on n-days associated with other days. It is also worth noting that the SML slopes upwards on q-days, regardless of whether one focuses on LEADS or other days, echoing our findings associated with macroeconomic news.

D Positive Intraday Reversal

The over-correction hypothesis builds on the insight that the cost of holding short positions overnight makes it difficult for noise traders to open short positions. As a result, the arbitrageur likely over-corrects only when the overnight return is positive. One implication of this reasoning is that a positive intraday reversal is unlikely to be a signal of over-correction.

To test this proposition, we define an alternative measure of firm-level tug-of-war:

$$ToW_t^{alternative,(i)} = \begin{cases} 1 & \text{if } R_{i,t,night} < 0 \ \& \ R_{i,t,day} > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{15}$$

where $ToW_t^{alternative,(i)}$ is a dummy variable that takes value 1 if there is a positive intraday reversal for stock i on day t.

We replace the tug-of-war variable (see Equation (2)) with this alternative measure and identify the corresponding n- and q-days. We then repeat the Fama and MacBeth (1973) estimation on the newly defined n-days. Consistent with our intuition, the untabulated analysis documents a positive SML slope (0.14, t-stat=6.37).

Overall, our empirical results support the over-correction hypothesis. The reader might ask: how long does it take to correct the over-correction? To shed some light on this, we focus on a subsample of n-days that are followed by two consecutive q-days. Our analysis consists of three steps. First, we repeat the asset pricing tests using the 1-day return, i.e., the n-day return, as the dependent variable in the cross-sectional regression of Fama and MacBeth (1973). Second, we replace the 1-day return with the 2-day return, which essentially covers the n-day and the following q-day. Third, we use the 3-day return, i.e., the cumulative return of the n-day and the following 2 q-days. To make the results comparable across estimations, we express all the dependent variables on a per day basis.

Figure 2 visually depicts the estimates of the market price of risk from the 3 analyses. Consistent with our baseline results, we see a negative average estimate of the risk premium (-0.17) on n-days. However, when we measure the dependent variable over the 2- and 3-day windows, we can see that the risk premium estimate turns to -0.01 and 0.08, respectively. These results suggest that, over our sample period, it takes on average 2 consecutive q-days to correct the mispricing observed on n-days.

V Conclusion

This paper provides new evidence on the time-variation in the performance of the CAPM. We introduce a novel indicator capturing the market-level tug-of-war and use it to classify trading days into two distinct types of days: q-days and n-days. Our analysis shows that the SML behaves fundamentally differently across these types of days. On q-days, the SML exhibits the positive slope predicted by the CAPM, whereas on n-days it slopes downward. These results are robust to alternative research design choices and cannot be attributed to the timing of major news releases or the sign of realized market excess returns.

Taken together, our findings suggest that the performance of the CAPM varies over time and is contingent on the underlying market's tug-of-war dynamics. This conditionality helps reconcile the theoretical prediction of a positive risk–return relationship with the empirically flat SML documented in prior studies. We show that the over-reaction hypothesis of Akbas et al. (2022) can account for the contrasting performance of the CAPM across n- and q-days.

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Figure 1: The Security Market Line on Noisy and Quiet Days

This figure shows the relationship between the average daily excess returns of the test assets, computed over either noisy (n) or quiet (q) days, and their full-sample beta estimates. The asset menu consists of 10 (value-weighted) beta-sorted portfolios. The vertical axis shows the average excess return of each asset for the subsamples of n- or q-days, represented by the blue and red colours, respectively. The horizontal axis shows the full sample beta estimate of each test asset. This beta estimate is the same for both n- and q-days. For each type of day, the line visually represents the security market line obtained after estimating the cross-sectional regression of the average excess returns of the test asset, calculated for each type of day, on an intercept and the full-sample portfolio beta estimates. The sample period is from July 1992 to December 2022.

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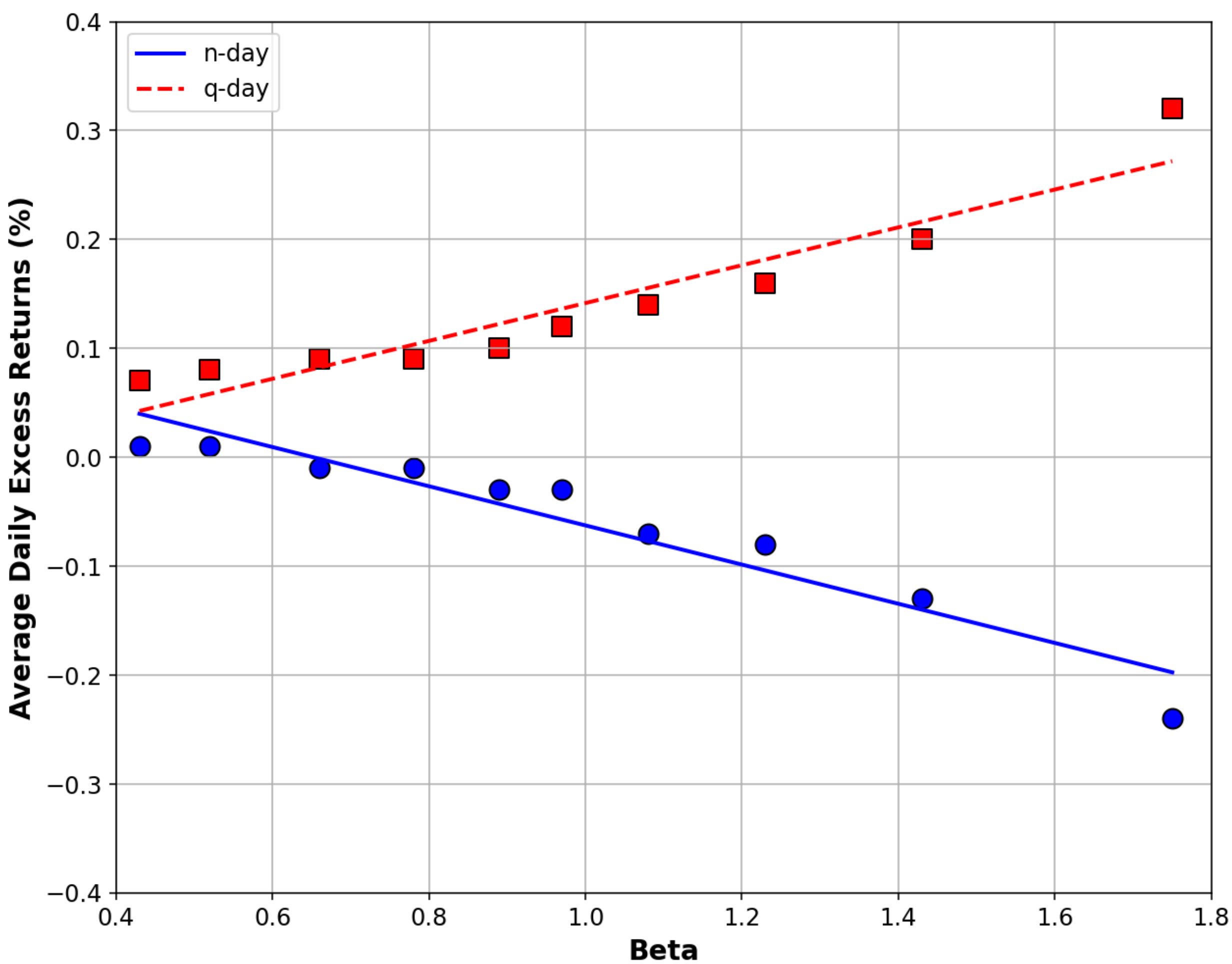

Figure 2: Resolution of the Over-correction

This figure shows the point estimate and the 95% confidence interval of the market risk premium based on the Fama and MacBeth (1973) methodology. The vertical axis shows the average estimate of the market risk premium i.e., the average loading on beta. The horizontal axis indicates the number of days over which the dependent variable of the cross-sectional regression is calculated. We focus on a subsample of n-days followed by 2 q-days. Day 1 indicates that we use the n-day excess return as the dependent variable in the estimation. Day 2 indicates that we use the average excess return over the n-day and the following q-day. Day 3 indicates that we use the 3-day average excess return, i.e., over the n-day and the 2 following q-days. The asset menu consists of 45 portfolios. The sample period is from July 1992 to December 2022.

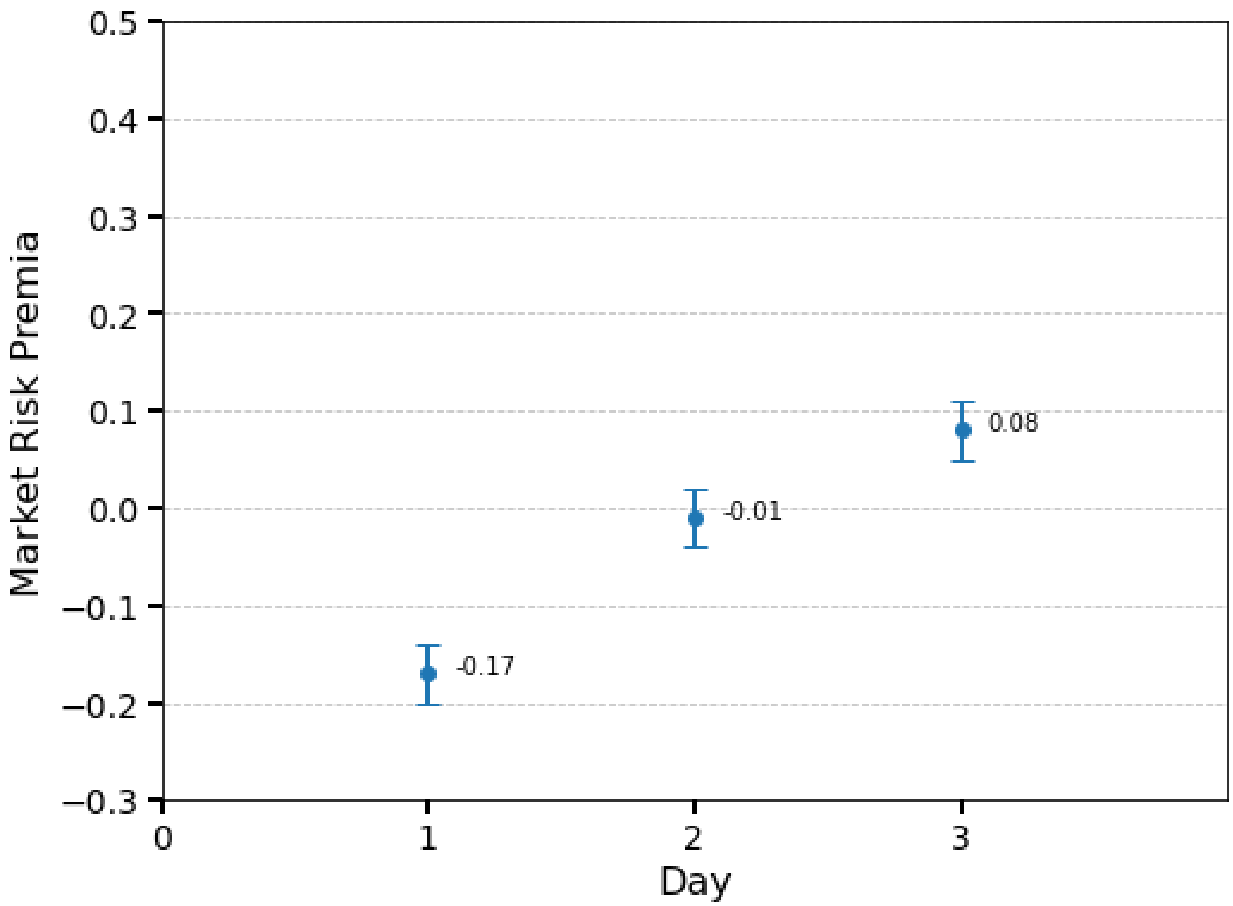

Table 1: Summary Statistics

This table presents key statistics. Panel A characterizes the aggregate tug-of-war variable (ToW^m). *Mean* and *Std Dev* denote the mean and standard deviation, respectively. *AR(1)*, *AR(2)*, and *AR(3)* are the first, second, and third order autocorrelations of ToW^m, respectively. *Min*, *Max*, and *Median* are the minimum, maximum, and median of ToW^m, respectively. Panel B reports the proportion of trading days [name in column] that are identified as an n-day. Panel C documents the proportion of trading days in the month [name in column] that are classified as n-days. Finally, Panel D summarizes the means of the market excess return, the TED spread, the VIX index, and the risk aversion index (Bekaert et al., 2022) on n- and q-days. The two rows preceding the last two report the proportions of macroeconomic (federal funds rate, producer price index, and unemployment rate; see Savor and Wilson (2014)) and non-macroeconomic news days, respectively, classified under each day type. The final two rows show the corresponding proportions for leading earnings announcement (LEAD) and non-LEAD news days. Following Chan and Marsh (2022), LEAD days are defined as those falling between Tuesday and Thursday of the first week of the earnings reporting quarter, provided that at least 50 S&P 500 firms announce earnings during that week.

Panel A. ToW^m

Mean	*Std Dev*	*AR(1)*	*AR(2)*	*AR(3)*	*Min*	*Max*	*Median*
0.28	0.12	−0.06	−0.02	−0.02	0.03	0.86	0.28

Panel B. Share of n-days on Each Day of the Week

Monday	*Tuesday*	*Wednesday*	*Thursday*	*Friday*
52.42%	50.60%	49.02%	48.58%	49.54%

Panel C. Share of n-days in Each Month of the Year

Jan	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
51.72%	51.48%	52.35%	52.02%	47.87%	53.21%	49.16%	48.83%	48.49%	50.59%	46.29%	48.17%

Panel D. Economic Variables

	$n-day$	$q-day$
Market Excess Return (%)	−0.05	0.12
TED (%)	0.45	0.45
VIX (%)	19.30	19.97
Risk Aversion	2.98	3.11
% Macro Days	50.63%	49.37%
% Non-Macro Days	49.91%	50.09%
% LEAD Days	47.92%	52.08%
% Non-LEAD Days	46.29%	53.71%

Table 2: Security Market Line: 10 (Value-Weighted) Beta-sorted Portfolios

This table summarizes the results of the asset pricing tests applied to the 10 (value-weighted) beta-sorted portfolios. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
Full Sample	0.03	0.01	43.08%
	(2.28)	*(0.56)*	
n-day	0.06	−0.13	40.46%
	(3.15)	*(−4.23)*	
q-day	−0.00	0.15	45.66%
	(−0.25)	*(5.15)*	
n-day − q-day	*0.07*	*−0.28*	
	(2.58)	*(−6.90)*	

Panel B. Pooled Estimation

α	λ	ψ	ϕ	*Adj* R^2
0.05	−0.01			0.00%
(3.25)	*(−0.33)*			
−0.00	0.14	0.10	−0.30	0.65%
(−0.01)	*(4.48)*	*(3.58)*	*(−7.65)*	

Table 3: Dissecting the SML on n-days: Overnight v.s. Intraday

This table summarizes the results of the overnight and intraday SML, based on the 45 portfolios, on n-days. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each n-day in the next month, we estimate a cross-sectional regression of the [name in row] excess returns of the test assets on a constant and the estimated betas. Following Lou et al. (2024), we compute intraday and overnight excess returns by subtracting the appropriate fraction of the daily risk-free rate from raw returns, 6.5/24 for the intraday trading window and 17.5/24 for the overnight period. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. $Adj\ R^2$ is the mean adjusted R^2. All returns are expressed in percentage points per day. In parentheses, we report the Newey and West (1987) t-statistics based on a Bartlett truncated at 10 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Trading Period	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
Overnight	−0.04	0.36	24.05%
	(−4.20)	*(19.10)*	
Intraday	0.16	−0.55	23.58%
	(8.48)	*(−20.45)*	

Table 4: Sentiment

This table presents the results of the asset pricing tests applied to the 45 portfolios over different sentiment periods. We identify a trading month as optimistic (pessimistic) if the Baker and Wurgler (2006) sentiment index measured at the end of the previous month is positive (negative). For each sentiment period, i.e., optimistic or pessimistic, we identify the n- and q-days and repeat our main asset pricing tests. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel A focuses on the optimistic sentiment period, while Panel B shows the results for the pessimistic period. All returns are expressed in percentage points per day. In parentheses, we report the Newey and West (1987) t-statistics based on a Bartlett truncated at 10 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Optimistic

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.10	−0.26	22.69%
	(4.83)	*(−7.84)*	
q-day	−0.01	0.23	25.60%
	(−0.24)	*(6.52)*	
n-day - q-day	*0.11*	*−0.49*	
	(4.05)	*(−10.69)*	

Panel B. Pessimistic

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.07	−0.13	21.68%
	(2.46)	*(−3.02)*	
q-day	0.01	0.12	26.67%
	(0.43)	*(2.71)*	
n-day - q-day	*0.06*	*−0.25*	
	(1.53)	*(−3.92)*	

Table 5: Macroeconomic News

This table summarizes the results of the asset pricing tests applied to the 45 portfolios over macroeconomic news and other days. The news days are associated with announcements of the (i) producer price index, (ii) unemployment rate, and (iii) federal funds rate. We refer to the remaining days as other days. For each type of day, we identify the n- and q-days and repeat our main asset pricing tests. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel A focuses on the macroeconomic news days, while Panel B shows the results for the other days. All returns are expressed in percentage points per day. In parentheses, we report the Newey and West (1987) t-statistics based on a Bartlett truncated at 10 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Macroeconomic News Days

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.05	−0.08	23.72%
	(1.02)	*(−0.98)*	
q-day	−0.10	0.38	27.61%
	(−1.71)	*(4.27)*	
n-day - q-day	*0.15*	*−0.47*	
	(1.96)	*(−3.98)*	

Panel B. Other Days

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.09	−0.18	21.63%
	(3.96)	*(−5.74)*	
q-day	0.01	0.12	
	(0.54)	*(3.72)*	26.12%
n-day - q-day	*0.08*	*−0.30*	
	(2.71)	*(−7.05)*	

Table 6: Leading Earnings Announcement Days

This table summarizes the results of the asset pricing tests applied to the 45 portfolios on earnings announcement days and other days. The leading earnings announcement days (LEADs) are the days between Tuesday and Thursday of the first week of the (earnings) reporting quarter that has a minimum of 50 (S&P 500) announcers. We refer to the remaining days as other days. For each type of day, we identify the n- and q-days and repeat our main asset pricing tests. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. $Adj\ R^2$ is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel A focuses on the leading earning release days, while Panel B shows the results for the remaining days. All returns are expressed in percentage points per day. In parentheses, we report the Newey and West (1987) t-statistics based on a Bartlett truncated at 10 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. LEADs

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	$Adj\ R^2$
n-day	−0.24	0.12	19.60%
	(−1.78)	*(0.69)*	
q-day	−0.09	0.54	28.58%
	(−0.97)	*(4.41)*	
n-day - q-day	−0.15	*−0.42*	
	(−0.95)	*(−1.75)*	

Panel B. Other Days

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	$Adj\ R^2$
n-day	0.08	−0.15	23.24%
	(3.04)	*(−3.77)*	
q-day	0.02	0.09	26.43%
	(0.84)	*(2.39)*	
n-day - q-day	*0.06*	−0.23	
	(1.78)	*(−4.62)*	

Market-Level Tug of War and Asset Pricing

Online Appendix

JEL classification: G11, G12, G41

Keywords: Capital Asset Pricing Model, Over-correction, Security Market Line, Tug-of-War

Figure A1: Share of n-Days Over Time

This figure shows the fraction of trading days, expressed in percentage points, in each calendar year classified as n-days. The sample period is from July 1992 to December 2022.

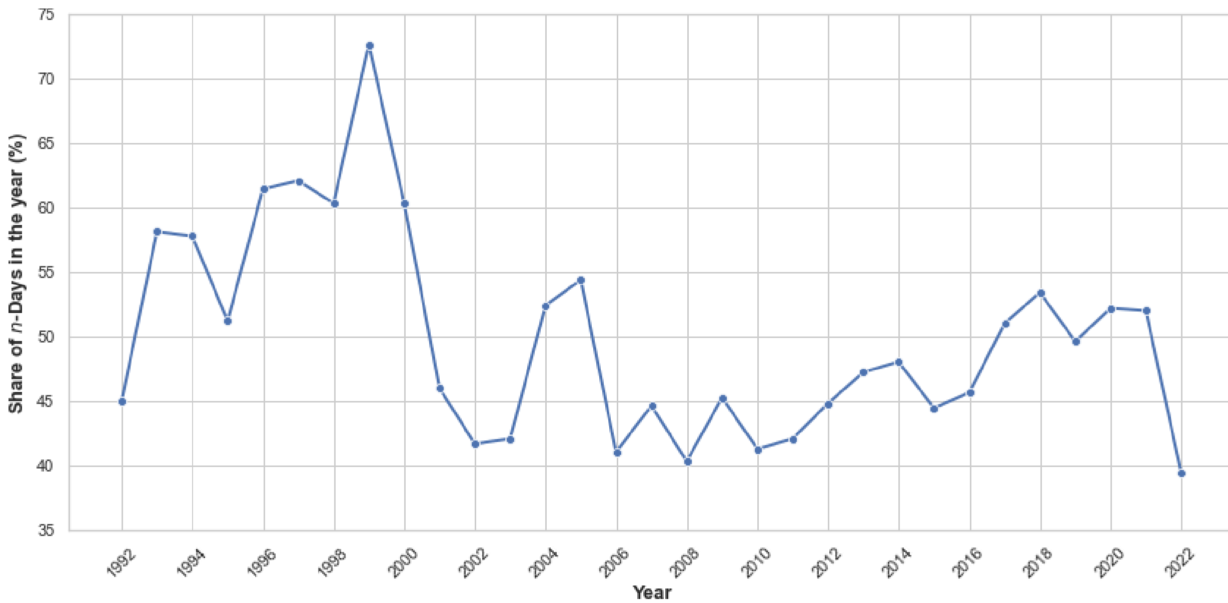

Figure A2: The Security Market Line: Unconditional Analysis

This figure shows the relationship between the average daily excess return of each test asset and its full-sample (post-ranking) beta estimate. We use full sample information to compute the average daily excess returns. The vertical axis shows the full-sample average daily excess return of each test asset. The horizontal axis shows the full-sample (post-ranking) beta estimate of each test asset. The line visually represents the empirical security market line obtained after estimating the cross-sectional regression of average excess returns on an intercept and the beta estimates. The asset menu consists of 10 (value-weighted) beta-sorted portfolios. The sample period is from July 1992 to December 2022.

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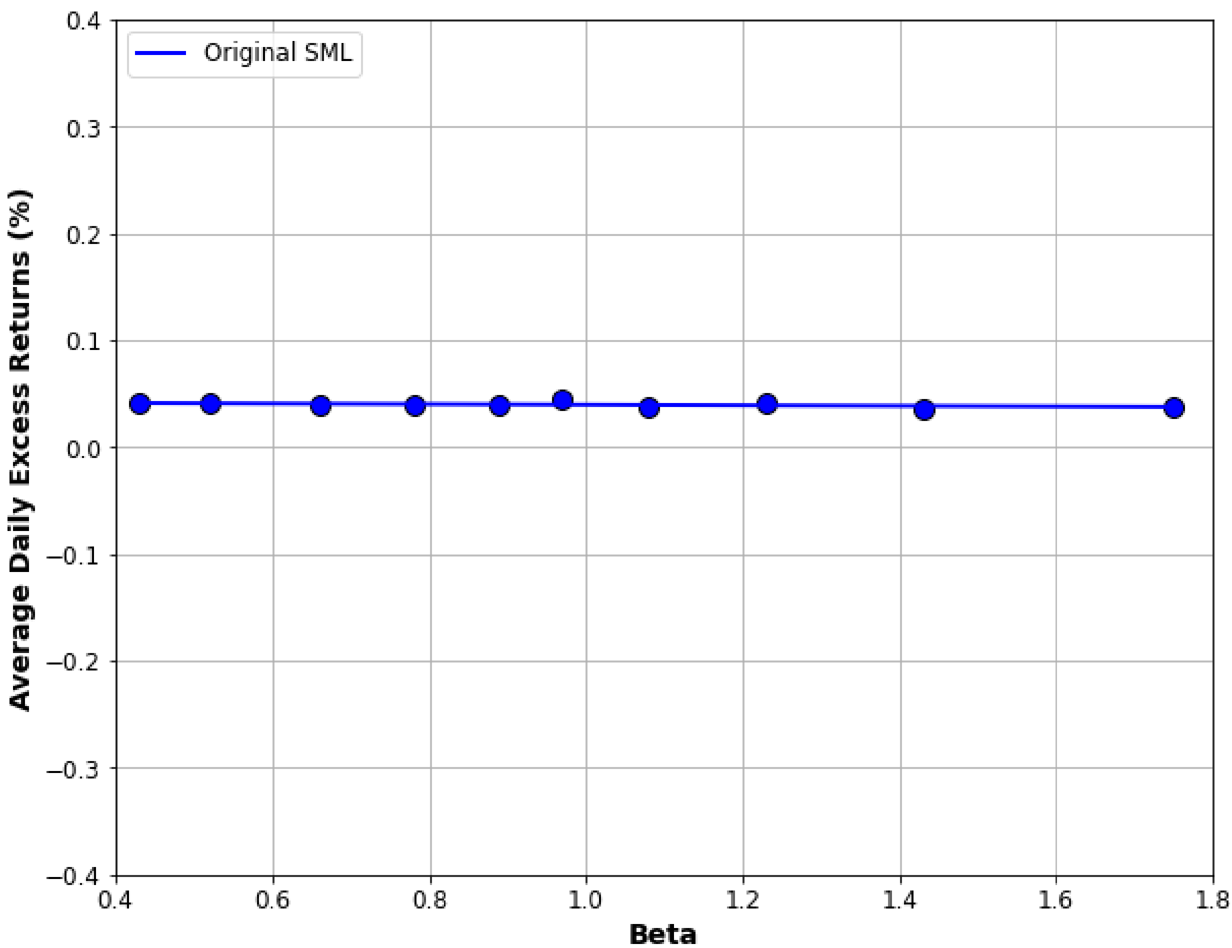

Figure A3: Security Market Line: Average Beta

This figure shows the relationship between the average daily excess return of the test assets, computed over either noisy (n) or quiet (q) days, and their average beta estimates. The asset menu consists of 10 (value-weighted) beta-sorted portfolios. The vertical axis shows the average excess returns of each asset for the subsamples of n- or q-days, represented by the blue and red colours, respectively. At the end of each month, we use a trailing window of 252 days to estimate the conditional beta of each portfolio. We then calculate the sample mean of the conditional beta estimates and report it on the horizontal axis. This beta estimate is used for both n- and q- days. For each type of day, the line visually represents the empirical security market line obtained after estimating the cross-sectional regression of the average portfolio excess returns calculated over the corresponding day-type, i.e., n- or q-day, on an intercept and the average portfolio beta estimates. The sample period runs from July 1992 to December 2022.

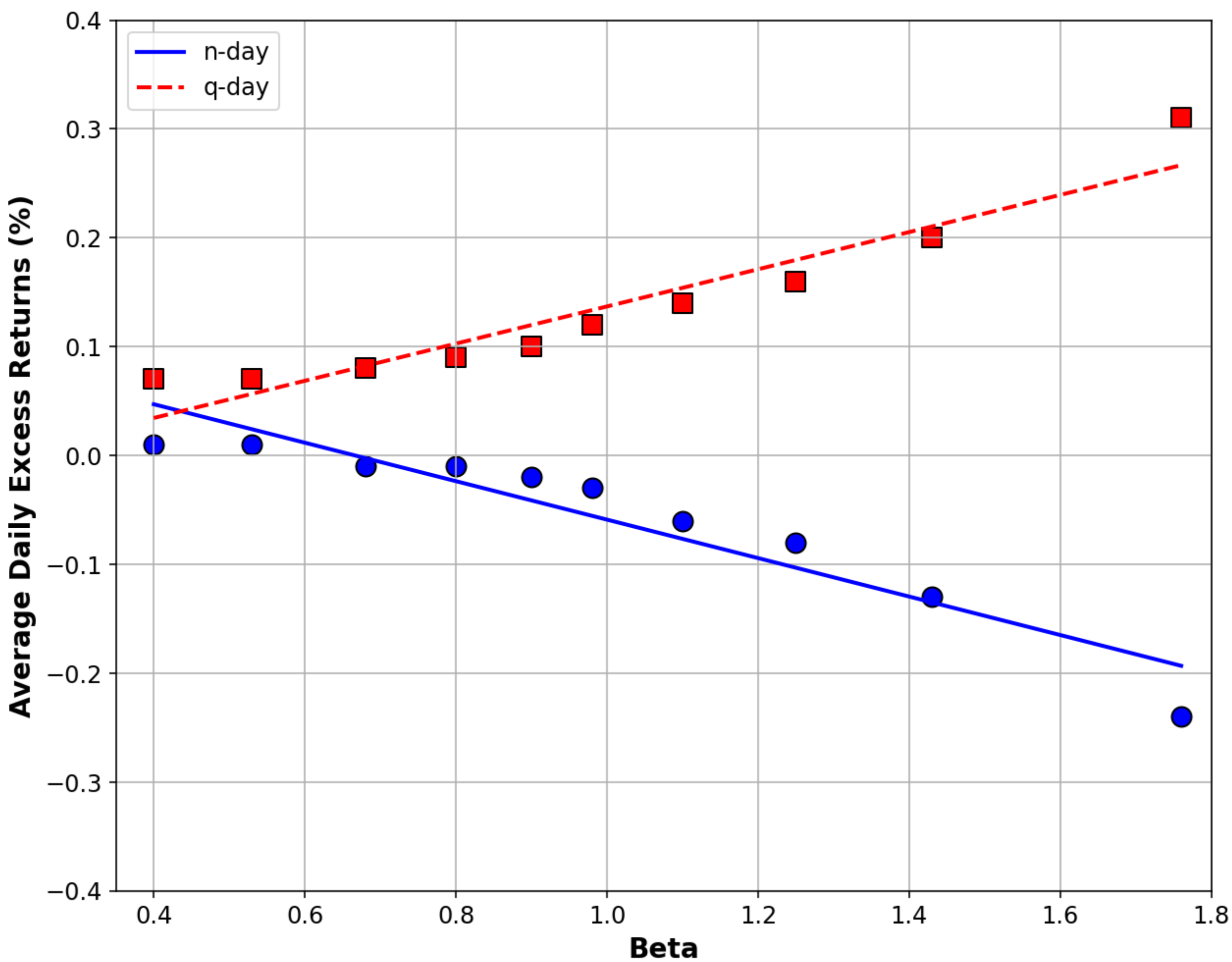

Figure A4: Bootstrap Results

This figure shows the histogram of the estimated market price of risk based on 1,000 pseudo-samples of n-days characterized by a positive market excess return. The bootstrap aims to create a pseudo-sample of the same length as our sample of n-days. To achieve this goal, we draw (with replacement) from the sample of n-days that are associated with a positive market excess return. We then run our Fama and MacBeth (1973) estimation and compute the average risk premium estimate. We repeat the above steps 1,000 times and report the distribution of the average risk premium estimate.

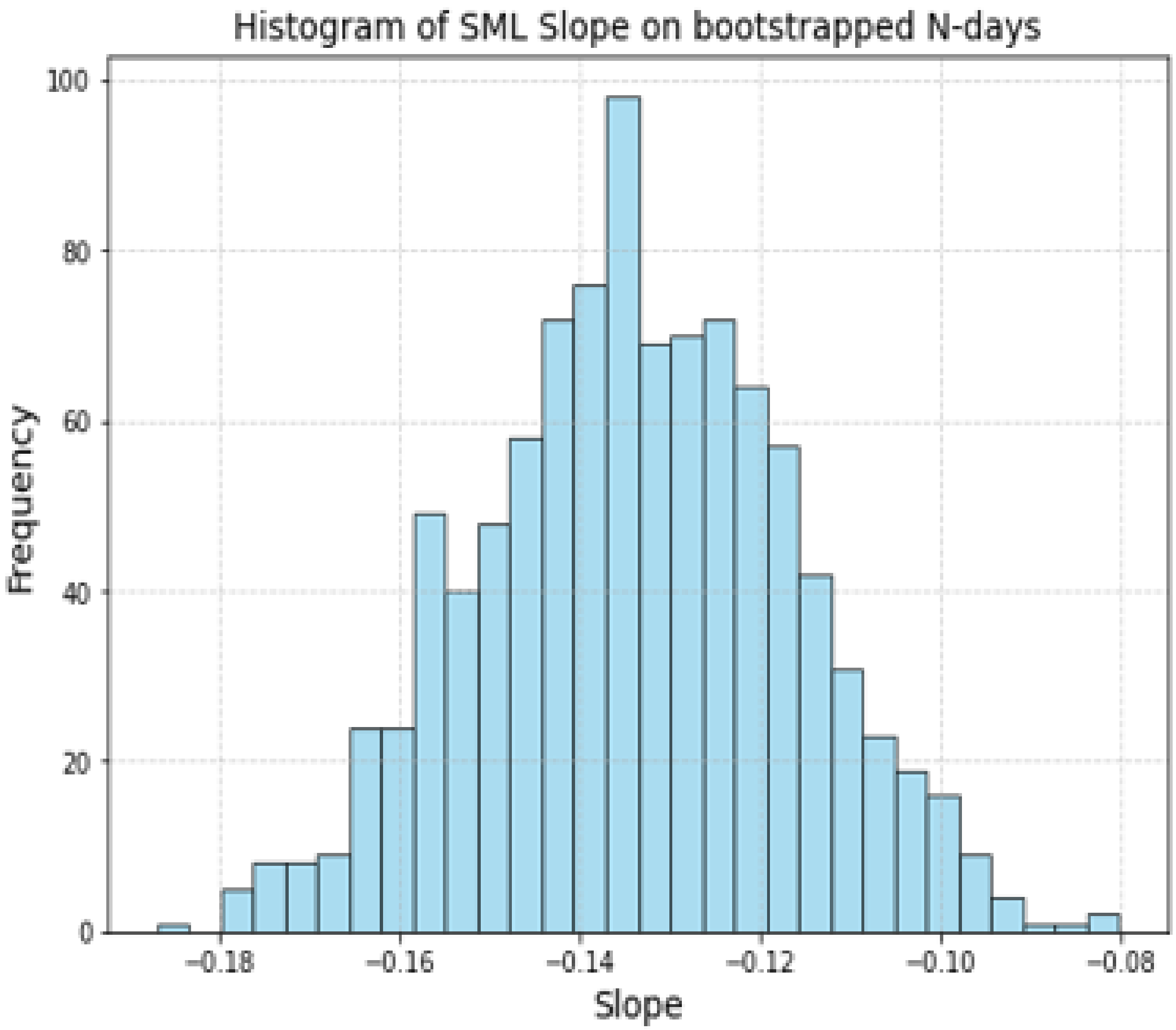

Figure A5: Beta estimates on n- and q-Days

This figure shows the relationship between the beta estimates of each test asset based on the sample of n- and q-days, respectively. The vertical axis shows the average conditional beta estimates linked to q-days, while the horizontal axis shows the average conditional beta estimates across n-days. The asset menu consists of 10 value-weighted and beta-sorted portfolios. The sample period is from July 1992 to December 2022.

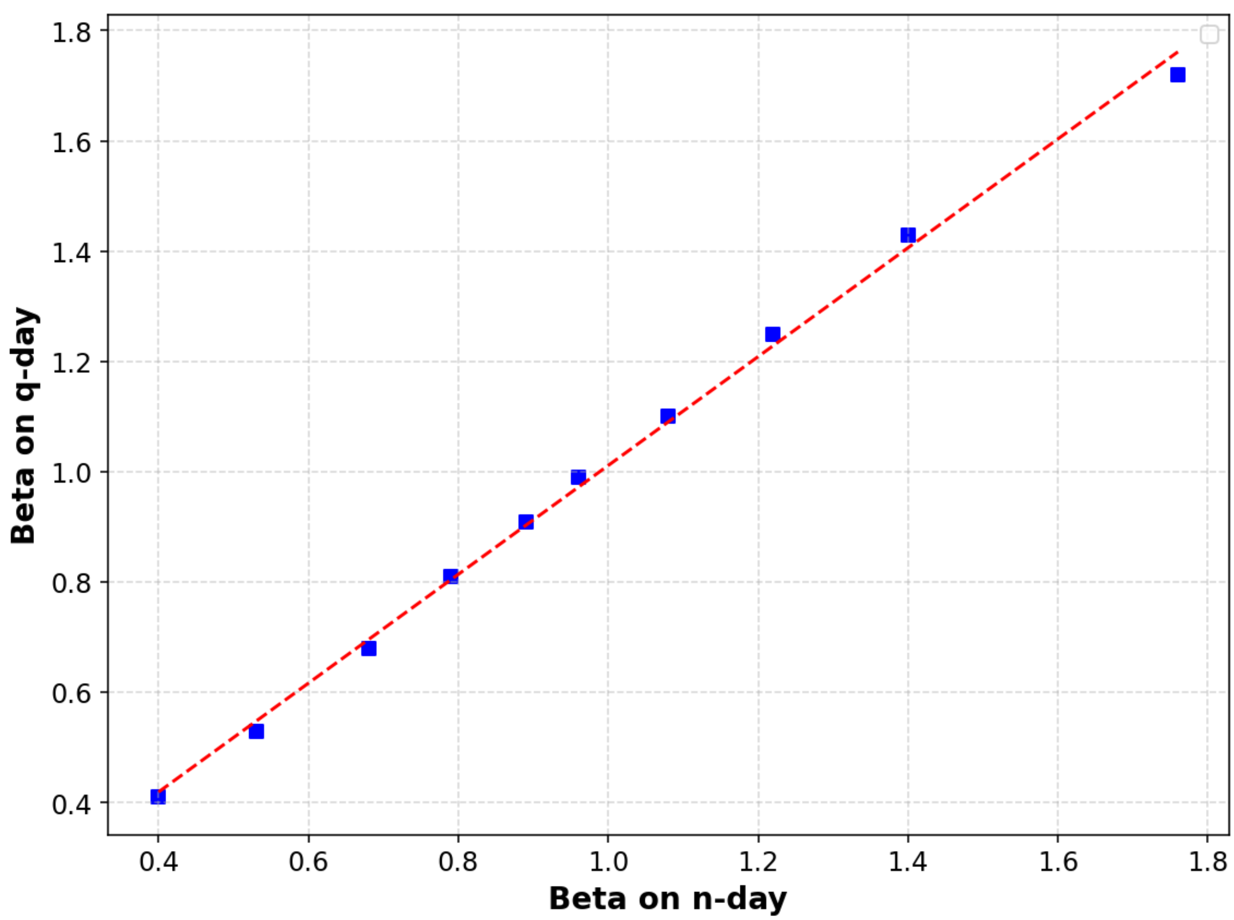

Table A1: Security Market Line: 10 (Equal-Weighted) Beta-sorted Portfolios

This table summarizes the results of the asset pricing tests applied to the 10 (equal-weighted) beta-sorted portfolios. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
Full Sample	0.13	−0.05	50.21%
	(9.61)	*(−2.57)*	
n-day	0.18	−0.25	47.22%
	(10.10)	*(−8.17)*	
q-day	0.07	0.15	53.16%
	(3.93)	*(5.70)*	
n-day - q-day	*0.11*	*−0.40*	
	(5.27)	*(−10.59)*	

Panel B. Pooled Estimation

α	λ	ψ	ϕ	*Adj* R^2
0.14	−0.06			0.03%
(9.39)	*(−3.10)*			
0.12	0.10	0.06	−0.34	1.09%
(4.97)	*(3.28)*	*(2.14)*	*(−8.86)*	

Table A2: Security Market Line: Individual Equities

This table summarizes the results of the asset pricing tests applied to the individual equities. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the conditional beta of each individual equity. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. $Adj\ R^2$ is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B controls for established characteristics, such as the market capitalization ($Size$), the Book-to-Market (BTM) and the momentum (MOM). Panel C shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panels A and B show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel C show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
Full Sample	0.07	0.00	2.18%
	(7.48)	*(0.29)*	
n-day	0.10	−0.16	1.15%
	(7.42)	*(−9.23)*	
q-day	0.12	0.10	1.77%
	(6.59)	*(5.68)*	
n-day - q-day	−0.02	−0.26	
	(−1.45)	*(−11.16)*	

Panel B. Fama and MacBeth (1973) with Controls

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Size*	*BTM*	*MOM*	*Adj* R^2
Full Sample	0.25	0.02	−0.02	0.00	−0.00	3.30%
	(8.19)	*(1.40)*	*(−6.75)*	*(0.38)*	*(−3.68)*	
n-day	0.38	−0.13	−0.02	0.03	−0.00	2.11%
	(6.20)	*(−8.01)*	*(−4.98)*	*(6.31)*	*(−2.47)*	
q-day	0.39	0.11	−0.02	−0.01	−0.00	2.76%
	(7.20)	*(6.55)*	*(−6.23)*	*(−2.71)*	*(−0.12)*	
n-day - q-day	−0.00	−0.25				
	(−0.07)	*(−10.98)*				

Panel C. Pooled Regression

α	λ	ψ	ϕ	*Size*	*BTM*	*MOM*	*Adj* R^2
0.10	−0.03						0.03%
(6.88)	*(−2.77)*						
0.15	0.08	−0.03	−0.28				0.19%
(6.68)	*(4.33)*	*(−1.38)*	*(−11.71)*				
1.54	0.11	−0.04	−0.27	−0.11	0.02	−0.00	0.22%
(16.60)	*(6.26)*	*(−1.57)*	*(−11.66)*	*(−14.94)*	*(2.15)*	*(−3.25)*	

Table A3: Security Market Line: 45 Portfolios

This table summarizes the results of the asset pricing tests applied to the 45 portfolios. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
Full Sample	0.04	−0.01	24.29%
	(3.15)	*(−0.39)*	
n-day	0.08	−0.17	22.25%
	(4.16)	*(−5.71)*	
q-day	−0.00	0.15	26.30%
	(−0.08)	*(5.06)*	
n-day - q-day	*0.09*	−0.32	
	(3.22)	*(−8.00)*	

Panel B. Pooled Estimation

α	λ	ψ	ϕ	*Adj* R^2
0.04	−0.01			0.00%
(2.36)	*(−0.30)*			
0.06	0.09	−0.01	−0.21	0.68%
(2.06)	*(2.83)*	*(−0.37)*	*(−5.18)*	

Table A4: Alternative Threshold: 0.25

This table summarizes the results of the asset pricing tests applied to the 45 portfolios. We identify a trading day as an n-day if the aggregate tug-of-war on that day is above 0.25. All other days are q-days. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.07	−0.09	22.43%
	(4.22)	*(−3.45)*	
q-day	−0.01	0.12	27.18%
	(−0.45)	*(3.21)*	
n-day - q-day	*0.08*	−0.21	
	(3.04)	*(−4.82)*	

Panel B. Pooled Estimation

α	λ	ψ	ϕ	*Adj* R^2
0.03	0.07	0.03	−0.14	0.18%
(0.94)	*(1.98)*	*(0.65)*	*(−3.23)*	

Table A5: Alternative Threshold: 70^{th} Percentile

This table summarizes the results of the asset pricing tests applied to the 45 portfolios. We identify a trading day as an n-day if the aggregate tug-of-war on that day is above the 70^{th} percentile of its distribution. All other days are q-days. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.10	−0.31	22.31%
	(3.64)	*(−7.76)*	
q-day	0.01	0.13	25.19%
	(0.83)	*(5.59)*	
n-day - q-day	*0.09*	*−0.44*	
	(3.04)	*(−10.67)*	

Panel B. Pooled Estimation

α	λ	ψ	ϕ	*Adj* R^2
0.07	0.07	−0.10	−0.24	1.30%
(3.25)	*(2.79)*	*(−2.79)*	*(−5.74)*	

Table A6: Alternative Aggregate Tug-of-War

This table summarizes the results of the asset pricing tests applied to the 45 portfolios. We compute the aggregate tug-of-war directly at the market level (See Equation (14)). We then use this alternative measure to identify n- and q-days. Panel A focuses on the Fama and MacBeth (1973) methodology. At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the pooled regression of portfolio excess returns on a constant and the explanatory variable(s) (see Equations (12)–(13)). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Fama and MacBeth (1973) Estimation

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.09	−0.40	20.98%
	(2.55)	*(−9.79)*	
q-day	0.03	0.09	24.66%
	(2.09)	*(3.99)*	
n-day - q-day	0.06	−0.48	
	(1.61)	*(−9.41)*	

Panel B. Pooled Estimation

α	λ	ψ	ϕ	*Adj* R^2
0.06	0.05	−0.06	−0.35	1.36%
(2.94)	*(2.29)*	*(−1.52)*	*(−7.41)*	

Table A7: Security Market Line: Individual Equities (Weighted Least Squares)

This table summarizes the results of the asset pricing tests applied to the individual equities. Panel A focuses on the weighted least square estimation of Asparouhova et al. (2010). At the end of each month, we use a trailing window of daily excess returns observed over the past 252 days to estimate the (post-ranking) conditional beta of each test asset. For each trading day in the next month, we estimate a cross-sectional regression of the excess returns of the test assets on a constant and the estimated betas. In estimating this regression, we use the sum of 1 and the lagged return of each asset as weights. We repeat these steps each month and obtain the time-series of the estimated coefficients. $\bar{\alpha}$ is the mean of the time-series of the intercept estimates. $\bar{\lambda}$ is the mean of the time-series of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B controls for established characteristics, such as the market capitalization ($Size$), the Book-to-Market (BTM) and the momentum (MOM). All returns are expressed in percentage points per day. Parentheses in Panel A show Newey and West (1987) t-statistics with a Bartlett truncated at 10 lags; parentheses in Panel B show the t-statistics based on standard errors clustered at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Weighted Least Squares

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.08	−0.15	1.14%
	(6.06)	*(−8.70)*	
q-day	0.10	0.11	1.78%
	(5.45)	*(6.19)*	
n-day - q-day	−0.02	−0.26	
	(−1.25)	*(−11.20)*	

Panel B. Weighted Least Squares with Controls

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Size*	*BTM*	*MOM*	*Adj* R^2
n-day	0.29	−0.13	−0.02	0.03	−0.00	2.10%
	(4.65)	*(−7.84)*	*(−3.57)*	*(6.15)*	*(−1.72)*	
q-day	0.28	0.12	−0.02	−0.01	0.00	2.75%
	(5.22)	*(6.77)*	*(−4.28)*	*(−2.30)*	*(0.70)*	
n-day - q-day	0.00	−0.25				
	(0.05)	*(−11.06)*				

Table A8: Assessing the Impact of the Market Excess Return

This table summarizes the results of the asset pricing tests applied to the 45 portfolios. Panel A controls for the effect of the market excess return. We sort all the trading days in our sample into terciles based on the daily market excess return. For each tercile, we run the Fama and MacBeth (1973) estimation for the n- and q-days, respectively. We then average the parameter estimates over all terciles and report the results in Panel A. $\bar{\alpha}$ is the mean of the estimated intercept. $\bar{\lambda}$ is the mean of the estimated market risk premium. *Adj* R^2 is the mean adjusted R^2. Each entry in the column refers to the sample of observations recorded over days [name in row]. Panel B shows the results of the analysis based on an alternative aggregate tug-of-war variable. We regress the time-series of the aggregate tug-of-war on a constant and the market excess returns. We save the residual, which is essentially the component of the aggregate tug-of-war that is orthogonal to the market excess return. We identify n-days as the days with an above median orthogonal aggregate tug-of-war and q-days as the remaining days. We then repeat the Fama and MacBeth (1973) estimation. All returns are expressed in percentage points per day. In parentheses, we report the Newey and West (1987) t-statistics based on a Bartlett truncated at 10 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Terciles Portfolios sorted by Market Excess Return

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.08	−0.07	22.28%
	(2.46)	*(−4.01)*	
q-day	−0.00	0.03	25.74%
	(−0.11)	*(2.59)*	
n-day - q-day	*0.08*	*−0.10*	
	(1.95)	*(−2.24)*	

Panel B. Orthogonalized Aggregate Tug-of-War

Type of Day	$\bar{\alpha}$	$\bar{\lambda}$	*Adj* R^2
n-day	0.08	−0.10	22.27%
	(3.85)	*(−3.03)*	
q-day	0.00	0.08	26.29%
	(0.12)	*(2.56)*	
n-day - q-day	*0.08*	*−0.18*	
	(2.91)	*(−4.32)*	