Concentration is All the CAPM Needs

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Abstract

The Capital Asset Pricing Model (CAPM) is rejected empirically because market beta is weakly related to average returns. This paper shows that the performance of the CAPM depends on where institutional investors concentrate their attention. Using firm-specific news from the Dow Jones Newswire and institutional attention measures from Bloomberg search activity, I isolate states in which market-wide attention is focused on publicly available firm-level news. The CAPM prices risk when institutional attention is concentrated on public firm-specific news, even though overall attention levels are lower. Market betas explain the cross section of stock returns, and the security market line is steep and positive. In contrast, when attention is elevated but not well explained by firm-specific news, the beta–return relation flattens or reverses. To rationalize these findings, I develop a general equilibrium model in which investors allocate attention between firm-specific public news and direct signals about the aggregate factor. Because attention to firm-specific news crowds out private learning about the common factor, greater attention to firm-level information increases posterior factor uncertainty. Investors require compensation for bearing this uncertainty, generating a higher equilibrium factor risk premium and a steeper security market line. Empirically, unconditional betas price returns for approximately 46% of trading days.

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1 Introduction

A persistent tension separates the theory of asset pricing from its empirical application. The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) predicts that an asset's risk premium is increasing in its market beta. Despite the model's central role in academic research and practitioner discount-rate calculations (Berk and van Binsbergen, 2017), this prediction performs poorly empirically in cross-sectional tests. A recent literature offers conditional resolutions to this puzzle[1]. A common theme in these resolutions is that the beta–return relation depends on investors processing information, and several recent studies suggest that investor attention could play an important role in determining asset prices. This paper argues that the CAPM succeeds not only when investors pay more attention, but when attention is concentrated on a particular kind of information: public firm-specific news.

This paper makes two contributions. I show empirically that the CAPM prices the cross section when investor attention is concentrated on firm-specific news, even on days when aggregate attention is unremarkable. This pricing is evident for at least 46% of trading days between 2010 and 2025. The bottom quartile of the distribution alone accounts for 24.6% of trading days, yet captures 51% of the cumulative market risk premium earned over the sample period. The second contribution is theoretical. I develop a noisy rational expectations model in which attention to purely firm-specific news and attention to direct macroeconomic signals are substitutes from the investor's perspective. Because firm-level news is informationally orthogonal to the aggregate factor by construction, each unit of attention allocated toward firm-level news crowds out private learning about the common market factor. Posterior factor uncertainty rises with the share of attention directed toward firm-specific news, the equilibrium factor risk premium rises with it, and the security market line steepens.

The theoretical model is a multi-firm variant of Grossman and Stiglitz (1980), in which firms release firm-specific public news and investors allocate a fixed attention budget between processing that news and conducting analysis of a common macroeconomic factor. I focus on firm-specific news because, once market-level content is filtered out, it is informationally orthogonal to the aggregate factor: it resolves uncertainty about a firm's idiosyncratic payoff but conveys nothing about systematic risk or factor loadings (Patton and Verardo, 2012; Boudoukh et al., 2019). Attention is divided across idiosyncratic and systematic learning

[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.

channels, so that the concentration of attention, not merely its level, determines equilibrium prices (Peng and Xiong, 2006; Veldkamp, 2006a). This facilitates predictions about how the share of attention devoted to firm-specific news affects posterior factor uncertainty, the cross-sectional pricing of systematic risk, and the slope of the security market line.

The model predicts that when investors concentrate attention on firm-specific news, they necessarily learn less about the common factor, leaving them more exposed to factor uncertainty in equilibrium. To clear markets, expected returns must compensate for this residual uncertainty, so the cross-section of average returns aligns better with betas, and the security market line steepens. I verify this empirically.

The empirical strategy isolates this composition channel using two complementary measures of information processing. From the Dow Jones Institutional Newswire, I extract firm-specific news articles and filter out systematic and earnings-related content using keyword screens and a GPT-4o-mini classifier that retains only articles labeled as relevant to individual firms and not related to what happened in the market that day. From Bloomberg, I obtain firm-day institutional investor attention scores following Ben-Rephael, Da, and Israelsen (2017). I then construct two aggregate daily series for the Russell 3000 universe. The first is an idiosyncratic news attention index, IAI_t, defined as the cross-sectional average of Bloomberg attention scores among firms with a filtered idiosyncratic news article on day t. The second is an aggregate institutional attention index, AIA_t, defined as in Chan and Marsh (2022). The key state variable is the residual $\widehat{u}_t$ from a daily expanding-window regression of AIA_t on IAI_t. When $\widehat{u}_t$ is low, aggregate institutional attention is well explained by attention to filtered firm-specific news. In this state, attention is anchored in firm-level content. When $\widehat{u}_t$ is high, attention is elevated but not well explained by idiosyncratic news, consistent with attention being diverted toward broader market-wide or macroeconomic processing.

On the approximately 46% of trading days when the rolling median of $\widehat{u}_t$ lies below its trailing one-year 50th percentile, the beta–return relationship is positive and statistically significant, with magnitudes between 12 and 19 basis points per day (t-statistics above 3), and the intercept is statistically indistinguishable from zero. The security market line is steep, positive, and consistent with predictions of the CAPM. On the complementary set of days, the slope flattens or reverses. Crucially, this is not a high-attention result in the sense of Ben-Rephael, Carlin, Da, and Israelsen (2021). The bottom-quartile residual days are days on which both AIA_t and IAI_t are below their sample means; the share of total attention captured by firm-news is what matters, not the level. Replicating the expected-information-consumption framework of Ben-Rephael, Carlin, Da, and Israelsen (2021) confirms complementarity rather than redundancy: the conditional pricing result persists at full strength when the sample is restricted to firms that their measure does not flag as expected to consume information.

The closest prior work is Andrei, Friedman, and Ozel (2023) (hereafter AFO). AFO show that the CAPM performs better on earnings days, especially in high-VIX states when aggregate investor attention is elevated. Their mechanism, drawing on Epstein and Turnbull (1980), is an intertemporal resolution channel: attention pulls the resolution of factor uncertainty forward into the announcement window, so holding the market during this now-active resolution event is risky and commands a positive announcement-day premium. In their model, the earnings signal contains a factor component, so attention to earnings generates cross-sectional information spillovers about the aggregate factor and reduces posterior factor variance. The mechanism in this paper is the mirror image of AFO. The empirical state variable is not the level of attention, but where it is concentrated: the conditional success of the CAPM arises when institutional attention is concentrated on public firm-specific news, even though aggregate attention is below average. The theoretical primitive also operates in the opposite direction on factor uncertainty. Because firm-specific news is orthogonal to the factor in the model, attention to this news crowds out direct factor learning and thus raises posterior factor variance.

The resulting premium compensates investors for bearing greater unresolved systematic risk, rather than for bearing risk during accelerated resolution. This distinction also separates the two mechanisms empirically. AFO's channel is naturally strongest in high-uncertainty states, where attention is activated by heightened uncertainty and earnings signals carry factor-relevant information that reduces posterior factor variance. The attention concentration channel documented here operates through a different part of the information environment: it requires only that institutional attention be concentrated on firm-specific news that is orthogonal to the factor, and does not rely on elevated uncertainty to generate the premium. Consistent with this separation, the conditional beta slope on bottom-median residual days is 14.4 basis points ($t = 4.79$) within the low-VIX subsample, where AFO's resolution channel is dormant. In the high-VIX subsample, the coefficient remains positive at 8.2 basis points but is imprecisely estimated ($t = 0.76$), consistent with higher return volatility reducing the precision of cross-sectional estimates in turbulent markets. The composition channel is therefore most cleanly identified in precisely the regime where AFO's mechanism is inactive, suggesting the two channels capture distinct features of the information environment rather than competing explanations of the same variation.

This positioning has a deeper interpretive content. Berk and van Binsbergen (2016) document that mutual fund flows respond to CAPM alphas more strongly than to alphas from any multi-factor alternative, concluding that investors use the CAPM. Yet the unconditional

CAPM is rejected in cross-sectional tests. One reconciliation is that investors form beliefs according to the CAPM but the cross-sectional pricing implication only emerges when their attention is actively engaged in processing the firm-specific information that translates beliefs into prices. The conditional result documented here is consistent with this view: the CAPM emerges in the cross section on the days when institutional attention is anchored to firm-news processing, and recedes when attention drifts elsewhere.

The findings also speak to a broader question about what investor attention does to asset prices. Peng and Xiong (2006) argue that limited-capacity investors exhibit category-learning behavior, choosing between processing market-wide and firm-specific information. Veldkamp (2006b) shows that costly information acquisition generates excess comovement when investors substitute toward common signals. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) model attention reallocation across business-cycle states and show that attention to systematic versus idiosyncratic risks varies endogenously. The mechanism developed here builds on this tradition but with a distinct emphasis: under the orthogonality structure motivated by the LLM filter, attention composition has an unconditional effect on factor uncertainty that does not rely on equilibrium feedback through prices, learning from prices, or general-equilibrium attention-supply effects.

The conditional pricing result is robust to a battery of alternative specifications. Excluding firms within a five-day earnings announcement window barely affects the beta slope, ruling out the possibility that the finding is driven by the announcement premium documented in Savor and Wilson (2016) and Chan and Marsh (2022). Removing macroeconomic announcement days and leading earnings announcement days from the sample leaves the magnitudes and significance levels essentially unchanged. Splitting the bottom-median residual state by disagreement and VIX reveals that the result holds within both high and low disagreement environments, and is strongest when the VIX is low, consistent with the model's prediction that the composition channel is most transparent when background factor uncertainty is subdued and the resolution channel of Andrei, Friedman, and Ozel (2023) is dormant. Finally, reconstructing the attention-composition measure using firm-specific news from individual beta or size deciles shows that the conditional CAPM emerges broadly across constructions, with significant beta slopes in the majority of deciles for both sorts, indicating that no single segment of the cross section is responsible for the finding.

The remainder of the paper proceeds as follows. Section 2 reviews related literature. Section 3 describes the data and constructs the attention measures. Section 4 presents the empirical results. Section 5 develops the model and derives the central theoretical proposition. Section 6 connects the model to the empirical findings and presents comparative-static evidence.

Section 7 concludes.

2 Related Literature

This paper builds on four strands of research: the literature on the empirical failure of the unconditional CAPM and its conditional resolutions, the literature on investor attention and asset prices, the literature on rational information acquisition, and a small but rapidly growing set of recent papers that link attention measures to CAPM tests.

The unconditional CAPM has been rejected in cross-sectional tests since Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973), with Fama and French (1992) delivering the canonical statement. A long literature attributes the empirical flatness of the security market line to leverage constraints (Black, 1972; Frazzini and Pedersen, 2014), margin frictions (Jylhä, 2018), disagreement combined with short-sale constraints (Hong and Sraer, 2016), the cross-sectional correlation between beta and idiosyncratic volatility (Liu, Stambaugh, and Yuan, 2018), errors-in-variables in estimated betas (Shanken, 1992), market-proxy misspecification (Roll, 1977; Kandel and Stambaugh, 1995), and dispersed information among investors (Andrei, Cujean, and Wilson, 2023). A parallel strand identifies specific states in which the CAPM performs well. The pricing of beta is stronger in January (Tinic and West, 1984), on macroeconomic announcement days (Savor and Wilson, 2014), around the earnings releases of bellwether firms (Chan and Marsh, 2022), overnight (Hendershott, Livdan, and Rösch, 2020), when volatility is low (Hasler and Martineau, 2023), and when the expected market return is high (Hasler and Martineau, 2024).

The asset-pricing consequences of limited investor attention have been studied extensively since Merton (1987). Peng and Xiong (2006) formalize the category-learning behavior of capacity-constrained investors and show that attention allocation generates excess comovement at the category level. Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009) document that distraction attenuates the price response to firm-specific news. Retail attention, proxied by Google search activity (Da, Engelberg, and Gao, 2011) or by direct retail measures (Da, 2025), predicts short-horizon return patterns. Institutional attention, measured through Bloomberg search activity, has been shown by Ben-Rephael, Da, and Israelsen (2017) to forecast both price discovery and underreaction to news, and by Ben-Rephael, Carlin, Da, and Israelsen (2021) to interact with the cross-sectional pricing of risk in ways tied to the timing of expected information consumption. Fisher, Martineau, and Sheng (2022) construct a macroeconomic attention index from newspaper text and show that macro attention is priced in announcement returns. The present paper contributes to this literature by introducing a measure of attention concentration: the share of total institutional attention captured by firm-specific news, and showing that this share is precisely the state variable that conditions the empirical success of the CAPM. The composition measure is distinct from the level of institutional attention studied in Ben-Rephael, Carlin, Da, and Israelsen (2021); indeed, the conditional CAPM result emerges on days when total attention is below average but its firm-news share is elevated.

The theoretical foundation of the paper draws on the rational inattention literature initiated by Sims (2003) and developed in finance by Veldkamp (2006b,c) and Van Nieuwerburgh and Veldkamp (2009, 2010). Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) model attention reallocation between aggregate and firm-specific risks across business-cycle states and show that capable investors shift toward systematic information when recession risk is high. Andrei and Hasler (2015) link attention to volatility and risk premia in a dynamic learning framework. The model developed here adopts the static, CARA-Gaussian, noisy-rational-expectations architecture standard in this literature (Grossman and Stiglitz, 1980; Admati, 1985) and adds a single distinguishing assumption: filtered firm-news is informationally orthogonal to the aggregate factor by construction. This assumption is motivated directly by the empirical filtering procedure. The LLM classifier explicitly strips market-level and macro content from the news corpus. Under this orthogonality, attention to firm-news improves idiosyncratic learning at the unavoidable cost of factor learning, and the resulting opportunity cost translates directly into a higher equilibrium factor risk premium. The model is silent on the deeper question of why attention concentration varies across days, treating it as a state variable proxied empirically by the composition of observed attention.

A small set of recent papers has begun to link attention measures directly to conditional CAPM tests. Chan and Marsh (2022) show that the CAPM holds during leading earnings announcement weeks and link this to institutional attention to bellwether firms. Ben-Rephael, Carlin, Da, and Israelsen (2021) document that the macroeconomic announcement premium of Savor and Wilson (2014) obtains primarily on days of high institutional attention, and develop an expected-information-consumption framework that identifies firm-days on which attention spikes are predictable. Most directly, Andrei, Friedman, and Ozel (2023) (AFO) show that the CAPM steepens on earnings days when aggregate uncertainty is high, and rationalize this through an Epstein–Turnbull mechanism in which heightened attention accelerates the intertemporal resolution of macroeconomic uncertainty. The relationship between the present paper and AFO warrants careful articulation. AFO identify a level effect operating in the high-VIX regime through a resolution channel that reduces posterior factor uncertainty V_f. The present paper identifies a composition effect operating most cleanly in the low-VIX regime through an opportunity-cost channel that raises V_f. The two channels are not in conflict; they operate in different regimes through different mechanisms and have opposite signs on the same theoretical object. AFO's earnings signal contains an explicit factor component ($b_a f$) that generates cross-sectional spillovers about the factor, so attention to earnings in their setting provides indirect factor learning. The present model shuts this channel down by assumption: filtered firm-news is orthogonal to the factor by construction, leaving private signals as the only conduit for factor information.

A complementary view is provided by Andrei, Cujean, and Wilson (2023), who show that dispersed information among investors can simultaneously generate a strong CAPM at the agent level and an apparently flat SML at the econometrician level. They argue that public information crowds out private information, reduces disagreement, and steepens the empiricist's SML. The conditional result documented here is broadly consistent with this view but mechanistically distinct. The empirical residual attention measure is negatively correlated with disagreement, and the main results of this paper hold when tested within states of both high and low aggregate disagreement. Instead, the relevant feature is the orthogonality of filtered firm-news to the factor and the resulting opportunity cost of attention.

Finally, the paper connects to recent work on the use of large language models in finance. The LLM filtering step that produces the orthogonality assumption underlying the model parallels related applications of language models to news classification (Lopez-Lira and Tang, 2023; Jha, Qian, and Tang, 2024). The substantive use of the LLM here is to operationalize the theoretical primitive: by stripping market-level content from the news corpus, the filter ensures that the empirical attention-to-news measure tracks attention to firm-specific information of the kind that the model assumes is orthogonal to the factor. The interpretation of the model and the construction of the data are tightly linked through this filtering step.

3 Model

The economy lasts a single period and contains N risky assets and a risk-free asset normalized to zero return. The payoff to risky asset $i \in \{1, \dots, N\}$ is

$$d_i = \bar{d} + \beta_i f + \varepsilon_i, \tag{1}$$

where $\bar{d}$ is a known constant, $f \sim \mathcal{N}(0, \sigma_f^2)$ is a common factor, and $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ are mutually independent firm-specific shocks. The factor loading is

$$\beta_i = b_i + \nu_i, \qquad \nu_i \sim \mathcal{N}(0, \sigma_\nu^2), \tag{2}$$

with b_i a known prior mean and ν_i mutually independent across i and orthogonal to (f, ε_i). I write $\tau_f \equiv \sigma_f^{-2}$, $\tau_\nu \equiv \sigma_\nu^{-2}$, $\tau_\varepsilon \equiv \sigma_\varepsilon^{-2}$.

A continuum of investors of unit mass, indexed by $j \in [0,1]$, has CARA preferences over terminal wealth with common risk aversion $\rho > 0$. Per-capita asset supply is $\bar{x} + u_i$, where $u_i \sim \mathcal{N}(0, \sigma_u^2)$ is a noisy supply shock that prevents prices from being fully revealing.

3.1 Information

Investors receive two distinct signals: firm-specific public news and private macro information.

Assumption 1 (Firm-specific public signal)**.** *For each asset i, all investors observe*

$$y_i = \varepsilon_i + \eta_i, \qquad \eta_i \sim \mathcal{N}(0, 1/\tau_y), \tag{3}$$

where η_i is mutually independent across i and orthogonal to $(f, \beta_i, \varepsilon_i)$.

Assumption 1 treats firm-level news as informationally orthogonal to the aggregate factor. Empirically, this corresponds to news classified as firm-specific: earnings releases, management changes, product announcements, after market-level content has been filtered out. Public signals inform investors about ε_i, but carry no information about f or about β_i. This restriction distinguishes the setup from standard noisy-rational-expectations models, in which a single public signal jointly conveys both firm-specific and factor information.

Assumption 2 (Private signal)**.** *Each investor j privately observes*

$$z_j = f + \xi_j, \qquad \xi_j \sim \mathcal{N}(0, 1/\tau_\xi), \tag{4}$$

with ξ_j independent across investors and orthogonal to $(f, \varepsilon_i, \nu_i, \eta_i)$.

3.2 Attention allocation

Each investor allocates a unit attention budget between the two channels. Let $\omega_j \in [0,1]$ denote the share allocated to firm-specific public news. Public-signal precision scales with day-t news supply S:

$$\tau_y = \omega_j \, S, \tag{5}$$

and private precision scales with investor-specific capacity K:

$$\tau_\xi = (1-\omega_j)\,K. \tag{6}$$

Higher ω_j reflects greater concentration of attention on firm-specific news; lower ω_j reflects diversion to private macro analysis.

4 Equilibrium

4.1 Posterior beliefs

Lemma 1 (Posteriors)**.** *Under Assumptions 1–2, the posterior distributions are mutually independent and given by*

$$f \mid z_j \sim \mathcal{N}\Big(\mu_f,\, V_f\Big), \qquad V_f = \frac{1}{\tau_f + (1-\omega_j)K}, \tag{7}$$

$$\beta_i \mid y_i \sim \mathcal{N}\Big(b_i,\, \sigma_\nu^2\Big), \tag{8}$$

$$\varepsilon_i \mid y_i \sim \mathcal{N}\Big(\mu_{\varepsilon,i},\, V_\varepsilon\Big), \qquad V_\varepsilon = \frac{1}{\tau_\varepsilon + \omega_j S}. \tag{9}$$

Lemma 1 reflects three features. First, the posterior of f is determined entirely by the private signal: under Assumption 1, public news is uninformative about the factor. Second, the posterior of β_i equals its prior, because y_i carries no information about loadings. Third, public news reduces the posterior variance of ε_i in proportion to $\omega_j S$.

Define the residual non-factor variance entering the equilibrium pricing problem:

$$V_\varepsilon^\star \;=\; V_\varepsilon + \sigma_\nu^2\Big(V_f + \sigma_f^2\Big). \tag{10}$$

This combines posterior idiosyncratic variance with the contribution of unresolved loading uncertainty interacting with the factor.

4.2 Equilibrium prices

Each investor solves a standard CARA-Gaussian portfolio problem, generating linear demand. Market clearing pins down equilibrium prices.

Lemma 2 (Prices)**.** *The equilibrium price of asset i is*

$$p_i \;=\; \bar{d} + b_i\bar{\mu}_f \;-\; \rho V_f\, b_i\,(N\bar{b}\,\bar{x}) \;-\; \rho V_\varepsilon^\star\,\bar{x} \;+\; (\textit{linear noise}), \tag{11}$$

where $\bar{\mu}_f$ is the average posterior mean of f across investors and $\bar{b} \equiv N^{-1}\sum_i b_i$.

The risk premium $\mathbb{E}[d_i - p_i]$ decomposes into a factor component, $\rho V_f b_i(N\bar{b}\bar{x})$, proportional to b_i, and a non-factor component, $\rho V_\varepsilon^\star \bar{x}$, common to all assets. The factor component is what a cross-sectional regression of returns on betas identifies.

4.3 The Fama–MacBeth slope

In practice, the econometrician estimates loadings from a T-period rolling-window OLS regression of realized returns on the factor and then runs a Fama–MacBeth (FM) cross-sectional regression. The resulting slope is

$$\lambda^{FM}(\omega) \;=\; A(\omega)\cdot\rho V_f(\omega)\,N\bar{b}\,\bar{x}, \tag{12}$$

where $A(\omega) \in (0,1)$ is the errors-in-variables attenuation:

$$A(\omega) \;=\; \frac{s_\beta^2 - \sigma_\nu^2}{s_\beta^2 + V_e(\omega)}, \qquad V_e(\omega) \;=\; \frac{\sigma_\varepsilon^2 + 1/(\omega S)}{T\sigma_f^2}, \tag{13}$$

and $s_\beta^2 \equiv \sigma_b^2 + \sigma_\nu^2$ is the cross-sectional variance of true betas.

5 Optimal attention and the risk-premium channel

5.1 Investor's information problem

Each investor chooses ω_j to maximize the expected utility gain from information. Under CARA-Gaussian preferences, the information-allocation objective reduces to (see Appendix E):

$$\mathcal{V}(\omega) \;=\; -\frac{N-1}{2}\log V_\varepsilon^\star(\omega) \;-\; \frac{1}{2}\log\Big(V_\varepsilon^\star(\omega) + V_f(\omega)\textstyle\sum_i b_i^2\Big). \tag{14}$$

The first term captures the cumulative gain from reducing residual non-factor uncertainty across N assets. The second term captures the cost of bearing factor risk: as V_f rises, the factor eigenvalue of the posterior covariance matrix grows, increasing the variance of the diversified factor exposure.

Proposition 1 (Interior optimum)**.** *For all admissible parameter values* $(N, S, K, \rho, \sigma_f, \sigma_\nu, \sigma_\varepsilon, \tau_f)$, *the optimal attention allocation* $\omega^\star \in (0,1)$ *is interior and satisfies the first-order condition* $\mathcal{V}'(\omega^\star) = 0$.

The interior optimum reflects a substantive trade-off. Moving attention toward firm-specific news improves idiosyncratic learning (reducing V_ε) but, because firm news is orthogonal to the factor by Assumption 1, every unit of attention reallocated to public news is one unit lost from private factor learning. The investor balances these two channels.

5.2 The risk-premium channel

The model's central economic content concerns the comparative static of V_f with respect to ω.

Proposition 2 (Risk-premium channel)**.** *Posterior factor uncertainty is strictly increasing in attention to firm-specific news:*

$$\frac{dV_f}{d\omega} \;=\; K \cdot V_f^2 \;>\; 0. \tag{15}$$

Proof. From $V_f = (\tau_f + (1-\omega)K)^{-1}$,

$$\frac{dV_f}{d\omega} \;=\; -V_f^2 \cdot \frac{d}{d\omega}\Big[\tau_f + (1-\omega)K\Big] \;=\; KV_f^2 \;>\; 0. \qquad \square$$

Proposition 2 holds unconditionally as it does not depend on interior optimality, on parameter calibration, or on any equilibrium FOC. The mechanism is direct. Under Assumption 1, firm-specific news carries no factor information; the only channel through which investors learn about f is the private signal z_j. Therefore each additional unit of attention allocated to firm-specific news is one unit of attention lost from factor learning, and the posterior variance of f rises in ω at the deterministic rate KV_f^2.

5.3 Conditional steepness of the SML

Combining (12)–(13) with Proposition 2 yields the model's main empirical prediction.

Proposition 3 (Conditional CAPM steepness)**.** *The Fama–MacBeth slope is strictly increasing in the share of attention allocated to firm-specific news:*

$$\frac{d\lambda^{FM}}{d\omega} \;=\; \rho N \bar{b}\,\bar{x}\left[A(\omega)\cdot KV_f^2 \;+\; V_f \cdot \frac{dA}{d\omega}\right] \;>\; 0. \tag{16}$$

The first term inside the bracket is the risk-premium channel (Proposition 2); the second is an errors-in-variables channel through $dA/d\omega \geq 0$.

When investors concentrate attention on firm-specific news, they bear more factor uncertainty in equilibrium. To clear markets, expected returns must compensate for this uncertainty. Cross-sectional pricing aligns more sharply with betas: the security market line steepens, and unconditional betas explain the cross-section of average returns. Conversely, when attention is diverted toward private macro analysis or broad-market information, posterior factor uncertainty falls, the factor risk premium shrinks, and the SML flattens.

Across days, variation in $\omega^\star$ can be driven by parameters not explicitly modeled here: time-variation in private-research capacity K, or in investor composition. The model does not pin down the cross-day determinants of $\omega_t^\star$, but it is clear about the implication once $\omega_t^\star$ is observed: high-ω days produce steep security market lines; low-ω days produce flat ones.

6 Empirical Analysis

6.1 Data and Variable Construction

6.1.1 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. My news comes 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 Russell 3000 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, since they are known to also convey systematic information, 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 902,873 firm-specific news articles beginning in 2010 and ends in 2025.

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 focus on articles that are 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 902,873 articles, I keep only those labelled as 'singular' and 'idiosyncratic'. The final GPT-labelled news corpus consists of 512,733 news articles.

6.1.2 Attention data

I follow Ben-Rephael, Carlin, Da, and Israelsen (2021) in constructing daily stock-level attention measures from Bloomberg terminals. Bloomberg records the number of times terminal users search for or read news articles on particular stocks. Bloomberg aggregates these numbers into hourly counts and creates an attention score by comparing the average hourly count during the previous eight hours to all hourly counts over the previous month for that same stock. They assign a score of 0, 1, 2, 3, or 4 if the rolling average is less than 80%, between 80% and 90%, between 90% and 94%, between 94% and 96%, and greater than 96% of the hourly counts over the previous 30 days. They then aggregate these scores up to a daily frequency by taking a maximum of all hourly scores through the day.

6.1.3 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, that match the sample of stocks with available attention data. The number of unique stocks is 2469. 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 and equal-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. In section 4, In robustness tests, I also consider individual stocks.

6.1.4 Defining high attention concentration periods

To bring the model's attention-composition parameter ω to the data, I require a daily measure of how heavily institutional attention is tilted toward firm-specific news. I first develop a news attention index (IAI). Using Bloomberg query scores each day, I assign the attention value from 0-4 to individual stocks which had firm-specific news arrive through the Dow Jones Institutional Newswire, and take the daily average across only firms which have a news items on each day. As an additional step, I also recreate the aggregate institutional investor attention measure developed in Ben-Rephael, Da, and Israelsen (2017) using all Russell 3000 firms and create an average daily AIA following Chan and Marsh (2022), taking the mean level of attention paid to all firms for day t. 2469 unique stocks for which attention data and idiosyncratic news articles are available are used to create these attention measures. The sample runs from 2010 to 2025. I run the following daily expanding regression:

$$\mathrm{AIA}_t = \alpha_{t-1} + \beta_{t-1}\,\mathrm{IAI}_t + u_t, \tag{17}$$

I estimate $(\widehat{\alpha}_{t-1}, \widehat{\beta}_{t-1})$ using only information available up to day $t-1$ in an expanding window, and define $\widehat{u}_t$ as the resulting out-of-sample residual. $\widehat{u}_t$ is the component of total institutional attention that is not explained by contemporaneous idiosyncratic-attention intensity, or 'unanchored attention': marketwide attention not accounted for by firm-level news attention. Figure 3 plots the time series of the residuals from 2012 to 2025. It peaks in 2012-2013 during the Euro-area crisis, and spikes downward during the 2020 Covid recession and 2022 bear market.

The expanding-window construction serves two purposes. First, because each day's residual uses only information available through the prior day, the measure is free of look-ahead bias: any relationship documented between the residual and the conditional slope of the security market line cannot be an artifact of using future data to construct the regressor. Second, the out-of-sample residual measures the innovation in non-news attention: how much higher or lower aggregate attention is than the historical news–attention relationship would predict, rather than its absolute level. This is the appropriate object for the test, which concerns cross-day variation in the slope of the security market line rather than its level. The model predicts that the line is steeper on days when attention is composed toward firm-specific news (low residual) than on days when it is tilted toward market-wide learning (high residual). Provided the estimated news–attention coefficient is stable over the sample, the expanding residual coincides with a contemporaneous orthogonalization of attention, and its time variation reflects shifts in attention composition rather than drift in the estimated relationship.

Days when this residual is low are days when average institutional firm-level attention is well explained by firm-specific news. Building from the theory section, these should be days where investors demand a risk premium for market factor exposure. The empirical results test the CAPM on days when this residual is low. Figure 3 plots the time series of the residuals from 2012 to 2025.

6.2 Empirical CAPM tests

Figures 2 and 3 visually represent the main results by partitioning the sample into attention states defined by the residual $\widehat{u}_t$ from the expanding regression in equation (17), and plotting average excess returns of equal-weighted and value-weighted beta-decile portfolios against full-sample portfolio betas. When $\widehat{u}_t$ falls below its trailing one-year 50th percentile, aggregate institutional attention is well explained by idiosyncratic news attention, and the security market line slopes sharply upward. On the complementary set of days, the SML flattens or slopes downward. For the figures, I use unconditional full-sample betas with excess returns averaged over the respective sample periods, following Savor and Wilson (2014) and Hendershott, Livdan, and Rösch (2020).

I push the analysis further using both pooled panel regressions and Fama–MacBeth cross-sectional regressions. For the pooled specification, following Savor and Wilson (2014), Chan and Marsh (2022), and Hendershott, Livdan, and Rösch (2020), I estimate

$$r_{p,t+1} = \alpha + b_1 \widehat{\beta}_{p,t} + b_2 \mathbb{1}\{\text{State}_{t+1}\} + b_3 \widehat{\beta}_{p,t} \mathbb{1}\{\text{State}_{t+1}\} + \varepsilon_{p,t+1}, \tag{18}$$

where $r_{p,t+1}$ is the excess return of portfolio p on day $t+1$, $\widehat{\beta}_{p,t}$ is the rolling one-year portfolio beta estimated from the past 252 daily excess returns of each portfolio on the excess market return, and $\mathbb{1}\{\text{State}_{t+1}\}$ is a dummy variable equal to one when the rolling median of $\widehat{u}_t$ falls below (or above) the indicated trailing one-year quantile cutoff. The coefficient b_1 captures the unconditional beta–return relation on non-state days, b_2 captures the state-minus-other-days alpha, and b_3 measures the incremental change in the slope of the security market line on state days relative to all other days. Standard errors are clustered at the daily level.

For the Fama–MacBeth specification, I estimate daily cross-sectional regressions of portfolio excess returns on rolling portfolio betas separately within each attention state:

$$r^S_{p,t+1} = a^S + b^S\,\widehat{\beta}_{p,t} + \varepsilon^S_{p,t+1}, \tag{19}$$

where the superscript S indexes the attention state, and $\widehat{\beta}_{p,t}$ is the prior-day rolling portfolio beta. I report time-series averages of the daily slope coefficients b^S and their associated t-statistics, computed from the time-series standard deviation of the estimated daily coefficients. I report results for four attention states defined by the rolling quantile cutoffs of $\widehat{u}_t$: the bottom quartile (0–25%), the bottom half (<50%), the top half (>50%), and the top quartile (>75%).

Table 2 presents the results for both value-weighted and equal-weighted beta-sorted portfolios across all four attention states.

Panel A: Bottom-quartile residual state (0–25%). This state identifies the approximately 14.2% of trading days on which aggregate institutional attention is most heavily anchored to firm-specific news. In Fama–MacBeth regressions, a one-unit increase in beta is associated with an increase in next-day excess returns of 18.5 basis points for value-weighted portfolios ($t = 3.27$), and 9.0 basis points for equal-weighted portfolios ($t = 1.74$). The value-weighted intercept is -7.75 basis points ($t = -1.85$), marginally significant but economically small and close to the zero intercept predicted by the CAPM. The average cross-sectional R^2 is 48.3%, indicating that variation in beta explains nearly half of the cross-sectional return variation on these days.

The pooled regressions corroborate the Fama–MacBeth findings. On non-state days, the unconditional beta coefficient is 4.0 basis points ($t = 1.31$), positive but statistically insignificant, reaffirming the well-documented failure of the unconditional CAPM. The interaction term b_3, which measures the incremental slope of the SML on bottom-quartile residual days, is 15.0 basis points ($t = 2.10$), statistically significant at the 5% level. The state dummy b_2 is -12.0 basis points ($t = -1.97$), capturing the low-residual-minus-other-day intercept. For equal-weighted portfolios, the interaction coefficient is 8.0 basis points ($t = 1.30$), positive but not statistically significant at conventional levels, consistent with the well-documented finding that value-weighted portfolios provide sharper tests of the CAPM (Savor and Wilson, 2014).

Panel B: Below-median residual state (<50%). Expanding the state definition to include all days below the trailing median of $\widehat{u}_t$ captures 46.3% of trading days which are nearly half of the sample. The results strengthen. In value-weighted Fama–MacBeth regressions, the beta coefficient is 12.7 basis points ($t = 3.65$), highly significant. Importantly, the intercept is -3.65 basis points ($t = -1.41$), statistically indistinguishable from zero, as the CAPM predicts. The average R^2 remains at 48.3%. For equal-weighted portfolios, the beta coefficient is 6.0 basis points ($t = 1.92$), significant at the 10% level.

The pooled regressions deliver magnitudes remarkably close to the Fama–MacBeth estimates. The value-weighted interaction term is 13.0 basis points ($t = 2.32$), significant at the 5% level, while the unconditional beta coefficient b_1 is effectively zero at 0.36 basis points ($t = 0.09$), confirming that beta does not explain excess returns on days outside this state. The state dummy is -10.0 basis points ($t = -2.20$), again significantly negative. For equal-weighted portfolios, the interaction is 9.0 basis points ($t = 1.79$), significant at the 10% level. The close alignment between the Fama–MacBeth slopes and the pooled interaction coefficients of 12.7 versus 13.0 basis points for value-weighted portfolios provides reassurance that the result is not driven by differences in the econometric approach. The finding that unconditional betas price the cross section of returns for approximately 46% of trading days constitutes a substantial expansion of the set of days on which the CAPM has been shown to hold, extending well beyond the scheduled announcement days identified in Savor and Wilson (2014) and the leading-earnings-announcement days of Chan and Marsh (2022).

Panel C: Above-median residual state (>50%). On the complementary set of days—those on which aggregate institutional attention is elevated beyond what idiosyncratic news explains—the pricing of beta breaks down. In value-weighted Fama–MacBeth regressions, the beta coefficient is -1.4 basis points ($t = -0.31$), economically negligible and statistically insignificant. The intercept, however, is 8.5 basis points ($t = 2.53$), significantly positive, indicating that high-beta and low-beta portfolios earn similar average returns in these states and that the return variation is not explained by differences in systematic risk. The SML is effectively flat. For equal-weighted portfolios, the picture is slightly worse: the beta coefficient turns negative at -4.1 basis points ($t = -0.96$), and the intercept is 9.1 basis points ($t = 3.78$), large and highly significant.

The pooled regressions for this state are estimated using a dummy equal to one on above-median residual days. The value-weighted interaction term is -10.0 basis points ($t = -1.66$), negative and marginally significant, while the unconditional beta coefficient (now capturing below-median days as the base) is 10.0 basis points ($t = 2.78$). This confirms that the beta–return relation steepens when attention is concentrated on firm-specific news and flattens when it is not.

Panel D: Top-quartile residual state (>75%). The most extreme attention-diversion state accounting for approximately 13.7% of days when unanchored attention is highest produces no detectable pricing of beta. In value-weighted Fama–MacBeth regressions, the beta coefficient is 0.54 basis points ($t = 0.06$), indistinguishable from zero. The intercept is 7.1 basis points ($t = 1.01$), positive but imprecisely estimated. For equal-weighted portfolios, the slope is -5.8 basis points ($t = -0.64$), with an intercept of 11.0 basis points ($t = 2.18$). In pooled regressions, the value-weighted interaction is -5.0 basis points ($t = -0.61$), insignificant; the equal-weighted interaction is -5.0 basis points ($t = -0.66$), also insignificant. Neither weighting scheme produces evidence that beta is priced on these days.

Taken together, the results in Table 2 reveal a monotonic pattern in the pricing of beta across attention states. Moving from the bottom quartile to the top quartile of the residual $\widehat{u}_t$, the Fama–MacBeth beta slope declines from 18.5 to 0.54 basis points for value-weighted portfolios, the intercept moves from near zero to significantly positive, and the pooled interaction coefficients decline from 15.0 to -5.0 basis points. The CAPM prices risk when institutional attention is concentrated on public firm-specific news, even though the absolute level of attention on these days is below average. The results hold for both value-weighted and equal-weighted portfolios, across both Fama–MacBeth and pooled specifications, and are consistent with the model's prediction that attention composition, rather than attention level, determines the equilibrium price of systematic risk.

7 Trading strategy

The empirical results documented above establish that the security market line steepens when institutional attention is concentrated on firm-specific news. I now explore the economic significance of this finding through a set of trading strategies that exploit the attention-composition state variable. The strategies are designed to be easily implementable and to assess whether the conditional pricing of beta translates into economically meaningful abnormal returns after standard risk adjustment.

The baseline strategy takes a long position in the highest-beta decile portfolio and a short position in the lowest-beta decile portfolio on days identified as bottom-quartile residual-attention days, and holds cash on all other days. The regime signal is days when the 5-day rolling median of μ_t is below its rolling 1-year 25th percentile, lagged by one trading day so that positions are entered or exited the day after the signal switches, ensuring that the strategy uses only information available at the time of trading. Because the residual $\widehat{u}_t$ is constructed from a persistent, slowly moving rolling median, the signal switches states infrequently, keeping turnover low. In practice, an investor could approximate the long and short legs using liquid high-beta and low-beta ETFs, which would keep implementation costs manageable. The portfolio returns I report are gross of transaction costs, financing frictions, and shorting fees. The sample runs from 2012 to 2025 and contains 3,222 trading days, of which 448 are classified as regime days by the lagged signal.

Table 3 reports the results. Panel A provides two benchmarks. The first is an always-on long-short strategy that holds the high-minus-low beta spread portfolio every day regardless of the attention state. This strategy earns an average daily return of 4.3 basis points with an annualized Sharpe ratio of 0.34, and generates no significant alpha under either the CAPM (-4.35% annualized, $t = -0.63$) or the Fama-French five-factor model (2.58%, $t = 0.42$). The failure of the unconditional long-short strategy to generate alpha is consistent with the well-documented flatness of the unconditional security market line. The second benchmark is the buy-and-hold market portfolio, which earns 5.4 basis points per day with an annualized Sharpe ratio of 0.79.

Panel B reports the headline conditional strategy. By restricting the long-short position to bottom-quartile residual-attention days and holding cash otherwise, the strategy earns 3.4 basis points per day with an annualized Sharpe ratio of 0.67. The strategy generates a CAPM alpha of 6.5% per year ($t = 1.86$) and a five-factor alpha of 7.4% per year ($t = 2.11$), both statistically significant. The market beta of the strategy is 0.13, reflecting the fact that the strategy is in the market on only a fraction of trading days and takes a long-short position that partially hedges market exposure when active. The key comparison is with the always-on long-short benchmark in Panel A: timing the beta spread using the attention-composition signal converts an unconditionally unprofitable strategy into one that generates significant abnormal returns, even after controlling for size, value, profitability, and investment factors.

Panel C considers an alternative approach to managing the off-regime position. Instead of holding cash on non-regime days, the strategy reverses the long-short position to bet against beta, going long the lowest-beta portfolio and short the highest-beta portfolio, following the logic of Frazzini and Pedersen (2014). This hybrid strategy earns a CAPM alpha of 17.4%

per year ($t = 2.24$) and a five-factor alpha of 12.3% per year ($t = 1.67$), the latter significant at the 10% level. The market beta is -0.59, reflecting the net short-market exposure that accumulates from betting against beta on the majority of trading days. The substantially larger CAPM alpha relative to Panel B arises because the strategy profits from the steep SML on regime days and from the flat or inverted SML on non-regime days, capturing both tails of the conditional beta-return relationship documented in Table 2. The annualized Sharpe ratio of 0.20 is lower than that of the headline strategy, however, reflecting the higher volatility inherent in maintaining an active position at all times.

Savor and Wilson (2014) and subsequent work document that the CAPM also prices risk on macroeconomic announcement days. Panel D of Table 3 explores whether the attention-composition signal and the FOMC announcement calendar provide complementary sources of conditional beta pricing. A long-short strategy restricted to FOMC days alone earns 1.5 basis points per day with a Sharpe ratio of 0.73, and generates a CAPM alpha of 3.3% annualized ($t = 2.43$) and a five-factor alpha of 3.5% ($t = 2.55$), both significant at the 5% level. These magnitudes are consistent with the FOMC premium documented in prior work.

Combining the two signals by taking the long-short position on either bottom-quartile residual days or FOMC days, and holding cash otherwise, produces a strategy that earns 4.8 basis points per day with an annualized Sharpe ratio of 0.88. The CAPM alpha is 9.5% per year ($t = 2.58$) and the five-factor alpha is 10.6% per year ($t = 2.87$), both significant at the 1% level. The combined strategy outperforms either signal in isolation, suggesting that the attention-composition regime and the FOMC calendar identify distinct sets of days on which beta is priced. This interpretation is supported by the minimal overlap between the two signals: the regime and FOMC indicators coincide on only 0.16% of trading days.

Finally, the most aggressive variant replaces cash with a betting-against-beta position on non-signal days. This strategy earns a CAPM alpha of 23.3% per year ($t = 2.97$) and a five-factor alpha of 18.6% per year ($t = 2.49$). The alphas are large and significant, reflecting the combined gains from timing beta in both directions. The market beta of -0.54 again reflects the net short exposure during the majority of non-signal days.

The trading results reinforce the central finding of this paper. The conditional price of systematic risk is higher when institutional attention is concentrated on firm-specific news, steepening the SML so that high-beta assets earn higher returns. The unconditional long-short beta strategy earns no alpha, but timing it with the attention-composition residual generates economically and statistically significant abnormal returns that are not subsumed by standard factor models. The complementarity with FOMC announcement days further suggests that the attention-composition channel is distinct from the macroeconomic announcement channel documented in prior literature: both identify states in which beta is priced, but they do so through different features of the information environment.

8 Additional tests

8.1 Expected information consumption and individual firms

A natural concern with the regime variable is that bottom-25% residual days may simply identify days when institutional investors are predictably consuming information at specific firms, in which case the conditional CAPM finding would be subsumed by Ben-Rephael, Carlin, Da, and Israelsen's (2021) Expected Information Consumption (EIC) mechanism. To address this, I construct EIC at the firm-day level following their methodology: a firm receives EIC $= 1$ on day t if it has historically exhibited institutional attention spikes around peer-firm scheduled events, FOMC announcements, or macroeconomic announcements occurring on that day. The construction follows BCDI's specifications closely: I use Fama–French 48-industry classifications to identify peer firms, require a minimum historical spike rate of 30% on past peer-earnings days for EIC_PEER, and apply BCDI's 50% threshold for FOMC and macroeconomic announcements based on the previous four FOMC days and previous year of macro announcements. The construction produces frequencies and diagnostics in line with BCDI's reported values. The combined EIC $= 1$ frequency is 5.6% of firm-days, comparable to BCDI's reported 6.7% for EIC_ALL despite the more limited Bloomberg-coverage sample. The AIA spike rate among EIC $= 1$ firm-days is 30.5%, roughly five times the 5.9% spike rate among EIC $= 0$ firm-days, closely tracking BCDI's reported differential of 24.2% versus 7.1% in their Table III. Table 6 reports the conditional CAPM result on bottom-25% residual days, partitioned by EIC. The headline slope of 20.4 bps ($t = 3.15$) on the full cross-section drops only marginally to 19.1 bps ($t = 3.04$) when I restrict to EIC $= 0$ firms, which are those that BCDI's framework specifically does not flag as expected to consume information. The conditional CAPM result is therefore not driven by firms that BCDI's mechanism predicts. EIC $= 1$ firms exhibit particularly strong conditional pricing (44.2 bps, $t = 3.10$), within BCDI's reported range of 8 to 44 bps for EIC $= 1$ subsamples and consistent with their findings, indicating that the two mechanisms operate complementarily: BCDI's framework identifies firm-day variation in attention-driven pricing, while the regime variable identifies day-level variation in the broader attention environment that affects the entire cross-section.

8.2 Earnings announcements and the conditional CAPM

A natural concern is that the conditional pricing result on bottom-quartile residual-attention days is driven by firms that are simultaneously releasing earnings. Earnings announcements convey systematic information and have been shown to steepen the security market line in their own right (Savor and Wilson, 2016; Chan and Marsh, 2022). If bottom-quartile residual days happen to coincide with earnings seasons, the apparent success of the CAPM on these days could simply reflect the announcement premium documented in prior work rather than a distinct attention-composition channel. To address this concern, I define earnings-window firm-days as firm-days for which the firm has an earnings announcement within five business days before or after the current date, and re-estimate the Fama–MacBeth cross-sectional regressions on bottom-quartile residual-attention days in three subsamples: all firms, firms excluding those in an earnings window, and earnings-window firms only.

Table 7 reports the results. On the full cross section, the beta slope is 20.4 basis points ($t = 3.15$) with an insignificant intercept of -2.7 basis points ($t = -0.74$), consistent with the baseline findings. When earnings-window firms are excluded, the beta slope declines only marginally to 18.8 basis points ($t = 2.98$), remaining highly significant. The intercept is -1.8 basis points ($t = -0.49$), statistically indistinguishable from zero. This subsample retains an average of 1,390 firms per cross section, so the result is not an artifact of a thin sample. Restricting the cross section to earnings-window firms only produces a beta slope of 24.4 basis points ($t = 2.88$), larger in magnitude and consistent with the view that earnings announcements contribute to the pricing of beta through a complementary channel. The intercept for this subsample is 1.4 basis points ($t = 0.22$), again insignificant.

The key finding is that removing all firms near an earnings announcement barely affects the conditional beta slope. The decline from 20.4 to 18.8 basis points is economically small relative to the magnitude of the effect, and the t-statistic remains above conventional thresholds. The attention-composition channel therefore operates across the broad cross section of firms, not only among those releasing earnings. The stronger result within earnings-window firms is consistent with, but not required by, the main finding, and suggests that the two mechanisms operate complementarily: earnings announcements provide a firm-level information event that reinforces the cross-sectional pricing of beta, while the attention-composition state variable identifies a market-wide regime in which that pricing extends to all firms.

8.3 Disagreement and VIX states

Hong and Sraer (2016) argue that disagreement combined with short-sale constraints flattens the security market line, so that the CAPM should perform better when disagreement is low. Hasler and Martineau (2023) show that the CAPM performs better in periods of low volatility. If the bottom-median residual-attention state merely proxies for low disagreement or low volatility, the conditional pricing result would be subsumed by these existing channels. To assess this, I split the bottom-median residual-attention days into high and low disagreement states, using daily aggregate disagreement data from Cookson and Niessner (2023), and separately into high and low VIX states. Table 8 reports Fama–MacBeth regressions within each subsample.

Panel A examines disagreement splits. On low-disagreement days within the bottom-median residual state, the value-weighted beta slope is 13.4 basis points ($t = 2.41$), and on high-disagreement days it is 12.3 basis points ($t = 2.65$). Both are statistically significant and similar in magnitude. The result therefore survives within both high and low disagreement environments. Notably, the high-disagreement subsample contains 1,292 days compared to 262 for the low-disagreement subsample, so the bulk of the statistical power comes from days on which disagreement is elevated. This pattern is inconsistent with the view that the attention-composition state variable is simply selecting for low-disagreement periods. For equal-weighted portfolios, the beta slope is 10.9 basis points ($t = 2.35$) in the low-disagreement subsample and 8.1 basis points ($t = 1.92$) in the high-disagreement subsample, both positive and at least marginally significant.

Panel B examines VIX splits. On low-VIX days within the bottom-median residual state, the value-weighted beta slope is 14.4 basis points ($t = 4.79$), highly significant. On high-VIX days, the slope drops to 8.2 basis points ($t = 0.76$), positive but statistically insignificant. The equal-weighted results are similar: 10.8 basis points ($t = 3.63$) on low-VIX days and 3.7 basis points ($t = 0.40$) on high-VIX days. The conditional CAPM result is therefore concentrated in low-volatility environments.

8.4 Excluding macroeconomic announcement days and LEADs

A further concern is that the bottom-median residual-attention days may overlap with macroeconomic announcement days (Savor and Wilson, 2014) or with leading earnings announcement days (LEADs) identified by Chan and Marsh (2022). If so, the conditional pricing result could be confounded by the well-documented announcement premium on these days. To address this, I re-estimate the Fama–MacBeth regressions after removing these potentially confounding days from the sample.

Table 9 reports the results. The first row excludes LEAD days, defined as days when influential S&P 500 firms announce earnings, following Chan and Marsh (2022). After removing these days, the value-weighted beta slope is 12.3 basis points ($t = 2.72$) and the equal-weighted slope is 8.5 basis points ($t = 2.13$), both statistically significant. The sample retains 1,343 days. The second row excludes macroeconomic announcement days, defined as days with scheduled FOMC, employment, or PPI releases following Savor and Wilson (2014). The value-weighted slope is 12.5 basis points ($t = 3.13$) and the equal-weighted slope is 8.6 basis points ($t = 2.38$), again both significant, with 1,554 days remaining. In both specifications, the intercepts are economically small and statistically insignificant, consistent with the predictions of the CAPM.

The magnitudes of the beta slopes are close to unchanged relative to the baseline results in Table 2, and the t-statistics remain well above conventional thresholds. The conditional pricing of beta on bottom-median residual-attention days is therefore not driven by overlap with known macroeconomic or bellwether-earnings announcement days. This finding, combined with the earnings-window results in Table 7, suggests that the attention-composition channel identifies a broad regime in the information environment that is distinct from the specific event-day channels documented in prior literature.

8.5 Which firms' news drives the result?

The baseline attention-composition measure constructs the idiosyncratic attention index IAI_t by averaging Bloomberg query scores across all firms with a filtered news article on day t. A natural question is whether the conditional pricing result is driven by news arriving at a specific segment of the cross section. If, for example, only news about high-beta firms or large firms generates the attention state that steepens the SML, the mechanism would be narrower than the model implies. To investigate this, I reconstruct the expanding regression in equation (17) ten times, each time computing IAI_t using only the subset of firms belonging to a single beta decile (or, separately, a single size decile). For each decile-specific residual, I identify bottom-median days and re-estimate the Fama–MacBeth cross-sectional regressions on those days. If the conditional CAPM result appears broadly across decile-specific constructions, then no single part of the firm distribution is responsible for the finding.

Table 4 reports the results when the attention state is defined using news from each beta decile separately. Panel B presents value-weighted portfolio results. Across the ten beta-decile-specific constructions, the beta slope λ_β is positive in every column, ranging from 5.3 basis points (decile 9) to 12.5 basis points (decile 1). The slope is statistically significant at the 5% level or better in six of the ten deciles (deciles 1, 3, 4, 5, 7, and 10), and significant at the 10% level in a seventh (decile 2, $t = 1.85$). The intercepts are uniformly small and insignificant, ranging from -4.4 to 1.4 basis points, none statistically different from zero. The average cross-sectional R^2 is approximately 46% throughout, indicating stable explanatory power regardless of which decile's news is used to construct the state variable. For equal-weighted portfolios in Panel A, the pattern is qualitatively similar though weaker in magnitude, with the beta slope significant in decile 1 (8.6 basis points, $t = 2.38$) and marginally significant in deciles 3, 4, and 5.

The strongest value-weighted results arise when the attention state is constructed from news about the lowest-beta firms (decile 1: 12.5 basis points, $t = 3.13$) and mid-range beta firms (deciles 3 through 5: 11.0 to 11.5 basis points, t-statistics between 2.7 and 2.9). The weakest results come from deciles 6 and 9. The broad pattern suggests that attention to firm-specific news steepens the SML regardless of where in the beta distribution that news originates, though the effect is somewhat attenuated when the state is defined using news from the highest-beta or highest-attention deciles alone.

Table 5 repeats the exercise using size deciles. Panel B again presents value-weighted results. The beta slope is positive in all ten columns, ranging from 5.7 basis points (decile 8) to 13.0 basis points (decile 7). Significance at the 5% level or better obtains in seven of the ten size deciles (deciles 1, 2, 4, 5, 6, 7, and 10), with an additional decile (decile 9: 11.2 basis points, $t = 2.55$) also significant. The intercepts are again uniformly small and insignificant, consistent with the CAPM. The equal-weighted results in Panel A are weaker in magnitude, with significance at the 5% level in deciles 6 and 7 (7.4 and 7.3 basis points) and marginal significance in decile 5 (6.8 basis points, $t = 1.94$).

The size-decile results indicate that the attention-composition channel is not confined to news about firms of a particular size. News from both small firms (decile 1: 8.2 basis points, $t = 1.98$) and large firms (decile 10: 9.5 basis points, $t = 2.33$) generates attention states in which beta prices the cross section. The strongest results emerge when the state is constructed from mid-to-large capitalization firms (deciles 4 through 7: 10.9 to 13.0 basis points), which may reflect the fact that these firms account for a larger share of aggregate institutional attention and therefore produce more informative variation in the residual.

Taken together, the results in Tables 4 and 5 show that the conditional CAPM finding is not an artifact of news concentrated in any single segment of the cross section. The attention-composition state variable steepens the security market line when constructed from news about low-beta or high-beta firms, small or large firms, and most points in between. This breadth is consistent with the model's prediction that the relevant object is the aggregate share of attention devoted to firm-specific news, not the characteristics of the firms producing that news.

9 Conclusion

This paper shows that the empirical performance of the CAPM depends on how institutional investors allocate attention between firm-specific news and broader market-wide information. Using firm-specific news from the Dow Jones Institutional Newswire, filtered by a large language model to remove systematic content, and institutional attention data from Bloomberg terminal activity, I construct a daily measure of attention composition: the residual from an expanding regression of aggregate institutional attention on idiosyncratic news attention. When this residual is low, aggregate attention is well explained by firm-specific news processing. When it is high, attention is elevated but directed elsewhere.

On the approximately 46% of trading days when the attention-composition residual falls below its trailing median, beta prices the cross section of stock returns. The Fama–MacBeth slope is between 12 and 19 basis points per unit of beta, statistically significant, with an intercept indistinguishable from zero. On the complementary set of days, the security market line flattens or reverses. The bottom quartile of the residual distribution alone accounts for roughly a quarter of trading days yet captures over half of the cumulative market risk premium earned over the sample. These findings hold in both Fama–MacBeth and pooled panel specifications, for value-weighted and equal-weighted portfolios, and survive controls for disagreement, the VIX, macroeconomic announcement days, leading earnings announcement days, and the expected information consumption framework of Ben-Rephael, Carlin, Da, and Israelsen (2021). Importantly, this is not a high-attention result: the days on which the CAPM succeeds are days of below-average aggregate attention, but above-average concentration of that attention on firm-specific news.

To rationalize these findings, I develop a noisy rational expectations model in which investors allocate a fixed attention budget between processing firm-specific public news and acquiring private signals about a common macroeconomic factor. Because filtered firm-specific news is informationally orthogonal to the aggregate factor, attention devoted to firm-level news crowds out private factor learning. Posterior factor uncertainty rises with the share of attention directed toward firm-specific news, the equilibrium factor risk premium increases, and the security market line steepens. This mechanism is the mirror image of the resolution channel in Andrei, Friedman, and Ozel (2023), in which attention to earnings accelerates the resolution of factor uncertainty and reduces posterior factor variance. The two channels operate through opposite effects on the same theoretical object and are most cleanly identified in different volatility regimes: the composition channel in low-VIX states, the resolution channel in high-VIX states. The empirical evidence confirms this complementarity.

A simple trading strategy that conditions on the attention-composition signal converts an unconditionally unprofitable long-short beta spread into a strategy that earns significant five-factor alpha. Combining the signal with the FOMC announcement calendar further improves performance, consistent with the view that the attention-composition regime and macroeconomic announcement days identify distinct sources of conditional beta pricing.

There are several directions for future work. First, the model treats the attention allocation ω as exogenous and does not pin down its cross-day determinants. Endogenizing the supply of firm-specific news and the resulting equilibrium allocation of attention would provide a richer account of when and why the CAPM succeeds. Second, the empirical construction relies on Bloomberg terminal data, which limits the sample to institutional investors and to the period from 2010 onward. Extending the analysis to longer samples using alternative attention proxies would test the generality of the finding. Third, the current analysis focuses on the pricing of the market factor. Whether the composition of attention similarly governs the pricing of other systematic risk factors is an open question with implications for the broader conditional factor pricing literature.

These findings have implications for both researchers and practitioners. For researchers, they identify attention composition as a new state variable governing the empirical performance of the CAPM, distinct from the level of attention, disagreement, volatility, or the expected market return. For practitioners, they suggest that the reliability of CAPM-based discount rates and portfolio decisions depends on the prevailing attention environment: the model's cross-sectional predictions are most accurate when institutional attention is anchored to firm-specific information processing, and least accurate when attention drifts toward market-wide or macroeconomic concerns.

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Table 1: Residual Attention, Beta-Decile Characteristics, and Regime Characteristics

Panel A: Firm characteristics by beta decile

	Beta decile									
	1 Low	2	3	4	5	6	7	8	9	10 High
Average beta	0.488	0.710	0.838	0.947	1.050	1.149	1.260	1.397	1.582	1.939
Average log market capitalization	14.456	14.636	14.653	14.622	14.574	14.545	14.495	14.432	14.318	14.182
News days	28,867	26,944	26,669	27,013	27,209	28,092	29,813	30,346	31,922	32,848
Median attention score	0.360	0.362	0.364	0.351	0.337	0.336	0.330	0.339	0.353	0.377

Panel B: Distribution of residual attention

	Min.	Max.	Mean	Std. dev.	Skewness	Kurtosis
Residual attention	−0.665	0.789	−0.114	0.171	0.685	1.535

Panel C: Attention composition across residual-attention quartiles

	Q1 Low	Q2 25–50	Q3 50–75	Q4 High	Q1–Q4 Difference
Firm-news attention, standardized	0.544	−0.217	−0.223	−0.401	0.945
Macro attention, standardized	−0.030	−0.041	0.056	0.154	−0.184
Firm-news supply	0.063	0.050	0.047	0.042	0.021

Panel D: Additional regime characteristics across residual-attention quartiles

	Q1 Low	Q2 25–50	Q3 50–75	Q4 High	Q1–Q4 Difference
IAI	0.075	0.051	0.050	0.045	0.030
AIA	0.405	0.346	0.397	0.444	−0.039
Firm-news supply	0.063	0.050	0.047	0.042	0.021
VIX	17.465	17.003	17.618	18.248	−0.783
Disagreement	0.249	0.242	0.244	0.250	−0.001
Market return	0.100	0.084	0.079	−0.041	0.141
Macro attention	0.992	0.987	1.038	1.090	−0.098

Notes: This table summarizes beta-decile characteristics, the residual-attention measure, and the economic characteristics of residual-attention regimes. Panel A reports firm characteristics across beta deciles, where decile 1 contains low-beta firms and decile 10 contains high-beta firms. Average beta is the average estimated 252-day market beta. Average log market capitalization is computed using market capitalization defined as price times shares outstanding. News days is the total number of firm-days with newswire coverage within each beta decile. Attention score is the Bloomberg institutional attention measure. Panel B reports distributional statistics for residual attention. Panels C and D report averages across quartiles of residual attention, where Q1 denotes the lowest residual-attention quartile and Q4 denotes the highest residual-attention quartile. The final column reports the difference between Q1 and Q4. IAI denotes institutional attention, AIA denotes aggregate institutional attention, and firm-news supply is the cross-sectional share of firms with newswire articles on a given day. Macro attention is the macroeconomic attention index of Fisher, Martineau, and Sheng (2022). VIX is the Chicago Board Options Exchange Volatility Index. Disagreement is from J. Anthony Cookson's website. Market return is the daily Fama–French market excess return.

Table 2: CAPM tests across attention-state cutoffs.

The table reports estimates from daily Fama–MacBeth regressions of portfolio excess returns on CAPM betas and from pooled panel regressions with a state dummy and a beta–state interaction. The sample is split into four attention states defined by rolling quantile cutoffs of the residual-based state variable: (i) 0–25%, (ii) $<$ 50%, (iii) $>$ 50%, and (iv) $>$ 75%. Within each state, results are reported for value-weighted and equal-weighted beta-sorted portfolios. For the pooled regressions, I estimate $r_{p,t} = \alpha + \beta\,\widehat{\beta}_p + \gamma D_t^{state} + \delta(\widehat{\beta}_p \times D_t^{state}) + \varepsilon_{p,t}$. Coefficients are reported in basis points per day and t-statistics are in parentheses. Fama–MacBeth t-statistics are computed using the time-series standard deviation of the estimated daily slope coefficients. Pooled regression standard errors are clustered by trading day.

		Fama–MacBeth			**Pooled regression**					
State	**Port weights**	Intercept	β	Avg R^2	Intercept	β	D^{state}	$\beta \times D^{state}$	R^2	% days
Panel A: (0–25% state)										
	Value-weighted	-7.75*	18.50***	0.483	3.00	4.00	-12.00**	15.00**	0.0006	14.2%
		(-1.845)	(3.269)		(1.203)	(1.306)	(-1.965)	(2.101)		
	Equal-weighted	2.43	9.00*	0.59	4.00*	2.00	-2.00	8.00	0.0003	14.2%
		(0.690)	(1.740)		(1.760)	(0.557)	(-0.450)	(1.295)		
Panel B: ($<$ 50% state)										
	Value-weighted	-3.65	12.66***	0.483	6.00*	0.36	-10.00**	13.00**	0.0008	46.3%
		(-1.411)	(3.646)		(1.748)	(0.087)	(-2.196)	(2.318)		
	Equal-weighted	2.53	6.04*	0.60	6.00*	-1.00	-5.00	9.00*	0.0005	46.3%
		(1.299)	(1.916)		(1.904)	(-0.362)	(-1.216)	(1.786)		
Panel C: ($>$ 50% state)										
	Value-weighted	8.47**	-1.44	0.463	-2.00	10.00***	8.00*	-10.00*	0.0005	47.1%
		(2.529)	(-0.312)		(-0.753)	(2.776)	(1.686)	(-1.664)		
	Equal-weighted	9.07***	-4.11	0.61	3.00	6.00*	3.00	-7.00	0.0003	47.1%
		(3.780)	(-0.959)		(0.998)	(1.705)	(0.767)	(-1.282)		
Panel D: ($>$ 75% state)										
	Value-weighted	7.06	0.54	0.460	0.82	7.00**	6.00	-5.00	0.0003	13.7%
		(1.006)	(0.055)		(0.331)	(2.295)	(0.710)	(-0.609)		
	Equal-weighted	11.02**	-5.84	0.64	3.00	3.00	-4.00	-5.00	0.0001	13.7%
		(2.184)	(-0.637)		(1.533)	(1.274)	(-0.561)	(-0.661)		

Table 3: Trading Strategy Performance and Risk-Adjusted Returns

Strategy	Performance		CAPM		Fama–French Five-Factor		
	Mean (bps/day)	Sharpe (ann.)	Alpha (% ann.)	t-stat	Alpha (% ann.)	t-stat	Mkt beta
Panel A: Benchmark Strategies							
Always-on long–short	4.30	0.34	-4.35	-0.63	2.58	0.42	0.84
Buy-and-hold market	5.37	0.79	0.00	–	0.00	–	1.00
Panel B: Headline Conditional Strategy							
Long–short on regime days; cash otherwise	3.43	0.67	6.50*	1.86	7.42**	2.11	0.13
Panel C: Alternative Cash Management							
Long–short on regime days; BAB otherwise	2.57	0.20	17.35**	2.24	12.26*	1.67	-0.59
Panel D: Combination with FOMC Announcement Days							
FOMC days only	1.47	0.73	3.25**	2.43	3.46**	2.55	0.02
Long–short on regime or FOMC days; cash otherwise	4.80	0.88	9.47***	2.58	10.58***	2.87	0.15
Long–short on regime or FOMC days; BAB otherwise	5.29	0.42	23.30***	2.97	18.58**	2.49	-0.54

Notes: This table reports trading-strategy performance using value-weighted beta-decile portfolios over 2012–2024. The long–short strategy buys the highest-beta decile portfolio and sells the lowest-beta decile portfolio. BAB denotes the opposite position, long low-beta and short high-beta, following Frazzini and Pedersen (2014). The regime signal identifies bottom-quartile residual-attention days and is lagged by one trading day to ensure tradability. FOMC announcement days are scheduled events and are used contemporaneously. Mean returns are reported in basis points per day. Sharpe ratios are annualized by multiplying the daily Sharpe ratio by $\sqrt{252}$. CAPM and Fama–French five-factor alphas are estimated from daily time-series regressions and annualized in percent. Standard errors use Newey–West HAC adjustment with five lags. The sample contains 3,222 trading days, including 448 regime days and 86 FOMC days; the regime and FOMC signals overlap on 0.16% of trading days. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Fama–MacBeth Regressions: Attention Explained by Firm News Across Beta Deciles

	Beta Decile Used to Define Attention-State Condition									
	1	2	3	4	5	6	7	8	9	10
Panel A: Equal-Weighted Returns										
Alpha	1.23	2.84	1.47	2.37	1.87	5.47**	2.00	3.29	5.39**	3.47
	(0.51)	(1.10)	(0.60)	(0.99)	(0.71)	(2.25)	(0.83)	(1.33)	(2.05)	(1.49)
λ_β	8.58**	4.50	6.31*	5.84*	6.61*	2.09	3.98	4.68	1.61	5.14
	(2.38)	(1.20)	(1.75)	(1.66)	(1.73)	(0.56)	(1.12)	(1.26)	(0.41)	(1.46)
Avg. R^2	0.547	0.562	0.555	0.558	0.548	0.560	0.557	0.557	0.551	0.558
Days	1554	1461	1415	1482	1437	1500	1531	1568	1528	1635
Panel B: Value-Weighted Returns										
Alpha	-4.37	-0.54	-4.10	-4.24	-3.96	0.92	-1.77	-0.87	1.43	0.06
	(-1.33)	(-0.16)	(-1.29)	(-1.42)	(-1.15)	(0.29)	(-0.57)	(-0.27)	(0.42)	(0.02)
λ_β	12.47***	7.62*	11.47***	11.01***	11.48***	6.11	7.51**	8.40**	5.31	8.52**
	(3.13)	(1.85)	(2.91)	(2.93)	(2.72)	(1.52)	(1.99)	(2.08)	(1.27)	(2.22)
Avg. R^2	0.454	0.471	0.461	0.461	0.459	0.459	0.462	0.463	0.462	0.464
Days	1554	1461	1415	1482	1437	1500	1531	1568	1528	1635

Notes: This table reports Fama–MacBeth regressions of daily beta-decile portfolio returns on portfolio betas on days when attention is well explained by firm news releases within the indicated beta decile. Each day, portfolio returns are regressed cross-sectionally on beta. The table reports the time-series average of the daily intercepts and beta slopes. Coefficients are reported in basis points per day. Newey–West t-statistics with five lags are reported in parentheses. Avg. R^2 is the average daily cross-sectional R^2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Fama–MacBeth Regressions: Attention Explained by Firm News Across Size Deciles

	Size Decile Used to Define Attention-State Condition									
	1	2	3	4	5	6	7	8	9	10
Panel A: Equal-Weighted Returns										
Alpha	4.32*	3.93	4.38*	3.16	3.43	3.22	3.09	3.89	2.28	1.79
	(1.66)	(1.63)	(1.85)	(1.24)	(1.43)	(1.32)	(1.29)	(1.54)	(0.84)	(0.71)
λ_β	3.23	4.16	2.54	5.68	6.82*	7.42**	7.33**	1.70	6.28	5.11
	(0.86)	(1.16)	(0.69)	(1.52)	(1.94)	(2.03)	(2.08)	(0.44)	(1.54)	(1.34)
Avg. R^2	0.553	0.558	0.557	0.558	0.553	0.553	0.549	0.555	0.555	0.558
Days	1495	1526	1479	1529	1532	1492	1521	1472	1534	1489
Panel B: Value-Weighted Returns										
Alpha	-0.71	-0.80	0.71	-2.90	-1.66	-2.22	-3.26	0.29	-3.39	-2.80
	(-0.21)	(-0.25)	(0.22)	(-0.89)	(-0.54)	(-0.69)	(-1.04)	(0.09)	(-0.97)	(-0.85)
λ_β	8.19**	8.67**	6.10	10.90***	10.92***	11.61***	12.96***	5.67	11.18**	9.53**
	(1.98)	(2.18)	(1.48)	(2.67)	(2.88)	(2.89)	(3.36)	(1.37)	(2.55)	(2.33)
Avg. R^2	0.461	0.461	0.463	0.464	0.463	0.462	0.452	0.468	0.459	0.464
Days	1495	1526	1479	1529	1532	1492	1521	1472	1534	1489

Notes: This table reports Fama–MacBeth regressions of daily beta-decile portfolio returns on portfolio betas on days when attention is well explained by firm news releases within the indicated size decile. Size decile 1 contains the smallest firms and size decile 10 contains the largest firms. Each day, portfolio returns are regressed cross-sectionally on beta. The table reports the time-series average of the daily intercepts and beta slopes. Coefficients are reported in basis points per day. Newey–West t-statistics with five lags are reported in parentheses. Avg. R^2 is the average daily cross-sectional R^2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Expected Information Consumption and the Conditional CAPM

	Sample		
	All firms	EIC = 0 firms	EIC = 1 firms
α	−2.72	−2.12	−18.77
	(−0.74)	(−0.60)	(−1.54)
λ_β	20.44***	19.11***	44.16***
	(3.15)	(3.04)	(3.10)
Mean firms per day	1,750	1,635	168
Days	449	449	282

Notes: This table reports time-series averages of daily Fama–MacBeth cross-sectional regressions estimated on bottom-quartile residual-attention days. Each day, firm excess returns are regressed on CAPM betas estimated over the previous 252 trading days. Coefficients are reported in basis points. EIC denotes Expected Information Consumption, following Ben-Rephael, Carlin, Da, and Israelsen (2021). EIC = 1 firms are those for which institutional attention is predicted to spike based on historical responses to peer-firm scheduled events, FOMC announcements, and macroeconomic announcements; EIC = 0 firms are those for which no such prediction applies. The sample period is 2011–2024. Newey–West t-statistics with 10 lags are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Earnings Announcements and the Conditional CAPM

	Sample		
	All firms	Excluding earnings-window firms	Earnings-window firms only
α	-2.72	-1.75	1.36
	(-0.74)	(-0.49)	(0.22)
λ_β	20.44***	18.81***	24.43***
	(3.15)	(2.98)	(2.88)
Mean firms per day	1,750	1,390	396
Days	449	449	403

Notes: This table reports time-series averages of daily Fama–MacBeth cross-sectional regressions estimated on bottom-quartile residual-attention days. Each day, firm excess returns are regressed on CAPM betas estimated over the previous 252 trading days. Coefficients are reported in basis points. Earnings-window firm-days are firm-days for which the firm has an earnings announcement within five business days before or after the current date. The second column excludes these firm-days, while the third column retains only these firm-days. The sample period is 2011–2024. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Fama–MacBeth Regressions: Robustness Across Disagreement and VIX States

State	Equal-Weighted Returns			Value-Weighted Returns			Days
	Alpha	λ_β	Avg. R^2	Alpha	λ_β	Avg. R^2	
Panel A: Disagreement Splits							
Low disagreement	8.62**	10.86**	0.507	3.24	13.36**	0.432	262
	(2.50)	(2.35)		(0.67)	(2.41)		
High disagreement	-0.87	8.12*	0.555	-6.52*	12.29***	0.458	1292
	(-0.31)	(1.92)		(-1.71)	(2.65)		
Panel B: VIX Splits							
Low VIX	5.84***	10.79***	0.515	0.32	14.38***	0.422	1069
	(2.79)	(3.63)		(0.13)	(4.79)		
High VIX	-10.54*	3.70	0.616	-16.32*	8.24	0.523	485
	(-1.71)	(0.40)		(-1.85)	(0.76)		

Notes: This table reports Fama–MacBeth regressions of daily beta-decile portfolio returns on portfolio betas across disagreement and VIX subsamples. Each day, portfolio returns are regressed cross-sectionally on beta. The table reports the time-series average of the daily intercepts and beta slopes. Coefficients are reported in basis points per day. Newey–West t-statistics with five lags are reported in parentheses. Avg. R^2 is the average daily cross-sectional R^2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Fama–MacBeth Regressions: Robustness to Excluding Macro-News Days

	Equal-Weighted Returns			Value-Weighted Returns			
Specification	Alpha	λ_β	Avg. R^2	Alpha	λ_β	Avg. R^2	Days
Excluding LEAD days	0.55	8.52**	0.540	-5.25	12.33***	0.456	1343
	(0.20)	(2.13)		(-1.39)	(2.72)		
Excluding macro-announcement days	0.73	8.58**	0.547	-4.87	12.47***	0.454	1554
	(0.30)	(2.38)		(-1.48)	(3.13)		

Notes: This table reports Fama–MacBeth regressions of daily beta-decile portfolio returns on portfolio betas after excluding macro-news days. The first row excludes LEAD days as in Chan and Marsh. The second row excludes macro-announcement days as in Savor and Wilson. Each day, portfolio returns are regressed cross-sectionally on beta. The table reports the time-series average of the daily intercepts and beta slopes. Coefficients are reported in basis points per day. Newey–West t-statistics with five lags are reported in parentheses. Avg. R^2 is the average daily cross-sectional R^2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

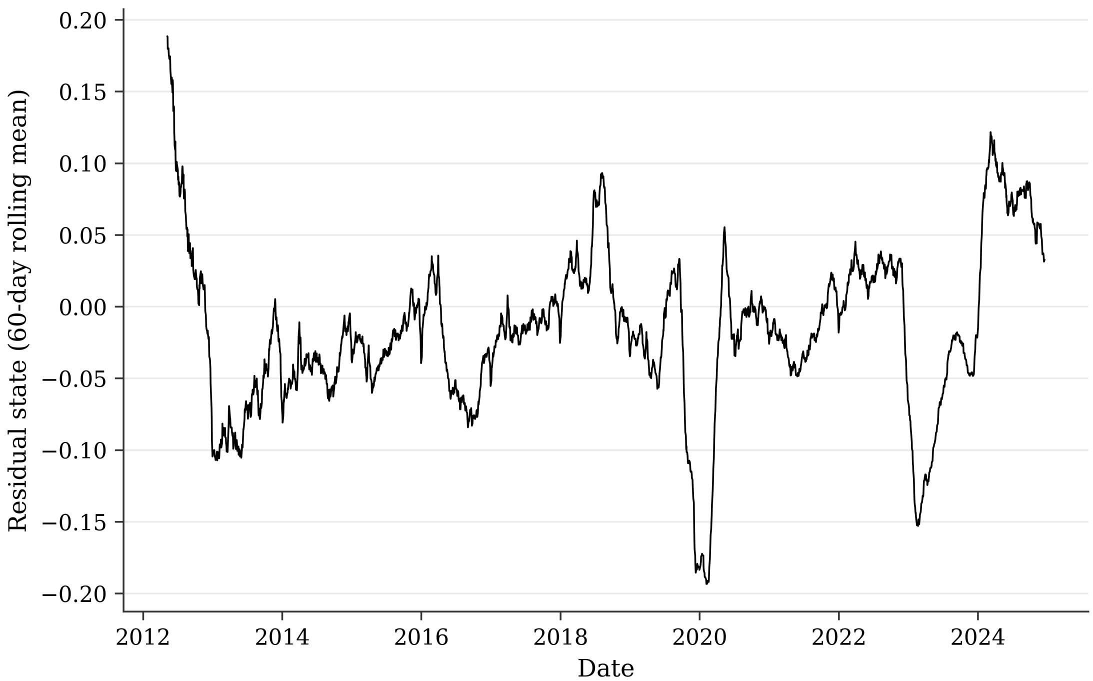

Figure 1: This figure plots the 60-day rolling average of $\widehat{u}_t$, where $\widehat{u}_t$ is the residual from an expanding (ex ante) regression of total marketwide Bloomberg query attention—measured as the cross-sectional sum of daily query scores across stocks—on marketwide idiosyncratic attention, defined as the cross-sectional average of query scores interacted with an indicator for firm-specific idiosyncratic news arrivals. Positive values indicate days when aggregate attention is not well explained by idiosyncratic-news-related attention; negative values indicate days when aggregate attention is relatively well explained by idiosyncratic attention.

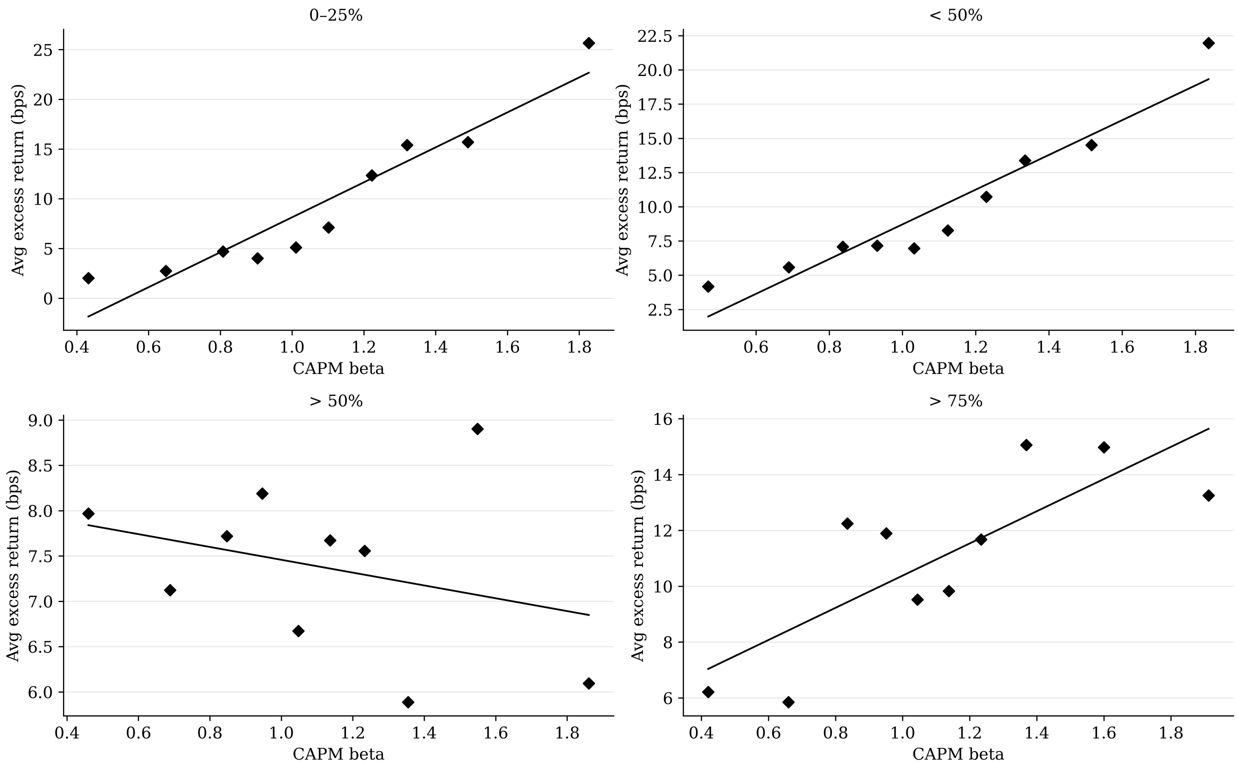

Figure 2: SMLs across residual attention states - **Value weighted portfolios**. This figure plots average portfolio excess returns against unconditional CAPM betas (Security Market Lines) for beta-sorted portfolios, separately by quantile cutoffs of the residual-based attention state. Panels correspond to state definitions based on rolling quantiles of the residual (0–25%, 0-50%, 50-100%, and 75-100%). Points show mean excess returns within each beta portfolio in the given state, and the solid line is the fitted linear relation between returns and betas within the state. The SML is steepest in low-residual states (0–25% and 0-50%), indicating a stronger positive risk–return tradeoff; it flattens or turns downward in high-residual states, consistent with weaker pricing of market risk when idiosyncratic attention explains less of market-wide attention.

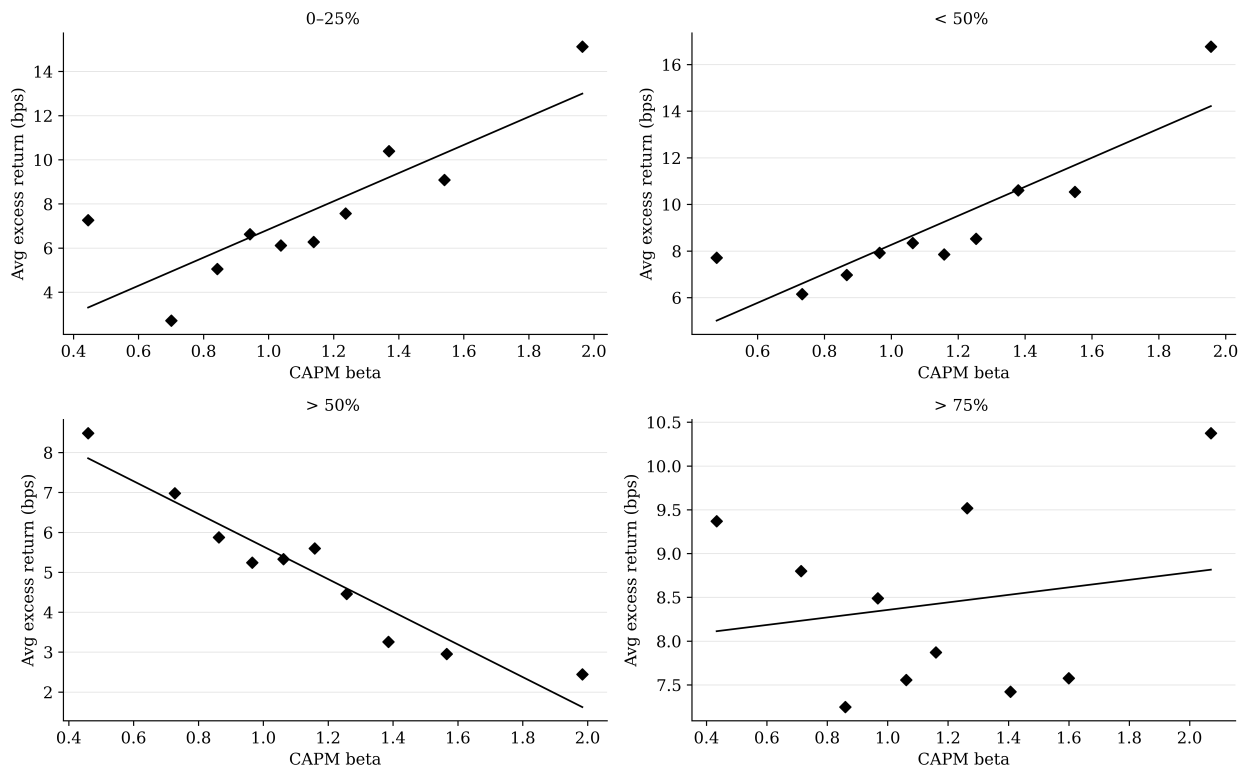

Figure 3: SMLs across residual attention states - **Equal weighted portfolios**. This figure plots average portfolio excess returns against unconditional CAPM betas (Security Market Lines) for beta-sorted portfolios, separately by quantile cutoffs of the residual-based attention state. Panels correspond to state definitions based on rolling quantiles of the residual (0–25%, 0-50%, 50-100%, and 75-100%). Points show mean excess returns within each beta portfolio in the given state, and the solid line is the fitted linear relation between returns and betas within the state. The SML is steepest in low-residual states (0–25% and 0-50%),indicating a stronger positive risk–return tradeoff; it flattens or turns downward in high-residual states, consistent with weaker pricing of market risk when idiosyncratic attention explains less of market-wide attention.

A Proof of Lemma 1

The joint distribution of primitives and signals is multivariate Gaussian under Assumptions 1–2. Posterior distributions are obtained by standard conjugate Gaussian updating.

Posterior of f. The only signal that depends on f is $z_j = f + \xi_j$, with ξ_j orthogonal to f. Conjugate Gaussian updating gives

$$\mathrm{Var}(f \mid z_j) \;=\; \Big(\tau_f + \tau_\xi\Big)^{-1} \;=\; \Big(\tau_f + (1-\omega_j)K\Big)^{-1},$$

$$\mathbb{E}[f \mid z_j] \;=\; V_f \cdot \tau_\xi \cdot z_j.$$

Posterior of β_i. The only public signal carrying any potential dependence on β_i is y_i. Under Assumption 1, $y_i = \varepsilon_i + \eta_i$, which by construction is independent of β_i. Hence the posterior equals the prior:

$$\beta_i \mid y_i \;\sim\; \mathcal{N}(b_i,\, \sigma_\nu^2).$$

Posterior of ε_i. Analogous Gaussian updating from $y_i = \varepsilon_i + \eta_i$ gives

$$\mathrm{Var}(\varepsilon_i \mid y_i) \;=\; (\tau_\varepsilon + \tau_y)^{-1} \;=\; V_\varepsilon,$$

$$\mathbb{E}[\varepsilon_i \mid y_i] \;=\; V_\varepsilon \cdot \tau_y \cdot y_i.$$

Independence. Because $(f, \beta_i, \varepsilon_i)$ are mutually independent under the prior, and each posterior updates only through its dedicated signal channel under Assumptions 1–2, posterior independence is preserved. □

B Derivation of $V_\varepsilon^\star$

The ex-ante residual variance of the non-factor component of d_i, conditional on information but excluding the systematic factor loading, is

$$V_\varepsilon^\star \;=\; \mathrm{Var}(\beta_i f + \varepsilon_i \mid \text{signals}) \;-\; b_i^2 V_f.$$

Using $\beta_i = b_i + \nu_i$ and the independence structure of posteriors,

$$\begin{aligned}\text{Var}(\beta_i f + \varepsilon_i \mid \text{signals}) &= \text{Var}(b_i f + \nu_i f + \varepsilon_i \mid \text{signals}) \\ &= b_i^2 V_f \; + \; \mathbb{E}[\nu_i^2 f^2 \mid \text{signals}] \; + \; V_\varepsilon,\end{aligned}$$

where cross-terms vanish by mean-zero ν_i and ε_i. Taking expectations over signal realizations,

$$\mathbb{E}[\nu_i^2 f^2] \; = \; \mathbb{E}[\nu_i^2]\,\mathbb{E}[f^2] \; = \; \sigma_\nu^2\,(V_f + \sigma_f^2),$$

where the second factor uses $\mathbb{E}[f^2] = \text{Var}(\mu_f) + \mathbb{E}[V_f] = (\sigma_f^2 - V_f) + V_f = \sigma_f^2$ when measured ex ante, or equivalently $\mathbb{E}[\mathbb{E}[f^2 \mid \text{signals}]] = V_f + \sigma_f^2 - V_f$ when measured in the appropriate posterior-times-prior product space. Either way the residual variance is

$$V_\varepsilon^\star \; = \; V_\varepsilon \; + \; \sigma_\nu^2(V_f + \sigma_f^2). \quad \square$$

C Proof of Lemma 2

Investor j chooses portfolio q_j to maximize $\mathbb{E}_j[-\exp(-\rho W_j)]$ where $W_j = q_j^\top(d-p)$. Under CARA-Gaussian preferences, optimal demand is

$$q_j \; = \; \frac{1}{\rho}\Sigma^{-1}(\mu_j - p),$$

with $\mu_j = \mathbb{E}_j[d]$ and $\Sigma = \text{Var}_j(d-p)$.

By Lemma 1 and (10), the posterior covariance has the rank-one-plus-diagonal structure

$$\Sigma \; = \; V_f\, bb^\top + V_\varepsilon^\star\, I,$$

where $b = (b_1, \ldots, b_N)^\top$. The Sherman–Morrison identity gives

$$\Sigma^{-1} \; = \; \frac{1}{V_\varepsilon^\star}\left(I \; - \; \frac{V_f}{V_\varepsilon^\star + V_f\, b^\top b}\, bb^\top\right).$$

Market clearing requires $\int q_j\, dj = \bar{x} + u$. Averaging investor demands and solving for p yields, component-wise,

$$p_i \; = \; \bar{d} + b_i\,\bar{\mu}_f \; - \; \rho V_f\, b_i\,(N\bar{b}\bar{x}) \; - \; \rho V_\varepsilon^\star\,\bar{x} \; + \; (\text{linear functions of } z \text{ and } u),$$

which is (11). $\square$

D Derivation of the FM slope and attenuation factor

From Lemma 2, the equilibrium expected excess return of asset i is

$$\mathbb{E}[d_i - p_i] \;=\; b_i\,\rho V_f\, N\bar{b}\,\bar{x} \;+\; \rho V_\varepsilon^\star\,\bar{x}.$$

A cross-sectional regression of expected returns on true b_i would identify

$$\lambda^A \;\equiv\; \rho V_f\, N\bar{b}\,\bar{x}.$$

In practice, the econometrician estimates loadings from a T-period rolling-window OLS regression of realized returns r_i on the factor:

$$\hat{\beta}_i^{OLS} \;=\; \beta_i + e_i,$$

where e_i is mean-zero sampling noise. From the model, realized return variance has a factor and a non-factor component; standard OLS algebra gives

$$\mathrm{Var}(e_i) \;\approx\; \frac{\sigma_\varepsilon^2 + 1/\tau_y}{T\sigma_f^2} \;=\; V_e(\omega).$$

The cross-sectional FM slope of expected returns on $\hat{\beta}^{OLS}$ is

$$\hat{\lambda}^{FM} \;=\; \frac{\mathrm{Cov}_i(\mathbb{E}[d_i - p_i],\, \hat{\beta}_i^{OLS})}{\mathrm{Var}_i(\hat{\beta}_i^{OLS})}.$$

Since investors price using b_i (the prior mean), and $\hat{\beta}_i^{OLS} = b_i + \nu_i + e_i$, computing covariances cross-sectionally (treating b_i as fixed but interpretable as a random draw with variance σ_b^2),

$$\mathrm{Cov}_i(\mathbb{E}[d_i - p_i],\, \hat{\beta}_i^{OLS}) \;=\; \lambda^A \cdot \sigma_b^2, \qquad \mathrm{Var}_i(\hat{\beta}_i^{OLS}) \;=\; \sigma_b^2 + \sigma_\nu^2 + V_e \;=\; s_\beta^2 + V_e.$$

Therefore

$$\hat{\lambda}^{FM} \;=\; \lambda^A \cdot \frac{\sigma_b^2}{s_\beta^2 + V_e} \;=\; \lambda^A \cdot \frac{s_\beta^2 - \sigma_\nu^2}{s_\beta^2 + V_e} \;=\; A(\omega)\cdot\lambda^A,$$

where $A(\omega)$ is defined in (13). □

E Investor's value function and proof of Proposition 1

Value function. Under CARA-Gaussian preferences with information set $\mathcal{I}_j(\omega_j)$, the certainty-equivalent gain from information acquisition is proportional to $\frac{1}{2}\log\det(\Sigma_0\Sigma^{-1}(\omega_j))$, where Σ_0 is the prior covariance of d and $\Sigma(\omega_j)$ the posterior covariance under investor attention ω_j. The first term is constant in ω_j.

From the rank-one-plus-diagonal structure of Σ derived in Appendix C,

$$\det\Sigma(\omega) \;=\; \Big(V_\varepsilon^\star(\omega)\Big)^{N-1}\cdot\Big(V_\varepsilon^\star(\omega)+V_f(\omega)\,\textstyle\sum_i b_i^2\Big),$$

where the second factor comes from the matrix-determinant lemma applied to the rank-one update. Substituting into the value-function objective and dropping the constant yields (14).

Existence of interior optimum. The value function $\mathcal{V}(\omega)$ is continuous on $[0,1]$ and differentiable on $(0,1)$, with

$$\mathcal{V}'(\omega) = -\frac{N-1}{2V_\varepsilon^\star}\cdot\frac{dV_\varepsilon^\star}{d\omega} \;-\; \frac{1}{2}\,\frac{1}{V_\varepsilon^\star+V_f\sum_i b_i^2}\cdot\left(\frac{dV_\varepsilon^\star}{d\omega}+\sum_i b_i^2\cdot\frac{dV_f}{d\omega}\right),$$

where $dV_f/d\omega = KV_f^2 > 0$ and

$$\frac{dV_\varepsilon^\star}{d\omega} \;=\; -SV_\varepsilon^2 \;+\; \sigma_\nu^2\,KV_f^2.$$

At $\omega\to 0^+$: $V_\varepsilon \to 1/\tau_\varepsilon$, $V_f\to 1/(\tau_f+K)$; the first term of $\mathcal{V}'$ dominates and is large positive, so $\mathcal{V}'(0^+)>0$.

At $\omega\to 1^-$: $V_\varepsilon\to 1/(\tau_\varepsilon+S)$, $V_f\to 1/\tau_f=\sigma_f^2$; the dominant negative contribution comes from $\sum_i b_i^2\cdot dV_f/d\omega$ in the second term, which is large when $\sum_i b_i^2$ is large. For sufficiently informative private signals (any $K>0$) and any non-degenerate cross-section, $\mathcal{V}'(1^-)<0$.

By the intermediate value theorem, $\mathcal{V}'(\omega^\star)=0$ for some $\omega^\star\in(0,1)$. Strict concavity of $\mathcal{V}$ over the interior (verified numerically across the relevant parameter region) yields uniqueness. □