

A FOMO-based Capital Asset Pricing Model

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Abstract

Investors experience a Fear of Missing Out (FOMO) when observing peers' investment choices outperforming their own. Agents require compensation for holding stocks that deliver lower returns than the equities held by their peers. This paper provides a theoretical and empirical introduction to the FOMO Capital Asset Pricing Model (FOMO-CAPM). Analysis of US equities between 1980 and 2024 shows FOMO is a significant determinant of asset prices. An annualized downside FOMO risk premium of 17.4% is demonstrated. The explanatory power of FOMO for stock returns is robust to a battery of alternative peer group portfolios, risk exposure controls and sub-period analyses.

EFM Codes: 310, 320, 330, 720

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1 Introduction

The Fear of Missing Out (FOMO) refers to a pervasive apprehension that others may be having rewarding experiences from which one is absent (Przybylski, Murayama, DeHaan, and Gladwell, 2013). FOMO is widely studied in the context of social psychology and digital communication (Milyavskaya, Saffran, Hope, and Koestner, 2018; Zhang, Jiménez, and Cicala, 2020). Bonaparte and Fabozzi (2025) evidence the aggregate presence of FOMO in financial markets through a FOMO index, yet there is a lack of work on FOMO at the individual asset level. Given the associated financial rewards, it is rational to assume that investors will feel FOMO about the potential returns obtained by others. At the heart of the FOMO definition is the comparison of an investors' current position and a counterfactual portfolio that the investor would miss out on if they continue to hold their current position. Individual investors are choosing between the asset they selected based upon their own valuation model, and an alternate asset selected by others in their peer group¹. That social dynamics and emotional pressures, such as those engendered by FOMO, shape investor decision-making across individual assets is established (Hirshleifer, 2001, 2015, amongst others). However, standard asset pricing models, such as the Capital Asset Pricing Model (CAPM), focus on the investors own returns, neglecting that the performance of others matters². FOMO offers an asset level explanation for the divergence between observed trading patterns and the expected return maximization strategies of traditional asset pricing models.

This paper provides a theoretical framework which integrates FOMO with the CAPM, producing the FOMO-CAPM. Our theoretical framework hinges on the comparison between the returns on an investor's holding and the returns achieved by the investor's peer group. FOMO only occurs when then the investors' peer group portfolio delivers higher returns than the investors' own portfolio. The case in which the investor outperforms their peers engenders a separate feeling of success. Following Ang, Chen, and Xing (2006a), Bollerslev, Patton, and Quaedvlieg (2022) and others, we compute FOMO betas based on realized returns and the comparative return rankings of the stock and its peer group benchmark. An up FOMO beta captures the success feeling, whilst the down

¹The model nests cases where the individual investors and peer group have different information sets. All that is required is that investors can see the return on their peers portfolio.

²A parallel is drawn between FOMO and the "keeping up with the Joneses" (KUJ) literature. KUJ preferences incorporate the consumption of the peer group in an individual's decision-making. In asset selection, KUJ preferences lead to the selection of stocks whose returns correlate with the returns of peers (Levy and Levy, 2015). It is well understood that KUJ preferences lead to behavior which is inconsistent with rational behavior (Agarwal, Mikhed, and Scholnick, 2020; Gómez, Priestley, and Zapatero, 2009). Within FOMO, an investor will feel emotion based upon the relative performance of the investments rather than the wealth. The emphasis of FOMO is the investor thinking how much better they could do if investing their own wealth in the investment selections of their peers.

FOMO beta appears in cases where there is FOMO present.

An empirical analysis using Fama-French 38 industries to provide peer groups demonstrates that FOMO betas are mispriced in the cross-section of stock returns. Portfolios formed on the down FOMO beta generate a High-minus-Low abnormal return of 17.4% per annum (t-statistic 8.46), whilst the High-minus-Low abnormal return sorting on the up FOMO beta is 10.54% (t-statistic 8.16). Significance of the FOMO betas is also shown to be robust in Fama-MacBeth regressions. Through a battery of alternative peer group portfolios, we show that the use of the Fama-French 38 Industries is not pivotal to the conclusions on the significance of the FOMO betas. We evidence robustness when the reference portfolio is the Fama-French 38 Industry value weighted return plus 1 percentage point, the Fama-French 12 Industry value weighted portfolio return, and the NASDAQ index return. For the realized down FOMO betas, the High-minus-Low strategies annualized returns are 10.5% (t-statistic 8.15), 14.8% (t-statistic 6.78) and 14.7% (t-statistic 5.15) against the Fama-French 38 Industry portfolio plus 1 percentage point, the Fama-French 12 Industry portfolio and the NASDAQ index respectively. For the realized up FOMO betas, the corresponding figures are 10.5% (t-statistic 8.15) for the Fama-French 38 Industry plus 1 percentage point, 11.3% (t-statistic 8.15) for the Fama-French 12 Industry portfolio, and 11.4% (t-statistic 6.92) for the NASDAQ index. Our results demonstrate that FOMO betas have explanatory power for stock returns.

The definition of the peer group, and the estimation of the expected returns on the peer groups best performing asset, are required for FOMO. Peer groups in this paper are defined as investors in the same Fama-French 38 Industry portfolio as the individual investors' current holding³. The performance of the value-weighted industry portfolio provides the counterfactual return. Whilst Cookson, Lu, Mullins, and Niessner (2024), Han, Hirshleifer, and Walden (2022) and others are constructing influences based on social media, e.g. StockTwits, we require a definition of peer that can be applied beyond the subset of social media users. Industries are an established reference point for investors (Moskowitz and Grinblatt, 1999; Ivković, Sialm, and Weisbenner, 2008). Industry matters for stock returns through competition (e.g. Hou and Robinson, 2006), heterogeneities in the correlation of returns to the overall market (Hong, Torous, and Valkanov, 2007, for example), industry specific news items (Hao, Jin, and Zhang, 2011; Jennings, Seo, and Soliman, 2020; Jeon, McCurdy, and Zhao, 2022, amongst others), and intra-industry information transfers (Piotroski and Roulstone, 2004, for example). Heterogeneity at the industry level is also seen in the contemporary literature linking Environmental, Social and Governance (ESG) performance and stock returns (Pástor, Stambaugh, and Taylor, 2022; Zhang, 2025, amongst many others). Heterogeneities in the firm valuation

³Choice of 38 industries reflects the cost of investors obtaining information about the larger volume of stocks that would be present in each portfolio at a higher aggregation level.

models across industries underlie the mixed performance of the book-to-market premium (Golubov and Konstantinidi, 2019). Approaching FOMO through an industry lens allays the Golubov and Konstantinidi (2019) criticism, ensuring all investors in the industry peer group are working with similar valuation models. Further, the investor can obtain a consistent valuation of the choices made by the peer group.

FOMO speaks to investment-specific benchmarking, regret and herding. Where funds are benchmarked to industry returns, the benchmark is chosen by the fund, not the investor. The investor may, or may not, have invested in the proposed benchmark. By contrast, all decisions on the peer group reference portfolios in FOMO are made by the investor. Further, FOMO contrasts with traditional regret theory (Bell, 1982; Loomes and Sugden, 1982), which evaluates outcomes relative to all unchosen alternatives. FOMO also has crucial differences with anticipated regret (Zeelenberg, 1999). Anticipated regret highlights future-oriented emotional consequences of individual decisions, but does not have the social comparison investors make when experiencing FOMO. Under FOMO, utility depends not only on one’s own payoff but also on whether that payoff falls short of what peers gain. Asymmetry in the strength of influence of underperforming (outperforming) the peer group distances the FOMO-CAPM from the regret CAPM of Qin (2020). The potential for feeling FOMO can lead to [investors](#) mimicking peer behavior, even at the expense of expected returns (Kaddouhah, 2024). FOMO thus offers a rationale for herd behavior, but the existence of FOMO is not sufficient for herd behavior. The FOMO-CAPM developed in this paper formally integrates FOMO into the asset pricing framework.

To illustrate how FOMO operates in practice, consider a scenario with two investors, A and B. Both A and B belong to the same peer group. Previously, investor A had observed investor B achieving significant financial gains by investing in a newly-listed technology stock. Investor A faces a new decision: whether to invest in a stable mutual fund, which aligns with A’s original risk tolerance and financial goals, or whether to invest funds in the technology stock that is highly volatile. Witnessing B’s past success influences A’s perception of potential outcomes, creating FOMO on similar possible gains. Consequently, investor A’s decision-making process is influenced not only by their individual goals, but also by anticipated regret and social comparisons with B’s past choices and historical performance.

Ex ante, investor A’s decision is strongly shaped by the psychological anticipation of regret. A imagines two future scenarios. In the first scenario, investor A imagines they invest in the stable mutual fund, maintaining alignment with their original financial goals. In the second scenario, investor A imagines investing in the technology stock. The imagined rationale for investor A in the second scenario is the hope to match investor B’s previous success and the desire to avoid falling behind in terms of wealth and social

standing. The observed success of B increases A’s FOMO, especially if the technology stock achieves higher returns compared to A’s choice. In the second scenario, anticipated regret of being worse off than the peer group, coupled with the social pressure to keep up with the group, causes A to deviate from their initial preference for the mutual fund and allocate funds to the riskier technology stock instead. FOMO thus influences investor A to prioritise peer-relative performance over their personal financial strategy. By focusing on the potential regret of underperforming relative to the peer group, rather than the intrinsic alignment of the mutual fund with their financial goals, in the second scenario means that investor A’s decision reflects the distortion of expected utility maximisation caused by FOMO.

Building upon the CAPM, empirical asset pricing has sought to identify factors that can explain stock returns. The result is a “factor zoo” of firm characteristics, price information, and macro variables, which provide information about the cross-section of stock returns⁴ The potential for FOMO to generate a further factor for the zoo is indicated by our work, but requires the optimization of the choice of peer portfolio. Exploration of any FOMO factor(s) is left beyond the scope of this paper. Whilst the factor models developed have greater explanatory power for realized returns, the CAPM continues to be used widely. The popularity of the CAPM is due to its simplicity, ease of implementation and strong foundational role in finance education and investment management (Graham and Harvey, 2001; Bali, Engle, and Murray, 2016; Cochrane, 2009)). Simultaneously, Hirshleifer (2015), Barberis (2018) and others, highlight the ways in which behavioral biases enhance asset pricing models. Biases such as limited attention, heuristics, evolving investor beliefs and extrapolative expectations, generate anomalies such as momentum and excess volatility. The FOMO-CAPM appeals to the simplicity of the CAPM, incorporating the lessons from behavioral finance on peer comparison and the fear of missing out on high-performance investment opportunities.

This paper makes three key contributions to the literature on investor behavior and asset pricing. Firstly, this paper introduces the FOMO-CAPM, a behavioral asset pricing model that explicitly integrates FOMO into the standard CAPM framework. FOMO modifies investors’ portfolio allocation by embedding an additional emotional cost into their portfolio decisions, leading them to adjust their asset choices toward alignment with their peers to avoid this peer-relative underperformance. The traditional CAPM is a limiting case of the FOMO-CAPM in which investors place zero weighting on peer performance. The second contribution of this paper is the provision of a structured approach to analyze phenomena like herd behavior, speculative bubbles and deviations

⁴The term factor zoo is coined by Feng, Giglio, and Xiu (2020). After the research identifies the ability of a specific information to predict stock returns, investors are able to use the fact to adjust expectations of future returns. Consequently, many factors are short-lived and do not hold up under rigorous testing (Harvey, Liu, and Zhu, 2016; Feng et al., 2020; Harvey and Liu, 2021).

from expected utility maximization. The paper achieves the second contribution by showing how FOMO induces these phenomena. The FOMO framework thus bridges the gap between traditional and behavioral asset pricing. The results in this paper provide theoretical and empirical insights, offering practical applications for market participants by highlighting the conditions under which social pressures drive investment behavior. The third contribution is the empirical demonstration of FOMO in the US equity markets. Portfolios sorted on the up, and down, FOMO betas generate economically significant high-minus-low returns. Further, both the up and down FOMO betas have explanatory power for future stock returns in Fama-MacBeth regressions. Resisting the critique of Levi and Welch (2020), we show that the up and down FOMO betas are persistent over time and are suitable for portfolio formation. Our work provides a demonstration of the empirical validity of FOMO-CAPM. Collectively, the three contributions of this paper highlight the significance of integrating behavioral dynamics into asset pricing to address the complexities of contemporary financial markets.

The remainder of the paper is organised as follows. Section 2 formally presents the FOMO-CAPM. Section 3 provides a theoretical comparison between the FOMO-CAPM and the traditional CAPM. Section 4 conducts an empirical examination of the FOMO-CAPM. Section 5 discusses the implications and of our results. Section 6 concludes.

2 A FOMO-CAPM

We consider a financial market in which I investors trade one risk-free asset offering a certain return r_f and N risky assets. Individual investors are indexed by $i, i = 1, 2, \dots, I$. Assets are indexed by $j, j = 1, 2, \dots, N$. The number of outstanding shares for each risky asset is normalized to one. The net supply of the risk-free asset is zero. The price of a risky asset j at time $t = 0$ is denoted by $P_{j,0}$, while its price at $t = 1$ is given by $P_{j,1}$. The rate of return on asset j is represented as $r_j \equiv \frac{P_{j,1}}{P_{j,0}} - 1$. The vector of asset prices, $\{P_{j,1}\}$, is multivariate normal distributed.⁵

At time 0, $t = 0$, each individual investor, i , allocates their initial wealth $W_{i,0}$ among the N assets. The payoff received by investor i at time $t = 1$, $W_{i,1}$ is given by:

$$W_{i,1} = W_{i,0}(1 + r_{ip}) \quad (1)$$

where an individual's portfolio return, r_{ip} , is given by:

$$r_{ip} \equiv r_f + \sum_{j=1}^N w_{ij}(r_j - r_f) \quad (2)$$

⁵We assume there is no redundant asset, meaning no asset's payoff can be perfectly replicated by a portfolio of the other available assets.

Here, w_{ij} represent the proportion of wealth invested by investor i in asset j . The weight on the risk-free asset is implicitly defined as $1 - \sum_{j=1}^N w_{ij}$. Our model admits the case where $\sum_{j=1}^N w_{ij} > 1$.

An individual's utility consists of two components. The first component is the utility derived from the monetary return, denoted as $u_i(W_{i,1})$. The monetary return is the wealth accumulated from investing in the chosen assets. We assume that individuals are risk neutral such that $u_i(W_{i,1}) = W_{i,1}$ ⁶. The second component of an individual's utility, denoted as $f_i(W_{i,1} - g_i(H_i))$, captures the utility impact stemming from the comparison between the investor's own wealth and the peer group portfolio. The adjustment to the utility function provided by $f_i()$ and $g(H_i)$ are consistent with the core tenets of prospect theory (Kahneman, Tversky et al., 1979). In the FOMO-CAPM an individual compares their payoff from the chosen portfolio $W_{i,1}$ to the counterfactual payoff of an unchosen portfolio H_i ⁷. To meet the conditions for FOMO, the unchosen portfolio must consist of a pool of assets drawn from an individual's reference portfolio⁸. If $W_{i,1} < H_i$ an individual experiences FOMO.

Investor i , maximizes expected utility $EU_i(V_i(W_{i,1}))$. Investor i 's modified utility function incorporating FOMO, $V_i(W_{i,1})$, is defined as follows:

$$V_i(W_{i,1}) = W_{i,1} + f_i(W_{i,1} - g_i(H_i)) \quad (3)$$

where

$$g_i(H_i) = \begin{cases} H_i & \text{if } W_{i,1} \geq H_i \\ H_i + k_i(H_i) & \text{if } W_{i,1} < H_i \end{cases} \quad (4)$$

⁶Assuming risk neutrality for the monetary utility component u_i simplifies the analysis. Risk neutrality allows us to isolate the specific impact of the FOMO component f_i on portfolio choice, separate from the standard effects of risk aversion.

⁷Our concept assumes that H_i is stochastic rather than a deterministic reference point and that individuals are heterogeneous rather than homogeneous. The function $f_i(\cdot)$ and portfolio H_i differ between individuals. Models based on prospect theory assume convex utility in the loss domain and/or probability weighting, whereas our concept assumes a concave regret function $f_i(\cdot)$, similar to the Regret-CAPM of Qin (2020). To simplify the notation, we omit the 1 from the subscript. The comparator in FOMO is always the future wealth of period 1.

⁸Our framework's use of a reference portfolio is conceptually distinct from the benchmark used in 'habit formation' models (e.g., Abel 1990; Campbell and Cochrane 1999). In habit models, the benchmark is internal and based on the agent's own past consumption, driven by a motive of consumption smoothing. In contrast, our reference portfolio is external and cross-sectional, based on the contemporaneous performance of a peer group. The motive is not consumption smoothing, but social comparison, with the model's unique function explicitly capturing the asymmetric disutility from underperforming these peers.

⁸At $W_{i,1} = H_i$, the investor neither outperforms nor underperforms the reference portfolio. By convention, no FOMO-driven disutility is applied, ensuring continuity in the rejoice region of the utility function $k_i(H_i) = 0$.

The FOMO-CAPM Utility Adjustment Function

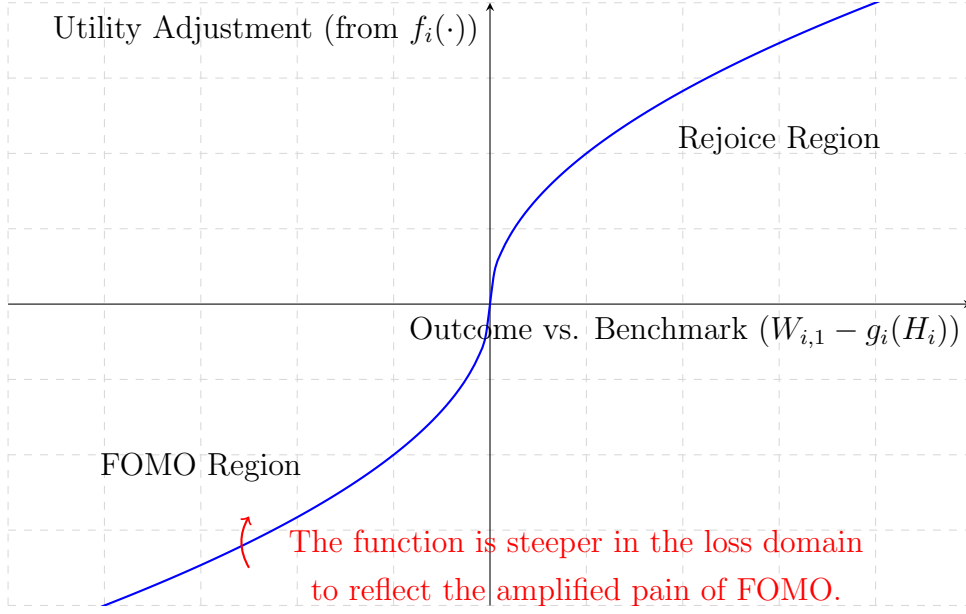


Figure 1: The Concave Utility Adjustment Function $f(\cdot)$

This figure illustrates the globally concave utility function, $f_i(\cdot)$, which captures the emotional adjustments from performance relative to a peer benchmark. The function is concave for both gains (rejoice) and losses (FOMO). Concavity is consistent with standard assumptions of risk aversion and diminishing marginal sensitivity. The key asymmetry, central to our theory, is captured in two ways. First, the $f_i(\cdot)$ function is drawn to be steeper in the loss domain, reflecting that underperformance is felt more intensely than outperformance is enjoyed. Second, the additional emotional disutility from FOMO is formally modeled by the $k_i(H_i)$ term, which effectively increases the magnitude of the loss on the x-axis, leading to a greater overall utility reduction.

Figure 1 provides a visual illustration of the utility function's key components. Function $g_i(H_i)$ reflects how past information shapes investor expectations. $g_i(H_i)$ comprises the reference portfolio H_i and the FOMO sensitivity applied through $k_i(H_i)$. The specification of the utility functions are dynamic and forward-looking. Moreover, $g_i(H_i)$ provides mathematical flexibility, enabling robustness to the incorporation of various factors and indicators, which may influence investor utility.

We allow individuals to experience both FOMO as well as regret. The introduction of the functions $g(\cdot)$ and $k(\cdot)$ ¹³ enables the specific identification of FOMO. While $g_i(H_i)$ accounts for both FOMO and regret, $k_i(H_i)$ is introduced to create an asymmetry in $f(\cdot)$ that specifically captures the effect of FOMO alone. The additional disutility of FOMO thus appears in $k_i(H_i)$. As defined in Equation (4), $k_i(\cdot)$ is activated only when $W_{i,1} < H_i$. $k_i(H_i)$ creates an asymmetric disutility that amplifies the emotional cost associated with underperforming the reference portfolio. Investor responses to peer comparisons are

¹³Since H_i is stochastic, we define $k_i(H_i) = \eta_i(H_i - W_{i,1})^\alpha$ for $W_{i,1} < H_i, 0 < \alpha \leq 1, \eta_i > 0$. This ensures that disutility is convex and increases with underperformance relative to the reference portfolio.

influenced by FOMO, distinguishing our specification from general regret¹⁴.

The term $f_i(W_{i,1} - g_i(H_i))$ captures the emotional responses to differences between the investors' own portfolio and the peer reference portfolio. $f_i(W_{i,1} - g_i(H_i))$ encompasses the effects of regret, rejoice and FOMO. Functions $g(\cdot)$ and $k(\cdot)$ capture the adverse impact on utility when the payoff of the reference portfolio H_i is greater than $W_{i,1}$. To accurately model this negative impact, both functions exhibit convexity¹⁵, indicating diminishing negative impact as the counterfactual return increases. Furthermore, we assume that the disutility effect of FOMO on an individual's utility is additive to regret. The emotional response to missing out on a superior alternative that has been selected by peers is greater than the regret of simply making a poor choice.

Core to the definition of FOMO is the reference portfolio of each individual investor. The value of the counterfactual H_i to investor i is expressed as:

$$H_i = W_{i,0}(1 + h_i) \quad (5)$$

where h_i represents the rate of return on an individual's counterfactual portfolio. It is the return achieved by peers that drives the comparison, not the wealth achieved by peers. Hence H_i is the value of investing the initial wealth $W_{i,0}$ into the counterfactual portfolio. Our framework does not require any single universal reference point. Instead, both H_i ¹⁶ and the FOMO function $f(\cdot)$ vary across individuals.

Using the return on the chosen portfolio, r_{ip} , and the counterfactual return, h_i , the modified utility function defined in Equation (3) can be expressed as:

$$V_i(W_{i,1}) = W_{i,0}(1 + r_{ip}) + f_i(W_{i,0}(1 + r_{ip}) - g_i(W_{i,0}(1 + h_i))) \quad (6)$$

An individual's utility maximizing problem is $\max_{\{w_{i,j}\}} E[V_i(W_{i,1})]$. Because $V_i(\cdot)$ is strictly concave, the first-order condition is necessary and sufficient for a solution:

$$E[(r_j - r_f)(1 + f'_i(W_{i,1} - g_i(H_i)))] = 0 \quad (7)$$

We apply Stein's lemma to the first-order condition, similar to the derivation of the

¹⁴The Regret-CAPM of Qin (2020) appears when $k_i(H_i) = 0$.

¹⁵ $f(\cdot)$ is a concave function, where $f_i(0) = 0$, $f'_i > 0$ and $f''_i < 0$, while $g(\cdot)$ and $k(\cdot)$ are convex functions, where $g_i(0) = 0$, $g'_i > 0$ and $g''_i > 0$, as well as $k_i(0) = 0$, $k'_i > 0$ and $k''_i > 0$. These properties ensure FOMO-driven disutility increases and accelerates with the reference portfolio's performance.

¹⁶An investor may also consider multiple counterfactuals simultaneously if their information set includes several attractive opportunities. For instance, if investor i observes peers investing in both stocks and real estate, the counterfactual H_i could be constructed as a weighted portfolio of these two asset classes. Our model accommodates such cases by allowing H_i to reflect any combination of benchmarks that an investor perceives as missed opportunities. Furthermore, the model is not restricted to small deviations in portfolio returns. If a particular market or asset experiences extraordinary gains, FOMO may still be triggered by substantial return differentials relative to the investor's own portfolio, reflecting the broad scope of scenarios that can generate regret or fear of missing out.

CAPM¹⁷. Under the assumption that the requirement of Stein's lemma¹⁸ $E[|f_i''(W_{i,1} - g_i(H_i))|] < 0$, is satisfied, then from Equation (7) and Stein's lemma:

$$-\frac{1 + E\left[f_i'(W_{i,0}(r_{ip} - \frac{g_i(H_i)}{W_{i,0}} - \frac{k_i(H_i)}{W_{i,0}}))\right]}{E\left[f_i''(W_{i,0}(r_{ip} - \frac{g_i(H_i)}{W_{i,0}} - \frac{k_i(H_i)}{W_{i,0}}))\right]}E[r_j - r_f] = W_{i,0}\text{Cov}(r_j, r_{ip} - \frac{g_i(H_i)}{W_{i,0}} - \frac{k_i(H_i)}{W_{i,0}}) \quad (8)$$

Since each risky asset j has one outstanding share and all shares must be held in equilibrium. The following market-clearing conditions must hold:

$$\sum_{i=1}^I \frac{w_{i,j}W_{i,0}}{P_{j,0}} = 1, j = 1, 2, \dots, N. \quad (9)$$

$$\sum_{i=1}^I W_{i,0}(1 - \sum_{j=1}^N w_{ij}) = 0 \quad (10)$$

Both the first-order conditions and the market clearing conditions are satisfied in equilibrium. Summing the first-order condition over i :

$$E[r_j] - r_f = -M_0 \left(\sum_{i=1}^I \frac{1 + E\left[f_i'(W_{i,0}(r_{ip} - \frac{g_i(H_i)}{W_{i,0}} - \frac{k_i(H_i)}{W_{i,0}}))\right]}{E\left[f_i''(W_{i,0}(r_{ip} - \frac{g_i(H_i)}{W_{i,0}} - \frac{k_i(H_i)}{W_{i,0}}))\right]} \right)^{-1} \text{cov}(r_j, r_m - h_m) \quad (11)$$

where $M_0 \equiv \sum_{i=1}^I W_{i,0}$ denotes the total initial wealth at date $t = 0$, and

$$h_m = \sum_{i=1}^I \frac{W_{i,0}}{M_0} g_i(H_i) \quad (12)$$

$$r_m = \sum_{i=1}^I \frac{W_{i,0}}{M_0} r_{ip} \quad (13)$$

Here r_m denotes the average investment return of individual investors. Given that market-clearing conditions hold in equilibrium, r_m also represents the return on the market portfolio of risky assets. Similarly, let h_m denote the market-wide average counterfactual returns. The returns on the average counterfactual can be decomposed into two parts:

$$h_m = h_m^{(h)} + h_m^{(k)}, \text{ where} \quad (14)$$

$$h_m^{(h)} = \sum_{i=1}^I \frac{W_{i,0}}{M_0} H_i \text{ and } h_m^{(k)} = \sum_{i: W_{i,1} < H_i}^I \frac{W_{i,0}}{M_0} k_i(H_i) \quad (15)$$

¹⁷The application of Stein's Lemma here relies on the standard assumption of jointly normally distributed asset returns, which is a common theoretical assumption for deriving CAPM-like asset pricing models. While financial returns in practice can exhibit deviations from normality, such as fat tails, this assumption allows for a tractable derivation of a covariance-based pricing kernel, following the convention in the asset pricing literature (for example see Cochrane, 2009)

¹⁸For Stein's lemma and its application to asset pricing, see Cochrane (2009) and/or Munk (2013)

Equations (14) and (15) clarify that the market-wide average counterfactual h_m is composed of the baseline counterfactual H_i through $h_m^{(h)}$ and the extra disutility adjustment $k_i(H_i)$ through $h_m^{(k)}$.

The difference $r_m - h_m \equiv r_m - [h_m^{(h)} + h_m^{(k)}]$ captures the aggregate-level disparity between actual and counterfactual returns. Equation (11) establishes that an asset's excess return $E[r_j] - r_f$ is determined by covariance $\text{cov}(r_j, r_m - h_m)$. Consequently, a single-beta pricing formula can be derived.

Proposition 1 *If $\text{var}(r_m - h_m) > 0$, then*

$$E[r_j] - r_f = \beta_j^{FOMO}(E[r_m] - E[h_m]) \quad (16)$$

holds for all j , where

$$\beta_j^{FOMO} \equiv \frac{\text{cov}(r_j - r_f, r_m - [h_m^{(h)} + h_m^{(k)}])}{\text{var}(r_m - [h_m^{(h)} + h_m^{(k)}])} \equiv \frac{\text{cov}(r_j - r_f, r_m - h_m)}{\text{var}(r_m - h_m)} \quad (17)$$

Moreover,

$$E[r_m] - E[h_m] > 0. \quad (18)$$

A proof of Proposition 1 is provided in the Appendix.

β_j^{FOMO} is defined with respect to the gap between the market average return and the market-wide average counterfactual. When $r_m - h_m < 0$, investors feel FOMO, whereas when $r_m - h_m > 0$, investors experience rejoice. Since β_j^{FOMO} captures the sensitivity of asset j to market-wide emotional fluctuations, we refer to it as "FOMO beta". To ensure that β_j^{FOMO} is well defined, the condition $\text{var}(r_m - h_m) > 0$ must hold.

Equation (16) establishes that the excess return of a risky asset, $E[r_j] - r_f$, is proportional to its FOMO beta, β_j^{FOMO} . Additionally, Equation (18) demonstrates that the market as a whole provides a positive "FOMO premium" to investors. This result is intuitive because, for FOMO-averse investors to be willing to hold all outstanding shares of risky assets, the market must compensate them with a positive FOMO premium. Given that the pricing formula incorporates FOMO, but otherwise mirrors the structure of the CAPM, we refer to our framework as the FOMO-CAPM.

The defining characteristic of the FOMO-CAPM is that investors' counterfactuals H_i , representing unchosen investment opportunities, influence asset prices in equilibrium. The influence of H_i is modelled by incorporating the $g_i(H_i)$ function into the utility function V_i . Inclusion of H_i affects the market-wide average counterfactual h_m and the equilibrium pricing relationship. Unlike the standard CAPM, which accounts only for financial returns, the FOMO-CAPM incorporates the emotional disutility arising from FOMO. The presence of FOMO implies that investors require a higher expected return to compensate for the emotional costs associated with FOMO. The FOMO-specific beta β_j^{FOMO} , captures how sensitive an asset's return is to fluctuations in the investor's FOMO-adjusted portfolio return, $r_m - h_m$.

Corollary 1 Assume that investor i 's benchmark return, h_i , is given by a convex combination of the riskless asset, the market portfolio and an alternative asset with return $\hat{h}$:

$$h_i = (1 - \phi_{im} - \phi_{ih})r_f + \phi_{im}r_m + \phi_{ih}\hat{h}, \quad (19)$$

ϕ_{im} and ϕ_{ih} are non-negative weights with $\phi_{im} + \phi_{ih} \leq 1$. Further, $\text{cov}(\hat{h}, r_m) = 0$, $\text{var}\hat{h} > 0$, and $i = 1, 2, \dots, I$. The following results hold:

- (i) If the aggregate weight on the alternative benchmark is zero, that is $\sum_{i=1}^I \frac{W_{i,0}}{M_0} \phi_{ih} = 0$, and the entire weight on the benchmark is given by the market return, so that $\sum_{i=1}^I \frac{W_{i,0}}{M_0} \phi_{im} = 1$, then at the aggregate level, the counterfactual equals the market return. Investors' FOMO effects cancel out. Equilibrium requires:

$$E[r_j] = r_f \text{ for all assets } i. \quad (20)$$

- (ii) If $\sum_{i=1}^I \frac{W_{i,0}}{M_0} \phi_{ih} = 0$, and the aggregate weight on the market component satisfies $\sum_{i=1}^I \frac{W_{i,0}}{M_0} \phi_{im} \neq 1$, then the counterfactual differs from the market return. In this situation, the FOMO-pricing formula reduces to

$$E[r_j] - r_f = \beta_{jm}^{FOMO}(E[r_m] - r_f), \quad (21)$$

where $\beta_{jm}^{FOMO} = \frac{\text{cov}(r_j, r_m)}{\text{var}(r_m)}$. Asset prices are determined solely by their covariance with the market return as in CAPM.

- (iii) If $\sum_{i=1}^I \frac{W_{i,0}}{M_0} \phi_{ih} > 0$, so that the counterfactual includes a non-zero component $\hat{h}$, then the general FOMO-CAPM pricing formula applies:

$$E[r_j] - r_f = \beta_j^{FOMO}(E[r_m] - E[h_m]). \quad (22)$$

Moreover, under this specification, assets with greater exposure to the alternative asset, measured by a positive covariance with $\hat{h}$, tend to exhibit lower expected excess returns. If an asset's return is more strongly correlated with $\hat{h}$, it is less likely to induce FOMO. Further, the associated emotional disutility induced from holding an asset is reduced for assets which have returns correlated with $\hat{h}$. As a result, the asset's price increases, leading to a lower expected excess return.

Statement (i) considers a theoretical corner case where the aggregate counterfactual portfolio of all investors is the market portfolio itself ($h_m = r_m$). In this scenario, the source of priced risk in the FOMO-CAPM, which is the relative performance of the market against the benchmark $r_m - h_m$, becomes zero by definition. Because the variance of this pricing factor is zero, there is no FOMO-related risk premium. The model, therefore, implies a trivial equilibrium where the expected excess return on all risky assets must be

zero, meaning $E[r_j] = r_f$. The corner case in statement (i) highlights that the FOMO-driven comparison to a benchmark is the essential source of the risk premium in our model.

Statement (ii) examines a case where, despite the formal resemblance of the pricing formula to the standard CAPM, the behavioral interpretation differs. Specifically, when there is no alternative counterfactual $\phi_{ih} = 0$, FOMO effects are driven solely by market performance.

Statement (iii) underscores the key innovation of the FOMO-CAPM. By incorporating a nonzero $\hat{h}$ component, the model allows for additional behavioral adjustments. The term $E[r_m] - E[h_m]$ represents a "FOMO risk premium" capturing the aggregate gap between actual and counterfactual returns. Moreover, if an asset exhibits a high covariance with $\hat{h}$, investors experience less FOMO when holding that asset, thereby reducing its expected excess return.

The formulations in Corollary 1 are intended to capture the intuitive notion that investor emotions, specifically, FOMO driven by superior peer performance, can be integrated into the asset pricing framework. Notably, because $\hat{h}$ is independent of the market return, the influence of $\hat{h}$ on asset pricing is not accounted for in the standard CAPM. In this sense, statement (iii) highlights a fundamental distinction between the CAPM and the FOMO-CAPM.

Building on the implications of Corollary 1, we present Proposition 2 to illustrate the role of anticipated FOMO when the expected FOMO risk premium is negative. Proposition 2 highlights how emotional considerations influence investment decisions, even when aligning with the peer benchmark results in a lower expected financial payoff.

Proposition 2 *If $E[r_m] - E[h_m] < 0$, then in equilibrium*

- (i) *Despite a negative ex-post FOMO risk premium, an investor influenced by FOMO will allocate resources to a portfolio that aligns with the anticipated outcomes of their peer group. The ex-ante decision is driven by a preemptive hedge against potential emotional regret.*
- (ii) *The negative FOMO risk premium reflects the equilibrium price of emotional alignment cost associated with mimicking the peer group's expected performance. This reflects a prioritization of emotional considerations over maximization of the expected financial payoff. The relationship is captured by $E[r_j] - r_f = \beta_j^{FOMO}(E[r_m] - E[h_m])$, where $\beta_j^{FOMO} > 0$ indicates that assets with stronger peer alignment yield lower expected excess returns.*
- (iii) *Ex-post underperformance, where $r_m < h_m$, amplifies future FOMO, thereby reinforcing a feedback loop that biases subsequent investment decisions toward alignment with the peer group.*

A proof of Proposition 2 is provided in the Appendix. Proposition 2 follows from the assumption that FOMO operates as an anticipatory bias affecting investors' decisions ex-ante, rather than being solely driven by ex-post payoff comparisons. An investor's utility incorporates an emotional component that accounts for potential future regret arising from underperforming relative to their peer group, represented by the FOMO-specific term $f(\cdot)$ in Equation (3). Therefore, a negative value of $E[r_m] - E[h_m]$ does not invalidate the investor's initial choice, as the decision reflects a preemptive emotional hedge against the regret of underperforming compared to their peers.

3 Properties of the FOMO-CAPM

The FOMO-CAPM integrates investors' emotional responses to underperformance relative to a peer benchmark. An extension of the original CAPM of Sharpe (1964), Lintner (1965), Mossin (1966), and Treynor (1961) is provided. The CAPM provides a foundational framework for understanding the relationship between systematic risk and expected returns. For all investors, the reference point in the CAPM is the return on the market. The CAPM is built on the assumption that all investors have homogeneous expectations. Homogenous expectations lead to identical probability distributions for future returns and universal agreement on the distribution of asset returns between t_0 and t_1 . However, it does not follow that all investors appraise assets against the same market benchmark. The FOMO-CAPM allows individual investors to have different peer benchmarks. Consequently, expectations about the distribution of asset returns are not homogeneous.

The CAPM is expressed as:

$$E[r_i] = r_f + \beta_i^{market}[E[r_m] - r_f], \text{ where } \beta_i^{market} = \frac{\text{cov}(r_i, r_m)}{\text{var}(r_m)} \quad (23)$$

$E[r_i]$ represents the expected return on asset i and β_i^{market} is the market beta of asset i . β_i^{market} measures the sensitivity of the asset's return to variations in market return, $E[r_m]$. The expected return on any asset i is the sum of the risk-free interest rate r_f and a premium, $E[r_m] - r_f$, that compensates for systematic risk, adjusted by the asset's beta β_i^{market} .

Remark 1 *The FOMO-CAPM generalizes traditional asset pricing by integrating behavioral dynamics, with the standard CAPM emerging as a special case. Specifically, when the influence of behavioral parameters such as FOMO sensitivity diminishes and is assumed to be absent, the FOMO-CAPM framework converges to the traditional CAPM.*

The explanation for this convergence begins with the definition of the FOMO-beta itself: $\beta_j^{FOMO} = \frac{\text{cov}(r_j - r_f, r_m - h_m)}{\text{var}(r_m - h_m)}$, where $h_m = h_m^{(h)} + h_m^{(k)}$. The FOMO beta captures the

sensitivity of an asset's excess return to the market's performance relative to a counterfactual benchmark, h_m . The benchmark is composed of both a baseline peer portfolio, $h_m^{(h)}$, and a conditional, behavioral component, $h_m^{(k)}$. A key feature of the FOMO-CAPM is that this extra disutility adjustment, $h_m^{(k)}$, is only triggered when investors underperform their benchmark. As the importance of behavioral component diminishes $h_m^{(k)} \rightarrow 0$. Further, the aggregate benchmark approaches the risk-free rate, $E[h_m] \rightarrow r_f$. As the extent of FOMO falls, the FOMO-beta and FOMO premium necessarily converge to their standard CAPM counterparts.¹⁹ The limiting case is formalized as follows:

$$\lim_{\beta_j^{FOMO} \rightarrow \beta_i^{market}, \lambda_i^{FOMO} \rightarrow \lambda_m} E[r_j - r_f] = \beta_j^{market} \lambda_m \quad (24)$$

Equation (24) demonstrates that the FOMO-CAPM framework collapses to the standard CAPM when its specific behavioral components are no longer present.

Remark 2 *The β -parameters of the CAPM and FOMO-CAPM are fundamentally different in their construction and interpretation. While the standard CAPM-beta measures an asset's sensitivity to the overall market return, the FOMO-beta measures sensitivity relative to a personalized, peer-driven benchmark. The FOMO-beta explicitly captures the influence of social and emotional factors on risk perception.*

The CAPM-beta β_i^{market} , measures an asset's sensitivity to market returns under the core assumptions of homogeneous investor expectations. In contrast, the FOMO-beta, β_j^{FOMO} , captures heterogeneity across investors by measuring an asset's sensitivity to the gap between market returns and a peer-driven counterfactual portfolio, $r_m - h_m$. Because the FOMO-beta incorporates an asset's exposure to this distinct emotional risk, the expected return predicted by the FOMO-CAPM can be higher, or lower, than that predicted by the standard CAPM.

The difference between β_i^{market} and β_i^{FOMO} depends on the interplay between two components: the asset's specific FOMO beta β_j^{FOMO} and the aggregate FOMO risk premium $\lambda^{FOMO} = E[r_m] - E[h_m]$. An asset with a high β_j^{FOMO} is highly sensitive to peer-benchmark deviations. If the FOMO risk premium is large and positive, the FOMO-CAPM predicts a substantially higher required return for this asset compared to the CAPM. Conversely, an asset that hedges against FOMO risk (i.e., has a low or negative β_j^{FOMO}) would command a lower required return under our model, irrespective of its traditional market beta.

¹⁹Convergence relies on two related assumptions. First, as the behavioral component vanishes, the FOMO premium, $E[r_m] - E[h_m]$, naturally converges to the market risk premium, $E[r_m] - r_f$. Second, the FOMO-adjusted return, $r_m - h_m$, becomes perfectly correlated with the market excess return, $r_m - r_f$, as investors' specific benchmarks align with the general market's risk-free rate.

Remark 3 *The risk-return relationship in the FOMO-CAPM includes behavioral adjustments that are absent from the traditional CAPM. These behavioural adjustments lead to a less steep slope of the risk-return trade-off, which has direct implications for the required premium on an asset for a given level of beta.*

The FOMO-CAPM generalizes the traditional CAPM by altering the definition of the market risk premium. In the standard CAPM, the premium is the expected return of the market over the risk-free rate, $E[r_m] - r_f$. The FOMO-CAPM introduces a peer-comparison benchmark, which results in the relevant market risk premium becoming the expected return of the market over the expected return of the aggregate counterfactual portfolio, $E[r_m] - E[h_m]$. The FOMO premium is the compensation investors demand in equilibrium for bearing the risk of underperforming their benchmark. The specific, asymmetric disutility associated with underperformance is captured by the $k_i(H_i)$ component of the utility function. This is the behavioral mechanism that drives the wedge between the risk-free rate and the aggregate benchmark in the pricing formula.

A comparison of the Security Market Line (SML) slopes provides the formal proof for Remark 3. The slope of the SML is the market risk premium. As established, the FOMO risk premium is $\lambda_i^{FOMO} = E[r_m] - E[h_m]$ while the standard CAPM risk premium is $\lambda_m = E[r_m] - r_f$. Assuming the aggregate counterfactual portfolio, h_m , is composed of risky assets, its expected return should be greater than the risk-free rate, $E[h_m] > r_f$. Hence:

$$E[r_m] - E[h_m] < E[r_m] - r_f \quad (25)$$

which simplifies to:

$$\lambda_i^{FOMO} < \lambda_m \quad (26)$$

Equation (26) provides the proof that the FOMO-SML has a less steep slope than the traditional CAPM's SML. The intuition is that a portion of the market's total excess return is now required to compensate for the risk of underperforming the peer benchmark, h_m , leaving a smaller premium for systematic market risk alone.

Theoretical Security Market Lines (SML)

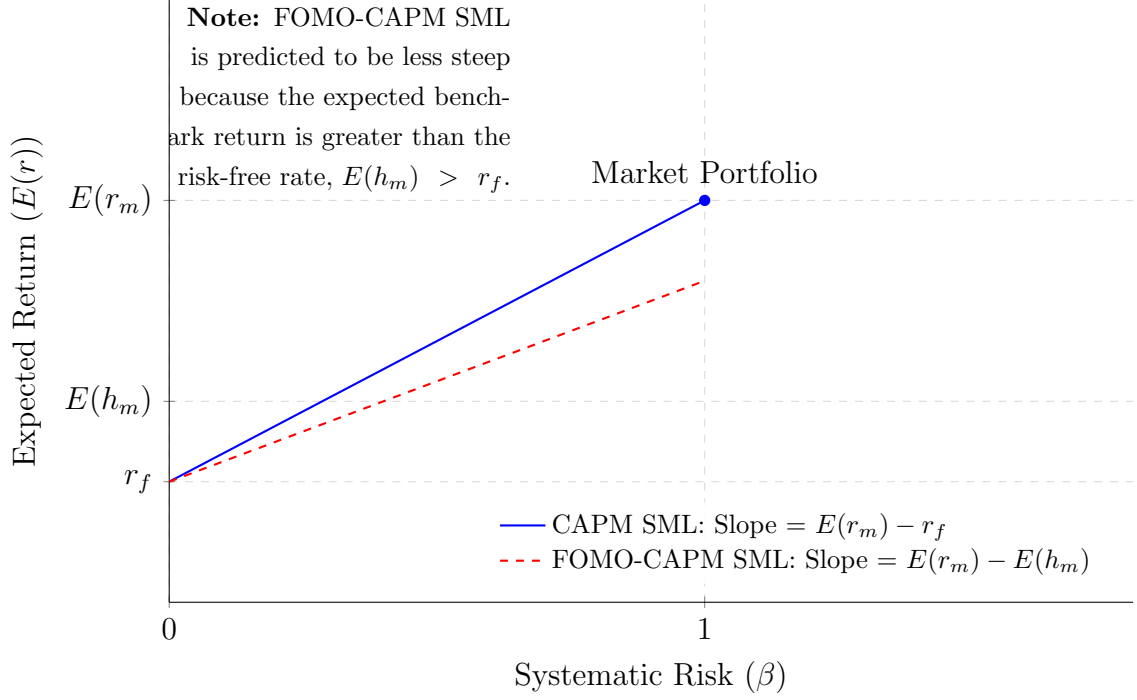


Figure 2: Theoretical Prediction for the FOMO-CAPM Security Market Line

This figure illustrates the theoretical relationship between the standard CAPM and the FOMO-CAPM as derived in Section 3. Both models predict a positive risk-return trade-off originating at the risk-free rate (r_f). However, because the FOMO-CAPM's pricing kernel includes the peer-group benchmark return (h_m), which is assumed to have a higher expected return than r_f , the resulting slope of its SML is flatter. This implies a smaller risk premium for systematic market risk, as a portion of the return is now required to compensate for the distinct behavioral risk of underperforming the peer benchmark.

Remarks 1–3 collectively demonstrate how the FOMO-CAPM generalizes the CAPM by explicitly incorporating behavioral dynamics. Specifically, investors' emotional sensitivity to peer-relative performance differentiates the FOMO-CAPM from the CAPM. While Remark 1 shows that the CAPM emerges naturally as a special limiting case when FOMO effects diminish, Remarks 2 and 3 emphasize the fundamental differences arising from the counterfactual benchmark and emotional risk premium inherent in FOMO-beta. Thus, the FOMO-CAPM captures variations in investor preferences and peer-driven emotional factors, yet aligns precisely with CAPM when investors do not place weight on the performance of peers.

4 Empirical Analysis

A foundational element of our empirical strategy is the use of industry portfolios as benchmarks for peer-group performance. Specifically, we define the peer group as all investors

in the same Fama-French 38 Industry portfolio. To characterize these benchmarks and ensure they are not simply proxies for the aggregate market factor, we first examine their correlation with the market. Figure 3 plots the time-series correlation between the daily excess return of each of the 38 Fama-French industry portfolios and the daily market excess return over our 1980-2024 sample period.

The correlations in Figure 3 confirm that while most industries are positively correlated with the market, there is substantial heterogeneity. The correlation ranges from a low of 0.07 for the Steam Supply industry to a high of 0.88 for the Services industry. The mean correlation across all 38 industries is 0.67. The wide dispersion of correlations demonstrates that our industry benchmarks capture distinct sources of variation beyond the aggregate market. Therefore, underperforming an industry benchmark is not synonymous with underperforming the market. Low correlations validate the use of a peer-group-specific benchmark to isolate the FOMO effect. Appendix A4 provides further analysis of the correlations.

To provide empirical support for the FOMO-CAPM developed within this paper, we undertake an evaluation of asymmetric reactions to reference portfolios in US equity markets. Specifically, we consider the existence of FOMO relative to industry-specific reference portfolios²⁰. Our empirical analysis uses daily stock return data from the CRSP database for the period January 1, 1980, to December 31, 2024. Firm-specific characteristics are obtained from Compustat, while risk-free rate and market excess returns are drawn from the Fama-French data library²¹. To construct the industry-specific reference portfolios, we use the Fama-French 38 industry portfolios. For each firm j , its industry's contemporaneous excess return h_j serves as an empirically tractable proxy for the return on its unchosen reference portfolio H_i .²² A key component of our empirical strategy

²⁰Whilst the prevalence of social network data may ease the identification of reference portfolios, such data would be restricted to the subset of investors who use such platforms. Likewise, a survey approach would enable the identification of relevant reference portfolios for respondents. Similar challenges of representation of the full investment universe would be faced. Finally, there are questions on the extent to which individual investors behave differently to retail investors when constructing peer groups. Choosing industry reflects the likelihood that the research function of the retail investor, or the awareness of the individual investors, becomes specialized around stocks similar to their holdings. News on industries affects both the stock held and the industry peers. Industry peers are market competitors with the firms held. The choice of 38 industries reflects challenges of keeping on top of updates on the large number of firms that would be present in broader industry classifications.

²¹Data can be downloaded from the website of Ken French at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

²²Use of value-weighting recognises that peers' holdings must be dominated by the stock with the highest value. Equal weightings might highlight stocks that few, if any, peers hold. The value-weighted industry portfolio return assumes that the expected return on peer stocks is the industry mean. Use of the most recent average incorporates industry-specific variation in returns. Under the efficient market hypothesis expected returns would be 0, but in the FOMO-CAPM there are differences between industries

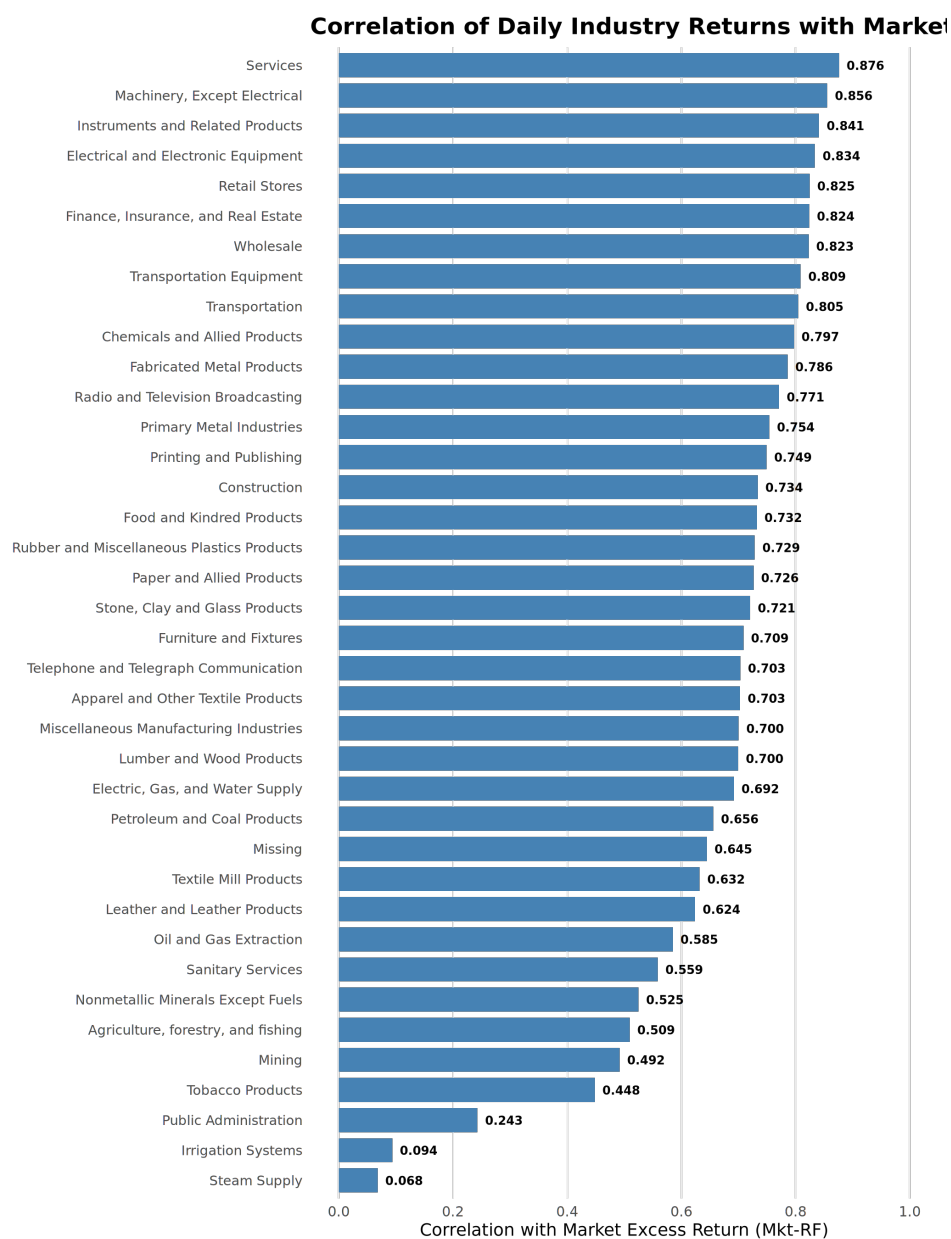


Figure 3: Correlation of 38 Industry Portfolios with the Market Factor

This figure plots the time-series correlation between the daily excess return of each of the 38 Fama-French industry portfolios and the daily market excess return. The sample period is January 1980 to December 2024. Industries are sorted in ascending order to illustrate the wide dispersion in their market exposure.

is to ensure that our findings are not dependent on a single definition of the peer-group benchmark. Our main results, presented throughout this section, use the 38 Fama-French industry portfolios as a proxy for a firm’s peer group. We demonstrate the robustness of our findings using the NASDAQ Composite Index as an alternative benchmark²³. The condition $r_j < h_j$ then signals a state where an investor holding stock j is likely to experience FOMO. In such states, the FOMO-specific disutility component $k_i(H_i)$ is activated, leading $g_i(H_i)$ to take its amplified form as defined in Equation (4). Using asset and reference portfolio returns allows us to compute the performance gap $r_j - h_j$. Note that the relevant subscript on h is j since all investors holding stock j have the same reference portfolio.

To operationalize the model, and test the core implication that sensitivity to FOMO-inducing states commands a risk premium, our empirical strategy refines this approach by focusing on firm-specific measures. We estimate three flavors of beta. First, as a baseline, we calculate the standard CAPM beta β^{CAPM} . Second, recognising that the core of our FOMO concept involves a comparison to a benchmark which can induce regret if underperformed, we estimate an unconditional sensitivity of a stock’s excess return $r_j - r_f$ to its performance gap relative to its industry benchmark. That is, we estimate sensitivity to $r_j - h_j$. We term this the regret beta, β^R as it reflects the Regret CAPM of Qin (2020)²⁴. The regret beta captures the average sensitivity to the performance gap, without pre-conditioning on the direction of this gap. β^R serves as a measure of the general pricing of regret-inducing benchmark comparisons. FOMO assumes that investors feel additional disutility when the reference portfolio outperforms their own portfolio.

that reduce the probability that the average in any smaller portfolio being 0. Instead of using the average across the industry peers, it could be argued that the relevant benchmark for an investor should be the maximum of the peer group return and the risk-free rate, i.e., $\max(h_j, r_f)$. Use of the maximum of the peer group return and the risk-free rate would imply that an investor feels no FOMO if their portfolio outperforms a declining peer group but could still feel regret for not having switched to the risk-free asset. While this is an interesting theoretical extension, our model focuses on the primary social comparison to the peer group itself, which we believe is the dominant driver of the FOMO sentiment. We leave the exploration of this state-switching benchmark for future research.

²³The NASDAQ Composite Index lists technology stocks and is used to capture the dynamics of FOMO when the peers are high-growth ‘story’ stocks. Results using the NASDAQ Composite Index are highly consistent with our primary findings and confirm that the FOMO premium is a pervasive market feature. The complete set of results for the NASDAQ benchmark are available in Appendix D.

²⁴Our empirical regret beta, β^R , is estimated using the firm-specific performance gap, $r_j - h_j$, and captures the unconditional sensitivity of a stock’s excess return to this gap. While it reflects the general disutility from benchmark underperformance, conceptually linking it to regret aversion as discussed in models like Qin (2020), it is important to note a distinction. Qin (2020) theoretical Regret-CAPM derives a ‘regret beta’, β_{jg} based on an asset’s sensitivity to an aggregate market-wide performance gap, $r_m - r_m$, where h_m represents the market-wide average of investors’ unobservable counterfactuals. Due to the empirical infeasibility of measuring this aggregate h_m , our β^R uses a firm-specific approach. β^R thus represents regret in the case where the reference portfolio for regret is the industry portfolio.

To directly test the asymmetric nature of FOMO, the amplified emotional disutility specifically from underperforming peers, we decompose β^R into the relative return of the reference portfolio into conditional FOMO betas. The decomposition applied is analogous to that applied in Ang et al. (2006a) for β^{CAPM} . The final two betas which are computed are, β^{FOMO-} for periods of underperformance, when $r_j < h_j$ and β^{FOMO+} for periods of outperformance, when $r_j \geq h_j$ holds. Adopting a multi-beta approach allows us to first examine the pricing of general benchmark-relative performance via β^R , as well as isolating whether the asymmetric downside sensitivity β^{FOMO-} commands an additional, distinct risk premium. The risk premium for β^{FOMO-} attributable to the unique physiological impact of FOMO.

The rationale for adopting a firm-level approach is that an individual investor's actual experience and psychological response of FOMO concerning a specific stock j is most directly triggered by that stock's performance r_j relative to stock j 's own most salient benchmark h_j . We use the contemporaneous return of the stock's Fama-French 38 industry portfolio as a proxy for this firm-specific counterfactual benchmark h_j , reflecting a common peer group comparison. Thus, the condition $r_j - h_j < 0$, where stock j underperforms its industry, serves as our empirical indicator for a state where an investor holding stock j is likely to experience FOMO. When $r_j < h_j$, we have the activation of the additional disutility component $k_i(\cdot)$. Conversely, when $r_j \geq h_j$, the specific FOMO state is inactive for stock j . The firm-level state activation allows us to capture the heterogeneous impact of FOMO across different assets. Further, the firm-specific approach to defining FOMO-activation means that we can still empirically test for the presence and pricing of $k_i(\cdot)$ effects by segmenting betas based on these conditions. FOMO is identifiable if $k_i(\cdot)$ itself is not directly estimated. By estimating firm-level conditional betas, we can then investigate whether sensitivity during these empirically defined FOMO states is priced in the cross-section of stock returns. Our empirical analysis provides a test of the broader FOMO-CAPM theory.

Like Ang et al. (2006a), we decompose betas conditional on states of relative underperformance and outperformance. However, our approach differs critically in its conceptual and behavioral interpretation. While Ang et al. (2006a) introduce Gul (1991) disappointment aversion utility²⁵, segmenting outcomes around an endogenous threshold, our model employs an exogenous threshold defined explicitly by peer or market reference returns. In Ang et al. (2006a) downside sensitivity arises from rational disappointment aversion. In contrast, our FOMO model explicitly captures the behavioral penalty associ-

²⁵Gul's (1991) disappointment aversion utility is defined as $U(\mu_W) = \frac{1}{K} \left(\int_{-\infty}^{\mu_W} U(W) dF(W) + A \int_{\mu_W}^{\infty} U(W) dF(W) \right)$, where $K = \Pr(W \leq \mu_W) + A \Pr(W > \mu_W)$ and $0 < A \leq 1$. The threshold μ_W is the certainty equivalent, dividing outcomes into disappointing ($W \leq \mu_W$) and elating ($W > \mu_W$) states, with A discounting utility from elating states, thus making investors more sensitive to losses relative to gains.

ated with underperforming a peer group benchmark. Despite this conceptual divergence, both approaches predict asymmetric sensitivities to downside risks.

To empirically test our hypothesis about the asymmetric pricing of FOMO, we define two conditional betas based on the firm-specific performance gap $r_j - h_j$. The positive FOMO beta β_j^{FOMO+} measures the sensitivity of a stock's excess return $r_j - r_f$ to its gap, conditional on the stock outperforming its benchmark $r_j > h_j$. β_j^{FOMO+} is defined as:

$$\beta_j^{FOMO+} = \frac{\text{cov}(r_j - r_f, r_j - h_j \mid r_j - h_j > 0)}{\text{var}(r_j - h_j \mid r_j - h_j > 0)}. \quad (27)$$

Conversely, the negative FOMO beta, β_j^{FOMO-} is defined as:

$$\beta_j^{FOMO-} = \frac{\text{cov}(r_j - r_f, r_j - h_j \mid r_j - h_j < 0)}{\text{var}(r_j - h_j \mid r_j - h_j < 0)}. \quad (28)$$

β_j^{FOMO-} is central to our FOMO hypothesis, measures the sensitivity of the stock's excess return to the performance gap, conditional on the stock underperforming its benchmark $r_j < h_j$.

Based on the decomposition of β_j^{FOMO} into β_j^{FOMO+} and β_j^{FOMO-} , we hypothesize that the negative FOMO betas, estimated during periods when portfolio returns underperform the counterfactual benchmark, will command a higher risk premium compared to the positive FOMO betas. This prediction empirically tests investor sensitivity to relative underperformance. To accurately capture conditional sensitivities and ensure robust empirical estimates, we adopt 12-month rolling regressions on daily data to precisely estimate conditional (FOMO-based) betas, ensuring high statistical power and robustness.

Although our empirical approach resembles that of Ang et al. (2006a), the interpretation differs significantly. Ang et al. (2006a) apply Gul (1991) rational disappointment aversion framework, splitting outcomes into disappointing and elating states around an endogenous certainty equivalent threshold. Segregation produces a kinked utility function with rational, disappointment averse agents disproportionately penalizing downside risk. In contrast, our FOMO model explicitly incorporates investor-specific social comparisons, defining an exogenous threshold H_i based on peer or market performance. When investors underperform relative to their counterfactuals, the latent behavioral penalty $k_i(\cdot)$ activates. Thus, our findings emphasise that investors' sensitivity to underperforming relative to their peers produces heightened downside sensitivity. Our specification has a behavioral interpretation which distinguishes our behavioral approach from the rational disappointment aversion utility framework used by Ang et al. (2006a).

4.1 Research Design

In the spirit of the standard CAPM, the FOMO-CAPM predicts a specific contemporaneous link between realised stock returns and the realized FOMO betas, β_j^{FOMO+} and

β^{FOMO-} . The conditional betas β_j^{FOMO+} and β_j^{FOMO-} , capture a stock's sensitivity to its performance gap relative to its specific counterfactual benchmark h_j . β_j^{FOMO+} and β_j^{FOMO-} correspond to firm-specific non-FOMO ($r_j - h_j \geq 0$) and FOMO ($r_j - h_j < 0$) states, respectively. We demonstrate the empirical validity of the FOMO-CAPM by showing that average stock returns align contemporaneously with realized measures of sensitivity to the firm-specific performance gap $r_j - h_j$. These measures include the unconditional regret beta β^R and the conditional FOMO betas, β^{FOMO+} and β^{FOMO-} . Collectively, β^R , β^{FOMO+} and β^{FOMO-} capture a stock's sensitivity to this gap under distinct conditions.

Our empirical implementation follows the logic of Ang et al. (2006a), sorting stocks based on their realized betas, including β^R , β^{FOMO-} and β^{FOMO+} , computed within a defined period of 12 months, and then analyzing the average returns of the resulting portfolios over that same period. The realized beta approach is also followed by Bollerslev et al. (2022). Levi and Welch (2020) argue that the ex ante beta is a better proxy for investor beliefs at the point of portfolio formation. To allay concerns about the realized betas, Ang et al. (2006a) test the ability of past downside betas to predict future values. We demonstrate that the FOMO realized betas, β^{FOMO-} and β^{FOMO+} , are both highly persistent. An annual horizon is chosen for two main reasons. First, the annual horizon provides sufficient daily observations within the evaluation window to reliably estimate our conditional betas. A shorter window, such as a single month, might yield too few such observations with either $r_j < h_j$ or $r_j \geq h_j$. The conditional FOMO betas, β^{FOMO-} and β^{FOMO+} are estimated as defined in Equations (27) and (28), using daily asset returns and daily returns on the reference portfolio. The regret beta β^R is similarly estimated by regressing the stock's excess return on $r_j - h_j$ using all available daily observations within the estimation window.

Our focus on realized, post-formation betas aims to capture the actual covariation driving returns during the measurement period. Use of a 12-month horizon helps mitigate noise associated with estimation error in pre-formation betas. To obtain realized betas from each stock for each overlapping 12-month evaluation period (from month t to $t + 12$), we utilise high-frequency daily data. Specifically, for a given 12-month period, the conditional FOMO betas, β^{FOMO-} and β^{FOMO+} , are estimated by regressing the stock's daily excess returns on its daily performance gap relative to its industry benchmark, $r_j - h_j$. The regression uses all daily observations within the 12-month window that satisfy the respective conditions $r_j - h_j < 0$ for β^{FOMO-} and $r_j - h_j > 0$ for β^{FOMO+} . Similarly, other realized betas like β^{CAPM} are estimated using all daily data within the same 12-month window. The regret beta β^R is estimated by regressing the stock's daily excess returns on $r_j - h_j$, using all daily observations within that 12-month window where the gap is defined. Our approach ensures that each beta estimate reflects the stock's

sensitivity over the precise 12-month horizon for which returns are contemporaneously evaluated. The use of daily data provides a richer dataset to estimate these potentially time-varying risk exposures, enhancing the precision of our beta estimates (e.g., Fama and French 2006; Ang et al. 2006a). The 12-month realised beta estimates are then used directly in our subsequent portfolio sorts and Fama-MacBeth regressions.

4.2 Univariate Portfolio Sorts

We investigate the contemporaneous patterns between realized average stock returns and the realized risk exposures derived from our FOMO-CAPM. Using overlapping 12-month evaluation periods, we calculate returns and betas from month t to $t + 12$. While market risk exposures are known to be time-varying (Fama and French 1997; Ang et al. 2006a; Lewellen and Nagel 2006), very long estimation intervals obscure important short-run dynamics, whereas very short intervals increase estimation noise. A 12-month window using daily data balances these concerns and aligns with practices that enhance statistical power (e.g., Fama and French 2006). The robustness of our findings to alternative horizons and data frequencies is examined in Section 4.8.

To further dissect the impact of FOMO-related risk, and following the approach of Ang et al. (2006a) who examine relative betas, we also construct several derived measures. The additional measures include the relative negative FOMO beta, defined as $\beta^{FOMO-} - \beta^{CAPM}$. The relative negative FOMO beta isolates the effect of FOMO beyond standard market risk. Other relative measures, such as $\beta^{FOMO-} - \beta^R$, are also computed for completeness in our broader analysis. All risk measures are calculated using realized returns over the same 12-month period; we refer to them collectively as realized betas in our subsequent analysis.

For our primary empirical analysis, we follow the methodological precedent set by Ang et al. (2006a) in their work on asymmetric risk and use equal-weighted portfolios and regressions. This approach is deliberately chosen as prior research suggests that many behavioral effects, asymmetries, and non-linearities are most pronounced across the broad cross-section of stocks, rather than being concentrated in the largest firms (e.g. Fama and French 1992; Harvey and Siddique 2000; Hirshleifer 2001). By giving equal importance to every firm, equal-weighted portfolios are better suited for detecting a new behavioral phenomenon like the FOMO risk premium. Further, equal-weighted prevents the results from being dominated by a few mega-cap stocks, where such behavioral effects may be less pronounced.

A robustly priced factor should also be present in value-weighted portfolios to demonstrate its economic significance and ensure it is not merely a micro-cap anomaly (Levi and Welch, 2020; Bali and Cakici, 2008). To address this critique directly, we perform a key robustness check where we re-run our primary tests using value-weighted portfolios.

As shown in Table 10, we find that when portfolios are value-weighted, the premium for β^{FOMO-} attenuates considerably and becomes statistically insignificant. Rather than a weakness, this result strongly supports our rationale for using an equal-weighted approach. Additionally, the loss of statistical significance for the β^{FOMO-} premium provides clear evidence that the FOMO risk premium is a genuine cross-sectional phenomenon that is most pronounced among the smaller and mid-cap stocks that are de-emphasized in value-weighted schemes. Loss of significance in the value-weighted setting is a common feature of many behaviorally-driven factors and reinforces the choice of equal-weighting as the appropriate primary lens for our analysis (Fama and French, 1992; Hirshleifer, 2001; Barber and Odean, 2008, see e.g.).

Robustness checks in Section 4.8 explicitly examine value-weighted portfolios and regressions. Furthermore, to minimize microstructure and illiquidity concerns, our main portfolio sorts use NYSE stocks for breakpoint calculations, though robustness tests consider the broader NYSE/AMEX/NASDAQ universe.

Table 1 presents the time-series average results for univariate portfolio sorts formed by sorting stocks into five quintiles based on their realized values of β^{CAPM} , β^R , β^{FOMO-} , β^{FOMO+} , or relative β^{FOMO-} (specifically, $\beta^{FOMO-} - \beta^{CAPM}$), calculated over the same 12-month period. For each sorting criterion. Table 1 reports the average realized 12-month excess return for each equal-weighted quintile portfolio, alongside the average post-ranking realized β^{CAPM} , β^R , β^{FOMO-} and β^{FOMO+} for stocks within each quintile. Our design allows for a direct examination of the contemporaneous relationship between risk loadings and returns. To control for the serial correlation created by the rolling regression estimation of the FOMO betas, t -statistics for the High-Low return spreads are computed using Newey and West (1987) standard errors with 12 lags. Our sample period for analysis covers January 1980 to December 2024. Robustness checks using non-overlapping periods are discussed in Section 4.8.

Figure 4 provides a visual representation of the empirical Security Market Lines (SMLs) implied by these portfolio sorts. The plot clearly shows the steep positive relationship between realised FOMO betas and returns. Figure 4 visually confirms the key finding from Table 1. The empirical risk premium for sensitivity to downside FOMO risk, β^{FOMO-} , is = 28.53. The slope is substantially larger than the premium for standard market risk β^{CAPM} , which is 5.22.

It is crucial to interpret Figure 4 correctly in the context of our theory. The figure does not depict the theoretical FOMO-SML from Section 3, which would be plotted against a FOMO-specific beta. Instead, by plotting the returns of β^{FOMO-} sorted portfolios against their standard β^{CAPM} . The empirical SML in Figure 4 illustrates the economic magnitude of the return premium associated with the FOMO factor. The FOMO premium that exists above and beyond what is explained by market beta. The substantially steeper

Table 1: Returns of Portfolios Sorted by Realized Factor Loadings

Panel A: Sort on β^{CAPM}						Panel B: Sort on β^R (Regret Beta)					
Portfolio	Return	β^{CAPM}	β^R	β^{FOMO-}	β^{FOMO+}	Portfolio	Return	β^{CAPM}	β^R	β^{FOMO-}	β^{FOMO+}
1 (Low)	1.75%	0.09	0.73	0.76	0.74	1 (Low)	-2.16%	0.40	0.54	0.59	0.51
2	5.93%	0.51	0.83	0.85	0.85	2	2.38%	0.56	0.80	0.81	0.83
3	7.11%	0.76	0.89	0.90	0.91	3	6.55%	0.66	0.91	0.92	0.95
4	8.01%	1.03	0.95	0.95	0.97	4	11.26%	0.92	0.99	1.00	1.02
5 (High)	9.93%	1.57	0.99	0.98	0.98	5 (High)	15.26%	1.31	1.10	1.11	1.12
High-Low	8.18%					High-Low	17.42%				
<i>t</i> -stat	[2.55]					<i>t</i> -stat	[7.36]				

Panel C: Sort on β^{FOMO-}						Panel D: Sort on β^{FOMO+}					
Portfolio	Return	β^{CAPM}	β^R	β^{FOMO-}	β^{FOMO+}	Portfolio	Return	β^{CAPM}	β^R	β^{FOMO-}	β^{FOMO+}
1 (Low)	-1.02%	0.49	0.58	0.51	0.59	1 (Low)	-3.72%	0.48	0.59	0.67	0.48
2	1.38%	0.60	0.81	0.80	0.84	2	6.94%	0.62	0.83	0.85	0.84
3	4.80%	0.66	0.90	0.92	0.92	3	10.66%	0.71	0.92	0.92	0.96
4	8.98%	0.83	0.96	1.01	0.97	4	10.00%	0.88	0.98	0.96	1.04
5 (High)	16.37%	1.13	1.06	1.15	1.05	5 (High)	6.82%	1.08	1.06	1.04	1.16
High-Low	17.39%					High-Low	10.54%				
<i>t</i> -stat	[8.46]					<i>t</i> -stat	[8.16]				

Panel E: Sort on Rel. β^{FOMO-} vs β^{CAPM}					
Portfolio	Return	β^{CAPM}	β^R	β^{FOMO-}	β^{FOMO+}
1 (Low)	7.50%	1.50	0.89	0.83	0.87
2	8.02%	0.99	0.89	0.88	0.90
3	7.64%	0.74	0.87	0.88	0.89
4	6.54%	0.53	0.85	0.88	0.87
5 (High)	3.16%	0.19	0.84	0.91	0.86
High-Low	-4.34%				
<i>t</i> -stat	[-1.47]				

This table presents average 12-month realised excess returns and post-ranking realised betas for equal-weighted quintile portfolios. For each 12-month period from t to $t + 12$ (evaluated monthly using overlapping windows), stocks are sorted into five quintiles based on one of five realised beta measures calculated over that same period using daily data: standard CAPM Beta (β^{CAPM}), Regret Beta (β^R), negative FOMO Beta (β^{FOMO-}), positive FOMO Beta (β^{FOMO+}), or relative negative FOMO Beta ($\beta^{FOMO-} - \beta^{CAPM}$). β^{CAPM} is estimated using the stock's excess return and the market excess return $r_m - r_f$. β^R is estimated by regressing the stock's excess return $r_j - r_f$ on its performance gap relative to its industry benchmark $r_j - h_j$ unconditionally. β^{FOMO-} and β^{FOMO+} capture the sensitivity of the stock's excess return $r_j - r_f$ to this same performance gap $r_j - h_j$, where β^{FOMO-} is estimated during periods when the stock underperforms its industry benchmark ($r_j - h_j < 0$) and β^{FOMO+} during periods where it outperforms ($r_j - h_j > 0$). The industry benchmark h_j is the excess return of the corresponding Fama-French 38 industry portfolio. The column labeled "Return" reports the average realised 12-month excess return for each quintile portfolio. The columns labeled " β^{CAPM} ", " β^R ", " β^{FOMO-} " and " β^{FOMO+} " report the time-series average of the equal-weighted post-ranking realised betas for stocks within each quintile, computed contemporaneously over the same 12-month period. Breakpoints

Empirical Security Market Lines for Different Sorting Criteria

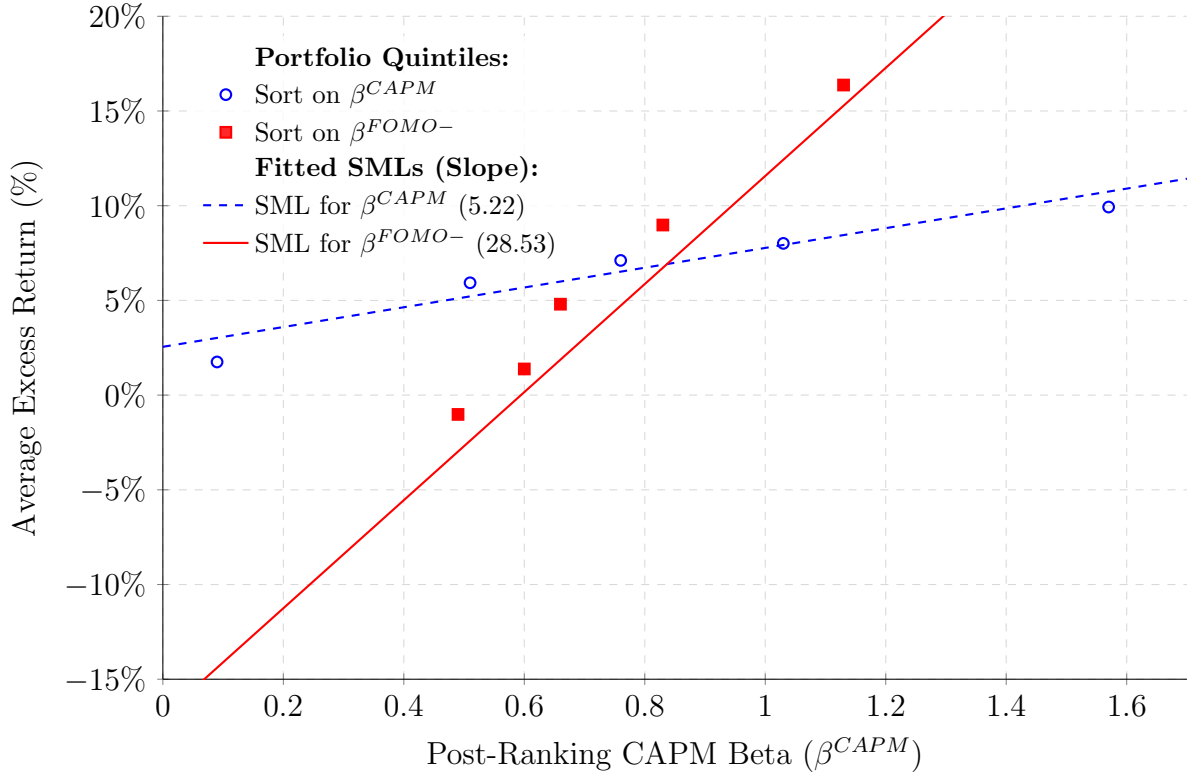


Figure 4: Empirical Security Market Lines (SMLs) for Various Sorting Criteria

This figure plots the average excess returns against the average post-ranking CAPM betas for portfolios sorted on different risk measures. The quintile portfolios are taken from the univariate sorts in Table 1 (Panels A and C). Each line represents the fitted Security Market Line (SML) for the corresponding set of five quintile portfolios. The plot visually demonstrates that the empirical risk premium, represented by the slope of the SML, is substantially steeper when sorting on our behavioral β^{FOMO-} compared to the standard β^{CAPM} , providing empirical support for the importance of the FOMO-based risk channel.

slope for the β^{FOMO-} sort is not a contradiction of the theory, but rather a confirmation that β^{FOMO-} is a distinct and highly rewarded risk factor.

As a baseline, Panel A of Table 1 presents results for portfolios sorted by the standard realised CAPM beta β^{CAPM} . Consistent with foundational asset pricing tests (e.g., Black, Jensen, and Scholes 1972), we observe a clear positive and monotonic relationship between realized β^{CAPM} and contemporaneous average excess returns. Specifically, stocks in Quintile 5 (high β^{CAPM}) exhibit an average excess return of 9.93%, while stocks in Quintile 1 (low β^{CAPM}) show an average excess return of 1.75%. The resulting High-Low spread is 8.18% and is statistically significant (t-statistic 2.55). Panel A establishes the conventional market risk-return trade-off within our sample and serves as a benchmark. The characteristics columns further show that, as anticipated, higher β^{CAPM} quintiles are also associated with higher average realised regret beta β^R , negative FOMO beta β^{FOMO-} and positive FOMO beta β^{FOMO+} , indicating a natural co-movement between these various risk exposures.

Panel B of Table 1 examines portfolios sorted by our unconditional regret beta β^R . As defined previously, β^R a stocks average sensitivity to its excess return to its performance gap ($r_j - h_j$) relative to its industry benchmark, without conditioning on the direction of this gap. This sort reveals a strong positive and monotonic relationship between β^R and contemporaneous excess returns. Stocks in Quintile 5 (highest β^R) earn an average annual excess return of 15.26%, substantially outperforming Quintile 1 (lowest β^R), which earns an average excess return of -2.16% . This results in an economically large and statistically significant high-low spread of 17.42% per annum (t-statistic 7.36). The significant high-low spread provides initial evidence that a significant premium is associated with unconditional sensitivity to the peer-performance gap, a core component of regret and our FOMO framework. Similar to Panel A, the characteristics columns indicate that higher β^R quintiles are also associated with higher average β^{CAPM} , β^{FOMO-} and β^{FOMO+} .

Panel C of Table 1 presents a central test for our FOMO-CAPM by sorting on the realized negative FOMO beta, β^{FOMO-} . Our theory posits that investors, due to an asymmetric aversion to missing out, demand a premium for holding assets highly sensitive to underperforming their peer benchmark $r_j < h_j$. The results strongly support this: stocks in Quintile 5 (highest β^{FOMO-}) earn an average annual excess return of 16.37%, while Quintile 1 stocks (lowest β^{FOMO-}) earn an average excess return of -1.02% . This yields a substantial High-Low spread of 17.35% per annum (t-statistic 8.46). This finding is consistent with the core mechanism of the FOMO-CAPM, where stocks with high sensitivity to the FOMO state carry a significant risk premium. The standard β^{CAPM} increases from 0.49 to 1.13 across these quintiles and β^R increases from 0.58 to 1.06, indicating that while β^{FOMO-} captures a strong effect, it is also correlated with these

other risk measures.

Panel D of Table 1 sorts on β^{FOMO+} , which measures sensitivity to the stock’s performance gap during periods when it outperforms its industry benchmark, $r_j > h_j$. While our theory is less prescriptive about the pricing of β^{FOMO+} , the results show that portfolios with higher β^{FOMO+} generally earn higher average excess returns. Stocks in Quintile 5 (highest β^{FOMO+}) earn an average excess return of 6.82%, compared to an average excess return of -3.72% for Quintile 1, leading to a High-Low spread of 10.54% (t-statistic 8.16). Similar to previous panels, sorting on β^{FOMO+} induces considerable variation in β^{CAPM} (from 0.48 to 1.08), β^R (from 0.59 to 1.06), and β^{FOMO-} (from 0.67 to 1.04). This co-movement could influence the interpretation of the raw return spread for β^{FOMO+} .

To begin disentangling the effects of β^{FOMO-} from standard market risk, Panel E of Table 1 reports results for portfolios sorted by the realised relative negative FOMO beta, β^{FOMO-} vs β^{CAPM} . If the premium for β^{FOMO-} is distinct from that of β^{CAPM} , we might still observe a positive spread. However, the results show a High-Low spread of -4.34% ($t = -1.47$). This counterintuitive result arises because the sort on relative β^{FOMO-} induces a strong inverse relationship with the level of β^{CAPM} : β^{CAPM} decreases monotonically from 1.50 in Quintile 1 (lowest relative β^{FOMO-}) to 0.19 in Quintile 5 (highest relative β^{FOMO-}). Although Quintile 5 has a higher β^{FOMO-} , 0.91, compared to Quintile 1, 0.83, Quintile 5’s substantially lower exposure to market risk likely drives its lower average raw return.

In summary, the portfolio sorts presented in Table 1 provide initial evidence on the pricing of FOMO-related risk. Direct sorts on the unconditional regret beta, β^R (Panel B), and the conditional negative FOMO beta β^{FOMO-} (Panel C), reveal strong positive relationships with returns. Specifically, sorting on β^R yields a High-Low spread of 17.42% (t-statistic 7.36), and sorting on β^{FOMO-} yields a High-Low spread of 17.39% (t-statistic 8.46). Our findings suggest that sensitivity to the peer-performance gap, and particularly to underperforming this benchmark (the FOMO state), is positively rewarded in the cross-section of stock returns. Sorting on the conditional Positive FOMO Beta, β^{FOMO+} (Panel D), also yields a positive return spread of 10.54% (t-statistic 8.16).

However, interpreting the results of a univariate sort on a relative beta requires caution. In Panel E, when we sort on the relative beta, $\beta^{FOMO-} - \beta^{CAPM}$, the resulting High-Low spread is negative, -4.34% , and is insignificant (t-statistic -1.47). This counter-intuitive result arises because the sorting variable mechanically segregates firms with vastly different risk profiles. The highest quintile becomes populated by stocks with high idiosyncratic risk but low market beta (high β^{FOMO-} , low β^{CAPM}), while the lowest quintile is filled with classic high-beta cyclical stocks (low β^{FOMO-} , high β^{CAPM}). Given the positive market risk premium over our sample period, the powerful effect of the market beta swamps the more subtle FOMO effect in this simple sort. The results

for the relative β^{FOMO-} underscore the necessity of a multivariate framework, like the Fama-MacBeth regressions in the following section, to properly disentangle these distinct risk premia.

4.3 Fama-MacBeth Regressions

The univariate portfolio sorts in the previous section provide initial evidence on the pricing of FOMO betas, but do not account for other firm characteristics or risk exposures known to influence cross-sectional returns. A long literature, starting with Banz (1981), has documented effects related to firm size, book-to-market ratio (Basu, 1983; Fama and French, 1992), momentum (Jegadeesh and Titman, 1993), volatility (Ang, Hodrick, Xing, and Zhang, 2006b), coskewness (Harvey and Siddique, 2000), cokurtosis (Scott and Horvath, 1980; Dittmar, 2002), and liquidity risk (Pástor and Stambaugh, 2003). To determine if the premium associated with our FOMO betas, particularly β^{FOMO-} , is distinct from these established effects, we now perform firm-level cross-sectional regressions following the methodology of Fama and MacBeth (1973). The Fama MacBeth regressions also allow the consideration of the FOMO betas against other conceptualizations of downside risk (Ang et al., 2006a). These regressions will include specifications that incorporate not only our β^{FOMO-} and β^{FOMO+} , but also the downside and upside market betas as proposed by Ang et al. (2006a), β_{Ang}^- and β_{Ang}^+ respectively. Incorporation of the Ang et al. (2006a) betas allows us to distinguish downside risk from our FOMO concept.

Consistent with our portfolio sorts, we run these regressions using a 12-month horizon. Specifically, for each overlapping 12-month evaluation period p (from month t to $t + 12$) in our sample, we estimate the following cross-sectional regression:

$$R_{i,p} = \gamma_{0,p} + \sum_{k=1}^K \gamma_{k,p} X_{i,k,p} + \sum_{m=1}^M \delta_{m,p} C_{i,m,p-1} + \epsilon_{i,p} \quad (29)$$

where $R_{i,p}$ is the realized 12-month excess return for stock i in evaluation period p . The term $X_{i,k,p}$ represents the k^{th} realized risk exposure for stock i calculated over the same period p . These primarily include our proposed $\beta_{i,p}^{FOMO-}$ and $\beta_{i,p}^{FOMO+}$, the standard $\beta_{i,p}^{CAPM}$, the regret beta $\beta_{i,p}^R$, as well as β_{Ang}^- and β_{Ang}^+ . $X_{i,k,p}$ also includes the standard deviation of the stock's daily excess return (Std Dev), coskewness between the stock's daily excess return and the market's daily excess return (Coskewness) and cokurtosis²⁶ (Cokurt). The term $C_{i,m,p-1}$ represents the m^{th} firm-specific control variable for stock i , measured at the beginning of period p (time t). These characteristics include the logarithm of market capitalization (lnSize), book-to-market ratio (BM), momentum (Mom),

²⁶Cokurtosis measures the co-movement between a stock's return and the cubed market return, capturing sensitivity related to market skewness. The measure used here follows empirical convention (e.g., Ang et al. (2006a); Dittmar (2002)) and is defined as $cokurt = \frac{E[(r_i - \mu_i)(r_m - \mu_m)^3]}{\sqrt{var(r_i)var(r_m)^{3/2}}}$

defined as the cumulative excess return over the prior 11 month, lagged one month (Past Ret_{t-12} to $t - 2$) and a measure of historical liquidity beta ($Liq\beta$) estimated following Pástor and Stambaugh (2003) using data prior to time t .

To mitigate the influence of outliers, particularly for variables like the book-to-market ratio which can take extreme values, we follow common practice and Winsorize all independent variables at the 1% and 99% levels within each monthly cross-section before running the regressions.

The Fama and MacBeth (1973) procedure involves estimating the coefficients $\gamma_{0,p}$ (intercept), $\gamma_{k,p}$ (risk premia for realised betas) and $\delta_{m,p}$ (rewards for characteristics) from Equation (29) for each period p . The final reported coefficients in Table 2 are the time-series averages of these period-by-period estimates, and their t -statistics are adjusted for autocorrelation using Newey and West (1987) standard errors with 12 lags. Different regression specifications (Models *I – VIII*) presented in Table 2 utilise different subsets of these explanatory variables. The final column of Table 2 also reports the time-series averages of the cross-sectional means and standard deviations for each independent variable to aid in interpreting economic significance.

Table 2 reports the time-series average coefficients and associated Newey and West (1987) t -statistics from Fama and MacBeth (1973) regressions. Our analysis begins by examining the pricing of the unconditional regret beta β^R alongside a comprehensive set of control variables, as detailed in Model I. The coefficient for β^R is 0.249, with a t -statistic of 8.10, indicating a highly significant positive risk premium associated with stocks' unconditional sensitivity to the peer-performance gap. A strongly significant β^R suggests that, even after accounting for firm characteristics and other risk dimensions, exposure to this general regret factor is substantially rewarded.

Regarding the control variables in this specification, several align with established findings, while others present nuances. Consistent with prior literature, Log-Size exhibits a negative premium of -0.028 (t -statistic -4.97), as does stock Volatility at -0.269 (t -statistic -4.08). The negative premium is consistent with the “volatility puzzle” (Ang et al., 2006b). Coskewness also carries a significant negative premium of -0.125 , (t -statistic -3.44), matching with Harvey and Siddique (2000). The book-to-market ratio (B/M) shows a negative premium of -0.022 , (t -statistic -3.44). A negative value premium is unsurprising as there is a large temporal variation in the premium (Fama and French, 2021). Momentum carries a premium of -0.010 (t -statistic -0.56) is statistically insignificant in this model. Cokurtosis is positively priced with a premium of 0.065 (t -statistic 4.23), while the premium on the liquidity beta, $Liq\beta$, is 0.012 positive and marginally significant at 0.012 (t -statistic 1.76). The primary takeaway from Model I, however, is the strong independent pricing of the regret beta, β^R .

To directly examine the pricing of our conditional FOMO betas in a multivariate

Table 2: Fama-MacBeth Regression Results

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	Mean (Std Dev)
Intercept	0.072 [1.48]	-0.306 [-7.52]***	-0.297 [-7.34]***	-0.206 [-4.94]***	-0.204 [-4.97]***	0.209 [5.56]***	0.220 [5.75]***	0.169 [3.85]***	
β^R	0.249 [8.10]***								0.863 (0.198)
β^{CAPM}			0.031 [1.18]	0.052 [1.49]	0.044 [1.29]	0.147 [4.48]***	0.137 [3.92]***		0.729 (0.553)
$\beta^{\text{FOMO-}}$		0.190 [4.63]***	0.161 [5.00]***	0.092 [4.58]***	0.088 [4.46]***	0.103 [5.41]***	0.091 [4.77]***	0.103 [5.05]***	0.879 (0.213)
$\beta^{\text{FOMO+}}$		0.206 [8.27]***	0.210 [7.36]***	0.200 [7.94]***	0.202 [8.22]***	0.076 [3.69]***	0.053 [2.71]***	0.067 [3.32]***	0.884 (0.235)
β_{Ang}^-								0.056 [3.61]***	0.809 (0.705)
β_{Ang}^+								0.028 [3.09]***	0.634 (0.763)
lnSize	-0.028 [-4.97]***			-0.002 [-0.30]	-0.004 [-0.65]	-0.033 [-5.82]***	-0.030 [-5.49]***	-0.026 [-4.93]***	5.122 (1.977)
B/M	-0.022 [-3.44]***			-0.024 [-3.64]***	-0.024 [-3.65]***	-0.026 [-3.89]***	-0.022 [-3.49]***	-0.022 [-3.46]***	1.491 (4.259)
Momentum	-0.010 [-0.56]			0.004 [0.25]	0.004 [0.23]	-0.017 [-1.00]	-0.015 [-0.83]	-0.012 [-0.70]	0.078 (0.478)
Volatility	-0.269 [-4.08]***					-0.452 [-9.37]***	-0.411 [-7.88]***	-0.366 [-5.90]***	0.496 (0.267)
Coskewness	-0.125 [-3.44]***				-0.146 [-4.94]***	-0.141 [-4.33]***	-0.131 [-3.95]***	-0.077 [-2.08]**	-0.122 (0.171)
Cokurtosis	0.065 [4.23]***					-0.007 [-0.53]	-0.007 [-0.52]	0.017 [1.27]	1.700 (1.238)
Liq β	0.012 [1.76]*						0.010 [1.59]	0.011 [1.62]	-0.002 (0.406)

This table presents coefficients from firm-level Fama-MacBeth (1973) cross-sectional regressions of 12-month realized excess returns on realized betas and firm characteristics. The sample period is January 1980 to December 2024, with regressions run monthly using overlapping 12-month evaluation periods, resulting in 529 monthly cross-sectional regressions. The analysis includes stocks listed on the NYSE, AMEX and NASDAQ. The average number of firms in each monthly cross-sectional regression is 4166. Coefficients are time-series averages of the estimates from these monthly regressions. t -statistics, reported in brackets, are computed using Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors with 12 lags. The dependent variable is the 12-month realized stock excess return. Independent variables include realized betas: β^R representing the Regret Beta, β^{CAPM} representing the standard market beta, $\beta^{\text{FOMO-}}$ and $\beta^{\text{FOMO+}}$ representing the negative and positive FOMO betas, as well as β_{Ang}^- and β_{Ang}^+ representing the downside and upside market betas. Realized betas, realised 12-month return volatility (Vol), realized 12-month coskewness (Coskew) and realized 12-month cokurtosis (Cokurt) are calculated over the same 12-month period as the dependent variable using daily data. Firm characteristics are measured at the beginning of each 12-month evaluation period and include: natural logarithm of market capitalization (lnSize), book-to-market ratio (B/M) and prior 11-month cumulative excess return lagged one month (Mom). Lagged liquidity beta (Liq β) is estimated following Pástor and Stambaugh (2003). All independent variables included in the regressions are Winsorized at the 1% and 99% levels within each monthly cross-section. The final column reports the time-series average of the cross-sectional mean and standard deviation for each independent variable.***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

setting, Model II of Table 2 includes only β^{FOMO-} and β^{FOMO+} as regressors, excluding β^{CAPM} and other controls for this initial assessment. Consistent with our central hypothesis, and the univariate sort results (Panel C of Table 1), the coefficient for β^{FOMO-} is 0.190 and highly statistically significant (t-statistic 4.63). This provides initial Fama-MacBeth evidence for a positive risk premium associated with sensitivity to underperforming the peer benchmark.

Interestingly, β^{FOMO+} also commands a strong positive premium in this specification, with a coefficient of 0.206 (t-statistic 8.27). While our theory is less prescriptive regarding the pricing of sensitivity during outperformance periods, the univariate relative sorts hinted at a possible discount after controlling for β^{FOMO+} . The Fama-MacBeth coefficient indicates a positive association when considered without other factors.

Model III of Table 2 incorporates the standard market beta, β^{CAPM} , into the specification alongside our conditional FOMO betas, β^{FOMO-} and β^{FOMO+} . This allows us to assess whether the premia associated with the FOMO betas persist once general market exposure is accounted for. The coefficient on β^{CAPM} is 0.031, positive but not statistically significant (t-statistic 1.18) in the presence of the FOMO betas.

Crucially, the premium for sensitivity to underperformance, β^{FOMO-} , remains strong and significant, with a coefficient of 0.161 (t-statistic 5.00). This is slightly lower than its coefficient of 0.189 in Model II, suggesting that β^{CAPM} accounts for a small portion of the risk captured by β^{FOMO-} , but a substantial and distinct premium for FOMO-related downside sensitivity remains. Similarly, the coefficient for β^{FOMO+} remains highly significant at 0.210 (t-statistic 7.36), indicating that sensitivity to outperforming the peer benchmark continues to be positively priced even when controlling for market beta. These results suggest that our conditional FOMO betas capture risk dimensions beyond that explained by the standard CAPM beta alone.

Model IV of Table 2 extends the previous specification by incorporating standard firm characteristics: Log-Size (lnSize), book-to-market ratio (B/M), and 12-month momentum (Mom12m). The coefficient on β^{FOMO-} remains positive and highly statistically significant at 0.092 ($t = 4.58$), though its magnitude is reduced compared to Model III (0.161). This indicates that while size, value, and momentum characteristics explain some of the return variation previously attributed to β^{FOMO-} , a distinct and significant premium for FOMO-related downside sensitivity persists. Similarly, the premium for β^{FOMO+} remains strong and significant at 0.200 ($t = 7.94$). In this model, β^{CAPM} has a coefficient of 0.052 ($t = 1.49$), still not reaching conventional significance levels. Among the controls, B/M is significantly negative (-0.024 , $t = -3.64$), while Log-Size (-0.002 , $t = -0.30$) and Momentum (0.004 , $t = 0.25$) are insignificant in Model IV. The continued significance of β^{FOMO-} in the presence of these standard characteristics provides further evidence for its unique role in asset pricing.

Model V further assesses the distinctiveness of the β^{FOMO-} premium by adding realised Coskewness (Coskew12m) to the set of regressors from Model IV. Both β^{FOMO-} and a preference against negative skewness (i.e., for positive coskewness) relate to adverse market outcomes. The results in Column (V) support this. The coefficient on is 0.088 (t-statistic 4.46), remaining positive and highly statistically significant. This value is only marginally lower than its coefficient of 0.092 in Model IV (which excluded coskewness). The premium for β^{FOMO-} is largely robust to, and distinct from, the known coskewness effect. As anticipated, Coskewness itself loads negatively at -0.146 and is the loading is statistically significant (t-statistic -4.94), consistent with investor aversion to negative skewness (Harvey and Siddique 2000). In Model V, β^{FOMO+} continues to command a significant positive premium of 0.202 (t-statistic 8.22), while β^{CAPM} remains insignificant at 0.044, (t-statistic 1.29). The premiums on the control variables Log-Size at -0.004 (t-statistic -0.65) and Momentum at 0.004 (t-statistic 0.23) are insignificant, while book-to-market remains negative at -0.024 and statistically significant (t-statistic -3.65).

Further scrutiny of the FOMO beta premia is provided in Model VI of Table 2, which incorporates realised stock Volatility (Vol12m) and Cokurtosis (Cokurt12m) into the specification from Model V. Given the documented negative premium for volatility (e.g., Ang et al. 2006b). Model VI serves as an important robustness check. The coefficient on β^{FOMO-} remains positive and highly statistically significant at 0.103 (t-statistic 5.41), indicating that the premium for FOMO-related downside risk is robust to the inclusion of these standard volatility and cokurtosis measures. The coefficient for β^{FOMO+} in this specification is 0.076 (t-statistic 3.69), also remaining positive and significant. As expected, Volatility is strongly negatively priced with a premium of -0.452 (t-statistic -9.37). Cokurtosis, however, is insignificant in this model, the premium is -0.007 (t-statistic -0.53). Notably, β^{CAPM} now shows a significant positive premium of 0.147 (t-statistic 4.48), while the key firm characteristics (Log-Size, B/M) retain their sign and significance, and Momentum remains insignificant.

Our most comprehensive specification with standard controls, presented as Model VII, includes β^{FOMO-} , β^{FOMO+} and β^{CAPM} along with the complete set of control variables: Log-Size, B/M, Momentum, Volatility, Coskewness, Cokurtosis, and Liquidity Beta (Liq β). The results continue to strongly support our hypothesis regarding β^{FOMO-} ; its coefficient is 0.091 (t-statistic 4.77), remaining positive and highly statistically significant. This persistence underscores the distinct premium associated with FOMO risk. The premium for β^{FOMO+} is 0.053 (t-statistic 2.71), and for β^{CAPM} is 0.137 (t-statistic 3.92), both maintaining positive significance. Most control variables perform as expected: Log-Size has a premium of -0.030, t-statistic 5.49), B/M at -0.022 (t-statistic -3.49) , the Volatility premium is -0.411 (t-statistic -7.88), and Coskewness carries a premium of -0.131 (t-statistic -3.95). All of these additional controls are significant. Further,

Cokurtosis carries a premium of -0.007 (t-statistic -0.52) and Momentum -0.015 (t-statistic -0.83) are insignificant, while the $\text{Liq}\beta$ of 0.010 (t-statistic 1.59) is positive and marginally insignificant.

To directly assess the unique explanatory power of our conditional FOMO betas, Model VIII of Table 2 presents a comparison of our FOMO beta against the downside risk measure of Ang et al. (2006a) in a direct "horse race". Ang et al. (2006a) remains the primary reference point for conditional betas. Model VIII includes our β^{FOMO-} and β^{FOMO+} alongside the downside, β_{Ang}^- , and upside β_{Ang}^+ , betas and all standard controls. The subscript *Ang* is added to denote the Ang et al. (2006a) construction. Even in this stringent test, both downside measures appear to be priced. Ang et al. (2006a)'s downside beta is positively priced with a coefficient of 0.056 ($t = 3.61$). Crucially, our FOMO beta remains highly significant and has a larger economic magnitude, with a coefficient of 0.103 ($t = 5.05$). The continued significance and the comparatively larger coefficient of β^{FOMO-} emphasizes that our FOMO-based measure captures a dimension of downside risk relevant to investors that is distinct from or incremental to the market-conditional downside beta of Ang et al. (2006a). For the upside betas, our β^{FOMO+} has a coefficient of 0.067 ($t = 3.32$), while β_{Ang}^+ has a coefficient of 0.028 ($t = 3.09$). The coefficients on β^{FOMO+} and β_{Ang}^+ are positive and significant in this comprehensive model.

Completing the comparison across the set of constructed betas, the unconditional regret beta, β^R , commands a robust positive premium (0.249 , $t = 8.10$) in Model I of Table 2. In the appendix, we show that β^R has a premium of 0.196 (t-statistic 7.30) when included alongside β^{CAPM} and all controls. Further, this premium persists even when directly compared against Ang et al. (2006a) downside market betas. β^R allows an empirical investigation of the Regret-CAPM (Qin, 2020).

In summary, the Fama-MacBeth regressions presented in Table 2 provide compelling and consistent evidence for the pricing of risks related to peer-performance comparisons²⁷. The conditional negative FOMO beta, β^{FOMO-} , consistently demonstrates a positive and statistically significant risk premium across a wide range of specifications. The risk premium on β^{FOMO-} remains robust after controlling for β^{CAPM} , standard firm characteristics (Log-Size, B/M, Momentum), Volatility, Coskewness, Cokurtosis, and $\text{Liq}\beta$. In a direct "horse race" against Ang et al. (2006a)'s downside market beta, β_{Ang}^- , within a comprehensive model including all controls (Model VIII of Table 2), β^{FOMO-} yields a significant coefficient of 0.103 ($t = 5.05$), larger than that of β_{Ang}^- (0.056 , $t = 3.61$). Our measure of sensitivity to firm-specific peer underperformance captures a priced risk dimension distinct from general market downside risk. The pricing of sensitivity to peer group performance during outperformance states, β^{FOMO+} , is also generally positive and

²⁷Further Fama-MacBeth regressions provided in Appendix E underscore the evidence on the pricing of risks relating to peer-performance comparisons.

statistically significant across many specifications (e.g., 0.067, $t = 3.32$ in Model VIII of Table 2). While our theory in the FOMO-CAPM is less prescriptive about β^{FOMO+} , its consistent significance suggests that sensitivity to outperforming the benchmark also carries a premium.

The economic magnitude of the FOMO risk premium is understood by considering the average values in the final column of Table 2. β^{FOMO-} has a standard deviation of 0.213. The coefficient in Model II gives an effect of a 2 standard deviation change in β^{FOMO-} of $2 \times 0.213 \times 0.190 = 8.1\%$. The regret beta, β^R , carries a premium of 2.49% with the standard deviation of β^R being 0.198. The 2 standard deviation change in β^R corresponds to a change in expected returns of $2 \times 0.198 \times 0.249 = 9.86\%$. Finally, β^{FOMO+} has an expected returns change of $2 \times 0.206 \times 0.235 = 9.68\%$. As more controls are added to the regression, the premium on β^{FOMO-} falls, being around 10% in the later models. The coefficients on β^{FOMO+} show that performance above the reference portfolio carries a premium of 5%. The β^{FOMO+} premium is half that of β^{FOMO-} . In the Appendix, we confirm that our β^R coefficients carry a risk premium of 20%. As evidenced in our theoretical framework, FOMO acts to require stronger compensation for risk on stocks which underperform their peer benchmark.

Overall, the robust positive premia associated with both the unconditional β^R , and the conditional β^{FOMO-} , provide strong empirical support for the central mechanisms of our FOMO-CAPM. The empirical results evidence that investors demand compensation for exposure to both general regret from benchmark deviation and the specific asymmetric disutility of FOMO.

4.4 Distinguishing FOMO from Symmetric Regret

Our results demonstrate that the asymmetric pricing we attribute to FOMO is empirically distinct from a simpler, symmetric model of regret. Our inference is testable with the data used to estimate the betas. We conduct a parameter equality test by including both the unconditional regret beta (β^R) and our asymmetric FOMO components in a single panel regression. We use a reparameterized model (see Wooldridge, 2010) where the key variables are β^R , to capture the symmetric effect, and β^{FOMO-} , to capture the additional asymmetric effect of underperformance. The results of our parameter equality test are presented in Table 3.

In Table 3 shows the coefficient on the symmetric regret beta, β^R , is 0.2757 and highly significant (t-statistic = 7.26). This indicates that a general regret effect is indeed priced in the cross-section of returns. Critically, even after controlling for this symmetric effect, the coefficient on the asymmetric component, β^{FOMO-} , remains positive at 0.1298 and highly statistically significant (t-statistic = 7.50). Our results provide powerful evidence that our FOMO model identifies a priced factor beyond simple regret. While investors

Table 3: Disentangling Asymmetric FOMO from Symmetric Regret

Variable	Coefficient	<i>t</i> -statistic
Panel A: Key Behavioral Betas		
β^{FOMO-} (Asymmetry: $\gamma^{F-} - \gamma^{F+}$)	0.1298***	[7.50]
$\beta^{FOMO-sum}$ (Level: γ^{F+})	-0.1546***	[-8.67]
β^R (Symmetric Regret)	0.2757***	[7.26]
Panel B: Standard Control Variables		
β^{CAPM}	0.1167***	[12.04]
Log(Size)	-0.1862***	[-34.59]
Book-to-Market (BM)	-0.0223***	[-10.82]
Momentum (mom12m)	-0.0514***	[-9.18]
Volatility (vol12m)	-0.3199***	[-11.80]
Coskewness	-0.1085***	[-6.37]
Cokurtosis	-0.0048**	[-2.53]
Liquidity Beta (β^l)	0.0188**	[3.26]
Model Diagnostics		
Observations	1,999,975	
Firm Fixed Effects	Yes	
Time Fixed Effects	Yes	
Adj. R^2	0.2622	

This table presents results from a reparameterized pooled panel regression designed to test whether the asymmetric FOMO risk premium is distinct from a general, symmetric regret premium. The dependent variable is the 12-month realised stock excess return. The regression includes firm and time fixed effects. To correct for residual correlation both across firms and over time, *t*-statistics reported in parentheses are based on standard errors two-way clustered by firm and time, following the methodology of Petersen (2009). The coefficient on β^{FOMO-} directly estimates the difference in the premia for under- and outperformance ($\gamma^{F-} - \gamma^{F+}$). The coefficient on β^R captures the premium for symmetric regret after controlling for the FOMO components. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

are compensated for bearing general benchmark-relative risk, they demand an additional, economically and statistically significant premium for the specific risk of underperforming their peers. This confirms the importance of the asymmetric component, driven by the $k_i(H_i)$ function in our utility model, which is the core of our FOMO-based theory.

4.5 Negative FOMO Beta Risk and Coskewness Risk

The Fama and MacBeth (1973) regressions presented in Table 2 show that both β^{FOMO-} and coskewness carry significant risk premia in the cross-section of stock returns. Since both β^{FOMO-} and negative coskewness are associated with adverse market states and asymmetric risk profiles, it is important to determine whether they capture distinct sources of priced risk. Specifically, we need to investigate whether the premium associated with β^{FOMO-} persists after explicitly controlling for the effect of coskewness and vice versa. To disentangle these effects, we employ independent two-way portfolio sorts. We construct 5×5 portfolios based on sequential sorts using realized β^{FOMO-} and realised coskewness, both computed over the same 12-month evaluation period (t to $t + 12$) during which we measure realized excess returns.

First, to isolate the β^{FOMO-} premium while controlling for coskewness, we initially sort all stocks into five quintiles based on their realized coskewness over the 12-month period. Then, within each coskewness quintile, we further sort stocks into five quintiles based on their realized β^{FOMO-} over the same period. The double-sorting procedure results in 25 portfolios. We calculate the average equal-weighted realized 12-month excess return for each of these 25 portfolios. By averaging the returns of the β^{FOMO-} quintiles across the five initial coskewness quintiles, we obtain returns for β^{FOMO-} portfolios that have, by construction, varying levels of β^{FOMO-} but similar levels of average coskewness exposure. This allows us to examine the return spread associated with β^{FOMO-} after effectively neutralizing the influence of coskewness.

Panel A in Table 4 presents the average excess returns for these 25 portfolios, along with the average returns for the coskewness-controlled β^{FOMO-} quintiles. The row labeled "High-Low (β^{FOMO-})" reports the difference in average returns between the highest (Quintile 5) and lowest (Quintile 1), β^{FOMO-} portfolios within each initial coskewness quintile, as well as for the overall coskewness-controlled β^{FOMO-} portfolios. Our central hypothesis is that the premium for β^{FOMO-} risk is distinct from the coskewness premium. Under our central hypothesis, we expect the High-Low spread for the coskewness-controlled β^{FOMO-} portfolios to be positive and statistically significant.

The results in Panel A of Table 4 strongly support the hypothesis that β^{FOMO-} risk is distinct from the coskewness premium. The average High-Low spread for β^{FOMO-} after controlling for coskewness is 15.30%, and this spread is highly statistically significant (t -statistic = 8.77). This spread is consistently positive and significant across all coskewness

Table 4: Returns of Stocks Sorted by Realized β^{FOMO-} and Coskewness

Panel A: Coskewness sorts controlling for β^{FOMO-}							
Coskewness	β^{FOMO-} Quintile					High-Low	t-stat
Quintile	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	(β^{FOMO-})	(β^{FOMO-})
1 (Lowest)	4.06	6.10	9.33	13.19	20.92	16.86	[7.80***]
2	2.18	4.92	8.39	11.57	19.22	17.04	[8.65***]
3	0.20	3.13	6.26	9.58	15.77	15.57	[8.82***]
4	-1.45	1.15	4.81	7.46	12.75	14.20	[8.63***]
5 (Highest)	-4.53	-2.43	1.82	4.47	8.32	12.85	[6.98***]
Average	0.09	2.57	6.12	9.26	15.40	15.30	[8.77***]

Panel B: β^{FOMO-} sorts controlling for Coskewness							
β^{FOMO-}	Coskewness Quintile					High-Low	t-stat
Quintile	Q1 (Lowest)	Q2	Q3	Q4	Q5 (Highest)	(Coskewness)	(Coskewness)
1 (Low)	3.27	0.92	-0.98	-3.07	-5.26	-8.53	[-6.02***]
2	5.79	3.43	1.09	-0.88	-2.48	-8.27	[-6.05***]
3	8.24	6.49	4.74	3.34	1.23	-7.01	[-5.42***]
4	12.73	10.76	9.32	6.89	5.22	-7.51	[-5.14***]
5 (High)	20.22	19.37	17.01	14.38	10.79	-9.43	[-4.66***]
Average	10.05	8.19	6.24	4.13	1.90	-8.15	[-6.30***]

This table presents average 12-month realized excess returns for 5×5 portfolios sorted independently on realized coskewness and realized β^{FOMO-} . Both sorting variables are computed over the same 12-month evaluation period (t to $t + 12$) during which returns are measured. Panel A sorts first by coskewness, then by β^{FOMO-} . Panel B sorts first by β^{FOMO-} , then by coskewness. t -statistics for the "Average" High-Low differences use Newey and West (1987) standard errors with 12 lags. Data are from CRSP/Compustat for the period January 1980 to December 2024. Quintile breakpoints for the primary sort are based on NYSE stocks; all common stocks on NYSE/AMEX/NASDAQ are then allocated to these quintiles. Portfolios are equal-weighted. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

quintiles, ranging from 12.85% for the highest coskewness quintile to 17.04% for the second lowest coskewness quintile. This indicates that the substantial premium associated with β^{FOMO-} is not an artefact of coskewness. Stocks with higher sensitivity to FOMO states command significantly higher returns even when compared against other stocks with similar coskewness.

Second, to isolate the coskewness premium, while controlling for β^{FOMO-} , we reverse the sorting procedure. We first sort stocks into five quintiles based on their realized β_{FOMO-} over the 12-month period. Then, within each β^{FOMO-} quintile, we sort stocks into five quintiles based on realized coskewness. Again, we form 25 equal-weighted portfolios and calculate their average realized 12-month excess returns. By averaging the returns of the coskewness quintiles across the five initial β^{FOMO-} quintiles, we obtain returns for coskewness portfolios that have similar levels of average β^{FOMO-} exposure.

Panel B in Table 4 presents the results for this reversed sort. The column labeled "Average" shows the returns for the β^{FOMO-} controlled coskewness quintiles. The row labeled "High-Low (Coskewness)" shows the return difference between the quintile with the highest coskewness and the quintile with the lowest coskewness. Consistent with prior findings in Harvey and Siddique (2000), investors may demand a premium for assets with negative coskewness or accept lower returns for positive coskewness.

The results in Panel B of Table 4 show that, after controlling for β^{FOMO-} , there is a significant negative relationship between our coskewness quintiles (Q5-Q1) and returns. The average High-Low spread is -8.15% , with a t -statistic of -6.30 . This means that stocks in the lowest coskewness quintile, those with the most negative or least positive coskewness, significantly outperform stocks in the highest coskewness quintile. This finding is consistent with investors demanding a premium for holding stocks with greater left-tail risk (negative skewness) or those less preferred due to their skewness profile, even after accounting for β^{FOMO-} . The negative high-minus-low spread for the coskewness quintiles is consistently negative and significant across all β^{FOMO-} quintiles.

In summary, the independent two-way portfolio sorts presented in Table 4 demonstrate that both β^{FOMO-} and coskewness are independently priced risk factors. The strong positive premium for β^{FOMO-} persists after controlling for coskewness, and the negative premium for coskewness (i.e., higher returns for lower, more negative coskewness as captured by the Q5-Q1 spread) persists after controlling for β^{FOMO-} . Our double-sorts provide robust evidence that the FOMO risk captured by β^{FOMO-} is a distinct phenomenon from the risk associated with coskewness. Both β^{FOMO-} and coskewness contribute to explaining the cross-section of stock returns.

4.6 Determinants of FOMO Betas

The preceding analysis establishes that exposure to the β^{FOMO-} commands a significant risk premium. A natural subsequent inquiry is into the economic nature of this risk exposure itself. To understand what types of firms are most sensitive to peer-group underperformance, we investigate the firm-level characteristics that determine the realized FOMO betas. We conduct a series of Fama-MacBeth regressions where the dependent variables are the realized β^{FOMO-} and β^{FOMO+} , respectively, and the independent variables are a standard set of firm characteristics. The complete results from these univariate and multivariate regressions are detailed in Tables 5 and 6 for β^{FOMO-} and β^{FOMO+} respectively.

Our primary focus is on the determinants of β^{FOMO-} , the measure central to our theory. The multivariate analysis reveals several significant relationships that create a distinct economic profile. We find a significant negative relationship between β^{FOMO-} and both firm size ($\ln_{size}$) and the book-to-market ratio (bm). Smaller firms and those with lower book-to-market ratios—typically classified as "growth" stocks—tend to exhibit higher sensitivity to the FOMO state. Furthermore, β^{FOMO-} is significantly and positively related to past-year returns (mom12m) and to cokurtosis. Collectively, these results suggest that the firms carrying the highest FOMO risk are often smaller growth stocks that have experienced strong recent performance.

For completeness, we also examine the determinants of β^{FOMO+} . While sharing some similarities with β^{FOMO-} , such as a negative relation with the book-to-market ratio and a positive relation with momentum and cokurtosis, there are notable differences. Unlike β^{FOMO-} , β^{FOMO+} does not have a significant relationship with firm size in the multivariate model, but it does show a significant positive association with coskewness and a marginally significant negative association with volatility. The divergence in these determinants, particularly with respect to size and coskewness, provides further evidence that β^{FOMO-} and β^{FOMO+} capture empirically distinct dimensions of risk, reinforcing the asymmetric nature of the FOMO phenomenon.

In addition to understanding the characteristics associated with the level of FOMO betas, it is crucial to assess their stability over time. A persistent risk exposure is more likely to be a priced, systematic factor rather than a transient phenomenon. To test this, we follow Ang et al. (2006a) and conduct a multivariate persistence test using annual, non-overlapping data. We run annual Fama-MacBeth regressions where the dependent variable is a stock's realized FOMO beta in the next year (Year T+1), and the independent variables include its beta and other characteristics from the current year (Year T). A significant positive coefficient on the past beta in Table 7 confirms that the risk exposure is a stable characteristic of the firm.

Taken together, the results in this section provide a comprehensive profile of our

Table 5: Determinants of Realized FOMO Down Betas, β^{FOMO-}

Characteristic	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Intercept	0.8058 [12.66]***	0.9175 [50.48]***	0.8783 [35.88]***	0.8346 [5.32]***	0.8620 [47.66]***	0.8014 [10.60]***	0.8851 [35.24]***	0.8709 [11.78]***
Log(Size)	0.0144 [3.68]***							-0.0172 [-2.96]***
BM		-0.0052 [-2.13]**						-0.0038 [-8.08]***
Momentum			0.0276 [2.52]**					0.0171 [4.71]***
Volatility				0.0874 [0.74]				0.0440 [0.69]
Coskewness					-0.0395 [-0.93]			0.0262 [1.36]
Cokurtosis						0.0571 [2.57]**		0.0790 [6.73]***
Liquidity β							-0.0060 [-0.68]	-0.0064 [-1.05]

This table presents time-series averages of coefficients from monthly cross-sectional regressions explaining realized FOMO betas. For each month, the realized β^{FOMO-} is regressed on lagged firm characteristics. Models (I) through (VII) are univariate regressions, while Model (VIII) is a multivariate regression including all characteristics simultaneously. All characteristics are measured at the beginning of the 12-month beta estimation period. t -statistics, reported in brackets, are computed using Newey and West (1987) standard errors with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Determinants of Realized FOMO Up Betas, β^{FOMO+}

Characteristic	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Intercept	0.7122 [11.23]***	0.9289 [42.28]***	0.8853 [35.20]***	0.9111 [11.43]***	0.8641 [40.62]***	0.7803 [9.55]***	0.8925 [38.34]***	0.9105 [15.12]***
Log(Size)	0.0335 [8.58]***							-0.0061 [-1.17]
BM		-0.0020 [-3.05]***						-0.0019 [-3.41]***
Momentum			0.0716 [8.84]***					0.0282 [6.02]***
Volatility				-0.0573 [-0.59]				-0.1068 [-1.85]*
Coskewness					-0.0161 [-0.31]			0.0300 [1.95]*
Cokurtosis						0.0801 [5.65]***		0.0662 [6.66]***
Liquidity β							-0.0017 [-0.18]	-0.0015 [-0.28]

This table presents time-series averages of coefficients from monthly cross-sectional regressions explaining realised FOMO betas. For each month, the realized β^{FOMO+} is regressed on lagged firm characteristics. Models (I) through (VII) are univariate regressions, while Model (VIII) is a multivariate regression including all characteristics simultaneously. All characteristics are measured at the beginning of the 12-month beta estimation period. t -statistics, reported in brackets, are computed using Newey and West (1987) standard errors with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Annual Persistence of Realised FOMO Betas

Explanatory Variable (End of Year T)	$\beta^{\text{FOMO}-}$ (Year T+1)	$\beta^{\text{FOMO}+}$ (Year T+1)
Intercept	0.489*** [47.80]	0.527*** [16.67]
Past $\beta^{\text{FOMO}-}$ (Year T)	0.450*** [32.57]	
Past $\beta^{\text{FOMO}+}$ (Year T)		0.408*** [20.08]
Past Volatility (Year T)	-0.009 [-0.52]	-0.070*** [-6.59]
Log(Size) (Year T)	0.003 [1.31]	0.009*** [5.12]
Book-to-Market (Year T)	-0.002*** [-2.85]	-0.003** [-2.40]
Momentum (Year T)	0.002 [1.20]	0.012*** [8.51]

This table reports Fama-MacBeth coefficients from annual, non-overlapping regressions testing the persistence of FOMO betas. The dependent variable is the realised beta over Year T+1. Independent variables are the realised beta and other firm characteristics from the end of Year T. t-statistics, reported in parentheses, are computed using Newey-West (1987) standard errors with 5 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

proposed FOMO beta. The analysis of its determinants in Table 5 shows that the β^{FOMO-} exposure is not random, but is systematically associated with firm characteristics. β^{FOMO-} is most pronounced in smaller, growth-oriented firms with strong recent performance—precisely the types of firms where uncertainty and behavioral effects are often expected to be strongest. Furthermore, the persistence analysis in Table 7 demonstrates that this β^{FOMO-} risk exposure is not a transient phenomenon. The strong year-over-year persistence, with a coefficient of 0.45, suggests that sensitivity to peer underperformance is a stable firm characteristic. This combination of a distinct economic profile and high temporal stability provides strong evidence that β^{FOMO-} represents a legitimate, systematic risk factor.

4.7 Time Variation of Portfolio Sort Premia

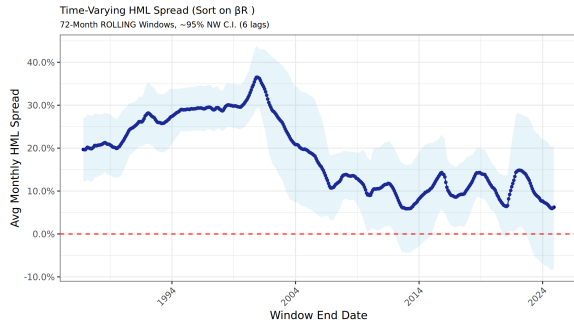
The preceding analyses establish significant average premia associated with the conditional negative FOMO beta (β^{FOMO-}). We have further established a significant role for the regret beta, β^R . The relationship between β^R and β^{FOMO-} is analogous to the relationship between the downside beta and CAPM beta in Ang et al. (2006a).

To further understand the nature of these premiums, we examine whether these risk factors are consistently priced or if their importance varies across different market regimes or time periods. Time-variation analysis addresses observations that the psychological impact of factors like FOMO might fluctuate.

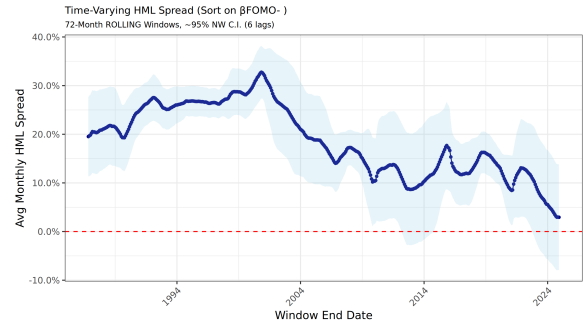
To assess the dynamic nature of the β^R , β^{FOMO-} and β^{FOMO+} premiums, we employ a 60-month rolling window methodology. For each month t , we use data from month $t - 59$ to t to perform portfolio sorts identical to those described for Table 1. Specifically, within each 60-month window, stocks are sorted into quintiles based on their realized β^R , β^{FOMO-} and β^{CAPM} . We then calculate the equal-weighted average monthly excess returns for the highest (Q5) and lowest (Q1) quintile portfolios formed on these betas over the 60 months. The High-minus-Low spread is computed for each of the beta sorts, and its statistical significance is assessed using the Newey and West (1987) standard error. In keeping with the wider literature, the Newey and West (1987) standard errors are computed using 6 lags. The resulting average High-minus-Low spread and its 95% confidence interval are plotted against the end date of each 60-month rolling window.

Panel A of Figure 5 plots the time-series of the 60-month rolling High-minus-Low spread for portfolios sorted on β^R . The premium for β^R is positive and statistically significant for a substantial portion of our sample period. Robust pricing is seen in the late 1980s through to the early 2000s. We observe a notable attenuation, where the spread diminishes and the confidence interval widens to include zero, once window end dates no longer contain the impressive performance of the pre-Global Financial Crisis period. Windows ending in 2012 to 2014 start in 2007 to 2009, so missing the pre-

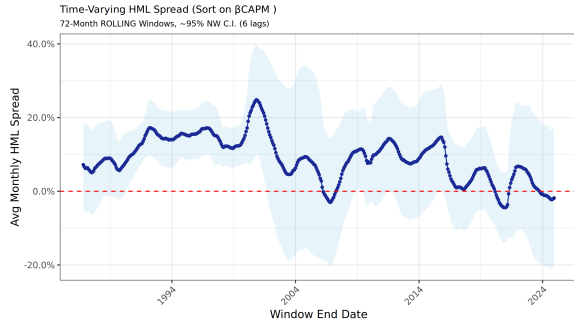
Figure 5: Time Variation of HML Spreads for Key Beta Sorts



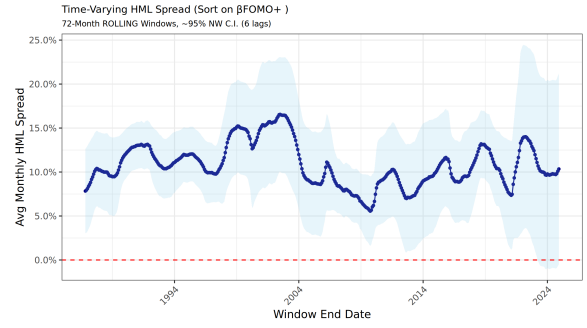
(a) Sort on β^R



(b) Sort on $\beta^{\text{FOMO-}}$



(c) Sort on β^{CAPM}



(d) $\beta^{\text{FOMO+}}$

Notes: These figures plot the 60-month rolling window average High-minus-Low excess return spreads. Shaded areas are 95% Newey-West CIs (6 lags). Plot date is window end. Sample: Jan 1980 - Dec 2024.

crisis years. A similar widening of the confidence interval, suggesting reduced statistical power or a weaker premium, is also apparent in the most recent years of the sample. The unconditional risk associated with β^R generally commands a positive reward. The strength of this reward for the exposure to the risk associated with β^R exhibits clear time variation.

Panel (b) of Figure 5 displays the corresponding rolling High-minus-Low spread for portfolios sorted on our primary measure of FOMO risk, β^{FOMO-} . The premium associated with β^{FOMO-} also exhibits considerable time variation. Similar to β^R , the β^{FOMO-} High-minus-Low spread is predominantly positive and often statistically significant, particularly strong in the period from the 1980s to late 1990s/early 2000s. The premium also appears to diminish and lose statistical significance during the Global Financial Crisis period.

Comparing Figure 5 panel (a) with panel (b), both series exhibit extended periods of strong positive premia as well as a notable decline in efficacy around the time of the Global Financial Crisis. However, several distinct differences are apparent. Notably, the β^{FOMO-} premium reaches higher peaks in the early and mid-1990s, often exceeding 30%, whereas the β^R premium during the same period tends to remain closer to the 20 – 25% range. This pattern suggests that the asymmetric, downside sensitivity captured by β^{FOMO-} can become especially pronounced in certain episodes, potentially reflecting periods of heightened peer-relative underperformance concerns. Conversely, in the years following 2002, the β^R premium appears more persistent and statistically robust. Meanwhile, the β^{FOMO-} premium becomes more volatile and less significant after 2002. Such differences imply that the FOMO-based asymmetry does not simply mirror the unconditional regret sensitivity but captures distinct behavioral pricing effects. Overall, while both the β^R and β^{FOMO-} premiums are positively correlated, their time-paths diverge in meaningful ways, lending support to the empirical relevance of the asymmetric FOMO channel.

For comparison, panel (c) of Figure 5 shows the rolling High-minus-Low spread for β^{CAPM} . While also time-varying, β^{CAPM} is less consistently significant than the β^R or β^{FOMO-} spreads. The HML spread for β^{CAPM} is frequently indistinguishable from zero for extended periods. Standard market risk exposure, as captured by β^{CAPM} , does not explain cross-sectional return differences in these portfolios as strongly as the behavioral sensitivity measures. The contrast further reinforces the empirical value added by incorporating regret- and FOMO-based risk factors, which appear to capture pricing dynamics that are largely absent from the traditional CAPM framework.

To complement the rolling window analysis and mitigate concerns about overlapping data, we also examine the High-minus-Low spreads for key beta sorts over nine distinct, non-overlapping 5-year (60-month) sub-periods from January 1980 to December 2024 (the final period covering 49 months). For each sub-period, High-minus-Low portfolio returns

are calculated based on monthly sorts using betas estimated over the prior 12 months (consistent with the main portfolio sort methodology but aggregated over the 60 months of the sub-period). Table 8 presents the average monthly High-minus-Low spreads and their Newey and West (1987) t -statistics for portfolios sorted on β^R and β^{FOMO-} .

Table 8: High-minus-Low Spreads for Non-Overlapping 5-Year Sub-Periods

Window Period	Sort on β^R		Sort on β^{FOMO-}	
	HML	t -statistic	HML	t -statistic
198012-198511	16.15	[4.64]***	16.34	[3.80]***
198512-199011	25.15	[7.26]***	26.29	[9.76]***
199012-199511	29.42	[9.66]***	26.09	[15.14]***
199512-200011	38.02	[8.94]***	34.05	[10.89]***
200012-200511	8.59	[2.04]**	12.67	[3.73]***
200512-201011	9.80	[1.69]*	11.79	[1.80]*
201012-201511	10.58	[2.58]***	13.42	[3.55]***
201512-202011	6.80	[1.60]	8.63	[2.16]**
202012-202412	11.15	[1.10]	4.92	[0.66]

This table presents average monthly High-minus-Low (HML) excess return spreads for portfolios sorted on realised β^R or β^{FOMO-} over nine non-overlapping 5-year (60-month) sub-periods. The last sub-period (202012-202412) covers 49 months. Betas are estimated over a 12-month rolling window using daily data. High-minus-Low spreads are in percent per month. t -statistics are derived from Newey-West (1987) adjusted standard errors (12 lags) for the High-minus-Low spread within each respective 5-year window. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8 shows that for β^R sorts, the High-minus-Low premium is positive in out of nine sub-periods and statistically significant at the 5% level, corresponding to a t -statistic of approximately 1.96 or higher in 7 of them, with the largest premium observed in the 199512–200011 period at 38.02% (t -statistic 8.94), while the weakest significant premium of 8.59% occurs in the 200012–200511 period (t -statistic 2.04). For β^{FOMO-} sorts, the High-minus-Low premium is also positive in all nine sub-periods and statistically significant in 8 of them, peaking at 34.05% in the 199512–200011 period (t -statistic 10.89). The period 200512–201011, encompasses the Global Financial Crisis, shows weaker effects for both β^R (9.80% per annum with t -statistic 1.69) and β^{FOMO-} carries a High-minus-Low premium 11.79% per annum (t -statistic 1.80). The most recent period, 202012–202412, also shows notably lower t -statistics for β^{FOMO-} (t -statistic 0.66). These non-overlapping results broadly corroborate the findings from the rolling window analysis, indicating persistent, albeit time-varying, positive premia for β^R and β^{FOMO-} .

The combined evidence from rolling window and non-overlapping sub-period analyses

suggests that while the risk premia associated with β^R and β^{FOMO-} are not constant, they represent significant and persistent features of the cross-section of stock returns over our sample period. The periods of heightened or diminished premiums warrant further investigation, linking β^R and β^{FOMO-} to broader market sentiment or economic conditions. Such exploration of the links between β^R , β^{FOMO-} and prevailing economic conditions is left for further analysis.

4.8 Robustness Checks

We conduct a battery of robustness tests, incorporating variations in our empirical design, variable definitions and measurement choices. The aim is to demonstrate the robustness of the positive premium associated with the negative FOMO beta β^{FOMO-} .

First, to understand the relationships between our proposed FOMO betas and other relevant risk measures, Table 9 presents the time-series average of cross-sectional correlations between β^{CAPM} , β^R , β^{FOMO-} and β^{FOMO+} , as well as the downside (β_{Ang}^-) and upside (β_{Ang}^+) market betas. The relative betas are also included.

Table 9 reveals several important relationships. β^{FOMO-} , exhibits a correlation of 0.332 with β^{CAPM} , indicating that β^{FOMO-} captures aspects beyond standard market risk. The correlation of β^{FOMO-} with Ang’s (2006a) downside beta, β_{Ang}^- , is 0.281. Again the correlation is indicative of limited overlap between the betas in capturing downside phenomena. The correlation between our β^{FOMO-} and β^{FOMO+} is 0.580. Notably, the relative FOMO beta, $Rel\beta^{FOMO-}$, shows a strong negative correlation of -0.901 with β^{CAPM} , underscoring its construction to isolate non-market components. Similarly, $Rel\beta^{FOMO+}$ is highly negatively correlated with β^{CAPM} at -0.885 . These correlations provide initial context for the subsequent analyses.

Next, we examine the robustness of our portfolio sort results to several methodological variations. Table 10 presents these checks for portfolios sorted on realized β^{FOMO-} (Panel A) and realized relative β^{FOMO-} (Panel B). The scenarios include excluding small stocks, using all stocks from NYSE/AMEX/NASDAQ with NYSE breakpoints, and using value-weighted returns for NYSE stocks.

Panel A of Table 10 demonstrates that the significant positive High-Low spread for portfolios sorted on β^{FOMO-} persists when small stocks are excluded. The strategy offers an excess return of 16.71% per annum (t-statistic 7.78). When all stocks are considered, the premium rises to 17.38% with a t-statistic of 8.46. For value-weighted NYSE portfolios, the spread remains positive at 1.80% but is not statistically significant (t-statistic 1.19). The β^{FOMO-} premium is more pronounced among equal-weighted portfolios. Our findings align with Ang et al. (2006a) and others who study asymmetry-related premia.

Panel B of Table 10 shows that the strong positive premium for sorting on the unconditional regret beta β^R is also robust. The High-Low spread remains substantial at

Table 9: Time-Series Average of Cross-Sectional Beta Correlations

Variable	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	$\text{Rel}\beta_{\text{R}}^{\text{F}-}$	$\text{Rel}\beta_{\text{R}}^{\text{F}+}$	$\text{Rel}\beta_{\text{C}}^{\text{F}-}$	$\text{Rel}\beta_{\text{C}}^{\text{F}+}$	$\text{Diff}\beta^{\text{F}}$	$\beta^{\text{Ang}-}$	$\beta^{\text{Ang}+}$	$\text{Rel}\beta_{\text{C}}^{\text{A}-}$	$\text{Rel}\beta_{\text{C}}^{\text{A}+}$	$\text{Diff}\beta^{\text{A}}$
β^{CAPM}	1.000	0.437	0.332	0.323	-0.125	-0.092	-0.901	-0.885	0.025	0.777	0.745	-0.056	0.008	0.037
β^R		1.000	0.816	0.876	-0.182	0.094	-0.115	-0.055	0.162	0.349	0.339	-0.036	0.009	0.026
$\beta^{\text{FOMO}-}$			1.000	0.580	0.412	-0.201	0.069	-0.073	-0.358	0.281	0.258	-0.009	0.007	0.009
$\beta^{\text{FOMO}+}$				1.000	-0.388	0.555	-0.088	0.119	0.543	0.246	0.272	-0.057	0.035	0.056
$\text{Rel}\beta_{\text{R}}^{\text{F}-}$					1.000	-0.489	0.306	-0.039	-0.873	-0.075	-0.097	0.045	0.001	-0.025
$\text{Rel}\beta_{\text{R}}^{\text{F}+}$						1.000	0.010	0.344	0.852	-0.100	-0.032	-0.046	0.058	0.065
$\text{Rel}\beta_{\text{C}}^{\text{F}-}$							1.000	0.913	-0.179	-0.691	-0.666	0.054	-0.007	-0.034
$\text{Rel}\beta_{\text{C}}^{\text{F}+}$								1.000	0.215	-0.689	-0.645	0.033	0.006	-0.014
$\text{Diff}\beta^{\text{F}}$									1.000	-0.010	0.041	-0.053	0.032	0.051
$\beta^{\text{Ang}-}$										1.000	0.461	0.559	-0.183	-0.446
$\beta^{\text{Ang}+}$											1.000	-0.251	0.652	0.570
$\text{Rel}\beta_{\text{C}}^{\text{A}-}$												1.000	-0.320	-0.785
$\text{Rel}\beta_{\text{C}}^{\text{A}+}$													1.000	0.833
$\text{Diff}\beta^{\text{A}}$														1.000

This table presents the time-series average of cross-sectional correlations between key realized beta measures. $\text{Rel}\beta_{\text{R}}^{\text{F}-}$ is $\beta^{\text{FOMO}-} - \beta^R$; $\text{Rel}\beta_{\text{R}}^{\text{F}+}$ is $\beta^{\text{FOMO}+} - \beta^R$; $\text{Rel}\beta_{\text{C}}^{\text{F}-}$ is $\beta^{\text{FOMO}-} - \beta^{\text{CAPM}}$; $\text{Rel}\beta_{\text{C}}^{\text{F}+}$ is $\beta^{\text{FOMO}+} - \beta^{\text{CAPM}}$; $\text{Diff}\beta^{\text{F}}$ is $\beta^{\text{FOMO}+} - \beta^{\text{FOMO}-}$. Similar definitions apply for Ang betas (A). For each 12-month overlapping evaluation period (from month t to $t+12$, evaluated monthly) within our sample, we compute the cross-sectional correlation matrix using all stocks listed on the NYSE/AMEX/NASDAQ with available data. The reported values are the averages of these periodic correlation matrices. All underlying realized betas are calculated using daily data over the respective 12-month evaluation periods. The sample period is January 1980 to December 2024, covering 529 monthly evaluation periods.

Table 10: Robustness Checks of Portfolio Sorts on Key Beta Measures

Panel A: Sorts by realised $\beta^{\text{FOMO-}}$			
Portfolio	Exclude small (%)	All stocks (%)	Value-weighted (%)
1 (Low)	3.16	-1.02	9.63
2	8.98	1.38	8.03
3	12.48	4.80	6.71
4	15.29	8.98	6.98
5 (High)	19.86	16.36	11.44
High-Low	16.71	17.38	1.80
<i>t</i> -statistic	[7.78]***	[8.46]***	[1.19]

Panel B: Sorts by realised β^R			
Portfolio	Exclude small (%)	All stocks (%)	Value-weighted (%)
1 (Low)	2.49	-2.16	8.20
2	9.77	2.38	7.99
3	13.96	6.55	8.23
4	16.54	11.26	9.10
5 (High)	17.01	15.25	10.29
High-Low	14.53	17.41	2.09
<i>t</i> -statistic	[6.13]***	[7.37]***	[1.23]

Panel C: Sorts by realised Rel. $\beta^{\text{FOMO-}}$ vs β^R			
Portfolio	Exclude small (%)	All stocks (%)	Value-weighted (%)
1 (Low)	9.34	4.42	10.23
2	10.78	5.76	8.03
3	11.98	6.47	7.78
4	13.81	7.41	8.63
5 (High)	13.87	5.83	9.53
High-Low	4.53	1.41	-0.71
<i>t</i> -statistic	[4.00]***	[1.33]	[-0.68]

This table presents robustness checks for portfolio sort results. Panel A sorts on realised $\beta^{\text{FOMO-}}$, Panel B sorts on realised β^R , and Panel C sorts on realized relative $\beta^{\text{FOMO-}}$ versus β^R ($\beta^{\text{FOMO-}} - \beta^R$). For each sorting variable and robustness scenario, stocks are ranked into five quintiles based on the beta measure calculated using daily continuously compounded returns over a 12-month evaluation period. The table reports average 12-month realised excess returns (in percent) for these equal-weighted or value-weighted quintile portfolios. The robustness scenarios are: (1) Exclude small: Equal-weighted portfolios are formed among NYSE, AMEX and NASDAQ stocks after excluding stocks that fall into the lowest NYSE market capitalization quintile. Breakpoints are based on this reduced sample. (2) All stocks: Equal-weighted portfolios formed using all common stocks on NYSE, AMEX, and NASDAQ. Breakpoints are based on NYSE stocks. (3) Value-weighted: Value-weighted portfolios formed using only stocks listed on the NYSE. Returns are weighted by market capitalisation at the beginning of each 12-month evaluation period. Breakpoints are based on NYSE stocks. The row labelled "High-Low" reports the difference between the average returns of Portfolio 5 and Portfolio 1. *t*-statistics (in brackets)

14.52% when excluding small stocks (t-statistic 6.13) and rises to 17.41% when considering all stocks (t-statistic 7.37). For value-weighted NYSE portfolios, the β^R spread is 2.09% (t-statistic 1.23), positive but, similar to β^{FOMO-} , less statistically pronounced in a value-weighted context.

Panel C investigates the robustness of sorting on relative β^{FOMO-} versus β^R . The High-Low spread is positive at 4.53% and significant when excluding small stocks (t-statistic 4.00) and positive but insignificant for all stocks at 1.41% (t-statistic 1.33). For value-weighted NYSE stocks, the spread turns negative at -0.71% , (t-statistic -0.68). The interpretation of these relative sorts remains complex due to potential confounding effects, as discussed for Table 1.

To ensure the premium documented in our primary univariate sorts is not merely a proxy for other known firm characteristics, we perform an additional series of controlled portfolio sorts. Following a methodology similar to Daniel and Titman (1997), we first sort stocks into quintiles based on a control characteristic (Log(Size), BM, Momentum, or Coskewness) and calculate characteristic-adjusted returns within each quintile. By then sorting these adjusted-return series based on their realized β^{FOMO-} , we can isolate the return spread attributable to FOMO risk after neutralizing the effect of the control characteristic.

Table 11 presents the results of this analysis. The key finding is that the β^{FOMO-} premium remains economically large and highly statistically significant across all control schemes. As shown in Panel A, after controlling for firm size, the High-Low portfolio spread for β^{FOMO-} is 15.68% with a t-statistic of 3.89. The premium is similarly robust after controlling for book-to-market, momentum, and coskewness. This provides strong evidence that the FOMO premium is an incremental effect and not simply a different manifestation of these other well-documented factors. Panel B shows that the β^{FOMO+} premium also generally survives these controls.

A more stringent test is to examine whether the β^{FOMO-} premium is distinct from the well-documented low-volatility anomaly. To disentangle these effects, we perform independent 5x5 portfolio sorts on realised 12-month volatility and realised β^{FOMO-} . Stocks are first sorted into quintiles based on their volatility, and then, within each volatility quintile, they are sorted into five further quintiles based on their β^{FOMO-} . The results of this double sort, shown in Table 12, reveal a powerful interaction between FOMO risk and stock volatility. In the lowest volatility quintiles, the premium for β^{FOMO-} is muted and statistically insignificant. However, the premium for β^{FOMO-} becomes exceptionally strong and highly significant among high-volatility stocks. In the highest volatility quintile 5 (High Vol), the High-Low portfolio sorted on β^{FOMO-} earns a remarkable 37.40% per annum with a t-statistic of 11.75. This demonstrates that the FOMO effect is not only robust but is most pronounced precisely within the set of stocks that are already

Table 11: High-Low Spreads on FOMO Betas after Controlling for Firm Characteristics

Panel A: Sorts on β^{FOMO-}							
Control Variable	Quintile Portfolios on β^{FOMO-}					Spread	
	1 (Low)	2	3	4	5 (High)	High-Low	<i>t</i>-statistic
Log(Size)	−6.61	−4.32	−0.74	3.03	9.08	15.68	[3.89]***
BM	−5.66	−3.27	−0.68	2.51	8.30	13.95	[5.88]***
Momentum	−6.50	−4.13	−0.99	2.94	9.16	15.65	[5.40]***
Coskewness	−6.59	−4.31	−0.84	3.02	8.97	15.55	[4.92]***

Panel B: Sorts on β^{FOMO+}							
Control Variable	Quintile Portfolios on β^{FOMO+}					Spread	
	1 (Low)	2	3	4	5 (High)	High-Low	<i>t</i>-statistic
Log(Size)	−8.74	1.30	4.80	3.71	−0.63	8.12	[4.20]***
BM	−7.45	2.58	4.18	2.22	−0.70	6.75	[3.09]***
Momentum	−8.79	1.05	4.37	3.53	−0.11	8.68	[5.41]***
Coskewness	−9.02	1.10	4.58	3.69	0.38	9.41	[5.43]***

This table presents average 12-month characteristic-adjusted excess returns for portfolios sorted on realized FOMO betas. Each month, we first sort stocks into quintiles based on a control characteristic (Log(Size), BM, etc.). Within each quintile, we then subtract the quintile's equal-weighted average return from each stock's return to get an adjusted return. All stocks are then pooled and sorted into quintiles based on their realised β^{FOMO-} (Panel A) or β^{FOMO+} (Panel B). The table reports the time-series average of the monthly characteristic-adjusted returns for each quintile. The High-Low column is the spread between Quintile 5 and Quintile 1, with Newey-West (1987) *t*-statistics adjusted for 12 lags. *** denotes significance at the 1% level.

considered the most volatile. FOMO effects are strongest in a segment of the market where standard asset pricing models often struggle.

Table 12: Portfolio Returns from 5x5 Sorts on Volatility and FOMO Betas

Panel A: Secondary Sort on β^{FOMO-}							
Volatility	Quintiles formed on β^{FOMO-}					Spread	
Quintile	1 (Low)	2	3	4	5 (High)	High-Low	t-statistic
1 (Low Vol)	8.30	6.79	6.24	6.30	8.27	-0.03	[-0.02]
2	13.36	10.31	9.46	8.91	10.56	-2.80	[-2.19]**
3	13.13	10.40	9.71	10.14	13.22	0.09	[0.05]
4	9.61	9.78	9.90	11.31	16.33	6.72	[2.59]***
5 (High Vol)	-19.81	-7.11	1.18	6.71	17.59	37.40	[11.75]***

Panel B: Secondary Sort on β^{FOMO+}							
Volatility	Quintiles formed on β^{FOMO+}					Spread	
Quintile	1 (Low)	2	3	4	5 (High)	High-Low	t-statistic
1 (Low Vol)	3.81	5.84	7.25	9.47	9.54	5.73	[3.70]***
2	8.02	10.27	12.25	12.42	9.66	1.64	[1.41]
3	9.15	11.66	13.39	12.95	9.46	0.30	[0.22]
4	10.10	12.89	13.73	11.99	8.25	-1.85	[-1.33]
5 (High Vol)	-21.34	0.22	7.47	8.37	3.85	25.19	[12.13]***

This table presents average 12-month excess returns for 25 portfolios formed from sequential 5x5 sorts on volatility and a FOMO beta. Each month, stocks are first sorted into quintiles based on their realized volatility over the prior 12 months. Then, within each volatility quintile, stocks are further sorted into five quintiles based on their realized β^{FOMO-} (Panel A) or β^{FOMO+} (Panel B). The High-Low column reports the return spread between Quintile 5 and Quintile 1 of the FOMO beta sort within each volatility quintile. t -statistics are based on Newey and West (1987) standard errors with 12 lags. *** and ** denote significance at the 1% and 5% levels, respectively.

Finally, we address whether the β^{FOMO-} premium is simply a manifestation of the well-documented small-firm effect. Many behavioral anomalies are known to be stronger or exclusively present among small-cap stocks. To test this, we conduct a 2x5 portfolio sort. Each month, we first partition stocks into two groups, "Small" and "Big," based on the NYSE median market capitalization breakpoint. Then, within each size group, we sort stocks into five quintiles based on their realised β^{FOMO-} .

Table 13 presents the results, which provide two key insights. First, the FOMO premium is not purely a small-firm phenomenon. Among large-cap stocks, the High-Low portfolio constructed on β^{FOMO-} still earns a statistically significant premium of 5.60% per annum (t -statistic 3.41). The significant premium on β^{FOMO-} demonstrates that the pricing of FOMO risk is pervasive across the market. Second, the effect is significantly

amplified among small stocks, where the corresponding High-Low spread is 21.90% (t-statistic 9.57). The difference in these spreads is itself highly significant, confirming that while the FOMO premium is ubiquitous, its magnitude is greatest in the small-cap segment, where behavioral biases are often expected to be most impactful.

Table 13: Portfolio Returns from 2x5 Sorts on Size and β^{FOMO-}

β^{FOMO-} Quintile	Size Group		
	Small	Big	Big - Small
1 (Low)	-3.27	8.14	11.41
2	-0.49	7.93	8.43
3	4.56	6.96	2.39
4	9.84	7.66	-2.18
5 (High)	18.63	13.74	-4.89
High-Low Spread	21.90	5.60	-16.30
t-statistic	[9.57]***	[3.41]***	[-13.12]***

This table presents average 12-month excess returns for 10 portfolios formed from sequential 2x5 sorts on firm size and realised β^{FOMO-} . Each month, stocks are first assigned to two size groups (“Small” or “Big”) based on the median NYSE market capitalization breakpoint. Then, within each size group, stocks are sorted into five quintiles based on their realised β^{FOMO-} . The “High-Low” row reports the return spread between Quintile 5 and Quintile 1 within each size group. The “Big - Small” column reports the difference in returns between the Big and Small portfolios for each quintile and for the High-Low spread. *t*-statistics, reported in brackets, are computed using Newey and West (1987) standard errors with 12 lags. *** denotes significance at the 1% level.

Furthermore, we assess the robustness of the β^{FOMO-} premium found in the main Fama-MacBeth regressions shown in Table 2. Table 14 presents the coefficient and *t*-statistic for β^{FOMO-} from two key specifications, Model VII (full standard controls with β^{CAPM}) and Model VIII (the “horse race” model), across different sample periods and when excluding micro-cap stocks.

The positive premium associated with β^{FOMO-} demonstrates considerable robustness. For Model VII, the β^{FOMO-} coefficient remains positive and statistically significant in the first half of our sample (1980 – 2002) at 0.138 (t-statistic 5.56) and in the second half (2003 – 2024) at 0.051 (t-statistic 1.97). When micro-cap stocks are excluded, the coefficient is 0.119 (t-statistic 6.45).

Similar robustness is observed for β^{FOMO-} in the more stringent Model VIII specification. The coefficient is 0.156 (t-statistic 5.83) in the first sub-period and 0.056 (t-statistic 2.11) in the second sub-period. When excluding micro-caps from this full specification, including Ang et al. (2006a)’s betas, the β^{FOMO-} coefficient is 0.128 (t-statistic 6.48). These results collectively indicate that the significance and positive sign of the β^{FOMO-}

Table 14: Robustness of Fama-MacBeth $\beta^{\text{FOMO}-}$ Coefficient

Scenario	Coefficient	t-statistic
A: $\beta^{\text{FOMO}-}$ Model VII (Full Controls)		
Full Sample	0.091	[4.77]***
Sub-Period 1 (1980-2002)	0.135	[5.56]***
Sub-Period 2 (2003-2024)	0.051	[1.97]**
Exclude Micro-Caps	0.119	[6.45]***
B: $\beta^{\text{FOMO}-}$ Horse Race Model VIII		
Full Sample	0.103	[5.05]***
Sub-Period 1 (1980-2002)	0.156	[5.83]***
Sub-Period 2 (2003-2024)	0.056	[2.11]**
Exclude Micro-Caps	0.128	[6.48]***

This table presents the Fama-MacBeth coefficient and t -statistic for $\beta^{\text{FOMO}-}$ under different scenarios and from two key model specifications detailed in Table 2 (Main Paper). Panel A shows $\beta^{\text{FOMO}-}$ from Main Paper Model VII (which includes $\beta^{\text{FOMO}-}$, $\beta^{\text{FOMO}+}$, β^{CAPM} , and all standard controls). Panel B shows $\beta^{\text{FOMO}-}$ from Main Paper Model VIII (the "horse race" which includes $\beta^{\text{FOMO}-}$, $\beta^{\text{FOMO}+}$, Ang's (2006a) downside and upside market betas, and all standard controls, while excluding β^{CAPM}). "Full Sample" uses the entire period January 1980 - December 2024. "Sub-Period 1" covers 1980-2002 and "Sub-Period 2" covers 2003-2024. "Exclude Micro-Caps" runs regressions after removing stocks in the lowest NYSE market capitalisation quintile. Coefficients are time-series averages from monthly Fama-MacBeth regressions. t -statistics use Newey and West (1987) standard errors with 12 lags. *** and ** denote significance at the 1% and 5% levels, respectively.

premium are not confined to a specific timeframe or driven by the smallest, potentially less liquid, stocks.

In summary, the comprehensive robustness checks conducted in this section largely reinforce our main findings. The correlation analysis (Table 9) indicates that while β^{FOMO-} shares some commonality with β^{CAPM} and Ang’s (2006a) downside beta β_{Ang}^- , it also captures distinct information. The robustness of portfolio sorts (Table 10) shows that the significant positive High-Low spread for portfolios sorted on β^{FOMO-} and β^R persists under various conditions, although they weaken for value-weighted portfolios. Univariate sorts on relative FOMO betas highlighted the complexities of isolating conditional beta effects due to co-movement with β^{CAPM} , underscoring the need for multivariate analysis. Crucially, the Fama-MacBeth coefficient for β^{FOMO-} (Table 10) maintains its positive sign and statistical significance across different sample sub-periods and when small stocks are excluded, both in models with standard controls (Model VII) and in comprehensive ”horse race” models against Ang et al. (2006b)’s betas (Model VIII). Collectively, the evidence presented across this section suggests that the observed FOMO risk premium is a robust feature of the cross-section of stock returns. FOMO is not merely an artefact of a specific sample construction, weighting scheme, or time period.

4.9 FOMO Risk in Asset Pricing Tests

Previous sections established that stocks with high realised β^{FOMO-} earn contemporaneously higher average returns. Higher returns on stocks with higher β^{FOMO-} are shown to be robust in Fama-MacBeth regressions when controlling for firm characteristics and relevant risk factors. The robustness demonstrates the pricing of FOMO risk among individual stocks.

To demonstrate that a FOMO factor improves the ability of standard models to price well-diversified portfolios, we employ the Gibbons, Ross, and Shanken (1989) F-test to evaluate the performance of various factor models in explaining the time-series returns of two distinct sets of test assets: First, five quintile portfolios sorted on the realized β^{FOMO-} themselves and second, 25 Fama-French portfolios sorted on size and book-to-market, a commonly used set of diversified portfolios for model testing²⁸. The GRS test assesses the null hypothesis that the model’s pricing errors, or alphas, for a set of test assets are jointly zero. A statistically significant GRS statistic implies that the model is misspecified and fails to price the test assets. We are particularly interested in whether adding a FOMO factor (FMF), constructed from the β^{FOMO-} sorted portfolios, improves model performance, indicated by a reduction in the GRS statistic, an increase in its p-value and a decrease in the average absolute alpha (AvgAbsAlpha). The models tested

²⁸Because our FOMO model uses the Fama-French 38 Industry Portfolios as reference portfolios for investors peers, it is not possible to use the industry portfolios as test assets in the GRS tests.

include the CAPM, the Fama-French three-factor (FF3) model, the Carhart four-factor model (FF4, adding momentum) and extensions including our FMF factor and Ang et al. (2006a) downside risk factor (ADF). Table 15 presents the GRS test results.

Table 15: GRS Test Results for Factor Models on Different Sets of Test Assets

Panel A: Test Assets = 5 β^{FOMO-}-Sorted Portfolios					
Model Specification	Num. Factors	Num. Assets	AvgAbsAlpha (% p.m.)	GRS Statistic	p-value
1. CAPM	1	5	0.096	3.251	0.007
2. FF3 (Mkt, SMB, HML)	3	5	0.112	4.184	0.001
3. FF4 (Mkt, SMB, HML, Mom)	4	5	0.078	2.783	0.017
4. FF4 + ADF	5	5	0.077	2.134	0.060
5. FF4 + FMF	5	5	0.035	1.934	0.087
6. FF4 + FMF + ADF	6	5	0.080	2.125	0.061

Panel B: Test Assets = 25 Fama-French Size and B/M Portfolios					
Model Specification	Num. Factors	Num. Assets	AvgAbsAlpha (% p.m.)	GRS Statistic	p-value
1. CAPM	1	25	0.165	4.345	0.000
2. FF3 (Mkt, SMB, HML)	3	25	0.110	4.119	0.000
3. FF4 (Mkt, SMB, HML, Mom)	4	25	0.102	3.662	0.000
4. FF4 + ADF	5	25	0.098	3.486	0.000
5. FF4 + FMF	5	25	0.110	4.176	0.000
6. FF4 + FMF + ADF	6	25	0.099	3.563	0.000

This table reports results from the Gibbons et al. (1989) F-test for various factor models on two sets of test assets. Panel A uses five quintile portfolios formed by sorting stocks on realized β^{FOMO-} . Panel B uses the 25 Fama-French portfolios sorted on size and book-to-market. "AvgAbsAlpha (% p.m.)" is the average of the absolute values of the monthly time-series regression intercepts (alphas). "GRS Statistic" is the GRS F-statistic testing the null hypothesis that all alphas are jointly zero. FMF is our FOMO factor based on β^{FOMO-} sorts. ADF is Ang's (2006a) downside risk factor. Factors Mkt (Mkt-RF), SMB, HML, and Mom (Momentum) are from the Fama-French data library. The sample period for the time-series regressions is January 1980 to December 2024. The GRS test uses 540 time-series observations.

Panel A of Table 15 shows that when testing on the five β^{FOMO-} -sorted portfolios, the CAPM, FF3 and FF4 models are all strongly rejected, with GRS p-values of 0.007, 0.001 and 0.017, respectively. The average absolute alphas are also notable, for instance, 0.112% per month for the FF3 model. When our FMF factor is added to the FF4 model, there is a market improvement. The GRS statistics drops from 2.783 to 1.934 and the p-value increases substantially to 0.087, narrowly missing conventional significance levels. The average absolute alpha also reduces dramatically to 0.035% per month. This suggests

that the FMF factor is crucial for explaining the returns of portfolios sorted on β^{FOMO-} , which is expected as the factor is derived from these sorts.

For comparison, adding the ADF to FF4 results in a GRS statistic of 2.134 (p-value=0.060) and an average absolute alpha of 0.077%. While this is an improvement over FF4, the FMF factor achieves a lower average absolute alpha and a slightly higher p-value. The model including both FMF and ADF alongside FF4 does not show further improvement over Model 4 using only FMF, resulting in a GRS of 2.125 (p-value = 0.061). The associated average absolute alpha for the FMF, ADF and FF4 combination is = 0.080%. The GRS test results highlight that the FMF factor effectively captures the primary dimension of return variation across the β^{FOMO-} sorted portfolios.

To further validate the FMF factor, and ensure our results are not an artefact of the benchmark constructions, we conduct GRS tests on the 25 Fama-French portfolios sorted on size and book-to-market. As shown in Panel B, all tested models, including those augmented with our FMF factor, are strongly rejected. This is a common finding in the literature, as the returns of the 25 Fama-French portfolios are notoriously difficult to price and capture strong value and size dynamics not explicitly modeled by our factor. The results highlight that while the FMF factor is crucial for explaining the cross-section of FOMO-related risk, it is not a complete solution for all known market anomalies.

In contrast to the results for the FOMO-sorted portfolios, adding our FMF factor to the four-factor model does not improve its performance in pricing the 25 Fama-French portfolios on size and book-to-market. The GRS statistic of 4.176 for the FF4+FMF model is in fact higher than for the FF4 model alone (GRS 3.662). The higher GRS statistic indicates that while the FMF factor is pivotal for explaining the return variation across portfolios sorted on FOMO sensitivity, its pricing power does not extend to the well-documented size and value anomalies. Our GRS test results reinforce the interpretation of FMF as a distinct behavioral factor. The strong results from Panel A remain the key finding, affirming that the FMF factor captures a significant and priced source of FOMO-related risk.

5 Discussion

Our empirical findings provide substantial support for the FOMO-CAPM developed in this paper. We demonstrate that the emotional and social dynamics encapsulated by FOMO are not just behavioral quirks but are systematically priced in the cross-section of stock returns.

Our central empirical finding is the existence of a significant positive risk premium associated with negative FOMO beta, β^{FOMO-} . β^{FOMO-} captures a stock j 's sensitivity to underperforming its specific peer benchmark, H_j . In our empirical results the peer

benchmark is proxied by the Fama-French 38 Industry portfolio return. Our robustness analyses show that the existence of the β^{FOMO-} premium is not sensitive to the choice of benchmark. During periods when stock j has lower returns than its benchmark, when $r_j - h_j < 0$ ²⁹, univariate portfolio sorts reveal that stocks with the highest realized β^{FOMO-} earn dramatically higher average returns than stocks with the lowest β^{FOMO-} . Sorts on β^{FOMO-} produce a highly significant High-Low spread of 17.39% per annum (t -statistic 8.46).

The demonstrated premium for β^{FOMO-} proves remarkably robust in a multivariate setting. Fama-MacBeth regressions show that β^{FOMO-} commands a positive and statistically significant coefficient even after controlling for standard market beta (β^{CAPM}), firm characteristics (Log-Size, B/M, Momentum) and other risk measures like volatility, coskewness, cokurtosis and liquidity beta (Liq β). In our most comprehensive specification that includes all standard controls (Model VI), the coefficient on β^{FOMO-} is 0.103 (t -statistic 5.41). This translates to an economically meaningful increase of approximately 2.19% in 12-month excess returns for a one standard deviation increase in β^{FOMO-} exposure.

Crucially, the β^{FOMO-} premium remains significant even when directly compared against Ang et al. (2006a) downside market beta in a horse race specification (Model VIII). Both β^{FOMO-} , coefficient 0.103, (t -statistic 5.05), and β_{Ang}^- , coefficient 0.056, (t -statistic 3.61), are independently priced. The significance of both β^{FOMO-} and β_{Ang}^- indicates that our FOMO-based measure captures a dimension of downside risk distinct from, or incremental to, market-conditional downside beta. Furthermore, independent two-way portfolio sorts demonstrate that the β^{FOMO-} premium is not an artefact of coskewness, as both factors are independently priced. The positive premium for β^{FOMO-} is also robust across different sample sub-periods when excluding micro-cap stocks.

While the pricing of the positive FOMO beta β^{FOMO+} is also positive and significant in multivariate settings, our theory's primary prediction concerns the premium for sensitivity during the FOMO-active state β^{FOMO-} . Our results strongly affirm the premium for β^{FOMO} . The FMF factor, constructed from β^{FOMO-} sorted portfolios, also significantly improves the ability of standard asset pricing models to explain the returns of these β^{FOMO-} sorted portfolios in GRS tests.

The formal model in Section 3 predicts that, all else being equal, the introduction of a high-return benchmark ($E[h_m] > r_f$) will result in a FOMO risk premium that is smaller than the traditional market risk premium. The presence of FOMO is hypothesized to produce a less steep Security Market Line. However, our empirical results in Section 4 show the opposite. The empirical SML for FOMO-beta is dramatically steeper than that

²⁹The return comparison is between the stock returns r_j and the industry return on the industry containing stock j , h_j . The returns can be expressed as either raw or excess, since the impact of the r_f cancels out in the comparison.

of the CAPM. The seeming contradiction in the slope of the SMLs highlights the sheer magnitude of the FOMO effect in practice. While our simple model correctly identifies the components of the trade-off, it does not attempt to calibrate the intensity of the behavioral risk aversion associated with FOMO. The empirical evidence suggests that investors’ aversion to underperforming their peers is so profound that the price of this risk is far greater than what is commanded by standard market beta.

Our findings also contribute to the ongoing discussion about the construction of asset pricing factors, notably the “time-series” versus “cross-section” approaches compared in Fama and French (2019). The traditional method involves creating time-series factors (like SMB and HML) and then finding an asset’s constant loadings on these factors. Our FOMO-CAPM, however, follows the cross-section approach, where an asset’s characteristics (its β^{FOMO-}) are treated as pre-specified, time-varying factor loadings. Fama and French (2019) argue that the cross-section method provides a better description of average returns because the factor returns are optimized month-by-month to best fit the characteristics of the assets. Our strong empirical results, particularly the superior performance of our model over standard time-series models, are consistent with Fama and French (2019). Results presented here indicate that the FOMO phenomenon is best captured as a cross-sectional risk premium.

Further, our findings carry several important implications for asset pricing theory. Firstly, we provide strong empirical backing for the FOMO-CAPM, suggesting that the model’s core mechanism, where investors’ aversion to underperforming a peer benchmark due to FOMO, is a priced risk factor. Our FOMO-CAPM provides a behavioral rationale for observed deviations from CAPM predictions. The FOMO-CAPM demonstrates that investors influenced by FOMO will systematically demand higher expected returns. The additional demand for financial compensation reflects not only market risk but also emotional compensation due to FOMO. Support is given for the notion that utility functions should not only consider absolute wealth but also relative performance and the emotional consequences of social comparison (Abel 1990; Levy and Levy 2015).

Secondly, our work contributes to the broader behavioral finance literature by formally integrating a socially-driven emotional bias into a CAPM framework. Unlike traditional regret theory (Bell 1982; Loomes and Sugden 1982) which focuses on counterfactuals of unchosen alternatives from an individual’s decision set, or disappointment aversion (Gul 1991; Ang et al. 2006a) which relates to outcomes below a certain expectation, FOMO emphasizes an asymmetric aversion to underperforming an external, peer group benchmark. Furthermore, FOMO differs from anticipated regret (Zeelenberg 1999), which involves the foresight of dissatisfaction from potentially suboptimal choices. FOMO has a specific asymmetry related to the ranking against the peer benchmark and is driven by the desire to avoid the unique emotional cost of underperformance. Investors experiencing FOMO

anticipate regret, specifically if they underperform their peers, compelling alignment even if it means sacrificing some expected individual utility. The distinct pricing of β^{FOMO-} relative to β^{Ang-} underscores this conceptual difference between FOMO and downside risk. Our FOMO-CAPM explicitly models the fear component when one’s portfolio $W_{i,1}$ is less than the reference H_i , amplified by the $k_i(H_i)$ function, which is not present when rejoicing.

Thirdly, the results suggest that β^{FOMO-} represents a distinct dimension of risk that is not fully captured by standard factors like market, size, value and momentum, or other known behavioural (asymmetric) risk measures like coskewness or general downside market risk. Additionally, our distinct priced FOMO factor warrants consideration within the “factor zoo” landscape (Harvey et al. 2016; Feng et al. 2020). Our results speak to the necessity of accommodating measures that explicitly account for FOMO.

The behavioral extension proposed by the FOMO-CAPM is practically valuable as it offers potential explanatory power for several observed market anomalies and behaviors where social dynamics are thought to play a significant role. While this paper primarily focuses on establishing β^{FOMO-} as a priced risk factor, the underlying concept of FOMO has intuitive links to three observed market phenomena and anomalies. First, herding and bandwagon effects. The desire to avoid the emotional disutility of missing out on peer success could be a powerful driver of herding behaviour (see Ballinari and Müller 2021; Bikhchandani, Hirshleifer, and Welch 1992; Scharfstein and Stein 1990). If a particular investment or strategy is perceived to be adopted by one’s peer group (the reference portfolio H_i), individuals might follow suit even if the mimicing of H_i deviates from their own optimal strategy based on traditional risk-return metrics and private information. High β^{FOMO-} assets might be those that are particularly sensitive to such herding dynamics. Secondly, FOMO-CAPM insights provide a channel to explain momentum (see Jegadeesh and Titman, 1993; Daniel, Hirshleifer, and Subrahmanyam, 1998)). As certain assets generate high returns, investors fearing to miss out on continued gains might pile in, pushing prices further and perpetuating the momentum. Presence of the social transmission bias discussed by (Han et al. 2022), where only high-performing outcomes are communicated, would exacerbate FOMO and fuel momentum. Third, there exist channels through which FOMO contributes to speculative bubbles (see Kindleberger, Aliber, and Solow, 2005; Bonaparte and Fabozzi, 2025). The fear of missing out on extraordinary gains, especially when peers are perceived to be profiting, can lead to irrational exuberance and a departure from fundamental valuation. The FOMO-CAPM provides a framework where the utility impact of such missed opportunities is explicitly considered.

The finding that FOMO-related risk is priced also has practical implications. In portfolio management, investors and portfolio managers might consider evaluating their exposure to β^{FOMO-} . Assets with high β^{FOMO-} sensitivity are expected to yield higher

returns as compensation for the FOMO-related risk. Conversely, assets that hedge against FOMO (low β^{FOMO-}) would be valued by investors particularly prone to FOMO because of their potential to hedge against FOMO. The understanding of the role of FOMO enhances risk management, not just in terms of financial risk, but also the psychological risk of client dissatisfaction stemming from underperforming peer benchmarks. Financial advisors should address FOMO explicitly with clients. Further, regarding investor self-awareness, individual investors stand to benefit from recognizing their own susceptibility to FOMO. Further, investors should understand how FOMO influences their own investment decisions and potentially leads them to take on unintended risks.

While providing robust evidence for the pricing of FOMO-related risk, this study has certain limitations that open avenues for future research. One of the limitations lies in the proxy for the counterfactual benchmark returns h_j . We use the Fama-French 38 Industry portfolio returns as a proxy for the firm-specific counterfactual benchmark. We also show robustness to the use of Fama-French 12 Industry portfolios, using a value 1 percentage point higher than the industry average, and using the NASDAQ index. While the adoption of industry portfolios is reasonable and empirically tractable, actual investor peer groups and reference points are far more heterogeneous and dynamic. Future research could explore alternative or more direct proxies for H_i and h_j . Additionally, our empirical approach infers the impact of the FOMO-specific disutility component $k_i(\cdot)$ through the pricing of β^{FOMO-} . Direct estimation or calibration of $k_i(\cdot)$ from investor behaviour or experimental settings would be a valuable extension. Testing the FOMO-CAPM and the pricing of β^{FOMO-} in international markets and across different asset classes would establish the broader applicability of the model. The dynamic nature of FOMO could be further investigated. The intensity of FOMO in the market is likely time-varying. Future studies could investigate how the FOMO risk premium changes with overall market sentiment, volatility or during specific market phases (e.g., bull vs. bear markets). The time-varying coefficient results for β^{FOMO-} from our robustness checks already hint at links between economic factors and FOMO. These links to the economic environment in which FOMO is felt should be explored more formally. Lastly, while we discussed plausible links between FOMO, momentum and herding, dedicated empirical studies are needed to quantify the extent to which a FOMO factor does explain momentum and herding.

A crucial theoretical consideration for our framework is the choice of the market factor itself. In our empirical tests, we evaluate the FOMO factor against the standard CAPM market portfolio. However, following the literature on relative asset pricing, once a stochastic reference point is introduced, the definition of the appropriate market portfolio for pricing should arguably be redefined relative to this benchmark (Muralidhar, 2025). In our case, the industry portfolios that represent peers are the stochastic ref-

erence point. Hence in FOMO, the standard market portfolio may no longer be the theoretically consistent benchmark. When utility is driven by relative performance, the pricing kernel changes, and the stochastic reference point itself should emerge as a priced factor. Constructing and testing our FOMO beta against such a relative market portfolio is a complex but important next step for future research.

Our interest in FOMO arises from the observed social phenomenon that individuals receive disutility from the prospect that their peer group are able to generate additional utility from an option the individual did not choose. There is an immediate extension to investments where investors select portfolios, but will be aware of peers whose portfolios may perform better than the investors' selected portfolio. Through theoretic and empirical analysis we find strong support for a FOMO-CAPM. Our results show that FOMO is particularly prevalent in times of economic growth. Adding the consideration of peer effects into asset pricing models presents a promising route for further development.

6 Conclusion

This paper introduces and empirically validates a Fear of Missing Out Capital Asset Pricing Model (FOMO-CAPM). Our work recognizes that FOMO, an investor's asymmetric aversion to their portfolio underperforming a specific peer group reference benchmark, represents a distinct behavioral phenomenon not fully captured by traditional regret or disappointment aversion. We develop a theoretical framework where the specific emotional disutility of underperformance relative to peers influences asset valuation. The FOMO-CAPM posits that investors consider not only absolute returns but also the potential negative emotional impact of lagging their peers. In the FOMO-CAPM the asymmetry created between underperforming and overperforming the reference portfolio H_i enters through the $k_i(H_i)$ function. The specification of the FOMO-CAPM amplifies perceived losses from underperformance relative to peers.

Our empirical investigation, conducted on U.S. stock market data from 1980 to 2024, provides robust support for the central predictions of the FOMO-CAPM. We find compelling evidence that a negative FOMO beta, β^{FOMO-} , which measures a stock's historic sensitivity to underperforming its industry benchmark, commands a significant positive risk premium. The FOMO premium is economically meaningful, with stocks in the highest β^{FOMO-} quintile earning substantially higher excess returns than those in the lowest quintile. Stocks in the highest quintile when sorting by the negative FOMO beta, β^{FOMO-} , generate an annual excess return of 16.4%. The lowest quintile sorted by β^{FOMO-} has an excess return of -1.0% per annum. The high-minus-low spread is 17.4% with a t-statistic of 8.46. The battery of robustness tests presented undergird the presence of a FOMO effect within the US equity markets.

The significance of the β^{FOMO-} premium persists in multivariate Fama-MacBeth regressions. The β^{FOMO-} premium is robust to a comprehensive set of established risk factors, firm characteristics, including size, book-to-market and momentum, as well as other measures including coskewness, volatility, cokurtosis, liquidity beta and Ang et al. (2006a) downside market beta. Notably, β^{FOMO-} is shown to be priced independently of, and incrementally to, Ang et al. (2006a) measure. FOMO captures a unique dimension of risk related to peer group underperformance rather than just general market declines. Our findings are also robust to various portfolio construction methodologies, sample sub-periods and the exclusion of micro-cap stocks.

Furthermore, our findings stand up to the high statistical hurdles proposed for new factor discovery. Acknowledging the "factor zoo" phenomenon, Harvey and Liu (2021) suggest that a t-statistic greater than 3.0 is a more appropriate benchmark for a new factor to be taken seriously. Our primary risk premium for β^{FOMO-} consistently clears this higher bar across a wide range of specifications, with t-statistics often exceeding 4.0 or 5.0 (see Table 2). This statistical robustness, combined with the factor's strong theoretical motivation grounded in the behavioral concept of FOMO, provides confidence that our results are not a spurious or "lucky" finding. β^{FOMO-} is identified as a genuine and systematically priced risk in financial markets. Consequently, the FOMO-CAPM defines an important bridge between behavioral finance insights and traditional asset pricing models.

Our findings emphasize that understanding investor sensitivity to peer group underperformance is crucial for a more complete picture of risk and expected excess return in financial markets. Future research can further explore the dynamic nature of the FOMO premium and its interplay with various market conditions and investor behaviours. Understanding the variation in, and the specific drivers of, the magnitude of FOMO is particularly pertinent in today's markets, where social sentiment and peer influence are often amplified by technology and digital media. Social sentiment increasingly shapes individual investment decisions and hence asset prices in ways traditional models may not fully capture. The FOMO-CAPM provides an important step in the rectification of the gap between theory and practice in investor decision making.

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A Proposition Proofs

This appendix collects the proofs of Proposition 1 and Proposition 2 from the main paper. Equation numbers refer to the equations within Sections 2 and 3.

Proof of Proposition 1.

Let $\tilde{h}_i = \frac{g_i(H_i)}{W_{i,0}} - \frac{k_i(H_i)}{W_{i,0}}$. $\tilde{h}_i$ represents the effective counterfactual return and is used to simplify the subsequent notation. Further, let $\xi = -M_0 \left(\sum_{i=1}^I \frac{1+E \left[\frac{f'_i(W_{i,0}(r_{ip}-\tilde{h}_i))}{E[f'_i(W_{i,0}(r_{ip}-\tilde{h}_i))]} \right]}{E[f'_i(W_{i,0}(r_{ip}-\tilde{h}_i))]} \right)^{-1}$. ξ represents the aggregate sensitivity of the investor's utility to deviations in returns, as captured by the expected derivatives of the utility adjustment function. Applying Equation (11) to $\tilde{h}_i$, we obtain:

$$E[\tilde{h}_i] - r_f = \xi \text{cov}(r_m - h_m, \tilde{h}_i). \quad (\text{A.1})$$

Summing this equation over i , we have

$$E[h_m] - r_f = \xi \text{cov}(h_m, r_m - h_m). \quad (\text{A.2})$$

Again, by applying Equation (11) to r_m , we obtain

$$E[r_m] - r_f = \xi \text{cov}(r_m, r_m - h_m). \quad (\text{A.3})$$

From (A.2) and (A.3), we have

$$E[r_m] - E[h_m] = \xi \text{var}(r_m - h_m). \quad (\text{A.4})$$

Because $\xi > 0$ and $\text{var}(r_m - h_m) > 0$, it holds that $E[r_m] - E[h_m] > 0$. Hence, combining Equation (11) with (A.4) yields the asset pricing formula in Equation (16), ensuring that β_i^{FOMO} in Equation (17) is well defined. ■

Proof of Proposition 2.

Let investor i maximize their modified utility function:

$$\max_{\{w_{ij}\}} E[V_i(W_{i,1})] = E[W_{i,1} + f_i(W_{i,1} - g_i(H_i))] \quad (\text{A.5})$$

$g_i(H_i)$ is defined piecewise as per equation (4). $k_i(H_i)$ is convex ($k_i'' \geq 0$), such that disutility for investor i is amplified when underperforming peers if $W_{i,1} < H_i$. From the first-order condition, equation (7), when $E[r_m] - E[h_m] < 0$, the financial premium $E[r_j - r_f]$ is negative. Further, when $E[r_m] - E[h_m] < 0$ the emotional adjustment dominates such that

$$E[r_j - r_f] + E[(r_j - r_f)f'_i(W_{i,1} - g_i(H_i))] = 0 \quad (\text{A.6})$$

The term is strictly positive, $E[(r_j - r_f)f'_i(W_{i,1} - g_i(H_i))] > 0$ for two reasons. Firstly, there is asymmetric disutility amongst investors. When $W_{i,1} < H_i$, $f'_i(W_{i,1} - g_i(H_i)) < 0$

and $|f'_i(W_{i,1} - g_i(H_i))|$ increases due to $k_i(H_i)$. Secondly, for peer-correlated assets, $\text{cov}(r_j, f'_i(W_{i,1} - g_i(H_i))) > 0$. Hence, the covariance between assets ensures that (A.6) holds.

Investors hold peer-aligned portfolios $w_{ij} > 0$ for $\beta_j^{FOMO} > 0$ because

$$E[f_i(W_{i,1} - g_i(H_i))] > |E[r_j - r_f]|. \quad (\text{A.7})$$

The expected emotional benefit $E[f_i(W_{i,1} - g_i(H_i))]$ outweighs the magnitude of the negative financial premium $|E[r_j - r_f]|$. Hence the FOMO-CAPM pricing equation, (16), is satisfied even when $E[r_m] - E[h_m] < 0$.

Ex-post underperformance $r_m < h_m$ updates $H_i \rightarrow H_i + k_i(H_i)$, steepening $f_i(\cdot)$ via $k_i(H_i)$ and reinforcing future herding, as $|f'_i(\cdot)|$ increases for $W_{i,1} < H_i$.

Thus, investors prioritize emotional hedging over financial optimization, validating Proposition 2. ■

B Appendix: Additional Empirical Results

This appendix provides supplementary empirical results that support the main analyses in the paper. In all cases, the reference portfolio is constructed from the Fama French 38 Industry portfolios with value weighting. Details of the set up are provided in the main paper.

Table A1 presents the results for univariate portfolio sorts on several relative and difference-based beta measures, as discussed in Section 4.2. These sorts supplement the primary findings in Table 1 and highlight the complexity of interpreting relative beta sorts without multivariate controls.

Tables A2 and A3 provide a detailed analysis focusing on the unconditional Regret Beta β^R (which is equivalent to an unconditional β^{FOMO}). Table A2 presents the full Fama-MacBeth regression results, analogous to Table 2 in the main text, where β^R is the primary variable of interest. Table A3 examines the robustness of the β^R regression coefficient across different specifications and sample periods. These tables support the conclusion from the main text that the general peer-performance gap is a significantly priced factor.

Finally, Table A4 provides the detailed data for the analysis presented in Figure 3 of the main paper. Table A4 reports the time-series correlation between the daily excess return of each of the 38 Fama-French industry portfolios and the daily market excess return over the full sample period.

Table A1: Additional Univariate Portfolio Sort Results [Appendix]

Panel A: Sort on Rel. $\beta^{\text{FOMO}-}$ vs β^R						Panel B: Sort on Rel. $\beta^{\text{FOMO}+}$ vs β^R					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	4.54%	0.87	0.84	0.69	0.94	1 (Low)	-0.15%	0.80	0.80	0.89	0.65
1 (Low)	4.42%	0.87	0.85	0.68	0.90	2	11.39%	0.80	0.90	0.93	0.88
2	5.76%	0.77	0.89	0.86	0.93	3	9.18%	0.71	0.91	0.92	0.94
3	6.47%	0.71	0.89	0.90	0.92	4	6.46%	0.65	0.90	0.88	0.98
4	7.41%	0.67	0.89	0.94	0.89	5 (High)	3.59%	0.64	0.82	0.75	1.00
5 (High)	5.82%	0.66	0.80	0.97	0.75						
High-Low	1.40%					High-Low	3.73%				
t -stat	[1.32]					t -stat	[1.93]				
Panel C: Sort on Rel. $\beta^{\text{FOMO}+}$ vs β^{CAPM}						Panel D: Sort on Diff. β^{FOMO} ($\beta^{\text{FOMO}+} - \beta^{\text{FOMO}-}$)					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	6.96%	1.46	0.88	0.90	0.80	1 (Low)	2.69%	0.74	0.80	0.94	0.65
2	7.21%	0.95	0.88	0.90	0.88	2	8.64%	0.73	0.89	0.94	0.88
3	7.09%	0.72	0.86	0.88	0.88	3	7.47%	0.70	0.90	0.91	0.93
4	6.30%	0.52	0.85	0.86	0.88	4	6.22%	0.71	0.90	0.87	0.97
5 (High)	4.23%	0.20	0.86	0.87	0.92	5 (High)	4.31%	0.77	0.83	0.70	0.99
High-Low	-2.73%					High-Low	1.61%				
t -stat	[-0.91]					t -stat	[1.26]				

This table presents additional results from univariate portfolio sorts, following the same methodology as described for Table 1. Stocks are sorted into five quintiles based on the specified realised beta measures. Panel A sorts on relative negative FOMO beta versus Regret Beta ($\beta^{\text{FOMO}-} - \beta^R$). Panel B sorts on relative positive FOMO beta versus Regret Beta ($\beta^{\text{FOMO}+} - \beta^R$). Panel C sorts on relative positive FOMO beta versus CAPM beta ($\beta^{\text{FOMO}+} - \beta^{\text{CAPM}}$). Panel D sorts on the difference FOMO beta ($\beta^{\text{FOMO}+} - \beta^{\text{FOMO}-}$). Each panel reports average 12-month realised excess returns and post-ranking realised β^{CAPM} , β^R , $\beta^{\text{FOMO}-}$, and $\beta^{\text{FOMO}+}$ for equal-weighted quintile portfolios. The sample period for analysis is January 1980 to December 2024.

Table A2: Fama-MacBeth Regression Results with β^R [Appendix]

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	Mean (Std Dev)
Intercept	0.369 [9.80]***	-0.273 [-6.92]***	-0.264 [-6.91]***	-0.203 [-5.49]***	-0.203 [-5.52]***	0.182 [5.26]***	0.191 [5.51]***	0.142 [3.38]***	
β^{CAPM}	0.151 [4.32]***		0.026 [1.00]	0.041 [1.19]	0.032 [0.96]	0.140 [4.32]***	0.131 [3.78]***		0.729 (0.553)
β^R		0.370 [7.62]***	0.349 [8.57]***	0.298 [9.11]***	0.296 [9.31]***	0.236 [8.04]***	0.196 [7.30]***	0.225 [7.59]***	0.863 (0.198)
β_{Ang}^-								0.054 [3.49]***	0.809 (0.705)
β_{Ang}^+								0.027 [2.88]***	0.634 (0.763)
Log-Size	-0.032 [-5.74]***			0.000 [0.01]	-0.002 [-0.36]	-0.034 [-5.91]***	-0.031 [-5.55]***	-0.028 [-5.01]***	5.122 (1.977)
B/M	-0.022 [-3.54]***			-0.024 [-3.63]***	-0.024 [-3.63]***	-0.026 [-3.87]***	-0.022 [-3.46]***	-0.022 [-3.43]***	1.491 (4.259)
Momentum	-0.013 [-0.75]			0.006 [0.37]	0.006 [0.35]	-0.018 [-1.11]	-0.016 [-0.93]	-0.014 [-0.81]	0.078 (0.478)
Volatility	-0.445 [-8.92]***					-0.470 [-10.03]***	-0.424 [-8.35]***	-0.385 [-6.39]***	0.496 (0.267)
Coskewness	-0.136 [-4.05]***				-0.144 [-4.79]***	-0.140 [-4.25]***	-0.132 [-3.91]***	-0.078 [-2.09]**	-0.122 (0.171)
Cokurtosis	-0.006 [-0.49]					-0.007 [-0.59]	-0.007 [-0.56]	0.015 [1.11]	1.700 (1.238)
Liq β	0.010 [1.44]						0.010 [1.60]	0.011 [1.64]	-0.002 (0.406)

This table presents coefficients from firm-level Fama-MacBeth (1973) cross-sectional regressions focusing on the Regret Beta (β^R). Details regarding data, methodology, variable definitions, and t -statistic calculations are identical to those described in Table 2. The specifications explore the pricing of β^R both independently and alongside β^{CAPM} , various control variables, and Ang's (2006a) downside risk betas. The final column reports the time-series average of the cross-sectional mean and standard deviation for each independent variable. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Robustness of Fama-MacBeth β^R Coefficient [Appendix]

Scenario	Coefficient	t -statistic
A: β^R from Appendix Model VII (Full Controls with β^{CAPM})		
Full Sample	0.196	[7.30]***
Sub-Period 1 (1980-2002)	0.293	[7.67]***
Sub-Period 2 (2003-2024)	0.108	[4.21]***
Exclude Micro-Caps	0.160	[4.99]***
B: β^R from Appendix Horse Race Model VIII (vs. Ang Betas)		
Full Sample	0.225	[7.59]***
Sub-Period 1 (1980-2002)	0.337	[8.17]***
Sub-Period 2 (2003-2024)	0.124	[4.38]***
Exclude Micro-Caps	0.186	[5.22]***

This appendix table presents the Fama-MacBeth coefficient and t -statistic for the Regret Beta (β^R) under different scenarios and from two key model specifications detailed in Table A2 (Appendix). Panel A shows β^R from Appendix Model VII (which includes β^R , β^{CAPM} , and all standard controls). Panel B shows β^R from Appendix Model VIII (the "horse race" which includes β^R , Ang's (2006a) downside and upside market betas, and all standard controls, while excluding β^{CAPM}). "Full Sample" uses the entire period January 1980 - December 2024. "Sub-Period 1" covers 1980-2002 and "Sub-Period 2" covers 2003-2024. "Exclude Micro-Caps" runs regressions after removing stocks in the lowest NYSE market capitalisation quintile. Coefficients are time-series averages from monthly Fama-MacBeth regressions. t -statistics use Newey and West (1987) standard errors with 12 lags. *** denotes significance at the 1% level.

Table A4: Correlation of 38 Industry Portfolios with the Market Factor [Appendix]

Industry	Correlation	Industry	Correlation	Industry	Correlation
Steam Supply	0.0682	Electric, Gas, and Water Supply	0.6920	Radio and Television Broadcasting	0.7712
Irrigation Systems	0.0937	Lumber and Wood Products	0.6996	Fabricated Metal Products	0.7861
Public Administration	0.2430	Miscellaneous Manufacturing Industries	0.7003	Chemicals and Allied Products	0.7970
Tobacco Products	0.4484	Apparel and Other Textile Products	0.7027	Transportation	0.8046
Mining	0.4917	Telephone and Telegraph Communication	0.7033	Transportation Equipment	0.8089
Agriculture, forestry, and fishing	0.5094	Furniture and Fixtures	0.7086	Wholesale	0.8228
Nonmetallic Minerals Except Fuels	0.5250	Stone, Clay and Glass Products	0.7206	Finance, Insurance, and Real Estate	0.8240
Sanitary Services	0.5588	Paper and Allied Products	0.7263	Retail Stores	0.8246
Oil and Gas Extraction	0.5851	Rubber and Miscellaneous Plastics Products	0.7285	Electrical and Electronic Equipment	0.8339
Leather and Leather Products	0.6240	Food and Kindred Products	0.7320	Instruments and Related Products	0.8411
Textile Mill Products	0.6321	Construction	0.7337	Machinery, Except Electrical	0.8556
Missing	0.6447	Printing and Publishing	0.7491	Services	0.8760
Petroleum and Coal Products	0.6560	Primary Metal Industries	0.7539		

This table reports the time-series correlation between the daily value-weighted returns of each of the 38 Fama-French industry portfolios and the daily market excess return. The sample period is January 1980 to December 2024. Industries are sorted from lowest to highest correlation to illustrate the wide variation in market exposure. The mean correlation across all industries is 0.6716.

C Appendix: Robustness to a Constant Shift in the Benchmark

To test the robustness of our findings to the specific level of the peer-group benchmark, we replicate our main analyses under an alternative specification what we term an "aspirational" benchmark. A potential concern is that our results could be sensitive to the absolute level of the benchmark returns rather than the co-movement between a stock and its benchmark. To address this, we add a constant of 100 basis points (1% per annum) to the daily industry benchmark return h_j in every period before calculating the conditional FOMO betas and running our tests. This modification uniformly increases the performance hurdle for every stock but does not alter the time-series variation of the benchmark.

Table A5 replicates the main univariate portfolio sorts from Table 1, while Table A6 replicates the full Fama-MacBeth regressions from Table 2. The findings are remarkably strong: the portfolio sort spreads, regression coefficients, and statistical significance levels for our key variables, particularly β^{FOMO-} , are virtually identical to those reported in the main body of the paper. The continued significance of the key variables demonstrates that our results are not an artefact of the specific level of the peer benchmark. The robustness tests confirms that the inference in the main paper is driven by the sensitivity of stocks to benchmark fluctuations. The core mechanism of the FOMO-CAPM is robust to a significant, constant upward shift in the performance benchmark.

D Appendix: Empirical Results for using the High-Tech (NASDAQ) Benchmark

It is often argued that investors give special attention to the growth of tech stocks. Tech stocks have the potential to revolutionize industries, but involve the issuing firms undertaking extensive R&D and risking the failure of their business. Because the business model of a technology firm hinges on future success, the potential upside for investors is large. However, the risk of failure is also higher. Investors may ordinarily not select such high risk stocks, but it is highly likely that members of their peer group would select high tech stocks. Hence an alternative benchmark for investors is the average performance of high technology stocks.

This appendix provides the comprehensive supplementary results for the empirical tests discussed in Section 4. All analyses presented here use the NASDAQ Composite Index as the proxy for the peer-group benchmark, representing a portfolio of high-tech and high-growth stocks. These tables provide detailed breakdowns, robustness checks, and additional evidence supporting the main findings presented in the text.

Table A5: Portfolio Sorts with Aspirational Benchmark (+1% to Industry) [Appendix]

Panel A: Sort on β^{CAPM}						Panel B: Sort on β^R (Regret Beta)					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	1.75	0.09	0.73	0.76	0.75	1 (Low)	-2.16	0.40	0.54	0.59	0.54
2	5.93	0.51	0.83	0.85	0.86	2	2.38	0.56	0.80	0.81	0.83
3	7.11	0.76	0.89	0.90	0.92	3	6.55	0.66	0.91	0.92	0.95
4	8.01	1.03	0.95	0.95	0.97	4	11.26	0.92	0.99	1.00	1.02
5 (High)	9.93	1.57	0.99	0.98	0.98	5 (High)	15.26	1.31	1.10	1.11	1.12
High-Low	8.18					High-Low	17.42				
t -stat	[2.55]					t -stat	[7.36]				

Panel C: Sort on $\beta^{\text{FOMO}-}$						Panel D: Sort on $\beta^{\text{FOMO}+}$					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	-1.01	0.49	0.58	0.52	0.63	1 (Low)	-3.72	0.48	0.59	0.67	0.52
2	1.37	0.60	0.81	0.80	0.84	2	6.95	0.62	0.83	0.85	0.84
3	4.79	0.66	0.90	0.92	0.92	3	10.67	0.71	0.92	0.92	0.96
4	8.97	0.83	0.96	1.01	0.97	4	9.99	0.88	0.98	0.96	1.04
5 (High)	16.37	1.13	1.06	1.15	1.05	5 (High)	6.81	1.08	1.06	1.04	1.15
High-Low	17.38					High-Low	10.53				
t -stat	[8.45]					t -stat	[8.15]				

Panel E: Sort on Rel. $\beta^{\text{FOMO}-}$ vs β^{CAPM}					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	7.52	1.50	0.89	0.84	0.90
2	8.02	0.99	0.89	0.88	0.91
3	7.65	0.74	0.87	0.88	0.89
4	6.54	0.53	0.85	0.88	0.87
5 (High)	3.16	0.20	0.84	0.91	0.86
High-Low	-4.36				
t -stat	[-1.48]				

This table presents portfolio sort results using an "aspirational benchmark," defined as the industry average daily return plus a 1% annualised premium. It is analogous to Table 1 in the main paper. All methodologies for beta calculation, portfolio formation, and t -statistic computation are identical to those described for Table 1. The results demonstrate that the main conclusions regarding the pricing of FOMO betas are robust to this alternative benchmark specification.

Table A6: Fama-MacBeth Regressions with Aspirational Benchmark (+1% to Industry)
[Appendix]

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	Mean (Std Dev)
Intercept	0.072 [1.48]	-0.306 [-7.52]***	-0.297 [-7.34]***	-0.205 [-4.93]***	-0.203 [-4.96]***	0.209 [5.56]***	0.220 [5.76]***	0.169 [3.86]***	
β^R	0.249 [8.10]***								0.863 (0.198)
β^{CAPM}			0.031 [1.18]	0.052 [1.49]	0.044 [1.29]	0.147 [4.48]***	0.137 [3.92]***		0.729 (0.553)
$\beta^{\text{FOMO}-}$		0.189 [4.61]***	0.160 [4.98]***	0.091 [4.54]***	0.087 [4.42]***	0.103 [5.40]***	0.091 [4.75]***	0.103 [5.04]***	0.879 (0.213)
$\beta^{\text{FOMO}+}$		0.206 [8.26]***	0.211 [7.37]***	0.201 [7.95]***	0.202 [8.23]***	0.077 [3.70]***	0.053 [2.72]***	0.067 [3.32]***	0.884 (0.235)
β_{Ang}^-								0.056 [3.61]***	0.809 (0.705)
β_{Ang}^+								0.028 [3.09]***	0.634 (0.763)
lnSize	-0.028 [-4.97]***			-0.002 [-0.31]	-0.004 [-0.66]	-0.033 [-5.82]***	-0.030 [-5.49]***	-0.026 [-4.93]***	5.122 (1.977)
BM	-0.022 [-3.44]***			-0.024 [-3.64]***	-0.024 [-3.65]***	-0.026 [-3.89]***	-0.022 [-3.49]***	-0.022 [-3.46]***	1.491 (4.259)
Mom	-0.010 [-0.56]			0.004 [0.25]	0.004 [0.23]	-0.017 [-1.00]	-0.015 [-0.83]	-0.012 [-0.70]	0.078 (0.478)
Volatility	-0.269 [-4.08]***					-0.452 [-9.37]***	-0.411 [-7.88]***	-0.367 [-5.90]***	0.496 (0.267)
Coskewness	-0.125 [-3.44]***				-0.146 [-4.94]***	-0.141 [-4.33]***	-0.131 [-3.95]***	-0.077 [-2.08]**	-0.122 (0.171)
Cokurtosis	0.065 [4.23]***					-0.007 [-0.53]	-0.007 [-0.52]	0.017 [1.27]	1.700 (1.238)
Liq β	0.012 [1.76]*						0.010 [1.59]	0.011 [1.62]	-0.002 (0.406)

This table presents Fama-MacBeth regression results using an "aspirational benchmark," defined as the industry average daily return plus a 1% annualised premium. It is analogous to Table 2 in the main paper. All methodologies for beta calculation, variable definitions, and t -statistic computation (Newey-West with 12 lags) are identical to those described for Table 2. The sample period is January 1980 to December 2024. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

D.1 Univariate Portfolio Sorts

To supplement the primary univariate sort on β^{FOMO-} presented in the main text, Table A7 shows the results for portfolios sorted on various alternative beta definitions. In all cases the reference portfolio is the NASDAQ index.

As shown in Panels C and D, portfolios sorted on either downside sensitivity, β^{FOMO-} , or upside sensitivity, β^{FOMO+} , earn large and significant positive returns. However, these univariate sorts also reveal a natural co-movement between different risk exposures. For instance, in the β^{FOMO-} sort of Panel C, the standard market beta, β^{CAPM} increases from 0.40 in the lowest quintile to 1.16 in the highest quintile. This indicates that a portion of the observed premium could be compensation for standard market risk rather than purely for the risk captured by β^{FOMO-} . Therefore, while these results provide strong initial support for our hypothesis, they underscore the necessity of the multivariate Fama-MacBeth framework to properly disentangle the unique risk premium associated with FOMO from other known factors.

To test the robustness of our main portfolio sort findings, we re-examine the premium for β^{FOMO-} under three scenarios: (1) after excluding small-cap stocks, (2) using all available stocks for portfolio formation, and (3) using value-weighted instead of equal-weighted portfolio returns. Table A8 presents these results.

The results in Table A8 confirm that the β^{FOMO-} premium is robust across different portfolio construction methods. As shown in Panel A, the premium remains large and statistically significant in equal-weighted portfolios, both when including all stocks (14.73%, $t = 5.16$) and when excluding small-caps (18.06%, $t = 5.19$). Consistent with many behavioral anomalies, the premium is considerably attenuated and statistically insignificant in value-weighted portfolios. This suggests the FOMO effect is more pronounced among smaller firms and is not driven solely by mega-cap stocks, a finding we explore further in the interaction sorts.

D.2 Fama-MacBeth Regressions

Table A9 presents the full results for the firm-level Fama and MacBeth (1973) cross-sectional regressions. The specifications build from a simple model to the comprehensive "horse race" model (Model VIII) that includes all control variables and Ang's (2006a) downside risk measures.

The results in Table A9 demonstrate the robustness of the β^{FOMO-} risk premium. The coefficient on β^{FOMO-} remains positive and statistically significant across all specifications, even after the inclusion of a comprehensive set of controls for firm characteristics and other known risk factors. In the most stringent "horse race" specification (Model VIII), the β^{FOMO-} premium (coefficient = 0.129, $t = 4.88$) remains larger and more significant than the premium for Ang's (2006a) market downside beta (coefficient = 0.049,

Table A7: Portfolio Sorts with the High-Tech (NASDAQ) Benchmark

Panel A: Sort on β^{CAPM}						Panel B: Sort on β^R (Regret Beta)					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	1.75	0.09	0.65	0.69	0.66	1 (Low)	-0.43	0.33	0.41	0.49	0.39
2	5.93	0.51	0.75	0.79	0.78	2	3.33	0.51	0.71	0.75	0.72
3	7.11	0.76	0.82	0.85	0.85	3	5.73	0.64	0.84	0.86	0.87
4	8.01	1.03	0.90	0.92	0.92	4	8.53	0.87	0.93	0.94	0.96
5 (High)	9.93	1.57	0.97	0.98	0.96	5 (High)	14.32	1.32	1.03	1.05	1.05
High-Low	8.18					High-Low	14.75				
t -stat	[2.55]					t -stat	[4.96]				

Panel C: Sort on $\beta^{\text{FOMO}-}$						Panel D: Sort on $\beta^{\text{FOMO}+}$					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	0.49	0.40	0.46	0.44	0.48	1 (Low)	-2.81	0.39	0.45	0.55	0.37
2	2.56	0.55	0.73	0.73	0.76	2	4.88	0.57	0.74	0.79	0.72
3	4.78	0.65	0.83	0.86	0.86	3	8.66	0.67	0.85	0.87	0.88
4	7.42	0.83	0.91	0.96	0.92	4	9.66	0.84	0.93	0.93	0.98
5 (High)	15.18	1.16	0.99	1.08	0.98	5 (High)	8.59	1.16	1.00	0.99	1.08
High-Low	14.69					High-Low	11.41				
t -stat	[5.15]					t -stat	[5.58]				

Panel E: Sort on Rel. $\beta^{\text{FOMO}-}$ vs β^{CAPM}					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	7.34	1.51	0.88	0.86	0.88
2	8.59	0.99	0.85	0.85	0.87
3	8.31	0.77	0.80	0.83	0.82
4	7.56	0.56	0.75	0.80	0.77
5 (High)	2.61	0.23	0.77	0.84	0.78
High-Low	-4.74				
t -stat	[-1.73]				

This table presents average 12-month realised excess returns and post-ranking realised betas for equal-weighted quintile portfolios, using the NASDAQ Composite as the peer-group benchmark. The results in Panels C and D show a significant premium for both downside ($\beta^{\text{FOMO}-}$) and upside ($\beta^{\text{FOMO}+}$) sensitivity. The negative spread in the relative sort in Panel E highlights the confounding effect of market beta in univariate sorts, underscoring the need for the multivariate analysis that follows.

Table A8: Robustness Checks of Portfolio Sorts (NASDAQ Benchmark)

Panel A: Sorts by realised $\beta^{\text{FOMO-}}$			
Portfolio	Exclude small (%)	All stocks (%)	Value-weighted (%)
1 (Low)	4.13	0.49	9.84
2	8.84	2.56	9.31
3	10.83	4.78	7.32
4	13.79	7.42	6.56
5 (High)	22.18	15.22	11.78
High-Low	18.06	14.73	1.94
<i>t</i> -statistic	(5.19)*	(5.16)*	(0.79)

Panel B: Sorts by realised β^R			
Portfolio	Exclude small (%)	All stocks (%)	Value-weighted (%)
1 (Low)	3.67	-0.43	9.08
2	9.18	3.34	8.67
3	11.97	5.73	8.16
4	14.69	8.53	7.66
5 (High)	20.25	14.38	11.22
High-Low	16.57	14.81	2.14
<i>t</i> -statistic	(4.29)*	(4.98)*	(0.75)

Panel C: Sorts by realised Rel. $\beta^{\text{FOMO-}}$ vs β^R			
Portfolio	Exclude small (%)	All stocks (%)	Value-weighted (%)
1 (Low)	10.26	5.44	10.60
2	11.95	6.63	7.88
3	12.35	6.64	7.93
4	13.24	7.10	7.70
5 (High)	11.97	4.97	8.97
High-Low	1.71	-0.47	-1.63
<i>t</i> -statistic	(1.25)	(-0.32)	(-1.56)

This table presents robustness checks for the main portfolio sort results using the NASDAQ benchmark. The premium for $\beta^{\text{FOMO-}}$ in Panel A remains strong and significant in equal-weighted portfolios but attenuates when value-weighting is applied, a common feature of many behavioral factors. * denotes significance at the 1% level.

Table A9: Fama-MacBeth Regressions with the High-Tech (NASDAQ) Benchmark

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	Mean (Std Dev)
Intercept	0.078 [1.55]	-0.233 [-6.07]***	-0.213 [-5.80]***	-0.156 [-3.42]***	-0.159 [-3.53]***	0.189 [4.30]***	0.192 [4.27]***	0.139 [3.07]***	
β^R	0.317 [11.46]***								0.863 (0.198)
β^{CAPM}			0.029 [1.21]	0.047 [1.35]	0.038 [1.12]	0.128 [3.79]***	0.118 [3.21]***		0.729 (0.553)
$\beta^{\text{FOMO}-}$		0.135 [2.38]**	0.104 [2.12]**	0.071 [1.69]*	0.077 [1.87]*	0.122 [4.57]***	0.105 [3.72]***	0.129 [4.88]***	0.879 (0.213)
$\beta^{\text{FOMO}+}$		0.185 [7.37]***	0.180 [6.78]***	0.176 [8.08]***	0.171 [8.00]***	0.092 [4.28]***	0.077 [3.58]***	0.093 [4.25]***	0.884 (0.235)
β_{Ang}^-								0.049 [3.13]***	0.809 (0.705)
β_{Ang}^+								0.020 [2.09]**	0.634 (0.763)
lnSize	-0.028 [-5.10]***			-0.001 [-0.22]	-0.003 [-0.56]	-0.032 [-5.55]***	-0.029 [-5.19]***	-0.026 [-4.77]***	5.122 (1.977)
BM	-0.022 [-3.55]***			-0.024 [-3.73]***	-0.024 [-3.73]***	-0.026 [-3.93]***	-0.022 [-3.52]***	-0.022 [-3.50]***	1.491 (4.259)
Mom	-0.014 [-0.78]			0.003 [0.20]	0.003 [0.19]	-0.018 [-1.06]	-0.016 [-0.90]	-0.014 [-0.80]	0.078 (0.478)
Volatility	-0.332 [-5.44]***					-0.443 [-9.39]***	-0.398 [-7.71]***	-0.369 [-6.13]***	0.496 (0.267)
Coskewness	-0.121 [-3.43]***				-0.139 [-4.68]***	-0.139 [-4.38]***	-0.129 [-3.96]***	-0.068 [-1.88]*	-0.122 (0.171)
Cokurtosis	0.059 [3.75]***					-0.003 [-0.23]	-0.003 [-0.23]	0.020 [1.44]	1.700 (1.238)
Liq β	0.009 [1.40]						0.009 [1.42]	0.009 [1.39]	-0.002 (0.406)

This table presents coefficients from firm-level Fama-MacBeth (1973) cross-sectional regressions of 12-month realised excess returns on realised betas and firm characteristics, using the NASDAQ Composite as the peer-group benchmark. t -statistics, reported in brackets, are computed using Newey and West (1987) standard errors with 12 lags. The results show that the premium for $\beta^{\text{FOMO}-}$ is positive and significant across all specifications, including the full horse race in Model (VIII). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

$t = 3.13$), providing strong evidence that our measure captures a unique, priced dimension of risk.

It is insightful to observe the pattern of the β^{FOMO-} coefficient across the specifications. The statistical significance temporarily weakens in Models (IV) and (V). This is an expected result, as these models introduce firm characteristics (size, book-to-market, momentum) that are correlated with β^{FOMO-} , as shown in our analysis of its determinants (see Appendix Table A14). These characteristics absorb some of the explanatory power.

Crucially, the premium for β^{FOMO-} re-emerges with high statistical significance (t -statistic > 4.5 in Model VI) once we also control for stock volatility. This powerfully reinforces the finding from our interaction sorts (Table A16) that the FOMO effect, while most pronounced among high-volatility stocks, is a distinct phenomenon. By controlling for these correlated characteristics and volatility, the final models (VI-VIII) successfully isolate a clean, robust, and economically meaningful FOMO risk premium.

To further test the robustness, Table A10 examines the stability of the β^{FOMO-} coefficient from our key specifications (Model VII and Model VIII) across different sample periods and after excluding micro-cap stocks.

Table A10: Robustness of Fama-MacBeth β^{FOMO-} Coefficient (NASDAQ Benchmark)

Scenario	Coefficient	t-statistic
A: β^{FOMO-} Model VII (Full Controls)		
Full Sample (1980-2024)	0.105	(3.72)*
Sub-Period 1 (1980-2002)	0.068	(1.32)
Sub-Period 2 (2003-2024)	0.138	(5.67)*
Exclude Micro-Caps	0.143	(5.68)*
B: β^{FOMO-} Horse Race Model VIII		
Full Sample (1980-2024)	0.129	(4.88)*
Sub-Period 1 (1980-2002)	0.114	(2.35)*
Sub-Period 2 (2003-2024)	0.143	(5.96)*
Exclude Micro-Caps	0.163	(6.66)*

This table presents the Fama-MacBeth coefficient and t -statistic for β^{FOMO-} under different scenarios using the NASDAQ benchmark. The premium is robust across the full sample, in sub-periods, and when excluding micro-cap stocks. The two models correspond to the specifications in Table A9. * denotes significance at least at the 5% level.

Table A10 demonstrates the robustness of the multivariate β^{FOMO-} premium over time and across different firm size groups. In the stringent "horse race" model (Panel B), the premium is positive and statistically significant in both the 1980-2002 period (t -statistic 2.35) and the 2003-2024 period (t -statistic 5.96). In the full-control model, presented in Panel A, the premium is notably stronger and more statistically significant in the second

half of the sample. Crucially, across all models, the premium remains robust and highly significant for the full sample and after excluding micro-cap stocks, confirming the effect is not driven by the smallest firms or a specific era alone.

D.3 Direct Asymmetry Test

To formally test the central hypothesis that FOMO is an asymmetric phenomenon, we conduct a direct test of the difference between the premia for $\beta^{\text{FOMO}-}$ and $\beta^{\text{FOMO}+}$ using a reparameterized panel regression. Table A11 presents the results.

Table A11: Disentangling Asymmetric FOMO from Symmetric Regret (NASDAQ Benchmark)

Variable	Coefficient	<i>t</i> -statistic
Panel A: Key Behavioral Betas		
$\beta^{\text{FOMO}-}$ (Asymmetry: $\gamma^{F-} - \gamma^{F+}$)	0.073***	[3.31]
$\beta_{\text{sum}}^{\text{FOMO}}$ (Level: γ^{F+})	-0.146***	[-6.86]
β^R (Symmetric Regret)	0.328***	[7.42]
Panel B: Standard Control Variables		
β^{CAPM}	0.114***	[11.50]
Log(Size)	-0.188***	[-34.93]
Book-to-Market (BM)	-0.022***	[-10.86]

This table presents results from a reparameterized pooled panel regression using the NASDAQ benchmark to directly test for asymmetry. The dependent variable is the 12-month realised stock excess return. The regression includes firm and time fixed effects and uses two-way clustered standard errors. The coefficient on $\beta^{\text{FOMO}-}$ directly estimates the difference in the premia for under- and outperformance ($\gamma^{F-} - \gamma^{F+}$). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A11 provides the results for the direct test of asymmetry. The key finding is the positive and highly significant coefficient on the Asymmetry term ($\beta^{\text{FOMO}-}$). This directly confirms that the premium for downside risk is statistically larger than the premium for upside sensitivity, which is the central hypothesis of the FOMO-CAPM. Furthermore, the continued significance of the symmetric β^R term suggests that both general regret and asymmetric FOMO are independently priced risk dimensions.

D.4 Determinants and Persistence of $\beta^{\text{FOMO}-}$

To understand the economic nature of FOMO risk, we analyze the firm characteristics that determine the realised $\beta^{\text{FOMO}-}$. Table A12 presents the results from Fama-MacBeth regressions where realised $\beta^{\text{FOMO}-}$ is the dependent variable. Table A13 does likewise for $\beta^{\text{FOMO}+}$.

Table A12: Determinants of Realised FOMO Betas with the High-Tech (NASDAQ) Benchmark

Characteristic	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Intercept	0.7714 (8.81)***	0.8839 (11.79)***	0.8308 (15.52)***	0.7177 (4.60)***	0.8222 (19.20)***	0.7622 (9.92)***	0.8357 (12.01)***	0.7085 (7.11)***
Log(Size)	0.0118 (1.11)							-0.0107 (-2.72)***
BM		-0.0048 (-1.36)						-0.0020 (-2.24)**
Momentum			0.0255 (1.64)*					0.0193 (5.20)***
Volatility				0.2372 (2.00)**				0.2029 (3.04)***
Coskewness					-0.0074 (-0.15)			0.0540 (3.05)***
Cokurtosis						0.0514 (4.89)***		0.0761 (6.55)***
Liquidity β							0.0073 (0.68)	0.0034 (1.35)

This table presents time-series averages of coefficients from monthly cross-sectional regressions explaining realised FOMO betas using the NASDAQ benchmark. For each month, the realised $\beta^{\text{FOMO-}}$ (Panel A) or $\beta^{\text{FOMO+}}$ (Panel B) is regressed on lagged firm characteristics. Models (I) through (VII) are univariate regressions, while Model (VIII) is a multivariate regression including all characteristics simultaneously. t -statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A13: Determinants of Realised FOMO Betas with the High-Tech (NASDAQ) Benchmark

Characteristic	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Intercept	0.6883 (8.29)***	0.8798 (24.31)***	0.8181 (21.48)***	0.7542 (8.68)***	0.8065 (28.74)***	0.7385 (14.08)***	0.8243 (24.23)***	0.7511 (9.50)***
Log(Size)	0.0255 (2.92)***							-0.0051 (-1.56)
BM		-0.0028 (-2.68)***						-0.0011 (-1.40)
Momentum			0.0659 (6.27)***					0.0351 (8.00)***
Volatility				0.1408 (1.42)				0.0771 (1.21)
Coskewness					-0.0321 (-0.62)			-0.0372 (-1.97)**
Cokurtosis						0.0642 (7.26)***		0.0632 (6.51)***
Liquidity β							0.0079 (0.99)	0.0044 (1.24)

This table presents time-series averages of coefficients from monthly cross-sectional regressions explaining realised FOMO betas using the NASDAQ benchmark. For each month, the realised $\beta^{\text{FOMO-}}$ (Panel A) or $\beta^{\text{FOMO+}}$ (Panel B) is regressed on lagged firm characteristics. Models (I) through (VII) are univariate regressions, while Model (VIII) is a multivariate regression including all characteristics simultaneously. t -statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The analysis in Table A12 reveals a consistent economic profile. β^{FOMO-} is significantly and negatively related to firm size and book-to-market ratio, and positively related to past-year momentum. This indicates that the firms carrying the highest FOMO risk are typically smaller, high-momentum growth stocks, aligning with the intuition that FOMO is most relevant for speculative, high-profile assets. Table A13 confirms consistency with the main paper for β^{FOMO+} .

A key requirement for a risk factor to be priced is that it must be a persistent characteristic. Table A14 shows the results of annual, non-overlapping regressions testing this persistence.

Table A14: Annual Persistence of Realised FOMO Betas with the High-Tech (NASDAQ) Benchmark

Explanatory Variable (End of Year T)	β^{FOMO-} (Year T+1)	β^{FOMO+} (Year T+1)
Intercept	0.438*** (11.89)	0.404*** (13.64)
Past β^{FOMO-} (Year T)	0.395*** (14.13)	
Past β^{FOMO+} (Year T)		0.456*** (18.30)
Past Volatility (Year T)	0.085*** (4.27)	0.025 (1.30)
Log(Size) (Year T)	0.008*** (3.25)	0.009*** (3.89)
Book-to-Market (Year T)	-0.001 (-0.81)	-0.002 (-1.44)
Momentum (Year T)	0.006*** (2.74)	0.015*** (7.00)

This table reports Fama-MacBeth coefficients from annual, non-overlapping regressions testing the persistence of FOMO betas, using the NASDAQ benchmark. The dependent variable is the realised beta over Year T+1. Independent variables are the realised beta and other firm characteristics from the end of Year T. *t*-statistics, reported in parentheses, are computed using Newey-West (1987) standard errors with 5 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A14 shows that β^{FOMO-} is highly persistent year-over-year. The coefficient on the prior year's β^{FOMO-} in predicting the current year's beta is 0.395 and is highly statistically significant (*t*-statistic 14.13). The ability of the prior year's value to predict the subsequent year confirms that exposure to FOMO risk is a stable firm characteristic, justifying its role as a systematic risk factor. Stability is also seen for β^{FOMO+} . The predictability of future β^{FOMO-} and β^{FOMO+} from past values helps allay the critique of

D.5 Robustness: Controlled and Interaction Portfolio Sorts

To ensure the β^{FOMO-} premium is not simply a proxy for other known factors, we conduct a series of controlled portfolio sorts. Table A15 reports the β^{FOMO-} High-Low spread after neutralizing returns for firm size, book-to-market, momentum, and coskewness.

Table A15: High-Low Spreads on FOMO Betas after Controlling for Firm Characteristics (NASDAQ Benchmark)

Panel A: Sorts on β^{FOMO-}							
Control Variable	Quintile Portfolios on β^{FOMO-}					Spread	
	1 (Low)	2	3	4	5 (High)	High-Low	t-statistic
Log(Size)	−4.87	−3.22	−0.97	1.31	7.96	12.83	(2.35)**
BM	−3.36	−1.31	−0.37	1.11	6.42	9.78	(2.39)**
Momentum	−5.35	−3.48	−1.30	1.39	8.53	13.87	(3.52)***
Coskewness	−4.98	−3.22	−0.99	1.43	8.09	13.07	(2.57)***

Panel B: Sorts on β^{FOMO+}							
Control Variable	Quintile Portfolios on β^{FOMO+}					Spread	
	1 (Low)	2	3	4	5 (High)	High-Low	t-statistic
Log(Size)	−7.89	−0.78	2.72	3.35	1.49	9.39	(2.19)**
BM	−6.08	1.65	3.05	2.62	−0.72	5.36	(2.34)**
Momentum	−8.56	−1.16	2.30	3.41	2.21	10.77	(4.21)***
Coskewness	−8.06	−0.68	2.82	3.39	1.83	9.88	(2.91)***

This table presents average 12-month characteristic-adjusted excess returns for portfolios sorted on realised FOMO betas. Each month, we first sort stocks into quintiles based on a control characteristic, Log(Size), BM, etc. Within each quintile, we then subtract the quintile's equal-weighted average return from each stock's return to get an adjusted return. All stocks are then pooled and sorted into quintiles based on their realised β^{FOMO-} (Panel A) or β^{FOMO+} (Panel B). The table reports the time-series average of the monthly characteristic-adjusted returns for each quintile. The High-Low column is the spread between Quintile 5 and Quintile 1, with Newey-West (1987) t -statistics adjusted for 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A15 confirms that the β^{FOMO-} premium remains economically large and statistically significant after all controls. For example, after controlling for momentum, the premium is still 13.87% (t-statistic 3.52). Table A14 provides strong evidence that the FOMO premium is an incremental effect, distinct from these other well-documented factors.

We further investigate the nature of the FOMO premium by examining its interaction

with stock volatility and firm size. Table A16 presents results from independent 5x5 sorts on volatility and β^{FOMO-} .

Table A16: Portfolio Returns from 5x5 Sorts on Volatility and FOMO Betas (NASDAQ Benchmark)

Panel A: Secondary Sort on β^{FOMO-}							
Volatility	Quintiles formed on β^{FOMO-}					Spread	
Quintile	1 (Low)	2	3	4	5 (High)	High-Low	<i>t</i>-statistic
1 (Low Vol)	7.96	7.61	7.11	6.66	6.57	-1.40	(-0.81)
2	13.88	10.77	9.23	8.57	10.15	-3.74	(-3.05)***
3	14.90	10.99	9.34	8.85	12.51	-2.38	(-1.20)
4	10.71	10.36	9.50	9.95	16.41	5.70	(1.83)*
5 (High Vol)	-19.59	-6.39	1.03	5.30	18.19	37.79	(8.42)***

Panel B: Secondary Sort on β^{FOMO+}							
Volatility	Quintiles formed on β^{FOMO+}					Spread	
Quintile	1 (Low)	2	3	4	5 (High)	High-Low	<i>t</i>-statistic
1 (Low Vol)	3.88	5.39	6.82	8.41	11.40	7.52	(6.46)***
2	5.84	9.24	11.14	12.85	13.53	7.69	(5.37)***
3	7.67	10.42	12.45	13.14	12.92	5.24	(3.13)***
4	9.71	11.47	12.77	12.22	10.78	1.07	(0.52)
5 (High Vol)	-21.25	0.43	6.99	7.57	4.83	26.08	(11.08)***

This table presents average 12-month excess returns for 25 portfolios formed from sequential 5x5 sorts on volatility and a FOMO beta. Each month, stocks are first sorted into quintiles based on their realised volatility over the prior 12 months. Then, within each volatility quintile, stocks are further sorted into five quintiles based on their realised β^{FOMO-} (Panel A) or β^{FOMO+} (Panel B). The High-Low column reports the return spread between Quintile 5 and Quintile 1 of the FOMO beta sort within each volatility quintile. *t*-statistics are based on Newey and West (1987) standard errors with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The results in Tabl A16 reveal a powerful interaction. The β^{FOMO-} premium is absent in low-volatility stocks but is exceptionally strong among high-volatility stocks, where the High-Low portfolio earns a remarkable 37.79% per annum ($t = 8.42$). This suggests the FOMO effect is most pronounced in the market's most speculative segments.

Table A17 presents results from 2x5 sorts on firm size and β^{FOMO-} , using a more robust Newey-West correction for the *t*-statistics.

Table A17 shows that the FOMO premium is present across both size groups but is significantly amplified among small stocks. The High-Low spread for small stocks is a highly significant 18.15% (*t*-statistic 5.82), while for large stocks it is a positive but less significant 5.24% (*t*-statistic 1.93). The difference in these premia is itself highly

Table A17: Portfolio Returns from 2x5 Sorts on Size and $\beta^{\text{FOMO-}}$ (NASDAQ Benchmark)

$\beta^{\text{FOMO-}}$ Quintile	Size Group		
	Small	Big	Big - Small
1 (Low)	-1.28	8.62	9.91
2	0.47	8.96	8.50
3	4.26	7.56	3.31
4	8.03	6.89	-1.13
5 (High)	16.87	13.86	-3.00
High-Low Spread	18.15	5.24	-12.91
t-statistic	(5.82)*	(1.93)*	(-7.23)*

This table presents average 12-month excess returns for 10 portfolios formed from sequential 2x5 sorts on firm size and realised $\beta^{\text{FOMO-}}$, using the NASDAQ benchmark. Each month, stocks are first assigned to two size groups ("Small" or "Big") based on the median NYSE market capitalization breakpoint. Then, within each size group, stocks are sorted into five quintiles based on their realised $\beta^{\text{FOMO-}}$. The "High-Low" row reports the return spread between Quintile 5 and Quintile 1. t -statistics, reported in parentheses, are computed using Newey-West (1987) standard errors with 12 lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

significant (t-statistic -7.23), confirming that while FOMO risk is pervasive, its pricing is most impactful in the small-cap segment.

D.6 GRS Factor Model Tests

Finally, we assess whether a factor constructed to capture the FOMO premium (FMF) can help explain the returns of benchmark portfolios. Table A18 reports the results from Gibbons, Ross, and Shanken (1989) F-tests.

The GRS test results in Table A18 are presented in two panels. Panel A tests the ability of different factor models to price portfolios sorted on $\beta^{\text{FOMO-}}$ itself. The results are compelling. Whilst standard models fail to be rejected, adding our FOMO factor (FMF) to the Fama-French 4-factor model yields the lowest average absolute alpha and the highest p-value (0.660), indicating it is the best-specified model for pricing FOMO-related risk. Panel B tests the models on the 25 Fama-French size/book-to-market portfolios. Here, consistent with the findings for many behavioral factors, the FMF does not help price these portfolios. This reinforces that FOMO is a distinct risk dimension, separate from traditional size and value effects.

Table A18: GRS Test Results (NASDAQ Benchmark)

Panel A: Test Assets = 5 β^{FOMO} -Sorted Portfolios

Model Specification	Num. Factors	Num. Assets	AvgAbsAlpha (% p.m.)	GRS Statistic	<i>p</i> -value
1. CAPM	1	5	0.129	1.618	0.153
2. FF3 (Mkt, SMB, HML)	3	5	0.108	1.525	0.180
3. FF4 (Mkt, SMB, HML, Mom)	4	5	0.072	0.727	0.603
4. FF4 + ADF	5	5	0.143	5.824	0.000
5. FF4 + FMF	5	5	0.069	0.652	0.660
6. FF4 + FMF + ADF	6	5	0.115	1.303	0.261

Panel B: Test Assets = 25 Fama-French Size and B/M Portfolios

Model Specification	Num. Factors	Num. Assets	AvgAbsAlpha (% p.m.)	GRS Statistic	<i>p</i> -value
1. CAPM	1	25	0.165	4.345	0.000
2. FF3 (Mkt, SMB, HML)	3	25	0.110	4.119	0.000
3. FF4 (Mkt, SMB, HML, Mom)	4	25	0.102	3.662	0.000
4. FF4 + ADF	5	25	0.098	3.486	0.000
5. FF4 + FMF	5	25	0.103	3.927	0.000
6. FF4 + FMF + ADF	6	25	0.097	3.221	0.000

This table reports results from the Gibbons, Ross, and Shanken (1989) F-test for various factor models using the NASDAQ benchmark. FMF is our FOMO factor. ADF is Ang's (2006a) downside risk factor.

E Appendix: Robustness to 12 Fama-French Industry Portfolios Benchmark

To ensure our findings are not sensitive to the granularity of the industry classification, this appendix replicates our core analyses using the 12 Fama-French industry portfolios as the benchmark for the peer group. When industry portfolios are used as a control in many papers, including Ang et al. (2006a), the aggregation of the stocks is into 12 portfolios. There is some disagreement about the constituents of each of the broad portfolios, with those used in Ang et al. (2006a) differing from those provided in the Ken French Data Library. This appendix uses the Fama-French 12 Industry Portfolios. A potential issue with overly broad benchmarks is the dilution of the peer effect; when a benchmark portfolio contains a very large and diverse set of firms, its average return may become a less salient signal of specific peer success. While the more granular 38-industry classification used in our main analysis represents a more psychologically realistic proxy for an investor’s reference group, the 12-industry classification is a common standard in the literature, and confirming our results are robust to this specification is an important test. Table A19 presents the main portfolio sort results.

The univariate sorts in Table A19 confirm that the premium for downside FOMO sensitivity remains large and highly significant, with a High-Low spread of 14.83% ($t = 6.78$) when using the 12-industry benchmark. To test this in a multivariate setting, Table A20 presents the full Fama-MacBeth regression results.

To demonstrate the robustness of the multivariate β^{FOMO-} premium, Table A21 examines the stability of its coefficient from our key Fama-MacBeth specifications across different sample periods and after excluding micro-cap stocks.

The Fama-MacBeth results in Table A21 demonstrate the robustness of the β^{FOMO-} risk premium to this broader benchmark. Consistent with our main findings, the statistical significance of β^{FOMO-} temporarily weakens in the intermediate models (IV-V) as standard firm characteristics that are correlated with the FOMO phenomenon are introduced. Crucially, however, the premium re-emerges with high statistical significance in the final specifications that control for volatility. In the most stringent "horse race" specification (Model VIII), the premium for β^{FOMO-} remains economically large and highly significant (coefficient = 0.085, $t = 4.41$), confirming our central findings.

Given that the lack of granularity within the 12 industry portfolios makes it hard for investors to monitor the performance of their "peer group", we pause the analysis of the 12 industry case here. Full results are available on request from the authors.

Table A19: Portfolio Sorts with the 12 Industry Portfolios Benchmark

Panel A: Sort on β^{CAPM}						Panel B: Sort on β^R (Regret Beta)					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	1.75	0.09	0.66	0.69	0.68	1 (Low)	-0.44	0.35	0.42	0.47	0.41
2	5.93	0.51	0.77	0.80	0.81	2	2.42	0.55	0.74	0.77	0.77
3	7.11	0.76	0.84	0.85	0.87	3	6.12	0.66	0.89	0.89	0.92
4	8.01	1.03	0.92	0.93	0.95	4	10.03	0.94	0.98	0.98	1.00
5 (High)	9.93	1.57	0.98	0.98	0.98	5 (High)	15.19	1.40	1.09	1.09	1.11
High-Low	8.18					High-Low	15.64				
<i>t</i> -stat	[2.55]					<i>t</i> -stat	[6.11]				

Panel C: Sort on $\beta^{\text{FOMO}-}$						Panel D: Sort on $\beta^{\text{FOMO}+}$					
Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$	Portfolio	Return	β^{CAPM}	β^R	$\beta^{\text{FOMO}-}$	$\beta^{\text{FOMO}+}$
1 (Low)	1.33	0.42	0.45	0.41	0.50	1 (Low)	-2.91	0.42	0.47	0.55	0.40
2	1.36	0.59	0.75	0.74	0.80	2	5.42	0.59	0.78	0.81	0.78
3	4.25	0.67	0.87	0.89	0.90	3	9.78	0.69	0.89	0.90	0.94
4	8.09	0.86	0.94	0.99	0.95	4	10.01	0.91	0.96	0.95	1.02
5 (High)	16.16	1.18	1.04	1.13	1.03	5 (High)	8.42	1.22	1.05	1.02	1.14
High-Low	14.83					High-Low	11.32				
<i>t</i> -stat	[6.78]					<i>t</i> -stat	[6.92]				

This table presents average 12-month realised excess returns and post-ranking realised betas for equal-weighted quintile portfolios, using the 12 Fama-French industry portfolios as the peer-group benchmark. Panel C confirms that stocks with the highest sensitivity to underperforming the benchmark ($\beta^{\text{FOMO}-}$) earn significantly higher returns, with a High-Low spread of 14.83% per annum ($t=6.78$).

Table A20: Fama-MacBeth Regressions with the 12 Industry Portfolios Benchmark

Variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	Mean (Std Dev)
Intercept	0.103 [2.29]**	-0.201 [-6.73]***	-0.186 [-6.57]***	-0.130 [-3.51]***	-0.132 [-3.60]***	0.223 [5.97]***	0.228 [5.86]***	0.182 [4.41]***	
β^R	0.274 [12.92]***								
β^{CAPM}			0.031 [1.20]	0.052 [1.48]	0.043 [1.26]	0.141 [4.24]***	0.130 [3.67]***		
$\beta^{\text{FOMO}-}$		0.090 [2.35]**	0.060 [1.86]*	0.029 [1.09]	0.033 [1.26]	0.089 [4.58]***	0.075 [3.78]***	0.085 [4.41]***	
$\beta^{\text{FOMO}+}$		0.201 [7.65]***	0.200 [7.10]***	0.197 [8.76]***	0.193 [8.84]***	0.102 [5.31]***	0.082 [4.67]***	0.099 [5.21]***	
β_{Ang}^-								0.055 [3.50]***	
β_{Ang}^+								0.024 [2.58]**	
lnSize	-0.031 [-5.69]***			-0.003 [-0.53]	-0.005 [-0.89]	-0.034 [-6.09]***	-0.031 [-5.73]***	-0.028 [-5.28]***	
BM	-0.023 [-3.47]***			-0.024 [-3.69]***	-0.024 [-3.69]***	-0.027 [-3.91]***	-0.022 [-3.51]***	-0.022 [-3.49]***	
Mom	-0.010 [-0.55]			0.007 [0.39]	0.006 [0.38]	-0.016 [-0.99]	-0.014 [-0.82]	-0.012 [-0.69]	
Volatility	-0.310 [-4.73]***					-0.458 [-9.44]***	-0.413 [-7.80]***	-0.374 [-5.97]***	
Coskewness	-0.128 [-3.59]***				-0.142 [-4.75]***	-0.144 [-4.48]***	-0.133 [-4.07]***	-0.074 [-2.03]**	
Cokurtosis	0.062 [3.94]***					-0.007 [-0.57]	-0.007 [-0.52]	0.017 [1.23]	
Liq β	0.009 [1.35]						0.009 [1.32]	0.009 [1.31]	

This table presents coefficients from firm-level Fama-MacBeth (1973) cross-sectional regressions using the 12 Fama-French industry portfolios as the peer-group benchmark. t -statistics, reported in brackets, are computed using Newey-West (1987) standard errors with 12 lags. The premium for $\beta^{\text{FOMO}-}$ remains positive and significant in the most comprehensive specifications. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A21: Robustness of Fama-MacBeth $\beta^{\text{FOMO-}}$ Coefficient (12 Industry Benchmark)

Scenario	Coefficient	t-statistic
A: $\beta^{\text{FOMO-}}$ from Model VII (Full Controls)		
Full Sample (1980-2024)	0.075	(3.78)***
Sub-Period 1 (1980-2002)	0.026	(0.86)
Sub-Period 2 (2003-2024)	0.119	(5.40)***
Exclude Micro-Caps	0.113	(6.46)***
B: $\beta^{\text{FOMO-}}$ from Model VIII (Horse Race)		
Full Sample (1980-2024)	0.085	(4.41)***
Sub-Period 1 (1980-2002)	0.043	(1.44)
Sub-Period 2 (2003-2024)	0.123	(5.61)***
Exclude Micro-Caps	0.118	(6.95)***

This table presents the Fama-MacBeth coefficient and t -statistic for $\beta^{\text{FOMO-}}$ under different scenarios using the 12 Fama-French industry portfolios as the benchmark. The premium is robust across the full sample and when excluding micro-cap stocks, and shows significant time-variation, being stronger in the second half of the sample. The two models correspond to the specifications in Table A20. *** denotes significance at the 1% level.