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Investor Turnover and Corporate Investment Efficiency: Evidence from S&P 500 Firms

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Abstract: The trading horizon of a firm's shareholders shapes both their incentive to monitor managers and the pressure they place on short-term performance. This paper examines whether investor turnover is related to the efficiency of corporate investment. Using 648 firm-year observations of 325 non-financial S&P 500 constituents over fiscal years 2013–2016, investment inefficiency is measured as the absolute deviation of capital and R&D expenditure from the level predicted by sale s growth, and investor turnover is measured as annual share turnover. After controlling for stock illiquidity, firm characteristics, and sector and year fixed effects, higher turnover is associated with significantly larger investment deviations; a one -standard-deviation increase in turnover raises inefficiency by about 14% of its sample mean. The effect is concentrated in over-investment, whereas under-investment is unrelated to turnover, which is consistent with a monitoring channel in which short -horizon shareholders exert weaker discipline over free cash flow. The association holds under a Q-based expected-investment model, a capital-expenditure-only measure, alternative turnover definitions, and portfolio sorts. The findings identify the trading horizon of the shareholder base as a relevant governance attribute for corporate capital allocation.

Keywords: Investor turnover, investment horizon, investment efficiency, over-investment, institutional investors, corporate governance.

1. Introduction

Capital investment is the principal channel through which firms create long-term value, yet observed investment often departs from the level justified by growth opportunities. Agency theory predicts that managers with access to free cash flow invest beyond the value-maximizing level to enlarge the resources under their control [1–3], whereas information asymmetry and debt overhang lead firms to forgo projects with positive net present value [4, 5]. A large empirical literature therefore treats investment efficiency—the absence of both over- and under-investment—as an outcome of the firm's information and governance environment, documenting the roles of financial reporting quality [6–9], internal control over financial reporting [10], accounting conservatism [11], and the quality of analyst forecasts [12].

Shareholders are a central part of that governance environment, but they differ sharply in how long they hold their shares. The concern that frequent trading by investors shortens corporate horizons has a long history in both policy debates and theory [13–16]. Empirically, firms held by high-turnover investors obtain worse terms in acquisitions [17], cut R&D to meet earnings targets [18], and reduce long-term investment after short-horizon ownership rises [19], while long-horizon institutions are associated with more effective monitoring and better corporate decisions [20–22]. At the same time, short-horizon investors can be better informed [23], can help firms adapt to radical change [24], and can discipline managers through the threat of exit [25, 26]. Whether a high-turnover shareholder base pushes investment toward or away from its efficient level is therefore an empirical question.

This paper addresses that question for large U.S. firms. Investment inefficiency is measured as the absolute residual from the expected-investment model of Biddle et al. [7], and investor turnover is measured as annual share turnover, which captures the frequency with which the shareholder base trades and has been used as a proxy for shareholder horizons in prior work [27]. Because turnover also reflects stock liquidity, which has independent effects on governance and investment [28, 29], the main specifications control for the Amihud [30] illiquidity ratio.

Using 648 firm-year observations of 325 non-financial S&P 500 firms, the analysis yields three main findings. First, investor turnover is positively and significantly associated with investment inefficiency: a one-standard-deviation increase in turnover raises the absolute deviation from expected investment by 0.54 percentage points of lagged assets, about 14% of the sample mean. Second, the relation is driven by over-investment, while turnover has no detectable relation with the magnitude of under-investment. Third, the result holds under a Q-based expected-investment model, a capital-expenditure-only investment measure, alternative turnover definitions, and quintile portfolio sorts, in which the frequency of over-investing firms rises from 35% in the lowest turnover quintile to 52% in the highest.

The paper contributes to two strands of research. It extends the investment-efficiency literature, which has concentrated on the quality of information, by showing that the trading horizon of the shareholder base is an additional determinant of capital allocation. It also complements studies of investor horizons [17, 21, 22, 31] by showing that, among large firms, the dominant cost of a high-turnover shareholder base is weaker discipline over excess investment rather than myopic under-investment. Section II reviews the literature and develops the hypotheses, Section III describes the data and research design, Section IV reports the empirical results, and Section V concludes.

2. Literature Review and Hypotheses

2.1. Investment Efficiency

In frictionless markets, firms invest until the marginal return on capital equals its cost, so investment responds only to growth opportunities. Two classes of frictions generate systematic deviations. The first is managerial agency: managers derive private benefits from firm size and may spend free cash flow on value-destroying projects or acquisitions [2, 32, 33], a tendency that weak disclosure reinforces [34]. Richardson [35] documents that over-investment is concentrated among firms with the highest free cash flow and is mitigated by certain governance structures. The second class arises from information asymmetry and financing frictions, which raise the cost of external capital and lead to under-investment [4, 5]; managerial preferences for a quiet life produce a similar shortfall [36].

Empirical work operationalizes efficiency as the deviation of actual investment from a predicted benchmark. Richardson [35] models expected investment as a function of growth opportunities and firm characteristics, while Biddle et al. [7] use a parsimonious specification in which next-year investment depends on current sales growth and classify positive and negative residuals as over- and under-investment. These designs underpin evidence that higher reporting quality, stronger internal control, conservatism, and better analyst information reduce investment deviations [6, 10–12, 37, 38], and they have been applied to private firms in emerging markets [9].

2.2. Investor Turnover and Corporate Decisions

Investor turnover can affect investment efficiency through three channels. The monitoring channel builds on the observation that large and committed shareholders have the incentive to gather information and intervene [39]. Monitoring is costly and its benefits accrue gradually, so investors who expect to hold a stock for only a short time capture little of its value. Consistent with this view, long-horizon independent institutions are the ones that discipline managers [20], and long-term investors are associated with stronger governance, fewer managerial misbehaviors, and more value-enhancing decisions [21, 22]. Long-horizon ownership also lowers investment–cash flow sensitivity and the cost of equity [31, 40]; stable and pressure-insensitive institutional ownership is associated with better operating performance and valuation [41–43]; and institutions engage through shareholder proposals and private negotiations [44, 45], with even passive owners influencing governance [46]. Short-horizon investors, by contrast, tend to sell rather than intervene when problems arise [47], and firms dominated by such investors make worse acquisition decisions [17]. Exit can discipline managers [25, 26, 48], and the threat of exit is more effective when stock liquidity is high [49].

The myopia channel holds that short-horizon investors reward current earnings and therefore pressure managers to cut long-term investment [13–15]. Survey evidence indicates that executives would sacrifice economic value to meet short-term earnings targets [50]. Transient institutions are associated with myopic R&D cuts [18] and with valuations that overweight near-term earnings [51], and they shape CEO contracts toward short-term performance [52]. Increases in short-term ownership around index inclusions are followed by reductions in long-term investment [19], and investor horizon is linked to managerial short-termism more broadly [53]. Polk and Sapienza [27] show that investment is more sensitive to mispricing in firms with high share turnover, consistent with managers catering to short-horizon shareholders, and Bebchuk and Stole [16] show that short-term objectives can produce either under- or over-investment depending on what the market observes. Comparisons of public and private firms likewise indicate that stock-market pressure alters investment behavior [54, 55].

The information channel emphasizes that frequent traders may be better informed [23] and that short-horizon investors facilitate adjustment to new technologies [24], although their trading also amplifies price shocks [56]. Finally, turnover is closely related to liquidity, which can impede governance by easing exit [57] or improve governance and firm value through block formation and more informative prices [28], [58]; liquidity also reduces innovation through takeover exposure and the presence of non-monitoring institutions [29], whereas institutional ownership in general supports innovation [59]. Separating the horizon content of turnover from its liquidity content is therefore central to the empirical design.

2.3. Hypotheses

The monitoring and myopia channels both predict that a high-turnover shareholder base moves investment away from its efficient level, whereas the information channel predicts the opposite. Fig. 1 summarizes the resulting framework, and the main hypothesis is stated in directional form.

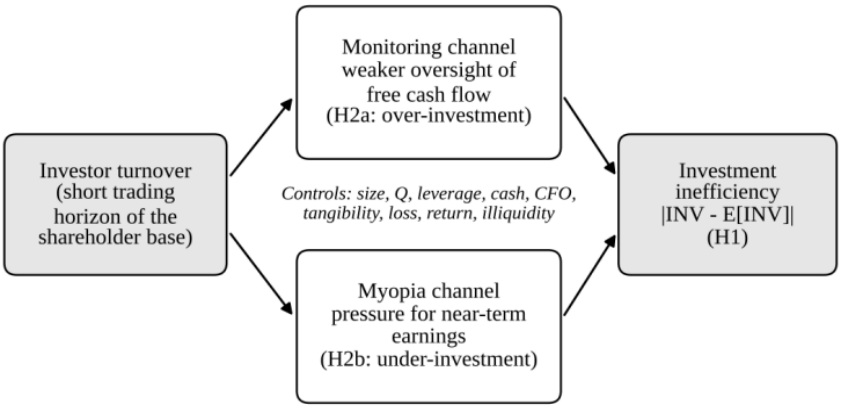

Figure 1. Conceptual framework linking investor turnover to investment inefficiency.

H1: Investor turnover is positively associated with corporate investment inefficiency.

The two channels differ in the direction of the deviation they produce. Weaker monitoring leaves free cash flow under

managerial discretion and manifests as over-investment, while short-term earnings pressure manifests as under-investment.

H2a: The positive association between investor turnover and investment inefficiency is concentrated among over-investing firms.

H2b: The positive association between investor turnover and investment inefficiency is concentrated among under-investing firms.

3. Research Design

3.1. Data and Sample

The sample consists of S&P 500 constituents. Annual financial statement data are extracted from 10-K filings for fiscal years 2012–2016, and daily closing prices and trading volumes for 2010–2016 are drawn from a public compilation of S&P 500 market data. A fiscal year ending before June is assigned to the previous calendar year. Firms in the Financials, Real Estate, and Utilities sectors are excluded because regulation shapes their investment and capital structure. Requiring lagged and lead accounting data, sales growth, and all control variables yields a final sample of 648 firm-year observations for 325 firms, with investment measured in fiscal years 2014–2016. The sample spans seven GICS sectors, led by Consumer Discretionary (147 observations), Industrials (124), and Information Technology including Telecommunication Services (120). All continuous variables are winsorized at the 1st and 99th percentiles.

3.2. Measuring Investment Inefficiency

Following Biddle *et al.* [7], expected investment is estimated as

$$INV_{i,t+1} = \beta_0 + \beta_1 SG_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

Where $INV_{i,t+1}$ is capital expenditure plus R&D expenditure in year t+1 scaled by total assets at the end of year t, and $SG_{i,t}$ is the percentage change in revenue from year $t-1$ to t. R&D is set to zero when not reported. Equation (1) is estimated cross-sectionally for each GICS sector–year with at least 20 observations; the remaining observations are fitted with a year-specific regression that includes sector intercepts. Investment inefficiency, $INEFF_{i,t+1}$, is the absolute value of the residual. Positive residuals identify over-investment (OVERINV) and negative residuals identify under-investment, whose magnitude is denoted UNDERINV.

3.3. Measuring Investor Turnover

Investor turnover is the annual share turnover of firm i in fiscal year t:

$$TURN_{i,t} = \Sigma_{d \in t} VOL_{i,d} / SHR_{i,t} \quad (2)$$

Where $VOL_{i,d}$ is the number of shares traded on day d of the fiscal year and $SHR_{i,t}$ is the number of shares outstanding at fiscal year-end, expressed on the same split-adjusted basis as volume; for 24 firm-years with missing or unstable share counts, shares outstanding are interpolated from adjacent fiscal years. TURN measures how many times the outstanding shares change hands in a year and thus inversely reflects the average holding period of the shareholder base. Because institutional investors hold a large and growing share of U.S. public equity [46, 59], share turnover in large-cap stocks reflects to a considerable extent the portfolio churning of institutions that is the focus of the investor-horizon literature [17, 23, 56]. Share turnover has been used to proxy for shareholder horizons [27] and trading activity [60, 61]. As alternatives, the analysis uses the natural logarithm of TURN (LnTURN), annualized turnover over the last six months of the fiscal year, and the within-year percentile rank of TURN.

3.4. Empirical Model

H1 is tested with the regression

$$INEFF_{i,t+1} = \alpha + \beta TURN_{i,t} + \gamma' X_{i,t} + \delta_s + \tau_t + u_{i,t+1} \quad (3)$$

Where δ_s and τ_t are sector and year fixed effects. The control vector X follows the investment-efficiency literature [7, 9] and includes firm size (SIZE, log of total assets), Tobin's Q (book liabilities plus market equity over total assets), leverage (LEV, short- and long-term debt over assets), cash holdings (CASH, cash over assets), operating cash flow (CFO, over assets), asset tangibility (TANG, net PP&E over assets), a loss indicator (LOSS), the fiscal-year stock return (RET), and the logarithm of the Amihud [30] illiquidity ratio (ILLIQ). ILLIQ separates the horizon content of turnover from its liquidity content. Standard errors are clustered by firm [62], and the fixed effects absorb time-invariant sector heterogeneity and common shocks [63]. H2a and H2b are tested by estimating (3) separately for over-investing firms with OVERINV as the dependent variable and for under-investing firms with UNDERINV as the dependent variable.

4. Empirical Results

4.1. Descriptive Statistics

Table I reports descriptive statistics. The mean (median) investment inefficiency is 0.038 (0.030), so the typical firm's investment deviates from its predicted level by 3–4% of lagged assets, against mean investment of 7.3% of assets. Mean annual turnover is 2.18 with a median of 1.94: the average share changes hands roughly twice a year, and the interquartile range from 1.41 to 2.70 shows substantial variation in shareholder horizons even among the largest U.S. firms. Investment inefficiency is positively correlated with turnover ($\rho = 0.14$). Turnover is only weakly correlated with ILLIQ in the raw data ($\rho = 0.12$), but conditional on firm characteristics and fixed effects the partial correlation is −0.45, which confirms that turnover carries a liquidity component that the regressions must hold constant.

Table I. Descriptive Statistics

Variable	Mean	SD	P25	Median	P75
INEFF	0.038	0.035	0.014	0.030	0.051
INVt+1	0.073	0.060	0.029	0.058	0.099
SG	0.062	0.136	-0.008	0.046	0.104
TURN	2.178	1.100	1.413	1.938	2.704
LnTURN	0.669	0.463	0.346	0.662	0.995
SIZE	23.319	1.102	22.493	23.201	24.131
Q	2.574	1.482	1.579	2.120	2.994
LEV	0.280	0.168	0.163	0.261	0.379
CASH	0.100	0.085	0.036	0.080	0.139
CFO	0.126	0.061	0.086	0.117	0.159
TANG	0.266	0.238	0.089	0.174	0.376
LOSS	0.043	0.203	0.000	0.000	0.000
RET	0.180	0.279	0.007	0.164	0.325
ILLIQ	-2.656	0.868	-3.164	-2.554	-2.022

N = 648 firm-years (325 firms). INEFF is the absolute residual of (1); INVt+1 is capital and R&D expenditure over lagged assets; SG is sales growth; TURN is annual share turnover; ILLIQ is the log Amihud ratio (×109). Continuous variables are winsorized at 1% and 99%.

4.2. Univariate Evidence

Fig. 2 sorts firm-years into turnover quintiles within each year. Mean inefficiency rises from 0.028 in the lowest quintile to 0.043 in the highest, and the difference of 0.014 is significant (t = 3.71). The pattern is driven by over-investment: the mean over-investment residual more than doubles from 0.024 to 0.051 (difference t = 4.37), and the proportion of over-investing firms increases from 35% to 52%. The magnitude of under-investment, in contrast, is flat across quintiles at 0.031–0.036.

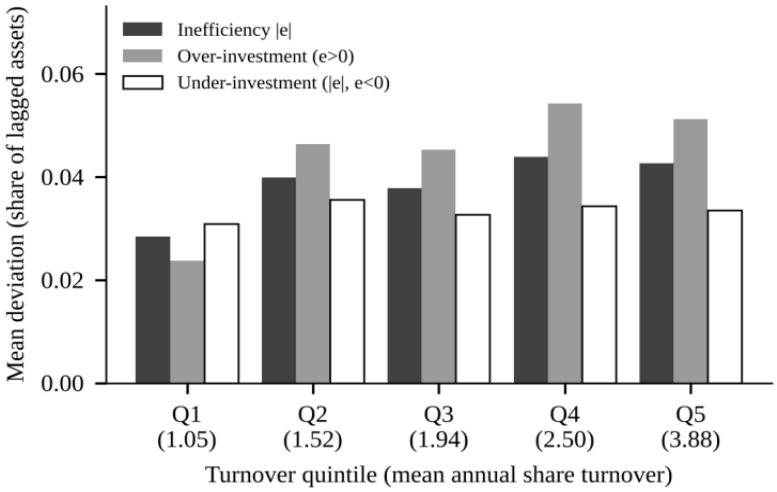

Figure 2. Investment inefficiency, over-investment, and under-investment by turnover quintile. Values in parentheses are mean annual share turnover; quintiles are formed within each fiscal year.

4.3. Baseline Regressions

Table II. Investor Turnover and Investment Inefficiency

Variable	(1)	(2)	(3)	(4)
TURN	0.0039**	0.0034*	0.0049**	
	(2.25)	(1.69)	(2.20)	
LnTURN				0.0138***
				(2.85)
SIZE		-0.0015	0.0076	0.0090*
		(-0.88)	(1.55)	(1.82)
Q		0.0059**	0.0082***	0.0090***
		(2.30)	(2.88)	(3.12)
LEV		0.0009	-0.0029	-0.0036
		(0.09)	(-0.28)	(-0.35)
CASH		0.0332	0.0359	0.0338
		(1.41)	(1.52)	(1.44)
CFO		-0.0456	-0.0139	-0.0163
		(-0.80)	(-0.23)	(-0.28)
TANG		0.0233*	0.0206	0.0196
		(1.67)	(1.46)	(1.40)
LOSS		0.0020	0.0003	-0.0014
		(0.22)	(0.03)	(-0.15)
RET			0.0033	0.0026
			(0.56)	(0.49)
ILLIQ			0.0111**	0.0117**
			(2.01)	(2.18)
Constant	0.0237***	0.0392	-0.1573	-0.1862*
	(4.97)	(0.96)	(-1.45)	(-1.72)
Sector/Year FE	Yes	Yes	Yes	Yes
N	648	648	648	648
Adj. R^2	0.104	0.166	0.176	0.180

Dependent variable: $INEFF_{t+1}$. Firm-clustered t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table II reports estimates of (3). Without firm controls (column 1), the coefficient on TURN is 0.0039 (t = 2.25).

Adding the standard controls (column 2) yields a coefficient of 0.0034, significant at the 10% level. When the stock return and ILLIQ are added (column 3), the coefficient rises to 0.0049 (t = 2.20). The increase follows from the negative conditional correlation between turnover and illiquidity: because illiquid stocks exhibit larger deviations, as the positive and significant coefficient on ILLIQ shows, omitting ILLIQ attenuates the turnover coefficient, and controlling for it isolates the trading-horizon component of turnover. Column 4 replaces TURN with its logarithm and obtains a coefficient of 0.0138 (t = 2.85). Economically, a one-standard-deviation increase in TURN (1.10) raises INEFF by 0.0054, or 13.9% of the sample mean. Among the controls, Tobin's Q enters positively, indicating that high-growth firms deviate more from expected investment. The evidence supports H1.

4.4. Over-Investment Versus Under-Investment

Table III separates the two directions of inefficiency. In the over-investment subsample (column 1), the coefficient on TURN is 0.0070 and significant at the 10% level; in the under-investment subsample (column 2), it is 0.0005 with a t-statistic of 0.35. Columns 3 and 4 repeat the analysis with residuals from a Q-based expected-investment model in the spirit of Richardson [35], in which investment is regressed on lagged Q, leverage, cash, size, stock return, and operating cash flow with sector and year fixed effects (N = 963, R^2 = 0.37). The turnover coefficient is 0.0074 (t = 2.15) for over-investment and −0.0006 (t = −0.39) for under-investment. The controls behave as expected: cash holdings are positively related to over-investment, consistent with the agency costs of free cash flow [2, 35], and tangibility increases over-investment while reducing under-investment. The results support H2a rather than H2b: higher investor turnover is associated with investment in excess of growth opportunities rather than with investment shortfalls.

Table III. Over-Investment Versus Under-Investment

Variable	Over	Under	Over (Q)	Under (Q)
TURN	0.0070*	0.0005	0.0074**	-0.0006
	(1.84)	(0.35)	(2.15)	(-0.39)
SIZE	0.0036	0.0064*	0.0046	0.0022
	(0.38)	(1.82)	(0.56)	(0.56)
Q	0.0097***	0.0008	0.0066	0.0042*
	(2.64)	(0.35)	(1.63)	(1.77)
LEV	0.0088	0.0012	0.0123	0.0103
	(0.54)	(0.16)	(0.80)	(1.39)
CASH	0.0941**	0.0176	0.0885**	0.0481*
	(2.52)	(0.83)	(2.35)	(1.90)
CFO	0.0191	-0.0076	0.0231	0.0938***
	(0.25)	(-0.30)	(0.28)	(2.69)
TANG	0.0746***	-0.0504***	0.0565***	-0.0696***
	(3.55)	(-4.68)	(3.93)	(-6.57)
LOSS	0.0194	-0.0105*	0.0270	-0.0019
	(1.35)	(-1.69)	(1.61)	(-0.33)
RET	0.0039	-0.0024	0.0035	0.0060
	(0.36)	(-0.50)	(0.44)	(1.29)
ILLIQ	0.0057	0.0100***	0.0051	0.0032
	(0.54)	(2.74)	(0.53)	(0.74)
Constant	-0.1226	-0.0900	-0.1378	-0.0349
	(-0.58)	(-1.14)	(-0.75)	(-0.39)
Sector/Year FE	Yes	Yes	Yes	Yes
N	278	370	437	526
Adj. R^2	0.251	0.323	0.255	0.405

Dependent variables are OVERINV (Over) and UNDERINV (Under). Columns (1)–(2) use residuals of the sales-growth model (1); columns (3)–(4) use residuals of the Q-based model, with regressors measured at t−1. Firm-clustered t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

4.5. Robustness

Table IV and Fig. 3 summarize additional tests, each including the full set of controls and fixed effects. The positive relation between turnover and inefficiency holds when expected investment is estimated with the Q-based model (coefficient 0.0040, t = 1.87, N = 963), when investment is restricted to capital expenditure (0.0063, t = 2.82), when turnover is measured over the last six months of the fiscal year (0.0042, t = 1.92), when turnover enters as a within-year percentile rank (0.0178, t = 2.49), and when firm-years with interpolated share counts are excluded (0.0045, t = 1.96). Fig. 3 expresses each estimate as the effect of a one-standard-deviation change in the turnover measure. The standardized effects range from 0.0046 to 0.0069 for total inefficiency and reach 0.0076 for over-investment, while the under-investment effect is close to zero.

Table IV. Robustness Tests

Specification	Coef.	t	N	Adj. R^2
Baseline (Table II, col. 3)	0.0049**	2.20	648	0.176
Q-based expected investment	0.0040*	1.87	963	0.208
Capital expenditure only	0.0063***	2.82	648	0.194
Turnover, last six months	0.0042*	1.92	648	0.173
Turnover percentile rank	0.0178**	2.49	648	0.174
Exclude interpolated shares	0.0045**	1.96	624	0.179

Each row reports the turnover coefficient from (3) with all controls and sector and year fixed effects. The measure is TURN except for the six-month turnover and percentile-rank rows. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

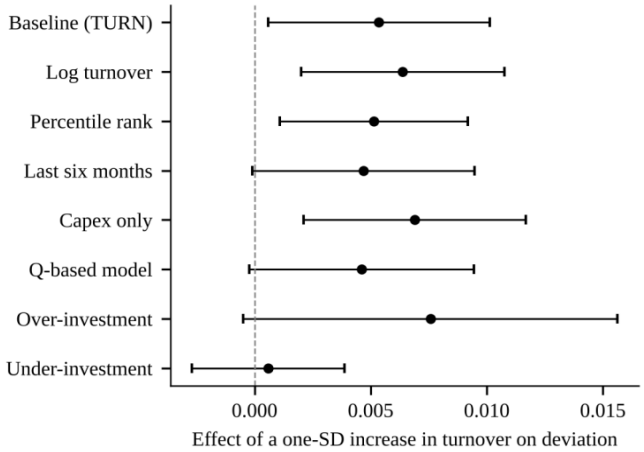

Figure 3. Standardized effect of investor turnover on investment deviations across specifications. Points are the effects of a one-standard-deviation increase in the turnover measure; bars are 95% confidence intervals based on firm-clustered standard errors.

4.6. Discussion

The concentration of the effect in over-investment indicates that, for large U.S. firms, the main cost of a high-turnover shareholder base is weaker discipline over the deployment of internal resources. This interpretation accords with evidence that high-turnover shareholders provide weak monitoring in acquisitions [17] and that long-term investors restrain managerial misbehavior and discourage value-reducing investment [22]. The absence of an under-investment effect differs from findings of myopic R&D cuts [18, 19], which concern R&D adjustments around earnings thresholds and smaller firms entering the Russell 2000. S&P 500 firms enjoy deep access to capital markets and broad analyst coverage, which limits the scope for investor pressure to push investment below its efficient level, while the agency costs of free cash flow remain first-order [2, 35]. The results also show that the horizon and liquidity content of turnover work in opposite directions: liquidity is associated with smaller investment deviations, whereas the trading-horizon component is associated with larger ones, so treating turnover purely as a liquidity proxy understates its governance implications.

5. Conclusion

This paper examines the relation between investor turnover and corporate investment efficiency for non-financial S&P 500 firms. Higher annual share turnover is associated with larger deviations of investment from the level predicted by growth opportunities, and the association is driven by over-investment. The effect is economically meaningful, strengthens once stock liquidity is held constant, and holds across alternative expected-investment models, investment definitions, and turnover measures. The evidence supports a monitoring view in which shareholders with short trading horizons provide weaker oversight of free cash flow.

The findings carry practical implications. Boards of firms with rapidly churning shareholder bases can strengthen internal oversight of capital budgeting and acquisitions, long-horizon investors can direct engagement toward capital allocation, and policymakers evaluating measures that lengthen shareholder horizons can count investment discipline among their benefits. Future research can extend the analysis with institution-level holdings data that distinguish among investor types, with longer panels and international samples, and with quasi-experimental variation in investor horizons such as index reconstitutions.

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