Horizon Bias and Equity Term Premia around Earnings News

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Abstract

I document that around half of the equity term premium is realized around earnings announcements, a pattern that is difficult to reconcile with risk- or friction-based explanations. Horizon bias, investors' greater optimism about long-term growth than short-term growth, explains this concentration. Systematic forecast biases across horizons create cross-sectional variation in speculative appeal: long-duration stocks attract more attention-induced trading from retail investors ahead of earnings, amplifying mispricing that fundamental information then corrects. I construct a firm-level measure of horizon bias as the disparity between long-term and short-term earnings growth expectations. The term premium around earnings news is primarily driven by firms with high horizon bias, suggesting that mispricing from horizon bias drives the spread between short- and long-duration stocks. Consistent with retail speculation, I show that retail investors disproportionately buy long-duration stocks before earnings announcements. Using the pilot program of Regulation SHO as a natural experiment, I find that removing short-sale constraints significantly reduces pre-announcement returns of long-duration stocks, confirming that limits to arbitrage allow the mispricing to build up. At lower frequencies, the term premium is high following periods of above-median aggregate horizon bias, and active institutions contribute to this time variation through shifts in their duration demand. Overall, horizon bias accounts for both the high-frequency patterns around earnings announcements and the lower-frequency time variation in the equity term premium.

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1. Introduction

Long-duration assets underperform short-duration assets in the stock market. At the aggregate level, dividend strips that pay in the near future command higher risk premia than the market index, an average over all strips (van Binsbergen et al. 2012; van Binsbergen and Koijen 2017). In the cross-section, short-duration individual stocks that make up the equity index have higher expected returns than long-duration individual stocks (Weber 2018; Gonçalves 2021b). This downward-sloping term structure of equity returns is inconsistent with classic models of long run risk and habit, which predict upward-sloping term structures. Recent work reconciles this puzzle through risk-based channels (Lettau and Wachter 2007; Gonçalves 2021a; Gormsen 2021), market frictions (Schulz 2016; Bansal et al. 2021; Li and Xu 2024), and behavioral biases (Croce et al. 2015; Weber 2018; Cassella et al. 2023). These theories focus on low-frequency variation in returns, making it difficult to differentiate among competing explanations.

This paper documents that around half of the cross-sectional equity term premium—the return spread between short- and long-duration stocks—is realized around earnings announcements. This concentration provides a setting to distinguish among theories. Pure risk- or friction-based explanations struggle to explain this pattern. In risk-based models, the contemporaneous covariance of individual stock returns and pricing kernel is too low over short intervals to explain the announcement-window term premium (Ai and Bansal 2018). In friction-based models, the tightness of low-frequency constraints does not vary significantly around earnings, and temporary frictions, such as tracking error constraints, amplify price movements during earnings periods but cannot produce the permanent return gap between short- and long-duration stocks observed in the data.

I propose that horizon bias in earnings growth forecasts explains why the equity term premium is concentrated in the announcement window. Horizon bias is the tendency for investors to be more optimistic about long-term growth than short-term growth. I construct a firm-level measure of this bias from sell-side analyst forecasts as the disparity between long-term and short-term earnings growth expectations. Analyst forecasts are, on average, biased upward, and this bias increases in forecast horizon (van Binsbergen et al. 2023; Cassella et al. 2023). Long-duration stocks have cash flows concentrated in the distant future, making them more sensitive to optimistic long-term forecasts. Investors trading on these biased forecasts systematically misprice stocks across duration, generating a downward-sloping term structure of stock returns.

Earnings announcements serve as attention shocks that amplify mispricing, which fundamental information then corrects. Earnings reports convey both cash flow news and discount rate news (Penman and Yehuda 2019). Firms with backloaded growth profiles respond strongly to positive earnings surprises, primarily through the discount rate channel: surprises signal lower perceived risk, producing large valuation increases. The cash flow channel plays a secondary role through higher expected future cash flows. This high upside potential attracts retail investors seeking lottery-like payoffs. Speculative demand is likely to be more pronounced before earnings news because announcements draw attention and trading ahead reduces holding costs and inventory risk (Liu et al. 2020). Moreover, idiosyncratic volatility concerns leading up to earnings announcements weaken arbitrageurs' ability to counteract excess demand from noise traders (Di Maggio et al. 2023). Taken together, in the pre-announcement period, long-duration stocks become significantly overpriced relative to short-duration stocks. After earnings releases, speculative bets unwind and arbitrage forces restore, largely correcting the mispricing.

I document three main findings. First, the announcement-window term premium is primarily driven by firms with high horizon bias. Second, I trace mispricing to retail buying pressure and arbitrage frictions. Retail investors disproportionately buy long-duration stocks before earnings announcements, while higher limits to arbitrage deter rational speculators from correcting such mispricing. Exploiting the pilot program of the Regulation SHO, I show that removing short-sale constraints significantly reduces the pre-announcement returns of long-duration stocks. Third, aggregate horizon bias varies over time and explains time-variation in the equity term premium. Active institutional investors shift their holdings from long- to short-duration stocks as aggregate horizon bias subsides.

These findings reveal information rigidities in how investors process earnings news (Coibion and Gorodnichenko 2012, 2015). Biased beliefs lead to strong return predictability around earnings announcements, because of larger attention-induced bets and weaker arbitrage forces during these periods (Engelberg et al. 2018; Liu et al. 2020). However, information is incorporated slowly into expectations, especially for long-term growth (Da and Warachka 2011). Therefore, speculative bets repeat around quarterly earnings announcements and mispricing may persist outside announcement windows.[1]

I start by calculating the proportion of the equity term premium realized in the announcement window. The equity term premium is the difference in average returns between short- and long-duration quintile portfolios. Unlike macro announcements,[2] individual firms announce earnings on different dates, so I align event windows across firms by the earnings announcement day (Engelberg et al. 2018; Liu et al. 2020). Each quarter, I sort firms announcing earnings into five duration quintiles based on their equity duration measure from Gonçalves (2021b). I then compute equal-weighted returns for each duration quintile on each event day in the window $[-30, +30]$, which represents a fiscal quarter.[3] Around 50% of the cumulative term premium is realized in the announcement window $[-5, +5]$. The premium realized on the announcement day itself is 55 bps, over ten times the daily average of 4.5 bps.

To capture how horizon bias varies in the cross-section, I construct a firm-level measure of

[1] Security price reactions to earnings announcements are positively related to earnings persistence, so quarterly earnings announcements contain information about long-term cash flows (Easton and Zmijewski 1989; Penman 1992; Koch and Sun 2004).

[2] Xiao (2023) show that major anomalies earn more than half of their annual risk-adjusted returns before scheduled FOMC announcements, but these gains reverse after the announcements.

[3] The contribution of earnings announcements to the annualized term premium equals the proportion of the term premium realized in the announcement window over the fiscal quarter.

horizon bias as the difference between within-industry Z-scores of long-term and short-term growth forecasts. Within-industry ranking ensures that growth rates are comparable across firms—utility firms and AI firms have very different growth profiles. Realized long-term and short-term growth rates average 9.7% and 10.6%, respectively. Under the assumption that true long-term and short-term growth rates are similar (Cassella et al. 2023), I associate extreme disparities between forecast rankings with larger horizon bias. For long-duration stocks, high horizon bias mainly reflects over-optimism about long-term growth: these firms have low short-term growth forecasts, so high horizon bias is primarily driven by inflated long-term growth expectations. For short-duration stocks, high horizon bias may reflect pessimism about short-term growth. Bouchaud et al. (2019) show that analysts are on average too pessimistic about the future profits of high-profit firms, which tend to be short-duration firms (Gonçalves 2021b).

To investigate the role of horizon bias in announcement returns, I double-sort stocks on equity duration and horizon bias. Announcement returns in the $[-5, +5]$ window show opposite patterns: returns increase in horizon bias for short-duration stocks but decrease in horizon bias for long-duration stocks. This pattern is consistent with short-term pessimism and long-term optimism: investors are, on average, positively surprised by earnings for short-duration stocks and disappointed by earnings for long-duration stocks. The announcement term premium concentrates in firms with high horizon bias. Moving from the bottom to top horizon bias quintile, the daily average premium in $[-5, +5]$ increases from 2 bps to 15 bps. The term premium is significant only in the two highest horizon bias quintiles.

A potential concern is that true growth rates differ across firms between long and short horizons, even within the same industry. For example, market leadership changes over time through industry displacement (Dou et al. 2022). The empirical horizon bias measure may thus capture rational differences in forecasts across horizons rather than bias. To address this concern, I follow van Binsbergen et al. (2023) and construct rational earnings forecasts using a random forest model. I measure bias as the difference between analyst forecasts and these rational forecasts. Horizon-differenced forecast bias produces similar results as the main horizon bias measure, suggesting that the disparity in analyst forecasts mainly reflects horizon bias rather than rational differences in growth rates.

I decompose earnings news into risk and mispricing components to show that the announcement term premium reflects both sources. Following Glosten et al. (2021), I regress firm-level standardized unexpected earnings (SUE) on market-wide and industry-wide SUE. The fitted values capture the systematic component—the covariance between firm-level and aggregate cash flow news (Savor and Wilson 2016). The residuals capture the mispricing component—the idiosyncratic part unrelated to systematic risk. The systematic component is positive and decreases with duration. The mispricing component is negative and increases in magnitude with duration. For long-duration stocks, the negative mispricing component dominates the positive systematic component, producing negative SUE. This decomposition reveals that the announcement term premium reflects both risk and mispricing, with mispricing playing a larger role for long-duration stocks.

Next, to investigate the mechanism behind the announcement term premium, I examine retail order flow around earnings announcements using transaction data. Retail net trading before earnings announcements increases significantly with equity duration. The cumulative retail net buy is 14 times higher for long-duration stocks than for short-duration stocks in the pre-announcement window. Retail net buy spikes on the last trading day before the announcement, indicating speculative demand rather than buy-and-hold investment. This pattern is consistent with long-duration stocks earning positive returns before earnings announcements, even though their earnings are less informative about aggregate cash flows (Savor and Wilson 2016).

The "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). This preference stems from overconfidence that they can interpret earnings signals better than institutions (Odean 1998). To examine the interaction effect, I regress retail order flow on the interaction between equity duration and horizon bias. The coefficient on the interaction term is significantly positive, indicating that retail investors disproportionately buy long-duration stocks with high horizon bias before earnings announcements. This pattern holds after controlling for momentum (Aboody et al. 2010) and lottery-like features (Liu et al. 2020). High horizon bias creates a false impression that long-duration stocks have higher probability of reaching the performance hurdle, leading to greater speculative appeal before earnings announcements.

The literature suggests that higher arbitrage risk around earnings announcements weakens arbitrageurs' ability to act against excess demand from noise investors (Berkman et al. 2009; Di Maggio et al. 2023; Yang et al. 2020; Barber et al. 2013). I use pre-earnings-announcement idiosyncratic volatility (IVOL) as a proxy for limits to arbitrage, 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. The two extreme quintiles exhibit higher limits to arbitrage, which explains why mispricing is more pronounced. The high IVOL of long-duration stocks can be rationalized by retail trading (Laarits and Sammon 2024), while the high IVOL of short-duration stocks may reflect uncertainty about near-term earnings and informed trading (Campbell et al. 2009).

To further support the mispricing channel, I follow Chu et al. (2020) to exploit the pilot program of Regulation SHO as a natural experiment. If return predictability reflects rational risk premia that compensate investors for bearing factor risk, limits to arbitrage should not affect expected returns. Among stocks in the Russell 3000 index as of June 2004, the pilot program designated every third stock ranked by average daily trading volume on each of NYSE, Amex, and NASDAQ as pilot stocks. The program removed short-sale price tests on this quasi-randomly selected group from May 2005 to August 2007. During the pilot period, arbitrageurs could more easily short pilot stocks, which should reduce mispricing. I find that overpricing is weaker in the long-duration quintile constructed with pilot stocks. Long-duration pilot stocks experience a 17 bps decline in pre-announcement returns relative to non-pilot stocks, indicating that prices do not build up as much before earnings announcements. Removing short-sale constraints has no effect on short-duration stocks, so the pre-announcement term premium increases for the treated group. Furthermore, I split stocks in the long-duration quintile by median horizon bias and find that the pre-announcement return reduction is larger for high horizon bias stocks (21 bps versus 14 bps).

One may argue that duration is a filtered version of known anomalies, such as value and profitability (Fama and French 1993; Novy-Marx 2013; Gonçalves 2021b). To address this concern, I run double sorts on duration and value or profitability. The return patterns of value- or profitability-adjusted duration portfolios closely resemble those of the unadjusted duration portfolios. By contrast, duration-adjusted value and profitability long-short portfolios deliver near-zero announcement returns. These results indicate that duration captures information beyond value and profitability. As a placebo test, duration-adjusted momentum strategy produces significant announcement returns, as momentum captures positive feedback trading rather than cash flow duration (Gormsen and Lazarus 2023).

Finally, I find that horizon bias varies over time and helps explain the time-variation in the equity term premium. Following Cassella et al. (2023), I construct an aggregate horizon bias measure from market-level short-term and long-term earnings growth forecasts. The announcement term premium is high (6.4%) following above-median horizon bias periods and low (2.9%) following below-median horizon bias periods. For expected returns on long-duration stocks to fall with horizon bias, long-duration stocks must become less overvalued relative to short-duration stocks as bias decreases. A large share of the term premium is also realized outside the announcement window during high horizon bias periods, which suggests that institutional investors play a role beyond passively accommodating retail demand.

I use an asset demand system to estimate institutional investors' duration-related tilts (Koijen and Yogo 2019; Koijen et al. 2024). I document two findings. First, active institutional investors, such as hedge funds and active mutual funds, tend to hold long-duration stocks, and their duration preference varies significantly over time. This pattern contrasts with the prudent man's rule that restricts insurance companies, the primary long-term investors, from holding stocks that do not pay dividends. Second, institutional duration demand helps explain the time-variation in the term premium. In a counterfactual scenario, I drop institutions with the largest changes in duration preference between high- and low-horizon-bias periods, whose AUM represents 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 horizon bias states.[4]

[4] Several potential explanations exist for institutional duration tilts. Sophisticated fund managers may time market sentiment (Brunnermeier and Nagel 2004) or hedge reinvestment risk (Gonçalves 2021a). Alternatively, fund managers themselves may be susceptible to horizon bias. Without high-frequency institutional trading data, I cannot distinguish among these channels.

Related literature This paper relates to three main strands of literature. First, I contribute to the literature on the equity term structure. van Binsbergen and Koijen (2017) provides a comprehensive review. 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 equity 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 predicts the aggregate equity term premium in the time series. 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). I highlight the joint role of risk and mispricing in explaining the announcement term premium. Short-duration stocks comove more with aggregate cash flow news (Campbell and Vuolteenaho 2004; Dou et al. 2022), leading to higher expected returns. Speculation on out-of-the-money call-like payoffs and limits to arbitrage lead to overpricing of long-duration stocks before earnings announcements. A related strand of literature studies anomaly returns on news days (Aboody et al. 2010; Engelberg et al. 2018; Liu et al. 2020). I show that term premium absorbs the value and profitability premium around earnings announcements, which suggests that biased beliefs across horizons underlie these duration-driven anomalies (Gormsen and Lazarus 2023). This paper is closely related to Liu et al. (2020), who examine lottery demand ahead of earnings. I show that the term premium patterns are robust to controlling for lottery-like features.

Finally, this paper speaks to the literature on investor heterogeneity and imperfect risk-sharing in asset pricing. One strand of this literature 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. I differ by taking a sentiment-based view of retail trading behavior. Another strand studies asset pricing by estimating asset demand across markets, including equity, fixed income, and country-level assets (Koijen and Yogo 2019, 2020; Bretscher et al. 2022; Koijen et al. 2024; Jiang et al. 2024). I apply this framework to study institutional investors' duration tilts and the time-series variation in equity term premium.

2. Motivating framework

In this section, I first use a simple analytical framework to show that extreme disparities between long-term and short-term earnings growth forecasts closely approximate horizon bias—the difference between long-term and short-term forecast bias—which links directly to the equity term premium. Next, I develop hypotheses for why horizon bias is central to explaining the announcement term premium.

2.1. Forecast disparity and horizon bias

Suppose the earnings growth forecast x follows $x \sim \mathcal{N}(g, s^2)$, where the mean g itself is drawn from $g \sim \mathcal{N}(\mu, \sigma^2)$. Unconditionally, x has a mixture normal distribution:

$$x \sim \mathcal{N}(\mu, \sigma^2 + s^2).$$

We can express x as

$$x = \mu + \sigma\eta + s\varepsilon, \tag{1}$$

where η and ε are independent standard normal variables.

Here, the forecast x combines a signal component (η) and a noise component (ε). If $s = 0$, x reflects only the signal, so sorting by x is equivalent to sorting by η. If $\sigma = 0$, x reflects only noise, so sorting by x is equivalent to sorting by ε. I focus on the realistic case where both $\sigma > 0$ and $s > 0$.

Let c_p denote the $100p$-th percentile of x:

$$P[x \leq c_p] = p.$$

It follows that

$$c_p = \mu + \sqrt{\sigma^2 + s^2}\, z_p,$$

where z_p is the p-th quantile of the standard normal distribution.

I now compute the conditional distribution of ε given $x \geq c_p$. The joint distribution of (ε, x) is

$$\begin{bmatrix} \varepsilon \\ x \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ \mu \end{bmatrix}, \begin{bmatrix} 1 & s \\ s & \sigma^2 + s^2 \end{bmatrix} \right).$$

Conditioning on x, the distribution of ε is

$$\varepsilon | x \sim \mathcal{N}\left(\frac{s}{\sigma^2 + s^2}(x - \mu), \frac{\sigma^2}{\sigma^2 + s^2} \right).$$

Therefore, conditional on $x \geq c_p$, the density of ε is

$$f(\varepsilon|x \geq c_p) = \frac{1}{1-p} \int_{c_p}^{\infty} f(\varepsilon|x) f(x)\, dx.$$

The conditional mean of ε given $x \geq c_p$ is

$$\begin{aligned} \mathbf{E}[\varepsilon|x \geq c_p] &= \frac{1}{1-p} \int_{c_p}^{\infty} \frac{s}{\sigma^2 + s^2}(x-\mu) f(x) dx \\ &= \frac{s}{\sqrt{\sigma^2 + s^2}} \cdot \frac{\phi(z_p)}{1-p}, \end{aligned} \tag{2}$$

where $\phi(\cdot)$ is the standard normal density. For example, with $s = 1$, $\sigma = 0.5$, and $p = 0.8$, we have $\mathbf{E}[\varepsilon|x \geq c_p] = 1.252$. Thus, observations with high x tend to have large positive noise components. The effectiveness of sorting by x depends on the relative size of s and σ. When s is large relative to σ, i.e., there is a lot of forecasting error, sorting by x mostly sorts on noise, which reflects forecast bias.

Similarly,

$$\mathbf{E}[\varepsilon|x \leq c_p] = -\frac{s}{\sqrt{\sigma^2 + s^2}} \cdot \frac{\phi(z_p)}{p}. \tag{3}$$

For $p = 0.2$, this mean is -1.252, so low x observations have large negative bias.

Motivated by this, I define the long-term and short-term earnings growth forecasts as x^l and x^s. I measure forecast disparity as

$$d = \text{rank}(x^l) - \text{rank}(x^s), \tag{4}$$

where $\text{rank}(x^l)$ and $\text{rank}(x^s)$ are the within-industry ranks of x^l and x^s, respectively. Adjusting for industry is important because growth rates vary systematically across industries; this ensures that σ is comparable across firms and remains small relative to s.

Large values of d arise when the long-term forecast x^l ranks high (implying a large positive ε^l) and the short-term forecast x^s ranks low (implying a large negative ε^s). Thus, d effectively measures the difference in forecast bias between long-term and short-term growth expectations. When d is large,

$$d \approx \text{rank}(\varepsilon^l) - \text{rank}(\varepsilon^s), \tag{5}$$

so forecast disparity serves as a close proxy for horizon bias.

2.2. Hypothesis development

Motivated by the analytical framework, I discuss why horizon bias should help explain the announcement equity term premium. I define the equity term premium (ETP) as the difference between returns on short-term and long-term assets. At the market level, when the bias in long-term growth is greater than in short-term growth, long-term assets become more overpriced relative to short-term assets, leading to a larger equity term premium. In Appendix A.1, I follow Cassella et al. (2023) to show that the equity term premium is proportional to horizon bias.

The relationship between horizon bias and the equity term premium should be especially pronounced around earnings announcements. First, earnings announcements are major news events that capture investors' attention. Second, speculative demand tends to rise before announcements, as immediate payoffs reduce inventory costs. Long-duration stocks, in particular, are highly speculative because their valuations are subjective and sensitive to distant cash flows (Campbell and Vuolteenaho 2004). Third, concerns about inventory risk and idiosyncratic volatility ahead of announcements limit arbitrageurs' ability to counteract excess demand from noise traders (Di Maggio et al. 2023).

Next, I discuss how horizon bias affects returns across stocks with different cash flow duration. For long-duration stocks, whose cash flows are concentrated in the distant future, short-term growth forecasts are typically low. As a result, the ranking of horizon bias is mainly driven by the ranking of long-term forecasts. A high disparity usually reflects an overly optimistic long-term forecast relative to peers. This large gap between long-term and short-term growth signals a higher probability of a sudden "milestone" earnings event that allows the firm to catch up with its long-term targets. Speculative investors are drawn to these stocks, effectively betting on a jackpot outcome (Conrad et al. 2014). However, these stocks often underperform after the announcement, as the anticipated milestone earnings rarely materialize and long-term growth forecasts tend to be overly optimistic. Therefore, we expect long-duration stocks with higher horizon bias to exhibit lower announcement returns.

By contrast, short-duration stocks have cash flows concentrated in the near term, so their valuations are more sensitive to short-term growth forecasts. Bouchaud et al. (2019) show that analysts are on average too pessimistic about the future profits of high-profit firms, which tend to be short-duration stocks (Gonçalves 2021b). A high horizon bias for these stocks typically reflects an overly pessimistic short-term forecast relative to peers. Because short-duration stocks tend to have stronger fundamentals, this pessimism often signals positive short-term earnings surprises. However, these stocks are less appealing to speculative investors, as their valuations are less subjective and more closely tied to near-term cash flows. As described by Campbell et al. (2010), short-duration stocks are often out of favor, while long-duration stocks are considered glamorous. Therefore, we expect short-duration stocks with higher horizon bias to have higher announcement returns.

Taken together, horizon bias leads to lower announcement returns for long-duration stocks and higher returns for short-duration stocks. As a result, the announcement equity term premium should be larger among firms with higher horizon bias. In summary, I propose the following hypotheses:

Hypothesis 1: Long-duration stocks with higher horizon bias have lower announcement returns.

Hypothesis 2: Short-duration stocks with higher horizon bias have higher announcement returns.

Hypothesis 3: Announcement equity term premium is larger among firms with higher horizon bias.

3. Data

My empirical analysis uses several data sources. I obtain earnings announcement dates and analyst forecasts from IBES. Stock-level variables, such as prices and shares outstanding, come from CRSP, supplemented with accounting data from Compustat. I extract high-frequency retail trading data from the TAQ database and collect quarterly institutional holdings from FactSet. Below, I briefly describe how I construct key variables, with further details in Appendix C.

3.1. 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 (highest performing group) and those in the long duration quintile (lowest performing group). Equity duration is defined as the weighted average timing of stocks' payouts to investors:

$$\mathrm{Dur}_{i,t} = \sum_{h=1}^{\infty} w_{i,t}^{h} \cdot h = \sum_{h=1}^{\infty} \frac{\mathbf{E}_t[\mathrm{PO}_{i,t+h}] \cdot \exp(-h \cdot r_{i,t})}{\mathrm{ME}_{i,t}} \cdot h, \tag{6}$$

where $w_{i,t}^{h}$ represents the fraction of firm i's current market value that is due to the cash flow maturing in h years. Firms' total payouts (dividends + repurchases − issuances), $\mathrm{PO}_{i,t+h}$, are treated as cash flows to equity investors. $r_{i,t}$ is defined as the discount rate that equates the present value of firm i'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 11.26%.

3.2. Earnings announcement data

I obtain earnings announcement dates, analyst forecasts, and actual earnings from the Institutional Brokers' Estimate System (IBES). If a firm releases earnings before 4 pm EST on a trading day, I set that day as the effective earnings date. If the release occurs after 4 pm, on a weekend, or on a public holiday, I assign the next trading day as the effective date. I manually match IBES and CRSP records using CUSIP identifiers and exchange tickers. The sample period is from 1980:1 to 2024:12.

I focus on three types of forecasts: short-term quarterly EPS forecasts (FPI 6–7), medium-term annual forecasts (FPI 1–5), and long-term growth (LTG) forecasts (FPI 0). IBES defines LTG as the expected annual increase in operating earnings over the next full business cycle, typically three to five years. I fill missing forecasts by linearly interpolating EPS at horizons from 1 to 5 years. For quarterly forecasts, I manually compute the median from the IBES Unadjusted US Detail History file; for annual and LTG forecasts, I use the median from the IBES Unadjusted US Summary Statistics file. Realized EPS data come from the IBES Unadjusted US Detail Actuals file.

I construct quarterly standardized unexpected earnings (SUE) following DellaVigna and Pollet (2009):

$$\mathrm{SUE}_{i,t} = \frac{\mathrm{EPS}_{i,t} - \tilde{\mathbf{E}}_{t-1}[\mathrm{EPS}_{i,t}]}{S_{i,t}}, \tag{7}$$

where $\mathrm{EPS}_{i,t}$ is firm i's realized earnings per share in quarter t, and $\tilde{\mathbf{E}}_{t-1}[\mathrm{EPS}_{i,t}]$ is the median analyst forecast from IBES. The tilde indicates that these forecasts can be biased. I scale the earnings surprise by the last closing price before the announcement, $S_{i,t}$. For each firm-quarter, I keep the latest forecast from each analyst and include only forecasts made within 90 days of the announcement. I use the CRSP cumulative shares adjustment factor to account for stock splits.

[Figure 1]

I measure annual analyst forecast error using an annual version of SUE. Figure 1 plots annual SUE across forecasting horizons from 1 to 5 years. The figure shows that SUE is negative on average at all horizons, indicating that analyst forecasts consistently overestimate actual earnings.

Moreover, the degree of optimism increases in the forecasting horizon. This pattern reveals an upward-sloping term structure of forecast bias: analysts are increasingly optimistic about earnings as the forecast horizon lengthens.

Horizon bias If earnings forecasts are more optimistic at long horizons than at short horizons, long-term assets become especially overvalued because their cash flows are concentrated in the distant future. As a result, these assets have lower expected returns than short-term assets, producing a downward-sloping equity term structure. In other words, an upward-sloping term structure of forecast bias leads directly to a downward-sloping term structure of expected returns. Since the equity term premium measures the relative performance of short-term versus long-term stocks, any variable that explains this premium should capture the difference between these two types of stocks.

To capture the difference in forecast bias between long-term and short-term growth expectations, I define a firm-level horizon bias measure:

$$\mathrm{HB}_{i,t} = \mathrm{LTG}^{Z}_{i,t} - \mathrm{STG}^{Z}_{i,t}, \tag{8}$$

where $\mathrm{LTG}^{Z}_{i,t}$ is the within-industry standardized long-term growth forecast and $\mathrm{STG}^{Z}_{i,t}$ is the within-industry standardized short-term (current year-end) growth forecast. I standardize forecasts within each industry (two-digit SIC) and month to ensure comparability across firms. A higher horizon bias means investors are more optimistic about long-term growth than short-term growth.

3.3. Retail trading volume

To study retail trading behavior around earnings announcements, I extract retail trades from TAQ millisecond-level transaction data from 2010 to 2023. Because TAQ does not label retail trades, I follow Boehmer et al. (2021) and identify retail trades using the subpenny digit rule: wholesalers often provide subpenny price improvements to retail orders, a feature unique to retail trades. I determine trade direction using the quote midpoint rule from Barber et al. (2024), which helps address potential bias in the subpenny algorithm. I classify a trade as a retail buy (sell) if the trade price is above (below) the quote midpoint.

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

$$\mathrm{RNB}_{i,t} = \frac{\mathrm{BuyV}_{i,t} - \mathrm{SellV}_{i,t}}{\mathrm{TSO}_{i,t}} \tag{9}$$

where $\mathrm{BuyV}_{i,t}$ and $\mathrm{SellV}_{i,t}$ are the number of shares in retail-initiated buy and sell trades of stock i on day t, respectively. $\mathrm{TSO}_{i,t}$ is the total shares outstanding. I use TSO as the scaling factor so that retail net buy is additive over the announcement window.

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, RNB 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.

3.4. Institutional equity holdings

The ideal approach to studying institution-retail interaction would use high-frequency institutional trading data, but such data are not publicly available. To address this limitation, I use quarterly U.S. institutional equity holdings from 2000:Q1 to 2022:Q4 from FactSet. In estimating demand, I prioritize FactSet data on equity prices, shares outstanding, and market equity.

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

$$\mathrm{AS}_{j,t} = \frac{1}{2} \sum_{i \in \mathcal{N}_{j,t}} \left| w_{j,t}(i) - w^M_{j,t}(i) \right|, \tag{10}$$

which measures the extent to which investor j'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, 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 (Koijen et al. 2024).

4. Decomposing the equity term premium

In this section, I decompose the equity term premium into returns realized around earnings announcements and show that a large share of the annual term premium is concentrated in the announcement window.

4.1. Motivation

The earnings announcement setting is well suited for studying the equity term premium for several reasons. First, cash flow news has a lasting impact on long-duration stocks, as price changes driven by cash flow news are permanent (Campbell et al. 2010). In contrast, negative discount rate news (an increase in the discount rate) has only a temporary effect, since it is offset by higher expected returns in the future; its impact fades over time (Chen et al. 2013). Because long-duration stocks are more sensitive to discount rate changes, investors can often “ride out” these fluctuations and are compensated through improved future return prospects (Savor and Wilson 2016). Supporting 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 basis points per event.

Second, the earnings announcement setting helps isolate other sources of return predictability. Much of the literature attempts to reconcile classic asset pricing models with the downward-sloping equity term structure (van Binsbergen et al. 2012), but the large share of term premia realized around earnings announcements challenges most existing explanations. For example, if these returns were compensation for risk, the required discount rate changes would be implausibly large (Engelberg et al. 2018). Aggregate consumption does not adjust immediately to news (Ai and Bansal 2018), so consumption-based explanations contribute too little over short intervals to account for 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) suggest that institutional investors tilt away from long-duration stocks due to binding tracking error constraints before announcements, but this cannot explain the pre-announcement drift observed in long-duration stocks.

4.2. Announcement equity term premium

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 announcing earnings into five quintiles based on equity duration. Because firms report earnings on different dates, I follow the literature and align event windows by announcement day across firms (Engelberg et al. 2018; Liu et al. 2020). I then compute equal-weighted average returns for each duration quintile on each event day, rather than by calendar date. 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 premium by the number of event days in a year.

[Figure 2]

Figure 2 plots the cumulative equity term premium over a fiscal quarter, centered on the announcement day (day 0). I use a quarterly window because the sample includes only firms with earnings announcements, so a fair comparison is to benchmark the announcement term premium against the daily average for these firms over the entire quarter. I define the announcement window as the 10 days surrounding the announcement day. Two key findings emerge. First, about half of the cumulative term premium is realized within the announcement window. Second, most of this premium is concentrated on the announcement day itself—the premium on day 0 is more than ten times the daily average.

[Table 1]

Table 1 reports the daily term premium for different event window sizes, along with the corresponding annualized returns and each window's contribution to the overall term premium. The daily average over a quarter is 4.47 basis points, which I use as the unconditional daily average to compute an annualized term premium of 11.26%. On the earnings announcement day, the average term premium jumps to 55.04 basis points. Since most firms report earnings each quarter, the term premium realized over four announcement days accounts for 20% of the annualized total. Expanding the window to $[-5, +5]$ around announcement dates, this share rises to 42%.

4.3. Return dynamics in announcement window

Next, I examine returns in the announcement window across duration quintile portfolios. Figure 3 shows return dynamics for each duration quintile in the $[-10, +10]$ window around earnings announcements. Panel (a) plots cumulative abnormal returns, calculated as daily returns minus the market return. Panel (b) reports daily CAPM alphas. I estimate CAPM betas using a rolling window of 252 trading days, ending 21 trading days before the announcement, and apply the slope-winsorized method from Welch (2021) for more robust beta estimates.

Abnormal returns trend upward for all duration quintiles, as announcing firms earn higher returns than non-announcing firms (Savor and Wilson 2016). Cumulative returns move similarly across duration portfolios in the pre-announcement window $[-10, -3]$. However, long-duration stocks experience a sharp increase of about 20 basis points on days -2 and -1. After the earnings announcement, long-duration stocks decline sharply in value. Panel (b) in Figure 3 shows that both short-duration and long-duration stocks contribute substantially to the term premium on the announcement day, with the long-duration quintile making a slightly larger contribution. This underscores the importance of understanding the dynamics of long-duration stocks.

[Figure 3]

Table 2 reports the daily returns for each duration quintile portfolio in the $[-3, +3]$ window. I compute the difference between the short-duration and long-duration quintiles to assess whether a significant term premium is realized in this period. I also calculate the difference between the medium-duration and long-duration quintiles to illustrate the shape of the equity term structure. Even after adjusting for market returns, long-duration stocks earn significantly positive abnormal returns before the announcement. This adjustment actually disadvantages long-duration stocks, since they have higher betas than short-duration stocks (van Binsbergen et al. 2012).

[Table 2]

These results explain why only a small fraction of the term premium is realized *before* earnings announcements: long-duration stocks do not significantly underperform in the pre-announcement window. Instead, the data reveal a pronounced pre-announcement drift for these stocks. On the announcement day, long-duration stocks experience negative returns, suggesting they were relatively overpriced beforehand and that some of this mispricing is corrected when earnings news arrives. Taken together, the equity term structure is V-shaped before the announcement and shifts to a strictly downward-sloping pattern after the event.

5. Horizon bias and announcement term premium

This section examines whether horizon bias helps explain the announcement term premium. I first show that the announcement term premium is concentrated among firms with high horizon bias. Next, I demonstrate that time-series variation in aggregate horizon bias helps explain fluctuations in the announcement term premium over time. Finally, I decompose earnings news into risk and mispricing components, showing that systematic risk alone cannot account for the announcement term premium.

5.1. Horizon bias and announcement returns

To test the hypotheses from Section 2, I use a conditional double sort based on equity 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. For each portfolio, I compute the equal-weighted average abnormal return in the $[-5, +5]$ announcement window, where abnormal returns are defined as daily returns minus the market return. The term premium is measured as the difference in average returns between the short- and long-duration portfolios.

[Table 3]

Table 3 reports the average announcement returns for these two-way sorted portfolios. The relationship between horizon bias and announcement returns is asymmetric across duration groups. For short-duration stocks, higher horizon bias is associated with higher announcement returns, suggesting that high horizon bias mainly reflects short-term pessimism in earnings forecasts. When positive earnings news arrives, prices react strongly, resulting in higher announcement returns. In contrast, for long-duration stocks, higher horizon bias is linked to lower announcement returns, indicating that high horizon bias mainly reflects long-term optimism. Investors make speculative bets on these stocks, expecting a large positive earnings surprise. Because long-term forecasts are typically biased upward, investors overestimate the likelihood of such surprises. When the anticipated milestone earnings rarely materialize, these stocks tend to underperform after the announcement.

Given the asymmetric pattern of returns between short- and long-duration stocks, it follows that the announcement term premium is most pronounced among firms with high horizon bias. As we move from the lowest to the highest horizon bias quintiles, the daily premium rises from 2 bps to 15 bps. In other words, the announcement term premium is largely driven by the most underpriced short-duration stocks and the most overpriced long-duration stocks—both characterized by high horizon bias. Importantly, the term premium is significant only in high horizon bias portfolios, highlighting horizon bias as a key driver of the announcement term premium.

Da and Warachka (2011) find that, due to analyst incentives and investor inattention, information is incorporated slowly into long-term forecasts and long-term earnings expectations. As a result, quarterly earnings announcements have limited impact on updating long-term beliefs. The positive announcement returns for short-duration stocks with high horizon bias suggest that investors revise their short-term growth expectations upward when earnings news arrives. In contrast, the negative announcement returns for long-duration stocks are less about updating long-term forecasts and more about the unwinding of speculative bets on unlikely jackpot outcomes.

5.2. Machine-learning-based horizon bias

Thus far, I have implicitly assumed that rational long-term and short-term earnings growth forecasts are identical. Under this assumption, the disparity between analyst long-term and short-term growth forecasts reflects horizon bias.

In this section, I relax this assumption and allow rational growth forecasts to differ across horizons. I generate rational earnings forecasts using a random forest methodology following van Binsbergen et al. (2023). Random forests aggregate predictions from multiple decision trees constructed with injected randomness. Each decision tree partitions the training data by selecting predictors and split values that minimize the sum of squared errors. This process continues recursively until stopping criteria are met. I use three categories of predictors: (1) firm fundamentals, (2) macroeconomic conditions, and (3) sell-side analyst forecasts.

Using this procedure, I generate long-term and short-term rational earnings growth forecasts, denoted by $g^l_{i,t}$ and $g^s_{i,t}$, respectively. Bias is defined as the difference between analyst forecasts and rational forecasts:

$$\varepsilon^l_{i,t} = \mathrm{LTG}_{i,t} - g^l_{i,t}, \tag{11}$$

$$\varepsilon^s_{i,t} = \mathrm{STG}_{i,t} - g^s_{i,t}, \tag{12}$$

where $\varepsilon^l_{i,t}$ and $\varepsilon^s_{i,t}$ are the long-term and short-term forecast biases, respectively.

Horizon bias is then defined as

$$\mathrm{HB}^{ML}_{i,t} = Q(\varepsilon^l_{i,t}) - Q(\varepsilon^s_{i,t}), \tag{13}$$

where $Q(\cdot)$ denotes the within-industry percentile rank.

This decomposition separates the rational component from the bias component in horizon-differenced forecasts. The rational component captures differences in rational long-term versus short-term growth expectations, while the bias component captures differences in forecast errors across horizons.

Table A1 presents the announcement returns for portfolios sorted on equity duration and machine-learning-based horizon bias. The results closely mirror those using raw horizon-differenced forecasts. Announcement returns increase in horizon bias for short-duration stocks but decrease in horizon bias for long-duration stocks, suggesting that forecast disparity mainly reflects horizon bias rather than rational differences in growth expectations.

5.3. Price effect

To quantify the relationship between horizon bias and announcement returns, I estimate the following regressions separately for the pre- and post-announcement windows:

$$\begin{aligned} \mathrm{CAR}_{i,t} = {} & \beta_1 \,\mathrm{Dur}_{i,t-1} + \beta_2 \,\mathrm{HB}_{i,t-1} + \beta_3 \,\mathrm{Dur}_{i,t-1} \times \mathrm{HB}_{i,t-1} \\ & + \boldsymbol{\gamma}' \mathbf{x}_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \end{aligned} \tag{14}$$

where $\mathrm{CAR}_{i,t}$ is the cumulative market-adjusted abnormal return for stock i around its earnings announcement in quarter t, calculated over either the pre-announcement window $[-3,-1]$ or the post-announcement window $[0,+2]$. $\mathrm{Dur}_{i,t-1}$ and $\mathrm{HB}_{i,t-1}$ are the equity duration and horizon bias for firm i at the end of quarter $t-1$, respectively. $\mathbf{x}_{i,t-1}$ is a vector of firm characteristics: stock duration, nominal share price, firm age, momentum return, 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. The pre-event coefficients reflect cross-sectional variation in horizon bias, while the post-event coefficients capture within-firm variation over time.

For the post-announcement window, I also estimate an alternative specification that includes the earnings surprise $\text{SUE}_{i,t}$ for firm i in quarter t. This allows me to test whether the price response to earnings news varies with horizon bias and duration.

[Table 4]

Table 4 reports the regression results. In the pre-announcement window, announcement returns decrease in equity duration and increase in horizon bias. Notably, the coefficient on the interaction between duration and horizon bias is significantly positive, indicating that long-duration stocks with high horizon bias experience a larger pre-announcement drift. This finding supports the view that high horizon bias for long-duration stocks reflects long-term optimism, resulting in their relative overpricing before earnings announcements. The opposite pattern holds for short-duration stocks.

By contrast, in the post-announcement window, announcement returns decline in both equity duration and horizon bias. The negative coefficient on the interaction term indicates that long-duration stocks with high horizon bias experience an even larger post-announcement drop. This pattern is consistent with the unwinding of speculative bets.

Focusing on column (5) of Table 4, which includes the earnings surprise in the focal quarter. The interaction between SUE and duration is significantly negative, indicating that current earnings news has a smaller impact on long-duration stocks, whose cash flows are concentrated in the distant future. The triple interaction among SUE, duration, and horizon bias is also significantly negative, suggesting that long-duration stocks with high horizon bias are especially unresponsive to earnings news. This finding supports the view that the valuations of these stocks are weakly linked to fundamentals and are more influenced by investor sentiment.

5.4. Time-varying announcement term premium

To further investigate the relationship between horizon bias and the announcement term premium, I examine how time-series variation in aggregate horizon bias relates to fluctuations in the announcement term premium. I construct a market-level horizon bias measure as

$$\text{HB}_t = \text{LTG}_t^Z - \text{STG}_t^Z, \tag{15}$$

where LTG_t^Z and STG_t^Z are the time-series Z-scores of aggregate long-term and short-term growth forecasts, respectively.

A higher market-level horizon bias indicates that investors are more optimistic about long-term growth relative to short-term growth. This optimism can lead to overpricing of long-duration stocks, resulting in lower future returns on long-duration stocks relative to short-duration stocks. Therefore, I expect the announcement term premium to be high following periods of high horizon bias.

I compute the announcement term premium conditional on the beginning-of-period market-level horizon bias. High and low horizon bias periods are defined as months when the market-level horizon bias is above or below its median, respectively. I annualize the announcement term premium by multiplying the event-window $[-5, +5]$ return by 4. Panel A of Table 5 shows that the announcement term premium is 6.4% following high horizon bias periods, compared to only 2.9% following low horizon bias periods.

[Table 5]

Panel B of Table 5 presents the conditional term premium using full-month returns. 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 defined as the difference in average returns between the short- and long-duration portfolios. The unconditional term premium is 6.7% per year; it increases to 11.1% following high-disparity periods and drops to 2.4% following low-disparity periods. This pattern supports the horizon bias explanation: when investors are more optimistic about the cash flows of long-duration stocks, subsequent returns are lower.

5.5. 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) show that value stocks have a higher cash flow beta—so-called "bad beta"—than growth stocks. Building on this logic, because the cash flows of short-duration firms are concentrated in the near future, their cash flow news 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 mispricing component. Following Glosten et al. (2021), I estimate the following regression for each firm i in quarter t:

$$\mathrm{SUE}_{i,t} = \phi_{0,i,t} + \phi_{1,i,t}\mathrm{SUE}_t^{\mathrm{Market}} + \phi_{2,i,t}\mathrm{SUE}_t^{\mathrm{SIC2}} + \varepsilon_{i,t}, \tag{16}$$

where $\mathrm{SUE}_{i,t}$ is firm i's SUE in quarter t, and $\mathrm{SUE}_t^{\mathrm{Market}}$ and $\mathrm{SUE}_t^{\mathrm{SIC2}}$ are the market-wide and industry-wide value-weighted SUE in quarter t, respectively. I estimate Equation (16) 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 mispricing component.

[Figure 4]

Figure 4 shows the average risk and mispricing components of SUE by duration quintile. The risk component is positive and decreases in equity duration, consistent with the idea that cash flow news from short-duration firms is more informative about aggregate conditions (Campbell and Vuolteenaho 2004; Dou et al. 2022). In contrast, the mispricing component is negative and becomes larger in magnitude as duration increases. For long-duration stocks, the negative mispricing component dominates the positive risk component, leading to negative SUE and negative average returns on earnings days. If risk alone explained the announcement premium, long-duration stocks would appear 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 a purely risk-based explanation.

Before announcements, a V-shaped term structure of risk premia suggests that both risk and mispricing components are at work. The mispricing component inflates prices, and the interplay between risk and mispricing factors produces the observed V-shaped pattern. After earnings are released, biased beliefs are largely corrected, and the risk component becomes dominant, resulting in a downward-sloping term structure. Overall, the strong covariance between the long leg and aggregate cash flow news, combined with a speculative short leg that is sensitive to optimism bias, explains the announcement term premium.

An open question is what drives the comovement of anomaly long and short legs (Campbell et al. 2010). The fundamentals view argues that stocks in the long or short leg move together because of similarities in their cash flow characteristics. In contrast, the sentiment view attributes comovement to shifts in investor sentiment or changes in discount rates applied to favored or disfavored stocks. This decomposition sheds light on the debate: the strong correlation between the long leg and aggregate cash flow news supports the fundamentals view, while the short leg's sensitivity to behavioral biases is consistent with the sentiment view.

6. Inspecting the mechanism

This section investigates the underlying mechanism of the announcement term premium. First, I examine retail trading behavior around earnings announcements. Second, I analyze the causal effect of limits to arbitrage on the announcement term premium using a natural experiment. Finally, I demonstrate that the observed announcement term premium pattern cannot be explained by other common factors, such as value, profitability, or momentum.

6.1. Retail net trading

For long-duration stocks, a large gap between long-term and short-term growth forecasts signals a higher probability of a sudden "milestone" earnings event that could help the firm catch up with its long-term targets. Because these stocks are particularly attractive for speculation, excess demand for them should be especially high before earnings announcements. Moreover, since earnings announcements capture retail investors' attention and lottery-like stocks are predominantly traded by retail investors, attention-driven demand for long-duration stocks is likely to be especially pronounced in the days leading up to earnings announcements.

[Figure 5]

Figure 5 shows cumulative retail net trading by duration quintile in the $[-10, +10]$ window around earnings announcements. Retail net buy is defined as the difference between retail buy and sell volume, 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 basis points of total shares outstanding, comparable 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). This pattern confirms higher buying pressure from retail investors for long-duration stocks before earnings announcements, contributing to the overpricing of these stocks.

To quantify the effect of horizon bias on retail net trading, I estimate the following regression:

$$\begin{aligned} \mathrm{RNB}_{i,t} = {} & \beta_1\, \mathrm{Dur}_{i,t-1} + \beta_2\, \mathrm{HB}_{i,t-1} + \beta_3\, \mathrm{Dur}_{i,t-1} \times \mathrm{HB}_{i,t-1} \\ & + \boldsymbol{\gamma}' \mathbf{x}_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \end{aligned} \tag{17}$$

where $\mathrm{RNB}_{i,t}$ is the cumulative retail net buy volume for stock i over the $[-5, -1]$ window before its earnings announcement in quarter t; $\mathrm{Dur}_{i,t-1}$ is equity duration in the previous quarter; $\mathrm{HB}_{i,t-1}$ is horizon bias in the previous quarter; and $\mathbf{x}_{i,t-1}$ is a vector of firm characteristics: nominal share price, firm age, momentum return, 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 heterogeneity across stocks and changing market conditions.

[Table 6]

Table 6 reports the estimated coefficients. The coefficient on duration is significantly positive, indicating a strong link between equity duration and retail net buying before earnings announcements, even after controlling for other firm characteristics. Notably, the interaction between duration and horizon bias is also significantly positive, suggesting that retail buying pressure is especially pronounced for long-duration stocks with high horizon bias. These results imply that horizon bias, as captured by horizon bias, is a key driver of retail demand for long-duration stocks ahead of earnings announcements.

6.2. Pre-announcement idiosyncratic volatility

Previous results suggest that retail buying pressure contributes to the relative overpricing of long-duration stocks before earnings announcements. The literature suggests that concerns about idiosyncratic volatility leading up to announcements weaken arbitrageurs' ability to offset excess demand from retail investors (Berkman et al. 2009; Di Maggio et al. 2023; Yang et al. 2020; Barber et al. 2013). Several empirical studies show that idiosyncratic risk is a major impediment to arbitrage (Hong and Sraer 2016). To assess how limits to arbitrage vary across duration quintiles, I estimate 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 using past one-year daily returns to obtain daily residuals, $\varepsilon_{n,d}$. The pre-earnings-announcement period (PEA) is defined as the five business days before each of the most recent four earnings announcements, $[-5,-1]$. The annualized idiosyncratic volatility for stock i at the end of month t is

$$\mathrm{IVOL}_{i,t}^{PEA} = \sqrt{\frac{252 \times \sum_{d \in PEA} \varepsilon_{i,d}^2}{N_{PEA} - 1}}, \tag{18}$$

where N_{PEA} is the number of days in the pre-earnings-announcement periods.

[Figure 6]

Figure 6 shows that average pre-announcement IVOL follows a U-shaped pattern across duration quintiles: both short- and long-duration stocks have higher idiosyncratic volatility than medium-duration stocks. Recall that the announcement term premium is largely driven by the most underpriced short-duration stocks and the most overpriced long-duration stocks. These extreme groups are also associated with higher limits to arbitrage, which helps explain why mispricing is more pronounced for them.

6.3. The causal effect of limits to arbitrage

To further support the mispricing explanation, I examine whether limits to arbitrage affect the announcement term premium. The mispricing explanation is consistent with the idea that limits to arbitrage delay the flow of wealth from irrational to sophisticated investors (Shleifer and Vishny 1997). In contrast, if return predictability reflects rational risk premia that compensate investors for bearing factor risk, limits to arbitrage should not affect expected returns. The previous section uses idiosyncratic volatility as a proxy for limits to arbitrage. However, proxies based on firm characteristics are often correlated with risk (Chu et al. 2020), raising the possibility that effects attributed to limits to arbitrage may actually reflect rational risk premia.

Therefore, I follow Chu et al. (2020) and exploit a natural experiment—the Rule 202T pilot program of Regulation SHO[5]—to identify the causal effect of limits to arbitrage on announcement term premium. Among stocks in the Russell 3000 index as of June 2004, the pilot program designated every third stock ranked by average daily trading volume in the prior year on each of NYSE, AMEX, and NASDAQ as pilot stocks. The pilot program then removed short-sale price tests on this quasi-randomly selected group of pilot stocks. The form of short-sale price tests differed across exchanges: NYSE/AMEX imposed the uptick rule, while NASDAQ used the bid price test. The NASDAQ bid price test was not very restrictive, with much trading volume exempt, so its effect was likely minimal. Thus, my final sample includes pilot and non-pilot stocks listed on NYSE and AMEX at portfolio formation. The pilot program was in effect from May 2, 2005 to July 6, 2007.

If long-duration stocks are relatively overpriced before earnings announcements due to limits to arbitrage, then during the pilot period, arbitrageurs should be able to more easily short these overpriced stocks, reducing their overpricing. In contrast, this shock should have no effect on short-duration stocks, which are relatively underpriced before earnings announcements. Therefore, I hypothesize that the pilot program of Regulation SHO should increase the pre-event term premium for pilot stocks relative to non-pilot stocks during the pilot period.

I now test these hypotheses by examining whether the pilot program led to differences in pre-event term premia between pilot and non-pilot stocks during the pilot period. I construct event-time duration quintile portfolios separately for pilot and non-pilot stocks. Each month, I sort all pilot stocks announcing earnings into five duration quintiles and calculate the difference in average returns between the short- and long-duration quintile portfolios in the $[-5,-1]$ window before earnings announcements. I repeat this procedure for non-pilot stocks. To formally test for differences, I use a difference-in-differences (DiD) approach to compare the pre-event term premia of pilot and non-pilot stocks during the pilot period.

The main difference-in-differences test uses the following specification:

$$R_{p,t} = \alpha_t + \beta\,\mathrm{Pilot}_p \times \mathrm{During}_t + \beta_1\,\mathrm{Pilot}_p + \varepsilon_{p,t}, \tag{19}$$

where $R_{p,t}$ is the pre-announcement return in window $[-5,-1]$ of portfolio p (either the long leg, short leg, or the long-short portfolio) in month t, and α_t denotes time fixed effects. Pilot_p is a dummy equal to 1 if portfolio p is formed from pilot stocks, and 0 otherwise. During_t is a dummy equal to 1 if month t falls within the pilot period (July 2005 to June 2007). Since During_t is absorbed by time fixed effects, it is omitted from the regression. I exclude the first two months of the pilot program to avoid capturing short-term price adjustments. The unit of analysis is a portfolio-month observation. I estimate Equation (19) separately for the long leg, short leg, and long-short portfolios. The coefficient β is the main parameter of interest, capturing the difference in pre-announcement term premia between pilot and non-pilot stocks during the pilot period.

[5] See https://www.sec.gov/rule-release/34-50104.

Within both the short- and long-duration quintiles, I further split stocks by the median horizon bias to examine whether horizon bias influences the degree of mispricing. Results are reported in Table 7.

[Table 7]

In column (1), where the dependent variable is the return on the short-duration quintile portfolio, the coefficient β is close to zero and statistically insignificant. This indicates that removing short-sale constraints has no effect on the pre-announcement return of these stocks. In column (2), where the dependent variable is the return on the long-duration quintile portfolio, the coefficient β is significantly negative, suggesting that long-duration stocks experience a significant decline in pre-announcement returns during the pilot period. This indicates that arbitrageurs are able to partially correct the mispricing in these stocks. Column (3) shows that the relaxation of short-sale constraints increases the pre-announcement term premium by 24 basis points overall. Comparing column (2) and column (5) shows that higher horizon bias leads to more severe overpricing in long-duration stocks. Taken together, the difference-in-differences results provide support for the mispricing explanation of the announcement term premium.

6.4. Do value or profitability explain the announcement term premium?

Value and profitability are two of the most important cross-sectional equity factors (Fama and French 1993; Novy-Marx 2013). Control for value, long-duration stocks tend to be less profitable stocks; control for profitability, long-duration stocks tend to be growth stocks (Gonçalves 2021b). In this section, I examine whether value or profitability can explain the announcement term premium.

Each quarter, I sort firms with earnings announcements into five value or profitability quintiles based on their book-to-market ratio or gross profitability from the previous quarter. Within each quintile, I then sort stocks into five duration groups by equity duration. I then collapse across value or profitability quintiles to form five value- or profitability-adjusted duration portfolios and compute their market-adjusted returns in the $[-5, +5]$ window around earnings announcements. Panel A of Table 8 shows that the term premium pattern across duration quintiles remains largely unchanged after controlling for value or profitability, indicating that these factors do not explain the announcement term premium.

[Table 8]

By contrast, Panel B of Table 8 shows results for duration-adjusted value and profitability portfolios, constructed using the same procedure. The announcement returns for value and profitability factors are not significantly different from zero, suggesting that duration captures much of the return predictability of these factors during earnings announcement periods. As a placebo test, I also construct duration-adjusted momentum portfolios. The announcement returns for momentum are unaffected by controlling for duration, reinforcing that value and profitability are unique in their connection to cash-flow duration—a finding consistent with Gormsen and Lazarus (2023).

[Figure 7]

Panel B of Table 8 shows results for duration-adjusted value and profitability portfolios, constructed using the same procedure. The announcement returns for value and profitability factors are not significantly different from zero, indicating that duration captures much of the return predictability of these factors during earnings announcement periods. As a placebo test, I construct duration-adjusted momentum portfolios. The announcement returns for momentum remain unaffected by controlling for duration, confirming that value and profitability are unique in their connection to cash-flow duration—a finding consistent with Gormsen and Lazarus (2023).

Figure 7 plots announcement returns for 119 equity anomalies that are robust out of sample in Jensen et al. (2023). Value and profitability anomalies exhibit announcement returns substantially larger than other anomalies. These duration-related anomalies realize a large fraction of their total returns during earnings announcement periods, suggesting that the mechanism behind the announcement term premium may also explain these anomaly returns. Appendix D.1 shows that the short legs of duration-related anomalies experience substantial return reversals on the announcement day and contribute most to their announcement returns. Retail investors are net buyers of short-leg stocks before earnings announcements. This pattern provides external validation for biased beliefs about cash flows across horizons.

6.5. Robustness check

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 behavioral factors such as lottery preference (Liu et al. 2020) and positive feedback trading (Aboody et al. 2010). I perform robustness checks on these channels and show that none of them explains the announcement term premium.

Systematic risk I discussed systematic risk in Section 5.5. Savor and Wilson (2016) propose that earnings reports provide valuable information about the prospects of not only the announcing firm but also its peers and the broader economy. This spillover from the cash flow news of an individual announcer to the wider market creates covariance between firm- and market-level cash flow news, generating a high risk premium for the announcing firm. I decompose earnings news into risk and mispricing components and find that the risk component decreases in stock duration, while the mispricing component increases in duration. The long-duration quintile contributes around half of the overall announcement term premium, and the mispricing component is needed to rationalize the pre-announcement drift and return reversal for long-duration stocks.

Idiosyncratic risk Yang et al. (2020) argue that idiosyncratic risk reflects information asymmetry for uninformed investors and is positively associated with informed return run-ups before earnings announcements. Section 6.2 confirms this pattern. Both short- and long-duration stocks exhibit higher idiosyncratic risk, measured by pre-announcement idiosyncratic volatility, and experience stronger pre-announcement drifts. However, idiosyncratic risk cannot explain announcement returns. Short-duration stocks have higher announcement returns, while long-duration stocks have lower announcement returns. This asymmetric pattern indicates that idiosyncratic risk proxies for limits to arbitrage rather than a direct risk factor.

Lottery demand Liu et al. (2020) show that the long-short return spread on lottery stocks reverses sign before and after earnings announcements. Two findings stand out. First, while Liu et al. (2020) use raw returns, switching to CAPM alpha reveals that much of the return spread reflects market risk exposure, as the spread between lottery and non-lottery stocks shrinks considerably. Second, the return spread from buying non-lottery stocks and selling lottery stocks is close to zero in the announcement window, as shown in the low-risk category of Figure 7.

To further examine lottery preference, I double sort stocks by equity duration and lottery measure. I use pre-earnings-announcement idiosyncratic volatility (PEA IVOL) as the lottery measure, because high volatility creates the misconception of a high probability of realizing high returns (Liu et al. 2020). Each quarter, I first sort firms announcing earnings into five lottery quintiles using their PEA IVOL from the month before the announcement. Within each lottery quintile, I then sort stocks into five groups by equity duration from the previous quarter. I collapse across lottery groups to obtain five lottery-adjusted duration portfolios. Table A2 reports average pre- and post-announcement returns for these 25 portfolios and the five lottery-adjusted duration portfolios. The pre-announcement term structure remains V-shaped and the post-announcement term structure remains strictly downward-sloping after controlling for lottery preference. Lottery preference does not drive the announcement term premium.

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. I conduct several robustness checks to show that the announcement term premium is not driven by momentum or attention.

Table A3 reports the results. Columns (1) and (5) show baseline pre- and post-announcement returns across duration quintiles. Columns (2) and (6) show returns from a conditional double sort: each quarter, I sort firms with earnings announcements into five momentum quintiles based on past 12-month returns; within each momentum quintile, I then split stocks into five groups by equity duration from the previous quarter. I collapse across momentum groups to form five momentum-adjusted duration portfolios. Columns (3) and (7) exclude momentum winners (top quintile of past 12-month returns) before sorting by duration. Columns (4) and (8) exclude 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 attention.

7. Extension: Institutional duration tilts

This section investigates how institutional investors' duration preferences contribute to the time-varying term premium. Active institutional investors, such as hedge funds and active mutual funds, hold long-duration stocks, and their duration tilts vary substantially over time. I use a counterfactual exercise to show that institutional duration tilts help explain the time-series variation in the equity term premium between high and low horizon bias periods.

Recent studies document that the equity term structure is unconditionally downward-sloping and time-varying (van Binsbergen et al. 2012; Gormsen 2021; Gonçalves 2021a), but they remain silent on which investors are responsible for this pattern. For example, pension funds are often viewed as natural long-term investors. However, while their balance sheets may be net long-term overall, they invest in very high duration bonds while maintaining short-term equity exposure. Equity duration is a composite stock characteristic that correlates with other firm characteristics, such as book-to-market ratio, investment, profitability, and market beta (Gormsen and Lazarus 2023). To isolate duration effects, I follow the demand system asset pricing literature and estimate institutional investors' duration tilts (Koijen and Yogo 2019; Koijen et al. 2024).

7.1. Demand estimation

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 j and quarter t, I estimate the following equation using nonlinear generalized method of moments:

$$\frac{w_{j,t}(i)}{w_{j,t}(0)} = \delta_{j,t}(i) = \exp\left\{\alpha_{j,t} + \beta_{0,j,t}\mathrm{mb}_t(i) + \boldsymbol{\beta}'_{1,j,t}\mathbf{x}_t(i) + \gamma_{j,t}\mathrm{Dur}_t(i)\right\}\epsilon_{j,t}(i), \tag{20}$$

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

$$z_{j,t}(i) = \log\left(\sum_{j\notin\{j,1\}} A_{j,t}\frac{\mathbf{1}_j(i)}{1+\left|\mathcal{N}_{j,t}\right|}\right). \tag{21}$$

I estimate the demand Equation (20) based on the instrument $z_{j,t}(i)$ and all non-price characteristics using a two-step instrumental variables ridge estimation (Koijen 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.

Estimated demand coefficients Figure A3 summarizes the cross-sectional distribution of demand coefficients. Figure 8 plots the binned scatter of demand coefficients on equity duration against demand coefficients on log market-to-book ratio for all investors. The two coefficients are negatively correlated. Investors with larger coefficients on log market-to-book are less price-elastic. More price-elastic investors hold long-duration stocks.

[Figure 8]

Figure 9 plots the time series of demand coefficients on equity duration across investor active share quintiles. Active institutional investors display strong time variation in duration demand, reaching for duration during expansions. In contrast, passive institutions maintain stable duration demand slightly below zero, indicating a preference for short-duration stocks throughout the sample period.

[Figure 9]

7.2. Counterfactual analysis

For institutional investors to influence the equity term premium between high and low horizon bias periods, their duration tilts must change meaningfully. Table A7 examines conditional duration tilts by price elasticity and active share quintiles. Active institutional investors show much higher duration tilts when the aggregate horizon bias is high. Institutional investors play a less active role in correcting overpricing in long-duration stocks during these periods, allowing mispricing to persist and leading to lower future returns.

Motivated by this shift, I use a counterfactual exercise to assess the impact of institutional investors' duration tilts on time variation in the equity term premium. I consider a counterfactual scenario in which capital flows from institutional investors with the largest changes in duration tilts between high and low horizon bias periods to the remaining investors. I solve for counterfactual equity prices by market clearing, assuming shares outstanding and firm characteristics remain fixed.

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

$$A_{j,t}^{C}\left(\mathbf{P}_t^{C}\right) = \underbrace{A_{j,t}\left(w_{j,t}(0) + \sum_{i \in \mathcal{N}_{j,t}} \frac{P_t^{C}(i)}{P_t(i)} w_{j,t}(i)\right)}_{\text{Capital gain}} + F_{j,t}, \tag{22}$$

where the investor's initial portfolio is revalued at the counterfactual market equity vector $\mathbf{P}_t^{C}$. The counterfactual equity prices satisfy the market clearing condition:

$$P_t^{C}(i) = \sum_{j=1}^{J} A_{j,t}^{C}\left(\mathbf{P}_t^{C}\right) w_{j,t}^{C}\left(i; \mathbf{P}_t^{C}\right). \tag{23}$$

I solve for counterfactual equity prices using the algorithm in Koijen and Yogo (2019) Appendix C.

Repricing measure To measure how capital flows from one type of investor affect asset prices, I compute the price impact on a portfolio ω:

$$\mathrm{PI}_t(\omega) = \frac{P_t^{C}(\omega) - P_t(\omega)}{P_t(\omega)} = \frac{\sum_{i\in\omega} P_t^{C}(i) - \sum_{i\in\omega} P_t(i)}{\sum_{i\in\omega} P_t(i)}, \tag{24}$$

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

Following Barroso et al. (2025), I transform price impact into a repricing measure that can be computed directly from the abnormal return of a portfolio. I apply the Campbell and Shiller (1988) decomposition to an arbitrary portfolio ω with log return $r_{\omega,t}$:

$$r_{\omega,t} \approx \kappa_0 + \kappa_1 pd_{\omega,t} - pd_{\omega,t-1} + g_{\omega,t}, \tag{25}$$

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:

$$pd_{\omega,t} = \frac{\kappa_0}{1-\kappa_1} + \mathbf{E}_t\left[\sum_{h=0}^{\infty} \kappa_1^{h}\left(g_{\omega,t+1+h} - r_{\omega,t+1+h}\right)\right]. \tag{26}$$

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

$$r_{\omega,t} = \alpha_{\omega,t-1} + \boldsymbol{\beta}_{\omega,t-1}' \mathbf{f}_t + \varepsilon_{\omega,t}, \tag{27}$$

and the abnormal return decays according to an autoregressive process:

$$\alpha_{\omega,t} = \phi_\omega \alpha_{\omega,t-1} + \nu_{\omega,t}, \tag{28}$$

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

$$\mathrm{PI}_t(\omega) = \exp\left(\frac{\alpha_{\omega,t} - \alpha^C_{\omega,t}}{1 - \phi_\omega \kappa_1}\right) - 1. \tag{29}$$

If an asset is overpriced in the real world ($\alpha_{\omega,t} < 0$) but fairly priced in the counterfactual market ($\alpha^C_{\omega,t} = 0$), the price impact is negative: $\mathrm{PI}_t(\omega) < 0$.

[Table 9]

Counterfactual price effect The short-duration portfolio earns an FF3 alpha of 31 bps in the high-horizon-bias period and 9 bps in the low-horizon-bias period. The long-duration portfolio earns an alpha of −16 bps and −7 bps in these states, respectively. What price impact would be required to eliminate the 31 bps spread in alpha between the high- and low-horizon bias states? Let S and L denote the short- and long-duration portfolios, respectively. Let hi and lo denote the high- and low-horizon bias periods. I estimate the AR(1) coefficient ϕ_ω to be 0.8. The price impact required to render $\alpha^C = 0$ is:

$$\begin{aligned}
\Delta\mathrm{PI}(S-L) &= \mathrm{PI}_{hi}(S-L) - \mathrm{PI}_{lo}(S-L) \\
&= \exp\left(\frac{\alpha_{S,hi}}{1-\phi_\omega\kappa_1}\right) - \exp\left(\frac{\alpha_{L,hi}}{1-\phi_\omega\kappa_1}\right) - \left[\exp\left(\frac{\alpha_{S,lo}}{1-\phi_\omega\kappa_1}\right) - \exp\left(\frac{\alpha_{L,lo}}{1-\phi_\omega\kappa_1}\right)\right] \\
&= 4.65\%.
\end{aligned} \tag{30}$$

To conduct the counterfactual exercise, I compute the average demand coefficient on equity duration for each institution j across high- and low-horizon-bias periods, $\overline{\gamma}_{j,hi}$ and $\overline{\gamma}_{j,lo}$. I rank all institutions based on the difference $\overline{\gamma}_{j,hi} - \overline{\gamma}_{j,lo}$ and remove the institutions with the largest positive changes whose cumulative AUM represents 10% of total investor assets. I reallocate their AUM to all remaining investors on a pro rata basis. This procedure identifies the institutional investors that most actively increase duration tilts during high-horizon-bias periods.

Table 9 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. Institutional investors whose duration tilts increase the most during high-horizon-bias periods have a substantial effect on prices. Demand from just 10% of aggregate assets under management can account for nearly all of the spread in term premia across horizon bias states.

7.3. Are institutional investors horizon-biased?

Previous results show that institutional investors tilt toward long-duration stocks when market horizon bias is high. Institutional investors are typically conceptualized as "smart money". Why do smart investors hold long-duration stocks that earn lower returns on average? Two explanations are possible: institutional investors may be horizon biased themselves, or they may attempt to time the market.

To answer this question, I first measure stock-level institutional duration demand, $\Gamma_{i,t}$, as the value-weighted average demand coefficient on equity duration across all institutional investors:

$$\Gamma_{i,t} = \sum_{j \in J} \frac{A_{j,t} w_{i,j,t}}{\mathrm{ME}_{i,t}} \gamma_{j,t}, \tag{31}$$

where $A_{j,t}$ is the AUM of investor j in quarter t, $w_{i,j,t}$ is the portfolio weight of stock i for investor j in quarter t, $\mathrm{ME}_{i,t}$ is the market equity of stock i in quarter t, and $\gamma_{j,t}$ is the demand coefficient on equity duration for investor j in quarter t.

To examine whether institutional duration demand predicts future returns, I run Fama-MacBeth regressions of monthly excess returns on duration demand Γ and firm characteristics. I estimate cross-sectional regressions of excess returns on lagged characteristics each month and 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—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 10]

Table 10 shows that expected monthly returns increase by 0.126 percent per one standard deviation increase in duration demand Γ, with a t-statistic of 3. Importantly, I also control for duration in the specification, but the coefficient on duration is not statistically significant. 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). However, this is only suggestive evidence. Without higher-frequency data on institutional trades, I cannot distinguish between horizon bias and market timing. For example, if institutional investors split large orders into smaller trades and execute them over time, their duration tilts could also predict future returns.

8. Conclusion

This paper shows that horizon bias in earnings growth forecasts explains a large share of the equity term premium realized around earnings announcements. I first document that around 50% of the equity term premium is realized in the announcement window $[-5, +5]$. The announcement term premium concentrates in firms with high horizon bias. Moving from the bottom to top horizon bias quintile, the daily average premium increases from 2 bps to 15 bps.

I examine investor behavior to uncover the underlying mechanism. Retail investors disproportionately buy long-duration stocks with high horizon bias before earnings announcements. The cumulative retail net buy is 14 times higher for long-duration stocks than for short-duration stocks in the pre-announcement window. High horizon bias creates a false impression that long-duration stocks have higher probability of reaching the performance hurdle, leading to greater speculative appeal. Using the pilot program of Regulation SHO as a natural experiment, I find that removing short-sale constraints reduces pre-announcement returns for long-duration stocks by 21 bps. These findings demonstrate that horizon bias, together with limits to arbitrage, explains why retail price pressure builds up mispricing before earnings announcements.

Finally, I document that aggregate horizon bias varies over time and helps explain the time-variation in the equity term premium. The announcement term premium is high (6.4%) following above-median horizon bias periods and low (2.9%) following below-median horizon bias periods. Active institutional investors, such as hedge funds and active mutual funds, shift their demand from long- to short-duration stocks as aggregate horizon bias subsides. The resulting price impact is sufficient to explain the spread in term premia across horizon bias states.

Overall, this paper shows that biased beliefs about future cash flows drive the equity term premium around earnings announcements. Horizon bias generates strong speculative demand for long-duration stocks before earnings announcements, and limits to arbitrage allow this mispricing to persist. The interaction between retail and institutional investors significantly affects the time-variation in the equity term premium.

Table 1

Equity term premium around earnings announcements

This table reports the daily term premium realized in a fiscal quarter for different event window sizes, along with the corresponding annualized returns and each window's contribution to the overall term premium. Each quarter, I sort firms announcing earnings into five quintiles based on equity duration. Because firms report earnings on different dates, I align event windows by announcement day across firms. I then compute equal-weighted average returns for each duration quintile on each event day, rather than by calendar date. 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 premium by the number of event days in a year. The sample period is 1980 to 2023.

Window	# Days p.a.	Daily premium	*t*-stat	Premium p.a.	Proportion
$[-30,+30]$	252	4.47 bps	5.85	11.26%	100.00%
$[0,0]$	4	55.04 bps	8.01	2.20%	19.55%
$[-1,+1]$	12	25.36 bps	8.26	3.04%	27.03%
$[-3,+3]$	28	14.49 bps	8.04	4.06%	36.03%
$[-5,+5]$	44	10.71 bps	7.17	4.71%	41.85%

Table 2
Duration portfolio returns in the announcement window

This table reports the daily returns for each duration quintile portfolio in the $[-3, +3]$ window. Panel (a) reports daily abnormal returns, calculated as returns minus the market return. Panel (b) reports daily CAPM alphas. I estimate CAPM betas using a rolling window of 252 trading days, ending 21 trading days before the announcement, and apply the slope-winsorized method from Welch (2021) for more robust beta estimates.

Day	−3	−2	−1	0	1	2	3
			Panel A: Abnormal return				
Short Dur	14.55	19.77	23.82	25.67	6.52	10.45	9.32
Q2	8.39	10.57	15.92	22.39	3.93	−2.12	6.90
Q3	8.11	9.27	12.44	10.22	6.37	1.67	4.13
Q4	8.31	8.95	11.21	4.62	3.32	3.88	2.14
Long Dur	8.72	17.82	19.73	−28.40	−11.20	2.37	−1.52
Q1 – Q5	5.83	1.96	4.09	54.07	17.71	8.09	10.84
	(1.54)	(0.57)	(1.18)	(7.86)	(4.63)	(2.37)	(3.11)
Q3 – Q5	−0.61	−8.54	−7.29	38.62	17.56	−0.69	5.65
	(−0.17)	(−2.69)	(−2.42)	(7.37)	(4.64)	(−0.21)	(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	5.56	5.51	39.77	16.36	9.51	11.87
	(3.12)	(2.25)	(2.06)	(8.37)	(5.63)	(3.81)	(4.23)
Q3 – Q5	4.42	−2.16	−3.76	36.90	18.55	4.87	8.22
	(1.67)	(−0.99)	(−1.52)	(9.19)	(6.38)	(1.88)	(3.29)

Table 3
Horizon bias and announcement returns

This table reports portfolio returns from a double sort on equity 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 horizon bias. For each portfolio, I compute the equal-weighted average abnormal return in the $[-5, +5]$ announcement window, where abnormal returns are defined as daily returns minus the market return. The equity term premium (ETP) is the difference in average returns between the short- and long-duration portfolios. The t-statistics, based on the heteroskedasticity consistent standard errors, are reported in parentheses. I report t-statistics only for return differences between the top and bottom groups.

	Low HB (1)	Q2 (2)	Q3 (3)	Q4 (4)	High HB (5)	H – L (6)	*t*-stat (7)
Short Dur	3.71	4.70	4.98	7.29	10.44	6.73	(2.48)
Q2	2.39	4.98	5.28	5.45	7.21	4.81	(2.58)
Q3	1.15	3.03	4.40	4.14	5.00	3.84	(2.12)
Q4	0.01	3.18	2.33	1.49	1.45	1.44	(0.69)
Long Dur	1.67	1.46	1.16	−0.19	−4.90	−6.57	(−2.10)
ETP	2.05	3.24	3.82	7.48	15.35	13.30	
t-stat	(0.63)	(1.11)	(1.59)	(2.50)	(4.87)	(3.22)	

Table 4
Price effect

This table reports regressions of announcement returns on forecast disparity. *CAR* is the cumulative market-adjusted abnormal return around earnings news, calculated over either the pre-announcement window $[-3, -1]$ or the post-announcement window $[0, +2]$. *Dur* and *HB* are the equity duration and horizon bias at the end of the previous quarter, respectively. *SUE* is the standardized unexpected earnings in the focal quarter. I control for nominal share price, firm age, momentum return, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. All explanatory variables are cross-sectionally standardized. t-statistics, based on two-way clustered standard errors by firm and quarter, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR $[-3, -1]$		CAR $[0, +2]$		
	(1)	(2)	(3)	(4)	(5)
Dur	-0.028^{**}	-0.025^{**}	-0.068^{***}	-0.081^{***}	-0.059^{**}
	(-2.480)	(-2.130)	(-3.178)	(-3.038)	(-2.002)
HB		0.147^{**}		-0.316^{***}	-0.339^{***}
		(2.364)		(-2.835)	(-3.018)
Dur × HB		0.059^{*}		-0.222^{**}	
		(1.899)		(-2.497)	
SUE					2.191^{***}
					(20.562)
SUE × Dur					-0.289^{***}
					(-5.912)
SUE × Dur × HB					-0.561^{***}
					(-5.806)
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
Equity term premium conditional on aggregate horizon bias

This table reports the annualized equity term premium conditional on aggregate horizon bias. Aggregate horizon bias is defined as the difference between the time-series Z-scores of aggregate long-term and short-term earnings growth forecasts. High and low horizon bias periods are defined as months when the beginning-of-period market-level horizon bias is above or below its median, respectively. Panel A reports the announcement term premium (ETP) in the $[-5, +5]$ window, annualized by multiplying by 4. Panel B presents the conditional term premium using full-month returns. Each month, I sort stocks into five quintiles by equity duration, and compute value-weighted average returns for each portfolio. *Avg* denotes unconditional average returns, while *High HB* and *Low HB* represent average returns during high- and low-horizon bias months, respectively. The t-statistics, computed using heteroskedasticity-consistent standard errors, are reported in parentheses.

	Short Dur	Q2	Q3	Q4	Long Dur	S – L
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Announcement window $[-5, +5]$			
Avg	0.058	0.045	0.033	0.020	0.012	0.046
	(7.994)	(6.950)	(5.185)	(2.823)	(1.336)	(6.584)
High HB	0.069	0.052	0.038	0.020	0.005	0.064
	(6.878)	(6.030)	(4.268)	(2.097)	(0.441)	(6.809)
Low HB	0.048	0.039	0.029	0.020	0.019	0.029
	(4.548)	(3.979)	(3.106)	(1.917)	(1.342)	(2.819)
			Panel B: Full month return			
Avg	0.165	0.158	0.151	0.124	0.098	0.067
	(6.372)	(6.628)	(6.709)	(5.239)	(3.208)	(3.135)
High HB	0.164	0.148	0.132	0.083	0.054	0.111
	(4.882)	(4.639)	(4.247)	(2.459)	(1.198)	(3.405)
Low HB	0.166	0.168	0.169	0.165	0.142	0.024
	(4.204)	(4.737)	(5.220)	(4.991)	(3.438)	(0.856)

Table 6
Retail net trading around earnings announcements

This table reports regressions of retail net buy on firm-level characteristics. RNB is the cumulative retail net buy volume in the $[-5,-1]$ window before the earnings announcement. Retail net buy is defined as the difference between retail buy and sell volume, normalized by total shares outstanding. Dur is equity duration, and HB is horizon bias, both measured at the end of the previous quarter. I control for nominal share price, firm age, momentum return, prior month maximum return, market capitalization, book-to-market ratio, and idiosyncratic volatility. Both firm and quarter fixed effects are included. All variables are cross-sectionally standardized. 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 retail net buy $[-5,-1]$			
	(1)	(2)	(3)	(4)
Dur	0.030***	0.029***	0.037**	0.033**
	(3.241)	(3.081)	(2.337)	(2.114)
HB			0.142***	0.136***
			(6.184)	(6.094)
Dur × HB			0.046***	0.051***
			(2.683)	(2.791)
Controls		✓		✓
Fixed effects	Firm/Date	Firm/Date	Firm/Date	Firm/Date
Cluster	Firm/Date	Firm/Date	Firm/Date	Firm/Date
R^2	0.092	0.094	0.096	0.098
Observations	104,982	104,810	63,714	63,655

Table 7
Limits to arbitrage and announcement term premium

This table reports difference-in-differences regressions of pre-announcement portfolio returns. The dependent variable is the return in the $[-5, -1]$ window before earnings announcements for each portfolio in a given month. *Pilot* is a dummy variable that takes the value of 1 if the portfolio is formed from pilot stocks and 0 otherwise. *During* is a dummy variable that takes the value of 1 if the month falls within the pilot period (July 2005 to June 2007) and 0 otherwise. The regression is estimated separately for the short-duration quintile (columns 1 and 4), long-duration quintile (columns 2 and 5), and long-short portfolios (columns 3 and 6). Within each duration quintile, stocks are further split by the median horizon bias. Columns (1)–(3) show results for stocks with high horizon bias, while columns (4)–(6) show results for stocks with low horizon bias. The t-statistics, based on heteroskedasticity-consistent standard errors, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	High horizon bias			Low horizon bias		
	Short Dur	Long Dur	ETP	Short Dur	Long Dur	ETP
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot × During	0.034	−0.207***	0.242***	0.012	−0.142**	0.155**
	(0.735)	(−2.645)	(3.176)	(0.354)	(−2.134)	(2.286)
Pilot	−0.006	0.014	−0.020	0.005	0.008	−0.004
	(−0.335)	(0.719)	(−0.761)	(0.337)	(0.569)	(−0.188)
Fixed effects	Month	Month	Month	Month	Month	Month
R^2	0.590	0.625	0.538	0.647	0.681	0.558
Observations	988	988	988	988	988	988

Table 8
Announcement return on equity factors

This table reports announcement returns from conditional double sorts on equity duration and firm characteristics. Panel A shows announcement returns in the $[-5, +5]$ window for value- and profitability-adjusted duration portfolios. Each quarter, I sort firms with earnings announcements into five value or profitability quintiles based on book-to-market ratio or gross profitability from the previous quarter. Within each quintile, I then sort stocks into five duration groups by equity duration. I collapse across value or profitability quintiles to form five value- or profitability-adjusted duration portfolios and compute market-adjusted returns in the $[-5, +5]$ window around earnings announcements. Panel B shows announcement returns for duration-adjusted value, profitability, and momentum portfolios. The t-statistics, based on heteroskedasticity-consistent standard errors, are reported in parentheses.

	Short leg	Q2	Q3	Q4	Long leg	Premium	t-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Announcement term premium							
Book-to-market	−3.30	0.77	2.27	5.45	6.82	10.11	(8.16)
Gross profit	−4.68	−1.12	0.96	0.77	3.26	7.94	(6.47)
Panel B: Announcement return on equity factors							
Value	1.87	1.90	2.61	2.88	3.20	1.33	(0.79)
Profitability	1.85	1.99	2.77	3.49	3.70	1.85	(1.88)
Momentum	−1.21	2.11	3.29	3.74	4.03	5.25	(2.58)

Table 9
Counterfactual repricing statistics

This table reports the time-series means of repricing statistics from the counterfactual experiment. For each institution, I compute its average demand coefficient on equity duration across high- and low-horizon bias periods. I rank all institutions based on the difference and remove the institutions with the largest positive changes whose cumulative AUM represents 10% of total investor assets. I reallocate their AUM to all remaining investors on a pro rata basis. I compute the price impact statistics of the short- and long-duration portfolios from this counterfactual experiment. Each panel reports the time-series means of these metrics over the full sample (*Avg*), quarters with above-median bias (*High HB*), and quarters with below-median bias (*Low HB*). The t-statistics, based on heteroskedasticity-consistent standard errors, are reported in parentheses.

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

Table 10
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. *Gamma* is the value-weighted average institutional demand coefficient on equity duration at the stock level.

Characteristic	Coefficient
Gamma	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)

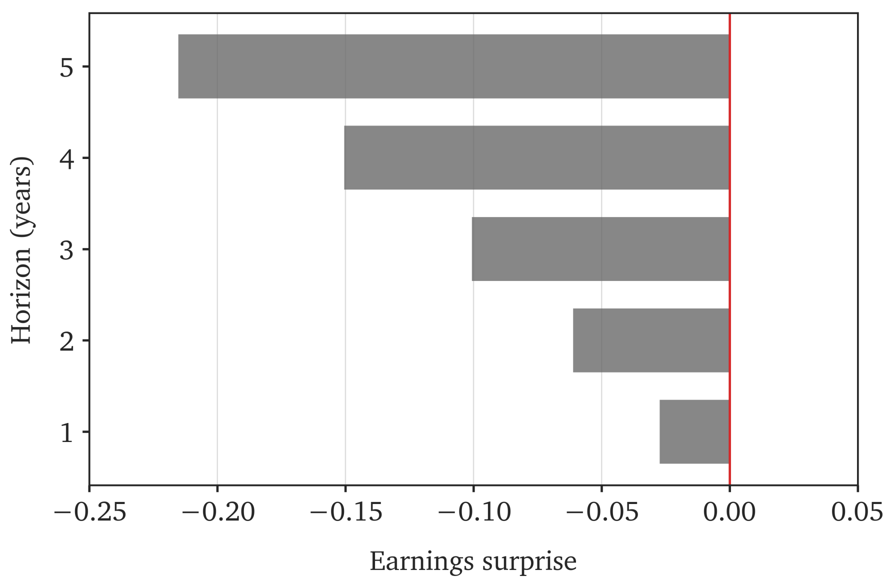

Figure 1. Term structure of forecast bias. This figure plots standardized unexpected earnings (SUE) across forecasting horizons from 1 to 5 years. SUE is calculated as the difference between actual earnings and the median analyst forecast, scaled by the last closing price before the earnings announcement.

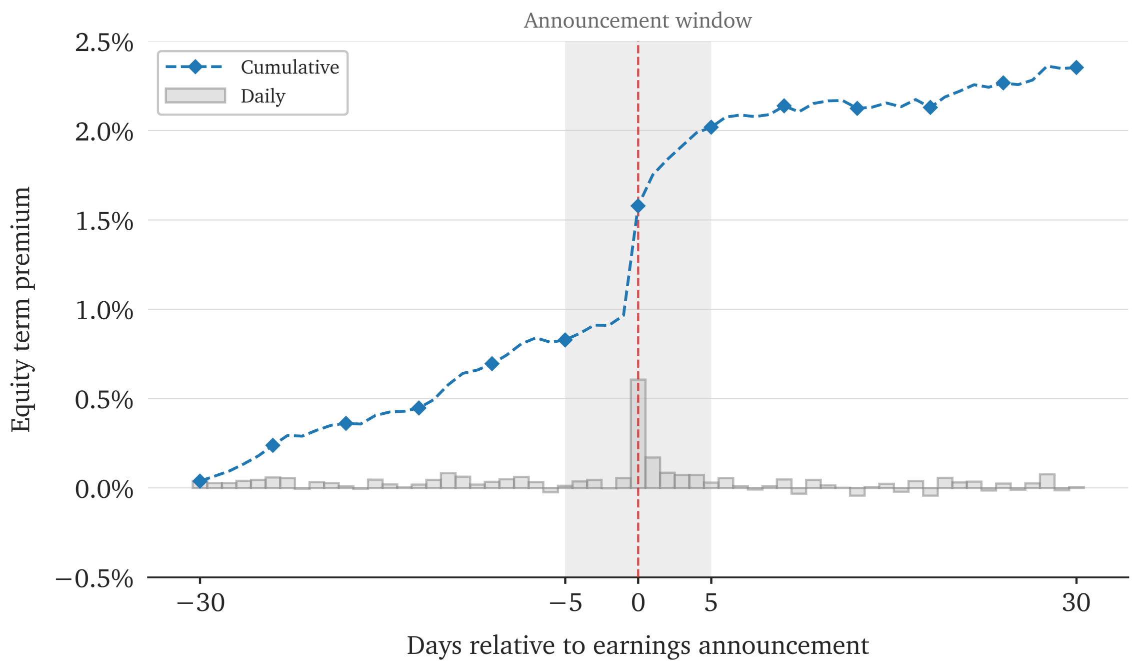

Figure 2. Announcement equity term premium. This figure shows the cumulative equity term premium within a fiscal quarter (blue dashed line) and the daily premium (gray bars). Each quarter, I sort firms announcing earnings into five quintile portfolios based on equity duration from the previous quarter. The daily premium is the equal-weighted average return difference between the short-duration and long-duration quintile portfolios on each event day. The announcement window covers the five business days before and after the earnings announcement, i.e., $[-5, +5]$.

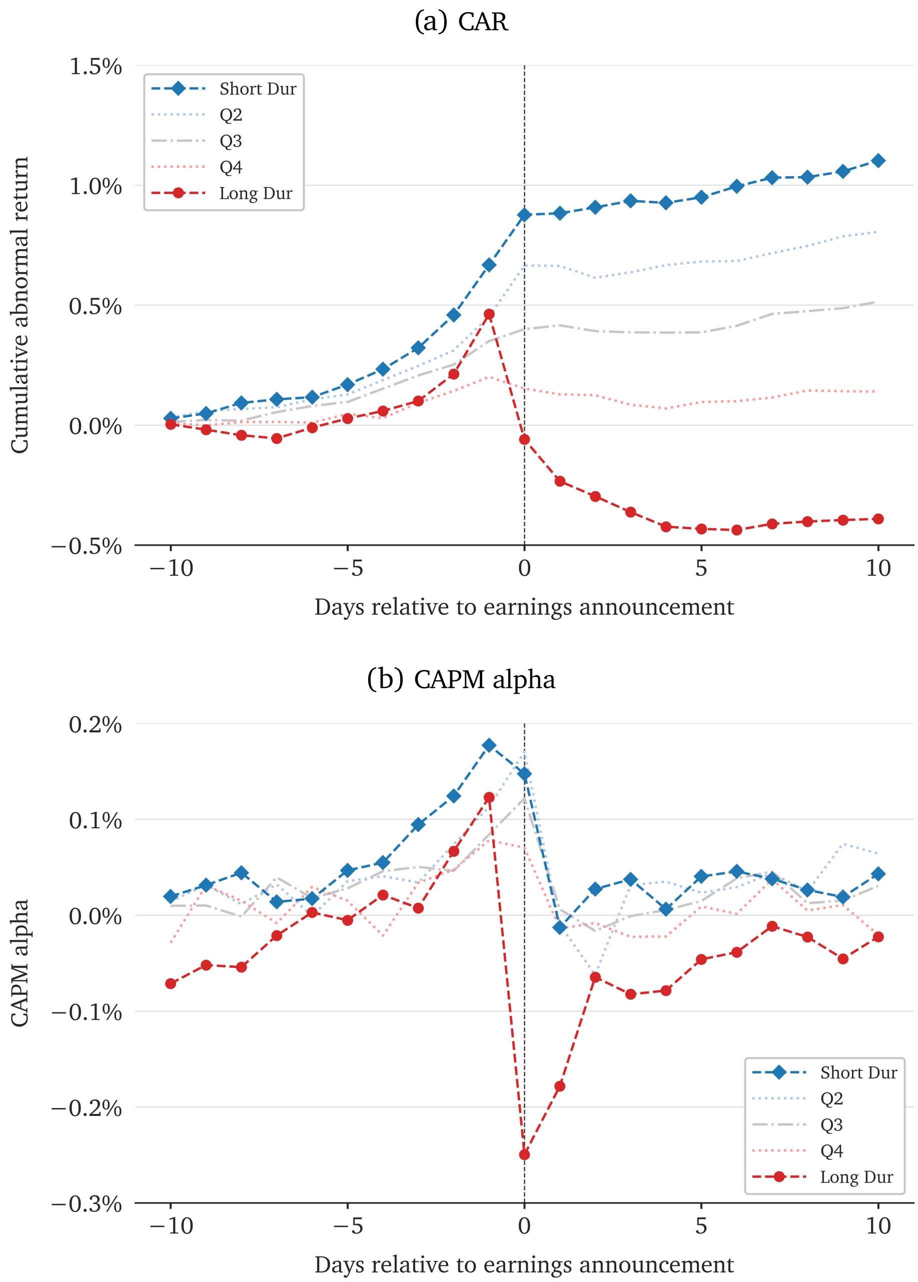

Figure 3. Returns in the earnings announcement window. This figure shows return dynamics for each duration quintile in the $[-10, +10]$ window around earnings announcements. Panel (a) plots cumulative abnormal returns, calculated as daily returns minus the market return. Panel (b) reports daily CAPM alphas. I estimate CAPM betas using a rolling window of 252 trading days, ending 21 trading days before the announcement, and apply the slope-winsorized method from Welch (2021) for more robust beta estimates.

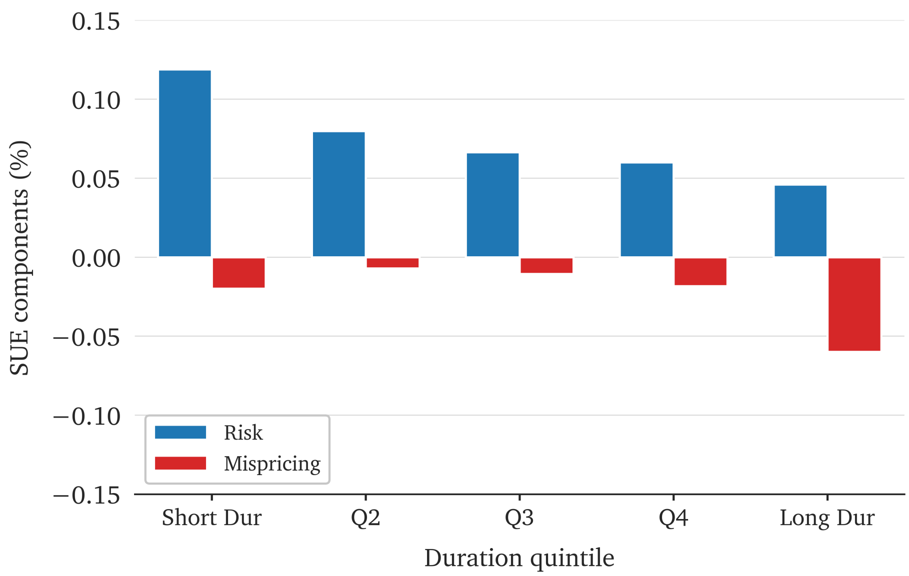

Figure 4. Earnings news decomposition. This figure decomposes standardized unexpected earnings (SUE) into risk and mispricing components across duration quintiles. Following Glosten et al. (2021), I estimate a regression of firm-level quarterly SUE on market-wide value-weighted average SUE and SIC-2 value-weighted average SUE in 15-year rolling windows. The fitted value from this regression represents the risk component, while the residual is the mispricing component.

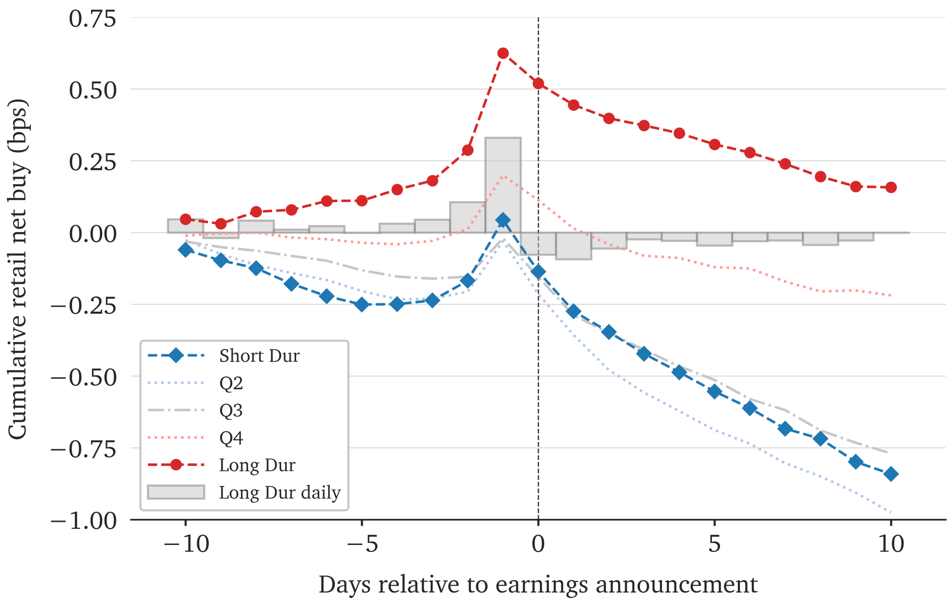

Figure 5. Retail trading behavior around earnings announcements. This figure plots the cumulative retail net buy by duration quintile in the $[-10, +10]$ event window around earnings announcements. Retail net buy is defined as the difference between retail buy and sell volume, normalized by total shares outstanding. The gray bars represent the daily retail net buy for the long-duration quintile.

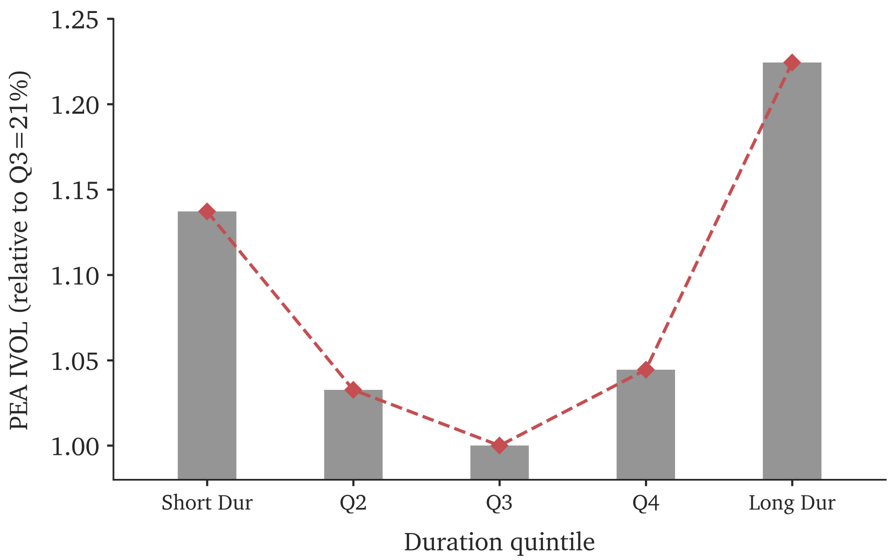

Figure 6. The IVOL smile. This figure shows the idiosyncratic volatility (IVOL) across duration quintiles in the pre-earnings-announcement (PEA) period. For each stock and month, I estimate the FF3 model using daily returns from the prior year to obtain daily residuals. The pre-earnings-announcement period is defined as the five business days before each of the most recent four earnings announcements, i.e., $[-5, -1]$. I then calculate annualized idiosyncratic volatility for each firm-month observation.

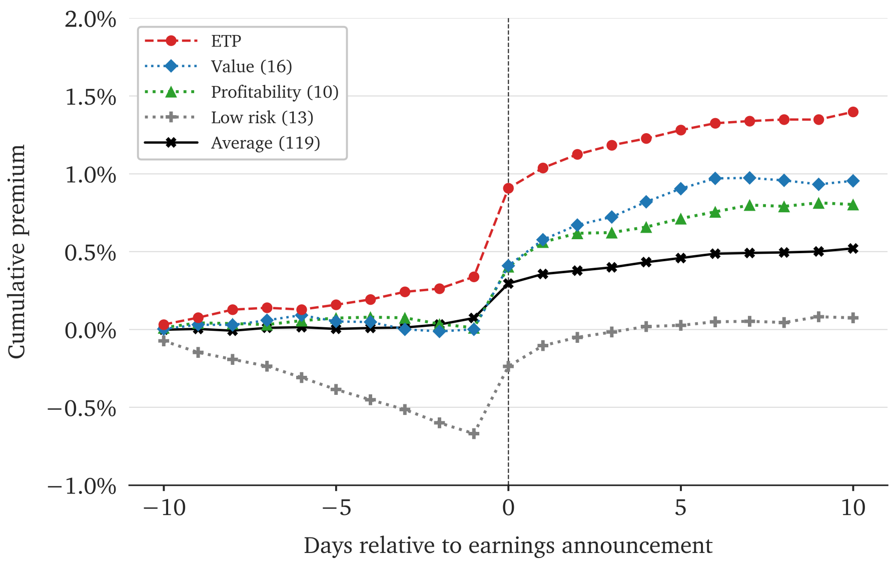

Figure 7. Announcement return on equity factors. This figure plots announcement returns by anomaly type in the $[-10, +10]$ window around earnings announcements. Anomaly characteristics are from Jensen et al. (2023). I form long-short portfolios based on these characteristics. Anomaly type level returns are the equal-weighted average return of the long-short portfolios within each anomaly type.

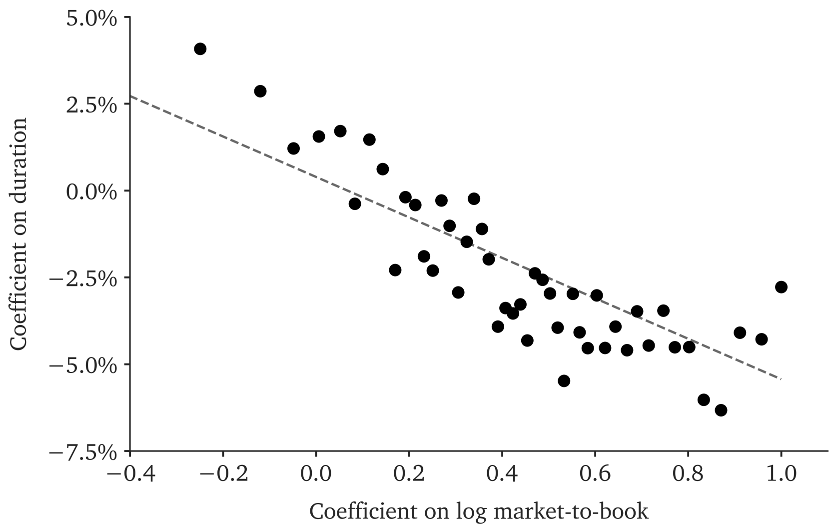

Figure 8. Binned scatterplot of demand coefficients. This figure plots the relationship between demand coefficients on duration and price inelasticity. Price inelasticity is the demand coefficient on log market-to-book equity.

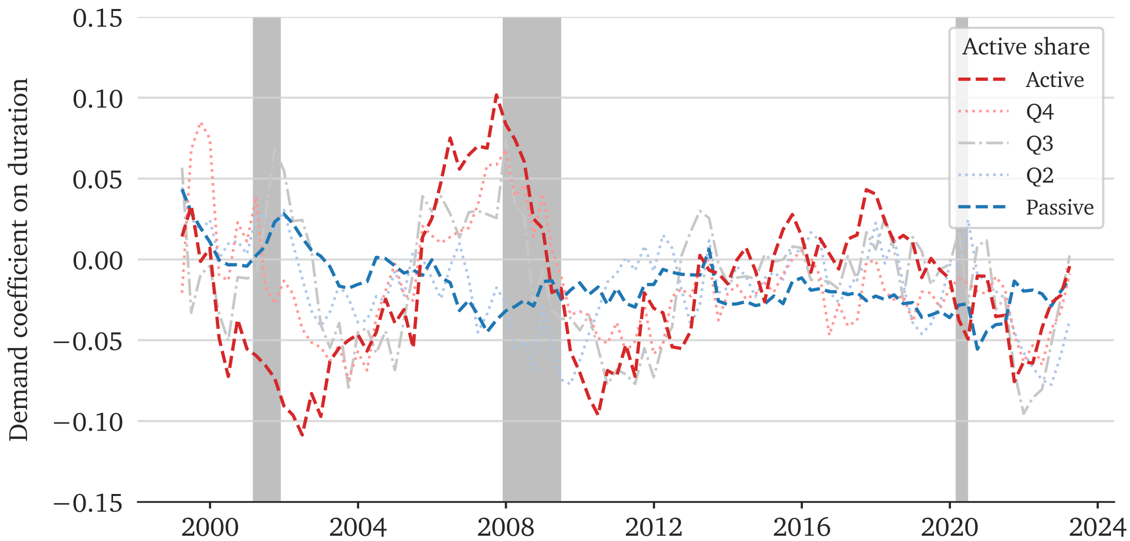

Figure 9. Institutional duration tilts. This figure plots the time series of the demand coefficient on equity duration across quintiles of investor active share. Active share is the deviation of an investor's portfolio weights from benchmark index weights. Within each quintile, I compute an AUM-weighted average of the demand coefficients across institutions. The shaded areas denote NBER recession periods.

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Appendix

A. Horizon bias and equity term premium

A.1. A present-value model

The price of an asset can be defined as

$$P = \frac{\mathbf{E}[\text{Future cash flows}]}{\text{Discount rate}}. \tag{A1}$$

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:

$$P_t^{ST} = \frac{D_t(1+x^s)}{1+r}, \tag{A2}$$

$$P_t^{LT} = \frac{D_t(1+x^s)}{1+r} + \frac{1}{1+r}\frac{D_t(1+x^s)(1+x^l)}{r-x^l}, \tag{A3}$$

where r is a constant required rate of return, D_t is the dividend observed at time t for the short- and long-term assets, respectively, x^s is investors' forecast of dividend growth rate in the next period, and x^l is investors' forecast of dividend growth in every period after that. Suppose that the actual dividend growth rate is constant at g.

Then, the next-period price of the short- and long-term assets and the next-period dividend are

$$P_{t+1}^{ST} = 0, \tag{A4}$$

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

$$D_{t+1} = D_t(1+g). \tag{A6}$$

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 $t+1$:

$$R_{t+1}^{ST} = \frac{D_{t+1}}{P_t^{ST}} = \frac{(1+g)(1+r)}{1+x^s}, \tag{A7}$$

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

$$= \frac{(1+g)(r-x^l)}{1+x^s} + (1+g)$$

$$= \frac{(1+g)(1+r)}{1+x^s} + \frac{(1+g)(x^s-x^l)}{1+x^s}. \tag{A8}$$

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

$$\text{ETP}_{t+1} = \mathbf{E}[R^{ST}_{t+1} - R^{LT}_{t+1}] = (x^l - x^s)\frac{1+g}{1+x^s}. \tag{A9}$$

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

$$x^l - x^s = \varepsilon^l - \varepsilon^s, \tag{A10}$$

where ε^l (ε^s) is the difference between investors' long-term (short-term) growth forecast and the actual growth rate.

A.2. Machine-learning-based horizon bias measure

I follow van Binsbergen et al. (2023) to construct rational forecasts of firm earnings growth rates using random forest models. I use the same set of predictors as in van Binsbergen et al. (2023), summarized into three categories: firm-specific variables, macroeconomic variables, and analysts' earnings forecasts.

1. Firm fundamentals
   - Realized earnings from the last period
   - Monthly stock prices and returns
   - Sixty-seven financial ratios from WRDS, such as the book-to-market ratio and dividend yields
2. Macroeconomic variables from FRED
   - Consumption growth
   - GDP growth
   - Industrial production growth
   - Unemployment rate
3. Analysts' forecasts
   - Analysts' consensus earnings growth forecasts from IBES unadjusted summary files

I choose the same hyperparameters as in van Binsbergen et al. (2023) for the random forest models: 2000 trees, maximum depth of 7, minimum node size of 5, and sample fraction of 1%. I train the random forest model using a rolling window of 12 months. The resulting model is used to predict the rational earnings growth forecasts for the next month. For short-term growth rate, the target variable is the current yearend earnings per share. For long-term growth rate, the target variable is the average annual growth rate of earnings per share over the next five years.

Let STG be the analysts' short-term growth forecast, LTG be the analysts' long-term growth forecast, and g^s and g^l be the machine-learning-based rational short-term and long-term growth forecasts, respectively. I define the machine-learning-based horizon bias measure as

$$\text{HB}^{ML} = \text{rank}(\text{LTG} - g^l) - \text{rank}(\text{STG} - g^s), \tag{A11}$$

where rank(·) denotes the within-industry percentile rank. A positive value of HB^{ML} indicates that the analyst long-term growth forecast is more optimistic relative to the machine-learning-based rational forecast than the short-term growth forecast.

A.3. Alternative firm-level horizon bias measure

Following Cassella et al. (2023), I compute the firm-level horizon bias measure. First, assume the short-term growth rate follows an AR(1) process

$$\text{STG}_{i,t+1} = \phi_0 + \phi_1 \text{STG}_{i,t} + \varepsilon_{i,t+1}. \tag{A12}$$

Then, compute the long-term growth rate implied by the short-term growth rate

$$\text{LTG}_{i,t}^{\text{Implied}} = \frac{1}{5}\left[4\phi_0 + 3\phi_0\phi_1 + 2\phi_0\phi_1^2 + \phi_0\phi_1^3 + \text{STG}_{i,t}(1 + \phi_1 + \phi_1^2 + \phi_1^3 + \phi_1^4)\right]. \tag{A13}$$

Define horizon bias as the difference between the long-term growth rate and the long-term growth rate implied by the short-term growth rate,

$$\text{HB}_{i,t} = \text{LTG}_{i,t} - \text{LTG}_{i,t}^{\text{Implied}}. \tag{A14}$$

B. 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 Koijen 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., $x(i)$ is the i-th element of the vector $\boldsymbol{x}$). 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 I financial assets indexed by $i = 1, \ldots, I$, and J investors indexed by $j = 1, \ldots, J$. The outside asset is denoted as the 0-th asset. Let $P_t(i)$ and $S_t(i)$ represent the price and shares outstanding of asset i 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 $k = 1, \ldots, K$, with the k-th characteristic of asset i at time t denoted as $x_{kt}(i)$, and the vector of characteristics as $\mathbf{x}_t(i)$.

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

$$\hat{\mathbf{x}}_{j,t}(i) = \begin{bmatrix} \mathrm{me}_t(i) \\ \mathbf{x}_t(i) \\ \log(\varepsilon_{j,t}(i)) \end{bmatrix},$$

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

$$\mathbf{y}_{j,t}(i) = \begin{bmatrix} \hat{\mathbf{x}}_{j,t}(i) \\ \mathrm{vec}\big(\hat{\mathbf{x}}_{j,t}(i)\hat{\mathbf{x}}_{j,t}(i)'\big) \\ \vdots \end{bmatrix},$$

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

I maintain the Assumption 1 of Koijen and Yogo (2019), so that the covariance of log excess returns is $\Sigma_{j,t} = \Gamma_{j,t}\Gamma'_{j,t} + \gamma_{j,t}\mathbf{I}$, where $\Gamma_{j,t}$ is a vector of factor loadings and $\gamma_{j,t}$ is idiosyncratic variance, and that expected returns $\boldsymbol{\mu}_{j,t}$ and factor loadings $\Gamma_{j,t}$ are polynomial functions of characteristics:

$$\mu_{j,t}(i) = \mathbf{y}_{j,t}(i)'\mathbf{\Phi}_{j,t} + \phi_{j,t}, \tag{B1}$$

$$\Gamma_{j,t}(i) = \mathbf{y}_{j,t}(i)'\mathbf{\Psi}_{j,t} + \psi_{j,t}, \tag{B2}$$

where $\mathbf{\Phi}_{j,t}$ and $\mathbf{\Psi}_{j,t}$ are vectors and $\phi_{j,t}$ and $\psi_{j,t}$ 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 $\mathbf{x}_t(i)$. Moreover, Appendix A of Koijen 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 i for investor j at date t is given by:

$$\frac{w_{j,t}(i)}{w_{j,t}(0)} \equiv \delta_{j,t}(i) = \exp\left\{\alpha_{j,t} + \beta_{0,j,t}\text{me}_t(i) + \boldsymbol{\beta}'_{1,j,t}\mathbf{x}_t(i)\right\}\epsilon_{j,t}(i), \tag{B3}$$

with equity duration entering as part of the characteristics $\mathbf{x}_t(i)$. Let $(K+1)$-dimensional vector $\hat{\boldsymbol{\beta}}'_{j,t} = \left[1, \boldsymbol{\beta}'_{j,t}\right]$ respresent the demand coefficients on stock characteristics. Appendix A of Koijen and Yogo (2019) further shows that:

$$\hat{\boldsymbol{\beta}}_{j,t} \propto \frac{1}{\gamma_{j,t}}\left(\mathbf{\Phi}_{j,t} - \kappa_{j,t}\mathbf{\Psi}_{j,t}\right), \tag{B4}$$

where $\kappa_{j,t}$ is a scalar that does not vary across stocks. However, the expression for $\hat{\boldsymbol{\beta}}_{j,t}$ 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 concertrated 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, Koijen 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 Koijen 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 j's holdings of stock i 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 $\boldsymbol{e}_t$ 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:

$$\mathbf{E}\left\{\underbrace{\left[\delta_{j,t}(i)\exp\left(-\beta_0 \mathrm{mb}_t(i) - \boldsymbol{\alpha}_j'\boldsymbol{e}_t - \boldsymbol{\beta}_1'\boldsymbol{x}_t(i)\right) - 1\right]}_{\varepsilon_{j,t}(i)}\begin{pmatrix} z_{j,t}(i) \\ \boldsymbol{e}_t \\ \boldsymbol{x}_t(i) \end{pmatrix}\right\} = \mathbf{0}. \tag{B5}$$

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

$$\mathbf{E}\left\{\left[\hat{\delta}_{j,t}(i)\exp\left(-\boldsymbol{\alpha}_j'\boldsymbol{e}_t - \boldsymbol{\beta}_1'\boldsymbol{x}_t(i)\right) - 1\right]\begin{pmatrix} \boldsymbol{e}_t \\ \boldsymbol{x}_t(i) \end{pmatrix}\right\} - \frac{\lambda}{\left|\mathcal{N}_{j,t}\right|^{\xi}}\begin{pmatrix} \mathbf{0} \\ \boldsymbol{\beta}_{1,j,t} - \hat{\boldsymbol{\beta}}_1 \end{pmatrix} = \mathbf{0}, \tag{B6}$$

where $\hat{\delta}_{j,t}(i) = \delta_{j,t}(i)\exp(-\hat{\beta}_0 \mathrm{mb}_t(i))$. This penalty is inversely related to $\left|\mathcal{N}_{j,t}\right|$, the number of investor j's stock holdings in quarter t. The penalty shrinks the demand coefficients toward the group-level estimate $\hat{\boldsymbol{\beta}}_1$. 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 $\lambda = 120$ and $\xi = 0.7$.

B.3. Estimated demand coefficients

?? 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 **??** 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 (23) 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

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

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:

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

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

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

$$\mathrm{CR}_{i,t} = \frac{\sum_n \left|\mathrm{Shares}_{i,t}(n) \cdot P_t(n) - \mathrm{Shares}_{i,t-1}(n) \cdot P_{t-1}(n) - \mathrm{Shares}_{i,t-1}(n) \cdot \Delta P_t(n)\right|}{\sum_n \left(\mathrm{Shares}_{i,t}(n) \cdot P_t(n) + \mathrm{Shares}_{i,t-1}(n) \cdot P_{t-1}(n)\right)/2}, \tag{C1}$$

where $\mathrm{Shares}_{i,t}(n)$ 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. Anomaly return around earnings announcements

I start with 119 anomalies shown to be robust out of sample in Jensen et al. (2023). For each firm-month observation, I sum the number of long-side and short-side anomaly portfolios that the observation belongs to, constructing the variables *Long* and *Short*, respectively. Following Engelberg et al. (2018), I estimate the following regression:

$$
\begin{aligned}
R_{i,t} = {} & \beta_1 \text{Long}_{i,t} + \beta_2 \text{Long}_{i,t} \times \text{Eday}_{i,t} + \beta_3 \text{Short}_{i,t} + \beta_4 \text{Short}_{i,t} \times \text{Eday}_{i,t} + \beta_5 \text{Eday}_{i,t} \\
& + \sum_{j=1}^{10} \gamma_j R_{i,t-j} + \sum_{j=1}^{10} \delta_j R^2_{i,t-j} + \sum_{j=1}^{10} \rho_j \text{Volume}_{i,t-j} + \alpha_i + \alpha_t + \varepsilon_{i,t}.
\end{aligned} \tag{D1}
$$

Here, $R_{i,t}$ is the daily return of stock i on day t. $\text{Long}_{i,t}$ and $\text{Short}_{i,t}$ are the counts of long-side and short-side anomaly portfolios that stock i belongs to at the end of the previous month. $\text{Eday}_{i,t}$ is an indicator equal to one on earnings announcement days for firm i and zero otherwise. $R_{i,t-j}$ is the daily return of stock i on day $t-j$, and $\text{Volume}_{i,t-j}$ is the daily trading volume of stock i on day $t-j$. The regression includes all daily stock return observations, with interaction terms capturing whether anomaly returns are higher on earnings announcement days. Both stock and day fixed effects are included.

Table A5 presents the results. Column (1) constructs *Long* and *Short* across all 119 anomalies, while columns (2)–(4) focus on the value, profitability, and low-risk categories, respectively. 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. These results indicate that the short leg accounts for most of the earnings-day anomaly returns, a pattern that also holds for value, profitability, and low-risk factors. In panel B, I replace the earnings-day dummy with $\text{Eday-L1}_{i,t}$, which indicates the last trading day before earnings announcements. In this case, 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 the cash flows of short-leg stocks.

Next, I show that retail trading behavior helps explain 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 based on their Z-scores. I then estimate the following regression:

$$\begin{aligned} \text{RNB}_{i,t} &= \sum_{k=1}^{5} \beta_k Q_k + \sum_{k=1}^{5} \phi_k Q_k \times \text{Eday-L1}_{i,t} + \psi\, \text{Eday-L1}_{i,t} \\ &\quad + \sum_{j=1}^{10} \gamma_j R_{i,t-j} + \sum_{j=1}^{10} \delta_j R^2_{i,t-j} + \sum_{j=1}^{10} \rho_j \text{Volume}_{i,t-j} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \end{aligned} \tag{D2}$$

Here, $\text{RNB}_{i,t}$ is the retail net buy volume for stock i on day t. Q_k is the quintile rank of stock i based on its Z-score at the end of the previous month. $\text{Eday-L1}_{i,t}$ equals one on the last trading day before earnings announcements for firm i, and zero otherwise. Stock and day fixed effects are included.

Table A6 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 $\text{Eday-L1}_{i,t}$ 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). This retail buying pressure helps explain why short-leg stocks outperform in the pre-announcement period.

Table A1
Machine-learning-based horizon bias and announcement returns

This table reports portfolio returns from a double sort on equity duration and machine-learning-based horizon bias. I generate rational earnings forecasts using a random forest methodology following van Binsbergen et al. (2023) and calculate forecast bias as the difference between analyst forecasts and rational forecasts. Horizon bias is the difference between long-term and short-term forecast bias. Each quarter, I sort firms with earnings announcements into five quintiles by equity duration. Within each duration quintile, I further sort stocks into five groups by horizon bias. For each portfolio, I compute the equal-weighted average abnormal return in the $[-5, +5]$ announcement window, where abnormal returns are daily returns minus the market return. The equity term premium (ETP) is the difference in average returns between the short- and long-duration portfolios. The *t*-statistics, based on heteroskedasticity-consistent standard errors, are reported in parentheses. I report *t*-statistics only for return differences between the top and bottom groups.

	Low HB^{ML} (1)	Q2 (2)	Q3 (3)	Q4 (4)	High HB^{ML} (5)	H – L (6)	*t*-stat (7)
Short Dur	4.03	3.95	4.90	4.69	8.85	4.82	(2.05)
Long Dur	3.94	0.99	−0.45	−2.18	−3.38	−7.32	(−2.33)
ETP	0.09	2.96	5.35	6.87	12.23	12.14	
t-stat	(0.03)	(1.14)	(1.72)	(2.63)	(4.22)	(3.34)	

Table A2
Announcement term premium controlling for lottery features

This table reports average pre- and post-announcement returns for 25 portfolios double sorted on lottery measure and equity duration, and five lottery-adjusted duration portfolios. The lottery measure is pre-earnings-announcement idiosyncratic volatility (PEA IVOL). Each quarter, I first sort firms announcing earnings into five lottery quintiles using their PEA IVOL from the month before the announcement. Within each lottery quintile, I then sort stocks into five groups by equity duration from the previous quarter. I collapse across lottery groups to obtain five lottery-adjusted duration portfolios. The *t*-statistics, based on 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	18.67	13.23	9.86	16.01
	(3.86)	(5.14)	(2.91)	(2.53)	(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	−15.50	−16.32	−23.78	−37.60
	(−1.19)	(−2.87)	(−3.45)	(−4.19)	(−6.21)

Table A3
Do momentum and attention play a role?

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

	Window $[-3,-1]$				Window $[0,2]$			
	Baseline	Mom	~Winner	No media	Baseline	Mom	~Winner	No media
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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	4.82	3.93	3.54	25.52	24.42	27.46	25.57
	(1.22)	(1.97)	(1.23)	(1.22)	(6.74)	(6.38)	(6.44)	(6.76)

Table A4
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	H	H − L	t_{H-L}	L	H	H − L	t_{H-L}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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
$\text{CAR}_{[-3:-1]}$	6.16	25.57	19.41	2.80	7.49	27.92	20.44	3.29
$\text{CAR}_{[-5:-1]}$	14.63	34.52	19.89	2.28	15.77	35.89	20.12	2.34

Table A5
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	Value	Profitability	Low-risk
	(1)	(2)	(3)	(4)
		Panel A: Earnings-day return		
Long	0.422***	1.164***	−0.563***	0.544***
	(18.440)	(10.707)	(−6.312)	(5.241)
Short	−0.143***	−0.360***	0.706***	0.026
	(−4.475)	(−3.985)	(6.990)	(0.162)
EDay × Long	0.495***	0.360	−3.833***	1.162**
	(3.319)	(0.756)	(−6.926)	(2.258)
EDay × Short	−2.677***	−8.626***	−10.858***	−10.080***
	(−15.653)	(−15.126)	(−13.335)	(−12.198)
EDay	44.949***	24.624***	25.667***	20.801***
	(10.587)	(9.870)	(10.675)	(8.213)
		Panel B: Pre-announcement return		
Long	0.423***	1.173***	−0.611***	0.583***
	(18.123)	(10.655)	(−6.821)	(5.597)
Short	−0.175***	−0.467***	0.575***	−0.105
	(−5.484)	(−5.160)	(5.713)	(−0.642)
EDay-L1 × Long	0.546***	−0.220	0.311	−1.791***
	(6.299)	(−0.826)	(1.032)	(−4.871)
EDay-L1 × Short	0.326***	0.925**	1.851***	1.892***
	(3.168)	(2.377)	(3.754)	(4.428)
EDay-L1	−2.968	12.809***	11.335***	14.417***
	(−1.133)	(7.951)	(8.189)	(8.756)

Table A6
Retail net trading: 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. $\mathbf{1}_{\text{Abr}-x}$ 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 × $\mathbf{1}_{\text{Abr1}}$	13.713***	6.490***	3.781***	13.111***	8.101***	4.303***
	(6.319)	(6.512)	(5.285)	(4.391)	(5.823)	(4.398)
EDay-L1 × $\mathbf{1}_{\text{Abr2}}$	11.076***	4.770***	2.588***	7.548***	4.759***	2.099***
	(7.053)	(7.313)	(5.832)	(3.841)	(4.805)	(2.855)
EDay-L1 × $\mathbf{1}_{\text{Abr4}}$	−6.327***	−2.037***	−1.117***	−9.844***	−2.834***	−2.083***
	(−5.640)	(−4.237)	(−3.288)	(−5.649)	(−3.239)	(−3.311)
EDay-L1 × $\mathbf{1}_{\text{Abr5}}$	−11.894***	−4.559***	−2.666***	−15.532***	−6.471***	−4.158***
	(−10.308)	(−9.416)	(−7.931)	(−9.217)	(−7.391)	(−6.527)
EDay-L1	23.467***	6.979***	3.523***	31.343***	10.185***	5.863***
	(22.470)	(16.087)	(12.203)	(21.248)	(14.131)	(11.210)
$\mathbf{1}_{\text{Abr1}}$	4.807***	4.760***	4.995***	6.981***	6.946***	7.325***
	(6.455)	(6.480)	(6.816)	(6.363)	(6.403)	(6.757)
$\mathbf{1}_{\text{Abr2}}$	0.005	0.049	0.171	0.533	0.455	0.597
	(0.016)	(0.157)	(0.555)	(0.962)	(0.826)	(1.098)
$\mathbf{1}_{\text{Abr4}}$	0.369	0.238	0.250	1.713***	1.375***	1.249***
	(1.616)	(1.067)	(1.132)	(3.701)	(3.059)	(2.813)
$\mathbf{1}_{\text{Abr5}}$	1.035***	0.919***	0.912***	3.768***	3.473***	3.242***
	(3.337)	(3.005)	(3.005)	(5.876)	(5.474)	(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 A7
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 horizon bias. *Avg* denotes unconditional average coefficients, while *High HB* and *Low HB* represent average coefficients during high- and low-horizon-bias periods, respectively, where horizon bias states are determined by the median of the aggregate horizon bias. *Price elasticity* is measured by one minus the demand coefficient on log market-to-book equity. *Active share* is defined in Equation (10). The t-statistics are computed using heteroskedasticity-consistent standard errors and reported in parentheses. The monthly sample period spans from 1973:8 to 2024:1.

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

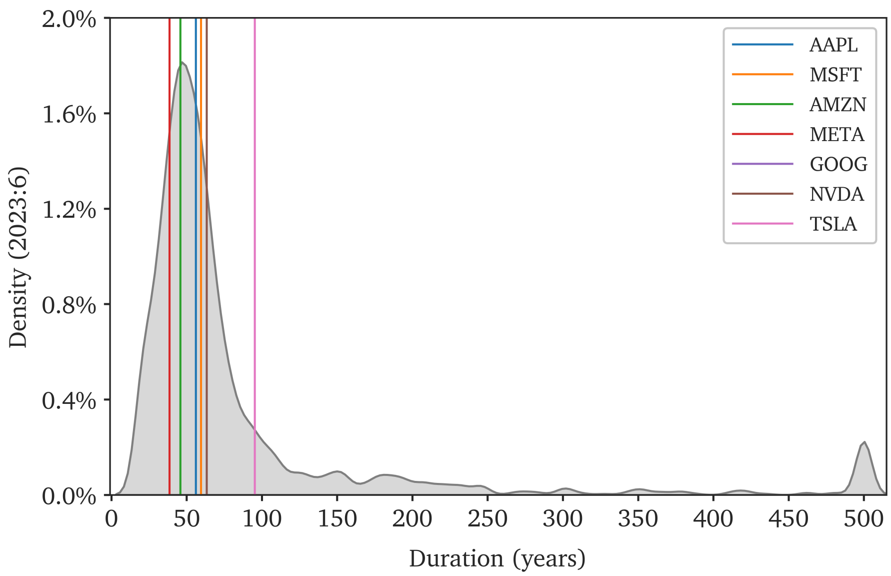

Figure A1. Distribution of equity duration in 2023. This figure reports the cross sectional distribution of equity duration in June 2023. I obtain the annual data on firm-level duration from Andrei S. Gonçalves' personal website. By construction, stock duration is capped at 500 years. The colored vertical 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.

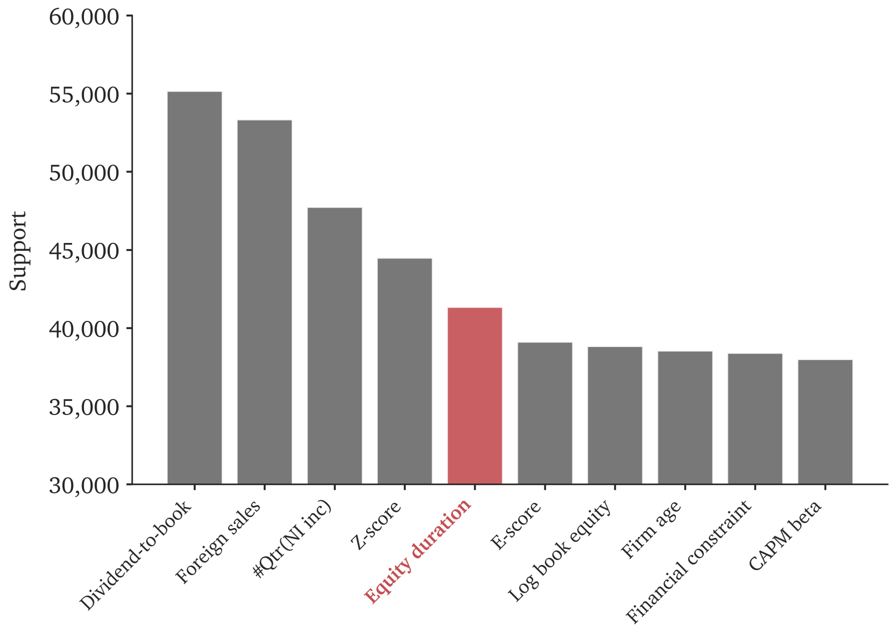

Figure A2. Top 10 factors from Lasso regression. This figure summarizes the results from a Lasso regression that selects firm characteristics predictive of portfolio weights in each quarter. I start from 153 firm characteristics provided by Jensen et al. (2023) and add equity duration. For each institution 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.

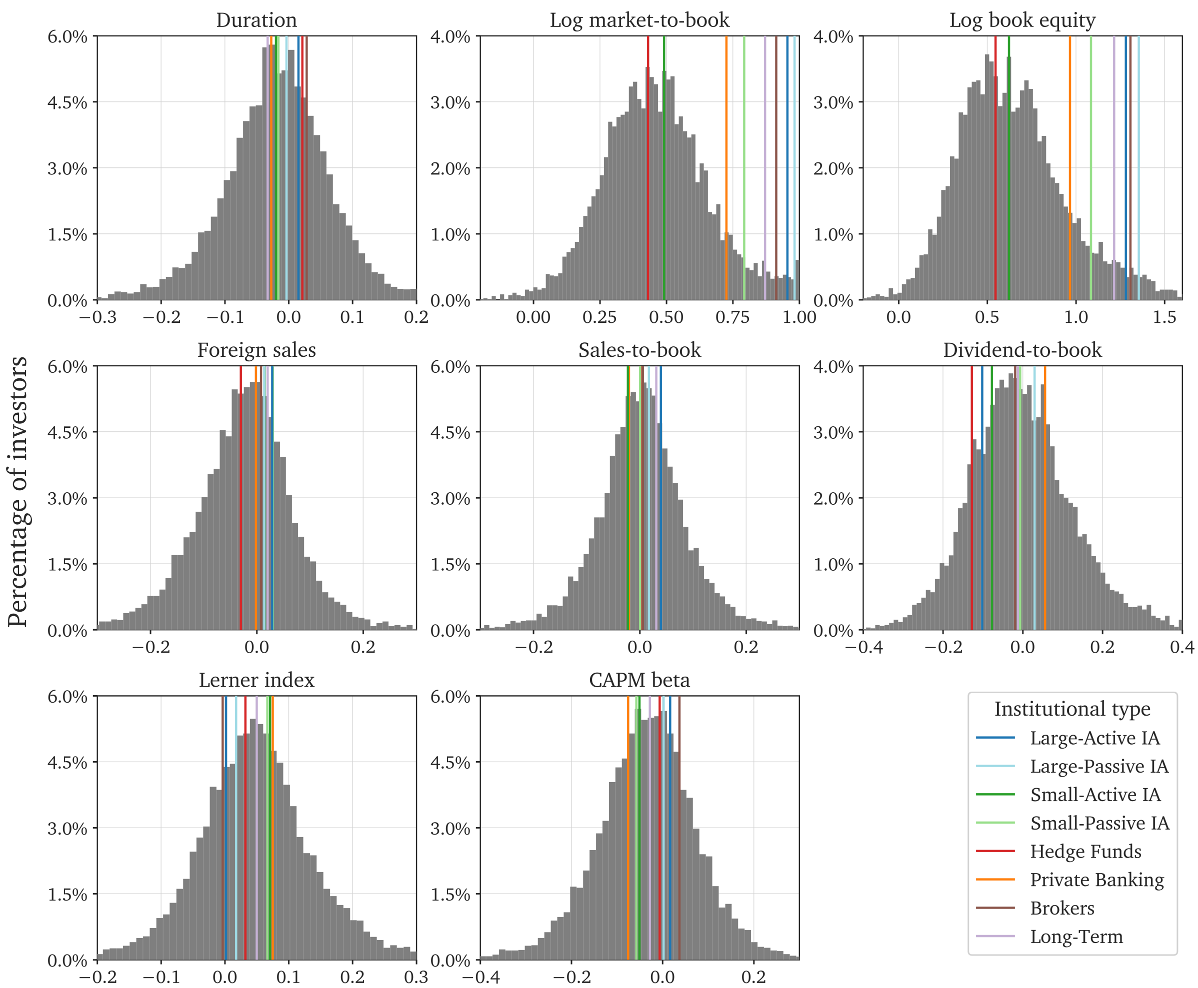

Figure A3. Cross-sectional distribution of demand coefficients. This figure illustrates the cross-sectional distribution of average demand coefficients across institutional investors. The asset demand of each investor is estimated from quarterly holdings. I compute the time-series average of the demand 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.