Pennies from Heaven, Barriers to Reinvestment:

Nominal Price and Predictable Price Pressure

by*

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This draft: Jan, 2026

Abstract

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JEL Classification: G12, G35, G41

Keywords: Dividend Reinvestment, Nominal Price, Predictable Price Pressure, Round-lot Trading, Fractional Trading

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1 Introduction

A growing body of research documents that predictable investor flows can generate meaningful price pressure in financial markets. While the literature has largely focused on large and infrequent shocks—include index reconstitutions (Shleifer, 1986; Harris and Gurel, 1986; Chang, Hong, and Liskovich, 2015; Greenwood and Sammon, 2025) and mutual fund flows (Coval and Stafford, 2007; Lou, 2012; Edmans, Goldstein, and Jiang, 2012). These settings provide ideal identification because the shocks are discrete and sizable, but they represent unusual market conditions. In contrast, the vast majority of trading activity in financial markets consists of *small, routine, and highly predictable* flows (Hartzmark and Solomon, 2018). Whether and why such flows move prices is a fundamental question for asset pricing, yet one that remains to be further explored.

This paper studies one of the most mechanical and recurring sources of flows in financial markets—dividend reinvestment—and shows that its price impact is systematically influenced by a simple but overlooked attribute of stocks: their nominal share price. Dividend payments occur on predetermined schedules, usually 10-45 days after ex-dividend days, and reinvestment is a widespread practice among both retail and institutional investors. If markets are highly liquid and arbitrage is unconstrained, such routine flows should be fully absorbed by liquidity providers, leaving no predictable price effects. However, we document that this is not the case. Instead, we show that lower priced stocks experience significantly stronger reinvestment induced price pressure, revealing a friction in how investors reinvest dividends.

The starting point of our analysis is the simple observation that reinvesting dividends into high-priced stocks is mechanically more difficult. Because dividends are typically small relative to share price, reinvestment in high-priced stocks often requires purchasing fractional shares or accumulating cash over multiple payment cycles. In contrast, reinvesting in

low-priced stocks is straightforward and aligns naturally with round-lot trading conventions. To illustrate, consider a stock with a 0.9% dividend yield. An investor must hold roughly $1,111 of a $10 stock to generate enough dividends to purchase one additional share without considering tax, whereas the required capital rises to about $5,556 for a $50 stock. These thresholds become even larger when minimum trading units or preferences for round-lot transactions are taken into account. For an investor who typically trades in lots of 10 shares, the capital needed to reinvest dividends into a new position increases by an order of magnitude—approximately $11,111 for the $10 stock and $55,556 for the $50 stock.

These frictions imply that nominal price influences the fraction of dividends that investors reinvest, thereby generating predictable variation in order flow around payment dates. Despite its simplicity, this mechanism has received little attention in the literature, which has largely treated nominal price as irrelevant for reinvestment demand. Dividend income, however, is small relative to principal, making it an ideal setting to examine this effect. When an investor allocates $1,000 to initiate a new position, the choice between a $10 stock and a $50 stock is largely inconsequential. Yet when reinvesting dividends generated from that same $1,000, the difference becomes substantial: the feasibility and scale of reinvestment are directly shaped by nominal price.

We begin by documenting a striking empirical pattern: dividend reinvestment generates substantially stronger price pressure for low priced stocks than for high priced stocks. Sorting stocks into portfolios based on nominal share price reveals a monotonic relationship between nominal price and reinvestment induced returns. On dividend payment days, the lowest priced quintile earns abnormal returns of 0.165% relative to the highest priced quintile. Over the subsequent 20 trading days, the cumulative abnormal return widens to 0.520%. These magnitudes are economically meaningful and comparable to the return spreads documented in well-known price pressure settings such as mutual fund flows (Lou, 2012). Furthermore, we

do not find significant reversals for low-price stocks when extending our event window to one year, which is consistent with the theorem of permanent price effect induced by permanent inflow (Gabaix and Koijen, 2021) and findings in Schmickler and Tremacoldi-Rossi (2023), Chen (2024), and Hartzmark and Solomon (2025).

The timing of these returns strongly suggests that they are driven by reinvestment flows. The return differential emerges precisely on payment days, when dividends are credited to investor accounts, and continues during the window in which reinvestment typically occurs. This pattern is difficult to reconcile with risk-based explanations or with information-based theories of dividend announcements, which would predict effects around declaration dates rather than payment dates. Instead, the evidence points to a demand driven mechanism: low priced stocks receive disproportionately larger reinvestment flows, and these flows exert price pressure.

A natural concern is that nominal price may be correlated with firm characteristics that also influence reinvestment behavior or price pressure. For example, low priced stocks may differ in size, liquidity, investor clientele, or growth opportunities. To address this concern, we exploit stock splits as a source of plausibly exogenous variation in nominal price. Stock splits mechanically reduce nominal price without altering fundamentals, cash flows, or dividend policy, and are intensively used as instruments in literature (see Green and Hwang, 2009; Baker, Greenwood, and Wurgler, 2009; Birru and Wang, 2016; Shue and Townsend, 2021; Du et al., 2025). If nominal price causally affects reinvestment flows, then reinvestment induced returns should increase following splits that lower nominal price. We therefore utilize the cumulative factor to adjust price (CFACPR) as the instrumental variable, which tracks the net (cumulative) level of splits over time. We find a negative and statistically significant relation between reinvestment returns and instrumented nominal price by stock splits with a magnitude that is similar to the ordinary least squares (OLS) estimates.

We next delve into the mechanisms. First, we examine trading and holdings data around dividend payments. We find that both retail and institutional investors reinvest dividends disproportionately into low priced stocks. This pattern operates through a simple but powerful interaction between nominal share price and investors' round-lot conventions. Because dividends are small relative to principal, reinvesting them into high-priced stocks almost inevitably produces odd-lot positions or fractional-share purchases—outcomes that investors systematically avoid due to psychological, cultural, and other reasons (e.g., Brown and Yang, 2016; Kuo, Lin, and Zhao, 2015; Li et al., 2024). Retail traders exhibit strong clustering in multiples of five and ten shares, while institutions, despite sometimes executing odd-lot trades algorithmically, tend to maintain portfolio holdings in round-lot blocks. As a result, a given dividend payment is far more easily reinvested into a low-price stock than a high-price one, generating a sharp cross-sectional decline in reinvestment propensity as nominal price rises. We find that this friction creates predictable order-flow imbalances around dividend payment dates and constitutes a previously overlooked channel through which nominal price shapes trading behavior.

Fractional trading provides an additional lens through which to examine the mechanism. If fractional trading eliminates mechanical barriers to reinvestment, then the nominal price effect should weaken in the presence of fractional trading (Da, Fang, and Lin, 2025). We find that the introduction of fractional trading reduces—but does not eliminate—the nominal price effect. This suggests that psychological frictions, such as round lot norms or mental accounting, continue to influence reinvestment behavior even when mechanical constraints are removed.

We also examine how dividend yield and liquidity conditions interact with reinvestment flows. Dividend yields rarely exceed 2.0% for most stocks, implying that investors typically face tight capital constraints when attempting to reinvest dividends. When dividend payments are extremely small, these constraints become binding, and the return differential between

high-price and low-price stocks should be negligible. As dividend yield increases, the effect of the nominal-price gap on reinvestment returns becomes larger. Our findings are consistent with this prediction that the nominal price effect is stronger among stocks with higher dividend yields. Furthermore, we find that the reinvestment return spreads between low- and high-price stocks are more pronounced among stocks with greater illiquidity, which is consistent with the price pressure mechanism (Hartzmark and Solomon, 2013).

Collectively, these cross-sectional patterns, together with the evidence from odd-lot and fractional trading tests, reinforce the interpretation that reinvestment price pressure drives the observed return patterns. We also examine two alternative explanations including non-proportional thinking (Shue and Townsend, 2021) and lottery demand (Kumar, 2009; Birru and Wang, 2016). Our results suggest that these two alternative channels cannot be the driver of our findings.

We conclude our empirical analysis by examining the implication of catering theory for dividend intensity. We have shown that reinvestment returns are higher for stocks with low-price and high-dividend yields and are not followed by reversals, suggesting that investors are willing to pay a premium for such firms. According to the catering theory (Baker and Wurgler, 2004), low-price firms should have stronger incentives to cater to these investors by distributing more dividends. Our results suggest that the dividend intensity, proxied by dividend yield and dividend payout ratio, declines significantly with nominal price. Instrumental-variable regressions further corroborate the causal relationship.

Related Literature: this study primarily contributes to three strands of literature.

First, we extend the literature on how investors trading dividends, especially dividend reinvestment. Early studies focus on announcement and ex-dividend days (Campbell and Beranek, 1955; Michaely and Vila, 1995; Graham and Kumar, 2006; Rantapuska, 2008). On

the dividend payment, prior literature often document that investors spend a large fraction of their dividends and seldom reinvest (Baker, Nagel, and Wurgler, 2007; Hartzmark and Solomon, 2019; Di Maggio, Kermani, and Majlesi, 2020; Bräuer, Hackethal, and Hanspal, 2022). Recently, Müller-Dethard, Reinhardt, and Weber (2025) suggest that in Germany, the majority of dividends are reinvested and account structure is a novel mechanism nudging investors to reinvest. They also find that the consumption rate of dividends also declines substantially in the US. Hackethal et al., (2025) find that educating investors to reinvest can also help enhance the propensity to reinvestment. These findings highlight the growing importance to understand the reinvestment behavior.

Some recent papers, including Kvamvold and Lindset (2018), Chen (2024), Schmickler and Tremacoldi-Rossi (2023), and Klos et al., (2025) find that investors tend to reinvest the dividends into stocks held in the same portfolio. Our study differs from theirs by investigating the choice of reinvestment on dividend payers. Furthermore, we find that nominal price serves as the barrier to reinvestment for high-price stocks, which contributes to the relatively flatter relationships between reinvestment and dividend yield documented in Hartzmark and Solomon, (2019).

Second, we identify a new mechanism and causality behind (uninformed) predictable price pressure of recurring firm events (Harztmark and Solomon, 2013, 2018, 2025; Bessembinder and Zhang, 2015; Chang et al., 2017): the interaction between nominal share price and dividend reinvestment. Unlike prior work that focuses on large institutional flows (Coval and Stafford, 2007; Lou, 2012; Edmans, Goldstein, and Jiang, 2012)[2] or infrequent

[2] Recent work also raises concerns about the mechanical construction of fund-flow-based shocks. Wardlaw (2020) shows that these measures embed characteristics related to momentum and size, complicating their interpretation as exogenous demand shocks. In contrast, Chen (2024) finds that payout-induced price pressure is not followed by meaningful reversals, making it less susceptible to this critique. Our results exhibit a similar pattern, suggesting that the reinvestment-driven price pressure we document is unlikely to be driven by the mechanical biases highlighted in this literature.

rebalancing events (Shleifer, 1986; Harris and Gurel, 1986; Chang, Hong, and Liskovich, 2015; Greenwood and Sammon, 2025), we show that small and routine reinvestment flows also move prices, and that their impact varies systematically with nominal price, which is unrelated to fundamentals in standard models. We also establish the causal relationships by exploiting stock splits as exogenous shocks on price levels and find that reinvestment-induced returns rise sharply when nominal price mechanically declines, isolating the causal effect of nominal price on predictable price pressure.

Third, we deepen the understanding of nominal share price. In frictionless and efficient markets, there is no optimal nominal (per share) stock price, and price should be irrelevant. However, prior studies show that nominal price is related to category thinking (Green and Hwang, 2009), nominal price illusion (Birru and Wang, 2016) and lottery demand (Kumar, 2009), and investor's non-proportional thinking (Shue and Townsend, 2021). Under the ideal setting of dividend reinvestment, where the reinvestment proceeds are naturally limited, our study highlights a more mechanical role of nominal price, which is similar in Du et al., (2025). However, unlike the explicit round-lot trading constraint in China, documented in Du et al., (2025), our mechanism arises from psychological preference for round-lot trading and holdings (Kuo, Lin, and Zhao, 2015).

Additionally, our results relate to two additional strands of literature. First, we connect microstructure conventions surrounding round-lot trading (Alexander and Peterson, 2007; O'Hara, Yao, and Ye, 2014; Kuo, Lin, and Zhao, 2015; Bartlett, McCrary, and O'Hara, 2025) and fractional trading (Bartlett, McCrary, and O'Hara, 2024; Da, Fang, and Lin, 2025) to reinvestment behavior. By showing how retail and institutional investors' trading and holding conventions amplify frictions in high-priced stocks, we link limited cognition and institutional practices to predictable price-pressure dynamics. Second, our findings on dividend intensity and nominal price extend the catering theory from the extensive margin (Baker and Wurgler,

2004; Baker, Greenwood, and Wurgler, 2009) to the intensive margin.

The remainder of the paper is organized as follows. Section 2 describes data sources. Section 3 presents the empirical analyses of the relation between nominal price and predictable price pressure of dividend reinvestment. Section 4 investigates the mechanism. Section 5 examines alternative explanations and robustness checks. Section 6 extends our study to the relationship between nominal price and dividend payment intensity. Section 7 concludes.

2 Data

The sample period for our baseline analysis spans 1963–2024. However, the sample period for each empirical test varies depending on when coverage begins and ends for supplementary data sources used in the analysis. We show that our results are robust across different time periods.

2.1 Stock Market Data

We obtain stock market data from CRSP, which contains stock returns, nominal share prices, cumulative factor to adjust price, volume, market capitalization, and value-weighted market returns. We restrict the sample to common stocks listed on the NYSE, AMEX, or NASDAQ, identified by CRSP share codes 10 and 11.

Ordinary cash dividends (distribution codes beginning with 12) are also sourced from CRSP. We retain dividend events only for firms with non-missing market capitalization at the end of the month preceding the dividend payment date. Unless otherwise indicated, all references to dividend timing correspond to the payment date. Dividend dates and dividend yields are likewise defined based on the payment date. Prices refer to nominal prices on the last trading day prior to the payment date.

For each dividend payment event, we compute the abnormal return for stock *i* on day *t* as:

$$AR_{i,t} = Ret_{i,t} - MarketRet_t, \quad (1)$$

where $MarketRet_t$ is value-weighted market return. We then construct the buy-and-hold abnormal returns (BHAR) as:

$$BHAR_i[0,T] = \prod_{t=0}^{T}\left(1 + Ret_{i,t}\right) - \prod_{t=0}^{T}\left(1 + MarketRet_t\right), \quad (2)$$

where *t*=0 refers to dividend payment days. In our main analyses, we set $T = 20$ trading days (approximately one month) in the main analysis. As a robustness check, we also compute cumulative abnormal returns (CAR):

$$CAR_i[0,T] = \sum_{t=0}^{T} AR_{i,t} \quad (3)$$

2.2 Firm Characteristics

Accounting data are from Compustat North America Fundamentals Annual. We follow Fama and French (1993) to match the accounting data for all fiscal yearends in calendar year *t*-1 with the dividend payouts for July of year *t* to June of *t*+1. The main control variables are the characteristics including Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity, following DeAngelo, DeAngelo, and Stulz, 2006), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth (growth rate of sales), Tobin's Q (the ratio of (total assets + market value of equity – book value of equity) to total assets), Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage (book leverage, measured as the total liability scaled by the sum of total liability and equity value). Expected skewness is constructed following Boyer, Mitton, and Vorkink (2010). All variables except stock returns are winsorized at the 0.1% and 99.9% levels.

2.3 Investor Trading Data

We use four sources of investor trading data:

First, we use retail transaction data from a large discount broker (LDB), as in Barber and Odean (2000, 2001, 2002). The dataset contains all trades from 77,037 individual accounts between January 1991 and December 1996. Following Ben-David and Hirshleifer (2012) and An (2016), we retain only common stocks, eliminate investor–stock pairs with negative positions or positions opened before 1991, and drop observations with negative commission values. We match LDB securities to CRSP using 8-digit CUSIPs and restrict the sample to investors with non-zero net positions prior to the ex-dividend date.

Second, we obtain retail trading flow based on the retail trade algorithm developed by Boehmer, Jones, Zhang, and Zhang (2021) (BJZZ)[3]. According to BJZZ, Regulation National Market System (Reg NMS) requires a broker/dealer to give a slight price improvement relative to the National Best Bid or Offer (NBBO) to retail orders. Specifically, a transaction is identified as a retail buy if the sub-penny price is between 60 and 100 basis points and a retail sale if the sub-penny price is between 0 and 40 basis points. We construct three proxies for retail trading: (i) cumulative net buy volume scaled by trading volume over the prior 252 trading days, (ii) order imbalance (cumulative net buys scaled by total buy and sell volume), and (iii) cumulative net buys scaled by shares outstanding prior to the payment date. Because compliance with Reg NMS improved gradually, high-quality retail trading data begin in late 2009. The sample therefore covers December 2009–December 2023.

Third, institutional holdings are obtained from LSEG 13F filings. Institutions with more than $100 million in assets under management must report long equity positions. Following McLean, Pontiff, and Reilly (2025), we classify institutions into six categories: mutual funds,

[3] We are grateful to Xinran Zhang for providing the retail trading data.

hedge funds, banks, insurance companies, wealth managers, and "others." To study reinvestment behavior, we restrict the sample to institutions with positive holdings prior to the payment date. The 13F sample spans 1980–2024.

Fourth, we use the one-share trade measure from Da, Fang, and Lin (2025) to proxy for fractional trading. This measure is the daily number of off-exchange one-share trades recorded in TAQ, scaled by total trades within the event window.

2.4 Summary Statistics

In our sample, there are 447,013 valid dividend payment events. The average nominal share price is $32.26, with substantial dispersion across the distribution: the 10th percentile is $8.75, while the 90th percentile is $58.12. Figure 1 plots the dynamics of price quintiles for dividend-paying firms in the proceeding quarter from 1965 to 2024 in Figure 1. Nominal price quintiles remain relatively stable around $30 between 1965 and 2010, consistent with the "nominal share price puzzle" documented by Weld et al. (2009). After 2010, however, quintile thresholds rise persistently. The lowest quintile threshold generally remains below $20, whereas the highest quintile increases from roughly $40 to $130 by 2024. The average dividend yield is 0.9%, rising from 0.2% at the 10th percentile to 1.7% at the 90th percentile.

[Insert Figure 1 Here]

The summary statistics underscore a key friction in dividend reinvestment: the required capital base is directly linked to the nominal share price. For example, with a dividend yield of 0.9%, an investor must hold shares worth approximately $1,111 to generate sufficient dividends to purchase one additional share priced at $10. For a $50 stock, the required capital increases to about $5,556. This reinvestment threshold is further magnified by minimum trading units or behavioral preferences for round-lot transactions. If investors typically trade in lots of 10 shares, the capital required to reinvest dividends into a new position escalates by an order of magnitude,

ranging from roughly $11,111 to $55,556 for stocks priced at $10 and $50, respectively. Thus, nominal share prices represent a meaningful friction in dividend reinvestment decisions, with lower nominal prices associated with lower reinvestment thresholds.

[Insert Table 1 Here]

These descriptive statistics also motivate our subsequent analysis, where we formally examine the relationship between nominal share prices and dividend reinvestment behavior.

3 Nominal Price and Predictable Price Pressure

This section examines the relationship between nominal share prices and the predictable price pressure around dividend payment dates. We begin with a portfolio analysis to assess the impact of nominal prices on dividend reinvestment returns. Next, we estimate panel regressions to control for potential confounding effects of firm and stock characteristics. We then exploit stock splits as a source of plausibly exogenous variation in nominal prices to establish a causal link. Finally, we conclude by constructing and evaluating a trading strategy that operationalizes the identified price effect.

3.1 Portfolio Analysis

The number of shares an investor can acquire through dividend reinvestment is determined by the stock's nominal price at the time of distribution. Because investors may reinvest dividends with some delay, the exact transaction price is difficult to observe. A reasonable proxy is therefore the nominal price on the trading day immediately prior to the payment date. Moreover, since the price associated with each dividend payment is not known at the end of the month, pooling observations by month may introduce look-ahead bias. To mitigate this concern, we sort stocks based on dividend payment prices observed during the preceding three months. This approach ensures that buy-or-hold decisions can be made without knowledge of the contemporaneous relative ranking of dividend payers.

We start with an event study covering the window [-5 days, +5 days] around dividend payment days. Stocks are sorted into quintiles, and we estimate the following regressions:

$$AR_{i,t,T} = a + \sum_{d=-5, d\neq -1}^{d=+5} b_d \times D_i(t - T = d) \times HP_{i,T} + c \times HP_{i,T}$$

$$+d \times D_i(t - T = d) + e \times Controls + FE + \varepsilon_{i,t,T}, \quad (4)$$

where $AR_{i,t,T}$ denotes the abnormal return of stock i on day t relative to the market return, for each dividend payment day T. $D_i(t - T = d)$ is an indicator variable equal to one if the interval between day $t$and payment day T is d. $HP_{i,T}$ equals one if the stock belongs to the top quintile by price prior to the payment day, and zero if the stock falls within the bottom quintile (lowest 20%). The set of control variables includes: Size (market capitalization at the end of the previous month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin's Q, Cash (cash holdings scaled by total assets), Tangibility (net property, plant, and equipment scaled by total assets), and Leverage (book leverage, total liability divided by the sum of total liability and equity value).

[Insert Figure 2 Here]

Figure 2 illustrates the dynamics of coefficient b_d. Return spreads between high-price and low-price stocks are generally insignificant prior to dividend payment days, except for a marginally significant effect on day -4 ($t = 1.68$) when controls are included. Reinvestment activity intensifies sharply during the first two trading days following dividend payments and persists thereafter. On the payment day and the subsequent day, the return spreads reach 0.26% and 0.13%, respectively. In the following days, average return spreads turn significantly negative, although their magnitude diminishes over time. These patterns suggest that the

observed return spread between low- and high-price stocks is most likely attributable to dividend payments. Confirming this, our analysis mainly concentrates on returns and trading activities after dividend payment days.

[Insert Table 2 Here]

Table 2 reports additional results from the portfolio analysis. Panel A presents the average characteristics of each price quintile. The distribution of stocks across quintiles is balanced, with roughly 120 firms per group, consistent with the stability of price thresholds. Nominal prices rise from \$9.70 in the lowest quintile to \$79.70 in the highest. Dividend yields decline with price, ranging from 1% to 0.6%, a negative correlation that we discuss later. Higher nominal prices are also associated with larger market capitalization, lower book-to-market ratios, higher Tobin's Q, greater retained earnings to equity (RE/TE), larger total assets, faster sales growth, lower Amihud illiquidity, greater tangibility, and lower leverage.

Panel B reports equal-weighted portfolio returns, including abnormal returns on dividend payment days, buy-and-hold abnormal returns over the subsequent 20 trading days (BHAR [0, 20]), and cumulative abnormal returns over the same horizon (CAR [0, 20]). On payment days, abnormal returns are highly significant across all quintiles, declining from 0.214% in the lowest quintile to 0.049% in the highest. The spread between low- and high-price stocks is 0.165% ($t = 5.88$).

Over longer horizons, BHARs for the top 80% of price-sorted stocks are indistinguishable from zero, consistent with transient price pressure induced by dividend reinvestment. Strikingly, however, the lowest quintile exhibits a significant BHAR [0, 20] of 0.534% ($t = 2.77$), without notable reversal following the demand shock. Value-weighted portfolios generate similar results in Panel C. The return spreads are 0.132%, 0.637%, and 0.798% for AR(0), BHAR [0, 20], and CAR [0, 20], respectively. Extending the horizon to one year does not produce a

reversal, though longer horizons introduce additional noise and confounding factors.

While traditional financial economics predicts reversal after uninformed demand shocks, Gabaix and Koijen (2023) argue that permanent inflows exert lasting effects on prices and expected returns under the inelastic market hypothesis. In this context, shocks induced by cash dividend payments may be permanent, or at least not quickly mean-reverting. Recent studies on dividend reinvestment provide consistent evidence: price pressure associated with reinvestment is not followed by significant reversal (Schmickler and Tremacoldi-Rossi, 2023; Chen, 2024; Hartzmark and Solomon, 2025; Klos et al., 2025). Müller-Dethard, Reinhardt, and Weber (2025) further show that most reinvestment occurs with a delay, as dividends are initially parked as brokerage cash. Moreover, most U.S. dividends are paid quarterly. Taken together, although dividend reinvestment amounts may be modest, they appear to be persistent, generating lasting price impacts without significant reversals.

3.2 Panel Regressions

Although single-sorting provides a straightforward way to illustrate economic significance, it does not explicitly control for other variables that may influence reinvestment decisions, such as dividend yield, market capitalization, and growth opportunities. The summary statistics in Table 2, Panel A, further indicate that low- and high-price stocks differ systematically along several dimensions. To address this concern, we estimate a series of panel regressions that allow us to control for additional firm characteristics and incorporate fixed effects to capture unobservable heterogeneity. Specifically, we estimate:

$$AR(0)_{i,t}/BHAR\ [0,20]_{i,t} = a + b \times logPrice_{i,t-1} + c \times Controls + FE + \epsilon_{i,t}, \qquad (5)$$

where $AR(0)$ denotes abnormal returns on dividend payment days and $BHAR[0,20]$ denotes buy-and-hold abnormal returns over the subsequent 20 trading days. $\log(\text{Price}_{i,t-1})$ is the logarithm of the nominal closing price prior to the payment date. We also control for

dividend yield, defined as dividends per share scaled by the price prior to payment. Additional control variables include firm size (market capitalization at the end of the prior month), book-to-market ratio (BM), retained earnings to equity (RE/TE), gross profitability, total asset growth, log Amihud illiquidity (average daily Amihud ratio in the prior month), sales growth, Tobin's Q, cash holdings (scaled by total assets), asset tangibility (net property, plant, and equipment scaled by total assets), and book leverage (total liabilities divided by total liabilities plus equity value). To mitigate the influence of unobservable firm-level characteristics and account for time-varying industry effects, we include firm fixed effects and quarter-by-industry fixed effects (SIC 2-digit). Standard errors are double-clustered at the firm and quarter-by-industry levels.

[Insert Table 3 Here]

Table 3 columns (1) to (3) present the results on AR (0). It is shown that in column (3), a 100% increase in nominal price is associated with a 13.2 basis point decline in abnormal returns, which is both economically meaningful and statistically significant. Adding more control variables generate similar coefficient estimations with column (1). Columns (4) to (6) reports the results on BHAR [0, 20]. From column (4), a 100% increase in nominal price corresponds to a 49.8 basis point decline in buy-and-hold abnormal returns. Overall, these findings indicate that, even after controlling for firm characteristics and fixed effects, nominal price exerts a significantly negative impact on reinvestment returns.

3.3 Identification Attempts

Although we have shown that nominal price is negatively related to dividend reinvestment returns after controlling for many observable factors, it remains possible that omitted variables drive this relation. To better address potential endogeneity concerns, we exploit stock splits as plausibly exogenous and mechanical shocks to nominal prices. Stock splits generate large changes in nominal prices without corresponding changes in firm fundamentals, thereby

providing a relatively clean setting to examine how nominal price influences dividend reinvestment (Green and Hwang, 2009). Stock splits have been widely used in prior studies of nominal price effects, see Green and Hwang (2009), Baker, Greenwood, and Wurgler (2009), Birru and Wang (2016), Shue and Townsend (2021), and Du et al., (2025)[4].

Specifically, we use the cumulative factor to adjust price (CFACPR) as the instrumental variable[5]. CFACPR tracks the net (cumulative) level of splits over time. For example, Microsoft's closing price on February 14, 2003 was $48.30, with CFACPR equal to 2. Following a 2-for-1 split, the closing price on February 18, 2003 fell to $24.96, with CFACPR equal to 1. Nominal price is thus positively related to CFACPR. In sum, CFACPR captures variation in nominal prices induced by stock splits, which is plausibly unrelated to firm fundamentals, consistent with the relevance and exclusion restrictions of instrumental variable estimation.

We estimate the following two-stage least squares (2SLS) regressions. In the first stage, we use CFACPR as the instrument to predict nominal price. In the second stage, we regress reinvestment returns on the fitted values of nominal price:

$$1st\ Stage: log(Price)_{i,t} = a_1 + b_1 \times CFACPR_{i,t} + c_1 \times Controls_{i,t-1} + \epsilon_{1,i,t},$$

[4] Although stock splits are plausibly unrelated to firm fundamentals and widely used as instruments for nominal price in prior literature, concerns persist that splits may relate to other motives, such as signaling (Lakonishok and Lev, 1987; McNichols and Dravid, 1990; Ikenberry, Rankine, and Stice, 1996) or liquidity considerations (Muscarella and Vetsuypens, 1996; Angel, 1997). We argue that our IV approach captures the cumulative price effects of splits, which reflect their long-term influence on price levels. Any signaling content should be incorporated into prices relatively quickly and confirmed in subsequent earnings announcements. Econometrically, we also include the Latest Split Ratio as an additional instrument, enabling an overidentification test. As shown in Table A1, the Hansen J-test yields a p-value of 0.674 and 0.242, failing to reject instrument exogeneity. While consistent with our identification strategy, instrument validity ultimately rests on theoretical justification; the test provides only auxiliary evidence.

[5] We employ an instrumental variables (IV) approach in lieu of an event study methodology for three primary reasons. First, the IV strategy is better suited to capturing the cumulative effects associated with stock splits. Second, it accommodates heterogeneity in split ratios across firms. Third, the IV framework readily captures the approximately one-to-one mapping between the nominal price changes induced by splits and corresponding reinvestment returns, which is easy to understand and be compared with baseline results.

$$2nd\ Stage: AR(0)_{i,t}/BHAR[0,20]_{i,t}$$

$$= a_2 + b_2 \times \widehat{logPrice}_{i,t} + c_2 \times Controls_{i,t-1} + \epsilon_{2,i,t}, \quad (6)$$

[Insert Table 4 Here]

The results are reported in Table 4. At the first stage, nominal price is significantly and positively correlated with CFACPR. The Kleibergen–Paap F-statistics in columns (1) and (3) are approximately 131, indicating that CFACPR is not a weak instrument. The second-stage results in columns (2) and (4) show that the coefficients on nominal price remain positive and statistically significant. Moreover, the IV estimates are comparable in magnitude to the OLS estimates, suggesting that our findings are not unduly affected by the concerns raised in Jiang (2017). Overall, the IV results corroborate our earlier evidence of a negative relation between nominal price and abnormal returns following dividend payment days.

3.4 Price Strategy

To evaluate the economic significance of our return predictability results, we form trading strategies. At the beginning of each month *t*, we sort the stocks issuing dividends in the last three months into five quintiles based on nominal prices. We next sort the dividend payments into five quintiles according to the pre-determined price thresholds. A portfolio that is long in low-price (bottom out-of-sample 20%) dividend payers and is short in high-price (top out-of-sample 20%) dividend payers until the end of month *t*. Both long and short legs are market adjusted. To mitigate the confounding effects related to ex-dividend days, our sample selection mandates that a stock's ex-dividend date must occur at least one calendar month prior to its dividend payment date. We refer this strategy as "Price Strategy" and plot the cumulative excess returns from 1965 to 2024 in Figure 4. We also consider a strategy buying low-price payers while shorting value-weighted market returns, which is referred as "P strategy (long)" to mitigate the short-selling constraint. For comparison, the cumulative value of the SMB and

HML portfolios are also shown. The cumulative excess returns in December 2024 are 201.12% for the Price Strategy and 237.29% for the P strategy (long), compared with 145.70% for SMB and 418.03% for HML. Notably, both strategies exhibit lower volatility than either SMB or HML.

[Insert Figure 4 Here]

4 Inspecting the Mechanisms

In this section, we investigate several possible explanations for the negative relation between reinvestment returns and the nominal price presented in Section 3. We consider the trading activities of retail investors and institutional investors, odd-lot effects, dividend yields, illiquidity, and the role fractional trading.

4.1 Retail Investor Trading Activities

For individual investors, we obtain the trading data from two sources. The first one is the trading data from a large discount brokerage firm (referred as "LDB" data) employed by Barber and Odean (2000, 2001, 2002) and the second one is the trading flow proposed by BJZZ. The LDB data spans from the time series from January, 1991 to December, 1996, and consist of 78,000 household accounts. We follow Ben-David and Hirshleifer (2012) in cleaning the data. First, we retain only securities that are common shares. For each investor, a position in a stock is built up through their transaction history. Any investor-stocks wherein any position observations become negative or open before 1991 are eliminated. Additionally, we remove any investor-stocks where commission values are negative in any of the entries. We restrict our focus to stocks listed on NYSE, AMEX, and NASDAQ and align the stocks traded through the LDB with the CRSP database using their 8-digit CUSIP. We only include observations with investors having net positions before ex-dividend days, who are eligible for receiving the dividends.

Retail investors' median principal investment for each dividend payer is $4925 in our sample, with the average dividend yield of 0.6%. Thus, the average dividend received is about $30. It is hard for them to buy one share for 50% stocks (median = $31.125) in our sample only using the dividend received. To explicitly examine the relationship between buy propensity and We then estimate the following regressions

$$Reinvestment_{i,t} = a + b \times logPrice_{i,t-1} + c \times Controls + FE + \epsilon_{i,t}, \quad (7)$$

where we employ two dependent variables to proxy for dividend reinvestment activity: *D(Net Buy)* is an indicator variable that equals one if an investor engages in net stock purchases during the 20-day window following the dividend payment date. To better display the results, we multiply it by 100. *Buy Principal* measures the net purchase dollar amount, scaled by the market capitalization (in thousand) prior to payment days. Control variables are consistent with prior tables. In columns (1) and (4), we add stock and industry × quarter fixed effects. In columns (2) and (5), we further add investor fixed effects to account for unobservable characteristics at the investor level. In columns (3) and (6), we employ a more restrictive specification including investor × stock and industry × quarter fixed effects to account for pairwise inclination for reinvestment.

[Insert Table 5 Here]

In Column (1), the coefficient on log(Price) for D(Net Buy) is -0.015 (t =2.89), indicating that one standard deviation increase in log(Price) (0.606) is associated with a decrease of D(Net Buy) by 0.909%, which is 6.34% of standard deviation (14.33%) or 43.29% of mean value (2.10%) of D(Net Buy). The negative relationship remains significant under more restrictive specifications and economically meaningful. For the intensity, we observe that one standard deviation increases in log(Price) (0.606) is associated with a decrease of Buy Principal by 0.182%, which accounts for 6.9% of standard deviation of Buy Principal. These results suggest that retail investors are less likely to reinvest high-price stocks, which are consistent with

observations that the nominal price is negatively related to dividend reinvestment returns. Furthermore, we observe that the coefficients on dividend yield are not significant, which is consistent with Baker, Nagel, and Wurgler (2007). We will discuss this in section 4.5.

Although LDB dataset provides detail transaction level records for us to understand to reinvestment behavior, which is extensively explored in the literature, including some recent studies like Hartzmark and Solomon (2019) and Daniel, Garlappi, and Xiao (2021), concerns persist regarding its limited coverage, raising questions about whether earlier findings remain valid in contemporary market environments. To address this problem, we provide complementary evidence on investors' inclination to reinvest in low-price stocks by using the BJZZ trading flow data, which spans from 2009 to 2023.

We employ three proxies for retail investors' dividend reinvestment activities. *CulBuy_Vol* is defined as the net trading volume of retail investors divided by the average daily trading volume over the past 252 trading days. *CulBuy_Share* is calculated as the net trading volume of retail investors divided by the shares outstanding at the end of the previous month. *Order Imbalance* measures the net buy volume divided by the total trading volume during the 20-trading-day window following the dividend payment date. We thus replace the dependent variables with these three variables and estimate similar regressions in model (7). Similar results are observed in Table 6 that the coefficients on log(Price) are negatively significant for these three dependent variables. Collectively, this pattern holds for different samples and robust to different proxies for reinvestment. These results confirm our conjecture about the role of nominal price in an investor's inclination for dividend reinvestment.

4.2 Do Institutional Investors Prefer Low-price Stocks to Reinvest?

It is shown that retail investors reinvest less low-price stocks. The remaining question is that whether institutional investors also prefer low-price stocks to reinvest. We thus examine this question using 13F institutional investor holding data. This sample starts from 1980 to

2024. Institutional investors are classified into six categories, including mutual funds, hedge funds, banks, insurance companies, wealth management companies, and other institutional investors, following McLean, Pontiff, and Reilly (2025). It is also required that the institutional investor holds net positive position one quarter prior to dividend payment days. We estimate the following regressions at the investor-quarter-stock level:

$$D(Reinvestment)_{i,j,q+1} = a + b \times log(Price)_{j,q} + c \times DY_{j,q} + d \times Controls_{j,q} + FE + \varepsilon_{i,j,q+1}, \quad (8)$$

where the dependent variable $D(Reinvestment)_{i,j,q+1}$ equals one if the institutional investors increase their holdings of dividend payer j in quarter q+1. The results presented in Table 7 show that all types of institutional investors reinvest less in high-price stocks. Furthermore, the coefficients on dividend yield are mostly significant across all types of institutional investors, except for insurance companies. These findings suggest that the preference for low-price stocks to reinvest not only exists among retail investors, but also holds for institutional investors.

[Insert Table 6 Here]

It is natural that retail investors cannot afford the money for reinvestment in high-price stocks. However, it seems that the institutional investors are less likely subjected to this constraint. We will discuss this concern in the following section.

4.3 The Role of Round-lot Trading

Odd lots have existed since the beginning of trading. However, retail investors prefer to use round numbers due to psychological, cultural, and other reasons (e.g., Brown and Yang, 2016; Kuo, Lin, and Zhao, 2015; Li et al., 2024). For informed traders, early research on stealth trading found that informed traders clustered their orders around round-lot multiples of 500 and 1,000 shares to disguise their intentions (Alexandera and Peterson, 2007). However, the

subsequent rise of algorithmic and high-frequency trading has shifted this activity downward, with modern informed trading now actively concentrated in odd lots (<100 shares) to avoid detection (O'Hara, Yao, and Ye, 2014; Bartlett, McCrary, and O'Hara, 2025). These informed traders may be institutional investors, who utilize algorithmic and high-frequency trading.

When considering dividend reinvestment, investors' propensity to trade in round numbers can further amplify the psychological barriers associated with reinvesting in high-priced stocks, particularly for retail investors. Similar trading convention may also shape reinvestment behavior among institutional investors. Although institutions can execute a relatively larger share of odd-lot trades—typically involving smaller transaction sizes—they may tend to maintain portfolio positions in round lots. Consequently, while odd-lot trades may affect individual transaction sizes, they are unlikely to materially influence the quarter-end holdings reported in our 13F sample. For instance, suppose an institutional investor holds 10,000 shares of Stock A, priced at $80 with a dividend yield of 0.9%. If the investor adheres to a round-lot constraint that favors holdings in multiples of 100 shares, then upon receiving a dividend payment of $7,200, the investor may choose to retain the proceeds as cash or reallocate them to other cheaper securities rather than reinvest in 90 additional shares of Stock A, which would generate a non–round-lot position. If the stock trades at $20 and the investor holds 40,000 shares, the dividend proceeds would allow the purchase of an additional 300 shares. Alternatively, the investor could retain the $1,200 in cash or allocate it to other assets.

To examine the role of round-lot and odd-lot trading, we start with presenting some stylized facts in LDB dataset and 13F sample. We display the distribution of the last digit (including the first decimal place) of trade sizes in the LDB database in Figure 5. For visual clarity in representing fractional trades, the decimal value is aggregated to the nearest half-unit (e.g., a trade of 3.3 shares is displayed at position 3.5). As shown in Figure 5, retail investors tend to trade shares in multiples of 10 or 5, both in regular trading and in transactions following

dividend distribution dates, which is consistent with Kuo, Lin, and Zhao (2015).

[Insert Figure 5 Here]

We next examine the role of round-lot trading[6] on reinvestment decisions. Round-lot clustering is measured using three proxies: Fraction (5), Fraction (10), and Fraction (100), defined as the proportion of an investor's total trading amount attributable to trades in which the number of shares transacted is a multiple of five, ten, or one hundred, respectively. They are constructed at the investor-stock level and at the investor level[7]. We interact these variables with nominal price based on specifications in Table 6 and present the results in Table A2. It is observed that the coefficients on the interaction terms of log(Price) and Fraction are all significantly negative. These findings suggest that investors exhibiting more propensity to trade in round-lots are significantly more subjected to the influence of nominal price and less likely to reinvest in high-price stocks.

We conduct analogous tests for institutional investors. Figure A1 shows that they tend to maintain stock holdings in round numbers. Moreover, following dividend reinvestment, institutional investors exhibit a clear tendency to adjust their positions in dividend-paying stocks toward round numbers, regardless of their pre-dividend holdings.

We also investigate how investors' holding conventions affect their propensity to reinvest in high-priced stocks. To this end, we construct a proxy, Fraction (100), which measures the proportion of an investor's portfolio value held in round lots of one hundred shares (as opposed to odd lots) prior to each dividend payment. Table A3 reports the results. The interaction terms between log(Price) and Fraction (100) are consistently negative and statistically significant for

[6] Unlike the existing literature, which typically defines round-lot trading as transactions in units of 100 shares, this study also considers trades in multiples of 5 and 10 shares. To avoid unnecessary conceptual complexity, we uniformly refer to these as round-lot trading.

[7] We construct these variables using the full sample, given the limited transaction records available for each investor. Our results remain robust when the measures are instead defined using data prior to reinvestment.

mutual funds, hedge funds, banks, and other institutional investors. The only exceptions are insurance companies and wealth management firms, which together represent a relatively small share of the institutional investor base. These findings support our conjecture that round-lot trading and holding preferences play an important role in reinvestment decisions and amplify the influence of nominal share prices.

Our analysis helps explain why retail and institutional investors exhibit a preference for reinvesting in lower-priced stocks. Nevertheless, alternative mechanisms not examined in this study may also contribute to this pattern, and exploring such explanations remains an interesting question for future research.

4.4 Does Fractional Trading Mitigate the Barriers to Reinvestment?

We have shown that nominal share price serves as a barrier to dividend reinvestment. In recent years, several brokers have expanded their fractional trading services, enabling investors to purchase "slices" of stocks with as little as one cent. According to Da, Fang, and Lin (2025), Interactive Brokers was the first major U.S. broker to introduce fractional trading on November 25, 2019, followed by Robinhood on December 12, 2019, Fidelity on January 29, 2020, and Charles Schwab on June 9, 2020. Because fractional trading allows investors to reinvest dividends into high-priced stocks, we expect that its introduction should mitigate the nominal-price-related barriers to reinvestment[8].

To test this prediction, we draw on the dataset from Da, Fang, and Lin (2025) and use the ratio of off-exchange one-share trades to total trades on the payment day (denoted %FT(0)) and over the 21-day window beginning on the payment date (denoted %FT[0,20]) as proxies for

[8] Retail investors can also acquire fractional shares through dividend reinvestment plans (DRIPs). However, as noted by Berkman and Koch (2018), detailed data on DRIP participation rates are difficult to obtain, preventing us from directly assessing their impact on our results. Moreover, Berkman and Koch (2018) report that only 622 firms offered DRIPs in 2008, suggesting that the overall coverage of such programs is relatively limited. Consequently, the influence of DRIPs on our findings is likely modest.

fractional trading activity. A higher %FT indicates a larger share of trades executed through fractional trading. We employ a continuous difference-in-differences framework by interacting log(Price) with an indicator for whether the payment day occurs after November 25, 2019, to capture the effect of fractional trading. Following Da, Fang, and Lin (2025), we estimate the regressions over an event window from January 2019 to December 2020.

$$Dep.\ Var_{i,t} = a + b \times logPrice_{i,t-1} \times Post - FT + c \times Controls + FE + \epsilon_{i,t}, \quad (9)$$

where the dependent variables include %FT(0), %FT[0, 20], AR (0), and BHAR [0, 20]. Because the event window is shorter than our baseline specification, we double-cluster the standard errors by stock and payment days.

[Insert Table 8 Here]

Table 8 reports the results. We find that the intensity of fractional trading is positively associated with nominal price. Furthermore, column (1) shows that although one-share trades on payment days increase with log(Price) after the introduction of fractional trading, the coefficient is not statistically significant. When we extend the event window, however, the interaction between log(Price) and Post-FT in column (2) becomes significantly positive, consistent with Da et al. (2025), who document that fractional trading enables investors to reinvest in high-priced stocks. The interaction term in column (3) remains insignificant, in line with column (2). In contrast, column (4) shows a significantly positive interaction coefficient, indicating that the return spread between low- and high-price stocks narrows after the introduction of fractional trading. Nevertheless, the magnitude of this effect is only about 6.51% of the coefficient on log(Price). Thus, while fractional trading mitigates the reinvestment barrier created by nominal price, it does not eliminate it. This residual effect may reflect investors' persistent preference for holding round-number share positions, as discussed earlier.

Overall, fractional trading reduces—but does not fully remove—the nominal-price barrier

to dividend reinvestment, particularly over a longer event window (i.e., 21 days). This examination also helps validate that the effect of nominal price on reinvestment returns likely arises from investors' limited ability in reinvesting dividends into high-price stocks.

4.5 Heterogeneous Effects: Dividend Yield and Illiquidity

We next examine the role of dividend yield and illiquidity. Dividend yields rarely exceed 2.0% for most stocks, implying that investors typically face tight capital constraints when attempting to reinvest dividends. When dividend payments are extremely small, these constraints become binding, and the return differential between high-price and low-price stocks should be negligible. As dividend yield increases, the effect of the nominal-price gap on reinvestment returns becomes larger. Put differently, reinvestment returns are positively related to dividend yield, a relationship well documented in prior work (Berkman and Koch, 2017; Chen, 2024; Hartzmark and Solomon, 2025). Yet this positive relation can be attenuated when high nominal prices impede investors' ability to reinvest dividends. Taken together, these considerations lead us to expect that the effects of nominal price should be more pronounced among high-dividend-yield stocks.

To test this prediction, we independently double-sort stocks into nine portfolios based on dividend yield and nominal price, and compute equal-weighted returns. Table 9, Panel A shows that among low-dividend-yield stocks, the return spreads between high-price and low-price stocks are insignificant for both AR(0) and BHAR[0,20]. In contrast, among high-dividend-yield stocks, low-price stocks outperform high-price stocks by 0.164% and 0.417% for AR(0) and BHAR[0,20], respectively. Moreover, the difference-in-difference estimate is significant for AR(0), although insignificant for BHAR[0,20], likely due to the higher volatility associated with longer holding periods. Motivated by these results, we construct a portfolio that is long low-price, high-dividend-yield stocks and short high-price, low-dividend-yield stocks. This portfolio generates significant excess returns of 0.202% and

0.438% for AR(0) and BHAR[0,20], respectively.

[Insert Table 9 Here]

Panel B formally presents the regression results. The coefficients on the interaction between log(Price) and dividend yield are significantly negative in columns (1) and (2), consistent with the portfolio evidence in Panel A. We further replace the dependent variables with the reinvestment activity measures used in Tables 5 and 6, and report the results in Table A4. The interaction terms remain significantly negative across all specifications. Moreover, once we control for these interaction effects, the coefficients on dividend yield become significantly positive. These patterns indicate that retail investors reinvest dividends in proportion to dividend yield when holding low-priced stocks, but this effect is largely offset when nominal prices are high. As a result, failing to account for the moderating role of nominal price can flatten or obscure the underlying relationship between reinvestment activity and dividend yield.

Taken together, our findings offer a plausible mechanism that reconciles two strands of the literature: investors do not actively reinvest dividends (Baker, Nagel, and Wurgler, 2007; Hartzmark and Solomon, 2019), yet abnormal returns around dividend payments are positive and increasing in dividend yield (Berkman and Koch, 2017; Chen, 2024; Hartzmark and Solomon, 2025).

We next investigate how the nominal price related predictable price pressure is related to liquidity. We follow Hartzmark and Solomon (2013) to examine the measure of illiquidity used in Amihud (2002), which is measured as the average daily Amihud illiquidity ratio in the month prior to payment days. This measure captures the price impact of each dollar traded, with large numbers indicating less liquidity. We also start with a double-sorting portfolio analysis in Table 10 Panel A. We observe that low-price stocks outperform significantly high-price stocks among

mid and high illiquidity stocks, while insignificantly among low-illiquidity stocks. The difference-in-difference portfolio generates significant excess returns for AR(0), though insignificant for BHAR[0, 20]. As a result, A portfolio, which longs the stocks with low price and high illiquidity and shorts ones with high price and low illiquidity can earn excess returns of 0.202% for AR(0) and 0.438% for BHAR[0, 20], respectively. The Panel B in Table 10 suggests that the effects of nominal price is amplified with higher illiquidity after including controls and fixed effects. These results indicate that the nominal price effects on dividend reinvestment relates to stock liquidity, which is consistent with their being associated with price pressure.

[Insert Table 10 Here]

5 Alternative Explanations and Robustness Checks

Thus far, our results support the view that predictable dividend-payment price pressure associated with nominal price arise from capital constraints—whether psychological or mechanical—that limit investors' ability to reinvest their dividends. In this section, we further examine alternative explanations, including non-proportional thinking and lottery demand.

5.1 Non-Proportional Thinking

The first potential explanation for our results is that investor partially think about price changes in dollar rather than percentage units, a phenomenon referred to as non-proportional thinking. Shue and Townsend (2021) show that such behavior causes lower-priced stocks to react more strongly to non-informative news that some investors mistakenly perceive as informative. Accordingly, it is possible that investors respond more strongly to dividend payments for lower-priced stocks. However, non-proportional thinking implies that investors should overreact to news in low-price stocks, leading to subsequent reversals. This prediction does not align with our findings, as reinvestment in low-price stocks is not followed by

reversals. Although we cannot fully disentangle the effects of nominal price into reinvestment barriers versus non-proportional thinking, we conduct an indirect test using dividend yield to suggest that non-proportional thinking is unlikely to be the dominant factor in dividend reinvestment decisions.

Specifically, if non-proportional thinking were the primary driver of dividend reinvestment, investors would base their reinvestment decisions on the dividend amount per share rather than the dividend yield they earn. In that case, dividend yield would serve as a noisier proxy for dividend amount per share. To examine this possibility, we augment our baseline regressions in Table 11 by including dividend per share (Div Per Share).

[Insert Table 11 Here]

We find in columns (1) and (5) that the coefficient on Div Per Share is significantly positive. However, once dividend yield is included in columns (2) and (6), the coefficient on Div Per Share becomes insignificant, while dividend yield remains positively associated with reinvestment returns. Similarly, the interaction effects between nominal price and dividend per share are subsumed by the interaction effects between nominal price and dividend yield in columns (4) and (8). Taken together, these results reinforce our view that non-proportional thinking is unlikely to be the primary driver of our findings.

5.2 Lottery Demand

The second explanation is that low-price represents the characteristics of lottery stocks (Kumar, 2009). A recent study by Klos et al., (2025) finds that the free dividend fallacy can drive investors to gamble with dividends in other lottery-like stocks. Furthermore, low-price stocks are associated with the "nominal price illusion", where investors overestimate the room to grow for low-price stock (Birru and Wang, 2016). To evaluate the effects of lottery demand in our study, we add the expected idiosyncratic skewness (E(ISKEW), Boyer, Mitton, and

Vorkink, 2010) into our baseline model[9] to proxy for lottery demand.

[Insert Table 12 Here]

Columns (1) and (4) in Table 12 show that the coefficients of E(ISKEW) are negative but insignificant. Controlling for lottery demand does not materially change the results on nominal price. Furthermore, if nominal price represents lottery demand in reinvestment decisions, we would expect that the effects should be more pronounced among lottery-like stocks, while the results in columns (2) and (5) contradict with this prediction. The interaction effects of E(ISKEW) and dividend yield are also insignificant in columns (3) and (6). Actually, when we use MAX (Bali, Cakici, and Whitelaw, 2011) instead of E(ISKEW) to proxy for lottery demand, we can obtain similar results. These findings suggest that lottery demand cannot explain our results.

5.3 Robustness Checks

We have shown that our results remain robust using different samples and sample periods in previous tests. Another potential concern may be that the effects of nominal price represent the confounding interaction effects of other stock characteristics and dividend yield. We thus consider a more restrictive specification to control for all the interaction terms of our observable stock characteristics and dividend yield. It is shown in Table A5 that our results remain even considering such restrictive specifications. Furthermore, our results are not sensitive to different model specifications. We re-examine the relation between dividend reinvestment price pressure and nominal price using Fama-MacBeth (1973) regressions in Table A6 and find consistent results.

[9] Although EISKEW incorporates nominal price in its construction, our results indicate that this more complex measure does not provide additional explanatory power beyond nominal price itself.

6 Nominal Price and Dividend Payout Intensity

In this section, we extend our analysis to examine the effect of nominal price on dividend payout intensity. Because investors are more likely to reinvest in low-price stocks, such stocks command a premium that can be amplified through dividend yield. According to catering theory (Baker and Wurgler, 2004; Baker, Greenwood, and Wurgler, 2009), firms with lower nominal prices have stronger incentives to cater to investor demand by increasing their dividend yield. We therefore expect a negative relationship between nominal price and dividend payout intensity.

To test this hypothesis, we employ two proxies for dividend payout intensity. The first is dividend yield, defined as the dividend amount per share scaled by nominal price at the end of the month preceding the dividend declaration day, consistent with the definition of log(Price). Because dividend yield may also reflect market valuation, which itself is related to nominal price, we introduce a second proxy: the dividend payout ratio, measured as total dividends relative to net income. In constructing this measure, we restrict the sample to firms reporting positive net income and with payout ratios below 100%. We then estimate the following regression specification:

$$Dividend\ Intensity_{i,t} = a + b \times log(Price)_{i,t-1} + c \times Control_{i,t-1} + \epsilon_{i,t}, \qquad (10)$$

where $Dividend\ Intensity$ is proxied by dividend yield and dividend payout ratio. The results are reported in Table 13.

[Insert Table 13 Here]

We observe that dividend intensity is negatively correlated with nominal price prior to the declaration day. In column (3), a one-standard-deviation increase in log(Price) (0.769) is associated with a 0.132% decline in dividend yield, representing 15% (15.4%) of the mean (standard deviation) of dividend yield. A similar pattern emerges for the dividend payout ratio.

In column (6), a one-standard-deviation increase in log(Price) (0.757) corresponds to a 1.582% decline in the dividend payout ratio, accounting for 13.2% (15.9%) of its mean (standard deviation). A potential concern is that these regressions may suffer from endogeneity issues such as omitted variables or reverse causality. To mitigate these concerns, we employ CFACPR as an instrumental variable and estimate 2SLS regressions, with results reported in Table A7. The economic magnitudes of the IV estimates are comparable to those from OLS, i.e., –0.216 (2SLS) versus –0.172 (OLS) for dividend yield, and –1.404 (2SLS) versus –2.090 (OLS) for the dividend payout ratio.

Baker and Wurgler (2004) focus on the discrete decision of whether to pay dividends, rather than on the intensity of payouts. They argue that once a firm initiates dividends, payout intensity is driven more by firm-level profitability than by the relative valuations of payers and non-payers. Our findings extend the catering theory by showing that payout intensity also responds to nominal price—an attribute unrelated to firm fundamentals. Firms are more likely to distribute higher dividends when their nominal prices are lower, which in turn is associated with more intensive reinvestment activity.

7 Conclusion

This paper examines the relationship between nominal share price and the predictable price pressure arising from dividend reinvestment. We document that dividend reinvestment returns are higher for lower-priced stocks. Simple difference portfolios yield abnormal returns of 0.165% on payment days and 0.520% over the subsequent 20 trading days. To establish a causal role for nominal price, we exploit variation induced by stock splits and show that reinvestment returns systematically vary with split-driven changes in nominal price.

Granular evidence indicates that both retail and institutional investors tend to reinvest dividends into low-price stocks. Round-lot trading conventions and investors' round-number

holding habitats amplify this pattern. Although the introduction of fractional trading alleviates part of the reinvestment barrier, it removes only a modest portion of it. Additionally, the nominal-price effect is stronger among stocks with higher dividend yields and greater illiquidity. These findings support the view that mechanical or psychological frictions hinder investors from reinvesting dividends into high-price stocks, thereby generating a negative relation between nominal price and predictable reinvestment price pressure. Alternative explanations—such as non-proportional thinking or lottery preferences—do not account for our results. Overall, we show that a purely mechanical feature of stocks—nominal price—creates persistent and predictable price pressure through dividend reinvestment, challenging the standard assumption that small, routine flows are fully absorbed by liquidity providers.

Our findings have several implications for future work. First, investors face frictions such as nominal share prices when considering dividend reinvestment, and these constraints directly affect the fraction of dividends that can be reinvested. Consequently, when estimating demand elasticity from dividend-induced price pressure using dividend yield and corresponding price changes, researchers must exercise caution: heterogeneity in nominal prices implies heterogeneity in reinvestment behavior, which can bias elasticity estimates if ignored. A more detailed characterization of the demand function for dividend reinvestment—explicitly accounting for such frictions—represents an important and promising avenue for future work.

Second, while fractional trading reduces some of the frictions associated with reinvestment, psychological barriers—such as round-lot trading norms—remain difficult to overcome. Recent evidence from Hackethal, Hanspal, Hartzmark, and Bräuer (2025) shows that educating investors about the benefits of dividend reinvestment can have persistent effects on reinvestment behavior. Whether such education can weaken entrenched round-lot trading habits, or whether simple behavioral nudges that alter default options (Thaler, 2018) can increase participation in automatic dividend reinvestment plans, are important open questions.

Investigating these mechanisms may provide valuable insights into investor literacy and the efficiency of capital markets.

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Table A. Variable Definition and Summary Statistics

Variable Name	Variable Definition
DY	Dividend Yield (DY), which is calculated as the dividend per share divided by the pre-payment stock price.
Size	Logarithm of market capitalization at the end of month *t*-1.
BM	Book-to-market ratio, following Fama and French (1993), is calculated as SEQ + TXDITC – PS, divided by market capitalization at the end of December of the last year. We derive the variable *PS* (preferred stock) by coalescing the values of PSTKRV, PSTKL, and PSTK, assigning a value of zero when all three source variables are missing.
RE/TE	Retained earnings to equity ratio, which is calculated as RE/TEQ. We replace RE/TE with zero if missing.
Gross Profit	Gross profitability is calculated as (REVT-COGS)/AT, following (Novy-Marx, 2013).
TA Growth	Total asset growth rate, which is calculated as $AT_T/AT_{T-1} - 1$, following (Cooper et al. 2008).
logAmihud	The logarithm of Amihud illiquidity ratio. The daily Amihud illiquidity ratio is calculated as $\frac{\lvert Ret \rvert}{Volume}$. We use logarithm of average daily Amihud illiquidity ratio in the past month in our empirical analysis, which is denoted by *logAmihud*.
Sales Growth	Sales growth rate, which is calculated as $Sales_T/Sales_{T-1} - 1$.
Tobin_Q	Tobin Q, which is calculated as (AT + PRCC_F*CSHO - BE) / AT.
Cash	Cash-asset ratio, which is calculated as CHE/AT. If CHE is missing, we replace it with zero.
Tangibility	Tangibility ratio, which is calculated as PPENT/AT. we replace PPENT with zero if missing.
Leverage	Book leverage, which is calculated as (DLC + DLTT)/(DLC + DLTT + CSHO * PRCC_F). We replace DLC or DLTT as 0 if those are missing.

Table 1. Summary Statistics

This table presents summary statistics on main variables. Price is defined as the closing price on the last trading day before the payment day. Dividend Yield (DY) is calculated as the dividend per share divided by the pre-payment stock price. The other variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth (growth rate of sales), Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage (long-term and short-term debts divided by the total value of debts and equities). The sample starts from 1963 to 2024.

Variable	Mean	SD	p10	p25	p50	p75	p90	N
Price	32.260	53.990	8.750	14.250	23.380	37.130	58.120	447013
DY	0.009	0.010	0.002	0.004	0.007	0.012	0.017	447013
Size	12.530	2.239	9.759	10.860	12.340	14.030	15.570	447009
BM	0.854	0.618	0.264	0.444	0.720	1.093	1.573	379429
logAmihud	-14.200	2.881	-18.190	-16.420	-13.990	-11.900	-10.520	374387
Div Per Share	0.229	0.254	0.050	0.090	0.160	0.300	0.460	447013
Gross Profit	0.312	0.266	0.038	0.092	0.263	0.453	0.663	392346
TA Growth	0.231	2.448	-0.036	0.021	0.081	0.166	0.308	391753
RE/TE	0.177	1.147	0.000	0.000	0.000	0.000	0.788	447013
Sales Growth	0.158	1.025	-0.065	0.016	0.089	0.182	0.316	389638
Tobin_Q	1.426	0.930	0.854	0.985	1.104	1.525	2.298	374815
Cash	0.095	0.112	0.008	0.023	0.054	0.125	0.234	394279
Tangibility	0.298	0.260	0.012	0.051	0.247	0.456	0.715	394279
Leverage	0.115	0.180	0.000	0.004	0.036	0.136	0.360	391565

Table 2. Portfolio Analysis

This table presents the results of portfolio analysis around dividend payment days. At the end of each month $m-1$, all dividend payers from the preceding three months are sorted into five portfolios based on nominal price. In month m, each dividend-paying stock is assigned to one of these portfolios according to its price prior to the payment date. Panel A presents equal-weighted portfolio characteristics. Panels B and C report the equal-weighted and value-weighted performance of price-sorted portfolios. Cumulative abnormal returns (CARs) are calculated as the cumulative difference between daily stock returns and value-weighted market returns, while buy-and-hold abnormal returns (BHARs) are computed as portfolio buy-and-hold returns minus the corresponding cumulative value-weighted market returns. We also report the return spreads and characteristics differences between high-price and low-price groups. T-statistics, reported in parentheses, are based on standard errors adjusted by Newey-West HAC. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Characteristics within Each Group

	1 (Low)	2	3	4	5 (High)	5-1
#stocks	121.460	121.060	120.518	120.415	131.829	5.398
Price	9.700	17.758	26.149	38.471	79.701	71.557***
DY	0.010	0.009	0.008	0.008	0.006	-0.004***
Size	11.001	11.966	12.788	13.529	14.437	3.512***
BM	1.029	0.894	0.807	0.716	0.591	-0.439***
RE/TE	0.110	0.166	0.204	0.251	0.331	0.228***
Gross Profit	0.327	0.290	0.280	0.297	0.336	0.008
TA Growth	0.115	0.126	0.122	0.125	0.129	0.016***
logAmihud	-12.729	-13.490	-14.259	-14.906	-15.517	-2.887***
Sales Growth	0.100	0.112	0.112	0.116	0.119	0.020***
Tobin_Q	1.219	1.274	1.364	1.520	1.807	0.597***
Cash	0.106	0.088	0.087	0.092	0.102	-0.004*
Tangibility	0.243	0.274	0.310	0.317	0.308	0.061***
Leverage	0.125	0.124	0.114	0.104	0.088	-0.035***

Panel B. Equal-weighted Portfolio Returns

	1 (Low)	2	3	4	5 (High)	5-1
AR 0	0.214	0.132	0.113	0.081	0.049	-0.165***
	(7.18)	(6.43)	(7.01)	(5.93)	(5.66)	(-5.88)
BHAR [0, 20]	0.534	0.196	0.144	0.070	0.005	-0.520***
	(2.77)	(1.32)	(1.10)	(0.64)	(0.07)	(-3.00)
CAR [0, 20]	0.805	0.319	0.208	0.106	0.027	-0.771***
	(4.16)	(2.16)	(1.59)	(0.96)	(0.40)	(-4.41)

Panel C. Value-weighted Portfolio Returns

	1 (Low)	2	3	4	5 (High)	5-1
AR 0	0.193	0.099	0.084	0.086	0.058	-0.132**
	(3.55)	(3.79)	(4.05)	(4.21)	(4.94)	(-2.56)
BHAR [0, 20]	0.458	0.188	0.045	-0.162	-0.179	-0.637**
	(2.06)	(1.29)	(0.40)	(-1.56)	(-2.73)	(-2.58)
CAR [0, 20]	0.659	0.277	0.088	-0.109	-0.139	-0.798***
	(2.84)	(1.86)	(0.78)	(-1.04)	(-2.13)	(-3.10)

Table 3. Nominal Prices and Performance Following Dividend Payments

This table reports the relationship between nominal stock prices and stock performance following dividend payment days. The dependent variables are the abnormal return on the payment day (AR (0)) and the buy-and-hold abnormal return over the post-payment window (BHAR [0, 20]). The key explanatory variables are log(Price), defined as the logarithm of the closing price on the last trading day before the payment day, and Dividend Yield (DY), calculated as the dividend per share divided by the pre-payment stock price. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. All regressions include stock and industry × year-quarter fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =		AR (0)			BHAR [0, 20]	
Log (Price)	-0.187***	-0.163***	-0.191***	-1.489***	-1.384***	-0.718***
	(-10.12)	(-9.78)	(-8.59)	(-12.08)	(-12.02)	(-6.10)
DY		0.071***	0.086***		0.313***	0.293***
		(6.04)	(5.71)		(5.75)	(4.70)
Size			0.024			-0.874***
			(1.58)			(-10.13)
BM			0.013			0.387***
			(0.76)			(3.75)
RE/TE			-0.000			0.006
			(-0.12)			(0.36)
Gross Profit			0.081			0.673**
			(1.30)			(2.33)
TA Growth			0.006			0.010
			(1.19)			(0.77)
logAmihud			0.051***			0.035
			(6.39)			(0.96)
Sales Growth			-0.017			-0.037
			(-1.37)			(-1.12)
Tobin_Q			0.018*			0.077
			(1.72)			(1.39)
Cash			0.025			0.131
			(0.34)			(0.42)
Tangibility			-0.021			0.019
			(-0.30)			(0.06)
Leverage			0.070			-0.106
			(1.18)			(-0.41)
Observations	445,422	445,422	343,823	443,400	443,400	342,789
Stock FE	YES	YES	YES	YES	YES	YES
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.023	0.023	0.029	0.066	0.066	0.071

Table 4. Instrumental Variable Regressions

This table reports instrumental-variable (IV) regression results examining the relationship between nominal stock prices and abnormal returns around dividend payment days. The dependent variables are the abnormal return on the payment day (AR (0)) and the buy-and-hold abnormal return over the post-payment window (BHAR [0,20]). The instrumental variable is the CRSP Cumulative Factor to Adjust Prices (CFACPR). Columns (1)–(2) present 2SLS estimates for AR(0), and columns (3)–(4) report results for BHAR [0,20]. Kleibergen–Paap F-statistics are shown in columns (2) and (4). All regressions include stock fixed effects and industry × year-quarter fixed effects. t-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
Dep Var =	Log (Price)	AR (0)	Log (Price)	BHAR [0, 20]
Cumulative Factor to Adjust Prices	0.009***		0.009***	
	(11.45)		(11.44)	
Log (Price)		-0.166***		-1.372***
		(-3.25)		(-4.98)
DY	-0.046***	0.087***	-0.047***	0.260***
	(-9.93)	(5.67)	(-9.93)	(4.23)
Size	0.565***	0.010	0.566***	-0.527***
	(54.06)	(0.33)	(54.05)	(-3.35)
BM	-0.052***	0.015	-0.052***	0.348***
	(-5.99)	(0.84)	(-6.02)	(3.33)
RE/TE	0.008*	-0.001	0.008*	0.011
	(1.84)	(-0.17)	(1.85)	(0.60)
Gross Profit	0.329***	0.073	0.328***	0.887***
	(8.45)	(1.14)	(8.41)	(2.86)
TA Growth	-0.002*	0.006	-0.002*	0.008
	(-1.93)	(1.21)	(-1.94)	(0.66)
logAmihud	0.121***	0.048***	0.123***	0.120**
	(27.50)	(4.54)	(27.71)	(2.41)
Sales Growth	0.005***	-0.018	0.005***	-0.033
	(2.64)	(-1.38)	(2.68)	(-0.99)
Tobin_Q	0.005	0.018*	0.005	0.076
	(0.76)	(1.73)	(0.79)	(1.36)
Cash	0.094**	0.022	0.094**	0.191
	(2.45)	(0.31)	(2.45)	(0.60)
Tangibility	-0.118**	-0.017	-0.118**	-0.070
	(-2.34)	(-0.24)	(-2.36)	(-0.19)
Leverage	0.005	0.071	0.006	-0.101
	(0.18)	(1.19)	(0.22)	(-0.39)
Observations	343,805	343,805	342,771	342,771
Kleibergen-Paap *F*-stat		131.035		130.947
Stock FE	YES	YES	YES	YES
Industry × Year-Quarter FE	YES	YES	YES	YES

Table 5. Retail Investor Trading Activities: Evidence from LDB Dataset

This table examines the relationship between nominal price and the propensity of retail investors to reinvest dividends using the LDB dataset. We employ two proxies for reinvestment activity. D(Net Buy) is an indicator equal to one if an investor engages in net stock purchases during the 20-day window following the dividend payment date. Buy Principal measures the net purchase amount scaled by market capitalization. The sample includes investor-stock observations with positive net positions prior to the ex-dividend date. Columns (1) and (4) include firm and industry × year-quarter fixed effects; columns (2) and (5) include investor, firm, and industry × year-quarter fixed effects; and columns (3) and (6) include investor-firm and industry × year-quarter fixed effects. The sample period is 1991–1996. t-statistics, reported in parentheses, are based on standard errors double-clustered by investor-stock and year-quarter. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =	D(Net Buy)			Buy Principal		
Log (Price)	-0.015***	-0.018***	-0.030***	-0.003***	-0.003***	-0.003***
	(-3.63)	(-3.74)	(-4.40)	(-6.79)	(-5.76)	(-5.24)
DY	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(-0.57)	(-0.68)	(-1.17)	(-0.79)	(-0.54)	(-1.48)
Size	0.026***	0.031***	0.042***	0.002***	0.002***	0.002***
	(5.44)	(5.58)	(5.75)	(5.98)	(3.55)	(3.36)
BM	-0.004	-0.003	-0.006	-0.000	-0.001	-0.001
	(-1.23)	(-0.97)	(-1.52)	(-0.30)	(-1.03)	(-0.57)
RE/TE	-0.047**	-0.043*	-0.038	0.000	0.001	0.001
	(-2.03)	(-1.70)	(-1.23)	(0.13)	(0.97)	(0.65)
Gross Profit	0.003	0.002	0.012	-0.002	-0.002	-0.005**
	(0.17)	(0.13)	(0.62)	(-1.55)	(-1.36)	(-2.00)
TA Growth	-0.000	-0.002	-0.002	0.001*	0.001	-0.000
	(-0.04)	(-0.60)	(-0.63)	(1.69)	(1.62)	(-0.13)
logAmihud	0.001	0.001	0.001	0.000	-0.000	-0.000
	(0.97)	(0.55)	(1.00)	(0.62)	(-0.81)	(-1.50)
Sales Growth	0.004	0.003	0.005	0.000	0.001	0.002
	(0.90)	(0.72)	(1.01)	(0.31)	(1.14)	(1.40)
Tobin_Q	0.002	0.003	0.003**	0.000	0.000	0.000
	(1.35)	(1.62)	(2.00)	(0.99)	(1.02)	(1.17)
Cash	-0.025*	-0.028*	-0.024	0.001	0.001	-0.002
	(-1.72)	(-1.74)	(-1.27)	(0.48)	(0.30)	(-0.78)
Tangibility	-0.026	-0.030	-0.042*	-0.002	-0.002	0.001
	(-1.28)	(-1.38)	(-1.72)	(-0.53)	(-0.47)	(0.16)
Leverage	0.010	0.022**	0.029**	-0.002	-0.001	-0.001
	(1.00)	(2.05)	(2.53)	(-1.07)	(-0.59)	(-0.58)
Observations	196,134	191,972	179,984	196,134	191,972	179,984
Investor FE	NO	YES	NO	YES	NO	NO
Stock FE	YES	YES	NO	YES	NO	NO
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Investor × Stock FE	NO	NO	YES	NO	YES	YES
Adjusted R-squared	0.024	0.055	0.085	0.074	0.086	0.066

Table 6. Retail Investor Trading Activities: Evidence from BJZZ Retail Flow

This table examines how retail investors' propensity to reinvest dividends varies with nominal stock prices using BJZZ retail flow data. We employ three proxies for dividend reinvestment behavior. CulBuy_Vol is the net trading volume of retail investors scaled by the average daily trading volume over the prior 252 trading days. CulBuy_Share is the net trading volume scaled by shares outstanding at the end of the previous month. Order Imbalance is defined as net buy volume divided by total trading volume during the 20-trading-day window following the dividend payment date. All regressions include firm fixed effects and industry × year-quarter fixed effects. t-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. The sample period is 2010–2023. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dep Var =	CulBuy_Vol	CulBuy_Share	Order Imbalance
Log (Price)	-0.016**	-0.066**	-0.009**
	(-2.43)	(-2.37)	(-2.21)
DY	-0.002	-0.000	0.001
	(-1.38)	(-0.00)	(1.33)
Size	0.005	0.028	0.004
	(0.84)	(1.08)	(1.14)
BM	-0.002	-0.057**	-0.004
	(-0.31)	(-2.02)	(-0.95)
RE/TE	0.000	0.000	0.000
	(0.30)	(0.18)	(0.02)
Gross Profit	-0.011	-0.093	-0.018*
	(-0.54)	(-1.07)	(-1.70)
TA Growth	0.001	0.020	0.003
	(0.17)	(0.89)	(1.03)
logAmihud	0.010***	0.041***	0.008***
	(2.79)	(6.58)	(4.07)
Sales Growth	-0.003	-0.010	0.001
	(-0.44)	(-0.38)	(0.21)
Tobin_Q	0.004**	0.014	0.004***
	(2.18)	(1.50)	(3.63)
Cash	-0.009	-0.002	-0.008
	(-0.49)	(-0.03)	(-0.74)
Tangibility	-0.083***	-0.298**	-0.040***
	(-3.35)	(-2.21)	(-2.76)
Leverage	-0.042*	-0.176***	-0.019
	(-1.79)	(-2.76)	(-1.31)
Observations	72,086	72,086	72,031
Investor FE	NO	YES	NO
Stock FE	YES	YES	NO
Industry×Year-Quarter FE	YES	YES	YES
Investor -Stock FE	NO	NO	YES
Adjusted R-squared	0.015	0.052	0.037

Table 7. Do Institutional Investors Prefer Low-Price Stocks in Reinvestment Decisions?

This table investigates whether institutional investors tend to reinvest low-price stocks. We follow Mclean, Pontiff, and Reilly (2025) to classify institutional investors from 13F into six categories, including mutual fund, hedge fund, bank, insurance, wealth management, and others. For each category of institutional investors, we estimate the following regressions:

$$D(Reinvestment)_{i,j,q+1} = a + b \times log(Price)_{j,q} + c \times DY_{j,q} + d \times Controls_{j,q} + FE + \varepsilon_{i,j,q+1},$$

where the dependent variable $D(Reinvestment)_{i,j,q+1}$ equals one if the institutional investors increase their holdings of dividend payer j in quarter q+1. $log(Price)_{j,q}$ is the logarithm of price prior to the payment days. $DY_{j,q}$ is the dividend yield. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. The sample is restricted to institutional investors who hold a net long position prior to the ex-dividend date and spans from 1980 to 2024. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Institutional Investor Type:	Mutual Fund		Hedge Fund		Bank		Insurance		Wealth Management		Others	
Log (Price)	-0.342***	-0.322***	-1.104***	-1.130***	-0.846***	-1.068***	-0.8483**	-0.801*	-1.766***	-1.459***	-1.195***	-1.260***
	(-3.60)	(-3.20)	(-5.56)	(-6.05)	(-4.03)	(-4.55)	(-2.10)	(-1.70)	(-3.62)	(-2.90)	(-7.62)	(-7.59)
DY	0.203***	0.121***	0.613***	0.415***	0.168**	0.092	0.1429	0.023	0.893***	0.636***	0.501***	0.327***
	(7.17)	(4.49)	(11.08)	(9.98)	(2.06)	(1.22)	(0.99)	(0.17)	(5.86)	(5.37)	(9.61)	(7.38)
Observations	30,218,629	30,142,337	13,911,961	13,820,528	5,145,195	5,123,247	862,841	859,133	1,292,630	1,282,054	17,926,616	17,833,306
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Investor FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Stock FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Investor -Stock FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Adjusted R-squared	0.038	0.177	0.065	0.246	0.050	0.189	0.124	0.248	0.092	0.272	0.064	0.223

Table 8. Nominal Price, Fractional Trading, and Stock Returns

This table presents the relationship between stock prices, fractional trading, and abnormal returns around dividend payment days. We compute %FT (0) as the ratio of off-exchange one-share trades to total trades on the payment date. Similarly, %FT [0, 20] is defined as the sum of off-exchange one-share trades divided by the sum of total trades over the 21-day window beginning on the payment date and extending through the 20 subsequent trading days. *Post-FT* indicates whether the payment day falls in the period after November 25, 2019, when FT first became available in the market. The other model specifications are consistent with previous tables. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and payment days. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep Var =	% FT (0)	% FT [0, 20]	AR (0)	BHAR [0, 20]
Log (Price)	0.492**	0.318***	-2.651**	-18.092***
	(2.25)	(2.90)	(-2.45)	(-8.18)
Post-FT	-0.034	-0.419***	-0.198	-6.223***
	(-0.09)	(-3.21)	(-0.56)	(-4.11)
Log (Price) × Post-FT	0.031	0.132***	0.040	1.178***
	(0.37)	(4.19)	(0.51)	(3.32)
DY	-0.018	0.026*	0.011	0.133
	(-0.74)	(1.76)	(0.20)	(0.57)
Size	0.207	0.062	1.932**	4.448**
	(0.96)	(0.53)	(2.07)	(2.33)
BM	0.181	0.021	-0.224	2.311
	(1.11)	(0.20)	(-0.76)	(1.54)
RE/TE	0.016*	0.013*	-0.054**	-0.105
	(1.89)	(1.76)	(-2.19)	(-1.54)
Gross Profit	0.340	0.348	1.192	-1.873
	(0.51)	(0.65)	(1.00)	(-0.45)
TA Growth	0.037	0.014	0.148	-0.679
	(0.59)	(0.31)	(1.11)	(-1.09)
logAmihud	0.059	0.065	-0.095	-0.734**
	(0.64)	(1.05)	(-0.97)	(-2.43)
Sales Growth	-0.023	-0.065	-0.223	1.012
	(-0.16)	(-0.78)	(-0.94)	(1.04)
Tobin_Q	0.167**	0.026	0.081	-0.167
	(2.28)	(0.58)	(0.87)	(-0.39)
Cash	-0.150	-0.239	-0.521	1.971
	(-0.27)	(-0.63)	(-0.54)	(0.59)
Tangibility	1.454	0.744	-0.161	15.961***
	(1.61)	(1.31)	(-0.13)	(2.76)
Leverage	-0.038	0.171	-0.829	2.513
	(-0.05)	(0.38)	(-1.00)	(0.93)
Observations	9,074	9,074	9,074	9,071
Stock FE	YES	YES	YES	YES
Industry × Year-Quarter FE	YES	YES	YES	YES
Adjusted R-squared	0.372	0.655	0.035	0.157

Table 9. Nominal Price and Dividend Yield

This table presents the results of portfolio analyses around dividend payment days. In Panel A, we report the equal-weighted performance of independently double-sorted portfolios by stock price and dividend yield. At the end of each month $m-1$, we sort all dividend payers in the past 3 months into three price-based portfolios using the 30th and 70th percentile ($P_{m-1}^{30\text{th}}$ and $P_{m-1}^{70\text{th}}$) price thresholds. In month m, we assign each dividend-paying stock to one of these portfolios based on its price prior to the dividend payment date. "Low price" refers to groups of stocks with price below $P_{m-1}^{30\text{th}}$ and "high price" refers to those with price above $P_{m-1}^{70\text{th}}$. BHAR [0, 20] are computed as the buy-and-hold difference between daily stock returns and value-weighted market returns. We further sort stocks into three groups (30%-40%-30%) according their dividend yield, which is calculated as the dividend per share divided by price at the last trading day prior to payment day. We also report the return spread between low-price-high-dividend and high-price-low-dividend groups. T-statistics, reported in parentheses, are based on standard errors adjusted by Newey-West HAC. In Panel B, we extend Table 3 by adding the interaction terms between logarithm of stock prices and dividend yields. Control variables and model specifications are consistent with previous tables. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Double-sorted Portfolio Performance by Price and Dividend Yield

	Price				
AR (0)	Low	2	High	High-Low	$L^P H^D - H^P L^D$
Low DY	0.109	0.095	0.046	-0.063	
	(2.47)	(4.26)	(4.96)	(-1.48)	
2	0.146	0.104	0.06	-0.086***	
	(5.97)	(6.00)	(4.13)	(-3.55)	
High DY	0.249	0.192	0.084	-0.164***	
	(7.67)	(8.44)	(4.01)	(-5.18)	
High-Low	0.140***	0.096***	0.038*	-0.102**	0.202***
	(3.64)	(3.71)	(1.77)	(-2.30)	(6.67)
BHAR [0, 20]	Low	2	High	High-Low	$L^P H^D - H^P L^D$
Low Price	0.243	0.052	-0.041	-0.284	
	(1.08)	(0.42)	(-0.58)	(-1.29)	
2	0.502	0.183	0.117	-0.385**	
	(2.62)	(1.36)	(1.14)	(-2.44)	
High Price	0.396	0.182	-0.021	-0.417**	
	(2.21)	(1.14)	(-0.14)	(-2.51)	
High-Low	0.153	0.131	0.02	-0.133	0.438***
	(0.82)	(1.01)	(0.14)	(-0.60)	(2.72)

Panel B. Stock Prices, Dividend Yields, and Stock Performance During Post-dividend Payment Days

	(1)	(2)
Dep Var =	AR (0)	BHAR [0, 20]
Log (Price)	-0.139***	-0.526***
	(-6.10)	(-4.45)
DY	0.276***	0.989***
	(3.59)	(3.50)
Log (Price)×DY	-0.069***	-0.253***
	(-2.97)	(-2.93)
Observations	343,823	342,789
Stock FE	YES	YES
Industry×Year-Quarter FE	YES	YES
Adjusted R-squared	0.029	0.072

Table 10. Nominal Price, Illiquidity, and Stock Returns

This table presents the relationship between stock prices, illiquidity, and abnormal returns around dividend payment days. In Panel A, we report the equal-weighted performance of double-sorted portfolios by stock price and Amihud illiquidity ratio. At the end of each month $m-1$, we sort all dividend payers in the past 36 months into three price-based portfolios using the 30th and 70th percentile ($P_{m-1}^{30\text{th}}$ and $P_{m-1}^{70\text{th}}$) price thresholds. In month m, we assign each dividend-paying stock to one of these portfolios based on its price prior to the dividend payment date. "Low price" refers to groups of stocks with price below $P_{m-1}^{30\text{th}}$ and "high price" refers to those with price above $P_{m-1}^{70\text{th}}$. CARs are computed as the cumulative difference between daily stock returns and value-weighted market returns. Within each group, we further sort stocks into three groups (30%-40%-30%) according their Amihud illiquidity ratio, which is calculated as the dividend per share divided by price at the last trading day prior to payment day. We also report the return spread between low-price-high-Amihud and high-price-low-Amihud groups. T-statistics, reported in parentheses, are based on standard errors adjusted by Newey-West HAC. In Panel B, we extend Table 3 by adding the interaction terms between logarithm of stock prices and dividend yields. Control variables and model specifications are consistent with previous tables. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Double-sorted Portfolio Performance by Price and Amihud Illiquidity Ratio

	Price				
AR (0)	Low	2	High	High-Low	$L^P H^D - H^P L^D$
Low illiquidity	0.109	0.095	0.046	-0.063	
	(2.47)	(4.26)	(4.96)	(-1.48)	
2	0.146	0.104	0.060	-0.086***	
	(5.97)	(6.00)	(4.13)	(-3.55)	
High illiquidity	0.249	0.192	0.084	-0.164***	
	(7.67)	(8.44)	(4.01)	(-5.18)	
High-Low	0.140***	0.096***	0.038*	-0.102**	0.202***
	(3.64)	(3.71)	(1.77)	(-2.30)	(6.67)
BHAR [0, 20]	Low	2	High	High-Low	$L^P H^D - H^P L^D$
Low illiquidity	0.243	0.052	-0.041	-0.284	
	(1.08)	(0.42)	(-0.58)	(-1.29)	
2	0.502	0.183	0.117	-0.385**	
	(2.62)	(1.36)	(1.14)	(-2.44)	
High illiquidity	0.396	0.182	-0.021	-0.417**	
	(2.21)	(1.14)	(-0.14)	(-2.51)	
High-Low	0.153	0.131	0.020	-0.133	0.438***
	(0.82)	(1.01)	(0.14)	(-0.60)	(2.72)

Panel B. Stock Prices, Amihud Illiquidity Ratio, and Stock Performance During Post-dividend Payment Days

	(1)	(2)
Dep Var =	AR (0)	BHAR [0, 20]
Log (Price)	-0.522***	-1.714***
	(-5.41)	(-4.47)
logAmihud	0.112***	0.000
	(5.14)	(0.00)
Log (Price)×logAmihud	-0.022***	-0.065**
	(-3.46)	(-2.59)
Observations	343,823	342,789
Stock FE	YES	YES
Industry×Year-Quarter FE	YES	YES
Adjusted R-squared	0.029	0.071

Table 11. Nominal Price, Non-Proportional Thinking, and Dividend Reinvestment Returns

This table presents the relationship between stock prices, non-proportional trading, and abnormal returns around dividend payment days. To achieve this, we use the dividend per share (*Div Per Share*) as the proxy for non-proportional thinking. Control variables and model specifications are consistent with previous tables. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var =	AR (0)				BHAR [0, 20]			
Log (Price)	-0.247***	-0.178***	-0.240***	-0.167***	-0.917***	-0.698***	-0.899***	-0.660***
	(-9.35)	(-7.63)	(-8.94)	(-7.02)	(-6.96)	(-5.46)	(-6.67)	(-5.14)
Div Per Share	0.219***	-0.063	0.381***	-0.421**	0.799***	-0.101	1.230**	-0.783
	(7.29)	(-1.02)	(3.83)	(-2.11)	(4.91)	(-0.37)	(2.09)	(-0.67)
DY		0.097***		0.309***		0.311***		1.106***
		(4.00)		(3.76)		(3.20)		(3.72)
Log (Price)× Div Per Share			-0.039*	0.125***			-0.104	0.350
			(-1.88)	(3.00)			(-0.82)	(1.61)
Log (Price)× DY				-0.080***				-0.320***
				(-3.25)				(-3.45)
Size	0.024	0.023	0.024	0.022	-0.873***	-0.875***	-0.872***	-0.879***
	(1.58)	(1.53)	(1.59)	(1.47)	(-10.14)	(-10.13)	(-10.12)	(-10.27)
BM	0.014	0.014	0.015	0.005	0.388***	0.387***	0.390***	0.356***
	(0.80)	(0.79)	(0.83)	(0.31)	(3.78)	(3.77)	(3.79)	(3.43)
RE/TE	-0.001	-0.000	-0.001	-0.002	0.004	0.006	0.005	0.000
	(-0.28)	(-0.06)	(-0.21)	(-0.55)	(0.22)	(0.38)	(0.27)	(0.00)
Gross Profit	0.084	0.081	0.082	0.090	0.681**	0.673**	0.677**	0.703**
	(1.34)	(1.30)	(1.32)	(1.45)	(2.35)	(2.33)	(2.33)	(2.43)
TA Growth	0.006	0.006	0.006	0.006	0.009	0.010	0.009	0.010
	(1.16)	(1.20)	(1.17)	(1.22)	(0.74)	(0.78)	(0.74)	(0.80)
logAmihud	0.049***	0.051***	0.050***	0.046***	0.029	0.036	0.031	0.015
	(6.20)	(6.39)	(6.27)	(5.81)	(0.79)	(0.97)	(0.84)	(0.40)
Sales Growth	-0.017	-0.018	-0.017	-0.018	-0.037	-0.037	-0.037	-0.040
	(-1.35)	(-1.37)	(-1.35)	(-1.43)	(-1.09)	(-1.12)	(-1.09)	(-1.18)
Tobin_Q	0.017	0.018*	0.018*	0.010	0.073	0.076	0.076	0.051
	(1.60)	(1.69)	(1.71)	(0.99)	(1.32)	(1.38)	(1.38)	(0.95)
Cash	0.040	0.025	0.037	0.031	0.180	0.131	0.173	0.157
	(0.54)	(0.34)	(0.50)	(0.43)	(0.58)	(0.42)	(0.56)	(0.51)
Tangibility	-0.024	-0.020	-0.024	-0.017	0.008	0.021	0.008	0.032
	(-0.35)	(-0.28)	(-0.35)	(-0.24)	(0.02)	(0.06)	(0.02)	(0.09)
Leverage	0.073	0.070	0.073	0.069	-0.097	-0.106	-0.097	-0.109
	(1.22)	(1.18)	(1.22)	(1.16)	(-0.38)	(-0.41)	(-0.38)	(-0.43)
Observations	343,823	343,823	343,823	343,823	342,789	342,789	342,789	342,789
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.029	0.029	0.029	0.030	0.071	0.071	0.071	0.072

Table 12. Nominal Price, Lottery Demand, and Stock Returns

This table presents the relationship between stock prices, lottery demand, and abnormal returns around dividend payment days. We construct E(ISKEW) following Boyer, Mitton, and Vorkink (2010), which incorporates all relevant past information to best form a future prediction of idiosyncratic skewness. Control variables and model specifications are consistent with previous tables. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =		AR (0)			BHAR [0, 20]	
Log (Price)	-0.182***	-0.184***	-0.182***	-0.691***	-0.698***	-0.686***
	(-7.58)	(-7.53)	(-7.62)	(-5.75)	(-5.78)	(-5.67)
DY	0.087***	0.087***	0.088***	0.283***	0.282***	0.334***
	(5.19)	(5.19)	(4.33)	(4.26)	(4.25)	(4.38)
E(ISKEW)	-0.022	-0.026	-0.021	-0.130	-0.147	-0.081
	(-0.87)	(-0.98)	(-0.79)	(-0.92)	(-0.99)	(-0.57)
Price × E(ISKEW)		0.000			0.000	
		(1.06)			(0.78)	
E(ISKEW) × DY			-0.001			-0.061
			(-0.11)			(-0.96)
Size	0.011	0.011	0.011	-0.906***	-0.908***	-0.908***
	(0.67)	(0.66)	(0.67)	(-9.52)	(-9.50)	(-9.54)
BM	0.010	0.010	0.010	0.407***	0.407***	0.405***
	(0.50)	(0.51)	(0.50)	(3.62)	(3.62)	(3.60)
RE/TE	0.000	0.000	0.000	0.001	0.001	0.001
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)
Gross Profit	0.060	0.060	0.060	0.481	0.480	0.483
	(0.89)	(0.88)	(0.89)	(1.47)	(1.46)	(1.47)
TA Growth	0.007	0.007	0.007	0.005	0.005	0.005
	(0.86)	(0.85)	(0.86)	(0.23)	(0.23)	(0.25)
logAmihud	0.061***	0.061***	0.061***	0.029	0.029	0.030
	(7.30)	(7.30)	(7.30)	(0.74)	(0.74)	(0.77)
Sales Growth	-0.026	-0.026	-0.026	-0.040	-0.040	-0.041
	(-1.29)	(-1.29)	(-1.29)	(-0.88)	(-0.88)	(-0.89)
Tobin_Q	0.025**	0.025**	0.025**	0.130**	0.130**	0.132**
	(2.17)	(2.17)	(2.16)	(2.12)	(2.12)	(2.14)
Cash	-0.063	-0.063	-0.063	-0.057	-0.059	-0.061
	(-0.79)	(-0.79)	(-0.79)	(-0.17)	(-0.18)	(-0.19)
Tangibility	-0.058	-0.059	-0.059	-0.020	-0.024	-0.032
	(-0.75)	(-0.76)	(-0.75)	(-0.05)	(-0.06)	(-0.08)
Leverage	0.106	0.106	0.106	-0.272	-0.271	-0.273
	(1.57)	(1.58)	(1.57)	(-0.92)	(-0.92)	(-0.93)
Observations	289,991	289,991	289,991	289,165	289,165	289,165
Investor FE	NO	YES	NO	YES	NO	NO
Stock FE	YES	YES	NO	YES	NO	NO
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Investor -Stock FE	NO	NO	YES	NO	YES	YES
Adjusted R-squared	0.033	0.033	0.033	0.072	0.072	0.072

Table 13. Dividend Payment Intensity

This table investigate the relationship between dividend payment intensity and stock price. From columns (1) to (3), we use dividend yield to proxy the dividend intensity. From (4) to (6), we proxy dividend intensity by dividend scaled by net income, where we retain only firms that report positive net income and have a dividend payout ratio below 100%. Both DY and Dividend Payout Ratio are in percentile. The sample only consists of dividend payers. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. All regressions include stock and industry × year-quarter fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =		DY			Dividend Payout Ratio	
Log (Price)	-0.320***	-0.177***	-0.172***	-1.976***	-2.161***	-2.090***
	(-27.89)	(-16.93)	(-16.55)	(-16.91)	(-15.47)	(-14.91)
Size		-0.028***	-0.010		-0.388***	-0.188
		(-3.25)	(-1.16)		(-3.06)	(-1.43)
BM		0.246***	0.245***		-1.603***	-1.748***
		(16.88)	(16.91)		(-10.63)	(-11.56)
RE/TE		0.002	0.003		-0.072*	-0.062
		(0.56)	(0.98)		(-1.67)	(-1.44)
Gross Profit		0.019	0.141***		-13.785***	-12.945***
		(0.52)	(3.54)		(-17.45)	(-15.43)
TA Growth		-0.001	-0.001		0.010	0.022**
		(-1.02)	(-0.73)		(1.36)	(2.14)
Sales Growth		0.003	0.002		-0.068***	-0.092***
		(1.13)	(0.79)		(-3.32)	(-3.16)
Tobin_Q			-0.054***			-0.401***
			(-10.69)			(-4.60)
Cash			0.342***			-0.420
			(6.95)			(-0.63)
Tangibility			0.027			4.996***
			(0.55)			(6.54)
Leverage			0.057**			4.153***
			(2.27)			(9.36)
Observations	439,649	373,748	367,732	371,859	352,544	346,823
Stock FE	YES	YES	YES	YES	YES	YES
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.508	0.528	0.531	0.369	0.379	0.382

Figure 1. Price Quintile Dynamics of Dividend-Paying Firms

This figure plots the monthly time series of price quintile thresholds for U.S. firms that paid dividends in the preceding quarter. At the beginning of each month *t*, we sort firms issuing dividends in the preceding three months into quintiles according to their prices. The resulting five threshold price levels (the 20th, 40th, 60th, and 80th percentiles) are then tracked from 1965 to 2024.

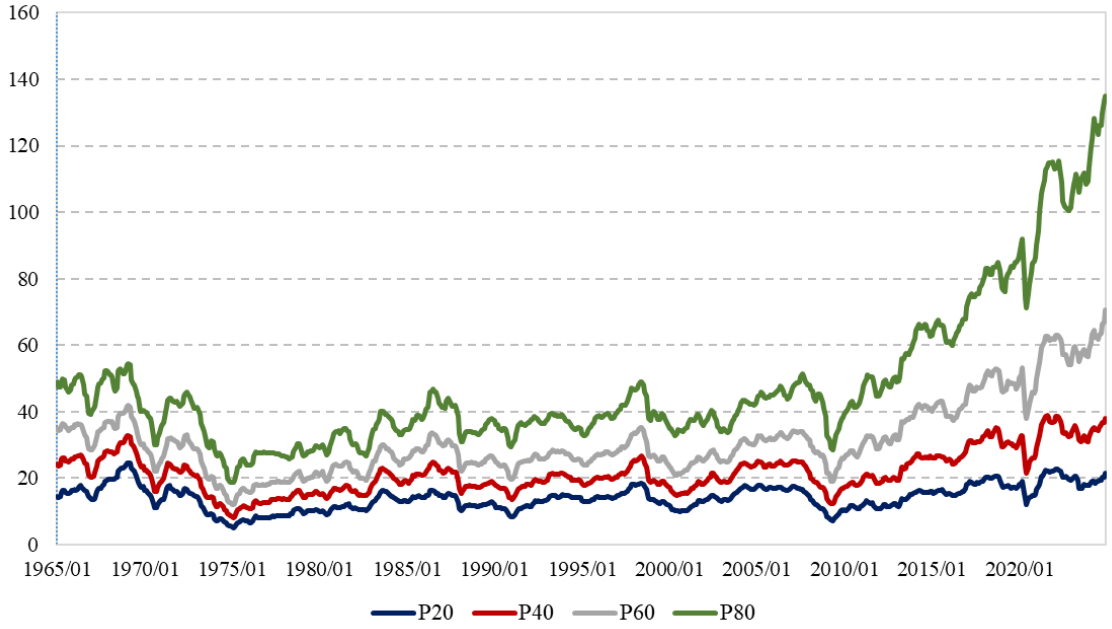


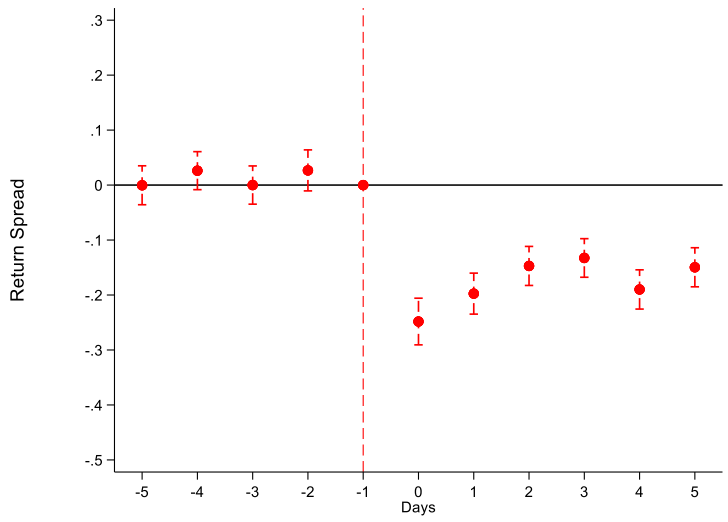
Figure 2. Return Spreads Around Payment Days

This plot displays return spreads between high-price and low-price groups with 95% confidence intervals. This figure is based on estimates of b_d from the following regression:

$$AR_{i,t,T} = a + \sum_{d=-5, d\neq -1}^{d=+5} b_d \times D_i(t - T = d) \times HP_{i,T} + c \times HP_{i,T} + d \times D_i(t - T = d) + e \times Controls + FE + \varepsilon_{i,t,T},$$

where $AR_{i,t,T}$ is defined as the difference between daily return of stock *i* and market return on day *t* for each payment day *T*. $D_i(t - T = d)$ equals one if the interval between day *t* and payment day *T* is *d*. $HP_{i,T}$ equals one if the stock belongs to the top 20% group by price before payment day, and zero if the stock is among the bottom 20%. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. Panel A presents the return spread dynamics without controls and Panel B displays results with controls. All regressions include stock and industry × year-quarter fixed effects. Standard errors are double-clustered by stock and year-quarter.

Panel A. Return Spread Dynamics (without Controls)



Panel B. Return Spread Dynamics (with Controls)

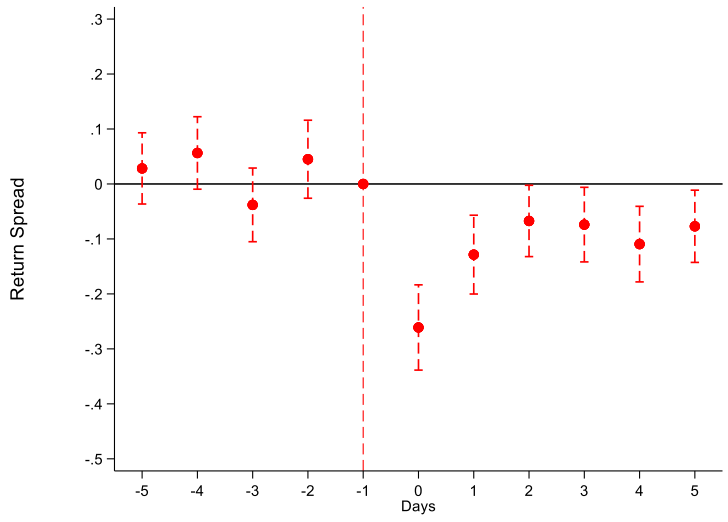


Figure 3. Cumulative Abnormal Returns

This figure displays the buy-and-hold abnormal returns (BHARs) around dividend payment days, grouped by stock price, with 95% confidence intervals. At the end of each month $m-1$, we sort all stocks into 5 price-based portfolios by quintiles. In month m, we assign each dividend-paying stock to one of these portfolios based on its price prior to the dividend payment date. "Low price" refers to groups of stocks with price below $P_{m-1}^{20\text{th}}$ and "high price" refers to those with price above $P_{m-1}^{80\text{th}}$. CARs are computed as the cumulative difference between daily stock returns and value-weighted market returns, aggregated into equal-weighted portfolio returns using market capitalizations as of month $m-1$. The sample period covers 1965 through 2024

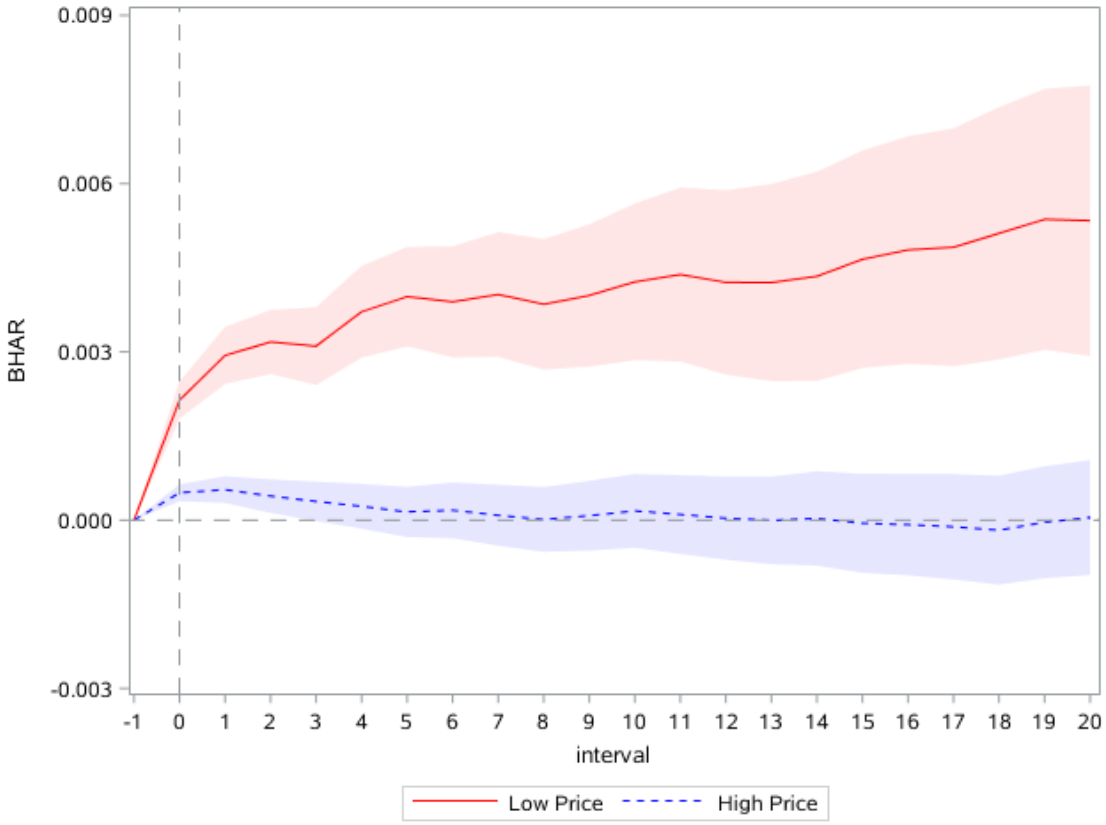


Figure 4. Price Strategy

This figure presents the cumulative return spreads between low-price and high-price dividend payers (P strategy) compared with the small minus big (SMB) and high minus low (HML) portfolios. In each case, the cumulative investment returns from January, 1965 is plotted on the y-axis, versus the date on the x-axis. The red line is for the P strategy, a portfolio that is long in low-price (bottom out-of-sample 20%) dividend payers and is short in high-price (top out-of-sample 20%) dividend payers until the end of month *t*. Both long and short legs are market adjusted. To mitigate the confounding effects related to ex-dividend days, our sample selection mandates that a stock's ex-dividend date must occur at least one calendar month prior to its dividend payment date. We also display an alternative strategy (P strategy long) by buying low-price payers while shorting value-weighted market returns in green dash line. The blue line is the cumulative return of the SMB portfolio and the dark line is the cumulative return of the HML portfolio, both taken from Ken French's website.

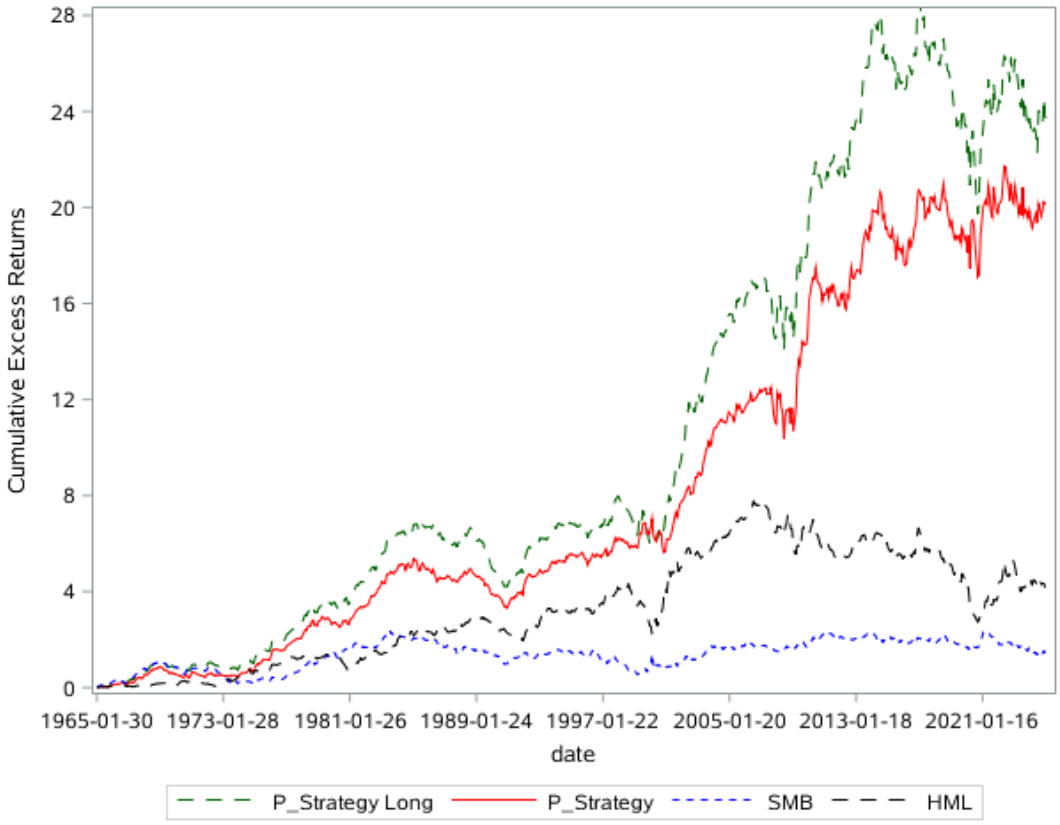
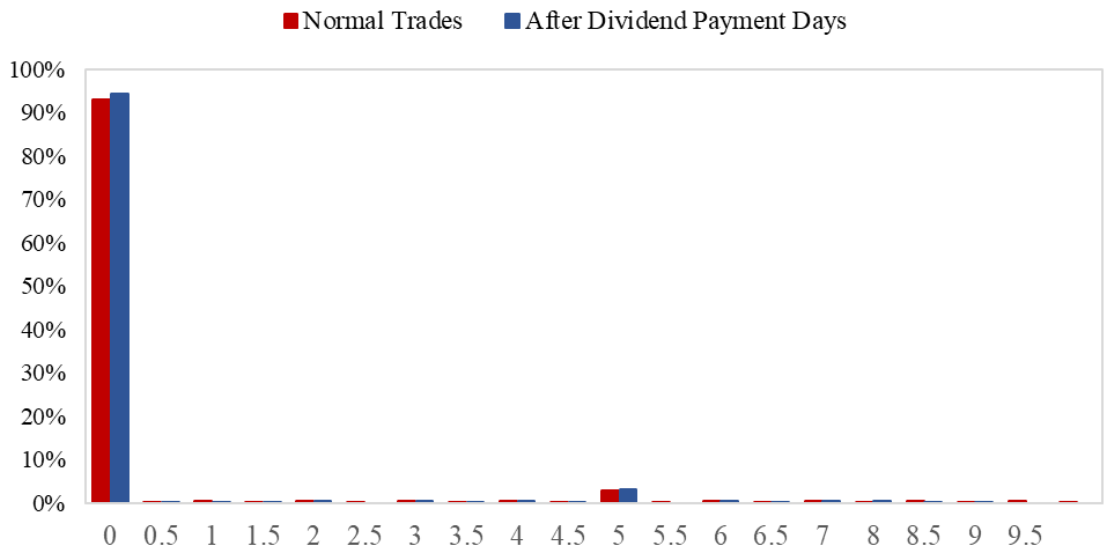


Figure 5. Distribution of Trade Size End Digits

This figure depicts the distribution of the last digit (including the first decimal place) of trade sizes in the LDB database. For visual clarity in representing fractional trades, the decimal value is aggregated to the nearest half-unit (e.g., a trade of 3.3 shares is displayed at position 3.5). The red bars represent the distribution across all trades in the sample. The blue bars show the distribution restricted to trades occurring within a 20-day window following a dividend payment.



Internet Appendix For

"Pennies from Heaven, Barriers to Reinvestment: Nominal Price and Predictable Price Pressure"

Table A1. Instrumental Variable Regressions: Robustness Check

This table presents the results of instrumental variable (IV) regressions investigating the relationship between stock prices and abnormal returns around dividend payment days. The dependent variables are the abnormal return on the payment day (Day 0) and the buy-and hold abnormal return over the post-payment window (BHAR [0, 20]). We construct two instrumental variables using stock splits. The first instrumental variable, Latest Split Ratio, is the split ratio during the latest stock split. The second instrumental variable is Cumulative Factor to Adjust Prices from CRSP. We present 2SLS regressions on AR (0) in columns (1) to (2) and results on BHAR [0, 20] in columns (3) to (4). Kleibergen-Paap F-stat and the p-value of Sargan-Hansen Test J-stat are shown in columns (2) and (4). All regressions include stock and industry × year-quarter fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
Dep Var =	Log (Price)	AR (0)	Log (Price)	BHAR [0, 20]
Latest Split Ratio	-0.125***		-0.125***	
	(-20.08)		(-20.12)	
Cumulative Factor to Adjust Prices	0.009***		0.009***	
	(11.47)		(11.46)	
Log (Price)		-0.173***		-1.441***
		(-3.34)		(-5.36)
DY	-0.046***	0.087***	-0.047***	0.257***
	(-9.88)	(5.64)	(-9.89)	(4.19)
Size	0.567***	0.014	0.568***	-0.490***
	(54.44)	(0.44)	(54.43)	(-3.17)
BM	-0.052***	0.014	-0.053***	0.344***
	(-6.01)	(0.82)	(-6.04)	(3.29)
RE/TE	0.008*	-0.001	0.008*	0.011
	(1.85)	(-0.16)	(1.86)	(0.62)
Gross Profit	0.331***	0.075	0.329***	0.909***
	(8.48)	(1.18)	(8.44)	(2.93)
TA Growth	-0.002*	0.006	-0.002*	0.008
	(-1.92)	(1.20)	(-1.94)	(0.65)
logAmihud	0.122***	0.049***	0.124***	0.129***
	(27.61)	(4.57)	(27.82)	(2.63)
Sales Growth	0.005***	-0.018	0.006***	-0.033
	(2.73)	(-1.38)	(2.77)	(-0.97)
Tobin_Q	0.005	0.018*	0.005	0.076
	(0.77)	(1.73)	(0.79)	(1.36)
Cash	0.095**	0.023	0.095**	0.197
	(2.48)	(0.32)	(2.48)	(0.62)
Tangibility	-0.120**	-0.018	-0.121**	-0.080
	(-2.38)	(-0.26)	(-2.40)	(-0.22)
Leverage	0.006	0.071	0.007	-0.101
	(0.20)	(1.19)	(0.24)	(-0.39)
Observations	343,805	343,805	342,771	342,771
Kleibergen-Paap F-stat		307.65		308.27
P(Sargan-Hansen Test J-stat)		0.674		0.242
Stock FE	YES	YES	YES	YES
Industry × Year-Quarter FE	YES	YES	YES	YES

Table A2. Round-lot Trading and Dividend Reinvestment Propensity

This table examines the impact of round-lot trading on the retail investors' propensity to reinvest dividends using the LDB dataset. The dependent variable, *D(Net Buy)*, is an indicator that equals one if an investor makes net stock purchases during the 20-day window following the dividend payment date. Round-lot trading is measured using three proxies: Fraction (5), Fraction (10), and Fraction (100), defined as the proportion of an investor's total trading amount attributable to trades in which the number of shares transacted is a multiple of five, ten, or one hundred, respectively. These measures are constructed at the investor-stock level (denoted *i,s*) and at the investor level (subscripted as *i*), respectively. The sample is restricted to investors who hold a net long position prior to the ex-dividend date. Control variables are consistent with those in preceding tables. Control variables are consistent with prior tables. We include firm and industry × year-quarter fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by investor-stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =				D(Net Buy)		
Log (Price)	-0.008	-0.008	-0.011**	0.001	-0.001	-0.006
	(-1.33)	(-1.62)	(-2.43)	(0.20)	(-0.13)	(-1.28)
Log (Price) × $Fraction(5)_{i,s}$	-0.008*					
	(-1.66)					
Log (Price) × $Fraction(10)_{i,s}$		-0.007**				
		(-2.22)				
Log (Price) × $Fraction(100)_{i,s}$			-0.005***			
			(-3.01)			
Log (Price) × $Fraction(5)_{i}$				-0.017***		
				(-2.99)		
Log (Price) × $Fraction(10)_{i}$					-0.016***	
					(-3.55)	
Log (Price) × $Fraction(100)_{i}$						-0.011***
						(-4.51)
Controls	YES	YES	YES	YES	YES	YES
Observations	196,134	196,134	196,134	196,134	196,134	196,134
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.413	0.390	0.377	0.460	0.447	0.438

Table A3. Institutional Investors' Round-lot Holdings and Preference for Low-price Stocks to Reinvest

This table investigates whether institutional investors tend to reinvest low-price stocks. We follow Mclean, Pontiff, and Reilly (2025) to classify institutional investors from 13F into six categories, including mutual fund, hedge fund, bank, insurance, wealth management, and others. For each category of institutional investors, we estimate the following regressions:

$$D(Reinvestment)_{i,j,q+1} = a + b \times log(Price)_{j,q} + c \times Fraction(100)_{i,q} + d \times log(Price)_{j,q} \times Fraction(100)_{i,q} + d \times Controls_{j,q} + FE + \varepsilon_{i,j,q+1},$$

where the dependent variable $D(Reinvestment)_{i,j,q+1}$ equals one if the institutional investors increase their holdings of dividend payer j in quarter q+1. $log(Price)_{j,q}$ is the logarithm of price prior to the payment days. Fraction (100) measures the share of an investor's total portfolio value that is composed of positions held in round lots of one hundred shares (as opposed to odd lots). Control variables include dividend yield, Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. The sample is restricted to institutional investors who hold a net long position prior to the ex-dividend date and spans from 1980 to 2024. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Institutional Investor Type:	Mutual Fund	Hedge Fund	Bank	Insurance	Wealth Management	Others
Log (Price)	0.062	-0.875***	-0.804***	-0.600	-1.296**	-0.876***
	(0.54)	(-4.38)	(-3.22)	(-0.96)	(-2.28)	(-4.79)
$Fraction(100)$	2.262**	7.168***	6.812***	-4.328	-0.154	3.014**
	(2.19)	(6.49)	(2.81)	(-0.98)	(-0.04)	(2.51)
Log(Price)×$Fraction(100)$	-1.521***	-1.803***	-1.961***	-0.351	-0.781	-1.332***
	(-5.81)	(-6.55)	(-3.30)	(-0.34)	(-0.77)	(-5.04)
Observations	28,678,518	13,237,303	4,816,883	815,311	1,173,912	16,420,578
Controls	YES	YES	YES	YES	YES	YES
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Investor -Stock FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.177	0.243	0.189	0.245	0.265	0.220

Table A4. Nominal Prices, Dividend Yield, and Dividend Reinvestment among Retail Investors

This table examines the propensity of retail investor to reinvest dividends using LDB dataset. We employ two proxies to capture the effects of dividend reinvestment. *D(Net Buy)* is an indicator variable that equals one if an investor engages in net stock purchases during the 20-day window following the dividend payment date. *Buy Principal* measures the net purchase amount, scaled by the market capitalization. We include observations with investors having net positions before ex-dividend days. In columns (1) and (4), we include firm and industry × year-quarter fixed effects. In columns (2) and (5), we include investor, firm, and industry × year-quarter fixed effects. In columns (3) and (6), we include investor-firm and industry × year-quarter fixed effects. This sample spans from 1991 to 1996. T-statistics, reported in parentheses, are based on standard errors double-clustered by investor-stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Retail Trading in LDB Dataset

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =	D(Net Buy)			Buy Principal		
Log (Price)	-0.011**	-0.014***	-0.024***	-0.002***	-0.002***	-0.003***
	(-2.53)	(-2.78)	(-3.41)	(-5.20)	(-4.20)	(-4.25)
DY	0.021***	0.020**	0.033***	0.003**	0.004**	0.005**
	(2.77)	(2.45)	(3.43)	(2.47)	(2.32)	(2.27)
Log (Price)×DY	-0.007***	-0.006**	-0.010***	-0.001***	-0.001**	-0.002**
	(-2.80)	(-2.49)	(-3.57)	(-2.60)	(-2.42)	(-2.47)
Controls	YES	YES	YES	YES	YES	YES
Observations	196,134	191,972	179,984	196,134	191,972	179,984
Investor FE	NO	YES	NO	YES	NO	NO
Stock FE	YES	YES	NO	YES	NO	NO
Industry×Year-Quarter FE	YES	YES	YES	YES	YES	YES
Investor -Stock FE	NO	NO	YES	NO	YES	YES
Adjusted R-squared	0.024	0.055	0.085	0.075	0.086	0.066

Panel B. BJZZ Retail Flow

	(1)	(2)	(3)
Dep Var =	CulBuy_Vol	CulBuy_Share	Order Imbalance
Log (Price)	-0.013**	-0.056**	-0.007**
	(-2.29)	(-2.04)	(-2.00)
DY	0.008	0.046**	0.007***
	(1.34)	(2.03)	(3.13)
Log (Price)×DY	-0.004*	-0.016**	-0.002***
	(-1.93)	(-2.33)	(-2.91)
Controls	YES	YES	YES
Observations	72,086	72,086	72,031
Investor FE	NO	YES	NO
Stock FE	YES	YES	NO
Industry×Year-Quarter FE	YES	YES	YES
Investor -Stock FE	NO	NO	YES
Adjusted R-squared	0.015	0.052	0.038

Table A5. Additional Controls and Other Channels

This table presents the relationship between stock prices, dividend yields, and abnormal returns around dividend payment days. The dependent variables are the abnormal return on the payment day (Day 0) and the cumulative abnormal return over the post-payment window (CAR [0, 20]). The key explanatory variables are Stock Price, defined as the closing price on the last trading day before the payment day, and Dividend Yield (DY), calculated as the dividend per share divided by the pre-payment stock price. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage, and their interactions with dividend yield. All regressions include stock and industry × year-quarter fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep Var =	AR (0)		BHAR [0, 20]	
Log (Price)	-0.186***	-0.104***	-0.687***	-0.439***
	(-8.22)	(-3.61)	(-5.92)	(-3.73)
DY	0.260**	0.140	1.876***	1.513***
	(2.59)	(1.40)	(4.10)	(3.56)
Log (Price) × DY		-0.102***		-0.312***
		(-2.75)		(-3.11)
Size× DY	-0.009	0.048***	-0.137*	0.036
	(-0.62)	(2.63)	(-1.74)	(0.57)
BM× DY	0.016	0.005	-0.115*	-0.149**
	(0.95)	(0.27)	(-1.89)	(-2.35)
RE/TE× DY	-0.006	-0.007*	-0.002	-0.003
	(-1.49)	(-1.67)	(-0.18)	(-0.27)
Gross Profit× DY	0.028	0.048	0.003	0.065
	(0.71)	(1.15)	(0.02)	(0.38)
TA Growth× DY	-0.002	-0.001	-0.004	0.000
	(-0.33)	(-0.09)	(-0.28)	(0.01)
logAmihud× DY	0.006	0.027***	-0.012	0.054
	(0.62)	(3.42)	(-0.25)	(1.31)
Sales Growth× DY	0.001	-0.001	-0.001	-0.008
	(0.07)	(-0.09)	(-0.03)	(-0.18)
Tobin_Q× DY	0.007	0.011	0.027	0.037
	(0.56)	(0.77)	(0.35)	(0.47)
Cash× DY	-0.177***	-0.188***	-0.844***	-0.867***
	(-3.05)	(-3.17)	(-3.03)	(-3.11)
Tangibility× DY	-0.006	0.015	0.685***	0.745***
	(-0.09)	(0.25)	(3.14)	(3.69)
Leverage× DY	0.220*	0.226**	0.245	0.272
	(1.95)	(2.00)	(0.88)	(0.94)
Controls	YES	YES	YES	YES
Observations	343,823	343,823	342,789	342,789
Stock FE	YES	YES	YES	YES
Industry×Year-Quarter FE	YES	YES	YES	YES
Adjusted R-squared	0.029	0.030	0.072	0.072

Table A6. Fama-MacBeth Regressions

This table presents the relationship between stock prices and stock performance after dividend payment days using monthly Fama-MacBeth regressions. The dependent variables are the abnormal return on the payment day (Day 0) and the buy-and-hold abnormal return over the post-payment window (BHAR [0, 20]). The key explanatory variables are Stock Price, defined as the closing price on the last trading day before the payment day, and Dividend Yield (DY), calculated as the dividend per share divided by the pre-payment stock price. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. T-statistics (in parentheses) are based on Newey–West (1987) HAC standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =		AR (0)			BHAR [0, 20]	
Log (Price)	-0.087***	-0.063***	-0.118***	-0.311***	-0.266***	-0.268***
	(-4.96)	(-4.51)	(-6.75)	(-3.11)	(-2.81)	(-3.20)
DY		0.116***	0.142***		0.172*	0.245**
		(4.57)	(5.58)		(1.78)	(2.30)
Size			0.069***			-0.031
			(6.48)			(-0.44)
BM			-0.012			0.120
			(-0.70)			(1.24)
RE/TE			0.020			0.299***
			(1.17)			(4.87)
Gross Profit			-0.044			0.107
			(-1.54)			(0.54)
TA Growth			0.049			-0.164
			(1.26)			(-1.44)
logAmihud			0.054***			-0.002
			(5.27)			(-0.05)
Sales Growth			0.012			0.078
			(0.31)			(0.49)
Tobin_Q			0.018**			0.028
			(2.09)			(0.52)
Cash			-0.182***			0.413
			(-2.89)			(1.59)
Tangibility			-0.044			-0.155
			(-1.64)			(-0.99)
Leverage			0.040			-0.255
			(0.74)			(-1.01)
Observations	446,805	446,805	345,151	444,767	444,767	344,101
Adjusted R-squared	0.001	0.003	0.008	0.005	0.010	0.030

Table A7. Nominal Price and Dividend Payment Intensity: IV Regressions

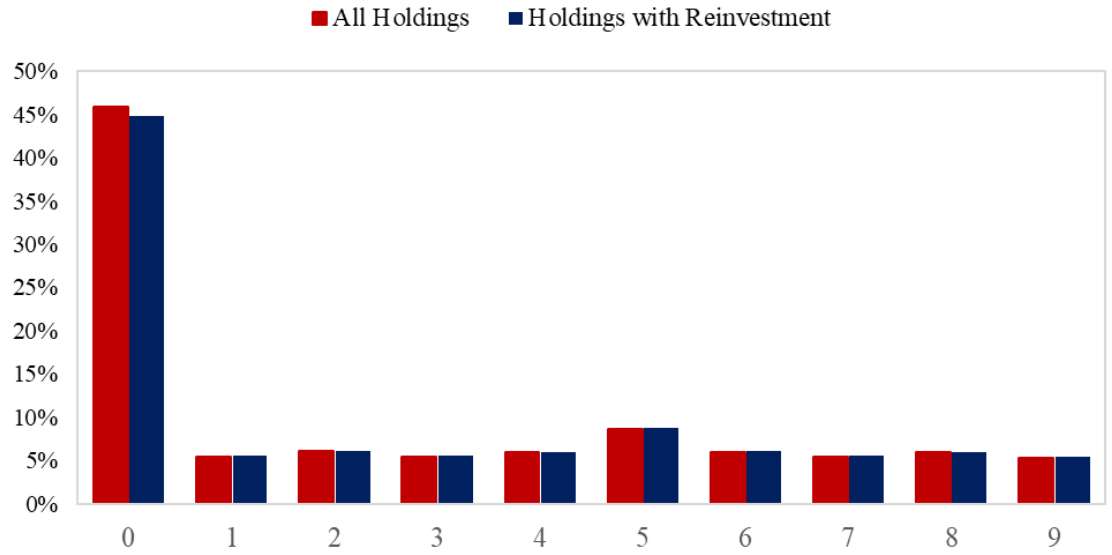
This table investigate the relationship between dividend payment intensity and stock price. From columns (1) to (3), we use dividend yield to proxy the dividend intensity. From (4) to (6), we proxy dividend intensity by dividend scaled by net income, where we retain only firms that report positive net income and have a dividend payout ratio below 100%. Both DY and Dividend Payout Ratio are in percentile. The sample only consists of dividend payers. Control variables include Size (market capitalization at the end of the prior month), BM (book-to-market ratio), RE/TE (retained earnings divided by total equity), Gross Profit (gross profitability), TA Growth (growth rate of total assets), logAmihud (the logarithm of the average daily Amihud illiquidity ratio in the prior month), Sales Growth, Tobin_Q, Cash (cash holding scaled by total assets), Tangibility (PPENT dividend by total assets), and Leverage. All regressions include stock and industry × year-quarter fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by stock and year-quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep Var =	DY		Dividend Payout Ratio	
	1st Stage	2nd Stage	1st Stage	2nd Stage
Cumulative Factor to Adjust Prices	0.009***		0.009***	
	(12.13)		(12.12)	
Log (Price)		-0.216***		-1.404**
		(-5.92)		(-2.05)
Size	0.382***	0.004	0.367***	-0.405*
	(34.84)	(0.29)	(33.68)	(-1.66)
BM	-0.273***	0.232***	-0.285***	-1.536***
	(-25.60)	(13.14)	(-26.02)	(-5.99)
RE/TE	0.010*	0.003	0.010**	-0.068
	(1.85)	(1.06)	(2.02)	(-1.63)
Gross Profit	0.199***	0.149***	0.167***	-13.047***
	(4.84)	(3.70)	(3.85)	(-15.01)
TA Growth	-0.001	-0.001	-0.001	0.022**
	(-1.12)	(-0.76)	(-1.21)	(2.18)
Sales Growth	0.002	0.002	0.002	-0.093***
	(1.50)	(0.83)	(1.28)	(-3.17)
Tobin_Q	0.022***	-0.054***	0.020***	-0.411***
	(3.20)	(-10.49)	(2.90)	(-4.58)
Cash	0.126***	0.347***	0.123***	-0.497
	(2.92)	(7.00)	(2.79)	(-0.73)
Tangibility	-0.089	0.022	-0.063	5.057***
	(-1.64)	(0.44)	(-1.11)	(6.58)
Leverage	-0.014	0.056**	0.005	4.153***
	(-0.48)	(2.23)	(0.15)	(9.37)
Observations	367,732	367,732	346,823	346,823
Stock FE	YES	YES	YES	YES
Industry×Year-Quarter FE	YES	YES	YES	YES
Kleibergen-Paap F-stat		147.118		146.993

Figure A1. Distribution and Transition of End Digits in Institutional Shareholdings

This figure depicts the distribution and transition of the last digit of shareholdings in the 13F database. In Panel A, we present the distribution of end digits of shareholdings. The red bars depict the unconditional distribution across all holdings in the sample. The blue bars show the conditional distribution for holdings observed following a cash dividend reinvestment. In Panel B, we show a transition matrix analyzing the quarterly persistence and change in the last digit of shareholdings specifically around dividend events. Each cell represents the percentage of holdings that transitioned from a given ending digit (row) in the quarter *preceding* a dividend payment to a new ending digit (column) in the quarter *following* the dividend reinvestment. Each row sums to 100%, characterizing the redistribution of end digits induced by reinvestment activity.

Panel A. Shareholdings End Digits Distribution



Panel B. Shareholdings End Digits Transition Matrix

End Digits	After Distribution									
Before Distribution	0	1	2	3	4	5	6	7	8	9
0	78.7%	1.9%	2.2%	1.9%	2.1%	5.1%	2.1%	1.9%	2.1%	1.9%
1	20.7%	18.6%	7.2%	7.1%	7.2%	8.5%	9.2%	7.1%	7.3%	7.1%
2	20.8%	7.2%	21.0%	6.5%	7.1%	8.1%	7.4%	8.4%	7.1%	6.6%
3	20.3%	7.3%	7.6%	18.6%	7.1%	8.5%	7.2%	7.1%	9.2%	7.0%
4	20.3%	6.9%	7.7%	6.9%	20.7%	7.9%	7.2%	6.9%	7.2%	8.4%
5	32.3%	5.1%	5.3%	5.2%	5.3%	26.5%	5.1%	5.1%	5.1%	5.0%
6	20.4%	8.6%	7.2%	6.9%	7.3%	8.3%	20.9%	6.6%	7.4%	6.5%
7	20.2%	7.1%	9.5%	7.0%	7.2%	8.8%	7.4%	18.8%	7.1%	6.9%
8	20.3%	6.6%	7.3%	8.4%	7.5%	8.2%	7.4%	6.8%	20.6%	6.8%
9	19.9%	7.2%	7.3%	7.1%	9.4%	8.7%	7.3%	7.2%	7.5%	18.4%