

Take the Long View: Horizon Bias and Equity Term Premia on Earnings Days

Xicheng Li*

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Abstract

Horizon bias—the tendency for investors to be more optimistic over long horizons than short horizons—helps explain why a substantial share of the equity term premium is realized around earnings announcements. Retail investors, who are more prone to horizon bias, amplify mispricing by bidding up long-duration stocks ahead of earnings release. High arbitrage risk during these events deters rational speculators from correcting the mispricing until news arrival. Horizon bias also accounts for the announcement returns of value, profitability, and low-risk factors, as these strategies invest in firms with near-future cash flows. Furthermore, long-term optimism is more pronounced following waves of investor sentiment, leading to larger horizon bias. I show that active institutional investors time market sentiment, and their time-varying duration tilts are sufficient to explain the 8.7% spread of term premia across sentiment states.

The term structure of discount rates underlies numerous economic applications. For example, accurately determining maturity-specific risk premia to discount future cash flows is essential for investment decision-making and asset valuation. Moreover, the duration of the equity market has increased substantially over time (Golez and Koudijs 2025). This secular shift reflects firms' strategic response to enhanced growth prospects through increased earnings reinvestment, as well as environmental concerns that drive capital allocation toward long-term climate change mitigation projects (Giglio et al. 2024). As cash flows are pushed further into the future, understanding the long end of the term structure becomes increasingly important. Several papers attempt to reconcile classic asset pricing models with the observed downward-sloping equity term structure (van Binsbergen et al. 2012; van Binsbergen and Koijen 2017). Existing explanations rely on

* Hong Kong University of Science and Technology (xicheng.li@connect.ust.hk)

risk-based factors, behavioral biases, or market frictions. However, it remains unclear which channel most effectively explains the equity term structure.

In this paper, I show that horizon bias accounts for the cross-sectional equity term premium. I document three main findings. First, roughly 40% of the annual term premium is realized around earnings announcements, and horizon bias explains this concentration. Second, I provide micro-level evidence that retail investors, who are more susceptible to horizon bias, bid up long-duration stocks before earnings, while high arbitrage risk during these periods deters rational speculators from correcting the mispricing. Third, long-term optimism is more pronounced following waves of investor sentiment because the valuation of distant-future cash flows is highly subjective and difficult to arbitrage. I show that active institutional investors time market sentiment, and their time-varying duration tilts are sufficient to explain the 8.7% spread in term premia across sentiment states.

These findings suggest that biased beliefs about future cash flows drive price movements, especially around news events, which leads to return predictability at earnings announcements. In addition, the results show that stock ownership does not fall cleanly along retail or institutional lines. Retail demand can crowd out or crowd in institutional investors depending on market conditions, and this interaction significantly affects asset prices.

I start by calculating the proportion of the equity term premium realized on earnings announcement days. The equity term premium is defined as the difference in average returns between the short- and the long-duration quintile portfolios. In the data, the annualized term premium is 10.92%. To highlight its significance around earnings announcements, I examine a $[-5, +5]$ window relative to quarterly earnings dates. The earnings announcement setting is ideal because price movements driven by cash flow news are permanent (Chen et al. 2013).¹ The annualized returns realized across the four quarterly windows sum to 4.53%, accounting for 41.45% of the annual term premium.² Moreover, long-duration stocks earn significantly positive returns in the days before the announcement, producing a V-shaped term structure. After the earnings news is released, returns for the long-duration quintile sharply reverse—the average earnings-day return is -27 bps—and the downward-sloping term structure emerges.

The concentrated realization of term premia and the sharp return reversal of long-duration stocks challenge most existing explanations for the downward-sloping term structure. If these returns were compensation for risk (Lettau and Wachter 2007; Gormsen 2021), the required discount rate changes would be implausibly large (Engelberg et al. 2018). Consumption-based models (Gonçalves 2021a) cannot explain the announcement premium, as the contemporaneous covariance between stock returns and aggregate consumption is too small over short intervals (Ai and Bansal 2018). Friction-based explanations (Frazzini and Pedersen 2014; Xiao 2023; Li and

¹ By contrast, discount rate news has only a temporary impact. Xiao (2023) show that major anomalies earn more than half of their annual risk-adjusted returns before scheduled FOMC announcements, but these gains largely reverse after the event.

² This proportion far exceeds the average anomaly returns around earnings announcements, underscoring the importance of earnings news for the equity term premium.

Xu 2024) also fall short, as these papers predict selling pressure on long-duration stocks before announcements, not the observed price drift.

Instead, horizon bias—the tendency for investors to be more optimistic over long horizons than short horizons—helps explain why a substantial share of the equity term premium is realized around earnings announcements (Cassella et al. 2023). Because long-duration stocks pay most of their cash flows far in the future, investors overestimate their cash-flow growth. I confirm horizon bias by showing that standardized unexpected earnings (SUE) decline with equity duration, indicating an upward-sloping term structure of optimism bias. SUE is negative for the long-duration quintile, so investors are, on average, disappointed by the earnings news of these firms. The SUE pattern suggests that investors are too pessimistic about the cash flow growth of short-duration firms and too optimistic about that of long-duration firms. The belief correction, even if partial, leads to the large spread observed between short- and long-duration stocks at earnings announcements.

To clarify the link between horizon bias and term premia around earnings announcements, I introduce a firm-level horizon bias measure, defined as the difference between cross-sectionally standardized long-term and short-term growth rate forecasts. The present value model from Cassella et al. (2023) predicts that when investors' long-term growth forecasts are more optimistic than their short-term forecasts, the subsequent equity term premium is positive.³ To test this prediction, I construct double-sorted portfolios. Each quarter, I first sort firms with earnings announcements into five quintiles by equity duration. Within each duration quintile, I then sort firms into five groups by their horizon bias measure. Sorting by duration first ensures that growth rates are comparable within each group. I find asymmetric effects: the relationship between horizon bias and announcement returns is positive for short-duration stocks but negative for long-duration stocks. As a result, the term premium is concentrated in the high horizon bias group—15.05 bps for the top quintile and only 1.93 bps for the bottom quintile, which is consistent with the model prediction.

I disentangle the sources of earnings-day term premia by decomposing SUE into risk and behavioral components. Following Glosten et al. (2021), I regress firm-level SUE on market-wide and industry-wide SUE; the fitted values form the risk component, and the residuals represent the behavioral component. The risk component captures the covariance between firm-level and aggregate cash flow news, reflecting the systematic risk of announcing firms (Savor and Wilson 2016). The behavioral component captures the idiosyncratic part unrelated to systematic risk. Empirically, the risk component is positive and declines with duration, while the behavioral component is negative and increases in magnitude with duration. For long-duration stocks, the negative behavioral component outweighs the positive risk component, resulting in negative SUE. This large behavioral component explains both the pre-announcement drift and return reversal in

³ Cassella et al. (2023) define the equity term as the difference in average returns between the market portfolio and short-term dividend strips, while this paper defines it as the difference in average returns between the short- and long-duration quintile portfolios, which is inverse.

long-duration stocks.⁴

Next, to further investigate the mechanism behind the earnings-day term premia, I use transaction data to examine retail order flow around earnings announcements.⁵ I find that retail net trading before earnings announcements increases significantly with equity duration. Retail order imbalance reflects buying pressure from retail investors, and this pattern is consistent with the finding that long-duration stocks earn positive returns before earnings announcements, even if their earnings are less informative about aggregate cash flows (Savor and Wilson 2016). Regressions of retail order flow on firm characteristics show that equity duration and horizon bias have significant explanatory power, even after controlling for momentum (Aboody et al. 2010) and lottery-like features (Liu et al. 2020). This “retail sort” aligns with evidence that retail investors trade hard-to-value stocks with more intangible capital and longer-duration cash flows (Laarits and Sammon 2024). Retail investors’ demand for long-duration stocks are more pronounced ahead of earnings announcements, because of lower inventory costs and/or enhanced investor attention. Overall, retail investors are horizon-biased, and their buying pressure before earnings news temporarily amplifies mispricing, which is corrected when the news arrives.

If retail investors’ price pressure builds up mispricing, a natural follow-up question is why rational speculators do not correct such mispricing before earnings announcements. I show that heightened arbitrage risk reduces institutional investors’ incentives to intervene. I measure arbitrage risk using the idiosyncratic volatility (IVOL) in the pre-announcement period, following Yang et al. (2020). IVOL shows a U-shaped pattern across duration quintiles, with short- and long-duration stocks both displaying higher volatility than medium-duration stocks. Since idiosyncratic risk is the main impediment to arbitrage (Hong and Sraer 2016), horizon bias and limits to arbitrage together explain why short-duration stocks tend to be underpriced and long-duration stocks tend to be overpriced. Institutional investors facing tracking error constraints also reduce their exposure to long-duration stocks with high market beta before earnings announcements. Performance contracts encourage institutions to overweight high-beta stocks for higher returns, but penalize excessive tracking error volatility (Barroso et al. 2025). Therefore, IVOL and tracking error concerns deter institutions from correcting mispricing, allowing retail buying pressure to persist. In this sense, retail investors crowd out institutional investors in the pre-announcement period.

Taken together, the preceding evidence suggests that horizon bias drives the term premium around earnings announcements. Cash-flow duration provides a unified perspective on major equity factors, because these strategies go long short-duration stocks and short long-duration

⁴ The large risk component of the short-duration quintile explains why the term premium does not turn negative prior to the announcement. Some anomalies earn negative returns before earnings announcements, e.g., Liu et al. (2020).

⁵ I identify retail trades using the subpenny digit rule from Boehmer et al. (2021), which relies on U.S. regulations requiring disclosure of price improvement for internalized retail trades. I sign retail trades using the quote midpoint rule from Barber et al. (2024) to address potential bias in the Boehmer et al. (2021) algorithm. While measurement error is a concern, the large volume of monthly trades means that even modest attribution rates likely preserve the correct ranking of retail activity across stocks, which is the main focus of this paper (Laarits and Sammon 2024).

stocks (Gormsen and Lazarus 2023). Building on this insight, I test whether the horizon bias mechanism extends to correlated investing styles (Barberis and Shleifer 2003). I find evidence of external validity—horizon bias explains earnings-day returns for value, profitability, and low-risk factors, and retail investors hold a large share of the short legs of these anomalies before announcements.

Finally, because the valuations of distant-future cash flows are highly subjective and difficult to arbitrage, long-term optimism strengthens after waves of investor sentiment (Baker and Wurgler 2006). I show that the spread in term premia between high- and low-sentiment states is 8.7%, with most of the term premium realized during high-sentiment periods. For expected returns on long-duration stocks to fall with investor sentiment, long-duration stocks must become less overvalued relative to short-duration stocks as sentiment subsides. To complement the analysis of retail-institutional interaction, I examine institutional investors' duration preferences. While previous results suggest segmentation between stocks held by retail and institutional investors (Laarits and Sammon 2024), I use a portfolio-based framework (Kojen and Yogo 2019) to show that retail demand can also crowd in institutional investors (Kyle 1985).

I provide three findings on institutional investors' duration tilts. First, institutional duration preferences are highly procyclical. Active investors, such as hedge funds and active mutual funds, tilt toward long-duration, retail-heavy stocks when market funding liquidity is abundant and investor sentiment is high. Second, the smart-money effect persists—institutional duration preferences positively predict short-run stock returns. A long-short portfolio sorted by institutional duration demand delivers a monthly alpha of 1%. I also show that institutional investors front-run retail order flow, consistent with the bubble-riding mechanism in Brunnermeier and Nagel (2004). Third, in a counterfactual scenario, I drop institutions with the largest changes in duration preference between high- and low-sentiment states, whose AUM represent 10% of total investor assets. I reallocate their AUM to the remaining institutions proportionally, and the resulting price impact is sufficient to explain the spread in term premia across sentiment states.

In sum, this paper provides a horizon-bias explanation for the cross-sectional equity term premium. Horizon bias, together with limits to arbitrage, explains why retail buying pressure builds up mispricing before earnings announcements. More broadly, I show that active institutional investors also display strong duration preferences during bubble periods, indicating that stock market ownership does not follow a strict retail-institutional divide. While this finding is consistent with institutional sophistication in timing market sentiment, I cannot rule out that inexperienced fund managers may also be susceptible to horizon bias (Greenwood and Nagel 2009).

Related literature This paper relates to three main strands of literature. First, I contribute to literature on the equity term structure. van Binsbergen and Kojen (2017) provide comprehensive reviews. Most existing work focuses on the unconditional term premium, either at the aggregate level (van Binsbergen et al. 2012; Gonçalves 2021a; Gormsen and Lazarus 2023) or in the cross-section of individual stocks (Weber 2018; Gonçalves 2021b). I complement this literature by

documenting that a large share of the term premium is realized around earnings announcements and that horizon bias explains this concentration. This paper is closely related to studies that link biased beliefs about cash flows to the term structure of equity returns (Croce et al. 2015; Weber 2018; Cassella et al. 2023). Cassella et al. (2023) show that horizon bias negatively predicts the aggregate equity term premium. I differ by focusing on the cross-section of long- and short-duration stocks and providing micro-level evidence on investor trading behavior.

Second, this paper adds to the literature on the earnings announcement premium. Prior work links its magnitude to both idiosyncratic (Barber et al. 2013; Yang et al. 2020; Di Maggio et al. 2023) and systematic risk (Patton and Verardo 2012; Savor and Wilson 2016). On the idiosyncratic side, I highlight the joint role of horizon bias and idiosyncratic volatility in explaining the term premium around quarterly earnings events. On the systematic side, I decompose earnings news into systematic and behavioral components, reconciling systematic risk with biased expectations. A related strand of literature studies anomaly returns on news days (Aboody et al. 2010; Engelberg et al. 2018; Liu et al. 2020). I propose horizon bias as a unified explanation for the announcement returns of value, profitability, and low-risk anomalies. This paper is closely related to Liu et al. (2020), who examine lottery demand around earnings release dates. I show that the term premium patterns are robust to controlling for lottery-like features. Moreover, idiosyncratic volatility is high for both short- and long-duration stocks, which supports a limits-to-arbitrage explanation rather than a pure gambling explanation.

Finally, this paper speaks to the literature that highlights the role of investor heterogeneity and imperfect risk-sharing in shaping the risk-return trade-off in security prices. One part of this literature studies asset pricing by estimating asset demand across markets, including equity, fixed income, and country-level assets (Kojien and Yogo 2019, 2020; Bretscher et al. 2022; Kojien et al. 2024; Jiang et al. 2024). I provide one application of this framework to study the countercyclicality of equity term premia. Another strand focuses on retail investors, including work on U.S. household trading behavior (Gabaix et al. 2024), the retail investment boom (van der Beck and Jaunin 2021), investor clienteles for stock characteristics (Balasubramaniam et al. 2023), and retail sort (Laarits and Sammon 2024). This paper is closely related to Laarits and Sammon (2024), who maintain a preferred habitat view of retail investing and emphasize retail investors' comparative advantage in trading hard-to-value stocks. The key difference is that I take a sentiment-based view of retail trading behavior and document time-varying retail-institutional segmentation.

1. Data

My empirical analysis draws on three primary data sources. First, I obtain earnings announcement data and analyst forecasts from IBES. Second, I obtain stock-level variables, such as prices and shares outstanding, from CRSP and supplement these with accounting data from Compustat. Finally, I collect quarterly institutional holdings data from FactSet. I briefly describe the variable

construction below and provide additional details in Appendix C.2.

1.1. Measuring the equity term premium

A growing body of literature documents evidence that the term structure of the stock market is downward-sloping (van Binsbergen et al. 2012; van Binsbergen and Koijen 2017). At the aggregate level, risk premia on short-term dividend strips are higher than those on the market index, an average over all strips. In the cross-section, a downward-sloping equity term structure implies that short duration individual stocks that make up the equity index have higher expected returns than their long duration counterparts (Weber 2018; Gonçalves 2021b; Gormsen and Lazarus 2023).

I measure the equity term premium in the cross-section as the difference in average returns between stocks in the short duration quintile (long leg) and those in the long duration quintile (short leg). Equity duration is defined as the weighted average timing of stocks' payouts to investors:

$$\text{Dur}_{n,t} = \sum_{h=1}^{\infty} w_{n,t}^h \cdot h = \sum_{h=1}^{\infty} \frac{\mathbf{E}_t[\text{PO}_{n,t+h}] \cdot \exp(-h \cdot r_{n,t})}{\text{ME}_{n,t}} \cdot h, \quad (1)$$

where $w_{n,t}^h$ represents the fraction of firm n 's current market value that is due to the cash flow maturing in h years. Firms' total payouts (dividends + repurchases – issuances), $\text{PO}_{n,t+h}$, are treated as cash flows to equity investors. $r_{n,t}$ is defined as the discount rate that equates the present value of firm n 's future cash flows to its current market equity (Gonçalves 2021b). I obtain the annual firm-level duration measure from Andrei S. Gonçalves' personal website. The duration data coverage starts in 1973 and ends in 2023. Figure A1 plots the cross-sectional distribution of equity duration in 2023.

I gather stock prices data from the Center for Research in Security Prices (CRSP). My sample consists of U.S. firms with ordinary common shares that are traded on the New York Stock Exchange, the American Stock Exchange, or NASDAQ. Specifically, I restrict to share codes (10, 11) and exchange codes (1, 2, 3). I additionally require a match to the IBES database to extract earnings announcement dates and construct the earnings surprises. As shown in the first row of Table 1, the spread found in the data is substantial—the annualized term premium is 10.56%.

1.2. Earnings announcement data

To quantify the magnitude of the term premium realized around earnings news, I need to construct the earnings announcement window. I obtain firms' earnings announcement date and time from the Institutional Brokers' Estimate System (IBES). If earnings are released before 4 pm EST on a trading day, that day will be designated as the effective earnings date. If earnings are released after 4 pm EST, over the weekend, or on a public holiday, the effective earnings date is the next trading

day. I manually construct the mapping file to link IBES and CRSP using the CUSIP identifier and exchange ticker.

I follow DellaVigna and Pollet (2009) to construct quarterly standardized unexpected earnings (SUE) as

$$\text{SUE}_{n,t} = \frac{\text{EPS}_{n,t} - \mathbf{E}_{t-1}[\text{EPS}_{n,t}]}{P_{n,t-}}, \quad (2)$$

where $\text{EPS}_{n,t}$ is the realized earnings per share (EPS) of firm n in quarter t , and $\mathbf{E}_{t-1}[\text{EPS}_{n,t}]$ is the median analyst forecast of EPS in IBES. The difference between actual and expected EPS is scaled by the last closing price before the earnings announcement, $P_{n,t-}$. I obtain the realized EPS data from the IBES Unadjusted US Detail Actuals file, and manually compute the median forecast from the IBES Unadjusted US Detail History file. I restrict FPI to be (6, 7) to select the quarterly forecast for the current and the next fiscal quarter. I keep the latest forecast of each analyst for each firm-quarter, and include only forecasts that are made within 90 days prior to the earnings announcement date. I use the cumulative shares adjustment factor from CRSP to adjust for stock splits.

I gather monthly data on analyst forecasts from the IBES Unadjusted US Summary Statistics file. I focus on EPS forecasts over the next 5 years (FPI between 1 and 5) and long-term growth (LTG) forecast (FPI 0). IBES defines LTG as the expected annual increase in operating earnings over the company's next full business cycle, typically spanning three to five years. I fill in missing forecasts by linearly interpolating EPS at horizons ranging from 1 to 5 years.

1.3. Retail trading volume

I identify marketable retail trades using the TAQ millisecond data from 2007 to 2023. Retail trades are identified using the subpenny digit rule proposed in Boehmer et al. (2021), which leverages U.S. securities market regulations requiring the disclosure of price improvement for retail-initiated trades that are internalized. I sign the retail trades using the quote midpoint rule advocated by Barber et al. (2024) to address the potential bias in the Boehmer et al. (2021) algorithm.

My key measure of net retail trading is the retail net buy, defined as

$$\text{NBuy}_{n,t} = \frac{\text{BuyVLM}_{n,t} - \text{SellVLM}_{n,t}}{\text{TSO}_{n,t}} \quad (3)$$

where $\text{BuyVLM}_{n,t}$ and $\text{SellVLM}_{n,t}$ are the number of shares in retail-initiated buy and sell trades of stock n on day t , respectively. $\text{TSO}_{n,t}$ is the total shares outstanding.

Although concerns about potential measurement error exist, I argue that my main findings are robust to these limitations for two key reasons. First, my analysis focuses on the retail sort—how retail investors differentiate among stocks based on cash flow duration, making the ordinal ranking

of stocks by retail interest the primary concern rather than precise measurement levels. Given the substantial volume of trades per month, even modest attribution rates are likely to preserve correct rankings (Laarits and Sammon 2024). Second, MROIB captures only marketable retail order flow, which systematically underestimates the true price impact of retail trading activity. Kelley and Tetlock (2013) demonstrate this using proprietary retail trading data that separately examines aggressive (market) and passive (limit) orders. Their findings show positive retail imbalance from executed limit orders, indicating that retail investors predominantly use limit orders for stock purchases. Consequently, the estimates presented in this paper likely represent a conservative lower bound for the actual retail order flow effects.

1.4. Institutional equity holdings

The most ideal way to study the institution-retail interaction is to use high-frequency (at least daily to match the retail trading activity) institutional trading data, which is not publicly available.⁶ Due to this data challenge, I move to a lower frequency. I obtain data on quarterly U.S institutional equity holdings from 2000:Q1 to 2022:Q4 from FactSet. I prioritize the data on equity prices, shares outstanding, and market equity from FactSet in demand estimation. Following Koijen et al. (2024), I classify institutional investors into investment advisors, hedge funds, long-term investors, private banking, and brokers. Given the substantial size of the investment advisor category, I further divide it into four subgroups based on assets under management (AUM) and active share.

Let $w_{i,t}(n)$ be stock n 's portfolio weight in investor i 's portfolio in quarter t . Let $w_{i,t}^M(n)$ represent the corresponding portfolio weight if investor i were to hold the market portfolio within its investment universe, $\mathcal{N}_{i,t}$. Thus, investor i 's active share at date t is

$$AS_{i,t} = \frac{1}{2} \sum_{n \in \mathcal{N}_{i,t}} |w_{i,t}(n) - w_{i,t}^M(n)|, \quad (4)$$

which measures the extent to which investor i 's portfolio deviates from the market weights. The division by two prevents double counting, ensuring that the active share ranges from zero to one.

Figure A2 summarizes the results from a Lasso regression that selects firm characteristics predictive of portfolio weights in each quarter. I start from a comprehensive set of firm characteristics provided by Jensen et al. (2023) and add equity duration. For each institution and quarter, I estimate a cross-sectional Lasso regression of log portfolio weights on a set of firm characteristics. I increase this penalty until 10 characteristics survive. Then, for each characteristic, I count the number of times it is included in the surviving characteristic. Equity duration turns out to be the top 5th characteristic in explaining the cross-section of institutional holdings. Therefore, I focus on eight characteristics in the specification of asset demand: equity duration, log book equity,

⁶ For example, the proprietary Abel Noser (also known as Ancerno) data contains institutional trading transactions from mutual funds, hedge funds, and pension funds between January 1999 and September 2011. Boehmer et al. (2021) document that the number of subpenny trades stabilizes after 2009, and they study retail order flow during the 2010 to 2015 period. Therefore, even with Ancerno data, the overlapping period is only from 2010 to 2011.

the foreign sales share, the Lerner index, the ratio of sales to book equity, the ratio of dividends to book equity, and market beta, which are shown to be relevant for expected profitability and profitability risk in the cross-section (Kojen et al. 2024).

2. Decomposing the equity term premium

This section analyzes how much of the equity term premium is realized around earnings announcements and investigates the underlying mechanisms. I show that roughly 40% of the annual term premium is concentrated around earnings news and that horizon bias explains this pattern. I then decompose earnings news into risk and behavioral components to disentangle the sources of the earnings-day term premium. Finally, I demonstrate that the term premium pattern remains robust after controlling for other existing channels of announcement returns.

2.1. Motivation

The earnings announcement setting is ideal for studying the equity term premium for several reasons. First, cash flow news is especially important for long-duration stocks, as price movements driven by cash flow news are permanent (Campbell et al. 2010). In contrast, negative discount rate news (an increase in the discount rate) in the current period is offset by higher expected returns in the future—the impact of discount rate news is temporary and attenuates over time (Chen et al. 2013). Because long-duration stocks are more sensitive to discount rate changes, investors can quickly “ride out” these changes and receive compensation through improved future return prospects (Savor and Wilson 2016). Consistent with this view, Xiao (2023) show that while major anomalies earn more than half of their annual risk-adjusted returns in the week before scheduled FOMC announcements (a discount rate event), the cumulative returns realized during macro announcement periods are modest, averaging only 10 bps per event.

Second, the earnings announcement setting helps isolate other sources of return predictability. A vast body of literature seeks to reconcile classic asset pricing models with the downward-sloping equity term structure (van Binsbergen et al. 2012). However, the large proportion of term premia realized around earnings announcements is at odds with most existing explanations. For instance, if these returns were compensation for risk, the required discount rate changes would be implausibly large (Engelberg et al. 2018). Aggregate consumption does not respond instantaneously to news (Ai and Bansal 2018). This lack of contemporaneous covariance between stock returns and consumption implies that consumption-based explanations contribute too little over very short intervals to explain the observed announcement premium (Lettau and Wachter 2007; Gormsen 2021; Gonçalves 2021a). Friction-based explanations (Frazzini and Pedersen 2014; Xiao 2023; Li and Xu 2024) predict that institutional investors tilt away from long duration stocks due to binding tracking error constraints before earnings announcements, yet this cannot

explain the pre-announcement drift observed in long duration stocks.

2.2. Term premia around earnings announcements

To demonstrate the significance of the equity term premium around earnings announcements, I compare returns on announcement and non-announcement days using a narrow window around quarterly earnings news. Each quarter, I sort firms with earnings announcements into five quintiles by equity duration. For each stock-quarter, I calculate the daily average return in the event window $[-k, +k]$, where k is the number of days relative to the earnings announcement date. I then compute the equal-weighted average return for each duration portfolio. The daily term premium is the difference in average announcement returns between the short- and long-duration quintiles. I annualize this premium by multiplying the daily value by the number of event days in a year. Table 1 reports the time-series average term premium on earnings days from 1980 to 2023.

[Table 1]

The unconditional daily average term premium is 4.33 bps, which annualizes to 10.92%. On earnings announcement days, the average term premium rises to 54.03 bps. With four quarterly announcements per year, the cumulative term premium on announcement days is 2.16% annually, or about 19.8% of the total annual equity term premium.⁷ Expanding the window to $[-5, +5]$ around announcement dates, this proportion increases to 41.5%. Although Engelberg et al. (2018) show that anomaly returns are higher on earnings days, the equity term premium realized during these periods is much larger, as shown in panel (a) of Figure 5.

In a second analysis, I calculate equal-weighted daily average returns and CAPM alphas for each day in the $[-10, +10]$ event window for each duration quintile. I estimate CAPM betas for individual stocks using daily returns from a pre-event window $[-273, -22]$, following the slope-winsorized method in Welch (2021), and require at least 152 daily observations for reliable beta estimates. Table 2 shows average daily returns for the focused $[-3, +3]$ event window, while Figure 1 displays cumulative return dynamics over the full $[-10, +10]$ period for each quintile.

[Table 2]

Cumulative returns trend similarly across duration portfolios in the pre-announcement window $[-10, -3]$. However, long-duration stocks experience a sharp increase of about 20 bps on days -2 and -1 . Even after adjusting for market returns, long-duration stocks earn significantly positive abnormal returns before the announcement. This market adjustment disadvantages long-duration stocks because they have higher betas than short-duration stocks (van Binsbergen et al. 2012). The term spread remains close to zero, producing a V-shaped term structure before the announcement. After earnings news is released, long-duration stocks underperform, and the downward-sloping

⁷ Most firms in the IBES sample release earnings at a quarterly frequency.

term structure reappears. The cumulative term spread peaks on day +5, with most of the term premium realized between days -2 and +5.

[Figure 1]

2.3. Horizon bias and term premia

Horizon bias is the tendency for investors to be more optimistic at long horizons relative to short horizons (Cassella et al. 2023). Using the present value model from Cassella et al. (2023), I show that horizon bias explains the term premium observed around earnings announcements. I leave full derivation for Appendix A.1, but the intuition is simple: when investors expect higher growth at long horizons than at short horizons, long-duration assets earn lower expected returns than short-duration assets. Specifically:

$$ETP_{t+1} = E_t[R_{t+1}^{ST} - R_{t+1}^{LT}] = (g^{LT} - g^{ST}) \frac{1 + g^R}{1 + g^{ST}}. \quad (5)$$

In this model, the equity term premium increases with the gap between long-term and short-term growth forecasts. When investors are more optimistic about long-term growth than short-term growth, the equity term premium is positive. If the rational growth rate follows a random walk, the term premium is proportional to the difference in bias between long-term and short-term growth forecasts:

$$ETP \propto (\text{Bias}^{LT} - \text{Bias}^{ST}), \quad (6)$$

where Bias^{LT} (Bias^{ST}) is the difference between investors' long-term (short-term) growth forecast and the rational growth rate. In other words, when the bias in long-term growth is larger than the bias in short-term growth, the long-term asset is overpriced more than the short-term asset, and such overpricing leads to a positive equity term premium.

[Figure 2]

Because long-duration stocks pay most of their cash flows far in the future, horizon bias leads investors to be more optimistic about these firms than about short-duration firms. Panel (a) of Figure 2 shows that standardized unexpected earnings (SUE) decline monotonically with equity duration, reflecting over-optimism about the growth prospects of long-duration firms. For the long-duration quintile, SUE is negative, indicating that earnings news typically disappoints.

Following Cassella et al. (2023), I measure firm-level horizon bias as the difference between the long-term and short-term growth expectations:

$$HB_t(n) = LTG_t(n) - STG_t(n), \quad (7)$$

where $LTG_t(n)$ and $STG_t(n)$ are the long-term and forward 1-year growth rate forecasts for firm n in quarter t , respectively. The long-term and short-term growth rates are cross-sectionally standardized. Cassella et al. (2023) also provide an alternative measure of horizon bias based on the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate, which is shown in Appendix A.2. However, this alternative measure depends on an AR(1) transformation and the estimation is noisy for individual firms. Therefore, I focus on the dispersion measure in Equation (7).

[Table 3]

Table 3 reports announcement returns in the $[-5, +5]$ window for portfolios sorted by duration and horizon bias. Each quarter, I first sort firms with earnings announcements into five quintiles by equity duration. Within each duration quintile, I then sort stocks into five groups by their horizon bias measure. Sorting by duration first ensures growth rates are comparable within each group. For long-duration stocks, higher horizon bias mainly reflects higher long-term growth expectations; for short-duration stocks, it mainly reflects lower short-term growth expectations. As a result, horizon bias affects short- and long-duration stocks differently. I find that the relationship between horizon bias and announcement returns is positive for short-duration stocks but negative for long-duration stocks. The term premium is 15.05 bps for the high horizon bias group and only 1.93 bps for the low horizon bias group, which is consistent with the model prediction in Cassella et al. (2023).

2.4. Price effect

To quantify the relationship between announcement returns and horizon bias, I regress the pre- and post-event returns on horizon bias:

$$R_{n,t}^{Pre} = \beta_1 HB_{n,t-1} + \gamma' \mathbf{x}_{n,t-1} + \alpha_t + \varepsilon_{n,t}, \quad (8)$$

$$R_{n,t}^{Post} = \beta_1 HB_{n,t-1} + \beta_2 SUE_{n,t} + \gamma' \mathbf{x}_{n,t-1} + \alpha_n + \alpha_t + \varepsilon_{n,t}, \quad (9)$$

where $R_{n,t}^{Pre}$ is the cumulative alpha in the $[-3, -1]$ window, and $R_{n,t}^{Post}$ is the cumulative alpha in the $[0, +2]$ window. $HB_{n,t-1}$ is the horizon bias of stock n in quarter $t - 1$, $SUE_{n,t}$ is the SUE for the announcement in quarter t , and $\mathbf{x}_{n,t-1}$ is a vector of firm characteristics: stock duration, nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. I include quarter fixed effects in the pre-announcement period, and both firm and quarter fixed effects in the post-announcement period. Thus, the pre-event coefficient reflects cross-sectional variation in horizon bias, while the post-event coefficient captures variation over time within each firm.

[Table 4]

Table 4 reports the regression results. Stocks with higher horizon bias display stronger pre-announcement drift but weaker post-announcement drift, consistent with partial correction of beliefs when news arrives. Column (5) adds an interaction between horizon bias and SUE to test if price response depends on horizon bias. The significantly positive coefficient shows that SUE has a larger price effect for stocks with high horizon bias.

2.5. Relation to previous research

The literature attributes the earnings announcement premium to systematic risk (Patton and Verardo 2012; Savor and Wilson 2016), idiosyncratic risk (Barber et al. 2013; Yang et al. 2020), and biased expectations (Engelberg et al. 2018). Yet, most studies examine these channels separately, so their relative importance remains unclear.

This paper addresses this gap by disentangling the sources of the term premium around earnings announcements. I find that the term premium’s long leg closely tracks aggregate cash flow news, while its short leg is highly sensitive to behavioral biases.

A. Systematic risk

Savor and Wilson (2016) argue that the conditional covariance between firm- and market-level cash flow news generates a high risk premium for announcing firms. Campbell and Vuolteenaho (2004) document that value stocks have a higher cash flow beta—the “bad beta”—than growth stocks. Following this line of reasoning, since the cash flows of short duration firms are concentrated in the near future, the cash flow news of these firms should be more informative about current aggregate cash flow conditions. Motivated by this fundamental perspective, I decompose earnings news into a risk component and a behavioral component. Following the methodology in Glosten et al. (2021), I estimate the following regression for each firm n in quarter t :

$$\text{SUE}_{n,t} = \phi_{0,n,t} + \phi_{1,n,t} \text{SUE}_t^{\text{Market}} + \phi_{2,n,t} \text{SUE}_t^{\text{SIC2}} + \varepsilon_{n,t}, \quad (10)$$

where $\text{SUE}_{n,t}$ is firm n ’s SUE in quarter t , and $\text{SUE}_t^{\text{Market}}$ and $\text{SUE}_t^{\text{SIC2}}$ are the market-wide and industry-wide value-weighted SUE in quarter t , respectively. I estimate Equation (10) using a rolling window of 15 years (60 quarterly observations). The fitted value from this regression represents the risk component, while the residual captures the behavioral component.

Panel (b) of Figure 2 shows the average risk and behavioral components of SUE by duration quintile. The risk component is positive and declines with equity duration, supporting the view that cash flow news from short-duration firms is more informative about aggregate conditions. In contrast, the behavioral component is negative and increases in magnitude with duration.⁸ For long-duration stocks, the negative behavioral component outweighs the positive risk component, resulting in negative SUE and negative average returns on earnings days. If risk alone explained

⁸ Short-duration stocks show a slightly larger behavioral component, possibly due to increased attention on stocks with extreme returns.

the announcement premium, long-duration stocks would be safer than short-duration stocks, since their cash flow news is less correlated with market-level news. The high returns on long-duration stocks are therefore inconsistent with pure risk-based explanations.

Forecasting errors, seen as negative SUE, increase with equity duration at quarterly horizon. Figure A4 shows a U-shaped term structure of optimism bias across duration quintiles, indicating that long-term cash flows are more difficult to predict. Before announcements, the behavioral component boosts prices, and the combined effect of risk and behavioral components produces the observed V-shaped term structure. After earnings are released, the biased beliefs are largely corrected, and the risk component dominates, leading to a downward-sloping term structure. Overall, the strong covariance between the long leg and aggregate cash flow news, along with a speculative short leg sensitive to optimism bias, explains the term premium realized on earnings announcement days.

An open question is what drives the comovements of anomaly longs and anomaly shorts (Campbell et al. 2010). The *fundamentals view* holds that stocks in the long or short leg move together because of the characteristics of their cash flows. In contrast, the *sentiment view* suggests that shifts in investor sentiment, or changes in the discount rates applied to cash flows, create correlated movements in the prices of stocks that investors favor or disfavor. This paper contributes to the debate by showing that investor sentiment can stem from the characteristics of cash flows, which supports the fundamentals view.

B. *Idiosyncratic risk*

Yang et al. (2020) show that abnormal idiosyncratic volatility, which reflects information asymmetry for uninformed investors, is positively associated to informed return run-ups before earnings announcements. Figure 3 plots pre-announcement idiosyncratic volatility (IVOL) by duration quintile, revealing a U-shaped pattern: both short- and long-duration stocks have higher IVOL than medium-duration stocks. I discuss estimation details in Section 3.2. Idiosyncratic risk explains the pre-announcement drift but does not account for announcement returns, as the asymmetric effects offset each other.

[Figure 3]

Instead, I argue in Section 3.2 that idiosyncratic risk is not directly priced; rather, it proxies for limits to arbitrage that prevent rational investors from correcting mispricing before announcements.

C. *Others*

Lottery demand Liu et al. (2020) show that the long-short return spread on lottery stocks reverses sign before and after earnings events. Two findings stand out. First, while Liu et al. (2020) use raw returns, switching to CAPM alpha reveals that much of the return spread is due to market risk exposure, as the spread between lottery and non-lottery stocks shrinks considerably.

Second, the weak performance of the long leg (less lottery-like stocks) reflects low covariance with aggregate cash flow news, which explains why only a small portion of lottery strategy returns are realized during earnings announcement periods.

Momentum and attention Aboody et al. (2010) show that momentum winners earn significantly positive market-adjusted returns before earnings announcements and significantly negative returns afterward. They argue that stocks with sharp past run-ups attract investor attention, leading to higher returns for past winners before announcements. To separate the momentum effect from pure attention, I conduct several exercises summarized in Table A1. Columns (1) and (5) report baseline pre- and post-announcement returns across duration quintiles.

Next, I perform a conditional double sort. Each quarter, firms with earnings announcements are first sorted into five momentum quintiles based on past 12-month returns; within each momentum quintile, stocks are then sorted into five groups by equity duration from the previous quarter. I collapse across momentum groups to form five momentum-adjusted duration portfolios, with average pre- and post-announcement returns shown in columns (2) and (6). I then exclude momentum winners by removing the top quintile of past 12-month returns and sort the remaining stocks into five duration quintiles, as shown in columns (3) and (7). Columns (4) and (8) report results after excluding stocks with media coverage in the Dow Jones edition of RavenPack news data. The return pattern across duration quintiles remains robust after controlling for momentum and media coverage.

3. Horizon bias and retail price pressure

This section further examines the mechanisms behind the earnings-day term premium. First, I show that retail investors, driven by horizon bias, are net buyers of long-duration stocks before earnings announcements. Second, I demonstrate that horizon bias, combined with limits to arbitrage, leads to underpricing of short-duration stocks and overpricing of long-duration stocks ahead of announcements. Finally, I extend the horizon bias explanation to announcement returns for value, profitability, and low-risk factors.

3.1. Retail net trading

The literature offers several reasons why retail investors buy stocks before announcements, such as limited attention, private information, momentum chasing (Aboody et al. 2010), and lottery preference (Liu et al. 2020). This paper adds that retail investors disproportionately hold long-duration stocks ahead of earnings announcements. Horizon bias fundamentally explains this herding behavior, as retail investors are drawn to stocks with distant cash flows. This finding aligns with Laarits and Sammon (2024), who show that retail investors trade hard-to-value stocks with long-duration cash flows and highly subjective valuations.

Figure 4 shows cumulative retail net trading by duration quintile in the $[-10, +10]$ window around earnings announcements. Retail net trading is the volume of retail buys minus sells, normalized by total shares outstanding. The red line indicates that long-duration stocks attract substantial retail buying before earnings announcements. On day -1 , retail net buy orders reach about 0.65 bps of total shares outstanding, similar to the levels reported for high retail stocks in Laarits and Sammon (2024). In contrast, retail buying for short-duration stocks is much smaller, barely above zero on day -1 . Most retail net buying occurs on day -1 , as shown by the gray bar, consistent with heightened retail investor attention before earnings announcements (Liu et al. 2020).

[Figure 4]

To quantify how retail net trading relates to horizon bias before earnings announcements, I estimate the following specification:

$$\text{NBuy}_{n,t} = \beta_1 \text{HB}_{n,t-1} + \beta_2 \text{Dur}_{n,t-1} + \gamma' \mathbf{x}_{n,t-1} + \alpha_n + \alpha_t + \varepsilon_{n,t}, \quad (11)$$

where $\text{NBuy}_{n,t}$ is the cumulative retail net buy volume for stock n over the $[-5, -1]$ window before its earnings announcement in quarter t , $\text{HB}_{n,t-1}$ is the cross-sectional rank of horizon bias for stock n in quarter $t - 1$, $\text{Dur}_{n,t-1}$ is the equity duration in the previous quarter, and $\mathbf{x}_{n,t-1}$ is a vector of firm characteristics: nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. I include both firm and quarter fixed effects to control for unobserved differences across stocks and changing market conditions.

[Table 6]

Table 6 reports the estimated coefficients. The coefficient on horizon bias rank is significantly positive, showing that horizon bias is strongly linked to retail net buying before earnings announcements. This relationship holds even after controlling for equity duration and other firm characteristics. Using horizon bias quintile dummies in column (5), I find that cumulative retail net buy increases steadily across duration quintiles, with Q3 as the reference group.

3.2. Institutional avoidance

My earlier analysis shows that retail price pressure build up the mispricing in long-duration stocks before earnings announcements. At the institutional side, rational speculators rarely correct this mispricing in the pre-announcement period for three main reasons. First, institutional investors often reduce their exposure before earnings announcements to avoid idiosyncratic volatility (Berkman et al. 2009; Di Maggio et al. 2023). The evidence of higher idiosyncratic risk during

these events suggests costly arbitrage during these events (Yang et al. 2020; Barber et al. 2013).⁹ Long-duration stocks tend to have higher idiosyncratic risk, making them more susceptible to mispricing.

Second, tracking error constraints often bind for institutional investors before earnings announcements (Barroso et al. 2025). Long-duration stocks have higher market betas than short-duration stocks (van Binsbergen et al. 2012). Performance contracts encourage institutions to overweight high-beta stocks, since these stocks tend to outperform unit-beta benchmarks.¹⁰ However, these contracts also penalize excessive tracking error volatility. When idiosyncratic volatility rises, managers reduce their exposure to long-duration stocks to stay closer to the benchmark.

Third, when retail sentiment is highly predictable, rational speculators may lack incentive to correct mispricing, even without limits to arbitrage (De Long et al. 1990). Instead, they often front-run retail investors to profit from the price upturn, then exit before the announcement (Brunnermeier and Nagel 2004). The “bubble-riding” strategy is easier to execute than a “pump-and-dump” strategy, since institutional investors do not need to trigger the initial price run-up to attract extrapolative retail investors (De Long et al. 1990).

Overall, these three factors dampen institutional investors’ incentives to correct mispricing before earnings announcements. To show how limits to arbitrage differ across duration quintiles, I examine idiosyncratic volatility in the pre-announcement period. Following Yang et al. (2020), I measure idiosyncratic volatility (IVOL) using the Fama and French (1993) three-factor model (FF3). For each stock and month, I estimate the FF3 model with past one-year daily returns and obtain daily residuals, $\varepsilon_{n,d}$. I define the pre-earnings-announcement period (PEA) as the five business days before each of the most recent four earnings announcements, $[-5, -1]$. The annualized idiosyncratic volatility for stock n at the end of month t is

$$IVOL_{n,t}^{PEA} = \sqrt{\frac{252 \times \sum_{d \in PEA} \varepsilon_{n,d}^2}{N_{PEA} - 1}}, \quad (12)$$

where N_{PEA} is the number of days in the pre-earnings-announcement periods. Figure 3 shows that average $IVOL^{PEA}$ follows a U-shaped pattern across duration quintiles: both short- and long-duration stocks have higher idiosyncratic volatility than medium-duration stocks. According to Stambaugh et al. (2015), IVOL reflects risk that deters arbitrage and allows mispricing to persist. As a result, short- and long-duration stocks are more susceptible to mispricing. Short-duration stocks tend to be overpriced, while long-duration stocks tend to be underpriced.

[Table 5]

To analyze how IVOL influences announcement returns across duration portfolios, I perform a

⁹ A number of empirical papers show that idiosyncratic risk is the biggest impediment to arbitrage (Hong and Sraer 2016).

¹⁰ Buying high-beta stocks is more efficient than leveraging up low-beta stocks when speculating on the common factor of firms’ cash flows (Frazzini and Pedersen 2014; Hong and Sraer 2016).

conditional double sort. Each quarter, I first sort firms announcing earnings into five IVOL quintiles using their PEA IVOL from the month before the announcement. Within each IVOL quintile, I then sort stocks into five groups by equity duration from the previous quarter. Table 5 reports the average pre- and post-announcement returns for these 25 portfolios.

Panel A shows that pre-announcement returns increase with IVOL across duration quintiles, consistent with Yang et al. (2020) that IVOL explains the pre-announcement drift. The V-shaped pattern in duration portfolio returns persists after averaging across IVOL quintiles, showing that idiosyncratic volatility alone does not explain the term premium. Panel B shows that post-announcement returns are flat with respect to IVOL for short-duration stocks, but turn negative for long-duration stocks. These results support the arbitrage risk hypothesis: high IVOL stocks are most overpriced among long-duration stocks, consistent with Stambaugh et al. (2015) on the joint role of arbitrage risk and arbitrage asymmetry.

3.3. Linking duration to major equity factors

Gormsen and Lazarus (2023) provide a duration-based explanation for the premia on major risk factors, including value, profitability, investment, low-risk, and payout. Firms in the long leg of these factors have large near-term cash flows and therefore short cash-flow duration, while firms in the short leg have long cash-flow duration. I test whether horizon bias also explains the announcement returns of related investing styles (Barberis and Shleifer 2003). I focus on the value, profitability, and low-risk factors because these characteristics are closely linked to cash-flow duration and depend on earnings news.

[Figure 5]

Figure 5 shows the difference in cumulative returns and retail net buy volume between the long and short leg portfolios across anomaly types. For value, profitability, and low-risk factors, anomaly returns are negative before earnings announcements but turn significantly positive on the announcement day. This pre-announcement underperformance is explained by retail price pressure: retail investors are net buyers of short-leg stocks ahead of earnings releases.

I start from 119 anomalies that are shown to work out of sample in Jensen et al. (2023). For each firm-month observations, I sum the number of long-side and short-side anomaly portfolios that the observation belongs to to construct variable *Long* and *Short*, respectively. Following Engelberg et al. (2018), I estimate the following regression equation:

$$R_{n,t} = \beta_1 \text{Long}_{n,t} + \beta_2 \text{Long}_{n,t} \times \text{Eday}_{n,t} + \beta_3 \text{Short}_{n,t} + \beta_4 \text{Short}_{n,t} \times \text{Eday}_{n,t} + \beta_5 \text{Eday}_{n,t} + \sum_{j=1}^{10} \gamma_j R_{n,t-j} + \sum_{j=1}^{10} \delta_j R_{n,t-j}^2 + \sum_{j=1}^{10} \rho_j \text{Volume}_{n,t-j} + \alpha_n + \alpha_t + \varepsilon_{n,t}. \quad (13)$$

$R_{n,t}$ is the daily return of stock n on day t . $\text{Long}_{n,t}$ and $\text{Short}_{n,t}$ are the number of long-side and short-side anomaly portfolios that stock n belongs to at the end of previous month. The variable

$Eday_{n,t}$ is an indicator equal to one on earnings days for firm n and zero otherwise. $R_{n,t-j}$ is the daily return of stock n on day $t - j$. $Volume_{n,t-j}$ is the daily trading volume of stock n on day $t - j$. This regression includes all daily stock return observations, and interaction terms indicate whether anomaly returns are higher on earnings announcement days. I include stock and day fixed effects.

[Table 8]

Table 8 reports the results. Column (1) constructs *Long* and *Short* across all 119 anomalies, while columns (2)–(4) count the number of long-side and short-side anomaly portfolios within the value, profitability, and low-risk categories. For a *Long* value of 10, expected returns are 4.22 bps higher on non-earnings days and 4.95 bps higher on earnings days. For a *Short* value of 10, expected returns are 1.43 bps lower on non-earnings days and 26.77 bps lower on earnings days. This shows that the short leg contributes to most of the earnings-day anomaly returns, which also holds for value, profitability, and low-risk factors. In panel B, I replace the earnings-day dummy with $Eday-L1_{n,t}$ to indicate the last trading day before earnings announcements. In contrast, the short legs of value, profitability, and low-risk factors outperform the long legs prior to earnings announcements, consistent with the horizon bias explanation that investors are overly optimistic about cash flows for the short-leg stocks.

Next, I show that retail trading behavior explains the price run-up of stocks in the short leg of these factors. I construct a Z-score across 39 anomalies in the value, profitability, and low-risk categories, signing each anomaly so that higher Z-scores indicate higher expected returns. Each month, I sort stocks into five quintiles by their Z-scores. I then estimate the following regression:

$$\begin{aligned} NBuy_{n,t} = & \sum_{k=1}^5 \beta_k Q_k + \sum_{k=1}^5 \phi_k Q_k \times Eday-L1_{n,t} + \psi Eday-L1_{n,t} \\ & + \sum_{j=1}^{10} \gamma_j R_{n,t-j} + \sum_{j=1}^{10} \delta_j R_{n,t-j}^2 + \sum_{j=1}^{10} \rho_j Volume_{n,t-j} + \alpha_n + \alpha_t + \varepsilon_{n,t}. \end{aligned} \quad (14)$$

$NBuy_{n,t}$ is the retail net buy volume for stock n on day t . Q_k is the quintile rank of stock n based on its Z-score at the end of the previous month. $Eday-L1_{n,t}$ equals one on the last trading day before earnings announcements for firm n , and zero otherwise. I include stock and day fixed effects.

[Table 9]

Table 9 reports the results. $NBuyV$ is retail net buy volume divided by the sum of retail buy and sell volume. The intervals $[-5, -1]$ and $[-10, -1]$ refer to the average retail net buy within each window. The coefficient on $Eday-L1_{n,t}$ shows that retail net trading increases for all stocks on day -1 before earnings announcements. The interaction term declines with anomaly quintile, indicating that retail investors are more likely to buy stocks in the short leg of value, profitability, and low-risk factors on the last trading day before earnings announcements (Chen et al. 2025).

Retail buying pressure thus explains why short-leg stocks outperform in the pre-announcement period.

4. Institutional duration tilts and time-varying term premia

This section examines how institutional investors' duration preferences shape the time-varying term premium. First, I show that the spread in term premia between high- and low-sentiment states is wide, with horizon bias more pronounced during high-sentiment periods. Next, I document that active institutional investors, such as hedge funds and active mutual funds, display strong procyclical duration preferences. I also find that institutional duration demand positively predicts future returns, consistent with the smart money effect. Finally, I demonstrate that institutional duration tilts are sufficient to explain the spread in term premia across sentiment states.

4.1. Term premia across sentiment states

Horizon bias essentially corresponds to an upward-sloping term structure of optimism bias: investors are more optimistic at long horizons relative to short horizons. While investor sentiment often captures broad optimism or pessimism about stocks (Baker and Wurgler 2006), horizon bias highlights how sentiment varies with cash flow duration. Because long-duration stocks have highly subjective valuations (Laarits and Sammon 2024) and are harder to arbitrage, horizon bias is especially strong during high-sentiment periods.

[Table 10]

Table 10 reports annualized monthly returns for duration portfolios, conditional on aggregate investor sentiment (Baker and Wurgler 2006). Each month, I sort stocks into five quintiles by equity duration and compute the value-weighted average return for each portfolio. The term premium is the difference in average returns between short- and long-duration portfolios. *Avg* denotes unconditional portfolio returns. High-sentiment periods are months when beginning-of-period investor sentiment is above the median; low-sentiment periods are those below the median. The unconditional term premium is 6.7% per year; it rises to 11.1% in high-sentiment periods and falls to 2.4% in low-sentiment periods.

These results support the horizon bias explanation: when investors are more optimistic about the cash flows of long-duration stocks, future returns are lower. As investor sentiment subsides, arbitrage forces help correct overpricing in long-duration stocks. This motivates the study of institutional investors' duration preferences.

On the surface, the previous section suggests a retail-institutional divide: retail investors favor long-duration stocks, while institutional investors avoid these stocks around earnings announcements. However, when arbitrage risk declines, institutions may still hold long-duration stocks

that are popular with retail investors. In this way, retail demand can also “crowd in” institutional investors.

While recent studies document that the equity term structure is unconditionally downward-sloping and countercyclical (van Binsbergen et al. 2012; van Binsbergen and Koijen 2017; Gormsen 2021; Gonçalves 2021b,a), they remain silent on which investors are responsible for this pattern. For example, although pension funds are often viewed as natural long-term investors, their balance sheets may be net long-term overall, yet they invest in very high duration bonds while maintaining short-term equity exposure.

[Figure 6]

Figure 6 shows excess portfolio-level duration by institutional investor type over the sample period. For each investor, I calculate portfolio-level duration as the value-weighted average duration of stocks in their portfolio, then aggregate to investor type using a wealth-weighted average. I subtract market-portfolio duration to obtain excess duration. Active institutional investors, such as hedge funds and active mutual funds, hold a large share of long-duration stocks. In contrast, primary long-term investors, including pension funds and insurance companies, consistently maintain short-term equity exposure. Yu (2020) finds that these long-term investors reach for duration in the corporate bond market, so they do not need to hold long-duration stocks to match their liabilities.

Equity duration is a composite stock characteristic that correlates with other firm-level features, such as book-to-market ratio, investment, profitability, and market beta (Gormsen and Lazarus 2023). If institutional investors tilt toward high-beta stocks, for example, the pattern in Figure 6 could also result. To isolate duration effects, I follow recent demand system asset pricing literature to estimate institutional investors’ duration-related tilts (Koijen and Yogo 2019; Koijen et al. 2024).

4.2. The asset demand system

Following Koijen and Yogo (2019), I set up an asset demand system in Appendix B.1, and the optimal portfolio choice relates the cross section of equity holdings to firm characteristics. I now estimate investor-level demand curves. For each investor i and quarter t , I estimate the following equation using nonlinear generalized method of moments:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp\{\alpha_{i,t} + \beta_{0,i,t}mb_t(n) + \beta'_{1,i,t}\mathbf{x}_t(n) + \gamma_{i,t}Dur_t(n)\}\varepsilon_{i,t}(n), \quad (15)$$

where $mb_t(n)$ is the log market-to-book ratio, $\mathbf{x}_t(n)$ is a vector of firm characteristics, including log book equity, the foreign sales share, the Lerner index, sales-to-book, dividend-to-book, and market beta, and $Dur_t(n)$ is the equity duration. To improve estimation stability, I add a ridge shrinkage as in Koijen et al. (2024).

I assume that the latent demand shock $\varepsilon_{i,t}(n)$ is exogenous to all stock characteristics except the log market-to-book ratio, each investors' assets under management $A_{i,t}$, and the set of stocks in the investor's investment universe $\mathcal{N}_{i,t}$. Under these assumptions, $mb_t(n)$ is the only endogenous regressor as it is correlated with latent demand $\varepsilon_{i,t}(n)$ through market clearing. To address this endogeneity concern, I construct the counterfactual log market capitalization of stock n if all investors other than i or the household sector holds an equal-weighted portfolio of their investment universes:

$$z_{i,t}(n) = \log \left(\sum_{j \notin \{i,1\}} A_{j,t} \frac{\mathbf{1}_j(n)}{1 + |\mathcal{N}_{j,t}|} \right). \quad (16)$$

I estimate the demand Equation (15) based on the instrument $z_{i,t}(n)$ and all non-price characteristics using a two-step instrumental variables ridge estimation (Kojien et al. 2024). The procedure pools data at the annual level in the first stage and applies shrinkage to investor-quarter level coefficients in the second. The construction of the instrumental variable and details of the estimation methodology are discussed in more detail in Appendix B.2.

A. *Estimated demand coefficients*

I summarize the cross-sectional distribution of demand coefficients in Figure A5. For each investor, I compute the time-series average of demand coefficient estimates, then aggregate to investor type using AUM-weighted averages. The colored vertical lines show the aggregate demand coefficients by investor type. I standardize stock characteristics in demand estimation, except for log market-to-book equity, so the coefficients represent the percentage change in demand per one standard deviation increase in each characteristic. The wealth-weighted coefficient on equity duration is 1.53% for hedge funds and -3.50% for long-term investors. A negative coefficient indicates that primary long-term investors, on average, prefer short-duration stocks, holding equity prices and other characteristics constant.

[Figure 7]

Figure 7 plots the binned scatter of demand coefficients on equity duration against log market-to-book ratio for all investors. The two coefficients are negatively correlated. Investors with a larger coefficient on log market-to-book are less price-elastic. This figure suggests that, on average, more price-elastic investors hold long-duration stocks.

B. *Explaining institutional duration tilts*

Figure 8 shows the time series of the demand coefficient on equity duration across investor active share quintiles. Active institutional investors display strong variation in duration demand, reaching for duration during long expansions. In contrast, passive institutions' duration demand is stable

and slightly below zero, indicating a preference for short-duration stocks throughout the sample period.

[Figure 8]

To investigate the timing of institutional investors' duration demand, I regress duration demand on macroeconomic variables by active share quintile. Details on variable construction are in Appendix C.2. Table A7 reports the results. The consistently positive coefficient on funding liquidity shows that investors favor long-duration stocks when market funding liquidity is high, which aligns with periods of bullish market sentiment (Greenwood et al. 2023).¹¹ The coefficients on funding liquidity and aggregate horizon bias increase with active share quintile, indicating that active institutional investors' duration tilts are more sensitive to market liquidity and sentiment.

Table A8 examines conditional duration tilts by price elasticity and active share quintiles. Active institutional investors show much higher duration tilts in high-sentiment periods. Therefore, institutional investors play a less active role in correcting overpricing in long-duration stocks during these periods, which allows mispricing to persist and leads to lower future returns.

4.3. Smart money effect

Institutional investors are typically conceptualized as “smart money”. Why do smart investors hold long-duration stocks that have, on average, lower returns? To answer this question, I first measure stock-level institutional duration demand, termed reaching for duration (RFD), as the value-weighted average demand coefficient on equity duration across all institutional investors:

$$\text{RFD}_t(n) = \sum_{i \in I} \frac{A_{i,t} w_{i,t}(n)}{\text{ME}_t(n)} \gamma_{i,t}(n), \quad (17)$$

where I is the set of institutional investors that hold stock n in quarter t , $A_{i,t}$ is the AUM, and $\gamma_{i,t}$ is the demand coefficient on equity duration for investor i in quarter t .

To examine whether institutional duration demand predicts future returns, I run Fama-MacBeth regressions of monthly excess returns on RFD and firm-level characteristics. Specifically, I estimate cross-sectional regressions of excess returns on lagged characteristics each month and then compute the time-series average of the estimated coefficients over the sample period from 2000:4 to 2023:3. To control for known sources of return predictability, I include all characteristics from the Fama-French five-factor model—namely, log market equity, book-to-market equity, profitability, investment, and market beta—as well as momentum, measured as the 11-month return excluding the most recent month. I use data that were public in month t to predict stock returns in month $t + 1$.

[Table 11]

¹¹When funding liquidity is high, institutional investors seek to outperform the market and hold long-duration stocks with high market beta (Barroso et al. 2025).

Table 11 shows that expected monthly returns increase by 0.126 percent per one standard deviation increase in RFD, with a t-statistic of 3. Importantly, I also control for duration in the specification, but the coefficient on duration is not statistically significant. This result suggests that institutional duration tilts positively predict future returns, even after controlling for equity duration itself. This finding is consistent with flow-based return predictability and the smart money effect (Lou 2012).

[Table 12]

Next, I perform a two-way conditional double sort on duration and RFD. Because the set of inside assets is relatively small (about 600 stocks per cross-section), I construct tercile portfolios. Each month, I first sort stocks into three duration portfolios based on their equity duration in the previous quarter. Within each duration portfolio, I then sort stocks into three RFD portfolios using last-quarter RFD. Panel A in Table 12 reports the average FF3 alphas. Within the long-duration portfolio, high RFD stocks outperform low RFD stocks by 1% per month, or 12% per year. For the short-duration portfolio, the return difference is not statistically significant. Panel B examines long-run stock returns using the approach in Bordalo et al. (2024). High RFD stocks underperform low RFD stocks by 10% over the next five years, indicating strong return reversal. These results suggest that institutional investors successfully time the market by tilting toward long-duration stocks during price run-ups.

Finally, I test the bubble-riding hypothesis by examining whether RFD predicts retail net buy volume. If retail sentiment is highly predictable, rational speculators may not have the incentive to correct mispricing even in the absence of limits to arbitrage (De Long et al. 1990). Rational investors may prefer to front-run retail investors temporarily to capture the upturn, then reduce their positions in stocks that are about to decline (Brunnermeier and Nagel 2004).

I regress the retail net buy volume in quarter t on RFD and firm characteristics in quarter $t - 1$:

$$\text{NBuy}_{n,t} = \beta \text{RFD}_{n,t-1} + \boldsymbol{\phi}' \mathbf{x}_{n,t-1} + \alpha_t + \varepsilon_{n,t}, \quad (18)$$

where the vector $\mathbf{x}_{n,t-1}$ includes: nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. I include quarter fixed effects, and the regression coefficients are most driven by cross-sectional variation.

Table A9 reports the regression results. The coefficient on RFD is positive and statistically significant, indicating that higher RFD is associated with greater retail net buy volume in the next quarter. This finding is consistent with the bubble-riding hypothesis. Column (1) shows the regression of the change in RFD on the lagged RFD level, and the coefficient is negative and statistically significant, suggesting that RFD is mean-reverting.

Figure A7 shows the cumulative return and retail net buy volume after portfolio formation by RFD quintile. Panel (a) shows that high RFD stocks outperform low RFD stocks by 50 bps over the

next 10 days, but the return pattern reverses after about two months. Panel (b) shows that high RFD stocks experience a significant increase in retail net buy volume in the following 10 days, indicating that persistent retail flows contribute to the price run-up of high RFD stocks.

4.4. Counterfactual analysis

I consider a counterfactual scenario in which capital flows from institutional investors with the largest changes in duration tilts between high- and low-sentiment periods to the remaining investors. I solve for the counterfactual equity prices by market clearing, assuming shares outstanding and firm characteristics remain fixed in the spirit of an endowment economy.

Following Kojien et al. (2024), I allow the investors' wealth to change endogenously with equity prices. Let $A_{i,t}$ denote the AUM of investor i in quarter t . Let $P_t(n)$ denote the market equity of stock n in quarter t , and let $\mathbf{p}_t$ represent the market equity vector of all stocks in quarter t . Let $F_{i,t}$ denote the capital flow. Let the superscript C denote the counterfactual values of the corresponding variables. Investor i 's wealth in the counterfactual world is

$$A_{i,t}^C(\mathbf{p}_t^C) = A_{i,t} \underbrace{\left(w_{i,t}(0) + \sum_{n \in N_{i,t}} \frac{P_t^C(n)}{P_t(n)} w_{i,t}(n) \right)}_{\text{Capital gain}} + F_{i,t}, \quad (19)$$

in which the investor's initial portfolio is revalued at the counterfactual market equity vector $\mathbf{p}_t^C$. The counterfactual equity prices are a solution to the market clearing condition:

$$P_t^C(n) = \sum_{i=1}^I A_{i,t}^C(\mathbf{p}_t^C) w_{i,t}^C(n; \mathbf{p}_t^C) \xrightarrow{\text{stack}} \mathbf{p}_t^C = \mathbf{f}(\mathbf{p}_t^C). \quad (20)$$

I assume that the investors maintain the same outside portfolio weights in the counterfactual market, i.e., $w_{i,t}^C(0) = w_{i,t}^C$, which ensures that the results are not driven by substitution into the outside asset, i.e., micro-cap stocks. I solve for the counterfactual equity prices by finding the fixed point of function $\mathbf{f}: \mathbf{R}^N \rightarrow \mathbf{R}^N$, using the algorithm in Kojien and Yogo (2019) Appendix C.

To measure how the demand from one type of investors would affect asset prices, I compute the price impact of a portfolio ω :

$$\text{PI}_t(\omega) = \frac{P_t^C(\omega) - P_t(\omega)}{P_t(\omega)} = \frac{\sum_{n \in \omega} P_t^C(n) - \sum_{n \in \omega} P_t(n)}{\sum_{n \in \omega} P_t(n)} \quad (21)$$

where $P_t^C(n)$ denotes the market equity of stock n in the counterfactual market.

I follow Barroso et al. (2025) to compute the required price impact that explains the empirical spread in term premia between high- and low-sentiment states. Applying the Campbell and Shiller

(1988) decomposition to an arbitrary portfolio ω with log return $r_{\omega,t}$:

$$r_{\omega,t} \approx \kappa_0 + \kappa_1 pd_{\omega,t} - pd_{\omega,t-1} + g_{\omega,t}, \quad (22)$$

where $pd_{\omega,t}$ denotes the log price-dividend ratio, $g_{\omega,t}$ denotes log dividend growth, and $\kappa_1 = 0.996$. Solving forward for $pd_{\omega,t}$ and taking expectations yields:

$$pd_{\omega,t} = \frac{\kappa_0}{1 - \kappa_1} + \mathbf{E}_t \left[\sum_{h=0}^{\infty} \kappa_1^h (g_{\omega,t+1+h} - r_{\omega,t+1+h}) \right]. \quad (23)$$

Next, I assume that $r_{\omega,t}$ follows the factor structure:

$$r_{\omega,t} = \alpha_{\omega,t-1} + \beta'_{\omega,t-1} \mathbf{f}_t + \varepsilon_{\omega,t}, \quad (24)$$

and the abnormal return decays according to an autoregressive process:

$$\alpha_{\omega,t} = \phi_{\omega} \alpha_{\omega,t-1} + \nu_{\omega,t}, \quad (25)$$

with $0 < \phi_{\omega} < 1$. Barroso et al. (2025) show that if we assume that dividends and the factor structure of assets are the same in the counterfactual as they are in reality, the percentage price impact of a portfolio ω in this experiment relative to the baseline case is given by

$$\text{PI}_t(\omega) = \exp \left(\frac{\alpha_{\omega,t} - \alpha_{\omega,t}^C}{1 - \phi_{\omega} \kappa_1} \right) - 1. \quad (26)$$

If an asset is overpriced in the real world ($\alpha_{\omega,t} < 0$), but fairly priced in the counterfactual market ($\alpha_{\omega,t}^C = 0$), the price impact will be negative, i.e., $\text{PI}_t(\omega) < 0$.

[Table 13]

Empirically, the short-duration portfolio earns an FF6 alpha of 31 bps in the high-sentiment state and 9 bps in the low-sentiment state. The long-duration portfolio earns alpha of -16 bps and -7 bps in these states, respectively. What price impact would be required to eliminate the spread in alpha of 31 bps between the high- and low-sentiment states? Let S and L denote the short- and long-duration portfolios, respectively. Let hi and lo denote the high- and low-sentiment periods. I estimate the AR(1) coefficient, ϕ , to be 0.8. Taken together, the price impact to required to render $\alpha^C = 0$ is:

$$\begin{aligned} \Delta \text{PI}(S - L) &= \text{PI}_{hi}(S - L) - \text{PI}_{lo}(S - L) \\ &= \exp \left(\frac{\alpha_{S,hi}}{1 - \phi \kappa_1} \right) - \exp \left(\frac{\alpha_{L,hi}}{1 - \phi \kappa_1} \right) - \left[\exp \left(\frac{\alpha_{S,lo}}{1 - \phi \kappa_1} \right) - \exp \left(\frac{\alpha_{L,lo}}{1 - \phi \kappa_1} \right) \right] \\ &= 4.65\%. \end{aligned} \quad (27)$$

To conduct the counterfactual exercise, I first compute the average demand coefficient on equity duration for each institution i across high- and low-sentiment periods, $\gamma_{i,hi}$ and $\gamma_{i,lo}$. I then rank all institutions based on the difference $\gamma_{i,hi} - \gamma_{i,lo}$ and drop the institutions with the most positive changes whose cumulative AUM represents 10% of total investor assets. I reallocate their AUM to all remaining investors on a pro rata basis. Intuitively, this procedure identifies the institutional investors that most actively time market sentiment when allocating their wealth between short- and long-duration stocks.

Table 13 reports the time-series means of the repricing statistics from the counterfactual experiment. The average spread in stock valuation changes between the two states is 10.76%, which exceeds the 4.65% price impact required to eliminate the alpha spread. This result suggests that institutional investors whose duration tilts drop the most as sentiment falls have a substantial effect on prices, and that demand from just 10% of aggregate assets under management can account for nearly all of the spread in term premia across sentiment states.

5. Conclusion

This paper shows that horizon bias explains the cross-sectional equity term premium. I first document that about 40% of the annual term premium is realized around earnings announcements. Long-duration stocks earn strong market-adjusted returns before earnings announcements, but these gains sharply reverse at the announcement. Horizon bias stands out from existing explanations by accounting for this concentrated realization and reversal in long-duration stocks.

I further examine investor behavior to uncover the underlying mechanism. Horizon bias, together with limits to arbitrage, explains why retail price pressure builds up mispricing in long-duration stocks before earnings announcements. This mechanism also generalizes to the announcement returns of value, profitability, and low-risk factors due to correlated investing styles.

Finally, I broaden the analysis to time-varying term premia. Horizon bias strengthens during high-sentiment periods, producing a wide spread in term premia between high- and low-sentiment states. I complement the retail-institutional interaction by studying institutional investors' duration preferences. Active institutions, such as hedge funds and active mutual funds, tilt toward long-duration stocks favored by retail investors during high-sentiment periods. These institutional duration tilts are sufficient to explain the spread in term premia across sentiment states. While this finding is consistent with institutional sophistication in timing market sentiment, inexperienced fund managers may also be susceptible to horizon bias.

Overall, this paper shows that biased beliefs about future cash flows drive the cross-sectional equity term premium. Stock ownership is not strictly divided between retail and institutional investors. Retail demand can crowd out or crowd in institutional investors depending on market conditions, and this interaction significantly affects asset prices.

Table 1
Equity term premium around earnings announcements

This table reports the time-series average term premium on earnings days. Each quarter, firms with earnings announcements are split into five quintile portfolios based on equity duration from the previous quarter. Stock-quarter level announcement returns are calculated as the daily average returns in event window $[-3, +3]$, where k is the number of days relative to the earnings announcement date. Then I compute a equal-weighted average announcement return for each quintile portfolio. The daily premium realized is defined as the difference in average announcement returns between the short-duration quintile (long leg) and the long-duration quintile (short leg). The premium per annum is computed by multiplying the daily premium by the number of event days within a year. The sample period is from 1980 to 2023.

Window	# Days p.a.	Daily premium	<i>t</i> -stat	Premium p.a.	Proportion
–	252	4.33 bps	5.34	10.92%	100.00%
[0, 0]	4	54.03 bps	7.84	2.16%	19.79%
[–1, +1]	12	23.66 bps	8.03	2.84%	26.00%
[–3, +3]	28	14.55 bps	7.53	4.07%	37.30%
[–5, +5]	44	10.29 bps	6.60	4.53%	41.45%

Table 2
Returns in the earnings announcement window

This table reports the equal-weighted daily average returns for each day during the $[-3, +3]$ event window for each quintile portfolio. Panel A presents the average raw returns, while panel B shows the CAPM alphas. I estimate CAPM beta for individual stocks in the pre-event window $[-273, -22]$ via the slope-winsorized method in Welch (2021). I require a minimum of 152 daily return observations for accurate beta estimation. The t -statistics, based on the heteroskedasticity consistent standard errors, are reported in parentheses.

Day	-3	-2	-1	0	1	2	3
Panel A: Raw return							
Short Dur	15.90	21.12	25.17	27.01	7.86	11.80	10.65
Q2	9.76	11.94	17.30	23.76	5.30	-0.75	8.26
Q3	9.46	10.62	13.79	11.57	7.71	3.02	5.47
Q4	9.66	10.30	12.56	5.97	4.67	5.24	3.49
Long Dur	10.06	19.16	21.07	-27.06	-9.86	3.70	-0.19
Q1 – Q5	5.83 (1.54)	1.96 (0.57)	4.10 (1.19)	54.07 (7.86)	17.72 (4.63)	8.09 (2.38)	10.84 (3.11)
Q3 – Q5	-0.61 (-0.17)	-8.54 (-2.69)	-7.28 (-2.42)	38.63 (7.37)	17.57 (4.64)	-0.68 (-0.21)	5.66 (1.70)
Panel B: CAPM alpha							
Short Dur	9.45	12.38	17.61	15.13	-1.54	2.89	3.59
Q2	3.39	7.32	11.35	17.21	-1.03	-6.26	3.21
Q3	5.06	4.66	8.34	12.26	0.65	-1.74	-0.06
Q4	3.44	4.73	7.74	7.17	-1.28	-0.98	-2.23
Long Dur	0.64	6.82	12.10	-24.64	-17.90	-6.61	-8.28
Q1 – Q5	8.80 (3.12)	5.56 (2.25)	5.51 (2.06)	39.77 (8.37)	16.36 (5.63)	9.51 (3.81)	11.87 (4.23)
Q3 – Q5	4.42 (1.67)	-2.16 (-0.99)	-3.76 (-1.52)	36.90 (9.19)	18.55 (6.38)	4.87 (1.88)	8.22 (3.29)

Table 3
Horizon bias and term premia

This table reports the cumulative returns in the $[-5, +5]$ announcement window by portfolios conditionally sorted on duration and horizon bias. *Horizon bias* is defined as the difference between long-term and short-term growth expectations, which are cross-sectionally standardized. Each quarter, firms with earnings announcements in that quarter are first sorted into five quintiles according to their equity duration; within each duration quintile, stocks are then sorted into five groups based on their horizon bias measure. The t -statistics, based on the heteroskedasticity consistent standard errors, are reported in parentheses.

Dur	Low HB (1)	Q2 (2)	Q3 (3)	Q4 (4)	High HB (5)	H – L (6)	t -stat (7)
Short Dur	8.62	9.34	9.57	12.22	15.07	6.46	(2.37)
Q2	7.54	8.58	9.38	10.12	12.40	4.85	(2.47)
Q3	6.43	7.63	8.97	9.02	9.70	3.27	(1.77)
Q4	5.00	7.55	6.64	6.59	6.27	1.27	(0.60)
Long Dur	6.68	6.39	4.44	4.41	0.02	-6.66	(-2.12)
S – L	1.93	2.95	5.13	7.81	15.05	13.12	
t -stat	(0.58)	(0.96)	(1.95)	(2.52)	(4.60)	(3.19)	

Table 4
Price effect

This table shows the regression results of pre- and post-announcement alpha on horizon bias. I estimate CAPM beta for individual stocks in the pre-event window $[-273, -22]$ via the slope-winsorized method in Welch (2021). I control for the following firm characteristics: nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. The t -statistics, based on the two-way clustered standard errors across firm and quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Cumulative CAPM alpha $[-3, -1]$		Cumulative CAPM alpha $[0, +2]$		
	(1)	(2)	(3)	(4)	(5)
Horizon bias	0.211*** (2.894)	0.148** (2.388)	-0.258*** (-2.873)	-0.229** (-2.265)	-0.339*** (-3.018)
Duration		-0.017 (-0.499)		-0.035 (-0.474)	-0.069 (-0.906)
SUE					2.101*** (20.865)
SUE $\times$ Horizon bias					1.325*** (8.072)
Controls	✓	✓	✓	✓	✓
Fixed effects	Date	Date	Firm/Date	Firm/Date	Firm/Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
R^2	0.013	0.014	0.068	0.067	0.096
Observations	249,960	149,545	249,960	149,545	134,825

Table 5
Term premia controlling for arbitrage risk

This table presents the average pre- and post-announcement returns for 25 portfolios double sorted on IVOL and equity duration. Each quarter, firms announcing earnings within that quarter are first sorted into five IVOL quintiles based on their PEA IVOL estimated in the month preceding the earnings announcement date (Yang et al. 2020). Subsequently, within each IVOL quintile, stocks are further sorted into five groups according to their equity duration from the previous quarter. The *t*-statistics, based on the heteroskedasticity consistent standard errors, are reported in parentheses.

IVOL	Short Dur (1)	Q2 (2)	Q3 (3)	Q4 (4)	Long Dur (5)
Panel A: Pre-announcement window $[-3, -1]$					
Low	11.51	5.97	6.99	9.25	10.76
Q2	14.37	10.47	7.92	5.54	11.01
Q3	18.41	13.27	11.73	10.56	13.52
Q4	23.03	18.28	15.26	12.97	14.88
High	28.40	24.64	20.21	19.11	26.78
AVG	19.14	14.53	12.42	11.49	15.39
H – L	16.88 (3.86)	18.67 (5.14)	13.23 (2.91)	9.86 (2.53)	16.01 (2.63)
Panel B: Post-announcement window $[0, +2]$					
Low	21.80	14.23	11.45	8.14	9.14
Q2	15.96	14.25	10.96	6.13	0.17
Q3	18.56	9.93	4.36	3.04	-0.04
Q4	13.24	11.29	1.68	3.71	-23.29
High	15.49	-1.26	-4.87	-15.64	-28.46
AVG	17.01	9.69	4.72	1.07	-8.50
H – L	-6.31 (-1.19)	-15.50 (-2.87)	-16.32 (-3.45)	-23.78 (-4.19)	-37.60 (-6.21)

Table 6
Predicting retail net trading prior to earnings announcements

This table reports the regression of average retail net buy volume on horizon bias in the pre-announcement window $[-5, -1]$. I control for the following firm characteristics: nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. I include both firm and quarter fixed effects. I use horizon-bias quintile dummies in column (5), with quintile 3 as the reference category. The t -statistics, based on the two-way clustered standard errors across firm and quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Average retail net buy $[-5, -1]$				
	(1)	(2)	(3)	(4)	(5)
Horizon bias	0.100*** (5.575)	0.117*** (6.286)	0.114*** (6.341)	0.135*** (6.142)	
Duration				0.032** (2.022)	0.029*** (3.040)
Q5					0.046*** (3.430)
Q4					0.022** (2.084)
Q2					-0.018* (-1.842)
Q1					-0.058*** (-3.898)
Controls			✓	✓	✓
Fixed effects	Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date	Firm/Date
R^2	0.002	0.103	0.104	0.098	0.095
Observations	103,395	103,395	97,283	63,655	104,810

Table 7
Limits to arbitrage and the term premium

This table reports the regression of average retail net buy volume on horizon bias in the pre-announcement window $[-5, -1]$. I control for the following firm characteristics: nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. I include both firm and quarter fixed effects. I use horizon-bias quintile dummies in column (5), with quintile 3 as the reference category. The t -statistics, based on the two-way clustered standard errors across firm and quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Short duration (1)	Long duration (2)	Term premium (S – L) (3)
Pilot $\times$ During	0.002 (0.903)	–0.011** (–2.474)	0.013*** (3.271)
Pilot	–0.001 (–0.711)	0.000 (0.041)	–0.001 (–0.473)
Fixed effects	Month	Month	Month
R^2	0.721	0.749	0.550
Observations	988	988	988

Table 8
Anomaly returns around earnings announcements

This table reports the daily stock returns on anomaly leg dummies. For each firm-month observations, I sum the number of long-side and short-side anomaly portfolios that the observation belongs to to construct variable *Long* and *Short*, respectively. In column (1), I construct *Long* and *Short* across all the 119 anomalies that work out of sample in Jensen et al. (2023), while columns (2)–(4) count the number of long-side and short-side anomaly portfolios within value, profitability, and low-risk category. *EDay* and *EDay-L1* are dummies for the earnings announcement date and the day before the earnings announcement date, respectively. The *t*-statistics, based on the two-way clustered standard errors across firm and date, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	All (1)	Value (2)	Profitability (3)	Low-risk (4)
Panel A: Earnings-day return				
Long	0.422*** (18.440)	1.164*** (10.707)	−0.563*** (−6.312)	0.544*** (5.241)
Short	−0.143*** (−4.475)	−0.360*** (−3.985)	0.706*** (6.990)	0.026 (0.162)
EDay × Long	0.495*** (3.319)	0.360 (0.756)	−3.833*** (−6.926)	1.162** (2.258)
EDay × Short	−2.677*** (−15.653)	−8.626*** (−15.126)	−10.858*** (−13.335)	−10.080*** (−12.198)
EDay	44.949*** (10.587)	24.624*** (9.870)	25.667*** (10.675)	20.801*** (8.213)
Panel B: Pre-announcement return				
Long	0.423*** (18.123)	1.173*** (10.655)	−0.611*** (−6.821)	0.583*** (5.597)
Short	−0.175*** (−5.484)	−0.467*** (−5.160)	0.575*** (5.713)	−0.105 (−0.642)
EDay-L1 × Long	0.546*** (6.299)	−0.220 (−0.826)	0.311 (1.032)	−1.791*** (−4.871)
EDay-L1 × Short	0.326*** (3.168)	0.925** (2.377)	1.851*** (3.754)	1.892*** (4.428)
EDay-L1	−2.968 (−1.133)	12.809*** (7.951)	11.335*** (8.189)	14.417*** (8.756)

Table 9
Retail sentiment: Evidence from value, profitability, and low-risk factors

The tables reports the daily retail net buy volume on anomaly quintile dummies. *NBuy* is defined as retail net buy volume scaled by total shares outstanding, and *NBuyV* is defined as retail net buy volume scaled by the sum of retail buy and sell volume. Intervals $[-5, -1]$ and $[-10, -1]$ indicate that the retail net buy is computed as the window-average. Each month, I construct a Z-score over 39 anomalies that belong to value, profitability, and low-risk category. I sign the Z-score of individual anomalies such that higher Z-scores indicate higher expected returns. Stocks are sorted into five quintiles based on their Z-scores. $1_{\text{Abr}-x}$ are the anomaly quintile dummies, and quintile 3 is the omitted category. The *t*-statistics, based on the two-way clustered standard errors across firm and date, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	NBuy			NBuyV		
	-1	$[-5, -1]$	$[-10, -1]$	-1	$[-5, -1]$	$[-10, -1]$
EDay-L1 $\times 1_{\text{Abr1}}$	13.713*** (6.319)	6.490*** (6.512)	3.781*** (5.285)	13.111*** (4.391)	8.101*** (5.823)	4.303*** (4.398)
EDay-L1 $\times 1_{\text{Abr2}}$	11.076*** (7.053)	4.770*** (7.313)	2.588*** (5.832)	7.548*** (3.841)	4.759*** (4.805)	2.099*** (2.855)
EDay-L1 $\times 1_{\text{Abr4}}$	-6.327*** (-5.640)	-2.037*** (-4.237)	-1.117*** (-3.288)	-9.844*** (-5.649)	-2.834*** (-3.239)	-2.083*** (-3.311)
EDay-L1 $\times 1_{\text{Abr5}}$	-11.894*** (-10.308)	-4.559*** (-9.416)	-2.666*** (-7.931)	-15.532*** (-9.217)	-6.471*** (-7.391)	-4.158*** (-6.527)
EDay-L1	23.467*** (22.470)	6.979*** (16.087)	3.523*** (12.203)	31.343*** (21.248)	10.185*** (14.131)	5.863*** (11.210)
1_{Abr1}	4.807*** (6.455)	4.760*** (6.480)	4.995*** (6.816)	6.981*** (6.363)	6.946*** (6.403)	7.325*** (6.757)
1_{Abr2}	0.005 (0.016)	0.049 (0.157)	0.171 (0.555)	0.533 (0.962)	0.455 (0.826)	0.597 (1.098)
1_{Abr4}	0.369 (1.616)	0.238 (1.067)	0.250 (1.132)	1.713*** (3.701)	1.375*** (3.059)	1.249*** (2.813)
1_{Abr5}	1.035*** (3.337)	0.919*** (3.005)	0.912*** (3.005)	3.768*** (5.876)	3.473*** (5.474)	3.242*** (5.149)
Stock-level controls	✓	✓	✓	✓	✓	✓
Fixed effects	Firm/Day	Firm/Day	Firm/Day	Firm/Day	Firm/Day	Firm/Day
Cluster	Firm/Day	Firm/Day	Firm/Day	Firm/Day	Firm/Day	Firm/Day
R^2	0.012	0.037	0.058	0.018	0.066	0.108
Observations	12,270,348	12,245,901	12,213,494	12,270,082	12,244,765	12,211,494

Table 10
Term premium conditional on sentiment

This table reports annualized monthly average returns across duration quintiles, conditional on beginning-of-period sentiment. I employ the market-wide sentiment index from Baker and Wurgler (2006). *Avg* denotes unconditional average returns, while *high sent* and *low sent* represent average returns during high and low sentiment months, respectively, where sentiment states are determined by the median of the sentiment index. The *t*-statistics, computed using heteroskedasticity-consistent standard errors, are reported in parentheses. The monthly sample period spans from 1973:8 to 2024:1.

	Short dur	Q2	Q3	Q4	Long dur	S – L
	(1)	(2)	(3)	(4)	(5)	(6)
Avg	0.165 (6.372)	0.158 (6.628)	0.151 (6.709)	0.124 (5.239)	0.098 (3.208)	0.067 (3.135)
High sent	0.164 (4.882)	0.148 (4.639)	0.132 (4.247)	0.083 (2.459)	0.054 (1.198)	0.111 (3.405)
Low sent	0.166 (4.204)	0.168 (4.737)	0.169 (5.220)	0.165 (4.991)	0.142 (3.438)	0.024 (0.856)

Table 11
Fama Macbeth regression

Monthly excess returns are regressed onto lagged characteristics. This table reports the time-series mean and t -statistics of the estimated coefficients. The monthly sample period is from 2000:4 to 2023:3.

Characteristic	Coefficient
RFD	0.126*** (2.998)
Log market equity	-0.621*** (-13.483)
Book-to-market equity	0.005 (0.088)
Profitability	0.135** (2.457)
Investment	0.026 (0.575)
CAPM beta	0.025 (0.140)
Momentum	-0.267** (-2.253)
Duration	-0.001 (-0.011)

Table 12
Conditional double sort on duration and RFD

Tercile duration and RFD portfolios are formed independently each month based on the signal from the past quarter. Panel A reports the FF3 alphas of two-way sorted portfolios, as well as those from long-short strategies. Short duration (short RFD) corresponds to the bottom tercile, while long duration (high RFD) denotes the top tercile. Panel B reports the five-year cumulative stock returns across RFD quintiles, where $\alpha = 0.9779$ is a constant from Bordalo et al. (2024).

Panel A: FF3 alpha of RFD portfolios						
	Low RFD	High RFD	H – L			
	(1)	(2)	(3)			
Long dur	–0.001 (–0.438)	0.008*** (12.391)	0.010*** (3.004)			
Short dur	0.005*** (3.893)	0.001 (0.094)	–0.005 (–0.506)			
S – L	0.007** (1.973)	–0.008 (–0.839)				
Panel B: Long-run stock returns						
	Low RFD	Q2	Q3	Q4	High RFD	H – L
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{j=1}^5 \alpha^{j-1} r_{t+j}(n)$	0.301*** (15.969)	0.315*** (17.613)	0.295*** (16.509)	0.272*** (13.899)	0.195*** (9.633)	–0.106*** (–7.429)

Table 13
Counterfactual repricing statistics

This table reports the time-series means of the repricing statistics from the counterfactual experiment. For each institution i , I compute its average demand coefficient on equity duration over high- and low-sentiment periods, $\gamma_{i,hi}$ and $\gamma_{i,lo}$. I then rank all institutions based on the difference $\gamma_{i,hi} - \gamma_{i,lo}$ and drop the institutions with the most positive changes whose cumulative AUM is 10% of that of all investors. I reallocate their AUM to all remaining investors, pro rata. I compute the price impact statistics, defined in Equation (21), of the short- and long-duration portfolios from this counterfactual experiment. Each panel report the time-series means of these metrics over the full sample (*Avg*), quarters with above-median sentiment (*High Sent*), and quarters with below-median sentiment (*Low Sent*). The t -statistics, based on the heteroskedasticity consistent standard errors, are reported in parentheses.

	Short dur (1)	Long dur (2)	Short – Long (3)
Avg	0.344 (0.461)	0.618 (1.932)	−0.274 (−0.291)
High sent	4.347 (3.695)	−0.815 (−1.849)	5.162 (3.811)
Low sent	−3.577 (−7.433)	2.023 (5.481)	−5.599 (−7.542)
High – Low	7.924 (6.280)	−2.838 (−4.945)	10.762 (7.005)

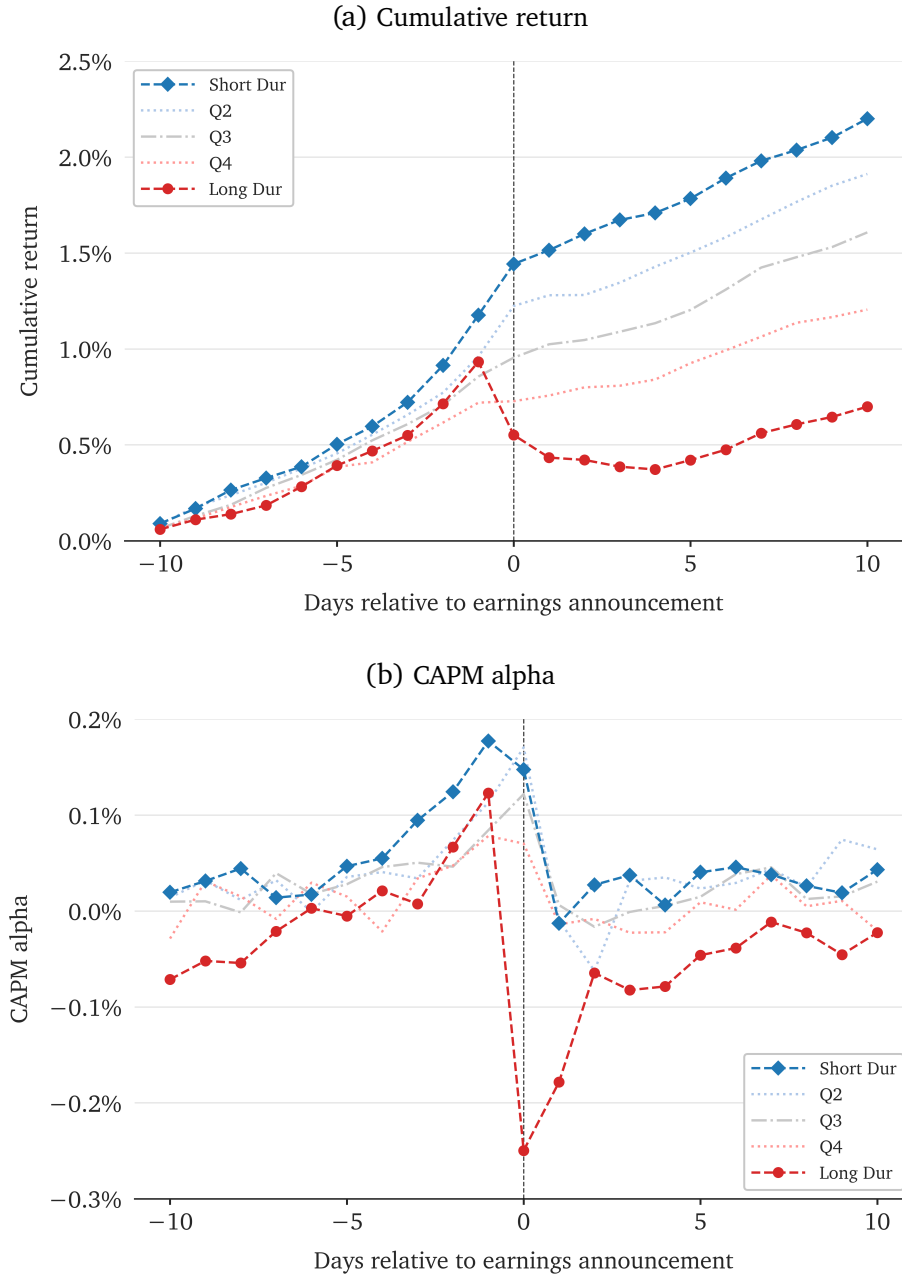


Figure 1. Returns in the earnings announcement window. The figure reports the cumulative return and CAPM alpha across duration quintiles in the $[-10, 10]$ window around earnings announcements. Each quarter, firms with earnings announcements are split into five quintile portfolios based on equity duration from the previous quarter. For each day during the event window for each portfolio, I compute the equal-weighted average return and CAPM alpha. I estimate CAPM beta for individual stocks using a pre-event window $[-273, -22]$ via the slope-winsorized method in Welch (2021).

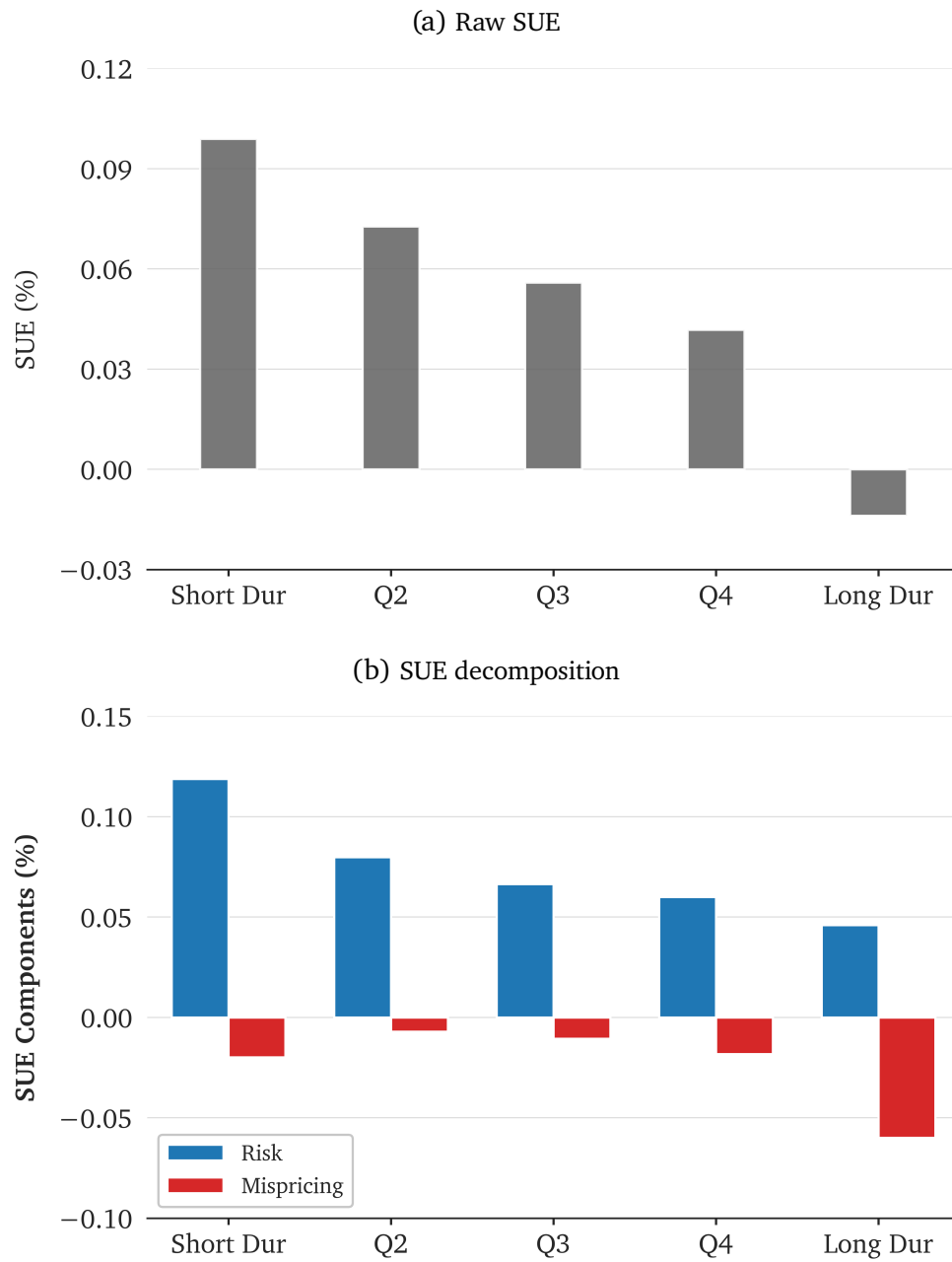


Figure 2. Earnings news decomposition. Following Glosten et al. (2021), I estimate a regression of firm-level quarterly SUE on market-wide value-weighted average SUE and SIC-2 value-weighted average SUE in 15-year rolling windows. The fitted value from this regression represents the risk component, while the residual is the behavioral component.

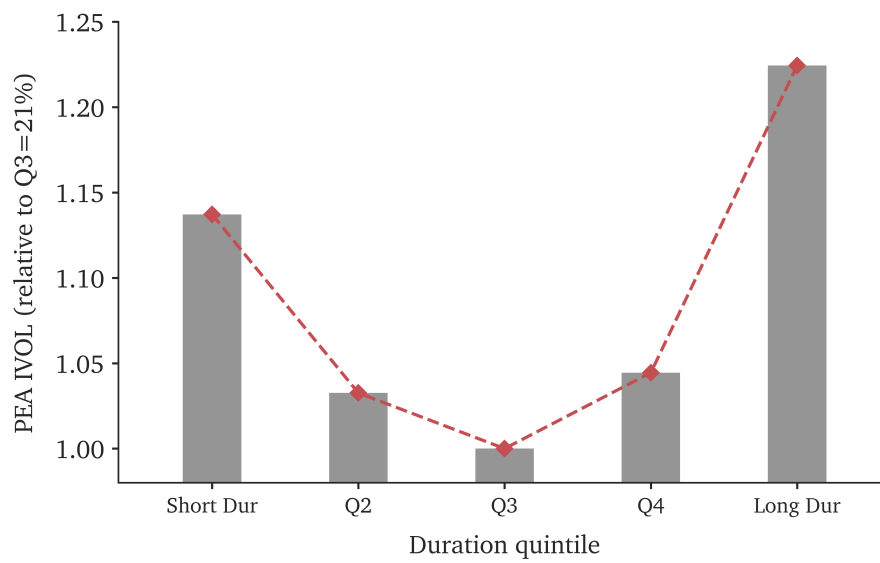


Figure 3. The IVOL smile. This figure presents the idiosyncratic volatility (IVOL) across duration quintiles in the pre-earnings-announcement period. Following Yang et al. (2020), I measure idiosyncratic volatility (IVOL) relative to the Fama and French (1993) three-factor model (FF3). For each stock and each month, I run the FF3 model using past one-year daily returns to obtain the estimated daily residuals. I define the pre-earnings-announcement periods (PEAs) as the five business days before the most recent four earnings announcement days, i.e., $[-5, -1]$. I then compute the annualized idiosyncratic volatility for each firm-month observation.

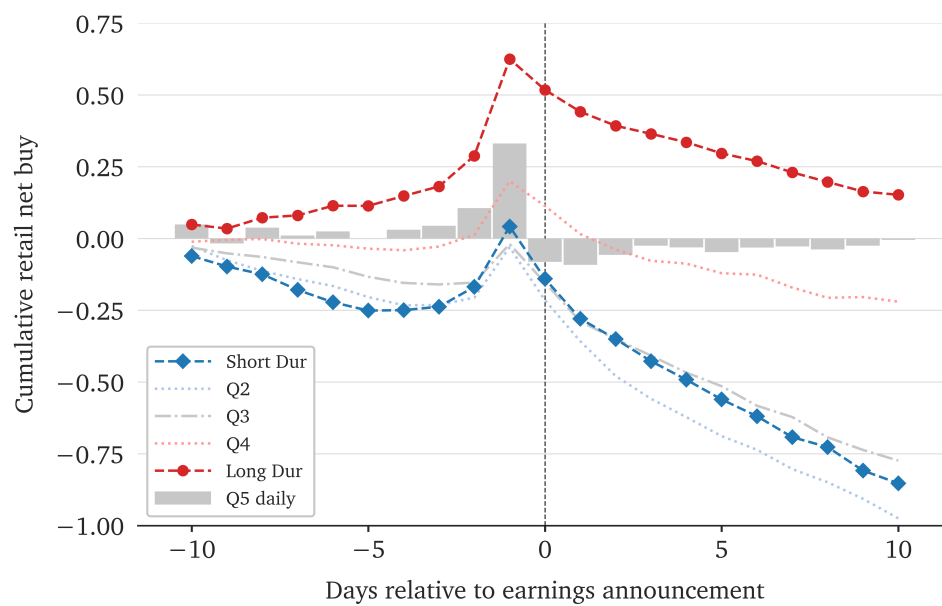


Figure 4. Retail activity around earnings announcement by duration. This figure plots the cumulative retail net trading by duration quintile in the $[-10, +10]$ event window around earnings announcements. Retail net trading is defined as the volume of retail buys minus the volume of retail sells, normalized by total shares outstanding.

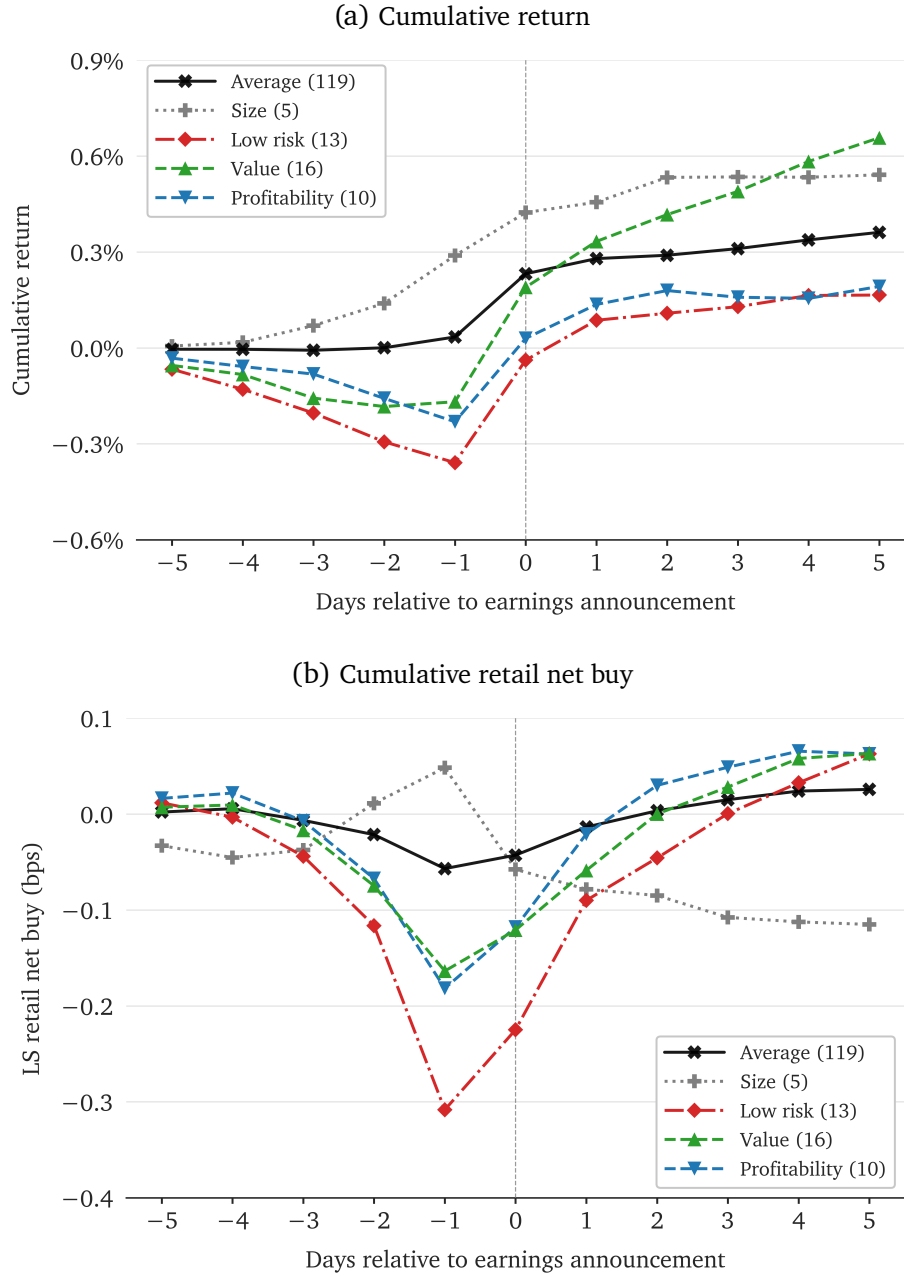


Figure 5. Anomaly return and retail net buy. The figure reports the difference in cumulative returns and retail net buy volume between the long and short leg portfolios across anomaly types in the $[-10, +10]$ event window around earnings announcements. I use 119 anomalies that work out of sample in Jensen et al. (2023). Within each anomaly category, I compute the equal-weighted average cumulative return and retail net buy volume across the anomalies in this category.

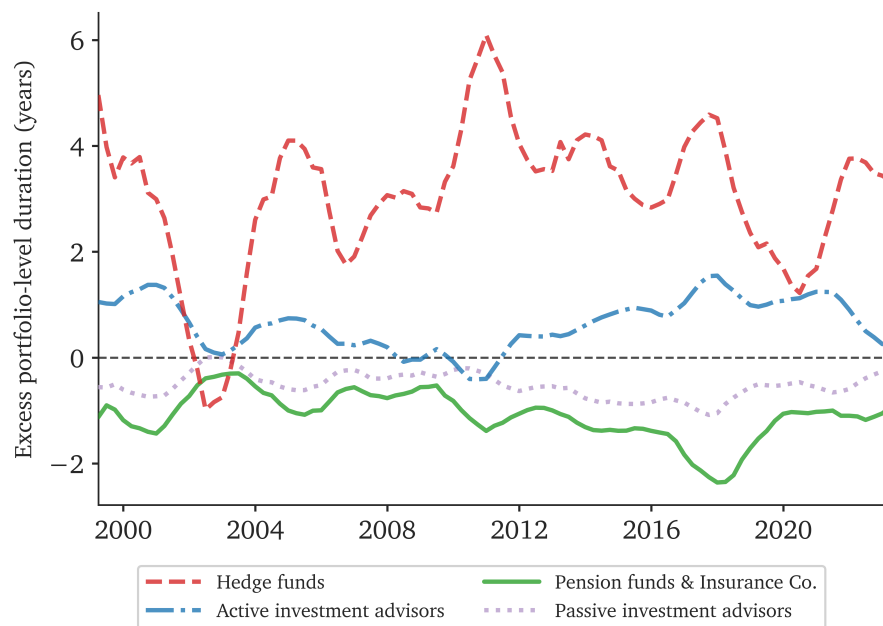


Figure 6. Value-weighted portfolio-level duration by investor type. This figure presents the time-series of portfolio-level duration by investor type. The portfolio duration at the investor level is calculated as a holding value-weighted average of individual stock duration. I then compute a wealth-weighted average of the portfolio duration by investor type. Note that IA denotes investment advisors.

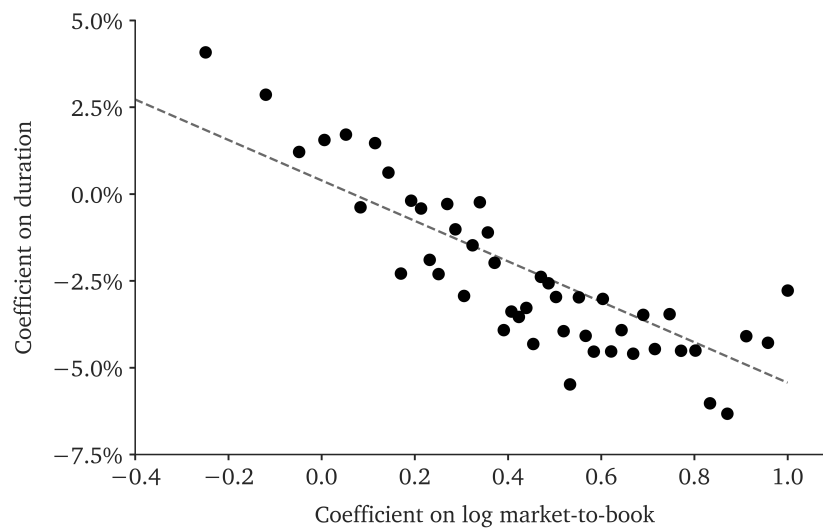


Figure 7. Binned scatterplot of demand coefficients. This figure shows the relationship between demand coefficients on duration and price inelasticity in the binscatter plot.

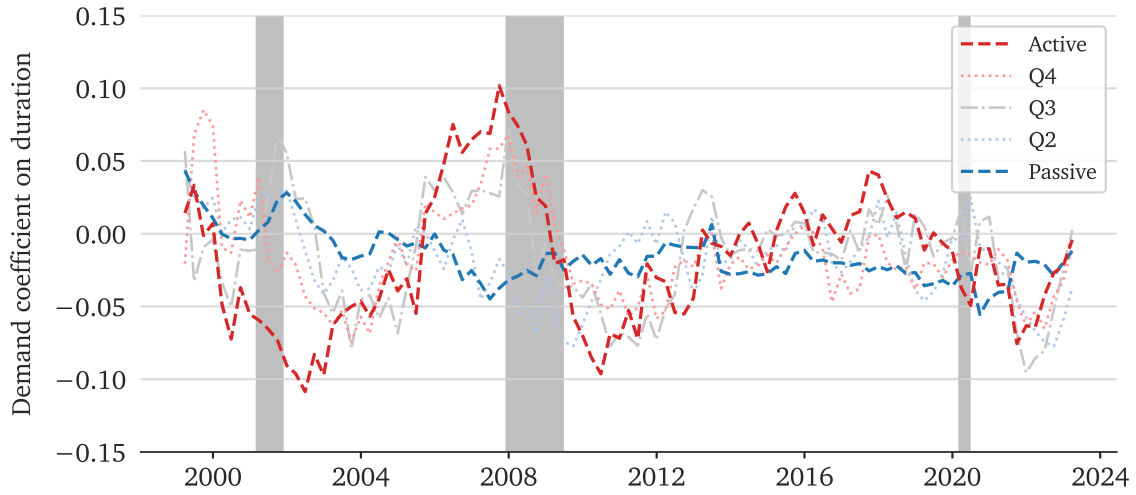


Figure 8. Institutional duration tilts. This figure reports the time series of the demand coefficient on equity duration across quintiles of investor active share. Active share is defined as $AS_{i,t} = \frac{1}{2} \sum_{n \in \mathcal{N}_{i,t}} |w_{i,t}^{\text{in}}(n) - w_{i,t}^{\text{M}}(n)|$, where $w_{i,t}^{\text{in}}(n)$ is the investor's portfolio weight on stock n among inside assets only, and $w_{i,t}^{\text{M}}(n)$ is the corresponding market weight if the investor were to hold the market portfolio among its inside assets. The shaded areas denote NBER recession periods.

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Appendix

A. Horizon bias and the equity term structure

A.1. Linking horizon bias to the equity term premia

The price of an asset can be defined as

$$P = \frac{\mathbb{E}[\text{Future cash flows}]}{\text{Discount rate}}. \quad (\text{A1})$$

There are two assets. The short-term asset (*ST*) entitles the owner to a dividend D_{t+1} in the next period. The long-term asset (*LT*) entitles the owner to an infinite stream of future dividends. Using the present-value relation, we can write the prices of the short-term asset and the long-term asset as:

$$P_t^{ST} = \frac{D_t(1 + g^{ST})}{1 + r}, \quad (\text{A2})$$

$$P_t^{LT} = \frac{D_t(1 + g^{ST})}{1 + r} + \frac{1}{1 + r} \frac{D_t(1 + g^{ST})(1 + g^{LT})}{r - g^{LT}}, \quad (\text{A3})$$

where r is a constant required rate of return, D_t is the dividend observed at the end of the current period, g^{ST} is investors' forecast of dividend growth rate in the next period, and g^{LT} is investors' forecast of dividend growth rate in every period after that. Suppose that the actual dividend growth rate is g^R . Then, the next-period price of the short- and long-term assets and the next-period dividend are

$$P_{t+1}^{ST} = 0, \quad (\text{A4})$$

$$P_{t+1}^{LT} = P_t^{LT}(1 + g^R), \quad (\text{A5})$$

$$D_{t+1} = D_t(1 + g^R). \quad (\text{A6})$$

We can write the gross return of the short-term asset, R_{t+1}^{ST} , and the long-term asset, R_{t+1}^{LT} , between times t and $t + 1$:

$$R_{t+1}^{ST} = \frac{D_{t+1}}{P_t^{ST}} = \frac{(1 + g^R)(1 + r)}{1 + g^{ST}}, \quad (\text{A7})$$

$$\begin{aligned} R_{t+1}^{LT} &= \frac{P_{t+1}^{LT} + D_{t+1}}{P_t^{LT}} \\ &= \frac{D_t(1 + g^R)}{\frac{D_t(1 + g^{ST})}{1 + r} + \frac{1}{1 + r} \frac{D_t(1 + g^{ST})(1 + g^{LT})}{r - g^{LT}}} + (1 + g^R) \end{aligned}$$

$$\begin{aligned}
&= \frac{(1 + g^R)(r - g^{LT})}{1 + g^{ST}} + (1 + g^R) \\
&= \frac{(1 + g^R)(1 + r)}{1 + g^{ST}} + \frac{(1 + g^R)(g^{ST} - g^{LT})}{1 + g^{ST}}.
\end{aligned} \tag{A8}$$

Taking the expected difference between the long- and short-term asset over the next period, we obtain

$$ETP_{t+1} = \mathbf{E}_t[R_{t+1}^{LT} - R_{t+1}^{ST}] = -(g^{LT} - g^{ST}) \frac{1 + g^R}{1 + g^{ST}}. \tag{A9}$$

With a constant actual growth rate in fundamentals g^R over all horizons, it also follows that

$$ETP \propto -(\text{Bias}^{LT} - \text{Bias}^{ST}), \tag{A10}$$

where Bias^{LT} (Bias^{ST}) is the difference between investors' long-term (short-term) growth forecast and the actual growth rate.

A.2. Firm-level horizon bias

Following Cassella et al. (2023), I compute the firm-level horizon bias measure. First, I compute the long-term growth rate implied by the short-term growth rate for firm n :

$$LTG_t^{\text{Implied}}(n) = \frac{1}{5} [4\phi_0 + 3\phi_0\phi_1 + 2\phi_0\phi_1^2 + \phi_0\phi_1^3 + STG_t(n)(1 + \phi_1 + \phi_1^2 + \phi_1^3 + \phi_1^4)], \tag{A11}$$

where ϕ_0 is the mean for the short-term growth rate ϕ_1 is the annual persistence. Define the horizon bias as the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate,

$$\text{Horizon Bias}_t(n) = LTG_t(n) - LTG_t^{\text{Implied}}(n). \tag{A12}$$

B. The asset demand system

I set up an asset demand system that incorporates the duration characteristic into investor demand curves. By allowing for heterogeneity across both investors and time, I can analyze how equity duration is demanded by various investors.

B.1. Setup and notation

I adopt the framework and notation from Kojien and Yogo (2019), introducing equity duration as a key extension. Investors may value sustainability for both pecuniary and non-pecuniary reasons, with supporting evidence for both motivations (e.g., Barber et al., 2021; Bansal et al.,

2018). While we do not take a stance on which motivation is more dominant, we demonstrate in Section 2.1 that greenness should be incorporated into the characteristics-based demand model in at least two scenarios: when greenness is indicative of expected returns, or when investors are constrained to maintain a green portfolio due to investment mandates or client pressure. Section 2.2 then explores the concept of institutional pressure.

To summarize the notation, I denote vectors and matrices in boldface and index their elements in parentheses (e.g., $x(n)$ is the n -th element of the vector $\mathbf{x}$). I denote an identity matrix as $\mathbf{I}$, a vector of zeros as $\mathbf{0}$, and a vector of ones as $\mathbf{i}$.

Consider an economy with N financial assets indexed by $n = 1, \dots, N$, and I investors indexed by $i = 1, \dots, I$. The outside asset is denoted as the 0-th asset. Let $P_t(n)$ and $S_t(n)$ represent the price and shares outstanding of asset n at time t , respectively. I denote the logarithms of these variables in lowercase letters and use boldface for N -dimensional vectors. Suppose each asset has K characteristics indexed by $k = 1, \dots, K$, with the k -th characteristic of asset n at time t denoted as $x_{kt}(n)$, and the vector of characteristics as $\mathbf{x}_t(n)$.

The investment universe is a subset of assets that an investor is allowed to hold, which in practice is determined by an investment mandate. Investor i optimally allocates her portfolio weights $\mathbf{w}_{it}$ at date t across assets in its investment universe $\mathcal{N}_{it} \subseteq \{1, \dots, N\}$ and an outside asset. Let A_{it} represent the assets under management for investor i at time t . Investor i seeks to maximize her expected terminal wealth $\mathbf{E}_{it}[\log(A_{iT})]$ subject to an intertemporal budget constraint. Investors are subject to short-sale constraints, $\mathbf{w}_{it} \geq \mathbf{0}$ and $\mathbf{w}_{it}'\mathbf{i} < 1$. They hold heterogeneous beliefs regarding the expected returns of assets, which are formed based on observed characteristics. The unobserved latent demand for asset (n) by investor (i) is denoted as $\log(\varepsilon_{it}(n))$. Consequently, investor i 's information set for asset n at date t can be expressed as:

$$\hat{\mathbf{x}}_{it}(n) = \begin{bmatrix} \mathbf{m}\mathbf{e}_t(n) \\ \mathbf{x}_t(n) \\ \log(\varepsilon_{it}(n)) \end{bmatrix},$$

and an M -th order polynomial of these characteristics through a $\sum_{m=1}^M (K+2)^m$ -dimensional vector:

$$\mathbf{y}_{it}(n) = \begin{bmatrix} \hat{\mathbf{x}}_{it}(n) \\ \text{vec}(\hat{\mathbf{x}}_{it}(n)\hat{\mathbf{x}}_{it}(n)') \\ \vdots \end{bmatrix},$$

which determines investor i 's beliefs about expected returns on asset n .

I maintain the Assumption 1 of Kojen and Yogo (2019), so that the covariance of log excess returns is $\Sigma_{it} = \Gamma_{it}\Gamma_{it}' + \gamma_{it}\mathbf{I}$, where Γ_{it} is a vector of factor loadings and γ_{it} is idiosyncratic variance,

and that expected returns μ_{it} and factor loadings Γ_{it} are polynomial functions of characteristics:

$$\mu_{it}(n) = \mathbf{y}_{it}(n)' \Phi_{it} + \phi_{it}, \quad (\text{B1})$$

$$\Gamma_{it}(n) = \mathbf{y}_{it}(n)' \Psi_{it} + \psi_{it}, \quad (\text{B2})$$

where Φ_{it} and Ψ_{it} are vectors and ϕ_{it} and ψ_{it} are scalars that are constant across assets, which implies a factor structure in which an asset's own characteristics are sufficient for its factor loadings.

Importantly, I further assume that firm-level cash flow duration is included in the vector of characteristics $\mathbf{x}_t(n)$. Moreover, Appendix A of Kojien and Yogo (2019) demonstrates that under a specific coefficient restriction, investors' optimal portfolio weights can be expressed as logit functions of prices, characteristics, and latent demand. Specifically, the optimal portfolio weight on stock n for investor i at date t is given by:

$$\frac{w_{it}(n)}{w_{it}(0)} \equiv \delta_{it}(n) = \exp\{\alpha_{it} + \beta_{0it} \text{me}_t(n) + \beta'_{1it} \mathbf{x}_t(n)\} \varepsilon_{it}(n), \quad (\text{B3})$$

with equity duration entering as part of the characteristics $\mathbf{x}_t(n)$. Let $(K + 1)$ -dimensional vector $\hat{\beta}'_{it} = [1, \beta'_{it}]$ represent the demand coefficients on stock characteristics. Appendix A of Kojien and Yogo (2019) further shows that:

$$\hat{\beta}_{it} \propto \frac{1}{\gamma_{it}} (\Phi_{it} - \kappa_{it} \Psi_{it}), \quad (\text{B4})$$

where κ_{it} is a scalar that does not vary across stocks. However, the expression for $\hat{\beta}_{it}$ indicates that the relationship between asset demand and observed characteristics cannot disentangle whether an investor's tilt toward a particular characteristic is driven by expected profitability, risk, or sentiment.

B.2. Estimation methodology

A significant challenge in demand estimation arises from the fact that most institutions maintain concentrated portfolios. Consequently, many investors lack sufficient observations in the cross-section of equity holdings for precise demand estimation. This issue is particularly pertinent given the definition of inside assets as the largest 90% of firms by market equity, which shrinks the cross-section relative to the entire universe of U.S. stocks. Moreover, Kojien et al. (2024) estimate the demand coefficients annually for each investor, while this paper allows for quarterly variations in the demand function. Consequently, the aforementioned identification challenge becomes even more pronounced for quarterly estimation.

I estimate the demand coefficients for all investors, including the household sector, using a two-step instrumental variables ridge estimation following Kojien et al. (2024). In the first step, I

conduct a pooled annual estimation to determine the group shrinkage target. Based on investor classification, I rank institutions by average market equity for each investor type annually, ensuring unique groupings. These institutions are then grouped into type bins, each containing at least 2,000 holdings across the four quarters. Consequently, investor i 's holdings of stock n in different quarters are treated as distinct observations, with smaller institutions' holdings more likely to be pooled to minimize estimation error. Let $\mathbf{0}$ be a vector of zeros, with a dimension equal to the number of moment conditions. Let $\mathbf{e}_t$ be a four-dimensional vector representing quarter fixed effects, where the t -th element is one and the other elements are zero. For each (Type Bin, Year) group, I estimate the demand coefficients using the following moment conditions:

$$\mathbf{E} \left\{ \underbrace{[\delta_{it}(n) \exp(-\beta_0 \text{mb}_t(n) - \alpha'_i \mathbf{e}_t - \beta'_1 \mathbf{x}_t(n)) - 1]}_{\varepsilon_{it}(n)} \begin{pmatrix} z_{it}(n) \\ \mathbf{e}_t \\ \mathbf{x}_t(n) \end{pmatrix} \right\} = \mathbf{0}. \quad (\text{B5})$$

Denote the first-stage pooled estimates for log market-to-book equity and other features as $\hat{\beta}_0$ and $\hat{\beta}_1$, respectively.

In the second step, I estimate the demand coefficients at (Investor, Quarter) level, using the first-stage pooled estimates as the shrinkage target. To mitigate weak identification, I use the group-level coefficient on log market-to-book equity for all investors within the (Type Bin, Year) group, corresponding to an infinite penalty on β_{0it} . The coefficients on the other characteristics are estimated through the following moment condition:

$$\mathbf{E} \left\{ [\hat{\delta}_{it}(n) \exp(-\alpha'_i \mathbf{e}_t - \beta'_1 \mathbf{x}_t(n)) - 1] \begin{pmatrix} \mathbf{e}_t \\ \mathbf{x}_t(n) \end{pmatrix} \right\} - \frac{\lambda}{|\mathcal{N}_{it}|^\xi} \begin{pmatrix} \mathbf{0} \\ \beta_{1it} - \hat{\beta}_1 \end{pmatrix} = \mathbf{0}, \quad (\text{B6})$$

where $\hat{\delta}_{i,t}(n) = \delta_{i,t}(n) \exp(-\hat{\beta}_0 \text{mb}_t(n))$. This penalty is inversely related to $|\mathcal{N}_{it}|$, the number of investor i 's stock holdings in quarter t . The penalty shrinks the demand coefficients toward the group-level estimate $\hat{\beta}_1$. I select the penalty parameters by cross-validation, minimizing the mean squared error of predicted demand by randomly splitting the estimation sample in half within each quarter and using one subsample for estimation and the other for validation. This process yields $\lambda = 100$ and $\xi = 1$.

B.3. Estimated demand coefficients

Figure A6 shows the time series of the demand coefficient on equity duration, $\gamma_{i,t}$, by investor type. I aggregate $\gamma_{i,t}$ at the investor type level, weighting each investor by their end-of-quarter wealth share. Panel (a) reports coefficients for active investors, and Panel (b) for passive investors. Active investors' demand for duration varies significantly over the business cycle: small active investors reach for duration during expansions and shift away from long-duration stocks during recessions. In contrast, passive investors' demand for duration remains stable over time. As shown

in Panel (b), the duration coefficient stays below but close to zero, indicating that passive investors generally prefer short-duration stocks.

I analyze the relationship between duration demand and investor characteristics using cross-sectional regressions. Column 1 in Table A6 reports the regression of the duration coefficient in the demand curve on investor characteristics, controlling for quarter fixed effects. The results indicate that investors with higher price elasticity, greater active share, and higher portfolio turnover exhibit a stronger demand for duration.

To investigate the timing of institutional investors' duration demand, I regress the duration demand on a set of macroeconomic variables. The positive coefficients in columns (3) and (4) indicate that institutional investors tilt toward long-duration stocks when the market is more optimistic about longer-term prospects. In column (5), the positive coefficient on the interaction term between horizon bias and skewness further implies that these periods coincide with positively skewed earnings forecast distributions.

B.4. Algorithm for computing the equilibrium

Note that finding the solution to Equation (20) is equivalent to finding the fixed point of function $\mathbf{f}()$. Therefore, starting with any price vector $\mathbf{p}_m$, the Newton's method would update the price vector through

$$\mathbf{p}_{m+1} = \mathbf{p}_m + \left[\mathbf{I} - \frac{\partial \mathbf{f}(\mathbf{p}_m)}{\partial \mathbf{p}'} \right]^{-1} [\mathbf{f}(\mathbf{p}_m) - \mathbf{p}_m] \quad (\text{B7})$$

For this application, this approach would be computationally slow because the Jacobian has a large dimension. Therefore, I approximate the Jacobian with only its diagonal elements:

$$\begin{aligned} \frac{\partial \mathbf{f}(\mathbf{p}_m)}{\partial \mathbf{p}'} &\approx \text{diag} \left(\min \left\{ \frac{\partial f(\mathbf{p}_m)}{\partial p(n)}, 0 \right\} \right) \\ &= \text{diag} \left(\min \left\{ \frac{\sum_{i=1}^I \beta_{0,i} A_i w_i(\mathbf{p}_m; n) (1 - w_i(\mathbf{p}_m; n))}{\sum_{i=1}^I A_i w_i(\mathbf{p}_m; n)}, 0 \right\} \right) \end{aligned} \quad (\text{B8})$$

where the minimum ensures that the elements are bounded away from one.

C. Data and variable construction

C.1. Countercyclical equity term premium

To illustrate both the average downward slope and the counter-cyclical, I compare the returns on the S&P 500 index with those on a short-term dividend strip, as depicted in Figure A3. The dividend strip data is sourced from the supplementary materials of Cassella et al. (2023). The maturities of these dividend strips range from 1.3 to 1.9 years, with rebalancing occurring biannually in

January and July. I classify periods as good or bad based on the median dividend-price ratio of the S&P 500 index. Figure A3 clearly demonstrates the pronounced counter-cyclicity of the equity term structure. During good times, indicated by the blue dash-dotted line, the average return on the short-term dividend strip is lower than that of the market index. Conversely, during bad times, this relationship reverses. Additionally, the gray solid line shows that the equity term structure exhibits an unconditional downward slope.

C.2. Variable construction

- **Earnings skewness** (Cassella et al. 2023): skewness of the earnings forecasts distribution, approximated by the difference between long-horizon skewness and short-horizon skewness
- **Horizon bias** (Cassella et al. 2023): Compute the long-term growth rate implied by the short-term growth rate

$$\text{LTG}_t^{\text{Implied}} = \frac{1}{5} [4\phi_0 + 3\phi_0\phi_1 + 2\phi_0\phi_1^2 + \phi_0\phi_1^3 + \text{STG}_t(1 + \phi_1 + \phi_1^2 + \phi_1^3 + \phi_1^4)], \quad (\text{C1})$$

where ϕ_0 is the mean for the short-term growth rate ϕ_1 is the annual persistence. Define the horizon bias as the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate,

$$\text{Horizon Bias}_t = \text{LTG}_t - \text{LTG}_t^{\text{Implied}}. \quad (\text{C2})$$

- **Investor turnover** (Gaspar et al. 2005): Churn ratio following

$$\text{CR}_{i,t} = \frac{\sum_n |\text{Shares}_{i,t}(n) \cdot P_t(n) - \text{Shares}_{i,t-1}(n) \cdot P_{t-1}(n) - \text{Shares}_{i,t-1}(n) \cdot \Delta P_t(n)|}{\sum_n (\text{Shares}_{i,t}(n) \cdot P_t(n) + \text{Shares}_{i,t-1}(n) \cdot P_{t-1}(n)) / 2}, \quad (\text{C3})$$

where $\text{Shares}_{i,t}(n)$ is the number of shares of stock n held by institution i in quarter t , and $P_t(n)$ is the price of stock i in quarter t . $\Delta P_t(n) = P_t(n) - P_{t-1}(n)$ denotes the price change.

- **Market LTG** (Bordalo et al. 2024): value-weighted long-term growth forecasts across all stocks in the inside asset sample
- **MF flow**: I measure market-level funding liquidity using the aggregate net inflow into the mutual fund sector (Ma et al. 2022).
- **Leverage factor** (Adrian et al. 2014)

D. Additional results

D.1. Equity term structure and individual stock returns

In the absence of arbitrage opportunities, there exists an SDF, M_t , such that the value of an equity index, $P_{e,t}$, is given by the discounted value of its dividends $\{D_{t+h}\}_{h=1}^{\infty}$,

$$P_{e,t} = \sum_{h=1}^{\infty} \mathbf{E}_t[D_{t+h} \cdot M_{t:t+h}] \equiv \sum_{h=1}^{\infty} P_{d,t}^h, \quad (\text{D1})$$

where the second equality defines the price of a dividend claim (or dividend strip) with maturity of h years. Dividing Equation (D1) by lagged index value, $P_{e,t-1}$, on both sides, we have that the market return, $R_{e,t}$, is equivalent to the return on a portfolio of dividend strips,

$$R_{e,t} = \sum_{h=1}^{\infty} \frac{P_{d,t-1}^{h+1}}{P_{e,t-1}} \cdot \frac{P_{d,t}^h}{P_{d,t-1}^{h+1}} \equiv \sum_{h=1}^{\infty} w_{d,t-1}^h \cdot R_{d,t}^h. \quad (\text{D2})$$

Taking expectations on both sides of this equation allows us to decompose the equity term premium into a term structure of risk premia, referred to as the equity term structure, i.e., $\{R_{d,t}^h\}_{h=1}^{\infty}$. Thus, a downward-sloping term structure translates into that the dividend strip return, $R_{d,t}^h$, is decreasing in maturity h . To see the connection between equity term structure and individual stock returns, decompose the price of an h -year dividend strip into prices of dividends paid on individual stocks,

$$P_{d,t}^h = \sum_{i \in I} \mathbf{E}_t[D_{i,t+h} \cdot M_{t:t+h}] = \sum_{i \in I} P_{i,t}^h, \quad (\text{D3})$$

where I is the set of stocks that contribute to the aggregate dividend at time $t+h$, D_{t+h} . Using the same trick and dividing Equation (D3) by lagged strip value, $P_{d,t-1}^{h+1}$, on both sides, we have that the return on an h -year dividend strip, $R_{d,t}^h$, is equivalent to the return on a portfolio of dividend strips on individual assets,

$$R_{d,t}^h = \sum_{i \in I} \frac{P_{i,t-1}^{h+1}}{P_{d,t-1}^{h+1}} \cdot \frac{P_{i,t}^h}{P_{i,t-1}^{h+1}} \equiv w_{i,t-1}^h \cdot R_{i,t}^h. \quad (\text{D4})$$

In the extreme case, there are only three periods $t = 0, 1, 2$ and two assets L and S . S pays dividend only in period 1, while L pays dividend only in period 2. The equity term structure $\{R_{d,0}^1, R_{d,0}^2\}$ becomes $\{R_{S,0}^1, R_{L,0}^2\}$, and a downward-sloping equity term structure implies that the short duration stock S has higher expected returns than the long duration stock L .

A. Counterfactual equity term premium

I measure the equity term premium as the monthly average return difference between the long-duration quintile and the short-duration quintile in the inside assets sample. Panel B of Table A10 presents the counterfactual equity term premium. For reference, I also report the percentage change relative to the actual value. The first two rows show the unconditional equity term premium in the counterfactual scenario, while the last two rows report the premium for the year following the 2008 financial crisis.

The true unconditional annualized equity term premium is -4.38% . For instance, if we mute the duration demand of small active investment advisors, the premium rises to -3.07% , which flattens the slope by 29.88% . In contrast, the true annualized equity term premium during the financial crisis is 9.19% . The last row indicates that the demand for duration by small active investment advisors differs from other active investors: the counterfactual equity term premium increases to 11.82% , while it decreases in other counterfactual scenarios. Referring back to Figure A6, small active investment advisors continued to tilt away from long-duration stocks, making this positive change unsurprising. Despite their small wealth share, hedge funds also significantly influence the equity term structure. Muting the demand for duration by long-term investors also flattens the equity term structure, as long-term investors maintained a negative duration tilt during the sample period.

Table A1
Do momentum and attention play a role?

This table reports the average returns in the pre- and post-earnings announcement windows across duration quintiles. Columns (1) and (5) report the baseline returns: firms with earnings announcements are split into five quintile portfolios based on equity duration from the previous quarter. Columns (2) and (6) report the returns from a conditional double sort: each quarter, firms with earnings announcements are first sorted into five momentum quintiles according to their past 12-month returns, and within each momentum quintile, stocks are then sorted into five groups according to equity duration in the previous quarter. I collapse across the momentum groups to obtain five momentum-adjusted duration portfolios. Columns (3) and (7) report the returns when momentum winners (top quintile of past 12-month returns) are excluded before splitting by duration. Columns (4) and (8) report the returns when stocks with media coverage in the Dow Jones edition of RavenPack news data are excluded. The t -statistics, based on the heteroskedasticity consistent standard errors, are reported in parentheses.

	Window $[-3, -1]$				Window $[0, 2]$			
	Baseline (1)	Mom (2)	~Winner (3)	No media (4)	Baseline (5)	Mom (6)	~Winner (7)	No media (8)
Short Dur	22.80	22.43	21.27	22.81	16.05	17.32	17.22	16.07
Q2	15.76	13.32	13.31	15.75	10.13	12.31	11.06	10.15
Q3	12.19	13.92	10.51	12.17	6.36	2.78	6.40	6.39
Q4	11.05	11.50	8.50	11.12	2.45	5.09	3.14	2.50
Long Dur	19.25	17.61	17.35	19.27	-9.47	-7.10	-10.24	-9.51
Q1 – Q5	3.55 (1.22)	4.82 (1.97)	3.93 (1.23)	3.54 (1.22)	25.52 (6.74)	24.42 (6.38)	27.46 (6.44)	25.57 (6.76)

Table A2
Returns by retail flow

This table reports the returns across retail net buy quintiles. *NBuy* is defined as retail net buy volume scaled by total shares outstanding. I report raw return, CAPM alpha, and market excess (AR) returns. I estimate CAPM beta for individual stocks using a pre-event window $[-273, -22]$ via the slope-winsorized method in Welch (2021). The t -statistics are based on the heteroskedasticity consistent standard errors.

	Cum RBuy $[-5, -1]$				Cum RBuy $[-7, -1]$			
	L (1)	H (2)	H – L (3)	t_{H-L} (4)	L (5)	H (6)	H – L (7)	t_{H-L} (8)
Cum NBuy	–4.54	5.82	10.36	28.01	–5.65	7.00	12.65	27.31
R_{-1}	9.03	17.13	8.10	1.68	7.23	19.90	12.67	3.17
$R_{[-3;-1]}$	19.91	38.72	18.81	2.16	19.75	42.03	22.28	2.90
$R_{[-5;-1]}$	36.45	57.61	21.17	2.17	35.61	59.66	24.05	2.44
α_{-1}	5.02	16.32	11.30	2.78	3.86	16.85	12.99	3.42
$\alpha_{[-3;-1]}$	10.03	30.16	20.12	2.95	12.58	31.69	19.11	3.12
$\alpha_{[-5;-1]}$	20.53	41.21	20.68	2.41	24.12	40.79	16.66	1.96
AR_{-1}	4.26	16.05	11.79	3.08	2.84	16.70	13.86	3.98
$CAR_{[-3;-1]}$	6.16	25.57	19.41	2.80	7.49	27.92	20.44	3.29
$CAR_{[-5;-1]}$	14.63	34.52	19.89	2.28	15.77	35.89	20.12	2.34

Table A3
Return sensitivity

This table reports the regression of pre-announcement return on retail net buy volume. *NBuy* is the cumulative retail net buy volume in the $[-3, -1]$ window prior to the earnings announcement. $\mathbf{1}_{\text{Dur}-x}$ are duration quintile dummies. I control for firm characteristics including nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. I include both firm and quarter fixed effects. The *t*-statistics, based on the two-way clustered standard errors across firm and quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CAPM alpha $[-3, -1]$
$\text{NBuy} \times \mathbf{1}_{\text{Dur1}}$	0.228*** (4.712)
$\text{NBuy} \times \mathbf{1}_{\text{Dur2}}$	0.170*** (3.836)
$\text{NBuy} \times \mathbf{1}_{\text{Dur3}}$	0.106*** (2.580)
$\text{NBuy} \times \mathbf{1}_{\text{Dur4}}$	0.139*** (3.170)
$\text{NBuy} \times \mathbf{1}_{\text{Dur5}}$	0.266*** (5.216)
Controls	✓
Fixed effect	Firm/Date
Cluster	Firm/Date
R^2	0.085
Observations	104,146

Table A4
Summary statistics for inside assets

This table reports the mean stock characteristics by quintiles of equity duration for inside assets only. Stock characteristics are calculated at the end of each quarter. The sample period is 2000:Q1 to 2022:Q4. *Inside assets* refer to the set of firms that collectively make up the top 90% of total market value. *Duration* is the firm-level duration measure as in Gonçalves (2021b). *VW return* is the value-weighted quintile portfolio return. *Market equity* equals price times total shares outstanding (in million dollars). *Assets* is assets total from CompuStat. *Log market-to-book* is the logarithm of market-to-book ratio. *Log book equity* is the logarithm of book equity. *Foreign sales ratio* is the ratio of foreign sales to the sum of foreign and domestic sales. The *Lerner index* is the ratio of operating income after depreciation to gross sales. *Sales-to-book* is the ratio of gross sales to book equity. *Dividend-to-book* is the ratio of total dividends to book equity. *CAPM beta* is the CAPM beta estimated from a rolling window of 60 months. *Investment* is the growth rate of total assets. *Shares repurchases* is the net stock repurchase that is equal to stock repurchase minus stock issuance.

	Short Dur	Q2	Q3	Q4	Long Dur
	(1)	(2)	(3)	(4)	(5)
N(stock)	83	82	82	82	82
Duration	36	48	56	66	109
VW return	0.143	0.111	0.095	0.101	0.093
Market equity	22,579	34,076	38,064	34,176	21,825
Total assets	14,038	19,464	21,965	22,541	25,750
Log market-to-book	1.094	1.228	1.176	1.132	1.230
Log book equity	8.089	8.214	8.360	8.354	8.079
Foreign sales ratio	0.258	0.373	0.361	0.321	0.272
Lerner index	0.130	0.174	0.176	0.156	0.075
Sales-to-book	3.054	1.947	1.855	1.877	2.844
Dividend-to-book	0.040	0.039	0.037	0.032	0.029
CAPM beta	0.996	1.018	1.034	1.119	1.280
Investment	0.088	0.097	0.106	0.113	0.143
Stock repurchase	654.799	665.270	868.307	553.426	225.387

Table A5
Explaining equity valuations with firm characteristics

This table reports the regression of log market-to-book equity on firm characteristics. Log market-to-book equity is measured at the end of year t . All characteristics are measured in year t and are standardized within each year. The t -statistics, based on robust standard errors clustered by firm-year, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Log market-to-book equity			
	(1)	(2)	(3)	(4)
Log book equity	−0.448*** (−21.526)	−0.451*** (−21.519)	−0.451*** (−21.170)	−0.475*** (−23.379)
Foreign sales	0.090*** (6.040)	0.095*** (6.418)	0.095*** (6.235)	0.098*** (6.683)
Lerner index	0.121*** (6.213)	0.149*** (8.173)	0.148*** (7.854)	0.148*** (8.247)
Sales-to-book	0.121*** (6.291)	0.111*** (5.884)	0.112*** (5.700)	0.123*** (6.734)
Dividend-to-book	0.190*** (11.633)	0.189*** (12.022)	0.189*** (11.590)	0.179*** (11.476)
CAPM beta	−0.039** (−2.122)	−0.060*** (−3.268)	−0.060*** (−3.283)	−0.065*** (−3.679)
Dur		0.141*** (9.317)	0.291*** (4.924)	0.091*** (5.108)
D/P			−37.547*** (−8.691)	
Dur × D/P			−8.182*** (−2.662)	
RFD				0.132*** (8.673)
Dur × RFD				−0.015 (−1.328)
Fixed effects	Date	Date	—	Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date
R^2	0.416	0.433	0.382	0.451
Observations	64,606	64,606	64,606	64,606

Table A6
Explaining institutional duration tilts

This table reports the regression of duration demand on investor characteristics and macroeconomic variables. The dependent variable is the demand coefficient on equity duration, estimated from quarterly holdings and multiplied by 100 for better interpretation. The macroeconomic variables are standardized over the sample period. *MF Flow* is the aggregate net inflow into the mutual fund sector. *LTG* is the long-term expected earnings growth index as in Bordalo et al. (2024). *Horizon Bias* is the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate (Cassella et al. 2023). *Skewness* is the skewness of the earnings forecasts distribution. The *t*-statistics, based on robust standard errors clustered by investor-quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Demand coefficient on duration				
	(1)	(2)	(3)	(4)	(5)
Log AUM	−0.295*** (−2.586)				
Active share	3.276*** (2.654)				
Churn ratio	1.313*** (3.354)				
MF flow		0.750*** (11.184)	1.252*** (16.228)	0.690*** (10.429)	1.321*** (13.860)
LTG		0.257*** (2.679)	0.527*** (3.964)		
Horizon bias				1.124*** (15.493)	−2.895*** (−13.564)
Skewness					−0.484*** (−5.418)
Horizon bias × Skewness					4.393*** (16.665)
Macroeconomic controls			✓		✓
Fixed effects	Date	Investor	Investor	Investor	Investor
Cluster	Investor/Date	Investor/Date	Investor/Date	Investor/Date	Investor/Date
Within R^2	0.002	0.004	0.030	0.012	0.041
Observations	38,664	38,672	38,672	38,672	38,672

Table A7
Duration tilts by active share

This table reports the regression of duration demand on investor characteristics and macroeconomic variables by active share quintiles. The dependent variable is the demand coefficient on equity duration, estimated from quarterly holdings and multiplied by 100 for better interpretation. The macroeconomic variables are standardized over the sample period. *MF Flow* is the aggregate net inflow into the mutual fund sector. *Leverage factor* is the funding liquidity factor in Adrian et al. (2014). *LTG* is the long-term expected earnings growth index as in Bordalo et al. (2024). *Horizon Bias* is the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate (Cassella et al. 2023). *Skewness* is the skewness of the earnings forecasts distribution. The *t*-statistics, based on robust standard errors clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Demand coefficient on duration				
	Passive (1)	Q2 (2)	Q3 (3)	Q4 (4)	Active (5)
<i>Panel A: Aggregate MF net inflows</i>					
MF flow	0.080 (0.690)	0.335** (2.231)	0.912*** (5.646)	1.008*** (5.802)	1.296*** (6.731)
<i>Panel B: Intermediary leverage factor</i>					
Leverage factor	0.942*** (8.085)	1.389*** (10.230)	1.729*** (10.880)	1.746*** (9.559)	1.964*** (10.277)
<i>Panel C: Horizon bias</i>					
MF flow	0.035 (0.303)	0.264* (1.763)	0.831*** (5.156)	0.915*** (5.293)	1.193*** (6.189)
Horizon bias	0.623*** (5.034)	1.226*** (7.632)	1.178*** (6.553)	1.431*** (7.760)	1.517*** (6.884)
<i>Panel D: Skewness of earnings forecast</i>					
MF flow	-0.118 (-0.916)	0.125 (0.764)	0.562*** (3.156)	0.570*** (3.010)	0.681*** (3.393)
Horizon bias	-0.303 (-1.295)	-0.225 (-0.759)	-0.642* (-1.855)	-0.167 (-0.452)	0.340 (0.863)
Horizon bias × Skewness	1.364*** (4.380)	2.134*** (5.720)	2.668*** (6.251)	2.338*** (4.940)	1.685*** (3.310)

Table A8
Conditional duration tilts

This table reports the average demand coefficient on equity duration across price elasticity and active share quintiles, conditional on end-of-period sentiment. I employ the market-wide sentiment index from Baker and Wurgler (2006). *Avg* denotes unconditional average returns, while *high sent* and *low sent* represent average returns during high and low sentiment months, respectively, where sentiment states are determined by the median of the sentiment index. *Price elasticity* is measured by one minus the demand coefficient on log market-to-book equity. *Active share* is defined in Equation (4). The *t*-statistics, computed using heteroskedasticity-consistent standard errors, are reported in parentheses. The monthly sample period spans from 1973:8 to 2024:1.

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (5)
Panel A: Across price elasticity quintiles					
Avg	−0.907 (−5.760)	−2.438 (−6.087)	−3.342 (−6.841)	−1.775 (−3.739)	−1.063 (−2.072)
High sent	−0.582 (−2.145)	−0.730 (−1.168)	−2.465 (−3.563)	−0.997 (−1.506)	0.561 (0.755)
Low sent	−1.267 (−10.225)	−4.331 (−14.521)	−4.315 (−6.473)	−2.638 (−3.965)	−2.863 (−4.743)
H − L	0.685 (2.217)	3.601 (5.025)	1.850 (1.916)	1.641 (1.744)	3.424 (3.528)
Panel B: Across active share quintiles					
Avg	−1.312 (−8.191)	−0.986 (−3.694)	−1.104 (−2.605)	−1.473 (−3.777)	−1.449 (−2.648)
High sent	−0.932 (−3.567)	−0.563 (−1.322)	0.014 (0.020)	−0.081 (−0.145)	−0.448 (−0.541)
Low sent	−1.733 (−11.234)	−1.456 (−4.905)	−2.344 (−7.244)	−3.016 (−6.819)	−2.559 (−3.807)
High − Low	0.801 (2.571)	0.894 (1.688)	2.359 (2.883)	2.935 (4.047)	2.111 (1.955)

Table A9
Predicting retail flow

This table reports quarterly retail net buy volume on lagged RFD value. *RFD* is the stock-level value-weighted duration preference of its shareholders. Column (1) reports the regression of RFD change on lagged RFD level. Firm-level controls include nominal share price, firm age, momentum return $R_{t-12:t-2}$, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. The *t*-statistics, based on the two-way clustered standard errors across firm and quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	ΔRFD_{t+1}	$NBuy_{t+1}$	
	(1)	(2)	(3)
RFD	-0.239*** (-15.804)	0.050*** (4.595)	0.034*** (4.447)
NBuy			0.290*** (17.373)
Firm-level controls	✓		✓
Fixed effects	Firm/Date	Date	Date
Cluster	Firm/Date	Firm/Date	Firm/Date
Within R^2	0.123	0.002	0.089
Observations	62,378	40,840	39,217

Table A10
Counterfactual equity term premium

This table reports the counterfactual equity term premium. IA is an abbreviation for investment advisors. Equity term premium is defined as the difference in average returns between the top and bottom quintile duration portfolios. In each scenario, I mute the duration preference of one investor type by setting their demand coefficient on duration, $\phi_{i,t}$, to zero. *Recession* indicates the forward one-year term premium following NBER recession periods. In the inside assets sample, the unconditional empirical term premium is -4.38% , while the empirical term premium in the year following NBER recession periods is 9.19% .

	Large-active IA (1)	Small-active IA (2)	Hedge funds (3)	Brokers (4)	Long-term (5)
$L - S$	-3.22	-3.07	-4.13	-4.41	-4.04
$\Delta/ -4.38 $ (%)	26.41	29.88	5.73	-0.75	7.78
$L - S$ recession	5.66	11.82	8.36	9.00	8.79
$\Delta/ 9.19 $ (%)	-38.46	28.53	-9.08	-2.07	-4.42

Table A11
Firm-Level RFD and LTG forecast

This table reports the regression of firm-level reaching for duration (RFD) on LTG forecast. $RFD_t(n)$ is the holding value weighted average of the duration coefficient across all investors for firm n at the end of quarter t . $LTG_t(n)$ is the firm-level long-term earnings growth forecast reported at quarter t . $Duration_t(n)$ is the firm level duration measure in Gonçalves (2021b). Other firm-level controls include log book equity, foreign sales ratio, the Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All the independent variables are standardized within each quarter. Market-level $Horizon Bias_t$ is the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate (Cassella et al. 2023). The t -statistics, based on robust standard errors clustered by firm-quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: RFD(n)		
	(1)	(2)	(3)
Dur(n)	1.024*** (14.842)	0.994*** (14.880)	0.963*** (14.386)
LTG(n)		0.221*** (5.159)	0.248*** (4.627)
Horizon bias(t)			0.326*** (3.608)
LTG(n) $\times$ Horizon bias(t)			0.145*** (4.264)
Firm controls	✓	✓	✓
Macroeconomic controls			✓
Fixed effects	Firm/Date	Firm/Date	Firm
Within R^2	0.092	0.096	0.146
R^2	0.117	0.124	0.146
Observations	22,370	22,370	22,370

Table A12
Institutional demand for duration and firms' cost of capital

This table reports the results on the perceived cost of capital, discount rates, and net stock issuance. All the variables are standardized within each quarter. The control variables are motivated by Gormsen and Huber (2023). The t -statistics, based on robust standard errors clustered by firm-quarter, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Cost of capital		Hurdle rate	NEI _{t+1}
	(1)	(2)	(3)	(4)
RFD	−0.033*** (−2.783)	−0.024** (−2.260)	−0.015 (−1.325)	0.023*** (3.075)
Duration		−0.026 (−1.644)		0.067*** (4.765)
CAPM beta	0.541*** (36.402)	0.543*** (36.875)	−0.004 (−0.304)	−0.005 (−0.716)
Debt-to-market	0.184** (2.566)	0.191*** (2.633)	0.638*** (9.709)	−0.060** (−2.078)
Firm age	−0.302*** (−23.116)	−0.302*** (−23.137)	−0.387*** (−21.491)	−0.013* (−1.936)
Market equity	−0.010 (−0.669)	−0.011 (−0.711)	0.046*** (2.862)	−0.006 (−1.447)
KZ index	−0.173*** (−9.999)	−0.174*** (−10.017)	−0.152*** (−7.523)	−0.006 (−1.146)
Idio. vol	0.165*** (13.660)	0.167*** (13.744)	0.500*** (30.332)	0.045*** (5.707)
Net debt-to-price	−0.523*** (−10.314)	−0.526*** (−10.481)	−0.887*** (−14.125)	0.098*** (3.078)
Asset to book equity	−0.058*** (−4.819)	−0.050*** (−3.698)	−0.012 (−1.071)	−0.052*** (−6.161)
Net equity issuance	0.014** (2.437)	0.014** (2.481)	−0.022*** (−2.732)	0.513*** (15.920)
Equity payout yield	−0.092*** (−8.962)	−0.095*** (−8.677)	−0.002 (−0.182)	−0.063*** (−4.604)
Fixed effects	Date	Date	Date	Date
Within R^2	0.644	0.644	0.333	0.152
R^2	0.818	0.818	0.694	0.305
Observations	28,331	28,331	28,331	27,225

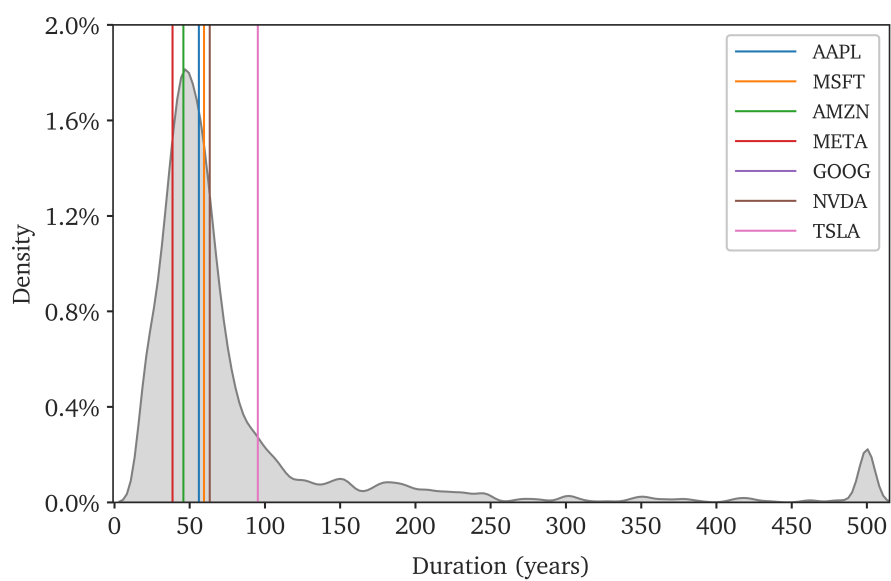


Figure A1. Distribution of equity duration in 2023. This figure reports the cross sectional distribution of equity duration in June 2023. I obtain the annual data on firm-level duration from Andrei S. Gonçalves' personal website. By construction, stock duration is capped at 500 years. The colored vertical lines represent the stock duration of the largest firms. Examples of firms in the right tail of the distribution include several pharmaceutical companies, reflecting their capital-intensive operations and substantial allocation of profits to R&D.

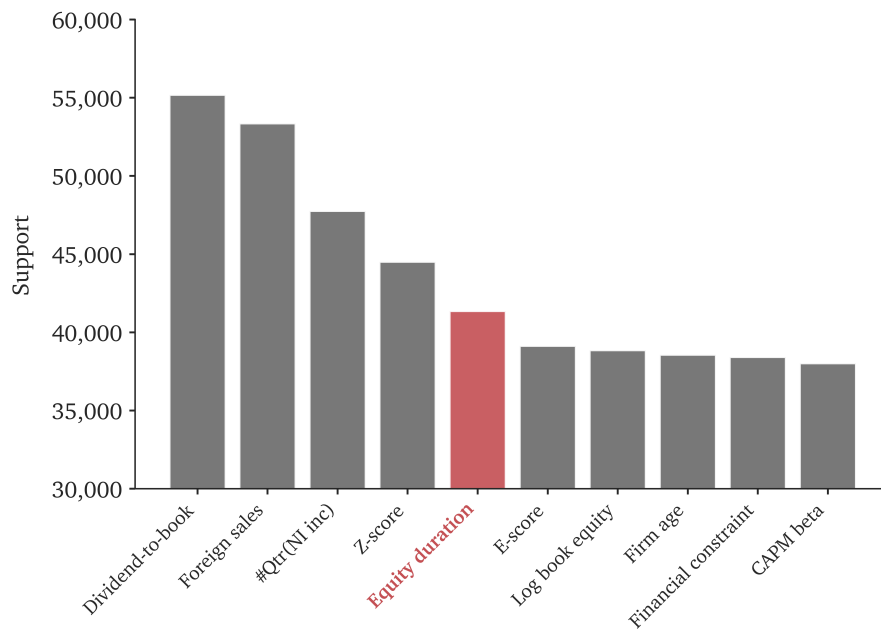


Figure A2. Top 10 factors from Lasso regression. This figure summarizes the results from a Lasso regression that selects firm characteristics predictive of portfolio weights in each quarter. I start from 153 firm characteristics provided by Jensen et al. (2023) and add equity duration. For each institution and quarter, I estimate a cross-sectional Lasso regression of log portfolio weights on a set of firm characteristics. I increase this penalty until 10 characteristics survive. Then, for each characteristic, I count the number of times it is included in the surviving characteristic. The bar chart displays the total count. Equity duration is highlighted in red.

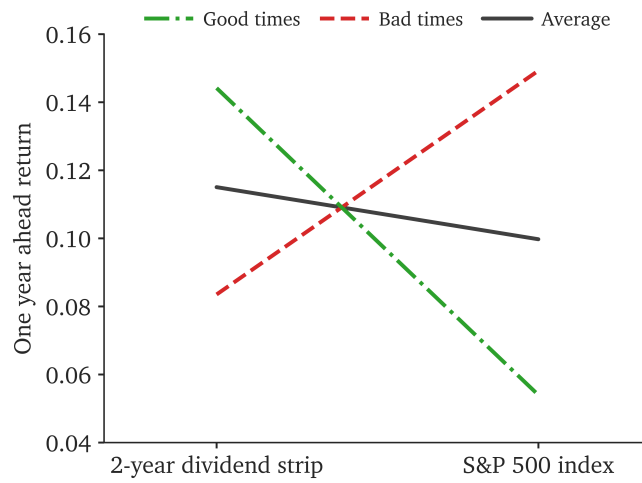


Figure A3. Counter-cyclical equity term premium. This figure plots the counter-cyclical equity term premium. I obtain dividend strips data from the supplementary material of Cassella et al. (2023). Good time and bad time are separated by the median dividend-price ratio: high dividend-price ratios indicating bad times.

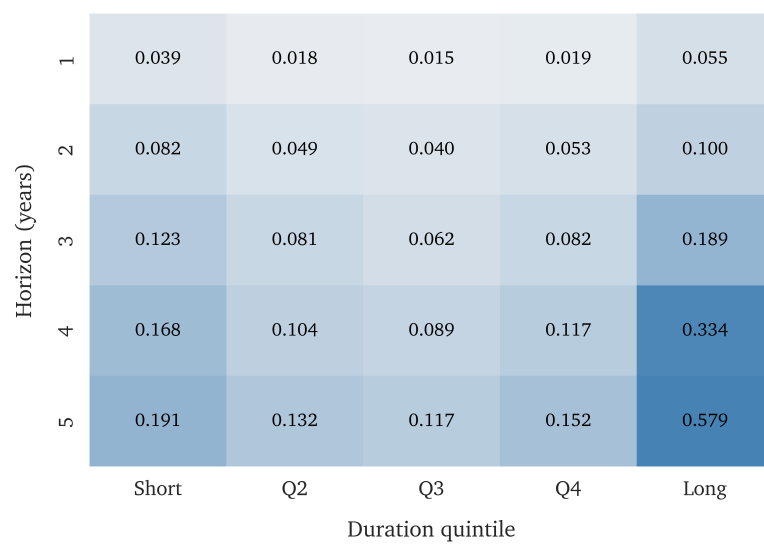


Figure A4. The term structure of optimism. This figure shows the term structure of optimism.

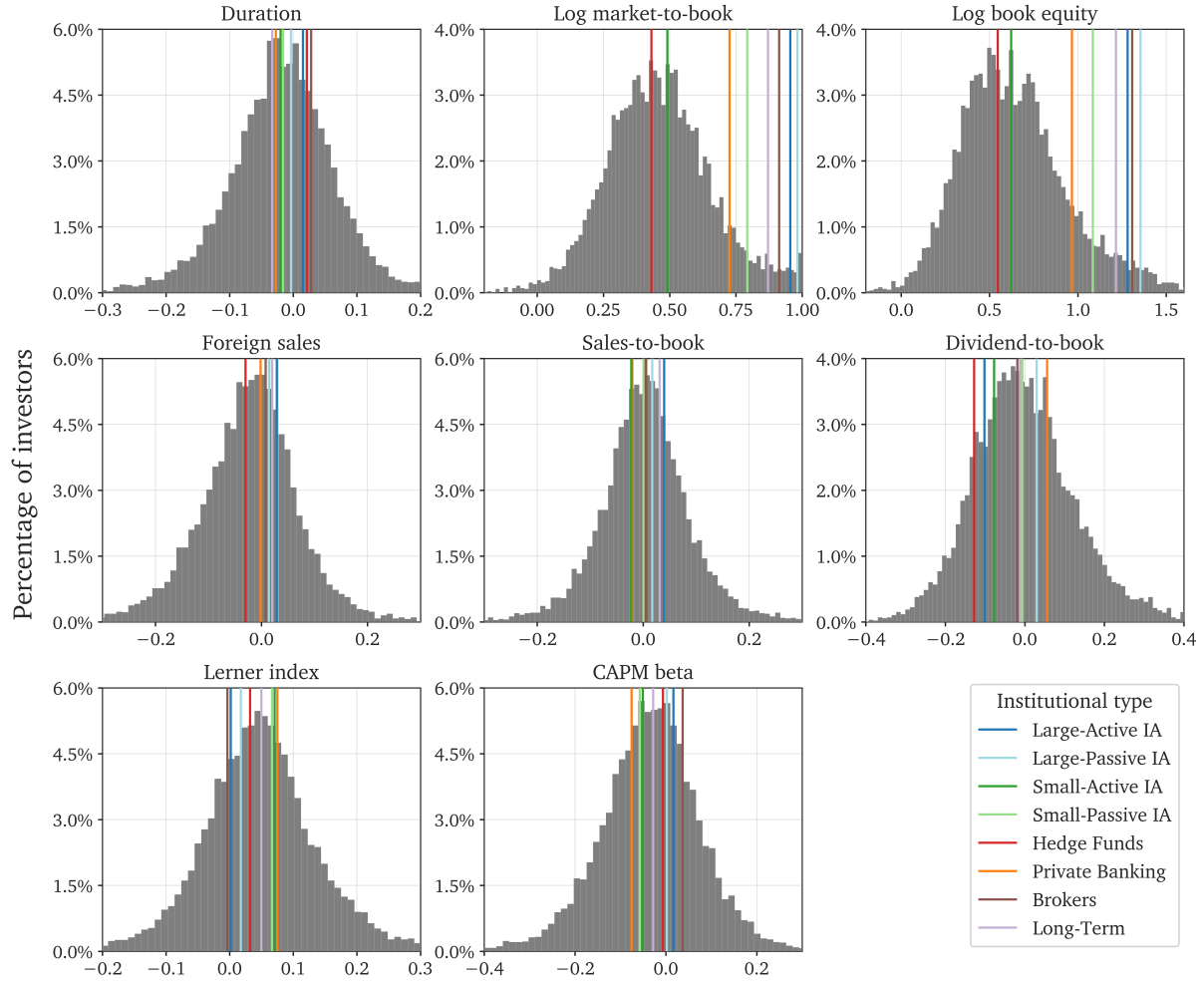


Figure A5. Cross-sectional distribution of demand coefficients. This figure illustrates the cross-sectional distribution of average demand coefficients across institutional investors. The asset demand of each investor is estimated from quarterly holdings. I compute the time-series average of the demand coefficients for each investor over the sample period, and aggregate to the investor-type level using a wealth-weighted average, in which an investor's weight is the time-series average of its AUM share within investor type. An investor's AUM is defined as the total 13F equity holdings. The colored vertical lines correspond to the wealth-weighted average demand coefficients by investor type. "IA" stands for investment advisors.

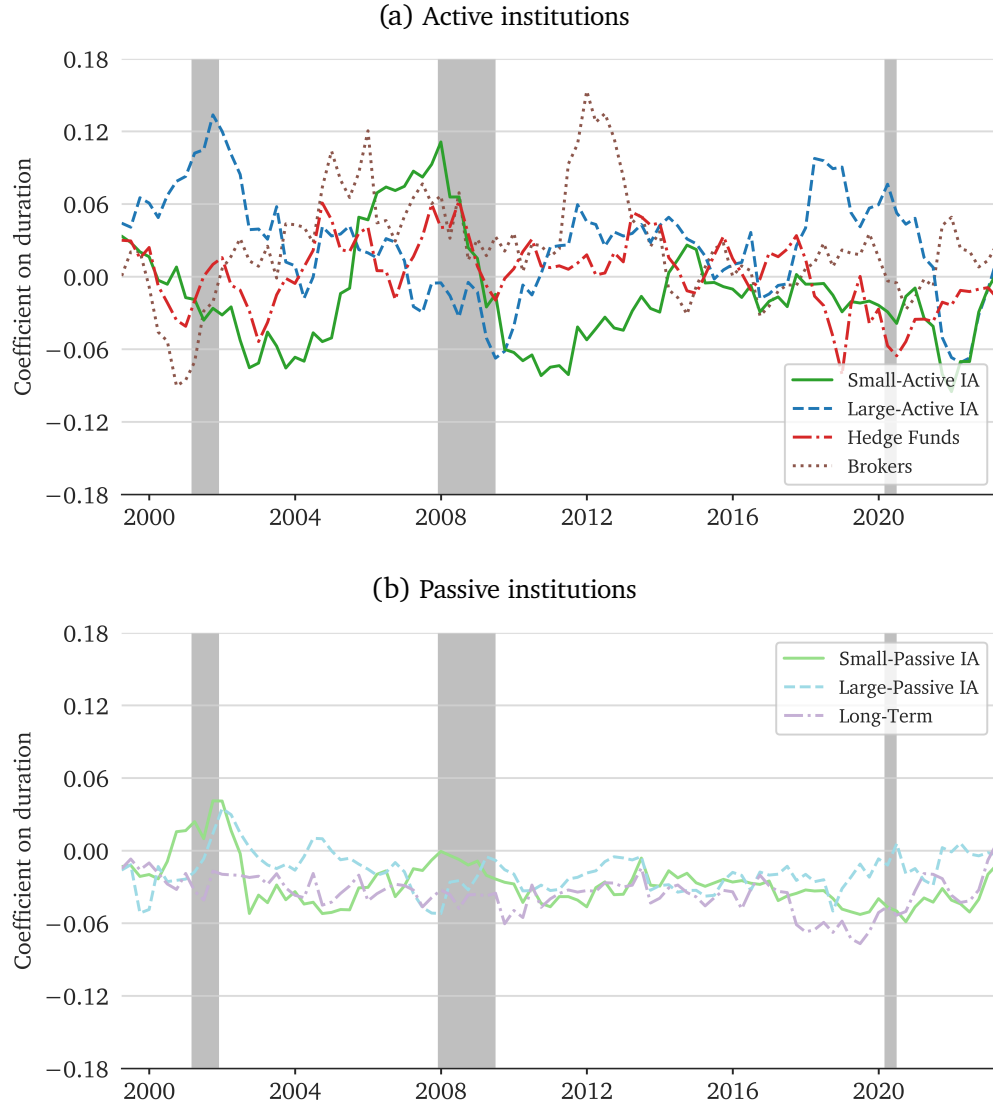


Figure A6. Time series of the demand coefficient on duration. The figure reports the time series of demand coefficient on equity duration by investor type. I compute a wealth-weighted average of the demand coefficients at investor type level, in which an investor's weight is the end-of-quarter wealth share within investor type. IA is abbreviation for investment advisors. Panel (a) shows four active investor types: small-active investment advisors, large-active investment advisors, hedge funds, and brokers. Panel (b) shows four passive investor types: small-passive investment advisors, large-passive investment advisors, long-term investors, and private banking. The shaded area denotes NBER recession periods.

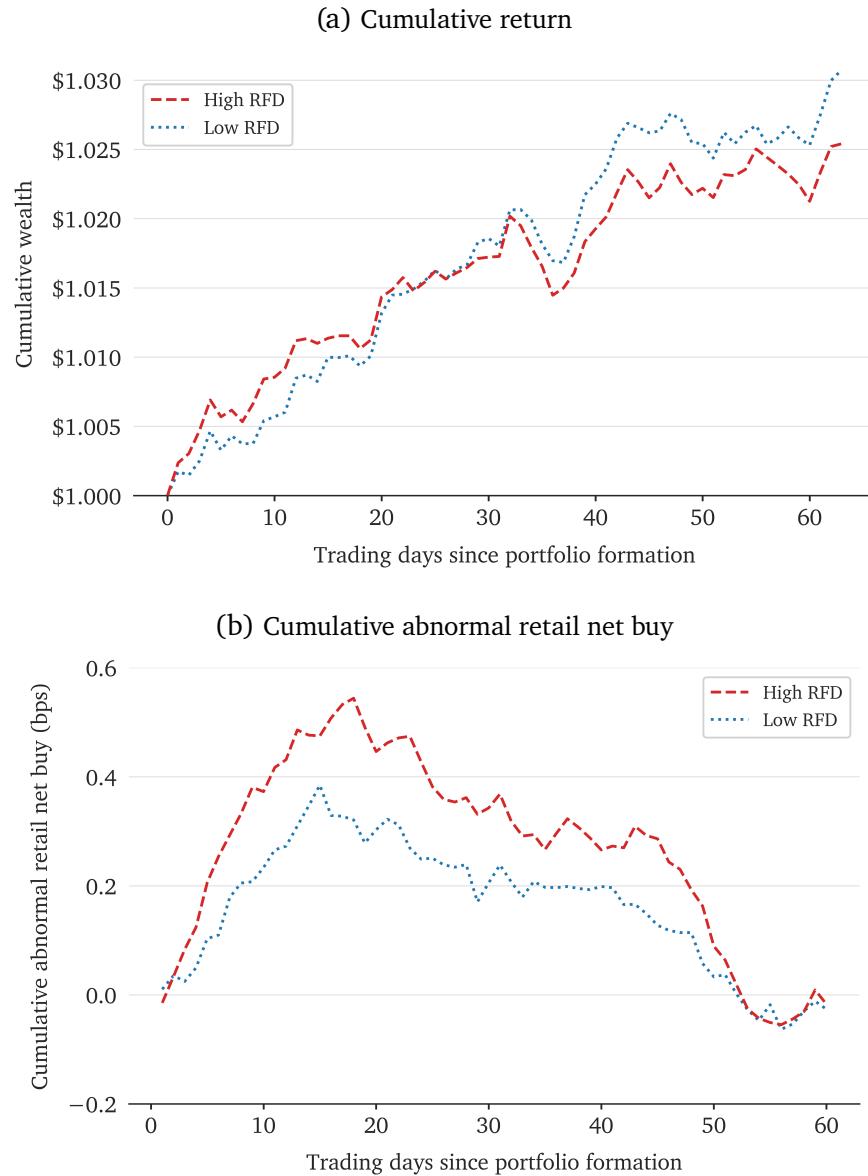


Figure A7. Return and retail net buy after RFD portfolio formation. The figure reports the cumulative returns and cumulative abnormal retail net buy after RFD portfolio formation for high RFD and low RFD quintiles. RFD is defined as the stock-level value-weighted average duration preference of its shareholders. Each month, I sort stocks into five quintiles based on their RFD from previous quarter.