Exploiting Myopia: The Returns to Long-Term Investing*

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Abstract

Investment managers often face short-term incentives, such as redemption pressure following recent weak performance, that discourage them from holding positions through temporary underperformance. These constraints can lead to systematic underinvestment in firms that require longer holding periods to realize value. We examine whether these horizon-driven frictions generate predictable return patterns across firms. We measure long-term ownership at the firm level using active managers' share-weighted holding periods (Horizon), and document that firms with longer Horizon generate significantly higher returns than those with shorter Horizon, particularly among stocks that are harder for myopic managers to hold. We exploit the 2004 SEC rule that increased mutual fund disclosure frequency to link our findings to myopia. We find that Treated firms experienced declines in Horizon and a stronger Horizon-return relation, consistent with increased myopia reducing long-termism and increasing mispricing. In contrast, we find no change in the Horizon-return relation following the XBRL mandate, which improved access to fundamental information but did not affect investor constraints. These results suggest that frictions in institutional holding horizons, not information-processing advantages, drive the observed returns to long-term investing.

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"It's still true that the biggest players in the public markets – particularly mutual funds and hedge funds – are not good at taking short-term pain for long-term gain. The money's very quick to move if performance falls off over short periods of time. We don't worry about headline risk – once we believe in an asset, we're buying more on any dips because we're focused on the end game three or four years out." – Jeffrey Ubben, ValueAct Capital

1 Introduction

Institutional investment managers in equity markets often exhibit a short-term orientation due to a range of incentive structures.[1] Managers face the continual threat of investor redemptions, which can be triggered by even brief periods of underperformance. As a result, they have strong incentives to ensure their returns benchmark well over short horizons, which can lead to fund managers prioritizing short-term returns over long-run fundamental value. Consequently, a large literature documents pervasive myopic behavior among institutional investment managers.[2]

However, some of the most successful asset managers explicitly embrace long-horizon investing. Warren Buffett famously states, "our favorite holding period is forever." Seth Klarman has argued that "the single greatest edge an investor can have is a long-term orientation." Their investment philosophy suggests that, while institutions may be incentivized to prioritize short-term outcomes, meaningful heterogeneity in investment horizons exists among investors. Because firms inherit the weighted average investment horizon of their shareholder base, this heterogeneity among shareholders creates systematic *firm-level* cross-sectional variation in time horizon. This variation in ownership structure is a persistent firm characteristic, yet its implications for cross-sectional asset pricing remain underexplored.

Firm-level heterogeneity in ownership horizons can affect prices if long-horizon capital is scarce relative to investment opportunities. Evidence shows that long-horizon investors outperform on average (Cremers and Pareek, 2016), consistent with patient capital being in limited supply. When firm demand for patient capital exceeds the supply from long-term investors, not all firms with

[1] These include relative performance benchmarking (Brown et al., 1996), managerial career concerns (Chevalier and Ellison, 1999; Makarov and Plantin, 2015; van Binsbergen et al., 2021), and fund-flows that reward short-term performance (Sirri and Tufano, 1998; Bailey et al., 2011)

[2] See, for example, Chevalier and Ellison (1999); Edelen (1999); Bushee (2001); Kempf et al. (2009); Manconi et al. (2012); Cella et al. (2013); Callen and Fang (2013); Agarwal et al. (2018); Bourveau et al. (2023).

delayed payoffs or significant interim risk attract sufficient investment. These firms may then trade below fundamental value, yielding higher subsequent returns. Conversely, firms that appeal to short-horizon investors may attract excess capital, driving valuations above fundamentals and implying lower subsequent returns.

In this paper, we study whether differences in institutional investor time horizons generate systematic mispricing in the cross-section of stocks. Specifically, we ask two questions. First, does a firm's average ownership horizon predict subsequent returns, after controlling for fundamentals and standard factors? Second, if such a premium exists, what drives it? We examine whether it reflects the informational advantages of long-horizon investors or a pricing effect stemming from the market's overall short-term orientation.

We begin by developing a simple, firm-level measure of investor time horizon, constructed from 13-F filings. The key variable, *Horizon*, measures the average number of consecutive quarters a firm is held by active institutional investors, weighted by each institution's ownership stake. To ensure the measure reflects strategic ownership Horizon rather than passive indexing, we exclude index and quasi-index funds using the Bushee (2001) classification. Because it aggregates revealed preferences across all active investors, Horizon captures the extent to which a firm is held by long-horizon institutions. Our main hypothesis is expected returns increase with a firm's shareholder-weighted Horizon, because institutional myopia creates a demand imbalance that can be proxied through Horizon.

In Fama-MacBeth regressions, we find that Horizon is positively priced, with a t-statistic greater than 5 in the full sample and greater than 4 when excluding microcaps. In terms of economic magnitude, a 1% increase in Horizon translates to around 20 basis points (bps) of monthly returns, or 2.4% annualized. To corroborate the findings, we sort firms into quintiles based on Horizon and find monotonic increases in average returns from the lowest to the highest quintile, with a spread of around 50 bps per month, or 6% annualized. These results show that Horizon is a significant predictor of returns and is not subsumed by traditional characteristics used in cross-sectional asset pricing models (Fama and French, 2015; Hou et al., 2020).

We next test whether Horizon more strongly predicts returns among firms that are harder for myopic managers to hold. We focus on two firm characteristics that proxy for frictions associated with short-term investment constraints. First, we examine idiosyncratic volatility (*IVol*), which captures firm-specific risk that is penalized under performance evaluation systems. Prior work shows that managers facing short-term incentives are less willing to hold high-*IVol* stocks, as short-run losses can be difficult to justify to clients or internal monitors (Chevalier and Ellison, 1999). If such constraints drive institutional underinvestment, then return premia associated with Horizon should be larger for high-*IVol* firms. Second, we consider recent stock performance (Ret_{-1}), a proxy for near-term momentum that attracts trend-chasing flows (Bailey et al., 2011; Frazzini and Lamont, 2008). Managers subject to short-run performance pressure are more likely to window-dress their portfolio by selling positions with weak recent returns, especially following negative news (Brown et al., 2014; Xin et al., 2024). These forced sales can depress prices, sharpening Horizon's ability to distinguish firms with genuinely long-term ownership.[3]

We find evidence consistent with the myopia mechanism in both cross-sectional tests. The predictive power of Horizon is higher among high *IVol* firms and low Ret_{-1} firms. In particular, the interaction between *IVol* and Horizon positively predicts future return, while the interaction between Ret_{-1} and Horizon negatively predicts future return.[4] These results provide suggestive evidence that among stocks that are difficult for managers with short-term pressure to hold, Horizon identifies mispricing. Among easier-to-hold stocks, Horizon does not identify mispricing.

We next examine the time-series properties of Horizon through portfolio sorts and spanning regressions. In 5×5 sorts, we find that the return spread between high- and low-Horizon firms is economically and statistically significant. Firms in the highest Horizon quintile earn 27 bps per month more than those in the lowest quintile, on average. These spreads are stronger in subsets of the cross-section where institutional myopia is more likely to bind. For example, the Horizon return spread rises to 65 bps in high-*IVol* stocks and 68 bps in low-Ret_{-1} stocks. We confirm these findings persist in time-series spanning regressions. The Horizon factor loads positively on value (HML), profitability (RMW), and investment (CMA), and negatively on size (SMB) and momentum (UMD), consistent with long-horizon managers identifying firms with attractive funda-

[3]Even if such firms remain in portfolios, they may be held at lower weights or for shorter periods, thereby correlating with both Horizon and future returns.

[4]Consistent with the cross-sectional regressions, in an alternative specification where we split the sample and run two separate regressions (Table B1), we find that the Horizon factor has a stronger effect among high *IVol* firms than among low *IVol* firms. The patterns are similar for the Ret_{-1} split.

mentals, potentially at the expense of short-horizon returns. In line with the myopia mechanism, the Horizon factor generates larger alphas in double-sorted portfolios formed within high-$IVol$ or low-Ret_{-1} firms.

While the cross-sectional and time-series tests suggest that institutional myopia drives the Horizon premium, an alternative explanation is that Horizon proxies for long-term investors' ability to conduct rigorous fundamental analysis. In this view, long-Horizon investors outperform not because they are more patient, but because they are better equipped to identify mispricing based on complex or opaque fundamentals. Short-Horizon investors, by contrast, may avoid such firms not due to holding constraints, but because they lack the capacity to process relevant information. Our proxies of idiosyncratic volatility and recent underperformance may thus reflect firms where there exist greater impediments to information processing and decision making (e.g., Barber and Odean, 2008; Rajgopal and Venkatachalam, 2011; Sicherman et al., 2016).

To disentangle these competing mechanisms, we implement two difference-in-differences (DiD) tests that separately exploit plausibly exogenous shocks to institutional myopia and to information processing capacity. If the Horizon premium reflects constraints related to institutional myopia, it should strengthen when myopia increases. If it reflects information processing advantages, it should strengthen when financial disclosures become more useful for sophisticated investors.

We first test the institutional myopia mechanism by leveraging a regulatory shock that increased the salience of short-term performance for fund managers. In May 2004, the SEC mandated that mutual funds disclose their portfolio holdings quarterly rather than semiannually. Prior research shows that this rule change heightened short-term pressure by increasing external monitoring of interim performance (e.g., Agarwal et al., 2018, 2023; Bourveau et al., 2023). However, the impact of the regulation was heterogeneous: many funds had already begun disclosing quarterly prior to the mandate, creating firm-level variation in exposure to the mandate (Agarwal et al., 2015; Dyakov et al., 2022; Li et al., 2023).[5] Note that while this variation is endogenous to the mutual fund's economics, given it is a voluntary disclosure choice by the fund, it is plausibly exogenous to the individual *firms* that the mutual funds hold, which is the variation we exploit in our tests.

We implement a DiD design that compares changes in Horizon and its return predictive power

[5] Recent evidence shows that quarterly portfolio disclosures explain more than 99% of the variation in daily fund returns, making this disclosure shock a salient basis for myopia evaluation (Mathis and Kaplan, 2024).

before and after the rule, across firms with higher versus lower exposure to newly affected funds. If Horizon captures a mispricing channel arising from institutional myopia, then we expect two effects in the treated group following the mandate. First, we expect that myopia increases as a result of the greater interim monitoring, such that Treated firms exhibit a relative decline in Horizon as a result of fund trading. Second, because the agency friction becomes more severe, we expect a stronger Horizon-return relation for Treated firms.

Consistent with both predictions, we find that (i) Horizon declines significantly more for firms with high exposure to affected funds following the disclosure shock, and (ii) the Horizon-return relation is significantly stronger for treated firms in the post-regulation period. In terms of magnitude, the return of the Horizon measure rises by over 60 bps per month in the treated group after the mandate. Both effects are concentrated in the non-microcap sample, where institutional monitoring is more credible and portfolio disclosures are more closely scrutinized. The evidence suggests that institutional myopia directly suppresses the ability of constrained investors to hold long-term positions, generating return premia that are increasingly concentrated among firms avoided by short-horizon capital.[6]

We next test the alternative hypothesis by exploiting a regulatory shock that plausibly improved sophisticated institutions' ability to conduct fundamental analysis: the 2009 mandate requiring firms to provide financial statements in machine-readable eXtensible Business Reporting Language (XBRL) format.[7] The change significantly improved the accessibility of detailed financial data and were designed to enhance information processing, especially by sophisticated investors (Blankespoor et al., 2014).[8] Critically, the XBRL filings affect firm-level disclosures, but they do not affect fund-

[6]The weaker treatment effects in the sample that includes microcaps reflect the fact that the 2004 disclosure mandate increased monitoring pressure primarily for large-cap holdings. Fund managers are evaluated based on their visible, benchmark-relevant positions, which are disproportionately large-cap firms. As a result, the shift from semiannual to quarterly disclosure meaningfully increased scrutiny over large-cap portfolio decisions, but had a limited impact on small-cap stocks.

[7]Alternatively, we conduct the same test using the 2019 inline XBRL (iXBRL) mandate, which embedded machine-readable tags directly into public filings. By embedding tags directly in the human-readable filing, iXBRL eliminated the clunky dual-document system and made it cheaper for analysts and active managers to harvest granular fundamentals (Call et al., 2023). We find directionally similar but less consistent results in untabulated tests, likely due to the post-COVID sell-off confounding the time-series shock.

[8]While there is evidence that XBRL eventually helped reduce information processing costs for less sophisticated investors (Bhattacharya et al., 2018), we only exploit variation related to the first implementation wave of the XBRL mandate. During the first wave, prior work finds that treated firms experienced increased information asymmetry, because sophisticated investors were initially better positioned to process the new structured data (Blankespoor et al., 2014; Gomez et al., 2024).

level myopia. If Horizon captures information-processing advantages for sophsiticated investors, then the returns to high-Horizon firms should increase for treated firms after these mandates.

We find no evidence that the XBRL filings changed the level of Horizon for the treated firms, nor did it increase the slope of the Horizon-return relation for treated firms. This suggests that XBRL did not enhance the return premium associated with Horizon. This is in contrast to our findings under the mutual fund disclosure shock, where increased monitoring of institutional holdings strengthens the link between Horizon and returns. Because the XBRL mandate improves access to fundamentals but does not affect institutional constraints or short-term performance pressures, these null results suggest that the Horizon premium is not driven by variation in fundamental analysis capacity. Instead, the collective evidence supports a myopia-based mechanism, where long-horizon investors earn returns by holding stocks that short-horizon institutions avoid.

This paper contributes to the literature on institutional myopia and asset pricing along three dimensions. First, we introduce a new, firm-level measure of investor time horizon that can proxy for investor myopia. *Horizon* captures the average number of consecutive quarters a stock is held by active institutional investors, weighted by ownership share. Unlike commonly used proxies for career concerns in the mutual fund literature, such as manager age or experience (Chevalier and Ellison, 1999), Horizon is based on the revealed preferences embedded in actual portfolio holdings, providing an objective signal of investment horizon. The measure is simple to construct and does not rely on manager characteristics as proxies.

Second, we find evidence that firms with longer-horizon shareholder bases tend to earn higher subsequent returns. While prior work has focused on this relation at the *fund-level* (Cremers and Pareek, 2016; Lan et al., 2023), our evidence indicates that a similar pattern emerges when fund horizons are aggregated to the firm level. Firms and funds are significantly different units of analysis, and cross-sectional findings on fund returns may not extend to firm returns. While the cross-section of firms is traditionally studied using firm characteristics, we aggregate fund characteristics to the firm level to determine if heterogeneity in investor demand can be used to price the cross-section of firms (Koijen and Yogo, 2019).

Third, we identify institutional myopia as the mechanism behind the Horizon premium, as opposed to information-processing advantages. We show that a 2004 SEC rule that increased disclosure frequency reduced Horizon and strengthened its return predictive power. In contrast, mandates that improved access to firm fundamentals through machine-readable filings (XBRL) had no effect. This evidence points to institutional agency frictions, not fundamental analysis skill, as the driver of the premium. Our findings contrast with past work on long-termism in institutional funds. Cremers and Pareek (2016) attribute the outperformance of long-term funds to limits to arbitrage and the interaction of long-termism with Active Share, while Lan et al. (2023) attribute their effect to the superior private information of long-horizon managers.

The remainder of the paper is organized as follows. Section 2 explains the institutional background of this paper and develops the hypotheses. Section 3 introduces the data sources and the construction of the Horizon measure. Section 4 presents the main results of this paper, including the Fama-MacBeth regressions, cross-sectional tests, and time-series tests. Section 5 explores the potential mechanisms behind the return predictability of Horizon. Finally, Section 6 concludes.

2 Background and Hypothesis Development

2.1 Institutional Background

Congress first sought to increase transparency into the trading activity of large institutional investors in 1975 by enacting Section 13(f) of the Securities Exchange Act, which directs the Securities and Exchange Commission (SEC) to collect quarterly position reports from every "institutional investment manager" that exercises investment discretion over at least $100 million in publicly traded equity securities. Form 13F requires each manager to aggregate all long positions across its accounts, report them within 45 days of quarter-end, and file summary-level information, including issuer, CUSIP, share count, and market value. Because the disclosure is manager-centric, a diversified asset management complex may file a single consolidated report covering its mutual funds, hedge funds, and separate accounts.[9]

Mutual funds have long faced separate disclosure requirements under the Investment Company

[9] The asset-manager level 13F can mask within-manager heterogeneity in investment strategies. For our purposes, this limitation is mitigated because when measuring investment Horizon, we aggregate the manager data to the firm-level, in order to focus on the overall mix of short- versus long-horizon institutional ownership in the cross-section of firms. Thus, compared to studies that focus on the cross-section of funds, our inferences are less reliant on identifying the precise mandates of individual funds within a complex.

Act, meant to provide information to the retail investors that hold such funds. For decades, mutual funds were required to disclose their complete portfolios twice a year in shareholder reports (Form N-CSR) and related filings (Form N-SAR), limiting the timeliness with which fund holdings could be monitored. The most significant change occurred in May 2004, when the SEC adopted enhanced portfolio disclosure rules that materially increased the frequency and scope of reporting. The final rule introduced Form N-Q and amended Form N-CSR, requiring every registered management investment company to file a complete *quarterly* schedule of investments within 60 days of quarter-end. Notably, prior to the mandate, roughly 40% of U.S. active domestic equity funds already provided quarterly snapshots, either to commercial data vendors (e.g., Thomson Reuters) or through voluntary SEC filings on Form N-30B2 (Agarwal et al., 2015; Dyakov et al., 2022; Li et al., 2023).

In this paper, we investigate the economics of long-term investing from the perspective of individual firms. We do so using holdings information from Form 13F filings by large, active institutional investment managers. This approach centers on the most economically significant market participants. Relative to relying on the full sample of mutual funds, it excludes funds with discretionary control below the $100 million Section 13(f) threshold and includes other major asset owners such as hedge funds, pension funds, and insurance companies.

We also exploit the May 2004 portfolio disclosure mandate as an exogenous shock to short-horizon incentives (myopia) among mutual fund managers. Because mutual funds account for an economically significant share of active institutional management, this shock plausibly alters the overall level of myopia in institutional holdings. Beyond external scrutiny, investment managers' decisions may also be shaped by research capacity. Accordingly, we exploit the implementation of eXtensible Business Reporting Language (XBRL), which facilitated investors' information processing and, in particular, enhanced the sophisticated institutional asset managers' ability to conduct fundamental analysis (Blankespoor et al., 2014; Gomez et al., 2024).

2.2 Main Hypothesis

Economic theory has long grappled with why rational agents might behave myopically. In a seminal model, Stein (1989) shows that when managers are partially motivated by near-term stock prices, they may forgo positive net present value long-term investments to boost current earnings, in order to impress rational stock market participants. The theoretical literature emphasizes that short-termism often arises as a rational response to distorted incentive structures (e.g., Narayanan, 1985; Holmström, 1999; Gigler et al., 2014). When markets or principals place disproportionate weight on short-term metrics, agents rationally choose myopic actions even when they are suboptimal for long-term value. In the context of asset management, institutional asset managers may behave myopically in a similar fashion. In particular, they could be incentivized to prioritize short-term returns over long-term fundamentals for multiple reasons, such as performance evaluation (Brown et al., 1996), agency conflicts (Chevalier and Ellison, 1997), flows-related pressure and trend-chasing behavior (Sirri and Tufano, 1998; Bailey et al., 2011), and career concerns (Chevalier and Ellison, 1999; Makarov and Plantin, 2015; van Binsbergen et al., 2021).

Asset managers' myopia can lead to suboptimal investment decisions (e.g., Scharfstein and Stein, 1990; Huang et al., 2011; Cremers and Pareek, 2016). In equilibrium, such behavior increases demand for stocks disproportionately favored by myopic investors above the optimal level implied by the market portfolio, thereby raising prices and lowering expected returns for those stocks. Conversely, stocks underinvested by myopic investors face depressed demand, lower prices, and higher expected returns. We hypothesize that firms whose institutional ownership is characterized by long holding periods are effectively those underinvested by short-horizon investors. Accordingly, we expect these stocks to outperform those predominantly held with shorter institutional holding horizons.[10] Therefore, we have the following main hypotheses:

- *H1: Stocks with longer institutional holding horizons tend to outperform the peer stocks.*

2.3 Cross-Sectional Hypotheses

We hypothesize that the Horizon factor will identify greater mispricing and yield stronger returns when the stock is harder for myopic managers to hold. In the cross-section, such stocks should exhibit more pronounced demand imbalances arising from myopic institutions' suboptimal portfolio choices. Accordingly, the effects hypothesized in Section 2.2 will likely be amplified.

[10] Consistent with this logic, Cella et al. (2013) show that short-term investors exacerbate market-wide negative shocks, and Gaspar et al. (2005); Harford et al. (2018) find that short-term shareholders weaken governance and lead to poorer corporate decision making.

We examine two firm characteristics that proxy for the difficulty myopic managers face in holding a stock. First, we consider idiosyncratic volatility. Holding stocks with high idiosyncratic volatility increases short-term performance risk within a manager's portfolio, raising the likelihood of adverse outcomes and potential forced selling by myopic managers. Consistent with Chevalier and Ellison (1999), who show that career concerns lead myopic managers to underinvest in stocks with higher unsystematic risk, such aversion should widen demand imbalances and raise expected returns for this subsample. Consequently, the Horizon effect should be stronger when idiosyncratic volatility more effectively separates long-horizon from short-horizon ownership.[11] Following this logic, we hypothesize that:

- *H2a: The Horizon–return sensitivity is stronger for firms with higher idiosyncratic volatility.*

Second, we consider recent stock performance. We hypothesize that the Horizon factor has greater predictive power for firms with poor recent returns. Prior research shows that individual investors and asset managers exhibit trend-chasing behavior, which is associated with lower investment performance (Sirri and Tufano, 1998; Bailey et al., 2011). Outside investors chase trends by reallocating assets from low- to high-performing mutual funds (Frazzini and Lamont, 2008). In response, asset managers window dress their portfolios by reallocating away from recently underperforming stocks (Xin et al., 2024). This pressure is especially salient for short-horizon managers facing career concerns (Chevalier and Ellison, 1999; Jiang and Verardo, 2018). Moreover, Brown et al. (2014) document that herding out of a stock on negative information is more common than herding into a stock on positive information. Based on this literature, we hypothesize that:

- *H2b: The Horizon–return sensitivity is stronger for firms with poor recent stock performance.*

Taken together, these arguments imply that asset managers facing stronger short-term concerns are more likely to reduce their exposure to recently underperforming stocks. This behavior exacerbates the demand imbalance delineated in Section 2.2. Consequently, the Horizon factor should more effectively separate long- and short-horizon investors within this subsample and have sharper return predictability.

[11] Note that this cross-sectional prediction runs in the *opposite* direction of the baseline idiosyncratic volatility effect. Ang et al. (2006) document a *negative* relation between idiosyncratic volatility and returns, whereas we predict that the Horizon–return relation strengthens with higher idiosyncratic volatility.

2.4 Institutional Myopia as the Mechanism

Our central hypothesis is that Horizon's outperformance is driven by the myopic behavior of institutional asset managers. As argued in Section 2.2, institutional asset managers face incentives that shorten their investment horizons (e.g., Brown et al., 1996; Chevalier and Ellison, 1999; Bailey et al., 2011; van Binsbergen et al., 2021), leading to distorted portfolio allocations. This behavior generates systematic demand imbalances: stocks that attract relatively less attention from myopic managers trade at lower prices and earn higher expected returns, while those favored by myopic managers trade at higher prices and earn lower expected returns.

If Horizon captures these mispricing pressures, its predictive power should be strongest when institutional myopia is more binding. In such periods, firms with shareholder bases more exposed to an increase in myopia should, on average, display shorter horizons, since their investors exit positions more quickly. At the same time, the return predictive power of Horizon should be amplified in precisely these firms, because the misallocations induced by myopic behavior are more severe. Together, this logic implies two testable predictions:

- *H3a: Firms with greater exposure to an increase in myopic institutional ownership exhibit lower Horizon measures.*
- *H3b: Firms with greater exposure to an increase in myopic institutional ownership exhibit stronger Horizon–return sensitivity.*

2.5 Fundamental Analysis as the Alternative Mechanism

As an alternative mechanism, Horizon may generate returns because long-horizon asset managers conduct deeper fundamental analysis (e.g., Lan et al., 2023).[12] That is, long-horizon managers may also be those with greater fundamental research capacity and, therefore, a superior understanding of intrinsic value.[13] Consequently, following the investments of long-term asset managers

[12] As anecdotal evidence, Bill Nygren, Partner and CIO of the Oakmark Select Fund, states that "At Oakmark, we are long-term investors...We will purchase stock in businesses only when priced substantially below our estimate of intrinsic value. After purchase, we patiently wait for the gap between stock price and intrinsic value to close."

[13] Our cross-sectional hypothesis is consistent with this alternative explanation. Specifically, high idiosyncratic volatility and recent underperformance may capture impediments to fundamental research, such as attention-driven behavioral biases in adverse events (Barber and Odean, 2008; Sicherman et al., 2016), deterioration in earnings quality associated with high idiosyncratic volatility (Rajgopal and Venkatachalam, 2011), and greater information asymmetry (Jiang and Sun, 2014).

effectively selects firms with better fundamentals priced below intrinsic value (Wermers, 2000). As prices converge to fundamentals over time, the Horizon factor earns excess returns (Abarbanell and Bushee, 1998; Piotroski, 2000).

Under the alternative hypothesis, when information processing costs decline for sophisticated investors, long-horizon managers' advantage in fundamental analysis increases, which should strengthen the Horizon–return relation. We thus hypothesize that:

- *H3c: When information processing costs decline for sophisticated investors, the Horizon–return relation is stronger among firms more affected by the decline.*

3 Data

3.1 Sample Construction

We construct our sample on the firm-month level using quarterly financial data from Compustat and monthly market data from CRSP over 1980Q1–2024Q4. We restrict the sample to U.S. common stocks (firms with CRSP share codes 10 or 11) listed on the NYSE, AMEX, or NASDAQ (following, e.g., Fama and French, 2015; Guo et al., 2020). We supplement these data with monthly factor returns from Kenneth R. French's Data Library.[14]

The primary empirical innovation in this paper is *Horizon*, a measure that identifies firms held by long-horizon fund managers. We construct Horizon from the Thomson Reuters S34 database of Form 13F filings. Because Horizon is intended to capture the time horizon of a firm's *active* institutional ownership, we merge the Bushee (2001) investor-classification data[15] (available 1981–2023) to exclude index and quasi-index investors. As we initialize Horizon at zero in 1981Q1, we allow a two-year warm-up period for the measure to develop sufficient cross-sectional variation.

The quarterly Compustat and Thomson Reuters datasets are merged with the monthly CRSP data using GVKEY and CUSIP, respectively. We align filings to market data with a three-month lag relative to the filing date to mitigate look-ahead bias. Because the Compustat and Thomson

[14] We thank Kenneth French for making the data publicly available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[15] We thank Brian Bushee for making the data publicly available at https://accounting-faculty.wharton.upenn.edu/bushee.

Reuters variables are reported quarterly, we forward-fill their values for two months when merging with CRSP. The resulting panel contains Horizon, financial, and market data from September 1983 to May 2024 (489 months).

For the mechanism tests on institutional myopia, we compute, at the firm level, the fraction of shares held by mutual funds affected by the 2004 SEC regulation, which increased the frequency of portfolio holdings disclosure. We obtain mutual fund holdings from the Thomson Reuters (formerly CDA/Spectrum) Mutual Fund Holdings database—which is of higher quality in the early 2000s than CRSP (e.g., Abis and Lines, 2024)—and filing data from the SEC's EDGAR system. We link these datasets to the CRSP Survivorship-Bias-Free Mutual Fund Database via the Ticker–CUSIP link and the WFICN mapping table, respectively. Following Agarwal et al. (2015); Sani et al. (2023); Bourveau et al. (2023), we construct a comparable sample of 1,430 affected active mutual funds prior to the 2004 regulation.[16] We then aggregate the number of shares held by these active funds at the firm level and scale by total shares outstanding. For the mechanism tests using the XBRL mandate, treated firms are identified using the public float data (Ewens et al., 2024)[17] and regulatory thresholds.

3.2 Horizon Measure

Horizon is measured quarterly at the firm level. For each firm–quarter, an institutional investment manager's Horizon is defined as the number of consecutive quarters the manager is reported as holding that firm. We then aggregate Horizon across all investment managers holding the firm, using share weights (i.e., the number of shares each asset manager holds). To allow for potential data errors in a particular quarter, we treat a single-quarter lapse in the Thomson Reuters S34 database as continuous.[18]

The Horizon measure employed in this paper differs in several important respects from the similar measures, termed "Duration," in Cremers and Pareek (2016) and Lan et al. (2023). First,

[16] The prior literature follows similar but heterogeneous approaches. We synthesize the screening procedures and follow Sani et al. (2023) to create a quarterly indicator for portfolio disclosure and identify the affected funds.

[17] We thank Michael Ewens for making the data publicly available at https://michaelewens.github.io/public_float_regulation.

[18] For example, if Fidelity holds Apple in 1980Q1, reports no position in 1980Q2, and resumes holding in 1980Q3, the Fidelity–Apple Horizon counter is 2 in 1980Q2 and 3 in 1980Q3. We view such lapses as more likely due to reporting error than to round-trip trading, given the transaction costs of buying and selling the same firm within six months.

we differ in how we aggregate the measure. Rather than aggregating Horizon at the fund–quarter level to gauge the capability of fund managers, we aggregate it at the firm–quarter level to evaluate the efficacy of the Horizon measure as a cross-sectional predictor for stock returns. Specifically, we test whether *stocks* held for longer investment horizons subsequently outperform stocks held for shorter horizons.

Second, our sample construction focuses on large, active institutions using 13F filings. This approach (i) excludes smaller funds below the $100 million 13F reporting threshold and (ii) includes hedge funds, pensions, and insurance companies, broadening the economic scope beyond mutual funds. This design captures a more comprehensive and behaviorally relevant set of institutional investors, while also addressing several limitations of mutual fund holdings data.[19]

Third, the construction of Horizon differs conceptually. In Cremers and Pareek (2016), when a fund adds a security to an existing position, the "Duration" of that holding changes to reflect the deployment of fresh capital. Their measure captures this capital addition by weighting the holding period of each fund-firm pair according to when the capital was deployed. For example, if "a fund owns 5% of the total shares of IBM, 2% of which it bought three quarters back, with the remaining 3% of shares bought five quarters back. The weighted age of IBM today in this fund is $2/5 \times 3$ quarters + $3/5 \times 5$ quarters = 4.2 quarters." By contrast, we are not concerned with when the fund allocates incremental capital, so long as the fund continuously holds the stock. Funds may accumulate the position of a specific stock quickly or gradually, depending on the execution strategy, but this variation is unrelated to the investment horizon we seek to capture. Accordingly, we simply count the number of consecutive quarters a fund has held the stock. In fund-level tests, the two measures have a correlation of around 0.50.

[19] The mutual fund holdings data derived from Forms N-CSR, N-CSRS, N-Q, and N-30D exhibit several limitations in our setting. First, these data are reported with longer lags than Form 13F and were required only semiannually prior to May 2004, limiting their timeliness. Second, according to the WRDS user documentation, the mutual fund holdings data contain frequent reporting gaps, introducing substantial noise. Third, there are known difficulties in merging the Thomson Reuters holdings with CRSP fund summary files for fund classification, whereas Bushee (2001) directly classifies institutions by investment style. In untabulated tests, we replicate our results using mutual fund holdings; the findings remain statistically significant, albeit somewhat attenuated, likely due to the data-quality issues noted above.

3.3 Descriptive Statistics

We report descriptive statistics in Table 1. Panel A presents summary statistics, and Panel B presents the correlation matrix. The Horizon measure ranges from 1 quarter[20] to 135.64 quarters, and the average firm is held by active investment managers for 10.48 quarters. Horizon is positively correlated with the one-month future stock return, and the correlation is statistically significant at the 1% level.

Figure 1 plots histograms of the Horizon measure and its natural logarithm in Panels A and B, respectively. The average firm–quarter exhibits a share-weighted holding period of approximately nine quarters, with substantial dispersion. The distribution is highly right-skewed; accordingly, we use the logarithm in all empirical tests and report the distribution of *Ln(Horizon)*. The log-transformed measure displays spikes at values corresponding to non-logged lengths of 1, 2, 3, and 4 quarters. The prevalence of integer values of Horizon likely reflects two factors: (i) newly public firms often have relatively stable initial shareholder bases, and (ii) firms with few large active institutional holders are more likely to produce integer values after share-weighted aggregation.

Figure 2 presents examples of the time-varying firm-level *Horizon* measure for two firms: Apple Inc. and Goodyear Tire and Rubber Company. For Apple, we observe a sharp rise in Horizon during its early years, followed by a collapse after Steve Jobs's was fired in 1985. Horizon then increased, with some volatility around Jobs's return in 1997, and declined during the dot-com bust circa 2000. As Apple became a large-cap stock in the late 2000s and thereafter, it exhibited consistently high Horizon, consistent with many fund managers maintaining positions to limit deviations from benchmark indices. In recent years, Apple's *Horizon* has continued to accumulate alongside the AI boom, albeit with fluctuations reflecting market uncertainty about the firm's AI integration. For Goodyear, Horizon was volatile in 1986–87, when activist investor James Goldsmith initiated a greenmail campaign by acquiring more than 10% of the firm. To fend off the attack, Goodyear repurchased Goldsmith's stake and undertook a tender offer for other shareholders (Hicks, 1986), prompting a sharp decline in Horizon. Beyond this incident, the firm experienced large reductions in Horizon during a major restructuring in 1991, upon eliminating its dividend in 2003, and amid

[20] This minimum arises by construction, as at least one institutional investor must hold the firm for the measure to be well defined.

a U.S. Department of Justice probe and a defective-tire recall in 2022.

The two examples illustrate that the Horizon measure tracks large movements associated with firm–specific events. Because these events are largely idiosyncratic, we present them as anecdotal evidence of Horizon's responsiveness. In the main empirical tests, our objective is to use Horizon to differentiate firms in the cross-section. For instance, during macroeconomic shocks that prompt a broad move out of equities, Horizon will likely decline for most firms. However, the measure will be able to identify securities that maintain their Horizon *relatively* better than others, which is the cross-sectional variation of interest.

4 Main Results

4.1 Fama-MacBeth Regressions

To test our main hypothesis on the return predictability of *Horizon*, we estimate Fama–MacBeth cross-sectional regressions using monthly data from September 1983 to May 2024.[21] The model is specified as follows

$$Ret_{1i,t} = \beta_1 Ln(Horizon)_{i,t} + \Gamma X_{i,t} + \varepsilon \tag{1}$$

where $Ret_{1i,t}$ is the one-month future return for firm i in month t and $Ln(Horizon)_{i,t}$ is the natural logarithm of the Horizon measure. In addition to a univariate specification, we also include $X_{i,t}$ as the vector of control variables following prior literature, including the book-to-market ratio (BTM), the logarithm of market capitalization (*Size*), short-term reversal (Ret_{-1}), intermediate momentum ($Ret_{-12,-2}$), and operating profitability (*Profitability*). We also include firm age (*Age*) as an additional control variable, since Horizon increases mechanically as the firm ages. See more detailed definitions for the control variables in Appendix A. We estimate models separately for the full sample and for a sample excluding microcaps (e.g., Fama and French, 2015), defined as firms with a market capitalization below the lowest NYSE size quintile at each date. t-statistics

[21] We start by estimating firm-level, rather than portfolio-level, Fama–MacBeth regressions, following Ang et al. (2020). They show that while portfolio aggregation reduces idiosyncratic volatility, it destroys information that is not offset by the reduction in noise; therefore, they recommend firm–level Fama–MacBeth procedures for estimating characteristic premia.

are based on Newey and West (1987) standard errors with three lags.

In Table 2, Panel A, we report the main asset-pricing tests of Horizon using Fama–MacBeth regressions. Horizon exhibits modest predictive power for future returns in univariate specifications, and its explanatory strength increases after controlling for known risk factors. The Newey and West (1987) t-statistic rises to 5.20 in the full sample and 4.17 when microcaps are excluded. These estimates are statistically significant at the 1% level and satisfy the higher significance threshold that Harvey et al. (2016) recommend.

In Table 2, Panel B, we sort the continuous Horizon measure into monthly quintiles and re-estimate the same Fama–MacBeth regressions. We observe a monotonic increase in the estimated return premium from the lowest to the highest Horizon quintile, with a total spread of around 50 basis points (bps) across all specifications. The largest incremental effect occurs between the first and second quintiles, suggesting that avoiding the shortest-horizon managers captures the most pronounced mispricing. This pattern is consistent with the institutional myopia mechanism, as the return premium reflects demand imbalances created by short-horizon fund managers.

The Horizon characteristic is motivated by the search for securities less exposed to myopic institutional ownership. Specifically, we seek to identify stocks favored by long-horizon managers and avoided by short-horizon managers. If a firm's investor base is tilted toward longer-horizon owners, its stock should perform well not only in the short run but also in the long run. Consistent with this conjecture, Figure 3 shows that the initial t-statistic exceeds 5, remains above the Harvey et al. (2016) threshold of 3 for around twenty months, and stays above 2 for more than two years. This pattern is consistent with myopic managers' focus on near-term performance, which allows long-term managers, as identified by Horizon, to capture long-run mispricing.[22]

4.2 Cross-Sectional Tests

To examine the mechanism underlying the return predictability of Horizon, we conduct a host of cross-sectional tests using Fama–MacBeth regressions. Following Section 2.3, we use idiosyncratic volatility ($IVol$) and short-term reversal (measured by the trailing one-month return, Ret_{-1}) as

[22]Note that the returns we observe are an *on average* effect when holding the full portfolio of long-horizon firms. Fundamental discretionary managers may not have the capacity to hold such a large number of stocks. Thus, even though the returns appear relatively quickly in our portfolios, individual securities may take time to generate outperformance. This is where the risk lies for short-horizon managers.

cross-sectional split variables and estimate the following model:

$$Ret_{1i,t} = \beta_1 S_{i,t} \times Ln(Horizon)_{i,t} + \beta_2 S_{i,t} + \beta_3 Ln(Horizon)_{i,t} + \Gamma X_{i,t} + \varepsilon \tag{2}$$

where $S_{i,t} \in \{IVol, Ret_{-1}\}$ denotes the cross-sectional variable of interest. Based on our hypotheses, myopic managers find it more difficult to hold stocks with high idiosyncratic volatility or poor recent performance. These frictions drive the demand for the stock even further below the unconstrained equilibrium, resulting in higher expected returns. Consequently, within these subsamples, high-Horizon stocks should earn higher expected returns. We therefore expect β_1 to be positive (negative) when using idiosyncratic volatility (short-term reversal) as the cross-sectional split variable. We report results for these cross-sectional tests in Table 3, Panels A and B.

In Table 3 Panel A, the interaction of *Ln(Horizon)*×*IVol* is positive and statistically significant in both the full sample and the sample excluding microcaps, in line with the hypothesis that the Horizon factor better predicts future returns when the idiosyncratic volatility is high. Once the interaction is included, the main effect of Horizon becomes negative or statistically indistinguishable from zero. This suggests that after controlling for the dependent relationship of Horizon and *IVol*, i.e., holding the return premia associated with *IVol* constant, higher-Horizon stocks earn similar or *lower* returns. This is likely due to the difficulty in using Horizon to separate short-term and long-term managers once *IVol* is held constant. The main effect of *IVol* remains negative and significant after including the interaction. This is consistent with the notion that *IVol* sharpens the ability of Horizon to sort stocks, rather than Horizon being the underlying driver of the *IVol* anomaly documented previously (Ang et al., 2006; Fu, 2009).

In Table 3, Panel B, a similar pattern can be found for poorly performing stocks: the coefficient on *Ln(Horizon)*×Ret_{-1} is negative and significant, consistent with *Horizon* predicting returns more strongly when past returns are lower. However, the effects are concentrated in the ex-microcap sample. The interaction subsumes the Ret_{-1} main effect but does not materially alter the *Horizon* main effect. In the full sample, the interaction exhibits weak predictive power, and the main effects of Horizon and Ret_{-1} remain unchanged. One interpretation is that small stocks, which constitute more than half of the sample, are influenced more by market microstructure frictions, which drive the short-term reversal phenomenon, than by the institutional-myopia mechanism.[23]

As an additional specification, we split the sample each month based on whether a firm's *IVol* or Ret_{-1} lies above or below the NYSE median. Consistent with our hypotheses, when *IVol* is high or Ret_{-1} is low, it should be harder for myopic asset managers to hold the stock, making the main effects more pronounced. We report the results in Table B1 in the appendix. We find that *Horizon* predicts returns only in the high-*IVol* subsample. When splitting on Ret_{-1}, the economic magnitude of the Horizon effect is notably larger in the low-Ret_{-1} subsample.

Overall, the cross-sectional tests indicate that the *Horizon* measure exhibits stronger predictive power among stocks that are harder for myopic managers to hold, consistent with the hypotheses in Section 2.3 and Section 2.4. However, the results are also plausibly consistent with the superior fundamental analysis hypothesis in Section 2.5, as high *Ivol* and low Ret_{-1} firms may be firms that require more fundamental analysis to evaluate. In Section 5, we explore which of the two potential mechanisms is more likely to drive the results.

4.3 Time Series Tests

In this section, we corroborate the main findings with time-series tests by examining long–short, equal-weighted portfolio returns formed on Horizon.[24] Additionally, consistent with the cross-sectional tests, we construct two additional long–short portfolios using 3×2 conditional sorts: (i) first on idiosyncratic volatility (*IVol*) and then on Horizon, and (ii) first on the trailing one-month return (Ret_{-1}) and then on Horizon. The $IVol \times Horizon$ strategy goes long the High $IVol \times$High *Horizon* portfolio and short the High $IVol \times$Low *Horizon* portfolio, while the $Ret_{-1} \times Horizon$ strat-

[23]Note that the Ret_{-1} factor is subsumed in the ex-microcap sample. This is consistent with evidence that short-term reversal occurs primarily among firms with low turnovers (Medhat and Schmeling, 2022). Firms with longer-horizon shareholder bases tend to have lower turnover than those with short-horizon owners, and larger firms generally exhibit lower turnover than smaller firms. Thus, Horizon may subsume Ret_{-1}, but only in the ex-microcap sample.

Furthermore, Da et al. (2013) show that the long side of the reversal anomaly is attributable to liquidity shocks from fire sales, whereas short-sale constraints drive the short side. The Horizon characteristic could be correlated with either fire sales or short-sale constraints, given evidence of mutual fund fire sales and mutual funds' short-sale constraints (Coval and Stafford, 2007; Jones and Lamont, 2002). However, these microstructure forces cannot fully account for Horizon's predictive power: It continues to forecast returns up to over two years ahead, well beyond horizons typically associated with microstructure-based explanations. These observations motivate future research comparing institutional myopia and microstructure mechanisms for the reversal anomaly.

[24]As an alternative specification, we test the returns of value-weighted portfolios in Appendix B. The results remain qualitatively robust, albeit less statistically significant, consistent with our premise that Horizon's effects are primarily driven by small-cap stocks.

egy goes long the Low Ret_{-1}×High *Horizon* portfolio and short the Low Ret_{-1}×Low *Horizon* portfolio. x

In Table 4, we report summary statistics for the long–short portfolio returns. We construct the Horizon factor following Fama and French (2015). Each month, using the NYSE-based breakpoints, we first sort stocks into two size groups and then, within each size group, into three Horizon portfolios based on the 30th and 70th percentiles. The Horizon factor return is the average return on the two high-Horizon portfolios minus the average return on the two low-Horizon portfolios, using equal-weighted portfolio returns. The excess returns in Table 4 indicate an average of 25.7 bps per month for Horizon, comparable in magnitude to other factors.

4.3.1 Double-Sorted Portfolio Returns

In Table 5, we double-sort on Horizon and another characteristic and examine the portfolio return. In particular, each month we first sort the stocks into quintiles using *Size*, *IVol*, and Ret_{-1}, respectively, and then by Horizon within each quintile. Panel A demonstrates that the spread in performance across Horizon quintiles is larger for small stocks, with a return difference of 56.5 bps between the high- and low-Horizon portfolios. This pattern can be interpreted as small stocks having larger factor exposures in general, or that the Horizon factor has a larger effect in harder-to-hold securities (e.g., small caps). When double-sorting on Horizon and idiosyncratic volatility in Panel B, we find that the Horizon spread varies across *IVol* quintiles and is positive and statistically significant only in the highest-*IVol* quintile (at 63.6 bps), consistent with the Fama–MacBeth results. Similarly, when double-sorting on Ret_{-1}, the Horizon-sorted return spread is the most pronounced in the lowest-Ret_{-1} quintile (at 65.4 bps).

The heterogeneous efficacy of Horizon in separating securities with short-term holdings across subgroups provides suggestive evidence of the mechanism, complementing the cross-sectional tests. Smaller firms, stocks with higher idiosyncratic volatility, or stocks with lower prior returns are harder for myopic asset managers to hold. Accordingly, if the myopic managers were to hold these stocks, they would likely fall into the lower Horizon quintiles. This strengthens the Horizon measure's ability to distinguish between short- and long-horizon ownership, thereby increasing the excess-return spread between low- and high-Horizon portfolios.

4.3.2 Spanning Regressions

Next, we estimate spanning regressions that regress portfolio returns formed based on Horizon and other known return predictors, including the Fama–French five-factor model and the momentum factor (Carhart, 1997; Fama and French, 2015). Specifically, we test (i) the portfolios formed purely based on Horizon and (ii) conditional portfolios that, following the cross-sectional logic, go long the high-$IVol$ (low-Ret_{-1}) *and* high-Horizon stocks and go short the high-$IVol$ (low-Ret_{-1}) *and* low-Horizon stocks. If the Horizon factor provides predictive power orthogonal to the known return predictors, the intercept (alpha) from these time-series regressions should be positive and statistically significant. In particular, we estimate the following time series regression model

$$
\begin{aligned}
Ret_t = \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 RMW \\
+ \beta_5 CMA + \beta_6 UMD + \beta_7 Ret_{-1} + \beta_8 IVol + \varepsilon
\end{aligned} \tag{3}
$$

where Ret_t is the long-short portfolio return in month t.

This is confirmed by the results in Table 6. In Column (1), we regress the Horizon portfolio returns on the Fama-French Five factors, momentum (UMD), Ret_{-1}, and $IVol$; the portfolio yields an alpha of 12.2 bps per month, statistically significant at the 10% level. Horizon loads positively on MKT, HML, RMW, and CMA, and negatively on SMB and UMD. Thus, following managers with a long-term orientation effectively tilts toward firms with high profitability, low investment, and low prior returns. This aligns with the holdings of Warren Buffett, a prominent long-term investor in U.S. equities, whose portfolio exhibits positive loadings on HML, RMW, and CMA, and a negative loading on UMD (Frazzini et al., 2018).[25]

In Columns (2) and (3) of Table 6, the alphas increase to 18.7 bps and 31.5 bps per month, respectively, if we form double-sorted long-short portfolios with idiosyncratic volatility and short-term reversal; the alphas are significant at a level of 1%. These results provide further evidence that the Horizon factor is more effective at distinguishes between short- and long-horizon investment

[25]The evidence suggests that long-horizon managers align their portfolios with well-known asset-pricing factors, aside from momentum. This contrasts with Engelberg et al. (2020), who find that sell-side analysts exacerbate asset-pricing anomalies, suggesting they do not internalize known factors. While outside the scope of this paper, future research could examine heterogeneity in fund managers' incorporation of academic findings into investment processes, and how such heterogeneity varies with investment horizons.

managers when *IVol* is high or when Ret_{-1} is low. Since we control for the long-short portfolio returns formed on *IVol* and Ret_{-1} in the spanning regressions, the incremental outperformance is above and beyond the *IVol* and Ret_{-1} anomalies documented previously (Jegadeesh, 1990; Ang et al., 2006; Fu, 2009).

Overall, the time-series tests corroborate the insights from the main Fama-MacBeth regressions: Horizon captures abnormal returns associated with long-horizon investing and exploits institutional myopia. Horizon delivers statistically significant excess returns as a standalone factor, and these returns are incremental to standard factors. The time-series tests also provide evidence consistent with the cross-sectional hypotheses. When double-sorting Horizon with economically related characteristics such as *IVol* and Ret_{-1}, the factor's performance is stronger among stocks that are harder for myopic asset managers to hold.

5 Mechanism Tests

Thus far, we have documented that firms with longer Horizons earn higher returns, particularly in settings where myopic institutions are most constrained. These results are consistent with institutional myopia driving the Horizon premium, but they do not rule out an alternative explanation: that long-horizon investors are simply better fundamental analysts, and the returns are generated from superior information processing. In this section, we will disentangle these mechanisms by exploiting regulatory shocks that plausibly shift one mechanism without affecting the other. Specifically, we exploit (i) the 2004 SEC rule increasing mutual fund disclosure frequency, which heightened interim performance monitoring and thus short-termism, and (ii) the 2009 XBRL mandate, which increased the ability of sophisticated investors to conduct fundamental analysis. By examining how Horizon and its return predictive power respond to each shock, we can test whether institutional myopia or fundamental analysis best explains our findings.

5.1 Institutional Myopia

We test the institutional-myopia mechanism using the 2004 SEC rule that required mutual funds to disclose holdings quarterly rather than semiannually. By increasing the frequency of interim monitoring, the rule heightened managers' short-horizon incentives, as shown in the prior literature (Agarwal et al., 2018). Importantly, because roughly 40% of funds voluntarily disclosed quarterly prior to the mandate (e.g., Agarwal et al., 2015; Dyakov et al., 2022), the regulation had differential effects on the institutional myopia across the cross-section of funds. Although voluntary adoption entails *fund*-level self-selection, at the *firm* level the mandate provides plausibly exogenous variation in the share of myopic institutional ownership.[26]

If institutional myopia drives the Horizon premium, two predictions follow. First, firms more exposed to affected funds should experience a decline in Horizon after the rule, reflecting shorter holding periods by constrained institutions. Second, the return–Horizon sensitivity should strengthen in these firms, as greater myopia amplifies the mispricing channel.

Following the prior literature (Agarwal et al., 2018; Bourveau et al., 2023; Sani et al., 2023), we exploit the firm-level variation in exposure to the regulation and implement a DiD design to compare the change in the firms' Horizon and to assess the effect of Horizon on stock returns. In particular, we estimate the following models:

$$Ln(Horizon)_{i,t} = \beta_1 Treat_i \times Post_t + \Gamma X_{i,t} + \xi_i + \zeta_t + \varepsilon \tag{4}$$

$$\begin{aligned} Ret_{1i,t} = {} & \beta_1 Treat_i \times Post_t \times Ln(Horizon)_{i,t} + \beta_2 Treat_i \times Post_t \\ & + \beta_3 Treat_i \times Ln(Horizon)_{i,t} + \beta_4 Post_t \times Ln(Horizon)_{i,t} \\ & + \beta_5 Ln(Horizon)_{i,t} + \Gamma X_{i,t} + \xi_i + \zeta_t + \varepsilon \end{aligned} \tag{5}$$

We estimate Equation 4 on the firm-quarter level by retaining the latest observation for each quarter and restricting the sample to a symmetric window of 12 quarters before and 12 quarters after the mandate; we estimate Equation 5 at the firm–month level with 12 months before and 12 months after. Observations in the transitional period (2004Q2 and May 2004) are excluded. *Post* is an indicator variable that equals one for the post-May 2004 periods, and zero otherwise. Following prior literature, *Treat* equals one if the firm's affected ownership is above the sample median in the last quarter of the pre-regulatory window (April 2003 to April 2004). $X_{i,t}$ denotes

[26] Although we focus on institutional asset managers broadly in this paper, mutual funds constitute an economically significant share of institutional ownership, such that the disclosure change represents a relevant shock to overall institutional myopia.

the vector of control variables, defined as in Section 4. ξ_i and ζ_t are the firm- and time-fixed effects, respectively.[27] The standard errors are clustered on the quarter and month level, respectively.

We report results from estimating Equation 4 and Equation 5 in Table 7, Panels A and B, respectively. In Panel A, we find that the treated firms, which are more likely to be exposed to mutual fund holdings subject to short-term concerns, exhibit a significant decline in their Horizon measure. The effects are concentrated in the ex-microcap subsample, with an average decrease of 6.8 to 7.2 percentage points (pp), significant at the 1% level. This pattern is consistent with the notion that larger-cap firms, which are more likely to be monitored by the end-investors in funds, experience more pronounced effects from the disclosure shock.

Panel B shows that the Horizon–return relation strengthens in treated firms. The interaction *Ln(Horizon)*×*Treat*×*Post* is positive and significant at the 5% and 10% levels in the ex-microcap subsample. Economically, a 10 pp increase in Horizon translates into an additional 58–62 basis points of monthly returns for treated firms in the post-period, relative to control firms. In other words, Horizon became a sharper predictor of returns precisely in the subset of firms where the mandate increased myopia.

Taken together, these findings provide evidence that intensifying short-horizon pressure reduces institutional holding periods and amplifies the Horizon premium. In the next subsection, we contrast this setting with a regulatory shock that enhanced sophisticated investors' ability to conduct fundamental analysis rather than altering their horizon constraints.

5.2 Fundamental Analysis

To test the fundamental analysis as an alternative mechanism, we exploit the SEC's mandate requiring U.S. public firms to file XBRL exhibits, announced in April 2009. The SEC viewed XBRL as a means to help market participants "capture and analyze information more quickly and at less cost" (SEC, 2009). The mandate outlined a three-year, three-phase implementation based on firms' public float. We only exploit variation between the first and second waves of XBRL implementation, as prior research shows that the first implementation wave was the period when sophisticated institutions reaped the greatest benefits, as information asymmetry only initially

[27]Since the two-way fixed effects structure accounts for the variation in firm age, we omit *Age* as a control variable in the mechanism tests, following Graham et al. (2020).

increased (Blankespoor et al., 2014; Bhattacharya et al., 2018; Gomez et al., 2024).

If Horizon captures informational advantages, two predictions follow. First, increasing the information advantage for sophisticated investors should increase their willingness to hold firms subject to the XBRL mandate, leading to higher Horizon in treated firms. Second, the return–Horizon sensitivity should strengthen in treated firms after adoption, as Horizon more sharply identifies stocks where informed investors' research advantages matter.

To test these predictions, we re-estimate the difference-in-differences models from Section 5.1, tailoring the treatment and timing to the XBRL rollout. Specifically, we define the treated group as firms with public float exceeding $5 billion, which entered Phase I with filings for fiscal periods ending on or after June 15, 2009. Consistent with the phased timeline, we define the pre- and post-periods as June 2008 to May 2009 and June 2009 to May 2010, respectively.[28]

The results, reported in Table 8, provide little support for the fundamental analysis channel. In Panel A, we find no systematic change in Horizon for treated firms relative to controls. In Panel B, the coefficients on the *Ln(Horizon)*$\times$*Treat*$\times$*Post* interaction are small and statistically insignificant. In economic terms, the XBRL shock did not meaningfully alter either the level of Horizon or its ability to predict returns.Untabulated tests using the 2019 inline XBRL (iXBRL) mandate yield similarly null results (Call et al., 2023).

Combining the mechanism tests for institutional myopia and fundamental analysis, we find that institutional myopia is likely the dominant channel through which Horizon predicts returns, while we do not uncover consistent evidence supporting the fundamental-analysis mechanism. We caveat, however, that these tests only provide suggestive evidence and do not fully rule out a role for fundamental analysis.

6 Conclusion

We study whether differences in institutional investor holding horizons generate systematic return premia in the cross-section of stocks. We construct a firm-level measure of long-term ownership, Horizon, from 13F holdings and show that firms with longer Horizon earn higher subsequent

[28] Although we do not have an *ex ante* prediction for how a fundamental analysis shock should affect the equilibrium level of Horizon, we include the DiD with Horizon as the dependent variable for completeness.

returns. The relation is stronger when myopic pressures plausibly bind: among high idiosyncratic-volatility firms, in recent losers, and in smaller stocks. These effects hold both in the cross-section and in the time-series. To distinguish between competing mechanisms, we leverage two disclosure changes. When mutual fund disclosure frequency increased in 2004, treated firms experienced a decline in Horizon and a stronger Horizon–return sensitivity, consistent with amplified myopia. In contrast, when the XBRL mandate improved the informational advantage of sophisticated investors in 2009, we find no systematic change in Horizon and no strengthening of the Horizon–return relation. Taken together, the evidence indicates that agency frictions associated with institutional myopia, rather than informational advantages in fundamental analysis, drive the Horizon premium.

Our study is subject to three caveats. First, the 13F-based construction of Horizon focuses on large, active institutions and aggregates across strategies within fund complexes; within-complex heterogeneity may remain and affect our results. Second, the premium's strength in smaller and harder-to-hold stocks suggests that the premium may rise with transaction costs, which we do not attempt to estimate in this paper. This is partially offset by the inherently low turnover nature of a long-term investing strategy. Third, our mechanism tests, while grounded in plausibly exogenous shocks, examine relatively short windows around the reforms; limited statistical power and measurement error in treatment assignment could attenuate detectable effects. Relatedly, although the null results around XBRL weigh against the fundamental analysis mechanism, they do not rule it out entirely.

These limitations suggest several avenues for future research. First, work that sharpens identification of horizon-induced demand imbalances, perhaps by using an asset demand system as in Koijen and Yogo (2019), could test the mechanism of the model more directly. Relatedly, future work could connect the Horizon measure to recent work on heterogeneity in investor demand. For example, Koijen et al. (2024) develop a framework to identify which investors are most informative for asset prices and expected returns. Embedding Horizon in such a setting could clarify which types of investors drive the demand imbalances underlying the Horizon premium, and whether its predictive power is concentrated among particular institutional groups. Second, studying international investors' time horizons could help determine the generalizability of Horizon beyond the US capital market. Third, examining how Horizon interacts with real outcomes, such as capital allocation, M&A, and payout policy, could connect the asset-pricing effects to the real effects literature. We leave these questions to future research.

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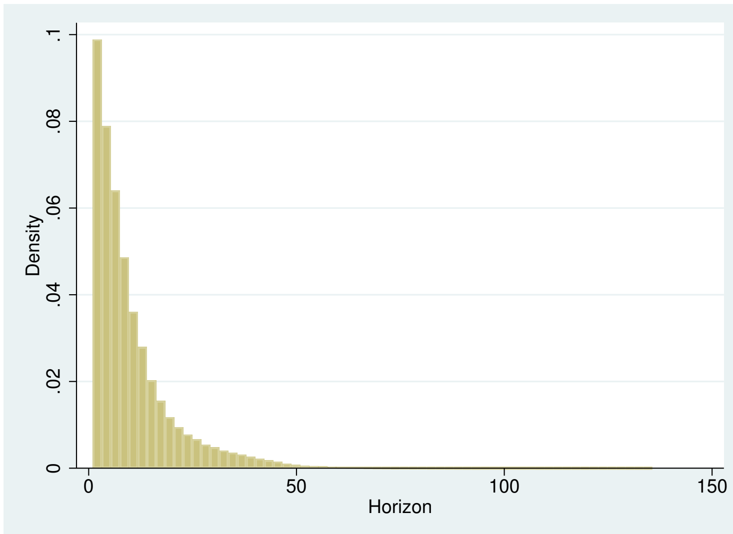
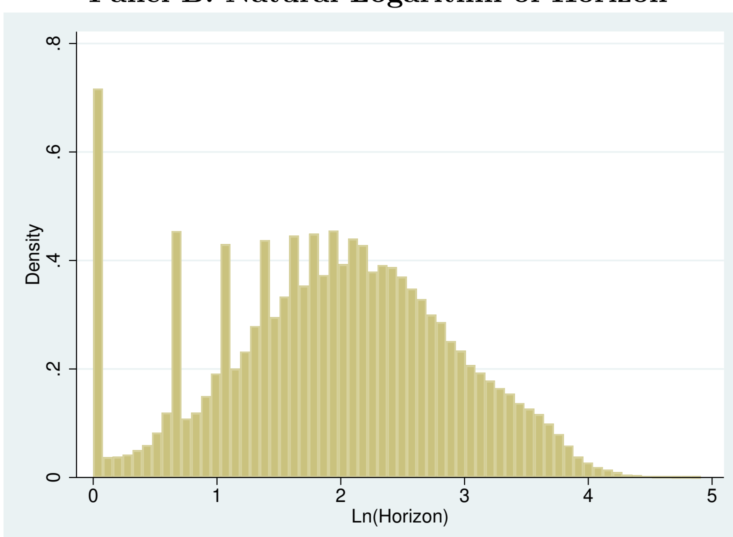
Figures and Tables

Figure 1: Distributions of the Horizon Measures

Panel A: Unscaled Horizon

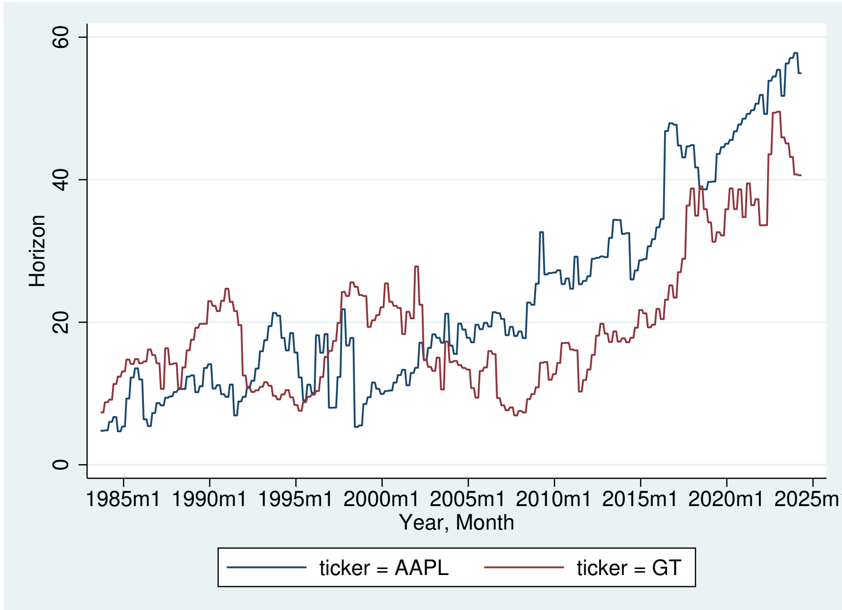


Panel B: Natural Logarithm of Horizon



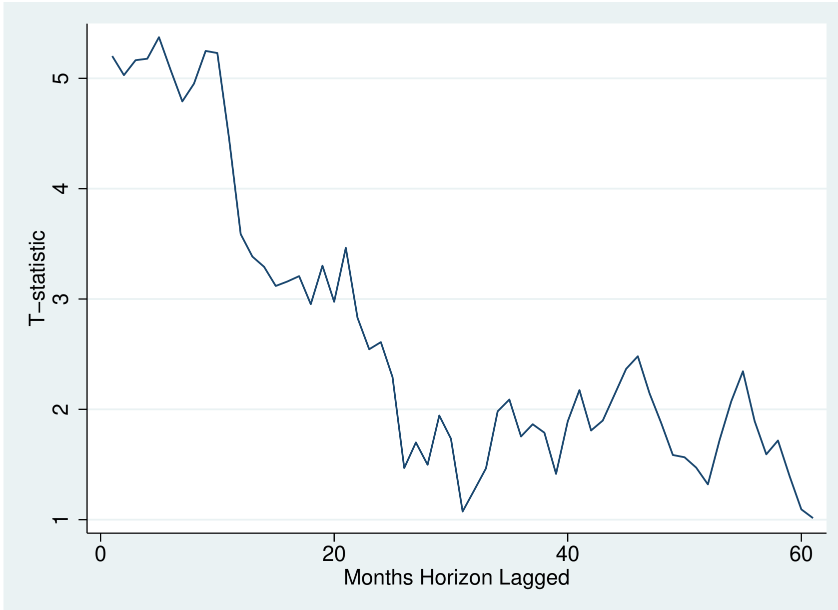
Note: The figures plot the histograms of *Horizon* and the natural logarithm of *Horizon* from September 1983 to May 2024. *Horizon* is measured as the share-weighted holding period of a firm at the quarterly level, based on data collected from 13-F filings.

Figure 2: Examples of Horizon Time Series - Apple and Goodyear



Note: The figure plots the time series of *Horizon* for Apple Inc. (blue) and Goodyear Tire and Rubber (red). Horizon is shown from September 1983 to May 2024.

Figure 3: Fama-MacBeth Horizon T-Statistic Over Time



Note: The figure plots the time-series of the t-statistic of *Ln(Horizon)* in Column (2) of Table 2 Panel A. t-statistics are calculated using Newey-West standard errors (Newey and West, 1987) with 3 lags used.

Table 1: Descriptive Statistics

This table reports descriptive statistics of the key variables used in the paper. Panel A presents the summary statistics for the firm-month level panel data, and Panel B presents the corresponding correlation matrix. The variables are defined in Appendix A. All continuous variables, except for Ret_1 and $Ln(Horizon)$, are winsorized at the 1% and 99% quantiles to limit the influence of outliers. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics

	Obs	Mean	Std. Dev	Min	Median	Max
Ret_1	1624099	0.813	17.693	-99.520	0.019	2399.660
Horizon	1624099	10.435	10.360	1.000	7.063	135.636
Ln(Horizon)	1624099	1.927	0.945	0.000	1.955	4.910
BTM	1523669	-7.595	0.909	-11.414	-7.523	-2.417
Size	1623929	12.607	2.109	5.988	12.464	18.588
Ret_{-1}	1623424	0.006	0.149	-0.729	0.000	1.995
$Ret_{-12,-2}$	1535992	0.088	0.561	-0.975	0.022	10.937
Profitability	1568229	0.029	0.203	-3.087	0.043	2.403
IVol	1435703	0.096	0.060	0.002	0.080	0.489
Age	1624099	4.609	1.011	0.693	4.745	6.293

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Ret_1	1.00***								
(2) *Ln(Duration)*	0.01***	1.00***							
(3) *Size*	0.03***	−0.09***	1.00***						
(4) *BTM*	−0.01***	0.51***	−0.42***	1.00***					
(5) Ret_{-1}	−0.01***	0.02***	−0.13***	0.07***	1.00***				
(6) $Ret_{-12,-1}$	−0.00	−0.05***	−0.33***	0.16***	0.00***	1.00***			
(7) *Profitability*	0.01***	0.11***	−0.04***	0.23***	0.03***	0.14***	1.00***		
(8) *IVol*	0.00***	−0.34***	−0.04***	−0.42***	0.01***	0.07***	−0.30***	1.00***	
(9) *Age*	0.01***	0.45***	0.00***	0.33***	0.01***	0.02***	0.11***	−0.25***	1.00***

Table 2: Fama-MacBeth Regressions

This table reports the Fama-MacBeth regressions at the firm-month level from September 1983 to May 2024. In Panel A, *Ln(Horizon)* is the natural log of *Horizon*. In Panel B, *Horizon* quintiles are formed each month using the NYSE breakpoints. In both panels, Columns (1) and (2) contain the entire sample of firms; Columns (3) and (4) exclude microcaps (NYSE-based lowest quintile), according to Fama and French (1995). The control variables are defined in Appendix A and are winsorized at the 1% level in both tails to limit the influence of outliers.

Panel A: Fama-MacBeth Regressions - Continuous Horizon

VARIABLES	(1) Ret_1	(2) Ret_1	(3) Ret_1	(4) Ret_1
Ln(Horizon)	0.158**	0.209***	0.139*	0.166***
	(2.43)	(5.20)	(1.84)	(4.17)
BTM		0.264***		0.157*
		(3.73)		(1.89)
Size		-0.114***		-0.084**
		(-3.21)		(-2.21)
Ret_{-1}		-3.338***		-1.577***
		(-7.83)		(-3.73)
$Ret_{-12,-2}$		0.484**		0.413**
		(2.27)		(2.00)
Profitability		2.175***		1.688***
		(5.89)		(4.34)
Age		0.059		0.074
		(0.98)		(1.27)
Constant	0.560	3.396***	0.525	2.237***
	(1.51)	(4.56)	(1.45)	(2.59)
Observations	1,624,099	1,440,838	966,630	882,707
R-squared	0.005	0.039	0.009	0.055
Number of groups	489	489	489	489
Including microcaps	Yes	Yes	No	No

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel B: Fama-MacBeth Regressions - Horizon Quintiles

VARIABLES	(1) Ret_1	(2) Ret_1	(3) Ret_1	(4) Ret_1
Horizon Q1	0.542*	3.331***	0.523	2.160**
	(1.66)	(4.51)	(1.64)	(2.51)
Horizon Q2	0.832***	3.639***	0.711**	2.373***
	(2.62)	(4.97)	(2.43)	(2.77)
Horizon Q3	0.901***	3.729***	0.856***	2.515***
	(3.13)	(5.11)	(3.19)	(2.91)
Horizon Q4	0.964***	3.813***	0.895***	2.570***
	(3.55)	(5.20)	(3.55)	(2.97)
Horizon Q5	0.942***	3.834***	0.890***	2.598***
	(4.12)	(5.28)	(4.18)	(3.02)
BTM		0.264***		0.157*
		(3.73)		(1.90)
Size		-0.109***		-0.078**
		(-3.07)		(-2.08)
Ret_{-1}		-3.328***		-1.587***
		(-7.80)		(-3.76)
$Ret_{-12,-2}$		0.481**		0.415**
		(2.24)		(2.01)
Profitability		2.175***		1.686***
		(5.91)		(4.34)
Age		0.077		0.078
		(1.34)		(1.33)
Observations	1,624,099	1,440,838	966,630	882,707
R-squared	0.006	0.040	0.011	0.058
Number of groups	489	489	489	489
Including microcaps	Yes	Yes	No	No

t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Fama-MacBeth Regressions - Cross-Sectional Regressions

This table reports the Fama-MacBeth cross-sectional regressions at the firm level from September 1983 to May 2024. Panel A and Panel B present the cross-sectional regressions on the idiosyncratic volatility ($IVol$) and the one-month trailing return (Ret_1), respectively. In both panels, Columns (1) and (2) contain the entire sample of firms; Columns (3) and (4) exclude microcaps (NYSE-based lowest quintile), according to Fama and French (1995). See detailed variable definition in Appendix A. The control variables are winsorized at the 1% level in both tails to limit the influence of outliers.

Panel A: Cross-Sectional Regression: Idiosyncratic Volatility

	(1)	(2)	(3)	(4)
VARIABLES	Ret_1	Ret_1	Ret_1	Ret_1
Ln(Horizon)×*IVol*	2.769***	1.845**	3.106***	3.925***
	(3.86)	(2.31)	(3.25)	(4.19)
Ln(Horizon)	-0.163**	0.011	-0.171**	-0.160**
	(-2.27)	(0.15)	(-2.39)	(-2.36)
IVol	-6.424***	-3.395*	-8.581***	-9.233***
	(-3.14)	(-1.67)	(-3.72)	(-4.40)
Observations	1,435,703	1,349,591	873,164	836,312
R-squared	0.021	0.048	0.028	0.068
Number of groups	489	489	489	489
Controls	No	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes
Including microcaps	Yes	Yes	No	No

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: Cross-Sectional Regression: Trailing One-Month Return

	(1)	(2)	(3)	(4)
VARIABLES	Ret_1	Ret_1	Ret_1	Ret_1
$Ln(Horizon) \times Ret_{-1}$	-0.360*	-0.286	-0.965***	-1.312***
	(-1.72)	(-1.10)	(-3.73)	(-4.81)
Ln(Horizon)	0.177***	0.206***	0.140**	0.159***
	(2.82)	(6.03)	(2.01)	(4.55)
Ret_{-1}	-2.338***	-3.013***	0.440	0.620
	(-3.70)	(-3.97)	(0.71)	(0.94)
Observations	1,623,424	1,349,591	966,244	836,312
R-squared	0.013	0.048	0.021	0.068
Number of groups	489	489	489	489
Controls	No	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes
Including microcaps	Yes	Yes	No	No

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Time Series Average Returns of of Long Short Factors

This table presents the average equal-weight returns across 489 months (September 1983 - May 2024) of the long-short portfolios. The Sharpe ratio is calculated by assuming the risk-free rate is 0. The long-short portfolio is constructed on 3×2 sorts of the factor and size, as in Fama and French (2015). *IVol*×*Horizon* uses a 3×2 sort on *Horizon* and *IVol*, going long the High *IVol*×High *Horizon* portfolio and short the High *IVol*×Low *Horizon* portfolio. Ret_{-1}×*Horizon* is constructed similarly, using Ret_{-1} in the place of *IVol*.

	Obs	Mean	S.E.	Min	Median	Max	Sharpe
MKT	489	0.721	0.203	-23.190	1.180	13.580	0.555
SMB	489	0.008	0.132	-15.540	-0.050	18.460	0.009
CMA	489	0.224	0.095	-7.080	0.060	9.010	0.370
HML	489	0.198	0.142	-13.830	0.000	12.860	0.219
RMW	489	0.412	0.111	-18.950	0.390	13.050	0.581
UMD	489	0.463	0.202	-34.300	0.600	18.000	0.359
Horizon	489	0.257	0.116	-13.774	0.144	12.545	0.347
IVol×*Horizon*	489	0.191	0.219	-14.977	-0.052	25.172	0.136
Ret_{-1}×*Horizon*	489	0.998	0.160	-22.006	0.722	20.420	0.975

Table 5: Excess Returns from 5×5 Sorts on Horizon

This table reports the equal-weighted monthly excess returns for 5×5 portfolios conditionally sorted on other factors and *Horizon* from September 1983 to May 2024. Firms are first sorted monthly into quintiles by lagged market value of equity (*Size*), idiosyncratic volatility (*IVol*), or short-term reversal (Ret_{-1}). Within each quintile, the portfolio is then conditionally sorted into quintiles by *Horizon*. Portfolio sorts are based on NYSE breakpoints.

Panel A: 5×5 Portfolio based on Horizon and Size

			Duration			
	1	2	3	4	5	Diff (5-1)
Size						
1	0.478	0.868	0.921	1.064	1.043	0.565***
2	0.621	0.823	0.885	1.060	1.002	0.381**
3	0.573	0.864	0.941	0.881	0.948	0.375**
4	0.652	0.752	0.783	0.953	0.923	0.270
5	0.717	0.882	0.696	0.836	0.774	0.056
Total	0.649	0.911	0.963	0.987	0.916	0.267*

Panel B: 5×5 Portfolio based on Horizon and Idiosyncratic Volatility

			Duration			
	1	2	3	4	5	Diff (5-1)
IVol						
1	0.840	0.887	0.952	0.883	0.808	-0.032
2	0.910	0.888	0.961	0.907	0.860	-0.050
3	0.860	0.937	0.944	0.922	0.945	0.085
4	0.895	0.928	0.921	0.987	0.988	0.093
5	0.616	0.961	0.971	1.175	1.252	0.636***
Total	0.649	0.911	0.963	0.987	0.916	0.267*

Panel C: 5×5 Portfolio based on Horizon and Short-Term Reversal

	Duration					
	1	2	3	4	5	Diff (5-1)
Ret_{-1}						
1	0.891	1.354	1.442	1.445	1.545	0.654***
2	0.750	0.973	0.985	1.172	1.026	0.276*
3	0.752	0.925	0.886	0.997	0.950	0.198
4	0.682	0.711	0.780	0.837	0.718	0.035
5	0.168	0.507	0.509	0.592	0.424	0.256
Total	0.649	0.911	0.963	0.987	0.916	0.267*

Table 6: Spanning Regressions

This table presents the spanning regressions, where we regress the equal-weighted monthly factor returns on the Fama-French Five factors, momentum, short-term reversal, and idiosyncratic volatility from September 1983 to May 2024. In Column (1), the dependent variable is the pure Horizon factor, constructed on equal-weighted 3×2 sort of Horizon×Size, as in Fama and French (2015). In Column (2), the dependent variable uses a 3×2 sort on *IVol*×*Horizon*, going long the High *IVol*×High *Horizon* portfolio and short the High *IVol*×Low *Horizon* portfolio. In Column (3), the dependent variable is constructed similarly to Column (2), using Ret_{-1} in the place of *IVol*.

	(1)	(2)	(3)
VARIABLES	*Horizon*	*IVol*×*Horizon*	Ret_{-1}×*Horizon*
MKT	0.051**	0.039*	0.045*
	(2.32)	(1.77)	(1.88)
SMB	-0.081**	0.106***	-0.087***
	(-2.34)	(3.13)	(-2.90)
HML	0.079*	0.074*	0.074
	(1.70)	(1.81)	(1.41)
RMW	0.210***	0.173***	0.237***
	(3.73)	(3.41)	(4.80)
CMA	0.313***	0.155***	0.182***
	(5.57)	(2.74)	(2.77)
UMD	-0.137***	-0.126***	-0.074***
	(-4.84)	(-5.47)	(-3.03)
Ret_{-1}	0.060**	-0.003	-0.882***
	(1.97)	(-0.10)	(-24.67)
IVol	-0.277***	0.976***	-0.163***
	(-6.72)	(23.13)	(-3.28)
Constant	0.122*	0.187***	0.315***
	(1.85)	(2.71)	(4.08)
Observations	489	489	489
R-squared	0.777	0.923	0.831

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Mechanism Tests Using the Mutual Fund Disclosure Shock

This table reports the mechanism tests using the 2004 mutual fund portfolio disclosure mandate as an exogenous shock. The DiD regressions are run on the panel data on firm-quarter and firm-month levels for Panels A and B, respectively. The treated group is defined as the firms with above-median percentage of mutual fund holdings that are affected by the regulation (See more details in Section 5.1). In Panel A, the regressions are on the firm-quarter level with the pre-(post-)treatment period being 2001Q2 to 2004Q1 (2004Q3 to 2007Q2), and the last monthly observation of each quarter is retained; in Panel B, the regressions are on the firm-month level with the pre-(post-)treatment period is May 2003 to Apr 2004 (Jun 2004 to May 2005). See detailed variable definition in Appendix A. The control variables are winsorized at the 1% level in both tails to limit the influence of outliers.

Panel A: The Effects on Horizon

	(1)	(2)	(3)	(4)
VARIABLES	*Ln(Horizon)*	*Ln(Horizon)*	*Ln(Horizon)*	*Ln(Horizon)*
Treat×Post	-0.010	-0.016	-0.068***	-0.072***
	(-0.44)	(-0.74)	(-4.02)	(-3.97)
Observations	80,109	76,052	49,096	47,065
R-squared	0.668	0.684	0.772	0.787
Controls	No	Yes	No	Yes
Including microcaps	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: The Effects on Stock Return

VARIABLES	(1) Ret_1	(2) Ret_1	(3) Ret_1	(4) Ret_1
Ln(Horizon)	0.817**	0.167	0.533	0.684*
	(2.13)	(0.47)	(1.08)	(1.80)
Ln(Horizon)×Post	1.226**	0.711*	0.561	-0.050
	(2.30)	(1.74)	(1.23)	(-0.12)
Ln(Horizon)×Treat	0.363	-0.015	0.269	-0.745*
	(0.90)	(-0.04)	(0.54)	(-1.88)
Treat×Post	-0.686	-0.120	-2.204**	-1.535
	(-0.57)	(-0.11)	(-2.25)	(-1.53)
Ln(Horizon)×Treat×Post	0.307	0.164	0.627**	0.585*
	(0.73)	(0.39)	(2.27)	(1.87)
Observations	81,033	76,471	50,942	48,562
R-squared	0.159	0.214	0.198	0.246
Controls	No	Yes	No	Yes
Including microcaps	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Mechanism Test Using the XBRL Mandate

This table reports the mechanism tests using the XBRL mandate as an exogenous shock for fundamental analysis. The treated group is defined as the firms subject to the regulation in Phase 1. The pre-period is Jun 2008 to May 2009, while the post-period is Jun 2009 to May 2010. In Panel A, the regressions are run on the firm-quarter level; in Panel B, the regressions are run on the firm-month level. See detailed variable definition in Appendix A. The control variables are winsorized at the 1% level in both tails to limit the influence of outliers.

Panel A: The Effects on Horizon

	(1)	(2)	(3)	(4)
VARIABLES	*Ln(Horizon)*	*Ln(Horizon)*	*Ln(Horizon)*	*Ln(Horizon)*
Treat×Post	0.037	0.029	0.033	0.027
	(0.54)	(0.41)	(0.63)	(0.49)
Observations	20,937	19,599	13,158	12,480
R-squared	0.811	0.806	0.874	0.875
Controls	No	Yes	No	Yes
Including microcaps	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel B: The Effects on Stock Return

VARIABLES	(1) Ret_1	(2) Ret_1	(3) Ret_1	(4) Ret_1
Ln(Horizon)	0.864*	0.310	1.310*	0.470
	(1.72)	(0.59)	(1.80)	(0.79)
Ln(Duration)×Post	0.643	0.440	0.385	-0.612
	(1.15)	(0.85)	(0.74)	(-1.24)
Ln(Duration)×Treat	-1.679	-0.439	-1.388	0.038
	(-1.05)	(-0.43)	(-0.72)	(0.03)
Treat×Post	-0.420	6.230**	0.656	2.063
	(-0.12)	(2.48)	(0.23)	(0.82)
Ln(Duration)×Treat×Post	0.193	-1.996**	-0.233	-0.659
	(0.15)	(-2.32)	(-0.30)	(-0.94)
Observations	55,123	51,812	35,245	33,484
R-squared	0.217	0.295	0.325	0.413
Controls	No	Yes	No	Yes
Including microcaps	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendices

A Variable Definitions

Variable	Data Source	Definition
Ln(Horizon)	LSEG s34	The logarithm of one plus holding shares-weighted average of active institutional investors' holding horizon, measured as the consecutive number of quarters for holdings (See more details in Section 3.2)
Horizon Qn	LSEG s34	An indicator variable equal to 1 if the firm's Horizon in the current quarter is within the n-th quintile across the cross section of firms
Ret_1	CRSP	The monthly return after the *Horizon* calculation date
BTM	Compustat	The logarithm of the book value of equity divided by the market value of equity
Size	Compustat	The logarithm of the market value of equity
Ret_{-1}	CRSP	The monthly return prior to the *Horizon* calculation date
$Ret_{-12,-2}$	CRSP	The cumulative return from the 12th month to the 1st month prior to the *Horizon* calculation date
Profitability	Compustat	The operating profitability, defined as the operating income after depreciation divided by the book value of equity
$IVol$	CRSP & French's Data Library	The idiosyncratic volatility of the stock, estimated with the Fama-French five-factor model on the monthly stock return and a rolling window of two years
Age	CRSP	The logarithm of one plus firm age, where the firm age is the number of calendar months since the company was first available in CRSP.

B Alternative Specifications

Table B1: Fama Macbeth Regressions - Cross Sectional Splits

This table reports the Fama-MacBeth cross-sectional regressions by splitting the sample from September 1983 to May 2024. Panel A and Panel B present the cross-sectional regressions by splitting on the idiosyncratic volatility ($IVol$) and the one-month trailing return (Ret_1), respectively. In both panels, Columns (1) and (2) contain the entire sample of firms; Columns (3) and (4) exclude microcaps (NYSE-based lowest quintile), according to Fama and French (1995). See detailed variable definition in Appendix A. The control variables are winsorized at the 1% level in both tails to limit the influence of outliers.

Panel A: Cross Sectional Split - Idiosyncratic Volatility

	(1)	(2)	(3)	(4)
VARIABLES	Ret_1	Ret_1	Ret_1	Ret_1
Ln(Horizon)	0.017	0.275***	0.035	0.248***
	(0.63)	(5.87)	(1.14)	(5.15)
Ret_{-1}	-5.262***	-3.439***	-4.517***	-1.433***
	(-10.74)	(-8.06)	(-8.41)	(-3.46)
$IVol$	0.788	-0.861	-0.993	-2.428
	(0.21)	(-0.59)	(-0.26)	(-1.48)
Constant	1.251*	4.041***	1.980**	2.233**
	(1.79)	(5.30)	(2.46)	(2.34)
Observations	472,766	876,825	377,620	458,692
R-squared	0.069	0.041	0.082	0.057
Number of groups	489	489	489	489
Controls	Yes	Yes	Yes	Yes
Including microcaps	Yes	Yes	No	No
Split	Low $IVol$	High $IVol$	Low $IVol$	High $IVol$

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel B: Cross Sectional Split - Trailing One-Month Return

VARIABLES	(1) Ret_1	(2) Ret_1	(3) Ret_1	(4) Ret_1
Ln(Horizon)	0.239***	0.139***	0.195***	0.104**
	(6.06)	(3.11)	(4.95)	(2.49)
Ret_{-1}	-5.949***	-2.497***	-1.477**	-1.387***
	(-8.39)	(-5.91)	(-2.19)	(-3.10)
IVol	-1.913	0.368	-4.642**	0.449
	(-1.09)	(0.20)	(-2.27)	(0.22)
Constant	2.671***	2.841***	2.158**	2.030**
	(3.76)	(3.97)	(2.49)	(2.32)
Observations	693,527	656,064	405,621	430,691
R-squared	0.050	0.051	0.072	0.069
Number of groups	489	489	489	489
Controls	Yes	Yes	Yes	Yes
Including microcaps	Yes	Yes	No	No
Split	Low Ret_{-1}	High Ret_{-1}	Low Ret_{-1}	High Ret_{-1}

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table B2: Value-Weighted Excess Returns from 5×5 Sorts on Horizon

This table reports the value-weighted monthly excess returns for 5×5 portfolios conditionally sorted on other factors and *Horizon* from September 1983 to May 2024. Firms are first sorted monthly into quintiles by lagged market value of equity (*Size*), idiosyncratic volatility (*IVol*), or short-term reversal (Ret_{-1}). Within each quintile, the portfolio is then conditionally sorted into quintiles by *Horizon*. Portfolio sorts are based on NYSE breakpoints.

Panel A: 5×5 Portfolio based on Horizon and Size

			Duration			
	1	2	3	4	5	Diff (5-1)
Size						
1	0.483	0.825	0.826	0.961	0.952	0.470***
2	0.621	0.833	0.888	1.050	0.970	0.349**
3	0.561	0.853	0.932	0.882	0.940	0.379**
4	0.655	0.738	0.784	0.944	0.936	0.281
5	0.755	0.809	0.692	0.836	0.594	-0.162
Total	0.531	0.799	0.787	0.794	0.750	0.219

Panel B: 5×5 Portfolio based on Horizon and Idiosyncratic Volatility

			Duration			
	1	2	3	4	5	Diff (5-1)
IVol						
1	0.814	0.888	0.771	0.869	0.541	-0.273**
2	0.771	0.837	0.816	0.786	0.826	0.054
3	0.755	0.749	0.975	0.669	0.923	0.168
4	0.632	0.796	0.759	0.953	1.045	0.413*
5	0.522	0.615	0.748	1.054	1.203	0.680***
Total	0.531	0.799	0.787	0.794	0.750	0.219

Panel C: 5×5 Portfolio based on Horizon and Short-Term Reversal

	Duration					
	1	2	3	4	5	Diff (5-1)
Ret_{-1}						
1	0.529	0.893	0.888	0.886	0.906	0.378*
2	0.879	0.941	0.979	0.884	0.904	0.025
3	0.571	0.812	0.864	0.960	0.823	0.252
4	0.662	0.721	0.783	0.787	0.671	0.009
5	0.316	0.539	0.764	0.521	0.564	0.248
Total	0.531	0.799	0.787	0.794	0.750	0.219

Table B3: Value-Weighted Spanning Regressions

This table presents the spanning regressions, where we regress the value-weighted monthly factor returns on the Fama-French Five factors, momentum, short-term reversal, and idiosyncratic volatility from September 1983 to May 2024. In Column (1), the dependent variable is the pure Horizon factor, constructed on equal-weighted 3×2 sort of Horizon×Size, as in Fama and French (2015). In Column (2), the dependent variable uses a 3×2 sort on $IVol \times Horizon$, going long the High $IVol$×High $Horizon$ portfolio and short the High $IVol$×Low $Horizon$ portfolio. In Column (3), the dependent variable is constructed similarly to Column (2), using Ret_{-1} in the place of *IVol*.

VARIABLES	(1) *Horizon*	(2) $IVol \times Horizon$	(3) $Ret_{-1} \times Horizon$
MKT	0.017	0.011	-0.020
	(0.76)	(0.31)	(-0.65)
SMB	-0.130***	0.022	-0.377***
	(-3.42)	(0.41)	(-8.19)
HML	0.026	-0.057	0.002
	(0.59)	(-0.80)	(0.04)
RMW	0.213***	0.017	0.057
	(3.61)	(0.21)	(0.78)
CMA	0.315***	-0.117	0.244***
	(5.26)	(-1.02)	(3.45)
UMD	-0.117***	-0.028	-0.077***
	(-5.13)	(-0.86)	(-3.24)
Ret_{-1}	0.049	0.061	-1.035***
	(1.56)	(1.40)	(-26.92)
IVol	-0.199***	1.021***	-0.110**
	(-4.16)	(15.18)	(-2.04)
Constant	0.059	0.321***	0.023
	(0.78)	(3.04)	(0.22)
Observations	489	489	489
R-squared	0.673	0.812	0.779

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1