The Elusive CAPM: Idiosyncratic News and the Tilt of the Security Market Line

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Abstract

The capital asset pricing model (CAPM) performs poorly empirically, as market risk (beta) is weakly related to average excess returns. In low news periods, identified using idiosyncratic news from the Dow Jones Newswire, market betas have a strong and positive relation with average returns. On days with news, firms with higher betas earn lower returns. Removing returns around news improves the pricing of beta unconditionally. Hybrid "betting-against-beta" trading strategies exploiting these periods earn 28% annually. I conclude that waves of high aggregate idiosyncratic news obscure the performance of the CAPM at the firm level and significantly influence asset pricing.

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1 Introduction

Systematic risk has been at the core of asset pricing since the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966). It states that the risk premium of an asset should be positively related to its market risk exposure, measured by beta. However, this relationship is not observed unconditionally in the data, dating back to Black, Jensen, and Scholes (1972). Since then, there has been renewed interest in the performance of the CAPM on days when systematic news is released (Patton and Verardo, 2012; Savor and Wilson, 2014, 2016; Chan and Marsh, 2022), and within specific periods or economic states.[1] This stream of literature shows that the CAPM can work conditionally; yet, there is still no consensus on what drives its poor performance in unconditional tests.

This paper tests whether the arrival of idiosyncratic news, and the attention it attracts, helps to explain when and why the CAPM prices risk. I show that idiosyncratic news obscures the performance of the unconditional CAPM, weakening the relation between returns and systematic risk. When the level of market-wide idiosyncratic news is low, systematic risk is priced and the CAPM explains the cross section of stock returns. When returns around idiosyncratic news are removed, the CAPM prices risk across all periods, suggesting that the CAPM's validity extends beyond specific economic states or sample periods, and depends on the level of noise introduced to the model in the form of idiosyncratic news.

Figure 1 displays the main findings that motivate this study. Following Savor and Wilson (2014), I estimate rolling 12-month daily stock market betas for all US stocks on each day. Because my main measure requires idiosyncratic news collected from newswires, my sample period is daily from 2009-2024. I then sort stocks into one of ten beta-decile value-weighted portfolios. Portfolio returns are then averaged, and daily rolling betas are estimated again for each portfolio. Panel A of Figure 1 shows the unconditional fit of the security market line (SML) for the sample period. The line is mostly flat, suggesting that market betas do not explain average excess returns.

Panel B shows the SML separately for low news days (with triangle markers) and other days (with circle markers). Low news days occur when the total number of idiosyncratic news items in the Dow Jones Institutional Newswire (DJIN) falls below its trailing one-year 25th percentile. The upward sloping linear relation on low news days suggests that an increase in market beta of 1 is associated with a statistically significant increase in average daily excess market returns of 34 basis points. The picture is very different on other days. The SML (with circle markers) has a downward slope, implying that an increase in market beta is

[1] See Tinic and West (1984), Savor and Wilson (2014), Hong and Sraer (2016), Jylhä (2018), Hendershott, Livdan, and Rösch (2020), Chan and Marsh (2022), Hasler and Martineau (2024) among others.

associated with a decrease in average daily excess returns (a finding that is inconsistent with the CAPM).

Next, I investigate why the SML steepens in low-news states. I explore several explanations that could account for the results in Figure 1. The first possiblility is that the CAPM holds, but its empirical performance is obscured by the arrival of idiosyncratic news. Since my news corpus aggregates firm-specific articles, a direct channel is plausible: if information arrivals move prices at the firm level, and if high-beta firms respond differently to idiosyncratic news than low-beta firms, then aggregate news conditions can tilt the cross-section by differentially loading on beta. I show that firm-day news has measurable effects on individual returns with the betas of those firms mediating the response. On news days, firms with higher betas earn lower returns. Further, the existing literature focuses on testing whether the relation between beta and returns is positive when tests are confined to certain periods or economic states. I show that removing firm-day return observations around news arrivals improves the pricing of beta over all time periods, using Fama and MacBeth (1973) and pooled regressions, providing evidence that the CAPM's validity is not conditional on specific economic states or periods of time, but rather on the level of noise introduced to the model in the form of idiosyncratic news.

Another explanation draws on the literature on investor attention and information processing. Peng and Xiong (2006) argue investors exhibit category-learning behavior, and suggests that investors tend to process more market-wide than firm-specific information. Veldkamp (2006) introduces a framework in which investors choose how much information to acquire. Costly acquisition leads to greater reliance on common signals and higher comovement among assets, even when their fundamental payoffs are uncorrelated. Although my setting focuses on the supply of firm-specific information rather than the demand for it, a similar implication arises: when the supply of idiosyncratic news is low, assets load more heavily on common factors and covary more.

This line of research motivates an attention-based explanation, in which investors allocate more focus to idiosyncratic information at some times than at others. To operationalize this idea, I use the macroeconomic attention index of Fisher, Martineau, and Sheng (2022) to test the CAPM on days with only high or low idiosyncratic attention, without conflicting macroeconomic attention. The results show the beta-return relationship is not only upward sloping in low idiosyncratic news states, but also downward sloping when idiosyncratic attention is high, and macroeconomic attention is not.

Lastly, the literature on voluntary disclosure may play a role in explaining the results. Following Acharya, DeMarzo, and Kremer (2011), managers have incentives to strategically cluster bad news when many peers also disclose bad news, creating periods of elevated news flow that distort the SML at the micro level. Using the ratio of negative news shares in low versus high-beta portfolios, I show that the SML's slope steepens on days when the ratio is greater than unity. I show that variation in this ratio is driven mainly by negative news concentration in high-beta firms, and their negative news concentration is significantly lower during low idiosyncratic news periods. Together, this evidence suggests flattening of the SML when aggregate idiosyncratic news is elevated. Bad news loads disproportionately in high-beta names, and the SML steepens when periods of high idiosyncratic news subside.

The results suggest that when the supply of idiosyncratic news is low, beta is an important measure of systematic risk. The relation in Figure 1 survives a battery of additional tests to suggest that these results are not driven by the findings of existing papers in the literature. These studies primarily focus on testing the CAPM on subsets of trading days or months in the year, and a few papers document specific predictable times when the CAPM works. Beginning with Tinic and West (1984), who find that the beta-return relationship holds in the month of January, I find this result holds conditionally on days with low news in January. Hendershott, Livdan, and Rösch (2020) also find an upward sloping SML overnight, but not during the day. Yet, when the level of idiosyncratic news is low, the CAPM still performs well even when testing is confined only to daytime returns. Further, Boudoukh et al. (2019) use newswire articles to challenge the rationale of French and Roll (1986) that private-information driving rational trading is the main driver of return volatility. They show that public information arrivals in the form of newswire articles increase volatility both overnight and during the day. Coupling this with the findings of Hasler and Martineau (2023) who show the unconditional CAPM works better in periods of low volatility, higher levels of idiosyncratic news may raise volatility and impair the performance of the CAPM.

The arrival of news can resolve disagreement among investors. Hong and Sraer (2016) argue that high beta stocks are more prone to disagreement and overpriced due to short-sales constraints, and lower disagreement steepens the SML. While tests at a daily frequency confirm this claim, they do not explain the performance of the CAPM in periods of low news. In addition, these studies do not consider the effect of market returns on the performance of the CAPM. Hasler and Martineau (2024) use existing variables in the literature to forecast the expected market return. They show that when the expected market return is high, the beta-return relationship is positive, and that many of the existing results in the literature tend to coincide with high realized market returns. However, low-idiosyncratic news days survive even when tested within high and low expected market return states, suggesting there may be other reasons for why the CAPM works when idiosyncratic news is scarce.

To assess the economic significance of the findings, I produce an easily implementable trading strategy following Hendershott, Livdan, and Rösch (2020) that exploits these low news periods. The simple trading strategy takes a long position in the highest beta portfolio and a short position in the lowest beta portfolio in low news periods, and then reverses both positions during high news periods (betting-against-beta), while holding the market portfolio in all other periods. When annualized, the strategy earns a 28% average return with a Sharpe ratio of 1.24 compared to the 0.78 Sharpe ratio of the market over the same period. Alphas remain significant even after controlling for five Fama-French factors plus momentum.

I structure the paper as follows. Section 2 describes the data and definition of low news periods. In section 3, I provide empirical support for the claim that stock prices behave differently during low news periods versus other days. Section 4 dives into the potential explanations for the results. Section 5 introduces a simple trading strategy, and section 6 considers a battery of robustness tests. Finally, section 7 concludes.

2 Data

2.1 News data

According to Hasler and Martineau (2023), the unconditional CAPM aligns more closely with the data during high-expected-return, low-volatility periods. As opposed to Savor and Wilson (2014) and Chan and Marsh (2022) who focus their analysis on days with scheduled market-relevant announcements, I focus my analysis on news that is firm-specific and not regularly scheduled. I suggest that noisy environments with high levels of idiosyncratic and firm-specific information weaken the cross-sectional pricing of beta, thereby distorting the SML. To determine the level of information in the market, I construct an aggregate measure of idiosyncratic news from the Dow Jones Institutional Newswire (DJIN) accessed through ProQuest TDM Studio. To search for news, I create a string containing the name of every company listed in the CRSP database since 2009 when DJIN coverage starts, with share codes 10 or 11. I then perform a search through the DJIN for articles whose title contains at least one of the 5768 unique CRSP company names. I keep only articles for which a company name is included in the title of the newswire article, as Aït-Sahalia, Li, and Li (2024) find these to be most relevant to the firm, and likely to cause immediate jumps in stock prices. To avoid capturing news about earnings, I exclude articles for which the title contains the word stem 'earning', as well as other words commonly associated with articles written about earnings reports. I further exclude news whose headlines include the words “Buzz”, “Wrap up”, and any other commonly repeated keywords associated with summaries of previously posted actual news. A full list of these filters is provided in the Appendix. The news corpus consists of 1,271,432 idiosyncratic news articles beginning in 2009 and ends in 2024. On each day, I sum the total number of news articles in the corpus and create a daily time series.

Newswire coverage is often noisy, and only weakly informative about firm fundamentals, making it difficult to locate relevant articles. A further challenge is to separate truly idiosyncratic news items from broad or market-wide news. Recent advances in large language models permit more refined filtering of such news, allowing me to isolate truly idiosyncratic news with greater precision. To refine the set of news articles used in the analysis, and increase the likelihood that each article is directly related to an individual firm, I use GPT-4.0 mini provided by TDM Studio to filter out news which is systematic or not relevant to individual firms. I use a prompt that instructs the model to use only information included in the text, and opt for a straightforward prompt to establish a foundation for the results. Nonetheless, employing more detailed prompts could allow for the extraction of more tailored information. The purpose of this step is to keep only articles written about individual firms and singular (as opposed to systematic) events. I ask GPT-4.0 mini to read each article and classify whether the article is related to one firm or many, and whether the article is written about one event or many (market-wide) events. The exact prompt is shown in the Appendix. Once ChatGPT has read and labelled each of the initial 1,271,432 articles, I keep only those labelled as ‘singular’ and ‘idiosyncratic’. The final GPT-labelled news corpus consists of 917,752 news articles. Table 10 in the appendix displays a random sample of article headlines from the finished news corpus.

2.2 Defining low news periods

Using my GPT-filtered news corpus, I take the sum of all idiosyncratic news items for all firms, each day, and create a daily time series. I define low news periods as days when the rolling 10-day average of idiosyncratic news counts is lower than the 1-year rolling 25th percentile, as follows: Let $\mathcal{N}_t \equiv Q_{0.5}\{N_{t-9}, \ldots, N_t\}$ be the median of daily aggregate news for the last 10 days, and let $\mathcal{H}_t \equiv Q_{0.25}\{N_{t-251}, \ldots, N_t\}$ be the 25th percentile of daily aggregate news for the last 252 days. I define low news days as follows:

$$\mathrm{LowNews}_t = \mathbf{1}\{\, N_t \leq \mathcal{H}_t \,\} \tag{1}$$

Figure 2 visually illustrates the measure in four separate periods throughout the sample.

The vertical red line denotes the beginning of a fiscal quarter, and grey bars denote the total number of earnings announcements on each day in the I/B/E/S database. Low news periods occur when the rolling 10-day average of news counts drops below the 1-year rolling 25th percentile, and can occur at the beginning, middle, or end of a fiscal quarter, normally after most firms have finished announcing quarterly earnings. These days tend to come after most firms have released earnings, suggesting that any results are not driven by the spillover effect of Savor and Wilson (2016) or Chan and Marsh (2022) . The choice of a 10-day rolling average and 25th percentile to define 'low news' periods is chosen for simplicity. Section 6 considers results with alternative percentiles and rolling windows.

2.3 Stock return data

I retrieve excess market returns from Kenneth French's website. Following (Black, Jensen, and Scholes, 1972) among others, I construct ten monthly beta-sorted portfolios using U.S. common stocks from CRSP which have a share code of 10 or 11. Daily stock betas are obtained from a rolling regression of the past 252 daily excess stock returns on the excess market returns. At the beginning of each month, stocks are sorted into one of ten beta-deciles, and the daily value-weighted excess return of each decile portfolio is computed over the month.

For each portfolio, I estimate daily rolling betas by regressing the past 252 excess returns of each portfolio on the market return. These ten beta-sorted portfolios form my main test assets. Panel A of table 2 provides summary statistics for the stocks that form these test assets. In section 4, I also consider individual stocks.

3 Asset returns versus Beta in low news states

Panel B of figure 1 visually represents the main results by partitioning the sample into low news and other days, and plotting average excess returns of the value-weighted beta decile portfolios on average market betas over the 2009-2024 sample period. Following Savor and Wilson (2014) and Hendershott, Livdan, and Rösch (2020), I use unconditional betas averaged over the full sample period for figures. The upward sloping SML (triangle markers) shows a strong positive linear relation between excess returns and market betas: a unit increase in beta is associated with a statistically significant increase in daily excess returns of 29.39 basis points (t-statistic = 14.29). The regression R^2 is 95.10% suggesting that the variation in market beta explains most of the cross-sectional return variation during low news periods. In contrast, the slope of the SML on other days (circle markers) has a slope of 0.87 basis points (t-statistic = 0.70), suggesting that betas do not explain average excess returns on days without low news.

As in Chan and Marsh (2022), Savor and Wilson (2014) and Hendershott, Livdan, and Rösch (2020) I push the analysis further using the following panel regression:

$$r_{i,t+1} = \alpha + b_1\,\beta_{i,t} + b_2\,\mathbf{1}\{LowNews_{t+1}\} + b_3\,\beta_{i,t}\,\mathbf{1}\{LowNews_{t+1}\} + \varepsilon_{i,t+1}. \tag{2}$$

Where $r_{i,t+1}$ is the excess return of portfolio i on all days, $\mathbf{1}\{LowNews_{t+1}\}$ is a dummy variable equal to 1 on low news days, defined by equation (1), and 0 on all other days. The b_2 coefficient captures the low news-minus-other day alpha. The b_3 interaction term captures the difference in the market risk premium on low news days versus other days. In essence, it measures the change in the slope of the security market line on low news days versus all other days. As is standard in the literature, I construct portfolios differently for figures and tables. For tables, I calculate betas using a daily rolling 12-month regression of excess returns of portfolio i on the daily excess market returns. Panel A of Table 1 presents the results. T-statistics are in parentheses and estimated using standard errors clustered at the daily level. The α and b_1 coefficients are -0.06 and 0.01 basis points respectively, and are both insignificant. Insignificance of the b_1 coefficient reaffirms the finding in Figure 1 that betas do not explain the cross section of excess market returns in periods separate from low news. However, the interaction term, measured by b_3, is 34 basis points with a t-statistic of 3.06. This suggests that during low news periods, higher beta assets earn higher returns, as the CAPM would predict. The b_2 coefficient is negative with a coefficient of -19 bps and statistically significant (t-statistic = -2.14), capturing the low-news-minus-other-days intercept.

I push further by estimating the following Fama and MacBeth (1973) procedure, modified from Chan and Marsh (2022), Savor and Wilson (2014) and Hendershott, Livdan, and Rösch (2020). I regress the excess returns of portfolio i on the prior-day portfolio betas using the regression:

$$r^{L}_{i,t+1} = a^{L} + b^{L}_{\text{MKT}}\,\beta^{\text{MKT}}_{i,t} + \varepsilon^{L}_{i,t+1} \tag{3}$$

Where $r^{L}_{i,t+1}$ are excess returns of portfolio i on low news days, $\beta^{\text{MKT}}_{i,t}$ is the unconditional prior-day portfolio beta. Similarly, I estimate the Fama–MacBeth regression for all other days as:

$$r^{O}_{i,t+1} = a^{O} + b^{O}_{\mathrm{MKT}}\,\beta^{\mathrm{MKT}}_{i,t} + \varepsilon^{O}_{i,t+1} \tag{4}$$

Panel B of Table 1 reports the regression estimates and corresponding t-statistics for Fama-MacBeth regressions on both types of days. Standard errors are calculated using the standard deviation of the time-series coefficients, and the significance levels barely change when I correct for heteroskedasticity and autocorrelation using Newey-West adjusted standard errors. The coefficient b^L, which prices systematic risk on low news days is 24.8 basis points, with a t-statistic of 2.47 - similar in magnitude to the unconditional betas measured as the slope of the SML in Figure 1, Panel B. The intercept is not statistically different from zero, as the CAPM predicts, with a coefficient of -0.51 basis points and a t-statistic of -0.67. This reaffirms the finding that during low news periods, stocks with a beta that is higher by one have higher average excess returns by about 24.8 basis points. In contrast, Fama-MacBeth regressions run on other days paint a different picture. The b^O coefficient is 0.9 basis points, with a t-statistic of 0.26, suggesting that higher beta stocks do not earn a significantly higher return, and the beta-return relationship is flat. The results suggest that on low news days, beta explains the cross-section of expected returns.

Lastly, I push the analysis one step further and perform a multi-factor Fama-MacBeth procedure. I re-run the specification of equations (3) and (4), while including the Fama-French size (SMB) and value (HML) factors, plus momentum (MOM). I obtain SMB, HML, and MOM factors from Kenneth French's website, and estimate factor loadings in the first stage using daily excess returns. I then perform a multi-factor Fama-MacBeth procedure by regressing next-day asset returns on β, SMB, HML, and MOM factors on both low news and all other days. Panel C of Table 1 shows a strong, significant positive coefficient on β of 42.4 bps (t-statistic = 3.18), suggesting the SML is strongly upward sloping when news is scarce, even after controlling for SMB, HML, and MOM betas. The HML and MOM factors have negative coefficients and t-statistics of -0.73 and -0.94 respectively, and are not significant. The intercept and SMB coefficients are -14.9 bps and -21.7 bps, but only weakly significant with t-statistics of -1.72 and -1.78 respectively. The results suggest that even in a multi-factor setting which controls for size, value, and momentum effects, added factors do not absorb the effect, and if anything reveal that omitting them understates the systematic risk premium in low news states.

The key results of this section suggest that stock prices behave very differently during low news periods than at all other times. It remains to supply the fundamental reason why the CAPM works at some times, and not at other times. Section 4 explores potential explanations for this result.

4 Explanations

4.1 Beta, news, and individual stock returns

One potential explanation is that the CAPM always holds, but is distorted during noisy periods of high idiosyncratic news reporting. To probe the mechanism behind the aggregate effect on the SML documented above, I first explore the link between firm-level news and individual stock returns. A key concern is whether my aggregate news measure is correlated with some unobserved systematic confounders; alternatively, periods of elevated news may themselves distort the SML at the micro level. Under the latter interpretation, firm-day news should have detectable effects on the corresponding stock's returns. I evaluate this prediction below.

I estimate the following firm-level panel regression using firm-level CRSP return data, and the GPT-4.0-filtered news corpus:

$$\mathrm{R}_{i,t} = \alpha_i + \gamma_1\,\beta_{i,t} + \gamma_2\,\mathrm{News}_{i,t} + \gamma_3\,(\mathrm{News}\times\beta)_{i,t} + \epsilon_{i,t} \tag{5}$$

Where $News_{i,t}$ is a dummy variable which takes a value of 1 if firm i in my CRSP sample of firms has a news item on day t, and 0 otherwise. $R_{i,t}$ is the return for firm i on day t. If a news item occurs after normal trading hours (after 4:00PM), $R_{i,t}$ is assigned the next day return. $\beta_{i,t}$ is the beta of firm i on day t, updated each day using the past 1-year of returns. The interaction term $News \times \beta_{i,t}$ captures how reactions to news arrivals may differ based on an individual firm's beta on that day. The sample contains 2071 CRSP firms with share code 10 or 11 that have at least one matched DJIN news item, and spans 2009 to 2024. Panel A of table 2 shows summary statistics for the news matched sample compared to the whole CRSP set of stocks. Date fixed effects are included in each specification, and standard errors are double-clustered by firm and date.

I run regression (5) in four different market regimes: first, unconditionally over all days. Then during periods of 'high news', when the level of news is above its 1-year rolling median. Third, when the level of news is below its 1-year rolling median, and lastly, when news is below its rolling 25th percentile as outlined in equation (1). Table 3 presents the results of this regression in each market regime in columns 1-4.

Column 1 runs the regression unconditionally. As expected, the γ_1 coefficient on beta is small and not statistically significant, implying that even at the firm level, β does not explain returns on non-news days. Next, the γ_2 coefficient on the $News_{i,t}$ dummy variable is

48 basis points, with a t-statistic of 7.8, implying that firms with an idiosyncratic news item on that day have a return that is 48 basis points higher than days without news. This result suggests that on average, idiosyncratic news from the DJIN has a statistically significant impact on returns at the individual stock level. Lastly, the interaction coefficient between beta and news, γ_3, is -0.17 basis points, with a t-statistic of -3.22. Thus, conditional on a news day occurring, higher beta firms either benefit less on average from news arrivals, or release more negative news during high-news periods.

Columns 2, 3, and 4 run the same regression in different market states, depending on the level of news. Column 2 re-runs the same regression in high news states, when the 10-day rolling news count average is above its rolling 1-year mean. In this state, γ_2 is similar to column 1 with a news item increasing returns of that firm by 0.49 basis points. However, γ_3, the coefficient on the News$\times$Beta interaction is higher in magnitude, at -0.19 basis points with a t-statistic of -2.16, implying high beta firms benefit even less from news than low beta firms during periods of high news. Column 3 runs the same regression when the rolling 10-day news mean is below its 1-year rolling mean. The results are similar, but lower in magnitude, with γ_3 decreasing in magnitude to -0.15 basis points, with a t-statistic of -2.72. Finally, column 4 runs the regression in low news states, defined by equation (1). Notably, the coefficient on γ_3 is now even lower in magnitude at -0.12 basis points, and not statistically different from zero.

The results paint a picture that suggests a distortion of the SML in high news periods. When the level of news is high, firms with higher betas tend to have more negative reactions to news than low beta firms, implying a flattening of the SML slope. This result subsides during periods of low news, as defined by equation (1), where firms with higher betas do not have a significantly different reaction to news than low beta firms, and all firms benefit positively on average to idiosyncratic news arrivals. This suggests that in the absence of news arrivals, the CAPM performs closer to what Sharpe (1964), Lintner (1965), and Mossin (1966) predicted it should.

4.1.1 Re-testing the full sample CAPM without news

If it is the case that firm-level news is obscuring the price of beta during high news periods, then removing firm-level observations around the time when news arrives should restore an upward sloping security market line for all time periods. Motivated by the finding that news-day returns are decreasing in beta, I re-run the Fama and MacBeth (1973) and pooled regressions outlined in equations (2) and (3) for all days of the year, after removing negative firm-day observations outside of low-news periods. Negative news days occur when a news item in the DJIN coincides with a negative close-close return for a given firm. I remove firm-day returns up to two days before, and seven days after news arrivals based on the results in Figure 3, which plots the coefficients of regression (5) modified to include +/- 10 news day lags for individual firms. Returns can remain significantly above or below zero, conditional on positive or negative news days, for up to seven days after the news arrival. Further, the results suggest a run-up in returns prior to news. This could imply either gradual dissemination of information or information leakage given that DJIN news is mostly unscheduled. For this reason, I remove all returns two days prior and seven days after news arrives for each firm in the sample of CRSP firms which were successfully mapped to news. After this step, 12.4% of firm-day observations are removed from the sample.

I keep the top firms by news-volume, given that the distribution of news for firms is heavily skewed. Panel B of Table 2 shows summary statistics for the distribution of news across individual firms. As documented by Jeon, McCurdy, and Zhao (2022) among others, most firms have very little news by volume, while few absorb a large portion of total media coverage. My sample, containing only news with firms mentioned in headlines, has a median of 83 news appearances per firm in the Dow Jones newswire between 2009 and 2024. This translates to news occurring on just over 2% of days in the entire sample for these firms. Thus, I choose to keep only firms above the median by total news count, given that removing such few observations from low-news firms is unlikely to make a difference in pricing beta. Further, Hou, Xue, and Zhang (2020) show that microcap stocks - those with a market capitalization less than the 20th percentile, are the main drivers of many published anomalies. As an additional step, I remove firms with a market cap less than the 20th percentile from the sample. This leaves me with 857 unique firms that fall above the median. Columns (3) of Panel A in Table 2 shows summary statistics of the sample of firms in question. Column (4) shows the new betas for the same sample once firm-day observations are removed, and betas are re-estimated.

Once return observations are removed, I re-estimate betas for individual stocks in the news-matched sample. With these new betas, I sort stocks into beta decile portfolios, rebalanced monthly. Using these portfolios I again estimate betas of the decile portfolios by regressing the excess market return against the equal weighted portfolio returns. These beta decile portfolios form my main test assets. I then perform unconditional Fama–MacBeth and pooled regressions of equation, modified to include the entire sample, with both low and high news periods.

Table 4 reports the results of Fama–MacBeth regressions for all time periods with and without news observations satisfying:

$$r_{i,t+1} = a + b_{\mathrm{MKT}}\,\beta_{i,t}^{\mathrm{MKT}} + \varepsilon_{i,t+1} \tag{6}$$

and pooled regressions for all time periods according to:

$$r_{i,t+1} = \alpha + b\,\beta_{i,t} + \varepsilon_{i,t+1}. \tag{7}$$

Starting with the Fama-MacBeth regression in panel A, which contains all firm-day return observations, we can see that market betas are not significantly related to portfolio excess returns unconditionally in the full sample, in both Fama–MacBeth and pooled regressions. The implied market risk premium in pooled regressions is 4 basis points (t-statistic 1.19), and is 4.1 basis points with a t-statistic of 1.13 in unconditional Fama–MacBeth regressions. Moving to panel B, which uses portfolios formed on betas re-estimated without days around negative news, we see a slightly larger implied market risk premium 8 basis points (t-statistic of 2.71) in pooled regressions, and 8.7 basis points with a t-statistic of 2.44 in Fama-MacBeth regressions, implying that beta is positively related to portfolio excess returns in the entire sample when news days are removed. The intercept with news observations removed is also economically small and statistically insignificant, with a magnitude of 2 basis points (t-statistic of 0.68) in panel regressions, and 1 basis point with a t-statistic of 0.51 in Fama–MacBeth regressions. Both a positive market risk premium and zero intercept are in line with what the CAPM predicts. The results suggest that idiosyncratic news can interfere with the pricing of beta. This result suggests that the CAPM's validity is not conditional on specific economic states or periods of time, but rather on the level of noise introduced to the model in the form of idiosyncratic news.

4.2 Attention: Idiosyncratic versus systematic

I define low idiosyncratic news days as days when the aggregate level of idiosyncratic news in the Dow Jones Institutional Newswire is below its trailing 25th percentile. This criterion is designed to select low idiosyncratic information days with minimal engineering. As noted at the outset, these days are likely to correlate with attention. Thus, my findings intersect with the growing number of studies examining the relationship between attention and risk premiums. For example, Ben-Rephael et al. (2021) show that macro news, including that for large firms in aggregate, is associated with micro-level risk premiums. They attribute higher premiums to an increase in institutional investors' attention on days when systematic information is released using Bloomberg query scores as instruments for institutional attention.

Chan and Marsh (2022) also find that on days when influential S&P500 firms announce earnings, the CAPM explains the cross section of large stock returns, and institutional attention is higher.

Attention to firm-specific news outside of scheduled news days, and their effect on the performance of the CAPM, are less explored. Veldkamp (2006) suggests that abundant firm-specific information reduces comovement between asset prices. She introduces a framework in which investors choose how much information to acquire. Costly acquisition leads to greater reliance on common signals and higher comovement among assets, even when their fundamental payoffs are uncorrelated. While this paper focuses on the supply of information, rather than the demand for it, I posit that a similar implication could arise. When the supply of firm-specific information is low, assets load more heavily on common factors, and systematic risk becomes an important measure of risk. Empirically, in a natural experiment Fox, Glosten, and Subrahmanyam (2003) showed a decline in comovement using legal reform in December 1980 which caused an abundance of information as information aquisition became less costly. Peng and Xiong (2006) also propose that investors tend to process more market-wide information than firm-specific information, reinforcing the idea that preferences for which type of information investors demand, firm-specific or systematic, may vary over time. In this section, I use attention as a guide for which type of information investors are primarily compounding into prices, and test the CAPM when attention to idiosyncratic news is low or high relative to systematic news.

I first contrast the findings thus far using idiosyncratic news counts with systematic attention using the macroeconomic attention index (MAI) developed in Fisher, Martineau, and Sheng (2022) as a proxy for systematic attention. The authors develop a measure of attention to the macroeconomy based on article counts related to macro-topic keywords in the Wall Street Journal and New York Times. First, I argue that the article count of idiosyncratic news may be itself a measure of idiosyncratic attention. I create a new measure of relative attention by normalizing the level of idiosyncratic news by MAI. Then, I take the rolling 10-day average of this relative measure and test the CAPM again using the Fama–MacBeth and pooled regressions outlined in equations (2) and (3) on days when the relative measure is low (below its rolling 1-year 25th percentile). I further remove known confounding macroeconomic announcement days used in Savor and Wilson (2014), as Ben-Rephael et al. (2021) shows these days are triggers for micro level attention. Row 1 of Table 5 displays the results. The left hand side reports the results of Fama-MacBeth regressions with Newey-West adjusted t-statistics, and the right-hand side, those of the pooled regressions with standard errors clustered by day. The slope coefficient is positive and statistically significant, with a magnitude of 15 basis points in Fama-MacBeth regressions (t-statistic 1.85), and 21 basis points in pooled regressions (t-statistic 2.57). This result holds for 20.1% of days in the sample, and shows that systematic risk is priced for a significant number of days outside of the few previously documented macroeconomic announcement days of Savor and Wilson (2014).

Next, I re-run pooled and Fama-MacBeth regressions in high and low idiosyncratic attention states, while excluding days with abnormally high and low macroeconomic attention. Table 5 displays the results. First, I test the sample of days for which my low news measure is below its trailing 1-year 20th percentile, and MAI is above its rolling 1-year 20th percentile. I do this to isolate days with low idiosyncratic news attention, while excluding days with abnormally low macroeconomic attention. Fama-MacBeth regressions yield a coefficient on beta of 30 basis points (t-statistic 1.90), while the pooled regression yields a coefficient of similar magnitude at 41 basis points (t-statistic 3.48). The results suggest the CAPM works when attention to idiosyncratic news is lower than attention to macroeconomic news. I also re-run the same regressions in high idiosyncratic news attention states, where the level of idiosyncratic news is above its rolling 1-year 80th percentile, and MAI is below its rolling 1-year 80th percentile. In Fama-MacBeth regressions, the coefficient on beta is -34 basis points, with a t-statistic of -3.00. In panel regressions, the coefficient on the interaction term is similar in magnitude at -38 basis points with a t-statistic of -3.21. The results suggest that when the level of idiosyncratic news attention is high, and macroeconomic attention is not, the beta return relationship is downward sloping – a finding that is inconsistent with the CAPM.

To further verify that my measure which counts idiosyncratic news articles captures attention, I develop an idiosyncratic-news attention index (IAI) based on the procedure in Ben-Rephael et al. (2017), which sorts stocks into quintiles based on the level of attention institutional investors paid to an individual stock on a given day using Bloomberg search queries. On each day, I assign a quintile value from 0-4 to individual stocks which had idiosyncratic news arrive through the Dow Jones Institutional Newswire, and take the daily average across only firms which have an idiosyncratic news items on each day. As an additional step, I also recreate the aggregate institutional attention measure developed in Ben-Rephael et al. (2017) using all Russell 3000 firms, and create *sumAIA* following Chan and Marsh (2022) which aggregates AIAs across all firms for day t.

Panel B of table 5 shows how these measures differ between low-idiosyncratic news periods, and all others. Idiosyncratic attention is significantly lower in low-news periods as noted by a t-test for differences in means for IAI between low news and all other periods, with a t-statistic of -3.17. In contrast, the difference between the same periods for MAI is also lower, with a t-statistic of -0.90 making it an insignificant difference. Further, aggregate institutional attention across all Russell 3000 stocks is virtually unchanged between periods, with a t-statistic of 0.072. The results suggest that idiosyncratic attention is significantly lower when the aggregate level of idiosyncratic news is low. Yet, market-wide attention is virtually unchanged when measured using macroeconomic attention (MAI), or market-wide instiutional attention to individual stocks (sumAIA).

The results bring into question what happens when more or less attention is paid to idiosyncratic news relative to systematic. When idiosyncratic attention is high, covariance with the market drops, and the beta-return relationship is flat or downward sloping. In contrast, when idiosyncratic news attention is low relative to macroeconomic attention, the SML is upward sloping and the CAPM survives.

4.3 News clustering

The work on voluntary disclosure may also play a role in explaining the results. Theoretical work by Acharya, DeMarzo, and Kremer (2011) shows that managers have incentives to strategically cluster bad news releases during times when public news is bad. Similarly, in periods without public news, stock returns will be positively skewed as firms voluntarily release good news. Ang, Chen, and Xing (2006) find that correlations between stocks and the market are much greater for downside moves than for upside moves. They also find that downside correlation is stronger for small stocks where, according to Acharya, DeMarzo, and Kremer (2011), managers' ability to time disclosure could be greater due to investor inattention, and for stocks that are past losers where there may be greater adverse information being delayed for release until market news arrives.

Table 2 shows that higher beta stocks tend to be smaller as measured by their market capitalization. This suggests that high beta stocks may be more prone to negative news clustering if managers can better control disclosure. Together this provides one potential explanation for why periods of high idiosyncratic news may distort the security market line downward. This idea has existing empirical support. Kothari, Shu, and Wysocki (2009) show that managers tend to accumulate and withhold bad news up to a certain threshold, but leak and immediately reveal good news to investors, and that the market reacts accordingly. They show that prices tend to drift downwards absent disclosure, and jump upward with the announcement of good news.

Figure 3 plots the distribution of negative idiosyncratic news releases for the two highest decile beta firms (dotted line) and lowest two beta firms (solid line) for two sample years in the study. Negative news occur when a DJIN news item coincides with a negative close-close return for a given firm. Higher beta firms release more negative idiosyncratic news on average, and visual inspection suggests that high beta firms tend to release news at times when other high beta firms are also releasing news. This clustering is more pronounced for high beta firms than low beta firms. Together, this offers one potential explanation for why the SML flattens during periods of high news.

4.3.1 Time varying concentration of negative news

I discuss another framework at an aggregate level which is consistent with high-beta firms driving a flattening of the security market line. Negative firm-specific news may concentrate in high beta firms at some times, and low beta firms at other times explaining the tilt in the SML. To this end, I create a measure of the relative concentration of bad news in upper to lower beta deciles as follows:

First, for group $g \in \{H, L\}$, denoting high (low) beta firms are firms in the top (bottom) 5 decile of portfolios. I define the daily negative-share:

$$\text{Negative Share}_{g,t} = \frac{\sum_{i \in g} N^{-}_{i,t}}{\sum_{i \in g} \left(N^{-}_{i,t} + N^{+}_{i,t}\right)}, \tag{8}$$

where $N^{-}_{i,t}$ and $N^{+}_{i,t}$ denote, respectively, the number of *negative* and *positive* news-day articles for firm i on day t that occurred before 4:00pm EST. I define negative news-days as days when a news article coincides with a negative close-close return for that firm. I then smooth each group's series with a 5-day rolling average and take the ratio:

$$M_t = \frac{\sum_{s=0}^{4} \text{NegativeShare}_{L,t-s}}{\sum_{s=0}^{4} \text{NegativeShare}_{H,t-s}}, \tag{9}$$

Equation 8 is the within-group share of negative articles, and equation 9 is the ratio of the five day rolling average of that share for low-beta to high-beta firms. Days when $M_t > 1$ can occur when high-beta firms have a lower concentration of negative news than low-beta firms. Panel A of Table 6 runs the same panel regression of equation (2), modified with a dummy variable to capture days when $M_t > 1$. The results suggest that the relative negative news concentration between high and low beta firms can explain the slope of the security market line. On days when M_t is high (above unity), the γ_3 coefficient on the interaction term is 55 basis points with a t-statistic of 9.46, implying a steeper slope when there is less negative news concentrated in high beta firms than low beta firms.

Given the construction of M_t it is not obvious whether the measure is driven by changes in high or low beta news concentration. Panel C of Table 6 reports the mean values of the negative news share separately for high and low beta firms during both high and low news periods, as well as a t-test for differences in means. High beta firms have a significantly lower concentration of negative news during low news periods, with a t-statistic of -3.174. In contrast, low beta firms also have a lower concentration of negative news during low-news periods, but the difference is not statistically significant from the mean in all other periods, with a t-statistic of -0.782. The results of Panel A suggest that the relative concentration of negative news between high and low beta firms can explain the slope of the SML concurrently, while changes in this concentration are driven by differences in the amount of negative news concentrated in high-beta firms. These findings support the idea that negative news tends to be more concentrated in periods of high idiosyncratic news flow, and negative news is significantly more concentrated in high-news periods for high beta firms. This implies a flattening of the security market line in periods when aggregate idiosyncratic news is high.

5 Trading strategy

I have documented a strong positive correlation between market betas and average excess returns for beta portfolios. I now explore several trading implications. In this section, I argue that one can use my rolling news measure to trade, given that the news measure is persistent, and can be easily updated daily. Panel A of Table 7 shows summary statistics for each beta-sorted portfolio in my sample comprised of all CRSP firms with share code 10 or 11, on both low news and other days. As expected, columns 1 and 2 show that low news periods feature increasing and linear average excess returns as betas increase, but other days do not share this same pattern. In contrast, columns 3 and 4 show that the standard deviation of beta portfolios is linear and increasing for beta portfolios on both types of days. This is in line with the finding that beta is only priced during low news periods, since riskier assets pay higher returns on average during low news periods, but not other periods. Columns 3–4 show that return volatility is uniformly lower on low-news days for every beta portfolio. Consistent with Hasler and Martineau (2023), who find that the CAPM fits better in low-volatility regimes, this pattern suggests that information arrivals coincide with higher volatility, which corresponds to a flatter SML.

Panel B of figure 5 plots, for each beta decile, the ratio of the Sharpe ratio on low-news days to the Sharpe ratio on other days. The ratio exceeds one for all deciles and rises with beta roughly from 3 for the lowest-beta portfolio to near nine for the highest-beta portfolio. The risk–return trade-off improves in beta during low news periods. The improvement reflects both higher average returns and lower volatility in low-news periods.

Next, I assess the performance of trading strategies that exploit low and high news periods. To ensure these strategies are easily implementable, I lag my news series by one day so that positions are entered or exited one day after the news signal switches. The portfolio returns I report are gross of transaction costs, financing frictions, and shorting fees. The key state variable derived from aggregate idiosyncratic news measure is highly persistent, so the trading rule switches states infrequently. In practice, an investor could approximate the long and short legs using liquid high-beta and low-beta ETFs, which keeps implementation costs low. I consider two strategies. The first strategy is a market timing strategy that invests in the risk free asset during high news periods, and the market during all other periods. I define high news periods as those in which the rolling 10-day average of idiosyncratic news counts is above its 1-year 75th percentile. The second strategy is a hybrid betting-against-beta strategy, which takes a long position in the highest beta portfolio, and a short position in the lowest beta portfolio during low news periods, and then reversing both positions during high news periods (betting against beta), while holding the market portfolio in all other periods. Panel A of Figure 5 motivates the strategy by plotting the SML separately for low-news, high-news, and all other days in the sample. Panel B of Table 7 shows the results.

The first trading strategy generates an average daily return of 0.063%, which translates to a compounded 17.2% annually, with a standard deviation of 0.97%, and an annualized Sharpe ratio of 1.03. Compared to buying the market portfolio, which generates 15.1% with a Sharpe ratio of 0.79, avoiding holding the market portfolio during high news periods improves both returns and the return per unit of risk on the market. The second trading strategy earns an average daily return of 0.1%, with a standard deviation of 1.28%. When annualized, these numbers turn into a compounded return of 28.3% with a Sharpe ratio of 1.24.

Lastly, I assess the performance of these strategies in a Fama-French 5 factor model with momentum. Panel C of Table 7 displays the results. In the Fama-French 5 factor model with momentum, strategy 1 and 2 both generate statistically and economically significant alphas. In particular, strategy 2 still earns an alpha of 0.1%, or 10 basis points per day, even after controlling for market, value, size, conservative minus aggressive, robust minus weak, and momentum factors. The results are consistent with other findings in this paper: the conditional price of market risk is higher when firm-specific information flows are low, steepening the SML where high beta assets earn higher returns. Further, high beta assets earn less when firm-specific information flows are high, and short positions generate additional returns beyond what the market can explain. This may imply that high-beta firms release more negative news during these periods, or that investors revise their beliefs about high-beta firms' prospects when new information is released. In either case, the strategy profits by timing exposure to beta across news states, and is not subsumed by standard factors.

6 Additional tests

6.1 The month of January

Tinic and West (1984) find that the beta-return relationship improves dramatically in the month of January, and not other months. Since low-news periods tend to occur near the beginning and end of fiscal quarters, one concern is that there is something special about the month of January that allows beta to be priced. Panel A of Table 8 re-reruns the panel regressions of equation (2) within only the months of January throughout the sample between 2009 and 2024. The results suggest that beta is priced only on low news days in January. The coefficient on the interaction term between β and low-news states is 78 basis points with a t-statistic of 4.52, despite having only 253 observations. Low news days constitute 52% of days in January, with the other 48% of days in January not qualifying as low news. On other days in January, the beta-return relationship is downward sloping.

6.2 Day and night portfolios

One concern with the analysis is that since news tends to arrive mostly overnight as documented in Boudoukh et al. (2019), that the overnight effect documented in Hendershott, Livdan, and Rösch (2020), who document a strong linear positive slope on the SML overnight, and not during the day, might be driving the effects of this paper. Panels B and C of Table 8 re-run the panel regressions outlined in equation (2) using day and night returns respectively. The coefficient on the interaction term between β and low-news states is 43 basis points with a t-statistic of 2.42. This suggests that even when the analysis is confined to using only daytime returns, the SML still has a more positive slope during periods of low news. Conversely, panel B shows the same analysis overnight. Interestingly, the coefficient on β is now weakly significant, with a coefficient of 32 basis points and t-statistic of 1.85, while the interaction term loses significance. This is in line with the findings of Hendershott, Livdan, and Rösch (2020), and suggests that beta might be priced overnight for reasons other than when the amount of idiosyncratic news is low. This encourages the explanation that the effect of news on the SML may have to do with the ability of informed traders to compound information into prices.

6.3 LEADs as confounders

An additional concern is that low news days overlap with days when influential S&P500 firms release earnings, known as Leading Earning Announcement Days (LEADs) in Chan and Marsh (2022). These days occur almost exclusively in weeks 2, 3 and 4 of the first month of the fiscal quarter. Given that low news periods tend to occur near the end or beginning of fiscal quarters, I re-run the panel regression outlined in equation (2) without weeks 2, 3 and 4 of each fiscal quarter in the sample period from 2009-2024. Panel D of Table 8 shows the results of the panel regression outlined in equation (2). Again, the coefficient on the interaction term between β and low news states is 35 basis points with a t-statistic of 2.21. The magnitude of the coefficient is roughly unchanged, despite a slightly smaller t-statistic, suggesting that the results are not driven by LEADs.

6.4 Macro announcements as confounders

Another concern is that the macroeconomic announcement days of Savor and Wilson (2014) may confound the results of low news periods. First, I obtain a comprehensive list of every day that PPI, FOMC and employment reports were set to release since 1960. I remove any of these days from the sample period, and re-run the analysis. Panel E of Table 8 presents the results of the panel regression outlined in equation (2) after removing these days. Again, the coefficient on the interaction term between β and low news states is 33 basis points with a t-statistic of 2.89. The magnitude of the coefficient is close to unchanged, suggesting that macroeconomic announcements are not driving the low news effect.

Lastly, Panel F removes both LEADs and macroeconomic announcement days from the analysis and re-runs the panel regression outlined in equation (2). Again, the coefficient on the interaction term between β and low news states is 38 basis points - relatively unchanged, with a t-statistic of 2.21, suggesting neither of these days are confounding the analysis.

6.5 Aggregate attention, news, and the SML

Ben-Rephael et al. (2021) show that the results of Savor and Wilson (2014) hold only conditionally on periods of aggregate high attention, introducing the importance of attention on the performance of the CAPM. They find that firms for which investors demand information earn a premium. Further, Fang and Peress (2009) show using Wall Street Journal articles that firms mentioned less in prominent press demand a premium for opacity. One further explanation why the CAPM performs better during periods of low news could be an opacity premium when demand for information is high, and the supply is low. To explore this I condition my panel regression in equation (2) on periods with high and low attention, using the monthly attention measure of Chen et al. (2022) obtained from Zhou's website. Panel H of table 8 presents the results.

Panel G runs the same regression defined in equation (2), conditional on months with high attention as defined in Chen et al. (2022). I define a high attention month as months where the level of attention is higher than its empirical mean. Within high attention months, the coefficient on b_3 increases in magnitude from 34 basis points to 50 basis points. This implies that a one unit increase in beta increases the average excess daily returns of beta portfolios by 50 basis points when attention is high. The result remains statistically significant with a t-statistic of 2.07. The results are consistent with the idea from Fang and Peress (2009) that opacity commands a higher risk premium, and with Ben-Rephael et al. (2021) showing that premia rise when investors' demand for information intensifies. Given this logic, the SML could be more upward sloping during periods of low news due to opacity in the market. When the information set is thin, investors demand greater compensation for beta, steepening the SML.

6.6 Unprocessed news

The nature of large language models is to give slightly different outputs given the same prompt. One concern is that the GPT-4.0 processed news corpus may have been filtered in a way that is not reproducible. To alleviate this concern, I report the results of the baseline panel regression again in Panel G of Table 8 using just the raw news corpus extracted from TDM studio, outlined in section 2.1. Once again, the results are similar. The coefficient on the interaction term between β and low news states is slightly smaller, at 31 basis points, with a t-statistic of 2.86, suggesting that even without the use of ChatGPT, one can obtain similar results with the raw news measure with manual text filters.

6.7 Alternative low-news definitions

Equation (1) outlines the definition of low news periods. The choice of a 10-day rolling average and a 25th percentile cutoff were chosen for simplicity, and not to maximize the magnitude of coefficients or statistical significance. Table 9 once again re-runs the panel regressions outlined in equation (2) with a multitude of different rolling averages and cutoffs to define low news. Panels A through D re-run the panel regression with a variety of different rolling averages. Evidently, the results remain robust when using rolling news averages which range from 8 days until 20 days, when the effect eventually subsides.

Panels E through G also present the results of alternative cutoffs to define low news in equation (2), again using a 10-day rolling average of news counts. Notably, the result tends to strengthen as the cutoff gets lower. The coefficient on the interaction term between β and low news states is increasingly larger in magnitude as the cutoff gets smaller, indicating that lower news environments increasingly steepen the SML. This result remains statistically significant at the 10% level until a cutoff of 35% (unreported), at which point over 26% of days in the entire sample are defined as low news days.

7 Conclusion

This study revisits the classic question of why the unconditional beta–return relation in the CAPM (Black, Jensen, and Scholes, 1972) often fails in the data. I show that when aggregate idiosyncratic news flow is low, constructed from the Dow Jones Newswire, the security market line (SML) is upward sloping. In contrast, the relation weakens outside these low-news states. The finding holds using daytime returns, is robust to excluding days with leading earnings announcements and major macroeconomic announcements, and is not sensitive to how “low news” is defined. Trading strategies exploiting these periods earn an average of 28% between 2009 and 2024, and are largely driven by negative news concentrating in high-beta names during periods of high aggregate idiosyncratic news flows.

The upward slope of the SML in low-news states implies a higher conditional price of market risk relative to other days. I test this claim using both Fama–MacBeth and panel regressions. I explore potential mechanisms that may account for the result. First, micro-level disclosure that obscures the pricing of beta in the cross-section during periods of elevated idiosyncratic news. Second, time-varying attention between idiosyncratic and systematic information, where beta is reliably priced when attention to systematic information is high relative to idiosyncratic. Third, high beta firms experience a higher concentration of negative news in high news periods, while their low-beta counterparts do not. Unconditional Fama–MacBeth regressions run throughout the entire sample, after removing firm-day news observations, improves the pricing of beta unconditionally. Finally, I present a simple, implementable hybrid "betting-against-beta" strategy that earns 10 basis points per day after controlling for Fama-French five factors with momentum. Annually, the strategy earns a Sharpe ratio of 1.24, with an average return of 28.3%, exceeding a buy-and-hold market benchmark over the same period.

These findings carry important implications for both academic research and practical applications. The results suggest that violations of the CAPM may reflect firm-level distortions rather than fundamental failures in the risk-return relationship. This insight should help practitioners refine their use of the CAPM when computing the cost of capital (Berk and van Binsbergen, 2017), particularly in periods when the level of news is elevated. Idiosyncratic news has market-wide and firm-level implications for equity prices, and for what drives the systematic risk-return relationship in equity markets. In summary, my findings suggest that idiosyncratic news plays a role in how and when the CAPM functions.

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Table 1: Regression results across specifications

This table reports the results of Fama-MacBeth and panel regressions of daily excess returns on market betas for beta-decile test portfolios. Returns are reported in percent, daily. I use a 1-year rolling regression with daily returns to estimate betas of individual stocks. I then sort stocks into beta-decile portfolios and calculate daily portfolio betas using the past 1-year of value-weighted returns. Panel A reports results of portfolio-level panel regressions. Panel B reports a simple test of the CAPM by running Fama-MacBeth on low-news days and all other days. Panel C runs the same style of regression with Fama-French 3 factors plus momentum. T-statistics are reported in parentheses, and estimated based on time-series variation (Newey-West) for Fama-MacBeth and clustering by days for panel regressions. The sample spans 2009–2024. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Panel regression

	Const	β	$\mathbb{1}\{\text{Low News}\}$	$\mathbb{1}\{\text{Low News}\} \times \beta$	R^2
Coefficient	-0.06	0.10	-0.19**	0.34***	0.002
t-stat	(-0.64)	(1.09)	(-2.14)	(3.06)	

Panel B: Fama–MacBeth regressions

	Intercept	β	Avg. R^2
Low news days:	-0.51	0.25**	0.46
	(-0.69)	(2.47)	
Other days:	0.034	0.09	0.42
	(1.33)	(0.26)	

Panel C: Fama–MacBeth with FF3+Momentum

	Intercept	β	SMB	HML	MOM	Avg. R^2
Low news days:	-0.22*	0.42***	-0.15*	-0.098	-0.015	0.75
	(-1.78)	(3.18)	(-1.72)	(-0.73)	(-0.94)	
Other days:	-0.50**	0.049	-0.027	-0.025	-0.013	0.74
	(-1.99)	(1.09)	(-0.95)	(-0.79)	(-0.36)	

Table 2: Summary statistics for beta deciles and news

Panel A reports beta, market capitalization (in billions), and news counts (in thousands) by beta decile for three samples. (1) All CRSP common stocks (share codes 10/11) from 2009–2024. (2) Subsample successfully matched to Dow Jones Newswire (DJIN). (3) High-news firms: above the median by total news volume. For summary statistics, beta-portfolio market capitalizations are equally weighted. Panel B summarizes the news measures used in the paper; row (1) is daily total DJIN items mapped to firms and row (2) is the across-firm distribution. Panel C shows correlations between aggregate daily news and other daily variables. VIX is the CBOE Volatility Index. 10Y–2Y is the term spread. ΔEPU is the change in the economic policy uncertainty index (Baker, Bloom, and Davis, 2016). ARA is aggregate retail attention (Da et al., 2025). $R^m - R^f$ is the excess market return from Kenneth French's library.

Panel A: Beta-sorted portfolios

	Decile (low β to high β)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	# Firms
(1) All CRSP											
Beta	0.08	0.46	0.68	0.83	0.96	1.09	1.21	1.36	1.55	1.99	7941
Mkt Cap	2.36	7.46	8.10	8.60	8.23	8.33	7.29	5.88	5.26	3.37	
(2) DJIN matched											
Beta	0.17	0.54	0.72	0.87	0.99	1.11	1.24	1.39	1.59	2.07	
Mkt Cap	7.16	15.22	14.23	14.47	14.16	16.35	12.85	12.74	7.90	4.61	2071
News	20.90	32.50	37.60	40.30	42.00	43.90	40.80	39.40	35.90	31.50	
(3) High-news											
Beta	0.19	0.54	0.73	0.87	1.00	1.12	1.24	1.39	1.59	2.04	
Mkt Cap	14.52	27.32	23.08	22.31	20.59	26.13	20.50	20.32	12.52	5.82	1019
News	16.46	28.46	34.19	36.98	39.19	40.60	37.46	36.45	32.76	28.42	

Panel B: News

	Mean	**Q25**	**Median**	**Q75**	**Std**	**Skew**	**Min**	**Max**
(1) Daily aggregate	223	175	219	266	71.2	0.4	23	539
(2) Distribution by firm	174	28	83	199	409.3	15.9	1	12 187

Panel C: Correlations

	Aggregate news	**Vix**	**10Y-2Y**	**ΔEPU**	**ARA**	**Disag.**	$R^m - R^f$
Aggregate news	1.000						
Vix	0.033	1.000					
10Y-2Y	0.397	-0.068	1.000				
ΔEPU	0.116	0.334	0.187	1.000			
ARA	0.119	-0.126	-0.250	-0.129	1.000		
Disagreement	-0.292	0.009	-0.729	-0.334	0.420	1.000	
$R^m - R^f$	-0.001	-0.149	0.025	0.027	0.002	-0.033	1.000

Table 3: Panel regression in various idiosyncratic news states

This table reports firm-level regressions of daily stock returns on a firm-day news variable indicating whether a firm had a Dow Jones Newswire news item that day (News), the prior-day market beta (Beta), and the interaction News×Beta. Coefficients are expressed in percent, daily. All specifications include firm and day fixed effects; t-statistics are reported in parentheses and standard errors are clustered at the firm level. Column (1) uses the full sample. Columns (2)–(4) restrict the sample by the market-wide news state: days when the rolling 10-day news count is above its rolling 1-year mean, below its rolling 1-year mean, or below its rolling 1-year 25th percentile, respectively. t-statistics are in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) All Days	(2) News > median	(3) News < median	(4) News < 25%
Intercept	0.06^{***}	0.03	0.09^{***}	0.11^{***}
	(2.80)	(0.84)	(3.25)	(2.58)
Beta	-0.01	0.01	-0.03	-0.001
	(-0.67)	(0.48)	(-1.54)	(-0.17)
News	0.48^{***}	0.49^{***}	0.47^{***}	0.52^{***}
	(7.80)	(4.71)	(7.50)	(4.93)
News×Beta	-0.17^{***}	-0.19^{**}	-0.15^{**}	-0.12
	(-3.22)	(-2.16)	(-2.72)	(-1.46)
Date Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE (Firm-Day)	Yes	Yes	Yes	Yes
Observations	8,169,473	3,877,513	4,291,960	1,844,348
R^2 (within)	0.0002	0.0001	0.0003	0.0003

Table 4: Full Sample Panel and Fama–MacBeth Regressions

The left side reports pooled PanelOLS regressions, and the right side reports Fama–MacBeth cross-sectional regressions. Panel A uses all observations between 2009–2024. Panel B excludes days two before to seven after non-low-news periods. The betas used to construct the portfolios in row (2) are re-estimated using a 252-day rolling regression on daily excess returns with news observations removed from the sample. I keep stocks above the median by total news volume, and the bottom two deciles of firms by size for both samples used in (1) and (2). The parenthesized t-statistics are estimated based on standard errors calculated using standard deviations of the time series coefficient estimates, Newey-West adjusted with 11 lags (for Fama-MacBeth), and with clustered (daily) standard errors (for panel regressions). ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. Return coefficients are expressed in %, daily.

	Panel Regression			**Fama–MacBeth Regression**		
	Intercept	Beta	R^2	Intercept	Beta	Avg. R^2
Panel A: News matched sample						
	0.01	0.04	0.01	0.05	0.041	0.48
	(0.35)	(1.19)		(0.31)	(1.13)	
Panel B: News days removed						
	0.02	0.08***	0.03	0.01	0.087**	0.49
	(0.68)	(2.71)		(0.51)	(2.44)	

Table 5: Fama–MacBeth and Pooled Regressions: Attention

Panel A reports estimates from Fama–MacBeth and pooled regressions of portfolio excess returns on beta. Fama–MacBeth regressions are run: (1) when the level of idiosyncratic news counts relative to macroeconomic news counts is below its trailing 1-year 20th percentile (excluding days with conflicting low macro attention). Macroeconomic announcement days when inflation, employment and interest rate announcements are made are further removed from the sample. Pooled regressions include an attention-day indicator and its interaction with beta; standard errors are clustered by day. Fama–MacBeth t-statistics use the time-series standard deviation of the cross-sectional estimates. Panel B reports differences in means for idiosyncratic (IAI) and macroeconomic (MAI) attention indices between low and high idiosyncratic-news days. The sample spans 2010 (limited by Bloomberg attention data) to 2020 (limited by MAI data). ***, **, and * denote two-tailed significance at 1%, 5%, and 10%.

Panel A: Regressions

	Fama–MacBeth			Pooled Regression			
	α	Beta	$\overline{R^2}$	α	Beta	$\mathbf{1}\{\text{Attn}\}$	$\mathbf{1}\{\text{Attn}\} \times \beta$
(1)**Low relative attention**							
(Idiosyncratic news)/MAI	−0.043	0.15*	0.43	−0.09	0.12	−0.13**	0.21**
	(−0.67)	(1.85)		(−0.90)	(1.24)	(−1.87)	(2.57)
(2)**Low news days**							
(Without conflicting MAI)	−0.14	0.30*	0.46	−0.05	0.09	−0.31**	0.41***
	(−1.19)	(1.90)		(−0.46)	(1.00)	(−2.77)	(3.48)
(3)**High news days**							
(Without conflicting MAI)	0.19**	−0.34***	0.50	−0.08	0.14	0.16	−0.38***
	(2.15)	(−3.00)		(−0.77)	(1.51)	(1.64)	(−3.21)

Panel B: Difference in Means (Attention on low-news versus other days)

Attention type	Mean (Low news)	Mean (Other)	Diff (Low–High)	t-stat
Idiosyncratic (IAI)	0.043	0.049	−0.006	−3.17***
Macroeconomic (MAI)	1.11	1.13	−0.053	−0.90
All institutional (sumAIA)	1132.17	1130.29	1.88	0.072

Table 6: Regressions and statistics: Relative concentration of negative news (M_t)

Panel A shows correlations between M_t and other daily variables. VIX is the Chicago Board Options Exchange Volatility Index. Term is the term spread, calculated as the difference between the long-term yield on government bonds and Treasury bills. ΔEPU is the change in the economic policy uncertainty index from Baker, Bloom, and Davis (2016). ARA is aggregate retail attention of Da et al. (2025), obtained from Tim Chih-Ching Hung's website. Disagreement is daily from J. Anthony Cookson's website. $R^m - R^f$ is the excess market return obtained from Kenneth French's website. Panel B reports summary statistics for the ratio of negative news shares for high- and low-β portfolios, M_t. Panel C reports results of the panel regression of daily excess returns on market betas for beta decile portfolios (value-weighted) for days when $M_t > 1$. Standard errors are clustered daily. Panel D reports means for negative news shares for high and low beta assets separately, defined by equation (8). Two-sample t-tests (unequal variances) for negative news share are split by low-news vs. other days, separately for high- and low-β portfolios. T-statistics are in parentheses. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

Panel A: Pooled regression

	Const	β	$(M_t > 1)$	$\beta \times (M_t > 1)$	R^2
Coefficient	-0.04	-0.01	-0.32***	0.55***	0.012
t-stat	(-0.40)	(-0.14)	(-6.99)	(9.46)	

Panel B: Correlation matrix (lower triangle)

	M_t	VIX	Term (10y–2y)	EPU	ARA	Disagreement	$R^m - R^f$
M_t	1.000						
VIX	−0.021	1.000					
Term (10y–2y)	−0.014	−0.068	1.000				
EPU	0.059	0.334	0.187	1.000			
ARA	−0.007	−0.126	−0.250	−0.129	1.000		
Disagreement	−0.042	0.009	−0.729	−0.334	0.420	1.000	
$R^m - R^f$	0.075	−0.149	0.025	0.027	0.002	−0.033	1.000

Panel C: Negative news share on low-news vs. other days

	Mean (Low news)	Mean (Other days)	Difference	t	p
High beta	45.75	47.74	-0.0199	−3.17***	0.0016
Low beta	46.46	46.88	-0.0043	-0.78	0.4348

Table 7: Trading strategy summary and FF 6-factor regression

Panel A reports average returns and standard deviations (expressed in %, daily) for beta-sorted portfolio on low news days and other days from July 2010 to January 2024. Panel B reports daily summary statistics (means, standard deviations, and Sharpe ratios) for three trading strategies: (i) buy and hold the market portfolio over the sample period; (ii): invest in the risk free asset during high news periods, and the market during all other periods; (iii): hybrid 'betting-against-beta' strategy that takes a long (short) position on high (low) beta decile portfolios in low news periods, and switches to betting against beta in high news periods, while holding the market portfolio otherwise. Low (high) news periods are defined when the 10-day rolling mean of idiosyncratic news counts is below (above) its 1-year rolling 25th (75th) percentile. Panel C reports results of regressions of strategy returns on Fama-French 5 factors plus momentum. T-statistics in parentheses. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

Panel A: Summary Statistics of Beta Portfolios

	1 (High)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 (Low)**	**High–Low**
$\bar{R}$ **(Low news)**	0.21	0.19	0.17	0.18	0.15	0.16	0.14	0.079	0.078	0.025	**0.182**
$\bar{R}$ **(Other)**	0.034	0.030	0.038	0.035	0.029	0.037	0.051	0.050	0.046	0.020	**0.014**
Std (Low news)	1.98	1.50	1.36	1.26	1.15	1.07	0.93	0.88	0.77	0.84	**1.142**
Std (Other)	2.16	1.81	1.64	1.45	1.35	1.28	1.16	1.05	0.91	0.99	**1.171**

Panel B: Summary Statistics of Trading Strategy

Strategy	**Mean Return (%)**	**Std. Deviation**	**Annualized Sharpe**
Market unconditional:	0.056	1.14	0.78
Strategy 1 (Market):	0.063	0.97	1.03
Strategy 2 (Beta portfolios):	0.099	1.28	1.24

Panel C: FF 6-Factor Model

	Alpha	**Mkt–RF**	**SMB**	**HML**	**RMW**	**CMA**	**Mom**
Strategy 1:							
Coefficient	**0.06*****	-0.04**	5.81*	-6.05*	4.56	-0.90	-0.04*
t-stat	**(3.683)**	(-2.220)	(1.816)	(-1.832)	(1.077)	(-0.149)	(-1.733)
$R^2 = 0.005$, Adj. $R^2 = 0.003$, Obs. = 3,043							
Strategy 2:							
Coefficient	**0.10*****	0.01	4.34	-4.07	-3.17	9.21	-0.0081
t-stat	**(4.230)**	(0.649)	(1.029)	(-0.937)	(-0.569)	(1.154)	(-0.303)
$R^2 = 0.001$, Adj. $R^2 = -0.001$, Obs. = 3,043							

Table 8: Robustness: panel regressions

Panel A: In January

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	0.44	-0.50	-0.59***	0.78***	2.23	253
t-stat	(1.0354)	(-1.3126)	(-3.5087)	(4.5248)		

Panel B: Daytime returns

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	0.04	-0.05	-0.20*	0.43**	0.13	33,750
t-stat	(0.3902)	(-0.3548)	(-1.8341)	(2.4216)		

Panel C: Overnight returns

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.09	0.32*	0.06	0.06	0.28	33,750
t-stat	(-1.3863)	(1.8503)	(0.5946)	(0.2495)		

Panel D: Without LEADs

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.14	0.17	-0.26**	0.35**	0.07	24,950
t-stat	(-1.1753)	(1.5837)	(-1.9901)	(2.2118)		

Panel E: Without Macro announcements

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.08	0.12	-0.20**	0.33***	0.15	29,620
t-stat	(-0.7599)	(1.1638)	(-2.1964)	(2.8945)		

Panel F: Without LEADs + Macro announcements

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.16	0.20*	-0.36**	0.38**	0.06	21,790
t-stat	(-1.3235)	(1.7219)	(-2.5061)	(2.2073)		

Panel G: Raw news corpus (unfiltered)

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.06	0.10	-0.23**	0.31***	0.08	33,750
t-stat	(-0.5770)	(1.1010)	(-2.5467)	(2.8569)		

Panel H: Low news | Attention

	Const	β	Low news	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.16	0.24	-0.23	0.50**	0.2	33,750
t-stat	(-0.79)	(1.23)	(-1.36)	(2.07)		

Notes: Panel regressions of portfolio returns on beta, low-news states, and their interaction for various robustness checks. Day and night returns, as well as macroeconomic announcement days are obtained from Charles Martineau's website. Panels A and B use day and night returns to form beta portfolios, following Hendershott et. al (2020), and regress day and night returns against the aggregate level of idiosyncratic news. LEADs are defined as days when influential firms from the S&P500 announce earnings as in Chan and Marsh (2022), and occur almost exclusively in weeks 2, 3 and 4 of the first month of each quarter. Panel F re-runs the same analysis using the raw news corpus from TDM Studio, without GPT-4.0 filtering. Panel G runs the same regression conditional on months with high attention using the monthly measure from Chen et. al (2022), from Zhou's website. t-statistics in parentheses; standard errors clustered daily. *, **, *** denote $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

Table 9: Robustness: panel regressions with alternative low news definitions

Panel A: Rolling 8-day median						
	Const	β	Low news (8-day)	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.07	0.10	-0.12	0.28^{***}	0.18	33,750
t-stat	(-0.6659)	(1.0966)	(-1.5002)	(2.6709)		

Panel B: Rolling 12-day median						
	Const	β	Low news (12-day)	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.06	0.10	-0.29^{***}	0.46^{***}	0.23	33,750
t-stat	(-0.5877)	(1.0335)	(-3.1547)	(3.9553)		

Panel C: Rolling 16-day median						
	Const	β	Low news (16-day)	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.06	0.10	-0.21^{***}	0.41^{***}	0.23	33,750
t-stat	(-0.5877)	(1.0335)	(-2.0959)	(3.3075)		

Panel E: 15th percentile cutoff						
	Const	β	Low news (15th pct.)	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.05	0.10	-0.41^{***}	0.56^{***}	0.09	33,750
t-stat	(-0.5157)	(1.0716)	(-2.6074)	(2.9682)		

Panel F: 20th percentile cutoff						
	Const	β	Low news (20th pct.)	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.06	0.10	-0.35^{***}	0.50^{***}	0.13	33,750
t-stat	(-0.5583)	(1.0765)	(-2.9797)	(3.6237)		

Panel G: 30th percentile cutoff						
	Const	β	Low news (30th pct.)	$\beta\times$ Low news	R^2 (within)	Obs.
Coefficient	-0.07	0.10	-0.16^{**}	0.27^{***}	0.16	33,750
t-stat	(-0.6759)	(1.0805)	(-2.4269)	(3.3227)		

Notes: Panel regressions of portfolio returns on beta, low-news states, and their interaction for various cutoffs and thresholds. Panels A through D compare various rolling averages using a 25% 1-year trailing threshold. Panels E through G compare results using various thresholds while holding a 10-day rolling average constant. Coefficients with t-statistics in parentheses; standard errors clustered. *, **, *** denote $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

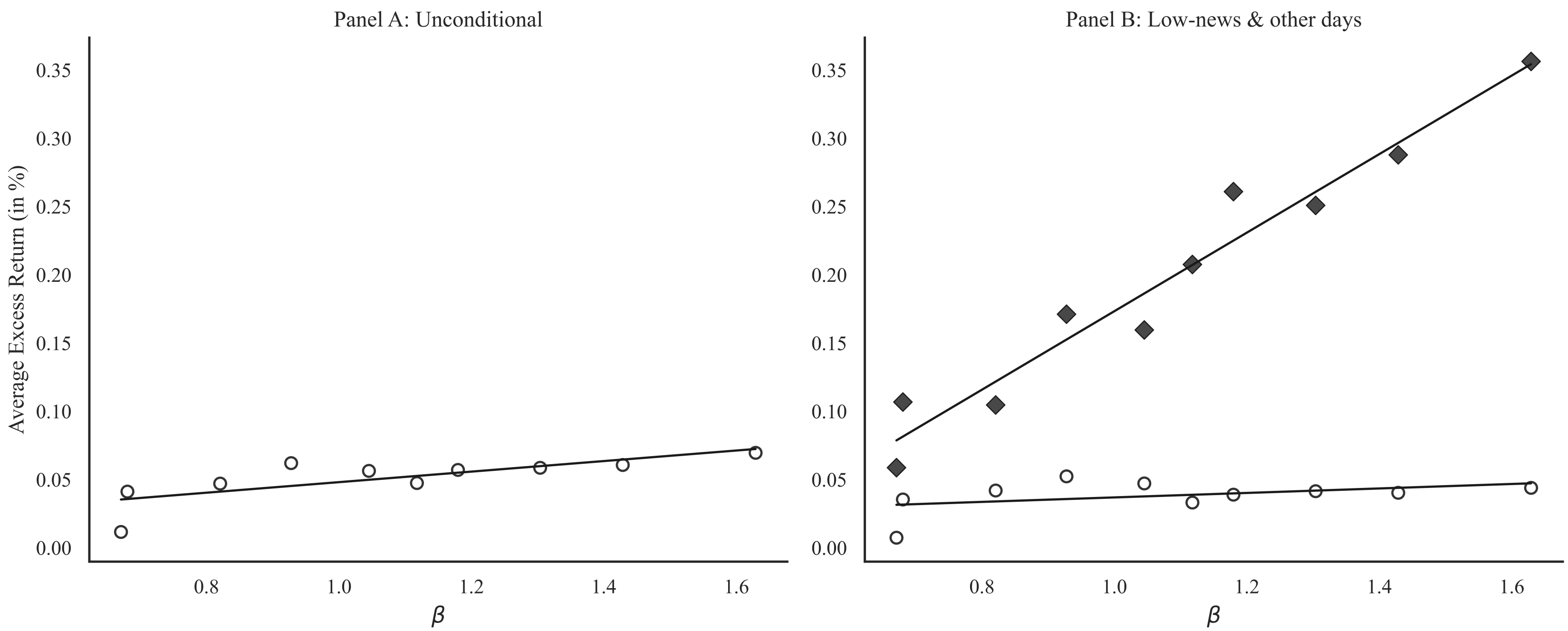


Figure 1: Average excess returns for beta decile portfolios. This figure plots the average daily excess returns (in percent) against market betas for 10 value-weighted beta-sorted portfolios. Panel A plots the unconditional SML, and panel B plots the conditional SML on low news days (with diamond markers) and on other days (circle markers). For each test portfolio in the figures, I use full-sample beta estimates for each type of day. I overlay an ordinary least squares line of best fit for each type of day. The sample covers the period from 2009 to 2024.

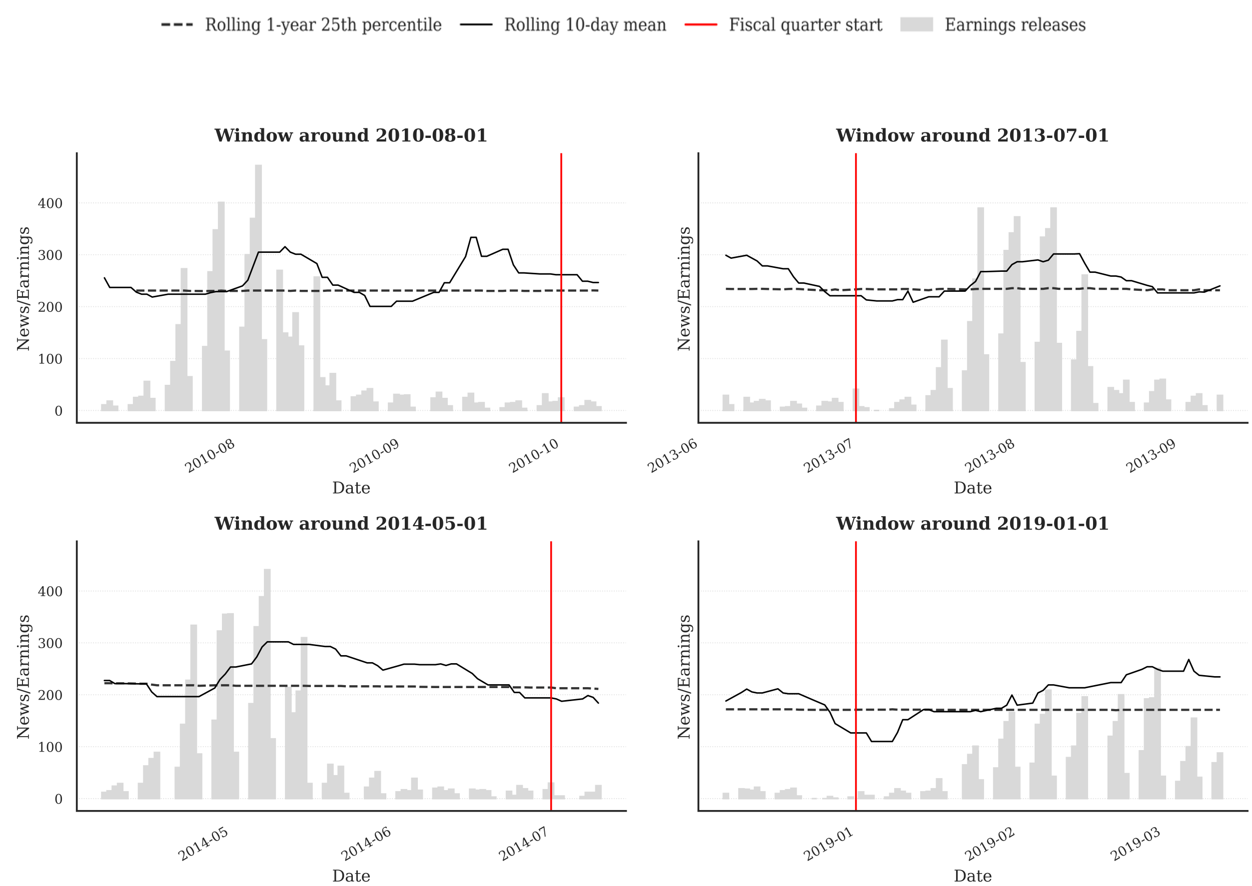


Figure 2: Each panel shows the evolution of the 10-day rolling news mean (solid black line) around the rolling 1-year 25th percentile of news (dotted black line) in a different period of the sample. The total number of earnings releases for a given day is given by grey bars. Vertical red lines denote the beginning of a new fiscal quarter. Earnings data is obtained from I/B/E/S, and news data is obtained through TDM Studio. Low news periods can occur at the beginning, middle or end of a fiscal quarter, but tend not to occur during periods where most firms are reporting earnings.

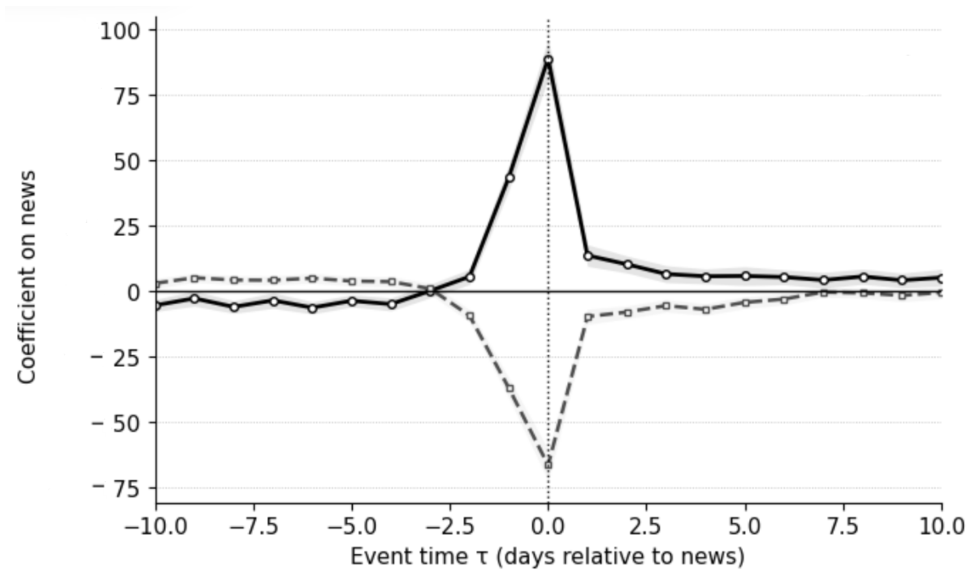
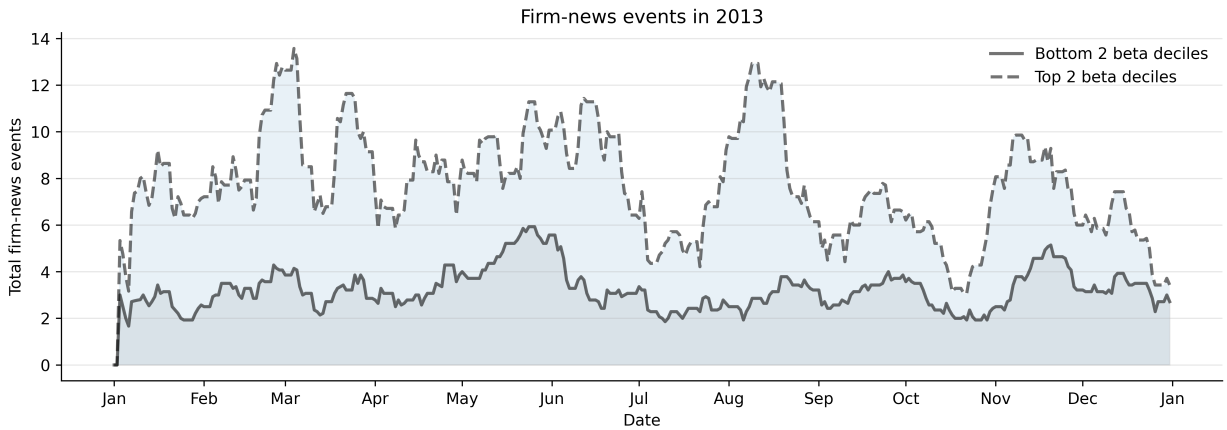


Figure 3: Event time plot of returns around news arrivals for individual firms. The x-axis plots coefficients of the panel regression of firm level returns on news-day dummy variables with their +/- 10-day lags. The y-axis plots the magnitude of the coefficients in basis points. The sample is all CRSP firms successfully matched to news, share code 10 or 11 between 2009 and 2024. The solid black line represents results conditional on positive news-day returns. The dotted black line represents results conditional on negative news-day returns. Gray bands denote 95% confidence intervals.



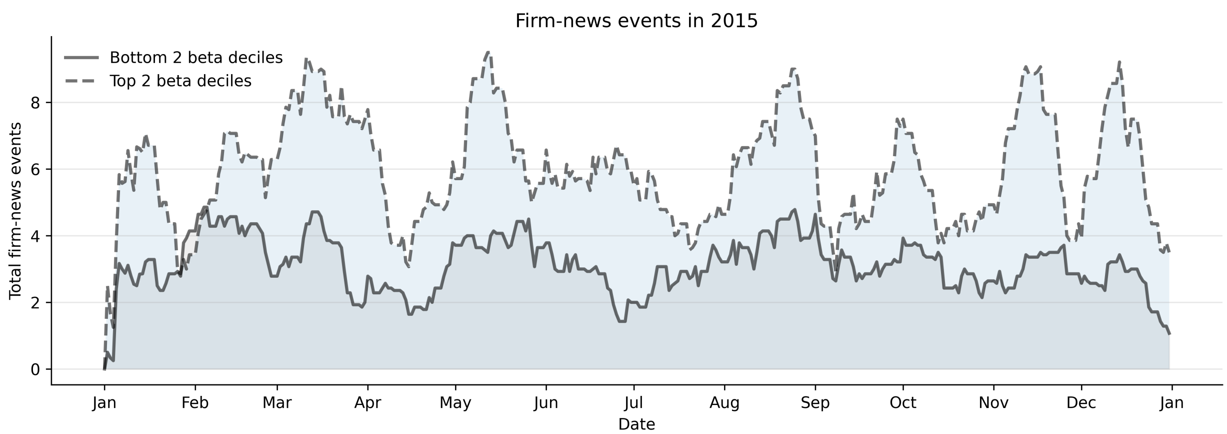


Figure 4: Distribution of negative idiosyncratic news releases, high and low beta firms for two sample years. Counts of negative firm-news events are summed across all firms daily and the 10-day rolling average is plotted for each day of the year. Negative firm-news events occur when a news item appearing in the Dow Jones Institutional Newswire coincides with a negative close-close return for a given firm. The dotted (solid) line denotes the level of news for firms in the two highest (lowest) beta-deciles on a given day. High beta firms tend to generate more news and exhibit more pronounced clustering of news over the year.

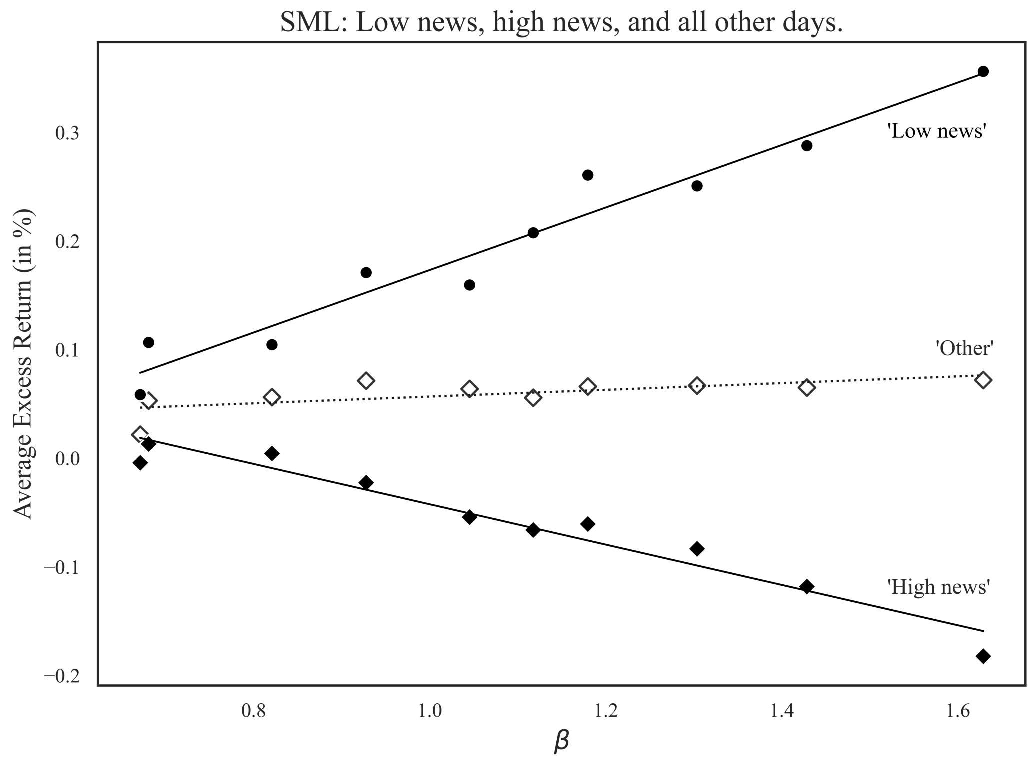


Figure 5: This figure splits the sample into three separate sets of days, and plots the average daily excess returns (in percent) against market betas for 10 value-weighted beta-sorted portfolios. The upward and downward sloping black SML lines plot the beta-return relationship on low-news and high-news days respectively. The white flat SML plots the beta-return relationship on all other days. For each test portfolio I use full-sample beta estimates for each type of day.

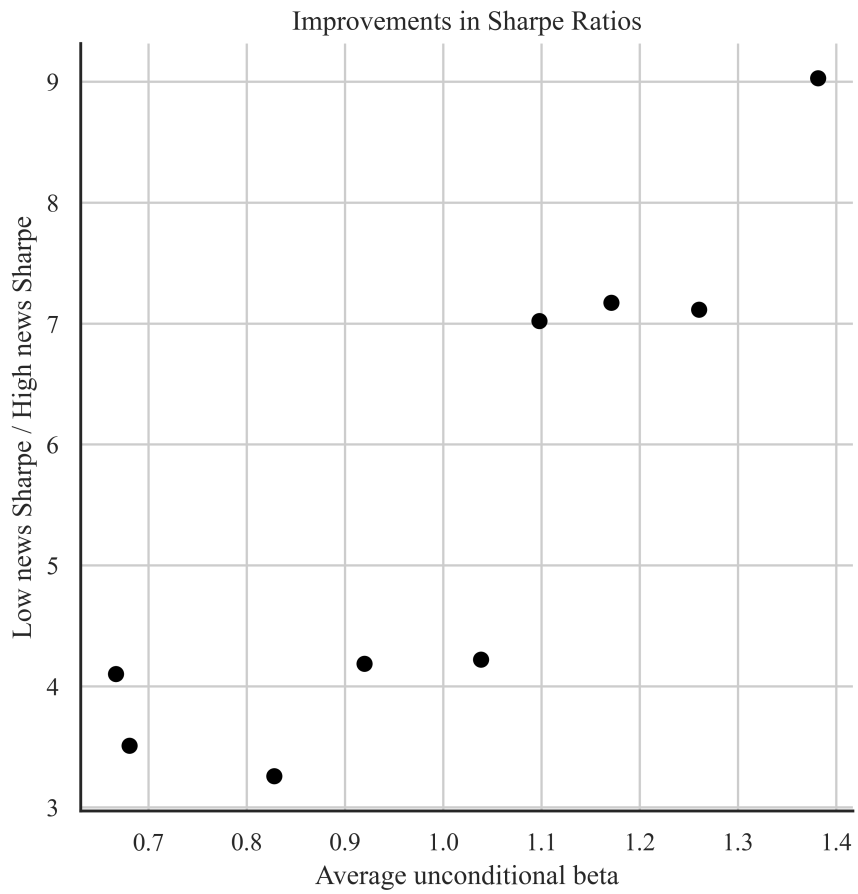


Figure 6: Improvements in Sharpe ratios as a ratio of Sharpe ratios in low news states to other states. Each dot plots the improvement in Sharpe on low-news days to other days for each beta-sorted portfolio. Ratios above one indicate higher risk-adjusted performance in low news states, with the improvement increasing in the beta of the portfolio. Low-news days are defined as those when the 10-day rolling news count is below the rolling 1-year 25th percentile.

A Appendix

Listing 1: ChatGPT prompt used to refine news corpus

```
Each historical news article you will read will contain information about a
    company, or a set of companies. Your tasks are the following:

Read the article, and determine whether the news is about a singular firm, or
    many firms Return either a keyword 'singular' or 'many'. If the article is not
     about any firms, return 'none'.

If the article is about a singular event, related to one firm, please return the
    keyword 'idiosyncratic'. Otherwise, if the article is about something that
    happened in the market, and the result simply affects the given firm, return '
    systematic'. Otherwise, if it is not clear, return 'none'.

Please apply rigorous economic reasoning and ensure your classifications are
    strictly based on evidence explicitly mentioned in the text. Before finalizing
     your answer, please reread the original body of text and identify any other
    considerations that might influence your answer.
```

Table 10: News Items: Random Sample

Date	**Title**
2012-03-15	CIT Launches New Global Integrated Advertising Campaign
2012-08-30	Lam Research Chairman To Retire, Vice Chairman To Replace Him
2017-03-13	Fluor Selected by Yara for Global Alliance Framework Agreement
2014-02-04	Seabridge Gold Reports Sale of Grassy Mountain NPI Not Proceeding
2014-05-14	Amicus Therapeutics to Present at UBS Global Healthcare Conference
2012-11-21	LSB Industries Expects Longer-Than-Anticipated Outage at Oklahoma Ammonia Plant
2016-02-29	CEO Hughes Registers 15,000 Of First Solar Inc >FSLR
2009-10-22	Morgan Stanley Smith Barney Announces Expanded Focus On Ultra Wealthy Clients
2016-02-08	Moody's Removes Provisional Status From Avago Cayman's Ratings Upon Closing Of Broadcom Acquisition
2009-04-01	ADTRAN Unveils Advanced Ethernet Capabilities For Next-Generation Mobile Backhaul Applications
2020-08-06	The Tesla Stock Debate Rages as Bears Dredge Up Old Lines of Attack – Barrons.com
2010-12-19	Anglo American Considering Oppenheimer De Beers Stake Buy-Report
2008-12-22	Treas CATTANACH Buys 62 Of PSB HOLDINGS INC (WI) >PSBQ
2013-07-31	SHAREHOLDER ALERT: Pomerantz Law Firm Investigates Claims On Behalf of Investors of General Cable Corp. – BGC
2020-02-04	Tesla's Epic Rally Echoes Past Oil, Bitcoin Bubbles
2016-04-25	Radiant Logistics Retires $25.0 Million In Subordinated Debt
2020-03-27	Student Loan Repayment Benefits Are Now Tax-free
2012-06-04	The Jones Group to Acquire Brian Atwood Designs
2020-10-30	DGAP-NVR: Diebold Nixdorf, Incorporated: Release according to Article 41 of the WpHG [the German Securities Trading Act] with the objective of Europe-wide distribution
2023-01-11	Air Lease Corporation Activity Update for the Fourth Quarter of 2022
1989-04-01	Berkshire Hathaway Inc. – Moody's Ratings Affirms General Re's Aa1 Financial Strength Ratings, Stable Outlook
2018-12-26	Holder Winder INVEST Pte Ltd Buys 120,700 Of INTL Flavors & Fragrances >IFF
2024-09-17	FOX News Digital Leads News Brands With Multiplatform Views and Minutes Throughout August
2012-02-10	Health Net Announces Annual Investor Day to Be Held in New York on February 16, 2012
2012-04-03	Dr. Abraham Verghese and Rosedale Infectious Diseases Honored with athenahealth Vision Awards
2022-07-08	GALIANO GOLD PROVIDES METALLURGICAL AND OPERATIONAL UPDATE AT ASANKO GOLD MINE
2011-12-06	U.S. Navy, Northrop Grumman Demonstrate First Manned-Unmanned Intel Sharing
2014-08-18	Orion Marine Group Appoints James L. Rose as Chief Operating Officer
2018-08-06	Capital Southwest Announces Financial Results for First Fiscal Quarter Ended June 30, 2018
2014-09-24	Holder DENTINO WILLIAM Registers 57,624 Of MOLINA HEALTHCARE >MOH
2012-05-07	Cleveland BioLabs Announces Annual Meeting and Investor Day on June 13
2012-02-28	Bristol-Myers Squibb to Present at Cowen and Company Health Care Conference
2009-07-01	Platinum Equity Acquires GEESINKNORBA from Oshkosh Corporation
2015-06-18	Analog Devices Welcomes Bruce Evans to Board of Directors
2018-10-31	Allstate Delivers Growth and Attractive Returns
2012-03-30	Chmn HOWLEY Registers 33,000 Of TRANSDIGM GROUP INC >TDG
2017-11-01	Argentine Court Rejects Attempt to Enforce Fraudulent Ecuadorian Judgment Against Chevron
2020-06-18	Target Is Raising Wages. Here's What It Means for Other Retailers. – Barrons.com
2012-05-16	Tenneco Announces Results of 2012 Annual Meeting
2023-10-31	Tyler Technologies Acquires AI Company ARInspect
2018-11-29	Officer/Dir Pieczynski Buys 10,000 Of PacWest Bancorp >PACW
2008-10-28	Lithia Motors Announces Third Quarter 2008 Results
2020-01-23	Xerox Launches Proxy Fight for HP and Nominates Full 11-Director Slate – Barrons.com
2012-05-01	Suncor Energy shareholders approve all resolutions at Annual General Meeting
2014-12-04	Dir GEORGE Registers 29,327 Of LIBERTY INTERACTIVE CORP >LVNTA
2023-03-07	W&T Offshore Announces Fourth Quarter and Full Year 2022 Results Including Year-End 2022 Proved Reserves; Provides Guidance for 2023
2009-11-09	Fitch: CH Energy Group's Partial Sale of Griffith A Credit Positive
2012-10-31	Seattle Genetics Announces ADCETRIS(R) Receives European Commission Conditional Marketing Authorization
2011-08-13	Winn-Dixie Issues Voluntary Recall on Certain Ground Beef Products Due to National Beef Packing Co. Recall
2012-01-24	Holder OSMIUM CAPITAL LP Buys 54,000 Of SPARK NETWORKS INC >LOV
	Dir Granadillo Registers 11,758 Of Haemonetics Corporation >HAE