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. When idiosyncratic news is widespread, the beta–return relation weakens and the Security Market Line flattens. To explain this pattern, I develop a simple model in which firm-specific news creates return variation not captured by the CAPM and can distort the cross-sectional relation between beta and returns when those news-day effects are unevenly distributed across stocks. Consistent with this mechanism, CAPM residual variance rises with aggregate news intensity, and the beta-return relationship is decreasing in the level of news. I provide evidence consistent with two channels: news partially corrects mispricing in anomaly-exposed firms, and managers cluster adverse disclosures when aggregate news flow is already elevated. Hybrid "betting-against-beta" trading strategies exploiting these periods earn high returns. I conclude that waves of high aggregate idiosyncratic news obscure the performance of the CAPM at the firm level and significantly influence asset pricing.

1 Introduction

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) predicts that an asset's risk premium is positively related to its market beta. Despite the model's central role in both academic research and practitioner decision-making (Berk and van Binsbergen, 2017), this prediction has long failed in unconditional tests of the cross section of returns (Black, Jensen, and Scholes, 1972). Recent work offers conditional resolutions to this longstanding puzzle by conditioning CAPM tests on information events and other economically salient states.[1] The information-based strand of this literature has focused primarily on news that conveys systematic information: announcements that increase comovement and sharpen the common component in cash flows or discount rates. This paper studies the opposite information environment. I introduce the prevalence of idiosyncratic news in the cross section as a new state variable, and show that the CAPM prices risk most strongly when the supply of idiosyncratic information is low.

Why might the supply of idiosyncratic news matter for the unconditional CAPM? Patton and Verardo (2012) show that firms' market betas rise around scheduled announcements, especially when the news contains information relevant for valuing other firms in the cross section, while Chan and Marsh (2022) and Andrei, Friedman, and Ozel (2023) show that the CAPM performs well in these settings. A less explored implication is that the CAPM should also perform well in the opposite information state. When genuinely firm-specific information flow is quiet, that is, when news does not simultaneously reveal information about common shocks across firms, the cross section should be less affected by idiosyncratic shocks and beta should be a more reliable measure of systematic risk. The main empirical finding of this paper is consistent with that prediction: the beta–return relation is strongest when the aggregate supply of such idiosyncratic information is low and weakens when it is high.

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. I then sort stocks into one of ten beta-decile value-weighted portfolios, and regress value-weighted excess returns on the excess market return to obtain portfolio betas. The sample period is daily from 2009-2025

[1] See Tinic and West (1984), Savor and Wilson (2014), Savor and Wilson (2016), Hong and Sraer (2016), Jylhä (2018), Hendershott, Livdan, and Rösch (2020), Chan and Marsh (2022), Andrei, Friedman, and Ozel (2023), and Hasler and Martineau (2023, 2024), among others.

and contains 7919 unique firms. Panel A of Figure 1 plots average realized excess returns for each portfolio against full-sample portfolio betas for all days in the sample. The line is mostly flat, suggesting that market betas do not explain average excess returns.

Panel B shows the Security Market Line (SML) separately for low news days (with triangle markers) and other days (with circle markers). Low-news days occur when the median number of idiosyncratic news items in the Dow Jones Institutional Newswire (DJIN) over the previous 10 trading days 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 flat slope, implying that an increase in market beta is not associated with an increase in average daily excess returns (a finding that is inconsistent with the CAPM).

I explore several explanations that could account for the results in Figure 1. The first possibility 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 returns at the firm level, periods with elevated idiosyncratic news may distort the security market line. I provide both theoretical and empirical support for this claim.

I develop a simple model in which the realized slope of the Security Market Line decomposes into three parts: the unconditional risk premium, a common factor surprise, and a news-driven component equal to the cross-sectional covariance between news-day return impacts and market beta, scaled by the cross-sectional variance of beta. This news-driven component is active whenever firm-specific news generates firm-specific return variation, and it tilts the security market line when those news-day return innovations are systematically related to beta. Consistent with this prediction, CAPM residual variance rises monotonically from low to high-news states within every beta decile, increasing from 6.64 to 10.41 in the lowest decile and from 10.74 to 17.14 in the highest. This pattern indicates that firm-specific news adds economically important return variation beyond the CAPM, especially when aggregate news intensity is high.

I then study two mechanisms that can generate a negative cross-sectional relationship between beta and CAPM-unexplained news-day returns. The first is biased beliefs, in which news partially corrects accumulated mispricing in anomaly-exposed firms that are unevenly distributed across the beta spectrum (Engelberg, McLean, and Pontiff, 2018). The second is strategic disclosure, in which managers cluster adverse releases when aggregate news flow is already elevated (Acharya, DeMarzo, and Kremer, 2011). Both mechanisms imply a flatter SML when aggregate news intensity is high, and both receive empirical support. The key question is therefore what makes news-day return impacts more negative for high-beta firms than for low-beta firms. I first consider biased beliefs, and then strategic disclosure, as two candidate explanations.

I begin with the biased-beliefs mechanism. I classify each stock by its net exposure to a standard set of return anomalies. In the data, firms on the long leg (underpriced by these signals, hereafter "anomaly-long") cluster among low-beta stocks, while firms on the short leg (overpriced, "anomaly-short") cluster among high-beta stocks over the sample period. This composition matters because, as Engelberg, McLean, and Pontiff (2018) show, news arrivals tend to raise returns for anomaly-long firms and lower returns for anomaly-short firms. I find the same asymmetry in my sample. Within each beta decile, news days increase returns for anomaly-long firms by between 9 and 64 basis points, while reducing returns for anomaly-short firms by as much as 34 basis points. Consistent with mispricing, for anomaly-long firms the correction grows linearly with the time since the previous announcement; on the short side, the response appears instead as a fixed level shift, consistent with short-sale frictions. Because anomaly-short firms are concentrated among high-beta stocks, these news-day corrections are disproportionately negative in the high-beta part of the cross section, suggesting a downward tilt of the realized SML when firm-specific news is widespread.

A second explanation comes from strategic disclosure. Following Acharya, DeMarzo, and Kremer (2011), managers may have incentives to cluster adverse disclosures when aggregate news flow is already elevated, creating periods in which firm-specific news distorts the cross-sectional pricing of beta. Consistent with this mechanism, higher-beta firms react more negatively to firm-specific news than lower-beta firms, and this pattern is concentrated in high-news states. In the full sample, a one-unit increase in beta is associated with news-day excess returns that are about 7 basis points lower ($t = -2.02$). In high-news states, the same increase in beta is associated with returns that are roughly 32 basis points lower ($t = -2.40$). In low-news states, by contrast, the coefficient turns positive and is statistically indistinguishable from zero at about 4 basis points ($t = 0.47$). To probe the mechanism further, I construct a measure of the relative concentration of negative idiosyncratic news in low versus high-beta firms. The SML is substantially steeper on days when this ratio exceeds unity, implying a stronger beta–return relation when negative news is less concentrated in high-beta firms. Moreover, variation in this ratio is driven mainly by the high-beta side of the cross section. High-beta firms have a significantly lower concentration of negative news during low-news periods ($t = -3.17$), whereas the corresponding difference for low-beta firms is not statistically significant ($t = -0.78$). Taken together, these results are consistent with the view that adverse firm-specific news is more concentrated in high-beta stocks when aggregate idiosyncratic news is elevated, contributing to a flatter SML in those periods.

I also discuss an alternative attention based mechanism that may explain the results. Peng and Xiong (2006) argue investors exhibit category-learning behavior, and suggests that investors choose between processing market-wide and 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 focus to idiosyncratic information at some times more 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.

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 28% average return (alpha of 7 basis points per day) 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.

This paper builds on a growing literature which identifies particular states where the CAPM performs well. Tinic and West (1984) show that the beta-return relation is concentrated in January, while Hendershott, Livdan, and Rösch (2020) find an upward-sloping security market line overnight but not during the trading day. Hasler and Martineau (2023) further show that the CAPM performs better in periods of low volatility. Andrei, Friedman, and Ozel (2023) find that heightened uncertainty and investor attention improve the beta-return relation. My results are related to, but distinct from, these findings. The CAPM continues to perform well on low-idiosyncratic-news days even when the sample is restricted to January, and success of the CAPM in January is conditional on low-news days. The low-news CAPM performance further persists when returns are confined to the daytime. Hasler and Martineau (2023) show that the unconditional CAPM fails because conditional betas covary with aggregate market moments so that the CAPM performs better in periods of low volatility and low uncertainty. I provide a complementary but distinct perspective: even holding market volatility fixed, the CAPM performs differently depending on the cross-sectional distribution of firm-specific information. In my sample, the beta–return relation associated with low idiosyncratic news survives controls for market volatility and VIX-tercile stratification.

Another set of papers emphasizes economic mechanisms that condition when beta prices risk. Hong and Sraer (2016) argue that disagreement and short-sales constraints flatten the security market line, so that lower disagreement steepens the beta-return relation. Hasler and Martineau (2024) show that the CAPM performs better when the expected market return is high, and Hasler and Martineau (2023) show more broadly how conditional success can coexist with unconditional failure. I provide a different perspective on the source of this state dependence. Low-idiosyncratic-news days strengthen the CAPM even within high and low-expected-market-return states, suggesting that variation in the supply of firm-specific news captures an additional dimension of the information environment that is not subsumed by disagreement or the expected market return.

Because public news arrivals can raise volatility both overnight and during the day (Boudoukh et al., 2019), the low-news state I identify is consistent with, but not reducible to, a volatility-based account of CAPM success. Boudoukh et al. (2019) show that firm-specific news accounts for roughly half of overnight idiosyncratic variance and a meaningful share of intraday variance, validating the premise that newswire text contains price-relevant information at the firm level. I take this finding as the foundation for an aggregate state variable and ask a different question: how does the prevalence of firm-specific news in the cross section affect the pricing of beta? Liu, Stambaugh, and Yuan (2018) provide a complementary static answer. They show that the beta anomaly arises from beta's positive cross-sectional correlation with idiosyncratic volatility, combined with a negative alpha–IVOL relation among overpriced stocks that reflects arbitrage asymmetry. In their setting, the SML flattens whenever overpriced, high-IVOL firms cluster at high beta. My mechanism shares this compositional logic but operates dynamically: the cross-sectional association between beta and anomaly exposure is activated by firm-specific news arrivals, which partially resolve accumulated mispricing and tilt the realized SML downward on high-news days. Consistent with this separation, the beta–return relation associated with idiosyncratic news survives controls for aggregate attention, market volatility, and the standard state variables studied in this literature. The economic magnitude is also meaningful, and monotonic rather than a feature of the discrete classification. Using a standardized continuous measure of idiosyncratic news, a one-standard-deviation increase in news intensity lowers the beta–return slope by about 6 basis points in the baseline specification, and by roughly 10 to 14 basis points after controlling for disagreement, the VIX, and aggregate attention.

2 Theoretical Motivation

I develop a reduced-form model of how idiosyncratic news affects the cross-sectional pricing of beta. The framework has two parts. Part 1 is mechanism-agnostic: it decomposes the realized Fama–MacBeth slope into a risk premium, a factor surprise, and a residual wedge, and shows that the wedge channel is active whenever firm-specific news generates firm-specific return variation. Part 2 considers candidate mechanisms that sign the wedge negatively, delivering the prediction that the realized SML flattens on high-news days.

2.1 Return Structure

There are N firms indexed by i. The excess return of firm i on date t satisfies

$$r_{i,t} = \beta_i \mu_\lambda + \beta_i \tilde{f}_t + x_{i,t}, \tag{1}$$

where $\mu_\lambda > 0$ is the unconditional risk premium per unit of beta; $\tilde{f}_t$ is a mean-zero common factor surprise with variance σ_f^2; $\beta_i > 0$ is firm i's systematic risk exposure; and $x_{i,t}$ is the non-systematic component of returns. The non-systematic component has two parts:

$$x_{i,t} = \delta_{i,t}\, g_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $\delta_{i,t} \in \{0,1\}$ indicates whether firm i receives firm-specific news on date t; $g_{i,t}$ is the news-day return impact with $\mathrm{Var}(g_{i,t} \mid \delta_{i,t} = 1) = \sigma^2_{g,i,t} > 0$; and $\varepsilon_{i,t}$ is pure idiosyncratic noise with variance σ_ε^2, independent of all other variables. The aggregate news state is $N_t = \frac{1}{N}\sum_i \delta_{i,t}$. Part 1 makes no assumption about $\mathbb{E}[g_{i,t}]$.

Proposition 1 (SML decomposition) *The Fama–MacBeth cross-sectional slope is*

$$\lambda_t^{FM} = \frac{\mathrm{Cov}_i(\beta_i, r_{i,t})}{\mathrm{Var}_i(\beta_i)}.$$

It satisfies

$$\lambda_t^{FM} = \mu_\lambda + \tilde{f}_t + w_t, \qquad w_t = \frac{\mathrm{Cov}_i(\beta_i, \delta_{i,t} g_{i,t})}{\mathrm{Var}_i(\beta_i)}. \tag{3}$$

Proof in Appendix A.1. The decomposition is an algebraic identity. Because μ_λ is constant and $\tilde{f}_t$ is independent of N_t, the wedge w_t is the only channel through which news intensity can affect the expected SML slope. The decomposition relies on the identifying assumption that the factor surprise $\tilde{f}_t$ is mean-independent of the news state, $\mathbb{E}[\tilde{f}_t \mid N_t] = 0$; Appendix A.5 discusses this assumption and its empirical support in detail.

Two limiting cases follow immediately. When the wedge is inactive, either because few firms receive news or because news-day return impacts are cross-sectionally independent of β_i, the expected slope equals the unconditional risk premium: $\mathbb{E}[\lambda_t^{FM}] = \mu_\lambda > 0$, and the SML slopes upward as the CAPM predicts. When the wedge is active and negative, the expected slope falls below μ_λ and the SML flattens or inverts. Signing the wedge requires assumptions about $\mathbb{E}[g_{i,t}]$, which Part 2 provides.

For the wedge to vary with N_t, the components $\delta_{i,t} g_{i,t}$ must be active at the firm level.

Corollary 1 (Residual variance) *Let $\varepsilon_{i,t}^{\mathrm{OLS}}$ denote the CAPM residual. In the large-N limit,*

$$\mathrm{Var}\big(\varepsilon_{i,t}^{\mathrm{OLS}} \,\big|\, \delta_{i,t}\big) = \delta_{i,t}\,\sigma_{g,i,t}^2 + \sigma_\varepsilon^2 + o(1), \tag{4}$$

and $\mathbb{E}[\mathrm{Var}(\varepsilon_{i,t}^{\mathrm{OLS}}) \mid N_t]$ is non-decreasing in N_t.

Proof in Appendix A.2. The prediction depends only on $\sigma_{g,i,t}^2 > 0$ and does not require any assumption about the sign or economic content of $g_{i,t}$. If Corollary 1 fails empirically, then $\delta_{i,t} g_{i,t}$ is not an active return component and the wedge channel is vacuous, regardless of any Part 2 mechanism. The prediction is also unconfounded by factor variance: because the CAPM residual removes $\beta_i \tilde{f}_t$ by construction, variation in σ_f^2 across news states does not enter (4).

The decomposition in Proposition 1 shows that the CAPM residual absorbs any firm-specific news-day return component that covaries with beta, making the expected Fama–MacBeth slope non-zero in the presence of idiosyncratic news arrivals. The next section develops candidate mechanisms that can sign the wedge, each of which delivers SML flattening under a small set of additional assumptions.

2.2 Mispricing and Biased Beliefs

Following Engelberg, McLean, and Pontiff (2018), suppose that investors systematically misestimate the cash-flow dynamics of anomaly-exposed firms[2]: the cash flows of anomaly-long firms have a positive unconditional drift that investors mistakenly perceive as zero, while the cash flows of anomaly-short firms have a negative drift that is similarly mispriced. Between news events, these

[2]The mechanism follows a long literature in which investors hold biased beliefs about firm fundamentals that accumulate in the absence of correcting information and revise discontinuously when news arrives (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Bordalo, Gennaioli, and Shleifer, 2018; Bordalo, Gennaioli, La Porta, and Shleifer, 2019).

cash-flow errors accumulate: investors' beliefs drift away from fundamentals at a firm-specific rate determined by the firm's anomaly exposure. When news arrives and reveals the accumulated cash position, prices adjust to the true accumulated value, delivering a correction whose magnitude scales with the time elapsed since the last news release. Formally, let a_i denote firm i's signed anomaly exposure ($a_i > 0$ for anomaly-long firms, $a_i < 0$ for anomaly-short firms), and let $\tau_i(t)$ denote the number of periods since firm i's previous news release. Under this structure, the conditional mean and variance of the news-day return impact satisfy

$$\mathbb{E}[g_{i,t} \mid \delta_{i,t} = 1] = \tau_i(t)\, \kappa\, a_i, \qquad \mathrm{Var}(g_{i,t} \mid \delta_{i,t} = 1) = \tau_i(t)\, \sigma_g^2, \tag{5}$$

where $\kappa > 0$ parameterizes the per-period magnitude of the cash-flow mispricing.[3] Anomaly-long firms experience positive expected news-day returns proportional to $\tau_i(t)$; anomaly-short firms experience negative expected news-day returns of equal magnitude but opposite sign. The variance scaling yields a refinement of Corollary 1: residual variance should rise not only with aggregate news intensity N_t, but also with time since the firm's last announcement.

The biased-beliefs mechanism is most defensible for scheduled announcements, where disclosure timing is predetermined. I formalize this with a timing assumption that rules out strategic disclosure for the purposes of Part 2.

Assumption 1 (Announcement Timing) *Conditional on date-t information and the announcement lag $\tau_i(t)$, the indicator $\delta_{i,t+1}$ is independent of β_i, a_i, $g_{i,t+1}$, $\varepsilon_{i,t+1}$, and $\tilde{f}_{t+1}$.*

Under Assumption 1, the conditional expected slope takes a clean form.

Proposition 2 (Conditional SML, biased beliefs) *Let $\mathcal{A}_{t+1} = \{i : \delta_{i,t+1} = 1\}$ denote the announcing set. Under Assumption 1 and the biased-beliefs parameterization (5),*

$$\mathbb{E}_t[\lambda_{t+1}^{FM} \mid \mathcal{A}_{t+1}] = \mu_\lambda + \frac{\kappa}{N \cdot \mathrm{Var}_i(\beta_i)} \sum_{i \in \mathcal{A}_{t+1}} (\beta_i - \bar{\beta})\, \tau_i(t)\, a_i. \tag{6}$$

[3] The linear scaling of both the mean and variance in $\tau_i(t)$ is the closed-form implication of accumulating independent period-level cash-flow shocks between announcements, mirroring the setup of Engelberg, McLean, and Pontiff (2018). The no-updating-between-announcements assumption connects to a broader literature on persistent biased beliefs: sticky beliefs (Mankiw and Reis, 2002), diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2018), and attribution of forecast errors to noise (Rabin and Vayanos, 2010). and is consistent with the post-publication persistence of anomaly returns documented by McLean and Pontiff (2016).

Proof in Appendix A.3. Proposition 2 conditions on the exact composition of the announcing set $\mathcal{A}_{t+1}$. Because the empirical analysis conditions on the aggregate news state N_{t+1} rather than on individual announcers, the following scalar approximation is more directly testable.

Corollary 2 (Approximate scalar form) *Under Assumption 1, when the announcing set is large and its composition across lag groups is representative of the population,*

$$\mathbb{E}_t[\lambda^{FM}_{t+1} \mid N_{t+1}] \;\approx\; \mu_\lambda + \kappa\, N_{t+1}\, \frac{\mathrm{Cov}_i(\beta_i,\ \tau_i(t)\, a_i)}{\mathrm{Var}_i(\beta_i)}. \tag{7}$$

Proof in Appendix A.4. Corollary 2 delivers the prediction in a form that maps directly onto the empirical tests. In low-news states (N_{t+1} small), the wedge is close to zero and the expected SML slopes upward at the unconditional risk premium μ_λ. In high-news states, if announcing firms are predominantly anomaly-short at high beta and anomaly-long at low beta — so that $\mathrm{Cov}_i(\beta_i,\ \tau_i(t)\, a_i) < 0$ — the expected slope falls below μ_λ and the SML flattens. The magnitude of the flattening is increasing in κ, in N_{t+1}, and in the absolute value of the covariance.

The biased-beliefs mechanism rests on a compositional condition about the cross section such that on average anomaly-short firms are concentrated at high betas and anomaly-long firms at low betas, so that $\mathrm{Cov}_i(\beta_i,\ a_i) < 0$, which is an input to the model rather than a prediction of it. The condition is empirically verifiable in the cross section of firm characteristics, and the remainder of the biased-beliefs results depend on it. Given this condition, the mechanism generates three predictions that the empirical sections test directly. First, directional corrections: within each beta decile, news arrivals should raise returns for anomaly-long firms ($a_i > 0$) and lower returns for anomaly-short firms ($a_i < 0$). Second, time-scaling: the magnitude of the news-day correction should grow linearly with $\tau_i(t)$, the time since the firm's previous news release, reflecting the accumulation of mispricing between announcements. Third, news-state dependence: the negative covariance between beta and news-day returns should be strongest when aggregate news intensity is elevated and attenuate in low-news periods, as implied by the N_{t+1} scaling of Corollary 2. These three predictions are specific to the biased-beliefs channel and require corrections to have a signed mean systematically related to beta through anomaly exposure; the variance prediction of Corollary 1, by contrast, holds for any source of firm-specific news.

2.3 Strategic disclosure

A second mechanism can generate the same downward pressure on the SML without relying on mispricing corrections. Following Acharya, DeMarzo, and Kremer (2011) and Kothari, Shu, and Wysocki (2009), managers may strategically time adverse disclosures to coincide with periods of heavy aggregate news flow, using widespread information arrivals as cover. If this behavior is more common among high-beta firms, for example, because such firms tend to be smaller and receive weaker analyst and media coverage (Fang and Peress, 2009), then negative news-day returns will become disproportionately concentrated among high-beta stocks when aggregate news is elevated. In that case, the cross-sectional relation between beta and news-day return impacts becomes negative in high-news states and close to zero in low-news states. This is exactly the firm-level pattern needed for Proposition 1 to imply a flatter realized SML. The qualitative prediction is therefore the same as under biased beliefs: in low-news periods, the expected slope remains close to μ_λ, while in high-news periods it tilts downward. The two mechanisms are not mutually exclusive. Both operate through the same firm-level channel of negative news-day return effects that are more concentrated among high-beta firms. Both can contribute to SML flattening when aggregate idiosyncratic news is high. Section 4.3 presents evidence consistent with the strategic-disclosure channel, although the paper does not separately identify its contribution from that of biased beliefs.

2.4 Relation to the Flat-SML Literature

The decomposition $\lambda_t^{FM} = \mu_\lambda + \tilde{f}_t + w_t$ connects to a long literature on why the empirical security market line is flatter than the CAPM predicts. The wedge $w_t = \mathrm{Cov}_i(\beta_i,\, \delta_{i,t} g_{i,t}) / \mathrm{Var}_i(\beta_i)$ is an algebraic property of the cross-sectional OLS projection, recognized at least since Black, Jensen, and Scholes (1972). Existing explanations treat this wedge as an unconditional or slowly-varying object: leverage constraints (Frazzini and Pedersen, 2014), disagreement with short-sale constraints (Hong and Sraer, 2016), the beta–idiosyncratic-volatility correlation (Liu, Stambaugh, and Yuan, 2018), errors-in-variables attenuation (Shanken, 1992), market proxy misspecification (Roll, 1977; Kandel and Stambaugh, 1995), and dispersed information (Andrei, Cujean, and Wilson, 2023). The contribution of this paper is to show that the wedge varies at a daily frequency with the aggregate intensity of firm-specific news, and to provide mechanisms. The interaction of news-activated corrections of anomaly-related mispricing, or the strategic clustering of adverse disclosures, with the cross-sectional distribution of the relevant firm characteristic across beta offer potential channels that explain this high-frequency variation. The unconditionally flat SML documented in the prior literature emerges in this framework as a time average across days of different news intensities: on low-news days the wedge is approximately zero and the SML reflects the risk premium, while on high-news days the wedge is negative and the SML flattens.

3 Data

3.1 News data

As opposed to Savor and Wilson (2014), Chan and Marsh (2022) and Andrei, Friedman, and Ozel (2023) 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. I then perform a search through the DJIN for articles whose title contains at least one unique CRSP company name. 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 2025. 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'. To define low news periods and construct an aggregate measure meant to capture low-news periods, I limit the stocks to those with share code 10 or 11 to best match the CRSP filters, leaving me with 2091 unique firms. For firm-level news-day regressions, I use the whole sample of 2880 stocks. The final GPT-labelled news corpus consists of 917,752 news articles. Table 14 in the appendix displays a random sample of article headlines from the finished news corpus.

3.2 Defining low news periods

Using my GPT-filtered news corpus, I take the sum of all idiosyncratic news items for all firms with share code 10 or 11, each day, and create a daily time series. I define low news periods as days when the rolling 10-day median 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:

$$\text{LowNews}_t = \mathbf{1}\{\, N_t \leq \mathcal{H}_t \,\} \tag{8}$$

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 median 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 median and 25th percentile to define 'low news' periods is chosen for simplicity. Section 7 considers results with alternative percentiles and rolling windows.

3.3 Stock return data

I retrieve excess market returns from Kenneth French's website. Following (Black, Jensen, and Scholes, 1972) among others, I construct ten beta monthly-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 1 provides summary statistics for the stocks that form these test assets. In section 4, I also consider individual stocks.

4 Empirical Analysis

In this section, I conduct empirical tests of the theoretical predictions from the model regarding the effect of aggregate idiosyncratic news on the cross-sectional pricing of beta, the CAPM-implied idiosyncratic variance of individual firm returns, and the distribution of news-day corrections across anomaly-exposed firms. In my first set of tests, I document a strong and significant daily beta-return relationship in low news states. Then I examine how CAPM idiosyncratic variance varies with the aggregate news state, providing a direct test of the wedge channel identified in the theoretical return decomposition of (1). I then examine the conditions under which biased beliefs about anomaly-exposed firms sign the wedge negatively, documenting the asymmetric distribution of anomaly exposure across beta deciles and the corresponding asymmetry in news-day return patterns. The sections that follow examine strategic disclosure and attention reallocation as alternative mechanisms through which the wedge channel may operate.

4.1 Documenting CAPM success 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 full-sample market betas over the 2009-2025 sample period. Following Savor and Wilson (2014) and Hendershott, Livdan, and Rösch (2020), I use unconditional full sample betas with excess returns averaged over the respective sample periods 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. The figure uses full-sample portfolio betas and state-specific average returns, while the econometrics for tables in the next portion of this section use rolling estimated betas in panel and Fama–MacBeth specifications. The magnitudes therefore need not coincide exactly, although they imply the same qualitative pattern.

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:

$$r_{i,t+1} = \alpha + b_1\,\beta_{i,t} + b_2\,\mathbf{1}\{LowNews_{t+1}\} + b_3\,\beta_{i,t}\,\mathbf{1}\{LowNews_{t+1}\} + \varepsilon_{i,t+1}. \tag{9}$$

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 (8), 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 2 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 -0.05 and 0.09 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 32 basis points with a t-statistic of 3.11. 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 = -2.27), 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:

$$r^L_{i,t+1} = a^L + b^L_{\text{MKT}}\,\beta^{\text{MKT}}_{i,t} + \varepsilon^L_{i,t+1} \tag{10}$$

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:

$$r^O_{i,t+1} = a^O + b^O_{\text{MKT}}\,\beta^{\text{MKT}}_{i,t} + \varepsilon^O_{i,t+1} \tag{11}$$

Panel B of Table 2 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 2.43 - 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 -0.61 basis points and a t-statistic of -0.83. 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 23 basis points. In contrast, Fama-MacBeth regressions run on other days paint a different picture. The b^O coefficient is 0.6 basis points, with a t-statistic of 0.17, 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.

Figure 3 provides a time-series counterpart to these cross-sectional results by plotting the aggregate idiosyncratic-news series against the Fama-MacBeth estimate of the daily market risk premium, with both series smoothed using six-month rolling averages and standardized for comparability. The figure shows that periods of elevated idiosyncratic news tend to coincide with lower estimated beta premia, whereas periods of subdued news are associated with a steeper security market line. This pattern is consistent with the model's central prediction that when firm-specific news is abundant, beta becomes a less informative measure of systematic risk and the cross-sectional estimated price of beta risk falls. Importantly, this relation is not limited to a discrete comparison between low-news and other days. In pooled regressions using a continuous version of the news variable presented in Table 10, the interaction between news and beta is negative, implying that the slope of the security market line declines smoothly as aggregate idiosyncratic news rises. The figure therefore complements the regression evidence by showing that higher levels of idiosyncratic news are associated with a flatter security market line over time.

4.1.1 Individual stocks

The portfolio results above establish that the security market line becomes sharply upward sloping on low-news days, while remaining essentially flat on other days. To assess whether this pattern is purely a consequence of aggregation through averaging away idiosyncratic noise within portfolios, I replicate the analysis at the individual-stock level using pre-sort market betas. I retain all CRSP common stocks used in the portfolio tests, subject to standard filters. Following convention, I exclude stock-days with returns exceeding 200% in absolute value, and firms below the 20th percentile of market capitalization based on NYSE size breakpoints from Kenneth French's website. Finally, I match Compustat's data records (required to compute the stock's book-to-market ratio) with stock data retrieved from CRSP. I end up with 3784 stocks.

I estimate daily cross-sectional (Fama–MacBeth) regressions separately on low-news days and on all other days, analogous to equations (10)–(11), and report Newey–West t-statistics based on the time-series of daily coefficients. I also report pooled panel specifications with standard errors clustered by day, consistent with the pooled portfolio regression in equation (9). Panel B shows that the state dependence visible in the portfolio sorts is also present in the stock-level cross section, albeit with substantially more noise. On low-news days, the Fama–MacBeth slope on β is positive and statistically significant: a one-unit increase in beta is associated with an increase in next-day excess returns of about 0.153 percentage points (15.3 bps) with a t-statistic of 2.13. On other days, the estimated slope is economically small and statistically weak (0.036 percentage points; $t = 1.61$). The average cross-sectional R^2 is approximately 4–5%, far below the portfolio-level fit, which is consistent with the idea that individual-stock returns contain much more idiosyncratic variation and that pre-sort betas are measured with error at the daily horizon. The pooled regression delivers a similar qualitative message: the unconditional beta coefficient is positive but only marginally significant, and the low-news interaction is positive. Though imprecisely estimated, the magnitude of the coefficient aligns with the Fama-MacBeth regression results.

Panels C and D add standard firm characteristics: size (market equity) and book-to-market, to assess whether the low-news beta premium is subsumed by the usual cross-sectional controls. In the Fama–MacBeth regressions (Panel C), the beta premium on low-news days remains essentially unchanged (0.154 percentage points; $t = 2.17$), while the beta slope on other days remains small and insignificant. At the daily frequency, size and book-to-market exhibit little explanatory power in the cross section in these specifications, which is consistent with the view that characteristic premia are difficult to detect day-by-day even when they are present in lower-frequency data. In the pooled specification with controls (Panel D), book-to-market enters positively and significantly, while the beta coefficient remains only marginally significant; importantly, the state-dependent beta term continues to be positive and close in magnitude to the Fama-MacBeth results.

The individual-stock evidence corroborates the portfolio results: the beta–return relation strengthens on low-news days and weakens on other days. The magnitudes are smaller and the fit is lower at the stock level, which is expected given the much higher idiosyncratic volatility and the additional measurement error in pre-sort betas. Taken together, the results suggest that the state-dependent pricing of market beta is not an artifact of portfolio construction, but rather a property that is visible in the underlying micro-level cross section as well.

The key results of this section suggest that stock prices behave very differently during low-news periods than at all other times. Before exploring explanations for this result, the next step is to link this aggregate state dependence to firm-level return behavior by asking whether higher aggregate news intensity is associated with greater idiosyncratic variation in returns.

4.1.2 Linking aggregate news intensity to idiosyncratic variance

I test Corollary 1 at the firm level using CAPM residuals estimated from rolling 12-month regressions of daily excess returns on the excess market return. Using the aggregate news state variable N_t, I classify days as low news, high news, or middle news according to whether the 10-day rolling median of N_t falls below its trailing one-year 25th percentile, exceeds its trailing one-year 75th percentile, or lies in between. For each firm, I compute residual variance separately in each regime, denoted V_L^i, V_M^i, and V_H^i, and examine the paired log-ratios $\log(V_M^i/V_L^i)$, $\log(V_H^i/V_M^i)$, and $\log(V_H^i/V_L^i)$. This within-firm design removes level differences in residual variance across firms, and the log transformation accommodates the skewness of the variance distribution. I then test whether the cross-firm mean of each log-ratio is different from zero. As an additional check, I stratify the sample by beta decile and VIX tercile, producing thirty cells in which the same prediction is tested separately. Since the CAPM residual removes $\beta_i \tilde{f}_t$ by construction, variation in factor volatility across news states should not account for the results.

Table 3 supports Corollary 1. Panel B shows that median CAPM residual variance rises monotonically from low-news to middle-news to high-news states within nearly every beta decile. The increase is economically large. For example, in the lowest-beta decile, median residual variance rises from 6.64 on low-news days to 9.72 in the middle-news state and 10.41 in the high-news state; in the highest-beta decile, it rises from 10.74 to 16.57 and 17.14. Panel C shows that this pattern is not driven by a small number of firms. The within-firm log-ratios $\log(V_M^i/V_L^i)$ and $\log(V_H^i/V_L^i)$ are positive and highly significant in every beta decile, while $\log(V_H^i/V_M^i)$ is positive and statistically significant in nine of the ten deciles. Panel D shows that the same conclusion survives within each beta-decile $\times$ VIX-tercile cell: the high-minus-low news log-ratio remains positive and significant throughout. Taken together, these results indicate that CAPM residual variance rises systematically with aggregate idiosyncratic-news intensity, even after holding fixed firms' beta rank and broad volatility conditions. This is exactly the pattern implied by Corollary 1, and it supports the view that firm-specific news enters returns through an active residual channel.

4.2 Explanations: Biased beliefs about anomaly-exposed firms

One possible explanation for why the SML flattens in high-news states is that firm-specific news corrects mispricing in anomaly-exposed firms, and that these corrections are distributed unevenly across the beta spectrum. Proposition 2 delivers the main prediction of the biased-beliefs mechanism. News partially corrects the accumulated mispricing of anomaly-exposed firms, as in Engelberg, McLean, and Pontiff (2018). As a result, the expected SML slope falls below the unconditional risk premium μ_λ when high-beta firms are disproportionately anomaly-short and low-beta firms are disproportionately anomaly-long. In the scalar approximation of Corollary 2, this requires $\mathrm{Cov}_i(\beta_i, a_i) < 0$. Panel A of Table 4 shows that the data match this composition: anomaly-short stocks become more prevalent as beta rises, while anomaly-long stocks are most concentrated in the low-beta portfolios on average across the sample period.

Given this composition, the mechanism yields two testable predictions. First, news-day returns load on signed anomaly exposure. Second, corrections grow linearly with the announcement lag $\tau_i(t)$. Section 4.1.2 has already verified the key prerequisite for this channel: CAPM residual variance rises monotonically with aggregate news intensity. This shows that news-day corrections are an active part of firm-level returns, and are consistent with the findings of (Boudoukh et al., 2019). I now test whether the cross section has the required composition of anomaly-exposed firms across beta-portfolios, whether the two directional predictions hold in the data, and whether these firm-level effects aggregate into the N_t scaling implied by Proposition 1.

4.2.1 Defining anomaly portfolios

Following the logic of Engelberg, McLean, and Pontiff (2018), I construct an aggregate anomaly-exposure measure at the firm-month level using a tractable subset of six canonical anomalies: size, 12–2 momentum, 1-month reversal, book-to-market, accruals, and asset growth. At the start of each month, firms are sorted cross-sectionally on each characteristic, and the extreme quintiles are assigned to the long and short sides according to the standard anomaly direction: small, past winners, recent losers, high book-to-market, low accruals, and low asset growth form the long side, while large, past losers, recent winners, low book-to-market, high accruals, and high asset growth form the short side. For each firm-month, I then count the number of anomaly signals on which the firm appears on the long side and the short side, and define its net anomaly exposure as $Net = Long - Short$. Firms in the top quintile of the monthly *Net* distribution are classified as anomaly-long (*HighNet*), firms in the bottom quintile are classified as anomaly-short (*LowNet*), and all remaining firms are classified as *Middle*. These monthly classifications are then merged onto the daily panel so that each firm-day inherits its firm's anomaly-exposure label for that month.

The composition varies sharply and monotonically across the beta spectrum. In the lowest beta decile, HighNet firms account for 37 percent of observations while LowNet firms account for only 7 percent. In the highest beta decile, the shares reverse to 22 percent HighNet and 25 percent LowNet. The HighNet share declines with beta while the LowNet share rises, and the gap between the two is widest at the extremes of the beta distribution. The compositional condition of Proposition 2 therefore holds in the sample: anomaly-long firms cluster at low betas, anomaly-short firms cluster at high betas, and the cross-sectional covariance $\text{Cov}_i(\beta_i, a_i)$ is negative.

4.2.2 News and corrections within beta deciles

If firm-specific news corrects anomaly-related mispricing, anomaly-long firms should earn positive news-day returns and anomaly-short firms should earn negative news-day returns. To test this, I estimate the panel regression

$$r_{i,t} = \alpha_i + \alpha_t + \gamma_1 \text{News}_{i,t} + \gamma_2(\text{HighNet}_i \times \text{News}_{i,t}) + \gamma_3(\text{LowNet}_i \times \text{News}_{i,t}) + \epsilon_{i,t} \quad (12)$$

separately within each daily beta decile, with firm and date fixed effects and standard errors double-clustered by firm and date. The coefficients γ_2 and γ_3 measure the news-day return premium for anomaly-long and anomaly-short firms relative to the middle group.

Panel B of Table 4 provides evidence consistent with the directional prediction of Proposition 2. The HighNet interaction, γ_2, is positive in every beta decile, ranging from 8.8 to 63.6 basis points. By contrast, the LowNet interaction, γ_3, is negative in nine of the ten deciles, ranging from -33.5 basis points in the lowest-beta decile to -1.2 basis points in decile 8. A Wald test of the restriction $\gamma_2 = \gamma_3$ is rejected at the 1 percent level in most deciles and at the 5 percent level in all but one. Taken together, these estimates suggest that news arrivals tend to raise returns for anomaly-long firms and lower returns for anomaly-short firms, in line with Engelberg, McLean, and Pontiff (2018). Combined with the cross-sectional composition in Panel A with anomaly-long firms more prevalent in low-beta deciles and anomaly-short firms more prevalent in high-beta deciles, this pattern is suggestive of a channel through which news may compress returns across the beta distribution and contribute to a flatter realized SML.

4.2.3 Accumulation of mispricing corrections

The results in Table 4 show that news-day returns differ systematically across anomaly-long and anomaly-short firms. This pattern is consistent with the biased-beliefs mechanism, but it is not unique to it: any mechanism that generates signed announcement-day corrections by anomaly type could produce similar level effects. Proposition 2 delivers a sharper prediction. In the model, mispricing accumulates between news events at a constant rate, so the size of the correction at the next announcement should increase linearly with the time since the previous announcement, $\tau_i(t)$. Formally, the conditional mean correction is $\tau_i(t)\kappa a_i$, implying both that announcement-lag should amplify the correction and that the effect should scale proportionally with signed anomaly exposure. I therefore turn to a direct test of the τ-scaling prediction. If the biased-beliefs mechanism is operative, corrections should become larger the longer a firm goes without a news event.

I construct $\tau_{i,t}$ as the number of calendar days since firm i's previous idiosyncratic news event in the GPT-filtered corpus, and estimate three specifications:

$$\begin{aligned} r_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{News}_{i,t} + \beta_2(\text{HighNet}_i \times \text{News}_{i,t}) \\ + \beta_3(\text{LowNet}_i \times \text{News}_{i,t}) + \epsilon_{i,t}, \end{aligned} \tag{13}$$

$$\begin{aligned} r_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{News}_{i,t} + \eta \tau_{i,t} + \theta_H(\text{HighNet}_i \times \text{News}_{i,t} \times \tau_{i,t}) \\ + \theta_L(\text{LowNet}_i \times \text{News}_{i,t} \times \tau_{i,t}) + \epsilon_{i,t}, \end{aligned} \tag{14}$$

and a joint specification including both the level interactions from (13) and the τ-scaled interactions from (14). The latter two specifications include $\tau_{i,t}$ as a main-effect control and restrict the sample to firm-days with $\tau_{i,t} \leq 90$ to avoid weighting the regression by extreme tail observations.

Table 5 reports the estimates. Column (1) reproduces the baseline pattern from Table 4 unconditionally in the whole sample: HighNet firms earn 18 basis points more than Middle firms on news days, LowNet firms earn 8 basis points less, and both interactions are highly significant. Column (2) replaces the level interactions with τ-scaled interactions. The HighNet $\times$ News $\times$ τ coefficient is 0.59 basis points per day with a t-statistic of 6.38, indicating that the anomaly-long correction grows by roughly 0.6 basis points for each additional day since the previous news event. The corresponding LowNet coefficient is 0.04 basis points per day with a t-statistic of 0.67, essentially zero. The τ main effect is statistically indistinguishable from zero, confirming that the interaction coefficients capture news-day scaling rather than a confounded time trend.

Column (3) provides a clear test of the biased-beliefs mechanism. When both level and τ-scaled interactions are included jointly, the HighNet level coefficient becomes small and statistically insignificant (3 basis points, $t = 0.91$), while the HighNet τ-scaled coefficient remains large and significant (0.48 basis points per day, $t = 4.06$). For anomaly-long firms, the news-day correction has no constant component once τ-scaling is accounted for. The entire return premium on news days for HighNet firms is driven by the amount of time over which mispricing has accumulated, which is precisely the functional form $\mathbb{E}[g_{i,t}] = \tau\,\kappa\,a_i$ predicted by Proposition 2.

For LowNet firms, the evidence does not support the τ-scaling prediction. In Column (3), the level coefficient remains economically and statistically large at -9 basis points ($t = -5.57$), while the τ-scaled coefficient is $+0.27$ basis points per day ($t = 3.50$), opposite to the model's predicted sign. This suggests that the short-side news-day correction is primarily a level effect rather than one that grows with the announcement lag. Put differently, whatever drives the negative LowNet correction does not appear to accumulate linearly with $\tau_i(t)$.

This asymmetry is consistent with short-sale frictions. Miller (1977), Stambaugh, Yu, and Yuan (2012, 2015), Nagel (2005), and Chu, Hirshleifer, and Ma (2020) document that anomaly returns concentrate on the short side because binding short-sale constraints prevent arbitrageurs from smoothly correcting overpricing through time. For anomaly-long firms, underpricing accumulates gradually between news events because arbitrageurs can build long positions as mispricing grows, and the resulting news-day correction scales linearly with the elapsed time since the previous announcement as Proposition 2 predicts. For anomaly-short firms, overpricing persists as a stable level that arbitrageurs cannot smoothly correct, and the news-day response therefore takes the form of a fixed adjustment rather than an accumulated one. The τ regression thus refines Proposition 2 asymmetrically: the linear-in-τ structure holds cleanly on the long side, while the short side exhibits a constant-correction pattern consistent with the limits-to-arbitrage literature. The exact form of Proposition 2 therefore describes the subset of announcing firms for whom arbitrageurs can freely adjust positions through time; departures from the form on the short side are themselves informative about where short-sale frictions bind most strongly.

Importantly, the asymmetry affects the timing of the correction more than its direction. Anomaly-short firms continue to earn lower news-day returns than anomaly-long firms, so the cross-sectional distribution of corrections can still imply a negative covariance between beta and news-day return impacts. The short-side departure from the exact linear-in-$\tau_i(t)$ structure of Proposition 2 therefore does not eliminate the broader implication for SML flattening in Proposition 1, which requires only that news-day corrections be disproportionately negative among higher-beta firms.

4.2.4 Do news-day returns vary with beta?

The firm-level results above suggest that news-day corrections are not randomly distributed across firms: they vary with anomaly exposure, but most importantly with firm betas. Proposition 1 implies that if these firm-level corrections are sufficiently concentrated in particular parts of the beta distribution, they can aggregate into a wedge that weakens the realized security market line, particularly when aggregate news intensity N_t is high. To assess whether the data are consistent with this prediction, I estimate the panel regression

$$r_{i,t} = \alpha_i + \alpha_t + b_1\beta_{i,t} + b_2\text{News}_{i,t} + b_3(\beta_{i,t} \times \text{News}_{i,t}) + \epsilon_{i,t} \tag{15}$$

separately in the full sample and in subsamples of high- and low-news days. The interaction coefficient b_3 measures whether higher-beta firms experience more negative returns on their own news days than lower-beta firms, after absorbing firm-level differences in average returns and common time-series variation through fixed effects. A negative b_3 in high-news states is consistent with the firm-level input that, by Proposition 1, would aggregate into a flatter realized SML.

Table 6 reports the estimates. On the full sample, the Beta $\times$ News interaction is -6.57 basis points with a t-statistic of -2.02. Column (2) restricts the sample to high-news days, defined as days on which the rolling 10-day median of aggregate idiosyncratic news exceeds its trailing one-year 75th percentile. Within this subsample, the interaction widens nearly fivefold to -32.1 basis points ($t = -2.40$): conditional on a news day occurring in a high-news regime, a one-unit increase in beta is associated with a reduction in daily excess returns of 32 basis points. Column (3) restricts to low-news days, defined using the corresponding 25th-percentile cutoff. The Beta $\times$ News coefficient is $+4.48$ basis points with a t-statistic of 0.47, statistically indistinguishable from zero.

The monotonic pattern in the Beta $\times$ News coefficient across Columns (3), (1), and (2) from statistically indistinguishable from zero in the low-news regime, to significantly negative but attenuated in the unconditional sample, to sharply more negative in the high-news regime, provides direct evidence that the aggregate news state activates the firm-level wedge channel. The wedge is empirically inactive when aggregate news intensity is low, present but diluted when news intensity is unconditional, and most strongly active when news intensity is elevated, matching the N_t scaling predicted by Proposition 1.

The results in this subsection provide support for the biased-beliefs mechanism as one possible explanation for the news-state dependence of the SML. The compositional condition of Proposition 2 holds in the cross section: anomaly-long firms cluster at low betas and anomaly-short firms cluster at high betas, and react assymetrically to firm-specific news in the sample. The directional prediction holds within every beta decile: news arrivals move anomaly-long firms up and anomaly-short firms down. The functional-form prediction that the long-side correction scales linearly with the announcement lag and has no constant component is supported by the results in Table 5, where the HighNet level coefficient is absorbed entirely by τ-scaling. The short-side pattern departs from the exact form of Proposition 2, but the deviation takes the specific form predicted by short-sale frictions: overpricing corrections appear as fixed levels rather than accumulating through time. Finally, the aggregate scaling predicted by Proposition 1 is borne out in the wedge regression: the beta–return interaction on news days is strongest when aggregate news intensity is elevated, attenuated on average, and absent in quiet periods.

Taken together, the results in this subsection are consistent with the biased-beliefs mechanism as one plausible explanation for the news-state dependence of the SML. The compositional condition in Proposition 2 is present in the data: anomaly-long firms are concentrated in lower-beta stocks, while anomaly-short firms are concentrated in higher-beta stocks, implying a negative cross-sectional association between β_i and a_i. The directional prediction is also supported: across beta deciles, news arrivals tend to move anomaly-long firms up and anomaly-short firms down. The timing prediction receives more selective support. On the long side, the specifications of equations (13) and (14) shows that the HighNet effect is absorbed by τ-scaling, consistent with a correction that accumulates between announcements rather than arriving as a fixed announcement-day shift. On the short side, the data depart from the exact form of Proposition 2, but in a way that is consistent with short-sale frictions: the correction appears primarily as a fixed level effect rather than one that builds with the announcement lag. Finally, the firm-level beta–news interaction is most negative when aggregate news intensity is high, weaker in the full sample, and close to zero in quiet periods. Although this last result is not a direct test of the SML, it is consistent with the idea that news-day corrections are distributed across firms in a way that can contribute to SML flattening when aggregate idiosyncratic news is elevated.

The next subsection evaluates a complementary mechanism based on strategic disclosure of negative news by firm managers, which delivers the same qualitative predictions through a different primitive.

4.3 Strategic disclosure

The literature 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 1 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 without disclosure, and jump upward with the announcement of good news.

Figure 5 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 News, beta, and returns

Table 6 reports the results of excess returns of firm beta, a news-day indicator, and their interaction. 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 (8), 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 pattern suggests the possibility of strategic timing of disclosure. Higher-beta firms have more negative reactions to news during periods where many other firms are also releasing news. The next section probes further.

4.3.2 Time varying concentration of negative news

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 deciles. I define the daily negative-share:

$$\text{Negative Share}_{g,t} = \frac{\sum_{i \in g} N_{i,t}^{-}}{\sum_{i \in g} \left(N_{i,t}^{-} + N_{i,t}^{+} \right)} , \tag{16}$$

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:

$$M_t = \frac{\sum_{s=0}^{4} \text{NegativeShare}_{L,t-s}}{\sum_{s=0}^{4} \text{NegativeShare}_{H,t-s}} , \tag{17}$$

Equation (16) is the within-group share of negative articles, and equation (17) 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 7 runs the same panel regression of equation (9), 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 7 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 Alternative Explanations

5.1 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 acquisition 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 the daily average of MAI topics. Then, I take the rolling 10-day median of this relative measure and test the CAPM again using the Fama–MacBeth and pooled regressions outlined in equations (9), (10) and (11) 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 8 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 8 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 assess whether my idiosyncratic-news measure captures investor attention, Panel B examines the determinants of attention allocation using two aggregate daily attention measures. The first is an idiosyncratic-news attention index constructed from Bloomberg institutional attention scores following Ben-Rephael et al. (2017). On each day, I assign Bloomberg's 0–4 attention score to firms that receive an idiosyncratic news article in the Dow Jones Institutional Newswire and compute the cross-sectional average across those firms. The second is the macroeconomic attention index, taken from Fisher, Martineau, and Sheng (2022) averaged across all categories of macroeconomic-attention in their sample to capture average aggregate macroeconomic attention. I then regress each attention measure on the daily share of firms with idiosyncratic news in the sample, absolute market returns, the VIX, and indicators for major macroeconomic announcement days, including CPI, FOMC, and unemployment releases, with month-year fixed effects. The results show that the share of firms with news in the sample strongly increases average attention paid to idiosyncratic news articles, while reducing macroeconomic attention, consistent with attention shifting toward firm-specific information when more firms receive news. One notable result is that FOMC days are associated with higher average attention to idiosyncratic news articles. Although this may seem surprising, it is consistent with Ben-Rephael et al. (2017), who document that firm-specific attention also rises on FOMC press conference days.

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.

6 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 9 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, rows 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, rows 3 and 4 show that the standard deviation of beta portfolios is linear and increasing for beta portfolios on both types of days. Rows 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 could coincide with higher volatility, which corresponds to a flatter SML.

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 median 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. Figure 4 motivates the strategy by plotting the SML separately for low-news, high-news, and all other days in the sample. Panel A motivates the leg of the strategy that goes long high-beta assets in low-news periods, and panel B motivates the strategy that bets against beta in high-news states. Panel B of Table 9 presents the mean and variance of the returns of each strategy alongside their annualized Sharpe ratios.

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.

I further assess the performance of these strategies in a Fama-French 5 factor model with momentum. Panel C of Table 9 displays the results. In the Fama-French 5 factor model with momentum, strategy 2 generates a statistically and economically significant alpha. In particular, strategy 2 still earns an alpha of 0.07%, or 7 basis points per day, even after controlling for market, value, size, conservative minus aggressive, robust minus weak, and momentum factors. One concern is that the findings of the paper could be driven by other state variables not accounted for in the strategy. For example, one possible variable is retail attention which had a documented increase in the post-COVID period. However, Table 10 runs robustness tests of the main results in the paper to ensure they are not driven by any known state variables in the previous literature.

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 return can explain. The strategy profits by timing exposure to beta across news states, and is not subsumed by standard factors. The next section explores alternative explanations for these results.

7 Robustness tests

7.1 Aggregate CAPM tests

7.1.1 Alternative state variables

Since the baseline tests classify days into discrete low- and high-news states, Table 10 complements that approach by using a standardized continuous measure of idiosyncratic news intensity. This allows the regression to capture how the slope of the security market line changes smoothly with the level of news, rather than only across coarse state partitions. Table 10 then shows that this continuous-news result is robust to controlling for other state variables that prior work links to time variation in the slope of the security market line. In each specification, I add an additional standardized state variable and its interaction with beta to the pooled regression. First, column (2) confirms the findings of Hong and Sraer (2016) that the SML slope is negatively related to disagreement using the daily aggregate disagreement data of Cookson and Niessner (2023). Column (3) confirms the claim of Hasler and Martineau (2023) that the CAPM works better in periods of low volatility, proxied by the VIX. Columns (4) and (5) control for both retail and institutional attention, using retail attention data from Da (2025) and aggregated firm-level Bloomberg query data of Ben-Rephael et al. (2021) to construct daily aggregate institutional attention. Variables are added in order of data availability.

The interaction between the continuous idiosyncratic-news measure and beta remains negative and statistically significant throughout. This indicates that the flattening of the SML in high-idiosyncratic-news environments is not subsumed by disagreement, the VIX, retail attention, or institutional attention. While disagreement and the VIX also exhibit negative interactions with beta, the idiosyncratic-news interaction remains economically and statistically important after these controls are included.

7.1.2 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 11 re-reruns the panel regressions of equation (9) within only the months of January throughout the sample between 2009 and 2025. 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. 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.

7.1.3 Day and night portfolios

A natural concern is that the main results are simply picking up the overnight beta–return relation rather than a distinct effect of aggregate idiosyncratic news. This concern is plausible because firm news arrives disproportionately outside market hours (Boudoukh et al., 2019), and Hendershott, Livdan, and Rösch (2020) show that the SML is strongly positive overnight but not during the day. To separate these effects, Panels B and C of Table 11 re-estimate equation (9) using daytime and overnight returns separately. The daytime results continue to support the central mechanism: the interaction between β and low-news states is 43 basis points with a t-statistic of 2.42, implying a significantly more positive SML during low-news periods even within trading hours. Overnight, however, the baseline coefficient on β remains only weakly significant at 32 basis points ($t = 1.85$), while the low-news interaction becomes insignificant. Taken together, the results suggest that the overnight pricing of beta documented by Hendershott, Livdan, and Rösch (2020) is distinct from the mechanism in this paper. The contribution here is to show that low-idiosyncratic-news states restore a more positive beta–return relation during the day, where the unconditional CAPM typically performs poorly.

7.1.4 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 (9) without weeks 2, 3 and 4 of each fiscal quarter in the sample period from 2009-2025. Panel D of Table 11 shows the results of the panel regression outlined in equation (9). 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.

7.1.5 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 11 presents the results of the panel regression outlined in equation (9) 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 (9). 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.

7.1.6 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 (9) 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 11 presents the results.

Panel H runs the same regression defined in equation (9), 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 results of Table 10, and suggest that attention alone, while adding a potentially complementary explanation to news, is not the main driver of results of this paper.

7.1.7 *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 11 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.

7.1.8 *Alternative low-news definitions*

Equation (8) defines low-news periods using a 10-day rolling median and a 25th-percentile cutoff. Panels A through D of Table 12 vary the rolling window while holding the percentile cutoff fixed, and Panels E through G vary the percentile cutoff while holding the rolling window fixed.

The interaction between β and the low-news indicator is positive and significant across rolling windows from 8 to 20 days. Beyond this range the coefficient attenuates and loses significance, consistent with longer windows smoothing through the short-lived news states that the measure is designed to capture.

The pattern across percentile cutoffs is informative about the mechanism. As the cutoff tightens from 30% to 20% to 15%, the interaction coefficient rises monotonically in magnitude, indicating that the beta–return relation is strongest in the quietest news environments. Moving in the other direction, the effect attenuates as the cutoff is relaxed and becomes statistically insignificant at the 10% level once the cutoff exceeds 30%, at which point more than 26% of sample days are classified as low-news. The 25% cutoff used in the baseline analysis sits inside this range and was selected for its symmetry with the 75th-percentile cutoff used to define high-news states elsewhere in the paper; the results are not sensitive to small perturbations within the range where the mechanism is active, and they attenuate outside of it in the direction the theory predicts.

7.2 Trading strategy

To support the efficacy of the trading strategy, Table 13 evaluates the sensitivity of the trading strategy to the timing of the signal by lagging the portfolio-switching rule by one to five trading days. Specifically, when the aggregate idiosyncratic-news measure moves into the low-news state (below its rolling one-year 25th percentile), the high-news state (above its rolling 75th percentile), or the residual "other" state, the strategy does not switch positions immediately, but instead implements the new position with a delay. The results show that both the mean return and the Sharpe ratio decline monotonically as the lag increases, indicating that the strategy performs best when the timing signal is most precise. To assess whether this performance could arise from random timing alone, I construct a placebo distribution by preserving the total number of high-news and low-news days in the sample, but randomly reassigning those dates across the full time series without replacement; all remaining dates are classified as "other" days. For each randomized assignment, I reconstruct the trading strategy, compute the daily return series, and calculate the annualized Sharpe ratio as $\sqrt{252}$ times the sample mean return divided by the sample standard deviation. Repeating this procedure 1,000 times yields a distribution of placebo Sharpes against which the realized strategy Sharpe is compared. As the implementation lag increases, the realized Sharpe moves progressively closer to the placebo distribution, which further supports the view that the profitability of the strategy is tied to the informational content and precise timing of the news-based state variable rather than arising mechanically from the structure of the trading rule.

8 Conclusion

This paper studies how the information environment shapes the empirical performance of the CAPM. I show that the beta–return relation is strongly state dependent: when aggregate idiosyncratic news is low, the security market line is upward sloping and beta prices risk in the cross section; when idiosyncratic news is high, the relation weakens substantially and the SML flattens.

This pattern appears in portfolio sorts, Fama–MacBeth regressions, and pooled panel specifications, and remains robust to alternative definitions of the news state, to restricting attention to daytime returns, to excluding major scheduled announcements, and to controlling for other state variables studied in the literature.

To explain these results, I develop a two-part model in which idiosyncratic news shapes the cross-sectional pricing of beta through a residual-variance channel. I show that the realized Fama–MacBeth slope decomposes into the unconditional risk premium, a common factor surprise, and a residual wedge; this wedge is the only channel through which aggregate news intensity can affect the expected security market line, and it is active whenever firm-specific news generates firm-specific return variation. Empirically, I document that CAPM residual variance rises monotonically with the aggregate news state, confirming that the wedge is an operative channel at the firm level. The model then signs the wedge through biased beliefs about anomaly-exposed firms: when news arrives, accumulated mispricing is corrected, and because anomaly-short firms are disproportionately high-beta, the aggregate correction on high-news days tilts the realized SML downward. A greater incidence of such news shocks in the cross section flattens the empirical beta–return relation even when the underlying price of market risk is unchanged. Consistent with this mechanism, the relation between beta and expected returns is stronger when attention to idiosyncratic information is low relative to macroeconomic attention, and the main results are not subsumed by disagreement, volatility, retail attention, institutional attention, or expected market return conditions.

The evidence therefore suggests that the unconditional failure of the CAPM partly reflects variation in the supply and salience of firm-specific information. When idiosyncratic news is scarce, beta is a more reliable measure of systematic risk; when idiosyncratic news is abundant, market exposures are obscured and the SML flattens. A natural extension is to broaden the news corpus beyond the DJIN to capture more firm-specific information which would permit sharper identification of genuinely news-free days and a tighter test of the unconditional CAPM in their absence. The DJIN does not capture every firm-specific information event. Disclosures in 8-K filings, conference calls, regional outlets, and social media are not fully indexed, and my GPT filtering step deliberately prioritizes precision in identifying genuinely idiosyncratic articles over breadth of coverage.

These findings have implications for both asset-pricing research and practice. For researchers, they identify aggregate idiosyncratic news as a new state variable governing when beta prices risk. For practitioners, they suggest that the usefulness of CAPM-based discount rates depends on the prevailing information environment. A simple trading strategy that conditions on these news states earns economically large and statistically significant abnormal returns, indicating that variation in idiosyncratic news is not only informative about CAPM performance, but also relevant for portfolio allocation.

References

Acharya, Viral V., Peter DeMarzo, and Ilan Kremer (2011). Endogenous Information Flows and the Clustering of Announcements. *American Economic Review*, 101(7), 2955–2979.

Aït-Sahalia, Yacine, Chen Xu Li, and Chenxu Li (2024). So Many Jumps, So Few News. *NBER Working Paper No. 32746*, National Bureau of Economic Research.

Andrei, Daniel, Julien Cujean, and Mungo Wilson (2023). The Lost Capital Asset Pricing Model. *Review of Economic Studies* 90(6), 2703–2762.

Andrei, Daniel, Henry Friedman, and N. Bugra Ozel (2023). Economic Uncertainty and Investor Attention. *Journal of Financial Economics*, 149(2), 179–217.

Ang, Andrew, Joseph Chen, and Yuhang Xing (2006). Downside risk. *The Review of Financial Studies*, 19(4), 1191–1239.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny (1998). A Model of Investor Sentiment. *Journal of Financial Economics*, 49(3), 307–343.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen (2017). It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies*, 30(9), 3009–3047.

Ben-Rephael, Azi, et al. (2021). Information Consumption and Asset Pricing. *The Journal of Finance*, 76(1), 357–394.

Berk, Jonathan B., and Jules H. van Binsbergen (2017). How Do Investors Compute the Discount Rate? They Use the CAPM (Corrected June 2017). *Financial Analysts Journal*, 73(2), 25–32.

Black, Fischer, Michael C. Jensen, and Myron Scholes (1972). The Capital Asset Pricing Model: Some Empirical Tests. In Michael C. Jensen (ed.), *Studies in the Theory of Capital Markets*, New York: Praeger, pp. 79–121.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2018). Diagnostic Expectations and Credit Cycles. *The Journal of Finance*, 73(1), 199–227.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer (2019). Diagnostic Expectations and Stock Returns. *The Journal of Finance*, 74(6), 2839–2874.

Boudoukh, Jacob, et al. (2019). Information, Trading, and Volatility: Evidence from Firm-Specific News. *The Review of Financial Studies*, 32(3), 992–1033.

Carhart, Mark M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1), 57–82.

Chan, Kam Fong, and Terry Marsh (2022). Asset Pricing on Earnings Announcement Days. *Journal of Financial Economics*, 144(3), 1022–1042.

Chen, Jian, et al. (2022). Investor Attention and Stock Returns. *Journal of Financial and Quantitative Analysis*, 57(2), 455–484.

Chu, Yongqiang, David Hirshleifer, and Liang Ma (2020). The Causal Effect of Limits to Arbitrage on Asset Pricing Anomalies. *The Journal of Finance*, 75(5), 2631–2672.

Cookson, J. Anthony, and Marina Niessner (2023). Investor disagreement: Daily measures from social media. *Available at SSRN 4529594*.

Da, Zhi (2025). Market Returns and a Tale of Two Types of Attention. *Management Science*, forthcoming.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance*, 53(6), 1839–1885.

Engelberg, Joseph, R. David McLean, and Jeffrey Pontiff (2018). Anomalies and News. *The Journal of Finance*, 73(5), 1971–2001.

Fama, Eugene F., and Kenneth R. French (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 116(1), 1–22.

Fama, Eugene F., and James D. MacBeth (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3), 607–636.

Fang, Lily, and Joel Peress (2009). Media Coverage and the Cross-Section of Stock Returns. *The Journal of Finance*, 64(5), 2023–2052.

Fisher, Adlai, Charles Martineau, and Jinfei Sheng (2022). Macroeconomic Attention and Announcement Risk Premia. *The Review of Financial Studies*, 35(11), 5057–5093.

Fox, Merritt B., Lawrence R. Glosten, and Ananth Subrahmanyam (2003). Law, share price accuracy, and economic performance: the new evidence. *Michigan Law Review*, 102, 331–386.

Frazzini, Andrea, and Lasse Heje Pedersen (2014). Betting Against Beta. *Journal of Financial Economics*, 111(1), 1–25.

French, Kenneth R., and Richard Roll (1986). Stock Return Variances: The Arrival of Information and the Reaction of Traders. *Journal of Financial Economics*, 17(1), 5–26.

Hasler, Michael, and Charles Martineau (2023). Explaining the Failure of the Unconditional CAPM with the Conditional CAPM. *Management Science*, 69(3), 1835–1855.

Hasler, Michael, and Charles Martineau (2024). Equity Return Predictability with the ICAPM. *The Review of Asset Pricing Studies*, 14(3), 481–512.

Hendershott, Terrence, Dmitry Livdan, and Dominik Rösch (2020). Asset Pricing: A Tale of Night and Day. *Journal of Financial Economics*, 138(3), 635–662.

Hong, Harrison, and David A. Sraer (2016). Speculative Betas. *The Journal of Finance*, 71(5), 2095–2144.

Hou, Kewei, Chen Xue, and Lu Zhang (2020). Replicating Anomalies. *The Review of Financial Studies*, 33(5), 2019–2133.

Jeon, Yoontae, Thomas H. McCurdy, and Xiaofei Zhao (2022). News as Sources of Jumps in Stock Returns: Evidence from 21 Million News Articles for 9000 Companies. *Journal of Financial Economics*, 145(2), 1–17.

Jylhä, Petri (2018). Margin Constraints and the Security Market Line. *Journal of Finance*, 73(2), 1281–1321.

Kandel, Shmuel, and Robert F. Stambaugh (1995). Portfolio Inefficiency and the Cross-Section of Expected Returns. *The Journal of Finance*, 50(1), 157–184.

Kothari, Sabino P., Susan Shu, and Peter D. Wysocki (2009). Do managers withhold bad news? *Journal of Accounting Research*, 47(1), 241–276.

Lintner, John (1965). Security Prices, Risk, and Maximal Gains from Diversification. *The Journal of Finance*, 20(4), 587–615.

Liu, Jianan, Robert F. Stambaugh, and Yu Yuan (2018). Absolving Beta of Volatility's Effects. *Journal of Financial Economics*, 128(1), 1–15.

Mankiw, N. Gregory, and Ricardo Reis (2002). Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve. *The Quarterly Journal of Economics*, 117(4), 1295–1328.

McLean, R. David, and Jeffrey Pontiff (2016). Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance*, 71(1), 5–32.

Mossin, Jan (1966). Equilibrium in a Capital Asset Market. *Econometrica*, 34(4), 768–783.

Miller, Edward M. (1977). Risk, Uncertainty, and Divergence of Opinion. *The Journal of Finance*, 32(4), 1151–1168.

Nagel, Stefan (2005). Short Sales, Institutional Investors and the Cross-Section of Stock Returns. *Journal of Financial Economics*, 78(2), 277–309.

Patton, Andrew J., and Michela Verardo (2012). Does Beta Move with News? Firm-Specific Information Flows and Learning about Profitability. *The Review of Financial Studies*, 25(9), 2789–2839.

Peng, Lin, and Wei Xiong (2006). Investor Attention, Overconfidence and Category Learning. *Journal of Financial Economics*, 80(3), 563–602.

Rabin, Matthew, and Dimitri Vayanos (2010). The Gambler's and Hot-Hand Fallacies: Theory and Applications. *The Review of Economic Studies*, 77(2), 730–778.

Roll, Richard (1977). A Critique of the Asset Pricing Theory's Tests Part I: On Past and Potential Testability of the Theory. *Journal of Financial Economics*, 4(2), 129–176.

Savor, Pavel, and Mungo Wilson (2014). Asset Pricing: A Tale of Two Days. *Journal of Financial Economics*, 113(2), 171–201.

Savor, Pavel, and Mungo Wilson (2016). Earnings Announcements and Systematic Risk. *The Journal of Finance*, 71(1), 83–138.

Shanken, Jay (1992). On the Estimation of Beta-Pricing Models. *The Review of Financial Studies*, 5(1), 1–33.

Sharpe, William F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 19(3), 425–442.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan (2012). The Short of It: Investor Sentiment and Anomalies. *Journal of Financial Economics*, 104(2), 288–302.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *The Journal of Finance*, 70(5), 1903–1948.

Tinic, Seha M., and Richard R. West (1984). Risk and Return: January vs. the Rest of the Year. *Journal of Financial Economics*, 13(4), 561–574.

Veldkamp, Laura L. (2006). Information Markets and the Comovement of Asset Prices. *The Review of Economic Studies*, 73(3), 823–845.

Table 1: Summary statistics for beta deciles and news

Panel A reports beta, market capitalization (in billions), and unique news counts (in thousands) by beta decile for three samples. (1) All CRSP common stocks (share codes 10/11) from 2009–2025. (2) Subsample successfully matched to Dow Jones Newswire (DJIN). For summary statistics, beta-portfolio market capitalizations and book-to-market 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
B/M	0.94	0.74	0.59	0.52	0.51	0.53	0.51	0.54	0.52	0.56	
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	2091
B/M	0.73	0.57	0.47	0.42	0.42	0.44	0.46	0.46	0.49	0.59	
News	20.90	32.50	37.60	40.30	42.00	43.90	40.80	39.40	35.90	31.50	

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 2: Fama–MacBeth and pooled panel regressions of daily excess returns

This table reports the results of Fama–MacBeth and panel regressions of daily excess returns on market betas for beta-decile test portfolios and individual stocks. Coefficients are reported in daily percentage returns. I use a 1-year rolling regression with daily returns to estimate betas of individual stocks. For Panel A, I sort stocks into beta-decile portfolios and calculate daily portfolio betas using the past 1-year of value-weighted returns. The following panels use individual stocks and pre-sort betas. Panels C and D present regression results controlling for market capitalization (size) and book-to-market ratios (bm). T-statistics are reported in parentheses and are estimated using time-series variation (Newey–West) for Fama–MacBeth regressions and clustering by day for panel regressions. The sample spans 2009–2025. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: 10 beta-sorted portfolios

	Fama–MacBeth			Pooled regression				
Type of day	Intercept	β	Avg. R^2	Const	β	$\mathbb{1}\{\text{Low}\}$	$\mathbb{1}\{\text{Low}\} \times \beta$	R^2
Low news days	-0.061	0.24**	0.46	-0.05	0.09	-0.19**	0.32***	0.0015
	(-0.83)	(2.43)		(-0.64)	(1.09)	(-2.27)	(3.11)	
Other days	0.036	0.006	0.46					
	(1.39)	(0.17)						
Low news − Other	-0.097	0.23						

Panel B: Individual stocks (beta only)

	Fama–MacBeth (Newey–West)			Pooled regression				
Type of day	Intercept	β	Avg. R^2	Const	β	$\mathbb{1}\{\text{Low}\}$	$\mathbb{1}\{\text{Low}\} \times \beta$	R^2
Low news days	0.023	0.153**	0.047	0.030	0.040*	-0.020	0.120	0.0003
	(0.54)	(2.13)		(1.09)	(1.73)	(-0.24)	(1.52)	
Other days	0.031**	0.036	0.044					
	(2.10)	(1.61)						
Low news − Other	-0.008	0.117						

Panel C: Individual stocks with controls (Fama–MacBeth)

Type of day	Intercept	β	Size	BM
Low news days	0.015	0.154**	2.02×10^{-7}	0.0067
	(0.33)	(2.17)	(1.26)	(0.27)
Other days	0.037**	0.033	-4.18×10^{-8}	-0.0054
	(2.39)	(1.48)	(-0.87)	(-0.71)
Low news − Other	-0.023	0.121	2.44×10^{-7}	0.0121

Panel D: Individual stocks with controls (Pooled regression)

Const	β	Size	BM	$\mathbb{1}\{\text{Low}\}$	$\mathbb{1}\{\text{Low}\} \times \beta$	R^2
0.020	0.040*	3.51×10^{-8}	0.020**	-0.020	0.120	0.0003
(0.60)	(1.66)	(0.79)	(2.02)	(-0.26)	(1.53)	

Table 3: Residual Variance Across Beta Deciles: News Regimes and VIX Cross-Sections

Notes. This table reports residual-variance patterns across beta-sorted deciles and across news and volatility states. Firms are assigned to beta deciles using their full-sample average market beta. For each firm, CAPM parameters (α_i, β_i) are used to compute residuals for all firm-days. Residual variance, denoted V, is aggregated to the firm–regime level, retaining only firms with at least 30 daily observations in each regime and strictly positive variance in all three news states. Panel A reports firm characteristics by beta decile. Panel B reports the cross-firm median residual variance within each decile and news regime. Panels C and D report paired within-firm tests: each entry is the mean of the indicated within-firm log ratio, with the corresponding t-statistic reported in parentheses. News regimes are defined using the top and bottom quartiles of aggregate idiosyncratic-news intensity. VIX terciles are based on the full-sample VIX distribution. The sample is restricted to firms with at least one recorded news event. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Beta decile (low to high)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Firm characteristics										
Mean β_i	0.39	0.66	0.82	0.95	1.06	1.15	1.25	1.35	1.49	1.85
Number of firms	288	287	288	287	288	287	287	288	287	288
Panel B. Median residual variance ($\times 10^4$)										
Low-news state, V_L	6.64	4.29	3.24	3.07	3.78	3.50	4.16	4.71	5.71	10.74
Middle-news state, V_M	9.72	6.31	4.62	4.27	5.49	5.70	6.31	7.04	9.01	16.57
High-news state, V_H	10.41	7.31	5.82	4.91	6.36	7.05	7.64	8.93	11.32	17.14
Panel C. Paired within-firm log-ratio tests										
$\overline{\log(V_M/V_L)}$	0.334***	0.320***	0.323***	0.284***	0.357***	0.388***	0.390***	0.355***	0.397***	0.471***
	(9.76)	(10.27)	(10.68)	(9.36)	(11.37)	(12.90)	(15.20)	(12.25)	(13.62)	(13.93)
$\overline{\log(V_H/V_M)}$	0.115***	0.112***	0.108***	0.086***	0.096***	0.099***	0.079**	0.148***	0.095***	−0.018
	(2.74)	(2.82)	(3.44)	(2.97)	(2.82)	(3.19)	(2.47)	(4.55)	(2.72)	(−0.45)
$\overline{\log(V_H/V_L)}$	0.449***	0.432***	0.432***	0.371***	0.454***	0.487***	0.469***	0.503***	0.492***	0.452***
	(10.55)	(10.40)	(11.66)	(9.18)	(10.96)	(13.49)	(13.91)	(13.50)	(13.20)	(11.45)
Panel D. $\log(V_H/V_L)$ **within VIX terciles**										
Low VIX	0.218***	0.252***	0.180***	0.160***	0.210***	0.233***	0.304***	0.290***	0.268***	0.415***
	(4.57)	(4.67)	(3.52)	(3.09)	(3.72)	(4.68)	(6.61)	(6.70)	(5.09)	(7.27)
Middle VIX	0.171***	0.157***	0.200***	0.129***	0.237***	0.204***	0.239***	0.244***	0.313***	0.279***
	(4.11)	(3.38)	(4.64)	(2.97)	(5.14)	(5.61)	(6.69)	(6.36)	(7.41)	(6.65)
High VIX	0.593***	0.534***	0.602***	0.487***	0.681***	0.616***	0.655***	0.621***	0.616***	0.373***
	(10.61)	(11.37)	(14.00)	(9.84)	(14.76)	(13.46)	(15.75)	(13.82)	(12.73)	(6.96)

Table 4: Anomaly Portfolio Composition and News-Day Returns Across Beta Deciles

This table reports the composition of anomaly portfolios and news-day return regressions across beta deciles. Panel A reports the share of firms within each beta decile classified as anomaly longs (High Net), anomaly shorts (Low Net), or neither (Middle), using the CRSP universe. Panel B reports estimates from regressions of excess returns on a news indicator and its interactions with High Net and Low Net indicators, estimated separately within each beta decile. All regressions include firm and date fixed effects. Coefficients are reported in basis points, and t-statistics based on standard errors double-clustered by firm and date are reported in parentheses.

	Beta decile (low β to high β)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Anomaly composition of beta portfolios										
Share of anomaly longs (%)	0.37	0.23	0.18	0.16	0.16	0.16	0.16	0.18	0.19	0.22
Share of anomaly shorts (%)	0.07	0.18	0.21	0.21	0.20	0.21	0.22	0.22	0.24	0.25
Share other (%)	0.56	0.59	0.62	0.63	0.64	0.63	0.62	0.60	0.57	0.53
Panel B: News-day returns within beta deciles										
News dummy, γ_1	42.49***	15.35***	16.92***	12.15***	13.56***	11.39***	16.37***	13.64***	21.55***	36.35***
	(4.90)	(4.51)	(5.71)	(5.80)	(5.44)	(4.97)	(6.42)	(5.35)	(6.65)	(8.83)
High Net × News, γ_2	63.59***	22.11**	11.28	25.55***	21.77***	8.83	18.75***	20.36***	18.15**	8.13
	(2.75)	(2.49)	(1.17)	(3.10)	(3.42)	(1.46)	(2.84)	(2.86)	(2.37)	(1.00)
Low Net × News, γ_3	-33.50***	-8.87**	-11.21***	-5.63*	-6.55*	1.20	-5.60	-1.15	-11.65**	-18.88***
	(-3.54)	(-2.32)	(-2.93)	(-1.70)	(-1.88)	(0.35)	(-1.37)	(-0.31)	(-2.56)	(-3.31)
Difference, $\gamma_2 - \gamma_3$	97.09	30.99	22.49	31.18	28.32	7.62	24.35	21.52	29.80	27.02
Wald $\chi^2(1)$: $\gamma_2 = \gamma_3$	16.80***	12.85***	5.56**	13.34***	19.29***	1.44	11.18***	8.32***	14.17***	10.12***
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,109,366	1,107,244	1,106,783	1,107,267	1,107,645	1,106,418	1,106,828	1,107,227	1,106,819	1,108,940

Notes: Panel A reports the fraction of firms in each beta decile classified as anomaly longs (High Net), anomaly shorts (Low Net), or neither (Middle). Panel B reports estimates from

$$r_{i,t} = \alpha_i + \alpha_t + \gamma_1 \text{News}_{i,t} + \gamma_2(\text{HighNet}_i \times \text{News}_{i,t}) + \gamma_3(\text{LowNet}_i \times \text{News}_{i,t}) + \varepsilon_{i,t},$$

estimated separately within each beta decile. Beta deciles are formed cross-sectionally each trading day. Coefficients are reported in basis points. t-statistics based on standard errors double-clustered by firm and date are reported in parentheses. The Wald row reports the test of the null hypothesis $\gamma_2 = \gamma_3$. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 5: Accumulation Test of News-Day Corrections

Notes. This table reports panel regressions of daily excess returns on news-day indicators, anomaly-portfolio interactions, and interactions with the elapsed time since the previous firm-specific news event. The sample is restricted to firms with at least one idiosyncratic news event during 2009–2025. Column (1) reports a baseline specification with News, HighNet × News, and LowNet × News. Column (2) replaces the level interactions with τ-scaled interactions, where $\tau_{i,t}$ denotes the number of calendar days since firm i's previous news event. Column (3) includes both the level and τ-scaled interaction terms jointly. Columns (2) and (3) include $\tau_{i,t}$ as a main-effect control and restrict the sample to observations with $\tau_{i,t} \leq 90$. All specifications include firm and date fixed effects. Coefficients on News, HighNet × News, and LowNet × News are reported in basis points. Coefficients on Tau and the τ-interaction terms are reported in basis points per day. t-statistics based on standard errors double-clustered by firm and date are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Dependent variable: daily excess return (bp)		
	(1) Baseline	(2) Tau-scaled	(3) Joint
News	18.00^{***}	13.00^{***}	15.00^{***}
	(15.37)	(14.28)	(14.07)
High Net × News	18.00^{***}		3.00
	(5.55)		(0.91)
Low Net × News	-8.00^{***}		-9.00^{***}
	(-5.39)		(-5.57)
Tau		0.0023	0.0006
		(0.33)	(0.09)
High Net × News × Tau		0.59^{***}	0.48^{***}
		(6.38)	(4.06)
Low Net × News × Tau		0.04	0.27^{***}
		(0.67)	(3.50)
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Tau control	—	Yes	Yes
Tau cap (days)	—	90	90
Observations	7,085,323	4,896,423	4,896,423

Table 6: Beta–Return Relation on News Days Across Aggregate News Regimes

Notes. This table reports panel regressions of daily excess returns on firm beta, a news-day indicator, and their interaction. The sample is restricted to firms with at least one idiosyncratic news event during 2009–2025. Column (1) uses the full sample of firm-days. Column (2) restricts the sample to high-news days, defined as days on which the rolling 10-day median of aggregate idiosyncratic news exceeds its trailing one-year 75th percentile. Column (3) restricts the sample to low-news days, defined as days on which the rolling 10-day median falls below its trailing one-year 25th percentile. All specifications include firm and date fixed effects. Coefficients on Beta and Beta × News are reported in basis points per unit of beta, while the coefficient on News is reported in basis points. t-statistics based on standard errors double-clustered by firm and date are reported in parentheses. The Beta × News coefficient is most negative in the high-news regime and close to zero in the low-news regime, consistent with a stronger wedge on news days when aggregate idiosyncratic news is elevated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Dependent variable: daily excess return (bp)		
	(1) Full sample	(2) High news	(3) Low news
Beta	−1.66	−4.63	−1.34
	(−1.05)	(−0.82)	(−0.21)
Beta × News	-6.57^{**}	-32.12^{**}	4.48
	(−2.02)	(−2.40)	(0.47)
News	31.35^{***}	56.80^{***}	22.53^{**}
	(7.61)	(3.55)	(2.13)
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Observations	8,475,948	914,602	614,042

Table 7: 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 8: 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 low (below its trailing 1-year 20th percentile), or excluding days with conflicting low (2) or high (3) macroeconomic attention. 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 HAC regressions of average attention paid to news articles and macroeconomic attention on the listed covariates, including month-year fixed effects. The sample spans 2010 (limited by Bloomberg attention data) to 2020 (limited by MAI data). ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels.

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: Determinants of attention allocation

	Share news	$\lvert Mkt-RF \rvert$	VIX	Macro att.	CPI	FOMC	Unemp.
Average attention to news							
Coefficient	17.8495***	2.0652	−0.0031	−0.0163	−0.1606***	0.1749**	−0.2162***
t-stat	(11.15)	(1.06)	(−0.51)	(−1.06)	(−3.25)	(2.56)	(−3.33)
Macroeconomic attention							
Coefficient	−4.1605**	5.6158*	0.0215***	—	0.0993	0.3100***	0.3300***
t-stat	(−2.55)	(1.79)	(2.90)		(1.36)	(3.70)	(4.38)

Panel B details: Both regressions include month-year fixed effects and HAC standard errors. For *avg_att_news*, the intercept is −0.4701 ($t = -1.32$), with 2,732 observations, $R^2 = 0.611$, and adjusted $R^2 = 0.590$. For *macro_att*, the intercept is 1.2163*** ($t = 5.09$), with 2,740 observations, $R^2 = 0.310$, and adjusted $R^2 = 0.274$.

Table 9: 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 2025. 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**
Coefficient	**0.07*****	0.56***	-0.065	-0.017	-0.055	00.25	-0.0012
t-stat	**(3.087)**	(4.386)	(-0.918)	(-1.242)	(-0.498)	(1.391)	(-1.315)
$R^2 = 0.253$, Adj. $R^2 = 0.252$, Obs. = 3,042							

Table 10: Robustness: standardized continuous news measure and alternative state variables in pooled regressions.

This table reports pooled panel regressions of portfolio excess returns on portfolio beta, a standardized continuous idiosyncratic news measure, and interactions between beta and standardized state variables. The baseline regressor is the standardized continuous news measure, constructed from the rolling news series. Columns (2)–(5) sequentially add disagreement, the VIX , retail attention, and institutional attention, along with their interactions with beta. Standard errors are clustered by date. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
β	0.15*	0.12	0.19*	-0.06	-0.07
	(1.71)	(1.35)	(1.85)	(-0.55)	(-0.73)
$News_z$	0.04**	0.07**	0.08***	0.07***	0.09***
	(2.00)	(2.52)	(2.98)	(2.63)	(3.23)
$News_z \times \beta$	-0.06**	-0.14***	-0.12***	-0.10***	-0.12***
	(-2.28)	(-4.32)	(-3.83)	(-3.06)	(-3.54)
$Disagreement_z$		0.03	0.05	0.09**	0.14***
		(1.01)	(1.59)	(2.38)	(3.59)
$Disagreement_z \times \beta$		-0.10***	-0.10***	-0.25***	-0.30***
		(-2.91)	(-2.93)	(-5.43)	(-6.25)
VIX_z			-0.03	-0.01	0.00
			(-0.47)	(-0.23)	(0.06)
$VIX_z \times \beta$			-0.14**	-0.25***	-0.27***
			(-2.40)	(-3.94)	(-4.20)
$Retail\ Attention_z$				-0.01	-0.01
				(-0.20)	(-0.36)
$Retail\ Attention_z \times \beta$				0.05	0.06
				(1.33)	(1.47)
$Institutional\ Attention_z$					0.02
					(1.44)
$Institutional\ Attention_z \times \beta$					-0.03
					(-1.50)
Constant	-0.10	-0.06	-0.15	-0.00	0.01
	(-1.06)	(-0.63)	(-1.28)	(-0.02)	(0.13)
Observations	33,730	30,210	30,210	25,160	24,990
R^2 (within)	0.0006	0.0043	0.0219	0.0406	0.0420

Table 11: 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 12: 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 median constant. Coefficients with t-statistics in parentheses; standard errors clustered. *, **, *** denote $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

Table 13: Placebo tests for the trading strategy across signal lags.

Placebo tests for the trading strategy across signal lags. For each lag length, the table reports the realized Sharpe ratio of the strategy, the mean and standard deviation of Sharpe ratios from placebo strategies, and the corresponding randomization p-value. In each placebo exercise, I preserve the total number of high-signal and low-signal days from the original strategy, then randomly reassign those dates across the sample without replacement. The remaining dates are classified as "other" days. Using these randomized signal assignments, I reconstruct the trading strategy and compute its annualized Sharpe ratio. This procedure is repeated 1,000 times for each lag length. The randomization p-value is the fraction of placebo Sharpe ratios that are at least as large as the Sharpe ratio of the actual strategy, and therefore measures how likely it is that the observed performance could arise from random timing alone.

Signal lag	Mean	Std. dev.	Real Sharpe	Placebo Sharpe	Randomization p-value
1 day	0.099	1.276	1.23	0.51	0.002
2 days	0.095	1.276	1.18	0.51	0.001
3 days	0.081	1.256	1.03	0.49	0.006
4 days	0.067	1.258	0.85	0.49	0.053
5 days	0.062	1.258	0.78	0.50	0.087

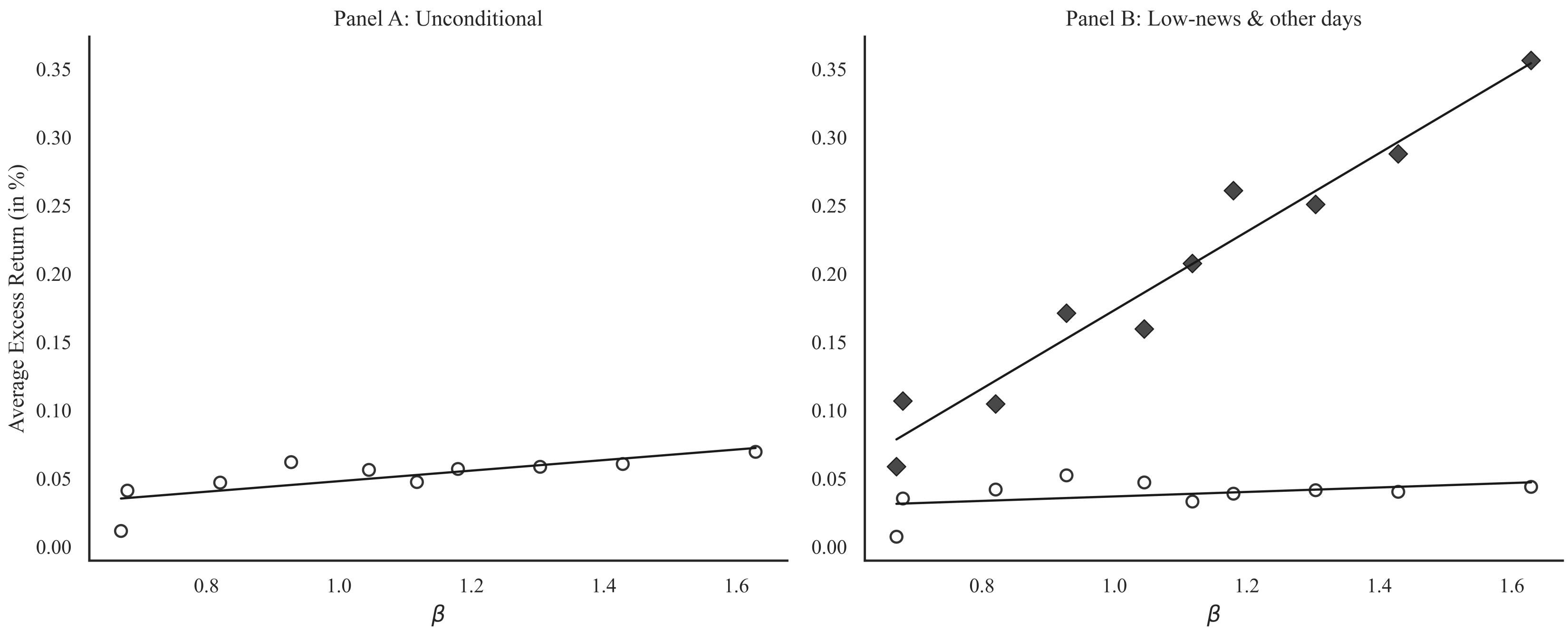

Figure 1: Average excess returns for beta decile portfolios. This figure plots the average daily excess returns (in percent) against market betas for 10 value-weighted beta-sorted portfolios. Panel A plots the unconditional SML, and panel B plots the conditional SML on low news days (with diamond markers) 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 2025.

Alt text: Panel A plots average excess returns against beta for 10 beta-sorted portfolios and shows a nearly flat unconditional security market line. Panel B compares low-news days with other days; the low-news line slopes upward, while the other-days line is flat or slightly downward sloping.

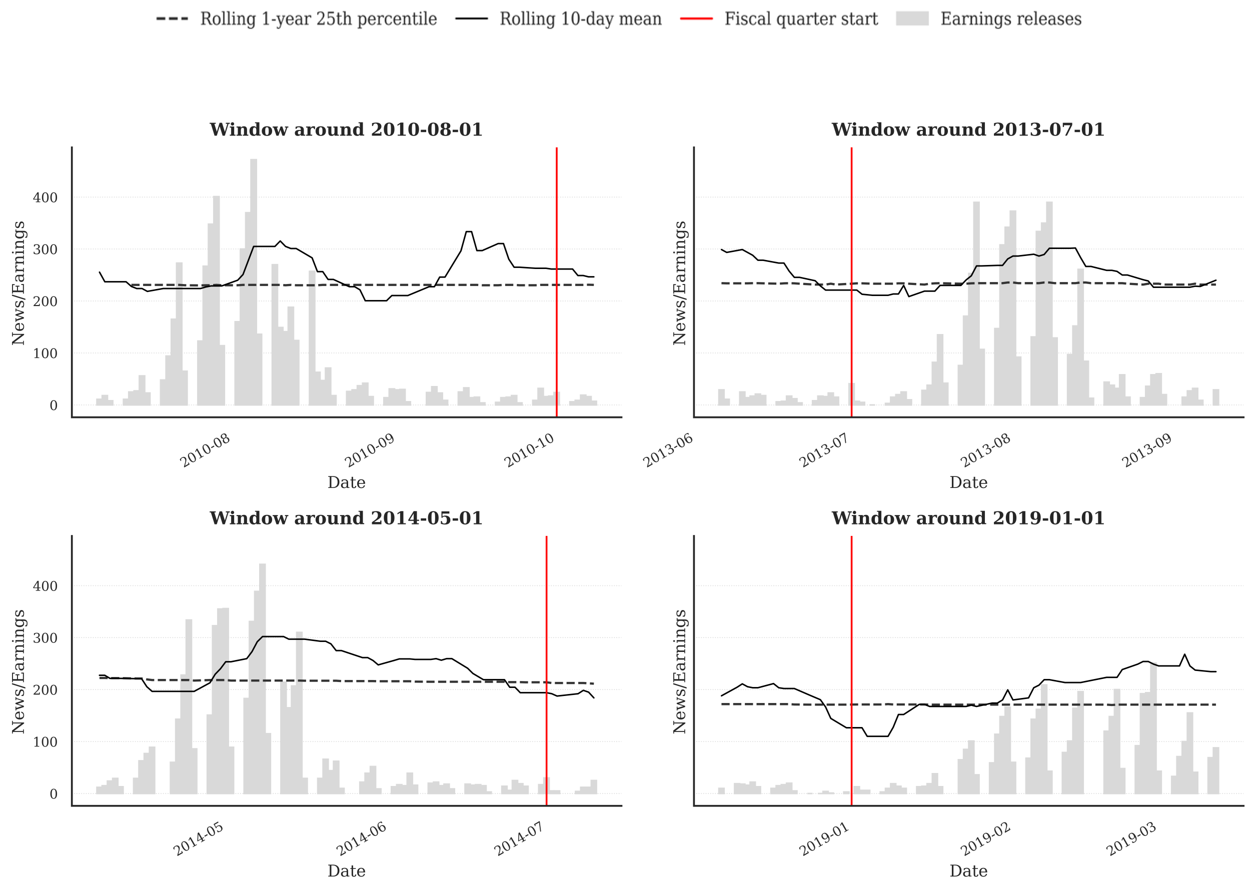

Figure 2: Each panel shows the evolution of the 10-day rolling news median (solid black line) around the rolling 1-year 25th percentile of news (dotted black line) in a different period of the sample. The total number of earnings releases for a given day is given by grey bars. Vertical red lines denote 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.

Alt text: The figure shows the construction of the low-news state over four sample periods. Aggregate idiosyncratic news falls below its rolling historical threshold in several stretches, often after most quarterly earnings announcements have passed, indicating that low-news periods are not confined to one part of the quarter.

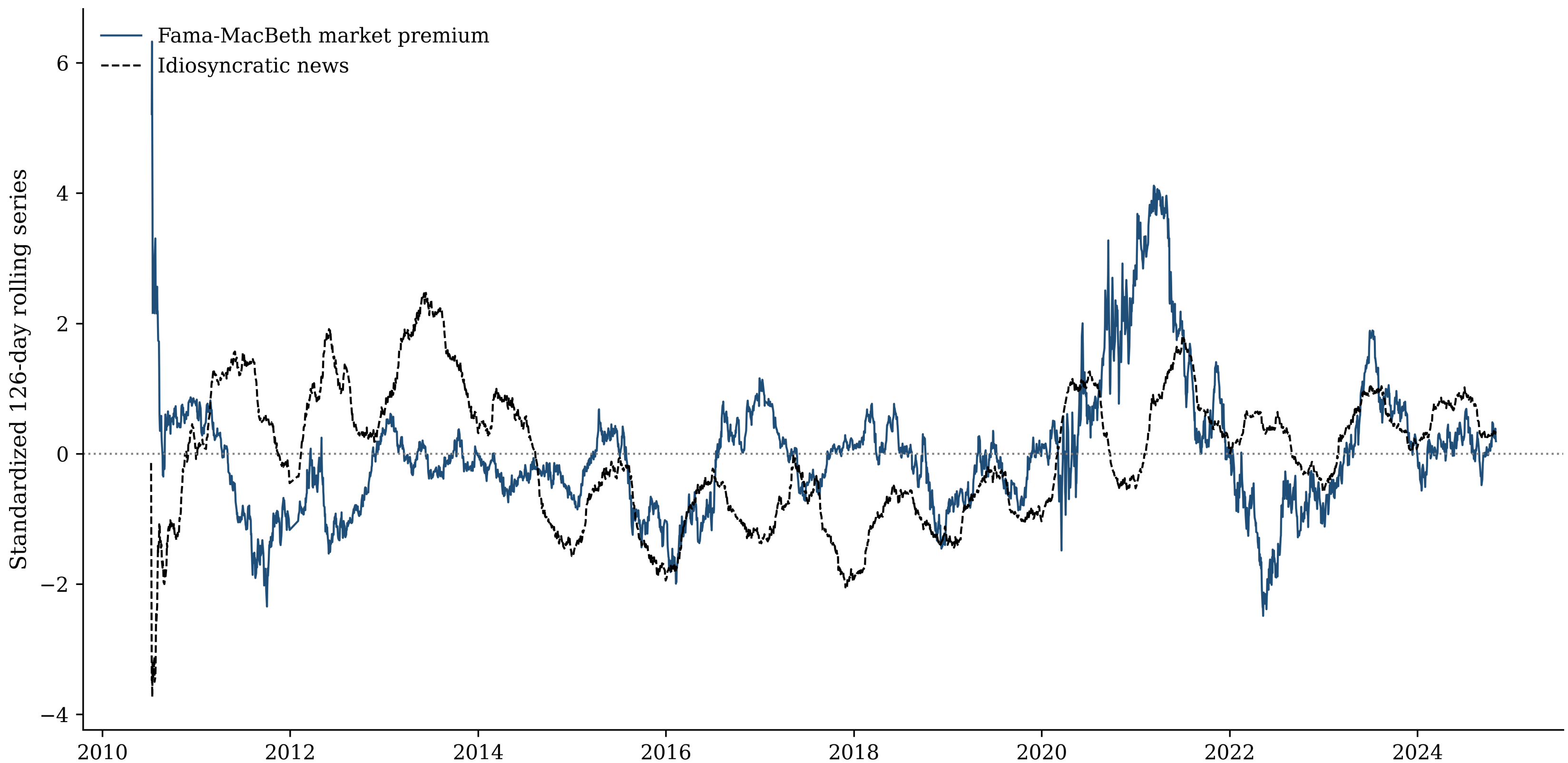

Figure 3: This figure plots the standardized, detrended series of aggregate idiosyncratic news and the Fama–MacBeth estimate of the market risk premium, each smoothed using a six-month rolling average. Both series are normalized to have mean zero and unit variance to facilitate comparison over time. The figure illustrates the time-series comovement between the aggregate idiosyncratic-news environment and the estimated slope of the security market line.

Alt text: The figure plots standardized aggregate idiosyncratic news and the standardized Fama–MacBeth estimate of the market risk premium over time, both smoothed with six-month rolling averages. Periods of higher idiosyncratic news tend to coincide with lower estimated beta premia, while quieter news periods coincide with a steeper security market line.

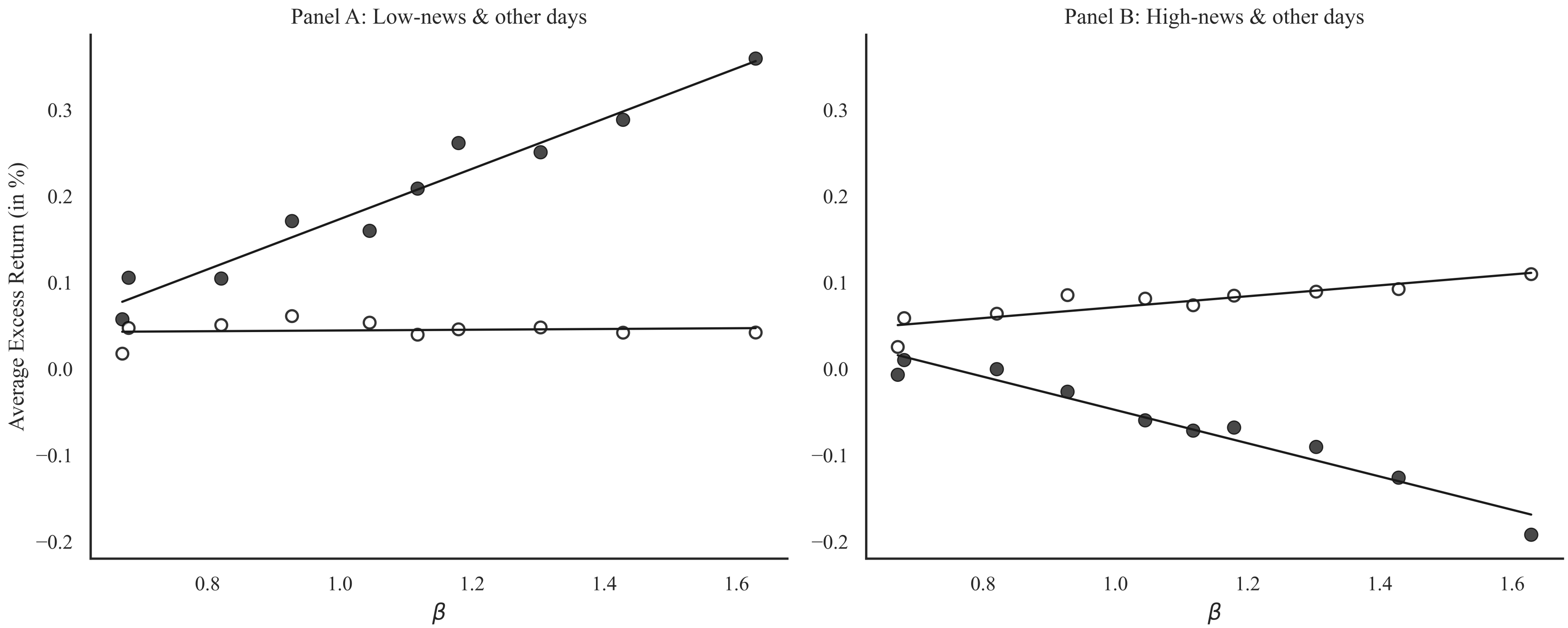

Figure 4: This figure splits the sample into four sets of days, and plots the average daily excess returns (in percent) against market betas for 10 value-weighted beta-sorted portfolios. The upward and downward sloping black SML lines plot the beta-return relationship on low-news and high-news days respectively. 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.

Alt text: The figure plots average excess returns against beta for 10 beta-sorted portfolios separately for low-news, high-news, and other days. The low-news line slopes upward, the high-news line slopes downward, and the line for all other days is close to flat.

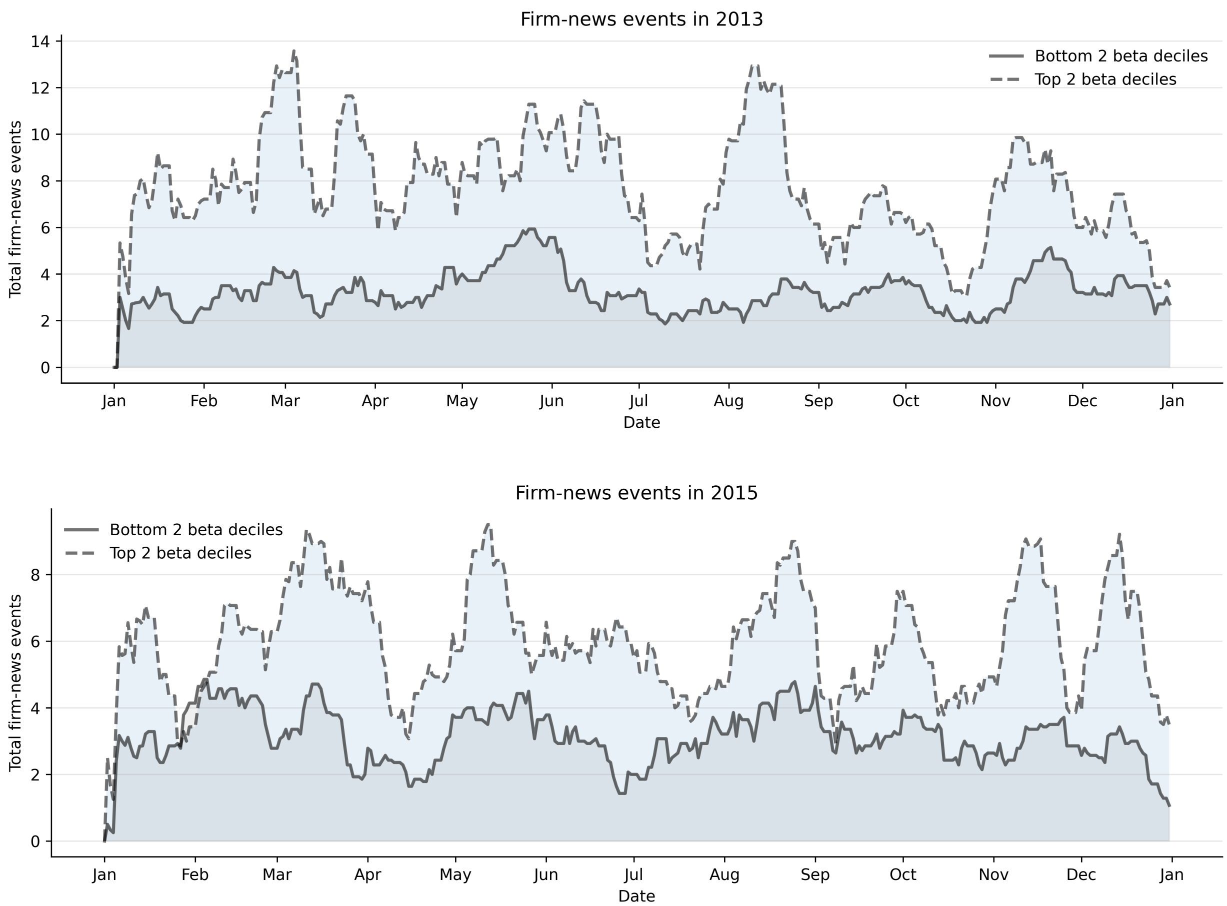

Figure 5: Distribution of negative idiosyncratic news releases, high and low beta firms for two sample years. Counts of negative firm-news events are summed across all firms daily and the 10-day rolling median is plotted for each day of the year. Negative firm-news events occur when a news item appearing 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.

Alt text: Two stacked time-series panels for 2013 and 2015 plotting the 10-day rolling count of negative firm-news events; the dashed line for top-two beta deciles sits well above the solid line for bottom-two deciles and shows more pronounced peaks throughout the year.

A Appendix

A.1 Proof of Proposition 1

Combining (1) and (2),

$$r_{i,t} = \beta_i \mu_\lambda + \beta_i \tilde{f}_t + \delta_{i,t}\, g_{i,t} + \varepsilon_{i,t}. \tag{18}$$

The cross-sectional covariance with β_i is

$$\begin{aligned}\mathrm{Cov}_i(\beta_i,\, r_{i,t}) &= \mathrm{Cov}_i\big(\beta_i,\ \beta_i(\mu_\lambda + \tilde{f}_t)\big) + \mathrm{Cov}_i\big(\beta_i,\ \delta_{i,t}\, g_{i,t}\big) + \mathrm{Cov}_i\big(\beta_i,\ \varepsilon_{i,t}\big) \\ &= (\mu_\lambda + \tilde{f}_t)\, \mathrm{Var}_i(\beta_i) + \mathrm{Cov}_i\big(\beta_i,\ \delta_{i,t}\, g_{i,t}\big) + 0,\end{aligned} \tag{19}$$

where the last term vanishes because $\varepsilon_{i,t}$ is independent of β_i. Dividing by $\mathrm{Var}_i(\beta_i)$:

$$\lambda_t^{FM} = \mu_\lambda + \tilde{f}_t + \frac{\mathrm{Cov}_i(\beta_i,\ \delta_{i,t}\, g_{i,t})}{\mathrm{Var}_i(\beta_i)} = \mu_\lambda + \tilde{f}_t + w_t. \tag{20}$$

A.2 Proof of Corollary 1

The market return is $r_{m,t} = \frac{1}{N}\sum_{j=1}^{N} r_{j,t}$. Substituting (1)–(2),

$$r_{m,t} = \bar{\beta}(\mu_\lambda + \tilde{f}_t) + G_t + E_t, \qquad G_t \equiv \frac{1}{N}\sum_{j=1}^{N} \delta_{j,t}\, g_{j,t}, \quad E_t \equiv \frac{1}{N}\sum_{j=1}^{N} \varepsilon_{j,t}. \tag{21}$$

Under the independence assumption on ε and conditional cross-firm independence of $\{\delta_{j,t} g_{j,t}\}_j$ given the aggregate state, both G_t and E_t have time-series variance of order $1/N$, so as $N \to \infty$,

$$\mathrm{Var}(r_{m,t}) = \bar{\beta}^2 \sigma_f^2 + O(1/N), \qquad \mathrm{Cov}(r_{i,t}, r_{m,t}) = \beta_i \bar{\beta}\, \sigma_f^2 + O(1/N), \tag{22}$$

where the $O(1/N)$ term in the covariance comes from the $j = i$ contribution to G_t and E_t. Without loss of generality, normalize $\bar{\beta} = 1$.[4] The OLS slope is therefore

$$\hat{\beta}_i^{\mathrm{OLS}} = \frac{\mathrm{Cov}(r_{i,t}, r_{m,t})}{\mathrm{Var}(r_{m,t})} = \beta_i + o_p(1). \tag{23}$$

[4] The normalization is innocuous: Proposition 1's denominator $\mathrm{Var}_i(\beta_i)$ is scale-equivariant, and all subsequent ratios are invariant to rescaling.

The OLS intercept is $\hat{\alpha}_i = \bar{r}_i - \hat{\beta}_i^{\mathrm{OLS}}\,\bar{r}_m$, where bars denote time averages. Writing $\mu_i \equiv \mathbb{E}[\delta_{i,t} g_{i,t}]$ and $\bar{\mu} \equiv \frac{1}{N}\sum_j \mu_j$,

$$\bar{r}_i = \beta_i \mu_\lambda + \mu_i + o_p(1), \qquad \bar{r}_m = \mu_\lambda + \bar{\mu} + o_p(1), \tag{24}$$

so $\hat{\alpha}_i = \mu_i - \beta_i \bar{\mu} + o_p(1)$. Combining,

$$\varepsilon_{i,t}^{\mathrm{OLS}} = r_{i,t} - \hat{\alpha}_i - \hat{\beta}_i^{\mathrm{OLS}} r_{m,t} = (\delta_{i,t} g_{i,t} - \mu_i) + \varepsilon_{i,t} + o_p(1), \tag{25}$$

where the $\beta_i \tilde{f}_t$ and $\beta_i \mu_\lambda$ terms cancel against the market projection and the G_t, E_t contributions are absorbed into $o_p(1)$.

Since μ_i is a constant that does not contribute to variance, conditioning on $\delta_{i,t}$ gives

$$\mathrm{Var}\big(\varepsilon_{i,t}^{\mathrm{OLS}} \,\big|\, \delta_{i,t}\big) = \delta_{i,t}\, \sigma_{g,i,t}^2 + \sigma_\varepsilon^2 + o(1), \tag{26}$$

which establishes (4).

For the monotonicity claim, let $p_i(N_t) \equiv \Pr(\delta_{i,t} = 1 \mid N_t)$ and $\mu_i^* \equiv \mathbb{E}[g_{i,t} \mid \delta_{i,t} = 1]$, and assume that $g_{i,t}$ conditional on $\delta_{i,t} = 1$ is mean-independent of the aggregate state N_t. By the law of total variance,

$$\mathrm{Var}\big(\varepsilon_{i,t}^{\mathrm{OLS}} \,\big|\, N_t\big) = p_i(N_t)\, \sigma_{g,i,t}^2 + \sigma_\varepsilon^2 + \mathrm{Var}\big(\mathbb{E}[\varepsilon_{i,t}^{\mathrm{OLS}} \mid \delta_{i,t}, N_t] \,\big|\, N_t\big) + o(1). \tag{27}$$

The conditional expectation inside the third term takes two values: $\mu_i^* - \mu_i$ with probability $p_i(N_t)$ and $-\mu_i$ with probability $1 - p_i(N_t)$, where $\mu_i = p_i^* \mu_i^*$ and $p_i^* \equiv \Pr(\delta_{i,t} = 1)$ is the unconditional announcement frequency. A direct calculation yields

$$\mathrm{Var}\big(\mathbb{E}[\varepsilon_{i,t}^{\mathrm{OLS}} \mid \delta_{i,t}, N_t] \,\big|\, N_t\big) = p_i(N_t)\, \big(1 - p_i(N_t)\big)\, (\mu_i^*)^2, \tag{28}$$

so that

$$\mathrm{Var}\big(\varepsilon_{i,t}^{\mathrm{OLS}} \,\big|\, N_t\big) = p_i(N_t)\, \sigma_{g,i,t}^2 + p_i(N_t)\big(1 - p_i(N_t)\big)\, (\mu_i^*)^2 + \sigma_\varepsilon^2 + o(1). \tag{29}$$

The first term is non-decreasing in N_t provided $p_i(N_t)$ is non-decreasing. This holds under either of two sufficient conditions: *(i)* the $\{\delta_{j,t}\}_{j=1}^N$ are exchangeable across j, in which case $p_i(N_t) = N_t$ exactly by symmetry and the tower property; or *(ii)* the $\{\delta_{j,t}\}_j$ are positively associated in the FKG sense, in which case $\mathbb{E}[\delta_{i,t} \mid N_t]$ is non-decreasing in N_t by the Harris–FKG inequality. Condition *(ii)* is the economically natural one: days on which the aggregate news count is high are days on which each firm is more likely to be announcing.

The third term in (29), $V(p) \equiv p(1-p)(\mu_i^*)^2$, is monotone increasing in p on $[0, 1/2]$ and monotone decreasing on $[1/2, 1]$. For (29) to be monotone non-decreasing in N_t, it therefore suffices that $p_i(N_t) \leq 1/2$ throughout the empirically relevant range of N_t.

Empirical justification of the bound $p_i(N_t) \leq 1/2$. This condition is satisfied by a wide margin in the sample. Table 1 reports that the daily aggregate news count $\sum_j \delta_{j,t}$ has mean 223 and 75th percentile 266, with an empirical maximum of approximately 500 articles per day. Given the data, this suggests the threshold of 1/2 at which $V(p)$ is maximized should not be reached on a given day. Realistically it is unlikely that more than half of firms in the cross section would have a firm-specific news arrival.

Because $p_i(N_t) \leq 1/2$ in the relevant range, the third term in (29) is non-decreasing in $p_i(N_t)$ wherever the first term is. Combining with the constancy of σ_ε^2, it follows that $\mathbb{E}[\mathrm{Var}(\varepsilon_{i,t}^{\mathrm{OLS}}) \mid N_t]$ is non-decreasing in N_t, which establishes the second claim of Corollary 1.

A.3 Proof of Proposition 2

Let $\mathcal{A}_{t+1} = \{i : \delta_{i,t+1} = 1\}$. Since $\delta_{i,t+1}\, g_{i,t+1} = 0$ for $i \notin \mathcal{A}_{t+1}$, the wedge simplifies to

$$w_{t+1} = \frac{\dfrac{1}{N} \displaystyle\sum_{i \in \mathcal{A}_{t+1}} (\beta_i - \bar{\beta})\, g_{i,t+1}}{\mathrm{Var}_i(\beta_i)}. \tag{30}$$

Under Assumption 1, $\delta_{i,t+1}$ is independent of $(\beta_i, a_i, g_{i,t+1})$ given $\tau_i(t)$ and date-t information, so conditional expectations over $g_{i,t+1}$ within the announcing set use the unconditional announcement mean. Applying $\mathbb{E}[g_{i,t+1} \mid \delta_{i,t+1} = 1] = \tau_i(t)\, \kappa\, a_i$ from (5):

$$\mathbb{E}_t[w_{t+1} \mid \mathcal{A}_{t+1}] = \frac{\kappa}{N \cdot \mathrm{Var}_i(\beta_i)} \sum_{i \in \mathcal{A}_{t+1}} (\beta_i - \bar{\beta})\, \tau_i(t)\, a_i. \tag{31}$$

Combining with $\mathbb{E}_t[\tilde{f}_{t+1}] = 0$ and Proposition 1:

$$\mathbb{E}_t[\lambda_{t+1}^{FM} \mid \mathcal{A}_{t+1}] = \mu_\lambda + \frac{\kappa}{N \cdot \mathrm{Var}_i(\beta_i)} \sum_{i \in \mathcal{A}_{t+1}} (\beta_i - \bar{\beta})\, \tau_i(t)\, a_i. \tag{32}$$

A.4 Proof of Corollary 2

Under Assumption 1, conditional on $\tau_i(t)$, the indicator $\delta_{i,t+1}$ is independent of (β_i, a_i). Partition the announcing set by lag: $\mathcal{A}_{t+1}(\tau) = \{i \in \mathcal{A}_{t+1} : \tau_i(t) = \tau\}$ with $n_{t+1}(\tau) = |\mathcal{A}_{t+1}(\tau)|$, and let $\mathcal{P}(\tau)$ with $N(\tau) = |\mathcal{P}(\tau)|$ denote the population with lag τ. Rewriting the exact sum in Proposition 2:

$$\sum_{i \in \mathcal{A}_{t+1}} (\beta_i - \bar{\beta})\, \tau_i(t)\, a_i = \sum_{\tau} \tau \sum_{i \in \mathcal{A}_{t+1}(\tau)} (\beta_i - \bar{\beta})\, a_i. \tag{33}$$

Within each lag group, announcing firms are a random draw from $\mathcal{P}(\tau)$ with respect to (β_i, a_i). Define $m(\tau) \equiv \frac{1}{N(\tau)} \sum_{i \in \mathcal{P}(\tau)} (\beta_i - \bar{\beta})\, a_i$.[5] For large $n_{t+1}(\tau)$:

$$\frac{1}{n_{t+1}(\tau)} \sum_{i \in \mathcal{A}_{t+1}(\tau)} (\beta_i - \bar{\beta})\, a_i \;\xrightarrow{p}\; m(\tau). \tag{34}$$

If the lag composition among announcers is representative of the population ($n_{t+1}(\tau)/n_{t+1} \approx N(\tau)/N$, where $n_{t+1} = |\mathcal{A}_{t+1}|$),[6]

$$\frac{1}{N} \sum_{i \in \mathcal{A}_{t+1}} (\beta_i - \bar{\beta})\, \tau_i(t)\, a_i \;\approx\; N_{t+1} \sum_{\tau} \frac{N(\tau)}{N}\, \tau\, m(\tau). \tag{35}$$

Since $\mathbb{E}_i[(\beta_i - \bar{\beta})\, \tau_i(t)\, a_i] = \mathrm{Cov}_i(\beta_i,\ \tau_i(t)\, a_i)$ (because $\mathbb{E}_i[\beta_i - \bar{\beta}] = 0$):

$$\mathbb{E}_t[\lambda_{t+1}^{FM} \mid N_{t+1}] \;\approx\; \mu_\lambda + \kappa\, N_{t+1}\, \frac{\mathrm{Cov}_i(\beta_i,\ \tau_i(t)\, a_i)}{\mathrm{Var}_i(\beta_i)}. \tag{36}$$

[5] The quantity $m(\tau)$ is the population mean of $(\beta_i - \bar{\beta})a_i$ among firms with lag τ, centered at the unconditional mean $\bar{\beta}$, not at the conditional mean $\mathbb{E}[\beta_i \mid \tau]$. It is not a conditional covariance. The unconditional centering arises because the wedge is defined through $\mathrm{Cov}_i(\beta_i, \delta_{i,t} g_{i,t})$, which centers β_i at $\bar{\beta}$.

[6] This is approximately satisfied during earnings seasons. During quiet periods, N_{t+1} is small and the wedge is negligible, so the approximation error is inconsequential.

A.5 Orthogonality of the factor surprise and the news state

Proposition 1 states that w_t is the only channel through which aggregate news intensity affects the conditional expected SML slope. This follows from μ_λ being constant and from the identifying assumption

$$\mathbb{E}[\tilde{f}_t \mid N_t] = 0. \tag{37}$$

Three considerations support (37) in the present empirical setting. First, the news corpus used to construct N_t is filtered to remove systematic news: articles about earnings are excluded at the keyword level, and remaining articles are further classified by GPT-4.0 mini and retained only if labeled both "singular" and "idiosyncratic." By construction, the measure is designed to vary with the supply of *firm-specific* information rather than with market-wide information releases. Second, the measure is empirically orthogonal to realized market returns in the sample: Panel C of Table 1 reports a correlation between aggregate idiosyncratic news and $R_m - R_f$ of essentially zero, and a correlation with the VIX of 0.033. Third, the wedge regressions in Table 6 and the residual-variance test in Table 3 control for VIX tercile and deliver the same qualitative conclusions within each volatility regime, so variation in realized factor volatility cannot be driving the results.

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 14: 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