Categorical Thinking and the Experience Effect: Evidence from Price-Based Return Predictability

by*

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February 2026

Abstract

Price-based categorical thinking and experience effects jointly imply that investor demand for a stock would be higher after similarly priced stocks earned high returns in the past. We show that price-comparable peers' recent performance positively predicts focal stocks' subsequent returns. A long-short strategy exploiting this price-based return predictability delivers 1.13% per month. Using stock splits as a quasi-natural experiment that reshapes price categories and disrupts experience associations, we show that the predictability declines sharply post-split. These findings suggest the unique role of categorical thinking and the experience effect in shaping investor tastes and attention.

JEL Classification: G12, G41

Keywords: Categorical Thinking, Experience Effect, Style Investing, Predictability

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* We thank Zhuo Chen, Jaewon Choi, David Hirshleifer, Xing Huang, Danling Jiang, Jung-Min Kim, Xin Liu, and Don Noh for helpful comments. All errors are our own. Author affiliation/contact information: Chun Liu is with the School of Economics and Management, Tsinghua University (liuch@sem.tsinghua.edu.cn); Huaixin Wang is with the Faculty of Business Administration, University of Macau (huaixinwang@um.edu.mo); Yuehan Wang is with the School of Finance, Central University of Finance and Economics (wangyh@cufe.edu.cn); Jianfeng Yu is with the School of Economics and Management, Tsinghua University (yujf@sem.tsinghua.edu.cn).

1 Introduction

Earlier studies such as Barberis and Shleifer (2003) argue that investors tend to trade categorically based on firm characteristics. Among other characteristics, the nominal stock price appears to act as a particularly salient cue with respect to guiding investment decisions. For instance, retail investors exhibit a preference for low-priced stocks (Kumar and Lee, 2006), whereas institutional investors tilt toward higher-priced stocks (Gompers and Metrick, 2001). Balasubramaniam et al. (2023) document a strong investor clientele effect associated with share prices. In a related study, Green and Hwang (2009) find that stocks that undergo splits experience an increase in comovement with low-priced stocks and a decrease in comovement with high-priced stocks, suggesting investors categorize stocks based on price.

The psychology literature emphasizes that personal experience also exerts a strong influence on individual decision-making (Weber et al., 1993; Hertwig et al., 2004). This perspective implies that positive (negative) past investment experiences would increase (decrease) investors' propensity to purchase new stocks that resemble prior holdings with similar features. Indeed, Huang (2019) shows that after realizing positive returns on a stock position, investors become more likely to buy other stocks that share similar attributes, such as size, book-to-market, and industry.

This paper investigates the asset pricing implications of jointly considering price-based categorical thinking and the experience effect. We posit that when investors are exposed to high returns among stocks in a given nominal-price range, that experience would increase the cognitive accessibility of other stocks with comparable prices. Since nominal price is a simple and salient categorization cue, this heightened attention spills over to other similarly priced stocks, increasing effective demand and pushing up their near-term prices.[1] As a result, strong recent performance among a focal stock's price-comparable peers predicts increased investor demand for the focal stock, thereby leading to high subsequent returns.

We define price-comparable peer stocks using proximity in nominal share price. For each stock, we calculate price-based peers' average return and examine its predictive ability for the focal stock's performance. Our analysis shows that focal stocks subsequently outperform

[1]While we are motivated by the experience effect literature, our mechanism does not hinge on return experiences being generated through an individual's own holdings. Investors may gain return experiences simply by being exposed to recent performance because of categorical thinking (e.g., through watch lists). These observed return experiences could shift attention and tastes, generating excess demand for stocks with comparable prices.

(underperform) when price-comparable peers realized strong (weak) returns in the prior month. A long-short strategy formed on the lagged one-month average return of price-comparable peers delivers a monthly return of 1.13% (t=5.52) and a Fama and French (2015) five-factor alpha of 1.31% (t=5.91). The effect remains robust to a broad set of factor adjustments and firm-level controls, as confirmed by both double-sorted portfolio tests and Fama and MacBeth (1973) regressions.

Unlike traditional categorical thinking based on size or book-to-market, which may proxy for fundamentals or risk exposure, price-based categorical thinking appears to be difficult to reconcile with a purely rational framework since prices can be altered arbitrarily by splits and reverse splits. These practices render firm-level nominal prices largely devoid of economic meaning. Thus, it is hard to rationalize price-based return predictability in the context of a purely risk-based story. To provide further evidence on our proposed mechanism, we investigate stock price-based return predictability around stock splits. This setting provides a quasi-natural experiment for testing whether price-based categorization and the experience effect jointly exert significant return predictability. Stock splits induce large mechanical changes in nominal prices without corresponding changes in firm fundamentals. Therefore, they offer a relatively clean setting for testing the asset pricing implications of category-based investing with few confounding effects. To proceed, we examine the shifts in split stocks' return predictability with price-indexed portfolios before and after stock splits.

We first perform an exercise similar to Green and Hwang (2009) by replacing their contemporaneous comovement time-series regressions with our predictive regressions. If investors categorize stocks by price, then after a split we would expect that low-priced stocks, rather than high-priced stocks, have stronger predictive power for the focal stock. Consistent with this hypothesis, we find that stocks undergoing splits exhibit a decline in the predictive power of high-priced stocks for the focal stock and an increase in the predictive power of low-priced stocks. Indeed, following splits, the predictive power of low-priced stocks is stronger than that of high-priced stocks. At the same time, returns of high-priced stocks preserve significance in predictive regressions, suggesting that some investors adjust only partially to the new nominal price category and continue to associate the focal stock with its pre-split price level.

We then turn to the cross-sectional price-based return predictability explored in this paper. In particular, our mechanism relies on the *interaction* of two ingredients: (1) categorical thinking by price (Green and Hwang, 2009) and (2) anchoring on past investment experience (Huang, 2019). While each channel may operate in isolation, their interaction is

critical in accounting for the full set of empirical patterns we document. More specifically, since individuals tend to anchor to prior experiences, their portfolio choices adjust sluggishly over time (Campbell et al., 2014; Kuhnen et al., 2017; Bazley et al., 2021). A stock split mechanically reduces the nominal share price, creating a wedge between the stock's new price-based peer group and the peer group that investors have mentally associated with the stock. Consistent with this implication, we document an immediate decline in price-based return predictability following split events.[2] To further isolate the mechanism, we implement a difference-in-differences design that contrasts 2-for-1 splits (a 50% price reduction) with moderate-factor splits that imply smaller price changes (e.g., 3-for-2 and 5-for-4). This design helps mitigate concerns that split decisions reflect unobserved fundamentals (Shue and Townsend, 2021). In line with our story, price-based return predictability declines more following larger nominal price cuts (i.e., 2-for-1 splits). These results highlight the importance of experience-based anchoring in generating return predictability among price-comparable stocks.

To further validate the role of price-based categorical thinking and complement our analysis, we conduct two placebo tests. First, we show that the return predictability does not exhibit systematic shifts after splits when peers are defined along alternative characteristics, such as industry (Moskowitz and Grinblatt, 1999), size, value (Lewellen, 2002; Froot and Teo, 2008; Wahal and Yavuz, 2013), profitability, or investment (Chou et al., 2019), rather than nominal price. As such, the traditional style investing (Barberis and Shleifer, 2003) alone cannot explain our findings. Second, we examine variations in price-based return predictability around alternative corporate events (Kwon and Tang, 2025). In contrast to stock splits, these events do not induce systematic changes in predictability.

Our evidence on stock splits supports the hypothesis that the cross-sectional return predictability we document is primarily driven by price-based categorization interacting with the experience effect. We also assess whether the traditional style investing (Barberis and Shleifer, 2003) contributes to this pattern using standard empirical tests. Teo and Woo (2004) and Froot and Teo (2008) provide evidence of positive-feedback trading in style portfolios, while Lewellen (2002) and Wahal and Yavuz (2013) report momentum in characteristic-sorted portfolios, consistent with style-driven capital allocation. To ensure that our price-

[2]To clarify, the Green and Hwang (2009) setting and our split test are related but different. In the Green and Hwang (2009) specification, we separately examine the predictive ability of pre-split (high-price) peers and post-split (low-price) peers. In our split test, by contrast, we always use the most recent nominal price to define price-comparable peers. The Green and Hwang (2009) setting provides time-series evidence at the individual-stock level, which motivates our main cross-sectional results.

based return predictability does not simply proxy for these style effects, we estimate Fama and MacBeth (1973) regressions that include explicit controls for style returns (Wahal and Yavuz, 2013) and for industry returns across multiple horizons. After these controls, the average past return of price-comparable peers remains a strong predictor of focal stocks' subsequent returns.

To verify that price-based return predictability is not an artifact of established anomalies, we provide additional robustness analyses. First, the effect remains statistically and economically significant after controlling for size, value, profitability, investment, past returns, idiosyncratic volatility, illiquidity, and skewness in double-sorted portfolios or Fama-MacBeth regressions. Second, we conduct a placebo test by redefining peers using randomly matched stocks. We show that the predictive power of the resulting variable indeed disappears. Lastly, we extend our analysis to 38 international markets and obtain broadly consistent results.

The price-based return predictability we document may reflect initial underreaction, subsequent overreaction, or a combination of both, analogous to momentum (Jegadeesh and Titman, 1993). On the one hand, strong recent returns among price-based peers may trigger unjustified demand for the focal stock, thereby sustaining price overreaction after portfolio formation. Price-based categorical thinking interacting with the experience effect implies such a channel. On the other hand, albeit less likely, stocks at similar price levels may share common fundamentals. If recent high returns among price-based peers convey favorable information about the focal stock's fundamentals, then the focal stock should subsequently earn abnormal returns because it was initially underpriced at portfolio formation, potentially due to limited investor attention. While our tests based on stock splits provide support for the continued overreaction hypothesis, we further inspect the mechanism by examining long-horizon return predictability and subsequent order imbalance.

Following the approach of Jegadeesh and Titman (1993), we construct price-peer return-based trading strategies with long holding periods. It turns out that the price-based return predictability completely reverses 30 months after portfolio formation. The strategy return even becomes insignificantly negative at longer horizons. This long-term reversal pattern aligns with the continued overreaction story and is difficult to reconcile with an initial underreaction explanation.

We proceed to investigate subsequent retail order imbalance for portfolios sorted on the recent performance of price-comparable peers. Stocks whose peers earned high recent returns

experience significantly larger increases in retail order imbalance than stocks whose peers performed poorly, indicating stronger retail demand following favorable peer performance. This evidence complements Huang (2019), who shows that individuals tend to purchase stocks sharing similar size and book-to-market after personally experiencing high returns.[3] The trading response is markedly weaker for large orders, where institutional investors are more likely to dominate. Taken together, these patterns suggest that experience-driven excess demand, rather than rational arbitrage, more plausibly underlies our price-based return predictability.

Lastly, we investigate heterogeneity in price-based return predictability. The effect is statistically significant across large and small firms, across high- and low-idiosyncratic volatility stocks, across high- and low-institutional ownership stocks, and in both early and recent periods. Whereas price-based return predictability is stronger among smaller firms, high-volatility stocks, low-institutional ownership stocks, and in the earlier sample, the pattern aligns with short-sale constraints impeding arbitrage in retail-dominated stocks (e.g., Nagel (2005)). Overall, these results indicate that price-based return predictability intensifies where retail participation is greater and arbitrage is more difficult.

Our paper relates closely to Green and Hwang (2009), who document that investors categorize stocks by nominal price and show that stock splits shift comovement toward lower-priced stocks and away from higher-priced stocks. Whereas Green and Hwang (2009) study the contemporaneous comovement, we examine the *predictive* power of similarly priced stocks for the focal stock. Our paper also relates closely to Huang (2019), who shows that investors' personal return experiences shape subsequent portfolio choices. While Huang (2019) emphasizes investor trading behavior, we examine the asset pricing implications of the experience effect interacting with price-based categorical thinking, namely, the predictive ability of price-comparable stocks' past performance for cross-sectional stock returns. Strategies that sort on this price-peer return signal generate economically large alphas, even after accounting for a broad set of firm characteristics.

More broadly, our analysis contributes to the literature on style investing and categorical thinking by identifying nominal price as a distinctive basis for return predictability. Seminal work on style investing (e.g., Barberis and Shleifer (2003) and Barberis et al. (2005)) argues that, to simplify portfolio choice, many investors categorize stocks and allocate capital

[3]Whereas Huang (2019) studies repeat category purchases by the same investors, the order-imbalance measure aggregates retail trading across all investors and does not require prior ownership by similarly priced peers.

at the category level rather than security by security. Such capital allocation can induce excess comovement among firms within the same category. Peng and Xiong (2006) provide a theoretical rationale for categorical thinking based on attention constraints.[4] Different from traditional style investing, our interpretation does not require coordinated capital flows at the style or industry level. Instead, we emphasize nominal price as a salient psychological cue that investors use to categorize and associate experiences. In fact, our price-based return predictability remains statistically and economically significant after controlling for the standard style effects documented in prior studies. More important, unlike firm size and book-to-market, price is less economically meaningful and is less likely to proxy for systematic risk. This feature further distinguishes our results from existing evidence.

A large literature links asset pricing anomalies to attention constraints and positive-feedback trading.[5] Participation in trading requires attention, and the stock selection process entails substantial search costs (Barber and Odean, 2008). We propose that, because of price-based categorical thinking or a price-based clientele effect, recent performance in a stock reallocates investor attention toward other stocks in the same nominal price range. This attention reallocation shapes demand and, consequently, predicts higher subsequent returns for stocks whose price-comparable peers have recently performed well. The positive-feedback channel also suggests that favorable realized returns lead investors to expand their holdings (Pearson et al., 2021). In fact, trading intensity increases after positive experiences even when those experiences are plausibly exogenous, such as winning IPO allocations by chance (Ben-David et al., 2018; Anagol et al., 2021; Gao et al., 2021). Relatedly, Chen et al. (2023) show that attention can spill over to firms with neighboring stock codes after a positive experience. Distinct from these studies, our mechanism suggests that favorable performance shifts trading toward stocks in a comparable nominal price range, even though firms with similar price levels need not share an economic connection.

Lastly, our paper is connected to the emerging literature on the role of memory in financial decision-making (e.g., Bordalo et al. (2025a,b); Wachter and Kahana (2024)). Exposure to high returns may heighten the cognitive accessibility of price-comparable stocks through associative memory, thereby shifting preferences toward such stocks. In addition, a positive experience may increase subsequent demand for similarly priced stocks since the past gain potentially serves as a cue that triggers memory retrieval and mental simulation of high

[4] A large subsequent literature documents that category investing influences price formation, particularly by amplifying within-category comovement. See, for example, Barberis et al. (2005); Greenwood (2008); Green and Hwang (2009); Boyer (2011); and Hameed and Xie (2019).

[5] See Daniel and Hirshleifer (2015), Barber et al. (2019), and Gabaix (2019) for reviews.

payoffs, amplifying investors' appetite for other similarly priced stocks. Consequently, prior exogenous investment gains can systematically distort subsequent portfolio choices through memory-based belief formation. Our setting provides a unique test of these memory-based implications by using nominal price as a salient associative cue that links past experiences to future portfolio choices.

The rest of the paper is organized as follows. We describe data sources and variable definitions in Section 2. Section 3 presents our main results using portfolio analysis and Fama-MacBeth regressions. Section 4 examines the mechanism underlying the predictability results. Section 5 further explores several additional robustness tests. Section 6 concludes.

2 Data Description and Summary Statistics

Our sample includes non-financial ordinary common stocks listed on the NYSE, AMEX, and NASDAQ (CRSP exchange codes 1 to 3; share codes 10 and 11) from 1963 to 2024. Stock return and price data are from the Center for Research in Security Prices (CRSP), and accounting data are from Compustat. Institutional ownership is obtained from the Thomson Financial 13F filings. We obtain trade-level transaction data from the Institute for the Study of Security Markets (ISSM) database for 1983 to 1992 and from the NYSE Trade and Quote (TAQ) database for 1993 to 2000. Data on non-U.S. firms are sourced from Compustat Global. Following Campbell et al. (2008), we also delete stocks with a price less than $1 at the portfolio formation date.

2.1 Definition of Key Predictor

The primary variable of interest is the average return of a stock's price-based peers. At the end of each month t, we standardize nominal share prices cross-sectionally to have zero mean and unit variance. For each focal stock i, we measure nominal price proximity relative to every other stock j as

$$\text{Distance}_{i,j,t} = |\text{Price}_{i,t} - \text{Price}_{j,t}|. \tag{1}$$

We define price-based peers as the 100 stocks with the smallest $\text{Distance}_{i,j,t}$. We then calculate the value-weighted average monthly return of these price-based peers, denoted by PSIM.

To mitigate the traditional short-term reversal effect (Jegadeesh, 1990; Lehmann, 1990; Lo and MacKinlay, 1990) and to address the concern that peer returns may merely proxy for investor attention to extreme returns of the focal stock, we follow Chen et al. (2023) and orthogonalize the peer-stock average return with respect to the focal stock's own return over the same window used to compute PSIM. This procedure yields a residual variable, denoted RPSIM, which serves as the key measure in our main analysis.[6] Importantly, RPSIM isolates the variation in similarly priced peers' returns that is orthogonal to the focal stock's performance, rather than conflating peer returns with short-term reversal effects. For robustness, we also report results using the unadjusted PSIM measure.

2.2 Control Variables

To assess whether our price-based return predictability is subsumed by other established anomalies, we consider a large number of firm-level characteristics, including (1) Size, measured as the natural logarithm of market capitalization; (2) book-to-market ratio (BM); (3) Profitability (Profit), measured by return-on-assets; (4) Investment (Invest), measured by growth in total assets; (5) Medium-term momentum (Mom), defined as the cumulative return from month $t-12$ to $t-2$; (6) Long-term reversal (Ltrev), defined as the cumulative return from month $t-60$ to $t-13$; (7) Idiosyncratic volatility (IVol) as in Ang et al. (2006); (8) Maximum daily return (MAX) within the month, as in Bali et al. (2011); (9) Skewness (Skew), computed as the skewness of monthly returns over the prior five years; and (10) Coskewness (Coskew), following Harvey and Siddique (2000) and estimated using five years of monthly returns.

In addition, we include style-related controls based on size, book-to-market, and industry. Following the procedure of Wahal and Yavuz (2013), we compute style returns using portfolios double-sorted on size and book-to-market. Specifically, at the end of each June, we form 5×5 portfolios using quintile breakpoints for size and book-to-market. NYSE size breakpoints are obtained from Kenneth French's website. We define the style return for a given size-BM cell as the value-weighted average return of stocks in that cell. For industry styles, we compute the value-weighted average return of stocks within each Fama-French 48-industry classification.

[6]Specifically, in each month we run a cross-sectional regression with PSIM as the dependent variable and the focal stock's corresponding monthly return as the regressor. We define RPSIM as the regression residual.

2.3 International Sample

Following Gao et al. (2018), we construct an international sample of common stocks drawn from 43 exchanges spanning 38 areas/countries. We convert all returns and accounting variables to U.S. dollars and implement data screens at the area/country level. For a given month (or week), we retain a market only if at least 50 stocks have non-missing return observations. In addition, we require each stock to have at least 12 monthly return observations during the sample period (Hou et al., 2011). We also exclude micro-cap stocks, defined as those whose nominal price or market capitalization falls in the bottom 5% of the corresponding market distribution. We further mitigate the impact of extreme returns by applying the filters of Ince and Porter (2006). First, we treat as missing any return above 300% that reverses within one month: if R_t or R_{t-1} exceeds 300% and $(1+R_t)(1+R_{t-1})-1 < 50\%$, then both R_t and R_{t-1} are set to missing. Second, we set returns to missing if they lie outside the 0.1% and 99.9% percentiles of the return distribution. The international sample spans the period 1997 to 2024.

2.4 Summary Statistics

Each month, we rank stocks by the prior-month residual average return of their 100 closest price-based peers and form decile portfolios. We hold these portfolios for one month and rebalance monthly. Table 1 summarizes firm characteristics for the resulting portfolios formed on RPSIM. Specifically, in each month we compute, for each decile, the cross-sectional mean of a set of firm characteristics across the stocks in that decile, and then we report the time-series averages of these monthly decile means. The reported variables include the sorting variable RPSIM, the next-month value of the sorting variable (RPSIM_{t+1}), market beta (Beta), share price (Prc), the natural logarithm of market capitalization (Size), the book-to-market ratio (BM), profitability (Profit), investment (Invest), the focal stock's past one-month return (R1m), the past 12-month return excluding the most recent month (Mom), idiosyncratic volatility (IVol), and the Amihud (2002) illiquidity measure (Illiq).

Overall, stocks in the high-RPSIM decile have slightly lower market betas, larger market capitalizations, higher nominal share prices, higher investment, and modestly higher profitability while exhibiting lower book-to-market ratios, idiosyncratic volatility, and illiquidity.[7] The last row of Table 1 reports the time-series averages of the cross-

[7]The average beta exceeds one across portfolios because portfolio characteristics are computed using

sectional correlations between RPSIM and other firm characteristics. We notice that RPSIM is positively correlated with firm size and share price. These correlations are unlikely to drive our predictability results, however, because prior studies document negative return predictability for size (Banz, 1981), whereas our price-based return predictability implies a positive relation with RPSIM. Our findings remain robust after controlling for size and price in regressions. We also report the next-month peer-return measure for each portfolio (RPSIM_{t+1}). Notably, RPSIM_{t+1} increases monotonically across the RPSIM deciles, which runs counter to the standard short-term reversal pattern.

3 Price-Based Return Predictability

This section presents our main empirical results. We begin with portfolio analysis based on our primary signal, RPSIM. We then assess robustness using double-sorted portfolios and Fama-MacBeth regressions that control for potential confounding variables.

3.1 Unconditional Sorts

Table 2 presents our main portfolio evidence using unconditional sorts on RPSIM. Each month, stocks are grouped into decile portfolios based on RPSIM. Portfolios are held for one month, and we report value-weighted returns.[8] Panel A shows that stocks whose price-comparable peers earned high returns in the previous month subsequently outperform those whose price-comparable peers earned low returns. The return spread between the top and bottom deciles is 1.13% per month ($t = 5.52$). Adjusting for prevailing asset pricing factors does not attenuate the effect. For instance, the Fama-French five-factor alpha is 1.31% per month ($t = 5.91$), and the alpha after additionally controlling for momentum is 1.10% per month ($t = 4.84$). Across various factor model specifications, the abnormal returns associated with price-based return predictability are economically large and statistically significant.[9]

Panel B repeats the analysis in Panel A using alternative formation horizons by replacing the past one-month peer return with the past one-year or past one-week peer return. When

equal weighting.

[8]Throughout the analysis, we focus on value-weighted portfolios to mitigate concerns about micro-cap stocks. In untabulated results, price-based return predictability remains robust when using equal-weighted portfolios.

[9]In Appendix Table A1, we evaluate the strategy performance under alternative factor-model adjustments and find that price-based return predictability remains economically meaningful and statistically significant.

RPSIM is constructed using past one-year peer returns, we continue to obtain a positive five-factor alpha of 0.62% per month ($t = 2.73$). However, the abnormal performance is largely absorbed once momentum is included (0.14% per month; $t = 0.67$). This pattern differentiates our results from the style-investing evidence in Wahal and Yavuz (2013), who emphasize the predictive ability of 12-month style returns, with weaker predictability at shorter horizons. Moreover, constructing RPSIM from past one-week peer returns yields an even stronger strategy performance than the baseline monthly specification.

Experiences might also be shaped by industry. For instance, Huang (2019) finds that investors who earn favorable returns on a stock subsequently tilt their purchases toward firms in the same industry. To assess whether our price-based return predictability instead reflects this industry experience-induced trading or classic industry momentum (Moskowitz and Grinblatt, 1999), we examine price-comparable peers drawn from different industries. Panel C of Table 2 reports the results. The price-based predictability remains economically large and statistically significant, with a five-factor alpha of 0.87% per month ($t = 4.43$). This evidence indicates that our findings are not fully explained by either experience-induced within-industry buying or industry momentum. We address industry effects more directly in subsequent Fama and MacBeth (1973) regressions.

Panel C also reports two additional robustness tests. First, although less likely, similarly priced stocks may share common fundamentals. We address this concern by excluding stocks with overlapping analyst coverage (Ali and Hirshleifer, 2020) when defining price-comparable peers, since Ali and Hirshleifer (2020) show that shared analyst coverage captures a substantial portion of firms' economic connectedness. The resulting RPSIM strategy continues to deliver a significant five-factor alpha of 1.16% per month ($t = 5.99$). Second, we conduct a placebo test by constructing RPSIM using randomly matched peers. As expected, this placebo measure exhibits no predictive power for focal stocks' subsequent returns.

Lastly, Panel D reports results based on the unadjusted peer-return measure, PSIM. The evidence remains qualitatively unchanged. For example, the value-weighted high-minus-low return spread is 0.92% per month ($t = 4.22$), with a five-factor alpha of 1.13% ($t = 4.52$). Overall, these results indicate that price-based return predictability does not depend on the orthogonalization procedure.

3.2 Double Sorting

To further assess the robustness of our price-based return predictability, we implement a series of double-sorted portfolio tests that account for established anomalies in the literature. Each month, we first partition the cross section into quintile portfolios based on an anomaly characteristic. Within each characteristic quintile, we then sort stocks into decile portfolios according to RPSIM. We hold the resulting portfolios for one month and compute the value-weighted excess returns. To summarize price-based return predictability net of the anomaly characteristic, we average the RPSIM-decile returns across the characteristic quintiles.

Table 3 shows that price-based return predictability remains statistically significant after conditioning on each anomaly characteristic separately. The set of controlled predictors includes size, book-to-market, profitability, investment, idiosyncratic volatility, maximum daily return, skewness, coskewness, illiquidity, past returns over multiple horizons, and industry momentum. These tests indicate that our price-based return predictability is distinct from existing anomalies. Importantly, the effect persists when we control for both multi-horizon past-return measures and industry momentum, implying that it cannot be attributed solely to correlations between RPSIM and other return-based predictors.

3.3 Fama-MacBeth Regressions

We complement the portfolio evidence with cross-sectional Fama and MacBeth (1973) regressions that test whether the average return of price-based peers exhibits predictive power for focal stocks' subsequent returns. The regression framework allows us to include a rich set of controls in a single specification, thereby assessing whether the documented price-based predictability is subsumed by established anomalies.

Additionally, we pay particular attention to the possibility that RPSIM proxies for canonical style returns. The style-investing literature argues that investors simplify portfolio choice by grouping securities into styles (e.g., size and value/growth) and allocating capital at the style level rather than at the individual-stock level (Barberis and Shleifer, 2003). Consistent with this mechanism, prior work documents positive-feedback trading in style portfolios (Teo and Woo, 2004; Froot and Teo, 2008), which can in turn generate return predictability in lagged style returns (Wahal and Yavuz, 2013). Since size and the book-to-market ratio are among the most widely used style dimensions in practice and are actively targeted by institutional and retail investors (Kumar, 2009; Froot and Teo, 2008), we follow

Wahal and Yavuz (2013) and explicitly control for size-BM style returns.

Table 4 reports Fama and MacBeth (1973) regressions of one-month-ahead stock returns on lagged RPSIM and controls for style and industry returns. Column (1) presents the baseline specification with RPSIM only, which shows that a one standard deviation increase in lagged RPSIM implies an increase in the focal stock's subsequent monthly return of 0.156% (t=5.65). Columns (2) to (4) add style and industry returns measured over the past 1 month, 6 months, and 12 months, respectively, and column (5) includes style and industry returns at all three horizons jointly.

Across all specifications, RPSIM remains positive and statistically significant with a stable magnitude. Thus, our price-based return predictability is not subsumed by the traditional style investing or industry momentum. In addition, consistent with Wahal and Yavuz (2013), style returns exhibit predictive ability primarily at longer horizons, whereas shorter-horizon (i.e., one-month) style returns are weak when included in isolation. Industry returns display strong continuation at multiple horizons, with positive and generally significant coefficients, consistent with the industry momentum literature (Moskowitz and Grinblatt, 1999). Importantly, controlling for these industry returns does not attenuate the RPSIM coefficient. As such, this short-horizon, price-based effect is distinct from conventional style-based comovement and predictability.

Overall, the regression evidence corroborates our portfolio results. Price-based return predictability persists after accounting for conventional style investing and industry momentum, and it remains economically meaningful and statistically significant in the presence of these controls.

4 Inspecting the Mechanism

In this section, we examine the key mechanisms underlying the documented price-based return predictability. First, we use stock splits as a laboratory to study the joint role of price-based categorical thinking and the experience effect. Second, we investigate the subsequent retail order imbalance to scrutinize the continued overreaction hypothesis. Finally, we examine long-horizon return dynamics to shed light on the underlying mechanism.

4.1 Evidence Based on Stock Splits

Our price-based predictability relies on the *interaction* of two elements: (1) categorical thinking by price (e.g., Green and Hwang (2009)) and (2) anchoring on past investment experience (e.g., Huang (2019)). In particular, either price-based categorical thinking or experience-driven positive feedback trading alone cannot generate our result. In this section, we use stock splits as shocks to nominal prices to further inspect the mechanism underlying our result.

First, if investors categorize stocks by share prices, then after a split we would expect that stocks undergoing splits exhibit a decline in the predictive power of high-priced stocks for the focal stock and an increase in the predictive power of low-priced stocks. More importantly, we argue that to the extent that investors anchor to prior investment experience, they may still pay attention to the pre-split price level and track the corresponding set of stocks in their trading. For instance, Campbell et al. (2014) find that individuals repeat investment behaviors and invest in categories that performed well for them in the recent past. Kuhnen et al. (2017) show that investors' portfolio choices are sticky over time, as prior investment choices hinder belief updating. Bazley et al. (2021) find evidence of overreliance on past decisions in investors' behavior. Since we define price-comparable stocks using the most recent month-end price, peer stocks based on the post-split nominal price may diverge from investors' mentally associated benchmark through past experience. Therefore, if price-based return predictability is experience driven, then we would observe reduced predictive ability of RPSIM after stock splits as a result of this mismatch between investors' reference set and the mechanically redefined peer group.

Stock splits also allow us to distinguish between price-based categorical thinking and alternative style-based investing (e.g., Barberis and Shleifer (2003)). We expect that the predictive ability of peer stocks' returns should be unaffected by split events when those peers are not defined by nominal price—for example, when they are identified by industry (Moskowitz and Grinblatt, 1999) or other characteristic classifications (Wahal and Yavuz, 2013).

We collect split event data from CRSP and design our empirical analysis following approaches in related studies, such as Green and Hwang (2009), Birru and Wang (2016), Shue and Townsend (2021), and Du et al. (2025). In this section, we focus on 2-for-1 splits, the most prevalent split scheme. We further exploit a difference-in-differences design by comparing results from 2-for-1 splits and moderate-factor splits in later analysis.

4.1.1 Revisit Green and Hwang (2009) with predictive regressions

We start with an exercise similar to the empirical design of Green and Hwang (2009). Specifically, we first replicate their comovement result by estimating the following regression for each stock split, before and after the event:

$$R_{i,d} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,d} + \beta_{HighPrc,i} R_{HighPrc,i,d} + \varepsilon_{i,d}, \tag{2}$$

where $R_{i,d}$ is the return of stock i on day d and $R_{LowPrc,i,d}$ ($R_{HighPrc,i,d}$) is stock i's respective low (high) price index on day d. We follow Green and Hwang (2009) in defining the low- and high-price groups and in constructing $R_{LowPrc,i,d}$ and $R_{HighPrc,i,d}$.[10] We then modify the design slightly by estimating predictive regressions:

$$R_{i,d+1} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,d} + \beta_{HighPrc,i} R_{HighPrc,i,d} + \beta_{Focal,i} R_{i,d} + \varepsilon_{i,d+1}, \tag{3}$$

where the main difference is that we replace the contemporaneous return on the left-hand side ($R_{i,d}$) with the one-day-ahead return ($R_{i,d+1}$) and control for the focal stock's lagged return to purge out the short-term reversal effect. For both specifications, the pre-event regression is run over the 12-month period ending one month before the split implementation, and the post-event regression is run over the 12-month period starting one month after the split implementation. The sample consists of 2-for-1 split events spanning the period 1964 to 2024. When summarizing the estimation results, standard errors are clustered by month when calculating the t-statistics.

Table 5 reports the results. We confirm that the price-based comovement documented by Green and Hwang (2009) remains highly significant in our extended sample. After splits, stocks comove more (less) with low-priced (high-priced) stocks. Panel A shows that the cross-sectional mean change in $\beta_{LowPrc,i}$ is 0.206 (t=9.01), whereas the cross-sectional mean change in $\beta_{HighPrc,i}$ is -0.085 (t=-4.39). Panel B presents the predictive regression results. First, we find that the past returns of price-comparable stocks exhibit positive predictive ability in the Green and Hwang (2009) setting. Moreover, split events alter this predictive

[10] Specifically, the low-price group (LowPrc) and the high-price group (HighPrc) are given by: $LowPrc \in \left[P_{post} - \frac{P_{pre}-P_{post}}{2}, P_{post} + \frac{P_{pre}-P_{post}}{2}\right]$, $HighPrc \in \left[P_{pre} - \frac{P_{pre}-P_{post}}{2}, P_{pre} + \frac{P_{pre}-P_{post}}{2}\right]$, where P_{pre} and P_{post} are the pre- and post-split stock prices measured one day before the split. As in Green and Hwang (2009), we focus on 2-for-1 splits, meaning $P_{pre} = 2P_{post}$. Therefore, the low-price group and the high-price group can also be written as $LowPrc \in [\frac{1}{4}P_{pre}, \frac{3}{4}P_{pre}]$ and $HighPrc \in [\frac{3}{4}P_{pre}, \frac{5}{4}P_{pre}]$. Then, $R_{LowPrc,i,d}$ ($R_{HighPrc,i,d}$) is the value-weighted average return of stocks belonging to LowPrc (HighPrc), excluding the focal stock.

relation. After stock splits, the coefficient on the low-price index ($\beta_{LowPrc,i}$) in predictive regression (3) increases from 0.063 to 0.144, while the coefficient on the high-price index ($\beta_{HighPrc,i}$) declines from 0.168 to 0.117. The corresponding changes in average coefficients are also statistically significant, with the difference in the mean $\beta_{LowPrc,i}$ being 0.081 (t=3.68) and the difference in the mean $\beta_{HighPrc,i}$ being -0.051 (t=-2.35).

These results suggest that, after split events, the focal stock is more associated with low-priced stocks as a result of price-based categorical thinking. Since high-priced stock returns still have significant power in predicting the focal stock after controlling for low-priced stock returns, it also implies that some investors may still link the focal stock with high-priced stocks as a result of their past association in memory. Therefore, a split-induced reclassification of price-comparable peers should exhibit declined predictive ability, because investors adjust only partially to the stock's new nominal price category. We examine this mechanism in greater detail in the analyses that follow.

4.1.2 Attenuated price-based return predictability after stock splits

We now turn to the price-based cross-sectional return predictability documented in this paper. To capture variations in predictability, we follow Du et al. (2025) and define a dummy variable, PredictPower$_{i,t}$, for each stock-month. Specifically, PredictPower$_{i,t}$ is set to one if either of the following conditions is met: (1) stock i's current monthly return and its RPSIM at $t-1$ are both in the top quintile; or (2) stock i's current monthly return and its RPSIM at $t-1$ are both in the bottom quintile. For all other cases, PredictPower$_{i,t}$ takes a value of zero. In other words, the average PredictPower$_{i,t}$ captures the probability that stocks with high (low) RPSIM in the past will outperform (underperform) in the subsequent month.

Figure 1 illustrates the timeline of variable construction and empirical tests. We estimate the following regression to examine the impact of stock splits on price-based predictability (Du et al., 2025; Shue and Townsend, 2021):

$$\text{PredictPower}_{i,t+1} = \alpha + \sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} + \tau_t + \eta_i + \varepsilon_{i,t+1}, \tag{4}$$

where the dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ equals one if month t is k months before or after a split event for stock i. The split event month is characterized by $k = 1$. We

include year-month fixed effects (τ_t) and firm fixed effects (η_i). The sample is limited to six months before and after a split.[11] Since the dependent variable represents the intertemporal relationship between RPSIM in period k and the return in period $k+1$, we use $k=-2$ as our estimation benchmark.[12] The coefficients β_k ($k=-6,...,-1,1,....,6$) thus measure the difference in predictive power in event month k relative to the benchmark (pre-split) period. If a split event attenuates price-based return predictability, one would expect to see a significantly negative β_k for $k \geq 1$.

Figure 2 presents the regression results. Consistent with our hypothesis, the predictive power of RPSIM declines sharply following stock splits. The estimated coefficient (β_k) is small in magnitude during the pre-event window and becomes significantly negative in the post-event period. This pattern suggests that price-based categorical thinking alone cannot fully explain our predictability findings. As Green and Hwang (2009) document, stocks exhibit increased (decreased) comovement with low-priced (high-priced) stocks after splits. Different from Green and Hwang (2009), who focus on *contemporaneous* and time-series return correlations, our results highlight the role of investor experience as a joint and critical determinant of *intertemporal* and cross-sectional return predictability.

4.1.3 Placebo tests based on alternative stock categories

To further examine the role of price-based categorical thinking and distinguish our story from other channels, we conduct a placebo test by re-estimating equation (4) using alternative return variables. Specifically, we consider two control variables employed in our Fama-MacBeth regressions: the one-month industry return (Moskowitz and Grinblatt, 1999) and the one-month style return (Wahal and Yavuz, 2013). We also consider four alternative characteristic-based peer returns, including size, book-to-market ratio, profitability, and investment. For each characteristic, we follow Section 2.1 and define peer stocks analogously

[11] To be included in the sample, for each stock split event, we also require that there are no other split events for the same stock occurring within a six-month window before or after the event. In addition, monthly stock returns should be non-missing throughout this window. As in our main analysis, the sample is restricted to stocks with a share price of at least \$1 at the end of each month. After these filters, our initial sample consists of 4,178 2-for-1 split events spanning the period 1964 to 2024.

[12] Specifically, β_k captures the predictive ability of period k's RPSIM for the return in $k+1$. For $k=-1$, since stocks would experience splits in the upcoming month ($k=1$), the estimated β_{-1} might be contaminated by many confounding factors such as shifts in comovement (Green and Hwang, 2009), changes in investor clientele (Dhar et al., 2004), or changes in liquidity (Copeland, 1979; Conroy et al., 1990; Easley et al., 2001; Lin et al., 2009). Therefore, β_{-2} serves as a more plausible benchmark since it is purely based on pre-split information. Nevertheless, we use $k=-1$ (one month prior to the split) for a robustness check and find similar results.

as when defining price-based peers, and then we calculate the value-weighted average monthly return of the focal stocks' characteristic-based peer stocks.[13] We conjecture that split events should not affect the predictive ability of these non-price-based variables in the same way as our price-based predictability.

Figure 3 shows estimation results based on alternative definitions of peer stocks. In sharp contrast, we detect no significant changes in return predictability around stock splits. The estimated coefficients appear randomly distributed and mostly insignificant throughout the event window. As such, characteristics-driven style investing (Barberis and Shleifer, 2003; Wahal and Yavuz, 2013) is unlikely to drive our priced-based return predictability. In addition, this pattern also suggests that potential changes in liquidity condition (Copeland, 1979; Conroy et al., 1990; Easley et al., 2001; Lin et al., 2009) around stock splits are less likely to be the main force underlying our result; otherwise, one should observe material shifts in the predictive power of these characteristics-based predictors. These placebo results highlight the distinctive roles of price-based categorical thinking and investment experience in generating the predictable return pattern documented in this paper.

4.1.4 Comparing 2-for-1 and moderate-factor splits

A potential concern with our analysis is that unobservable fundamental factors might drive split decisions. We argue, however, that our findings still support the behavioral interpretation over other channels such as sluggish information dissemination. First, even if splits partly reflect evolving fundamentals, such slow-moving forces are unlikely to generate an *immediate* decline in RPSIM's predictive power. Second, we employ a difference-in-differences design that compares 2-for-1 splits (a 50% price reduction) with a pool of moderate-factor schemes, specifically 3-for-2 splits (a 33% price reduction) and 5-for-4 splits (a 20% price reduction), which enables us to control for common fundamental factors underlying split decisions (Shue and Townsend, 2021).[14] We show that price-based return predictability weakens more following larger nominal price shocks (i.e., 2-for-1 splits), as the wedge between the post-split price level and prior investment experience becomes more substantial.

[13] To align with our main specification, we use the orthogonal versions of these alternative peer return variables. Specifically, for each variable, we estimate monthly cross-sectional regressions of the variable on the focal stocks' monthly return and take the residuals. Our conclusions remain valid using the original peer return variables.

[14] Using the same construction procedure, the sample includes 4,178 2-for-1 splits, 2,688 3-for-2 splits, and 655 5-for-4 splits from 1964 to 2024.

To examine the difference in the impact between 2-for-1 and moderate-factor splits, we estimate the following regression (Shue and Townsend, 2021):

$$\begin{aligned}\text{PredictPower}_{i,t+1} = &\sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} \\ &+ \sum_{k=-6}^{6} \gamma_k \mathbb{I}\{EventMonth_{i,t} = k\} \times \mathbb{I}\{TwoForOne_{i,t}\} \\ &+ \mathbb{I}\{TwoForOne_{i,t}\} + \alpha + \tau_t + \eta_i + \varepsilon_{i,t+1},\end{aligned} \tag{5}$$

where $\mathbb{I}\{TwoForOne_{i,t}\}$ is an indicator variable that is equal to one if the split event for stock i in month t is a 2-for-1 split, and zero if it is a 3-for-2 split or 5-for-4 split. Similar to equation (4), we use two months prior to the split event (i.e., $k = -2$) as our regression benchmark. We expect that the coefficient on the interaction term, γ_k, should be significantly negative in the post-event period ($k \geq 1$).

Figure 4 presents the regression results. We find support for the parallel trends assumption, as the estimated γ_k is insignificant for $k < 0$. More importantly, γ_k becomes negative and statistically significant after stock splits, indicating that the price-based return predictability diminishes more substantially following 2-for-1 splits. Since changes in fundamentals are unlikely to happen precisely in split execution months, and equation (5) controls for common fundamental movements, our result suggests that the documented variation in RPSIM's predictive ability is mainly explained by the nominal price-induced disruption in investor perceptions.

We also re-estimate regression (5) using alternative characteristics-based variables as placebo predictors. Figure 5 presents the results. Consistent with our interpretation and previous results, we find no material change in predictive power around stock splits when the predictor is not constructed from the nominal share price.

4.1.5 Placebo tests based on alternative corporate events

To complement our analysis, we examine a series of major corporate events that also potentially affect stock prices. Specifically, we employ 23 event categories related to firms' real economic activities, as studied by Kwon and Tang (2025). Quarterly earnings announcement dates are obtained from Compustat, while the dates for the remaining 22 event types (e.g., board changes and annual meetings) are extracted from the Capital IQ

Key Developments database.[15] For each event included in our analysis, we require that no stock split events occur within a six-month period preceding or following the event. We expect that these fundamental-driven corporate events exert minimal impact on price-based return predictability.

In addition, a large literature shows that demand shocks from index reconstitutions lead to abnormal returns and changes in stock return comovement (Harris and Gurel, 1986; Shleifer, 1986; Barberis et al., 2005; Chang et al., 2015). Since reconstitutions typically have requirements on market capitalization (e.g., Russell indexes) and fundamental performance (e.g., S&P 500 index), and not targeting on nominal prices, we expect that they would also have little influence on the predictive ability of RPSIM. Data on firm-level index reconstitution events are obtained from Greenwood and Sammon (2025).[16] We define the event month as the month in which the index-constituent change is implemented and apply the same filters used for other corporate events.

Figure 6 presents coefficients from equation (4), in which we define the event window using each event category. The final subfigure shows the result for index reconstitutions. Overall, these corporate events fail to produce the pattern observed in our benchmark test (Figure 2). In most cases, RPSIM's predictive power is statistically insignificant both before and after the event, or it changes in a direction inconsistent with our mechanism. These placebo results therefore reinforce our interpretation that price-based return predictability arises primarily from price-based categorization interacting with the experience effect, rather than from alternative channels such as sluggish diffusion of fundamental news.

Overall, stock splits provide a useful setting to inspect the key channel underlying our asset pricing results. Having established the split-based evidence on predictability, we next test two additional implications of our hypothesis for investor trading and investor attention.

4.2 Evidence Based on Order Imbalance

Section 4.1 suggests that fundamental factors play a minimal role in driving declines in price-based return predictability after split events. To further tease out the details in this

[15]The original sample of Kwon and Tang (2025) comprised 24 corporate event categories. However, structural changes in the Capital IQ Key Developments database in December 2023 resulted in the removal of Credit Watch-related events. Therefore, we focus on the remaining 23 categories.

[16]These events consist of S&P 500 additions and deletions, as well as additions to the Russell 1000 and 2000 from outside the Russell 3000 universe. We thank the authors for making the data available.

channel, we examine trading metrics in this section. In particular, categorical thinking by price suggests that investors employing such a heuristic would display trading habitats among price-comparable stocks. Since recent experience shapes current tastes, our mechanism predicts that the effective demand for focal stocks will increase (decrease) after price-comparable stocks have recently realized high (low) returns. Since retail investors are more likely to be drawn to categorical thinking and susceptible to experience anchoring, the demand response should be more evident for retail trading.

We study post-formation demand by tracking order imbalance across RPSIM-sorted portfolios. Retail trading activity is proxied by small orders and calculated based on the Lee and Ready (1991) algorithm.[17] We then analyze how order imbalance evolves over the month following portfolio formation. Figure 7 reports the results. It shows that retail order imbalance rises more (or falls less) for stocks whose price-comparable peers earned high returns in the prior month than for stocks whose peers earned low returns. This differential retail demand is consistent with the price-pressure channel and may contribute to the higher subsequent returns observed for high-RPSIM stocks.

Notice that the order imbalance pattern alone does not rule out the initial underreaction hypothesis. In particular, if firms with high RPSIM are underpriced more compared with firms with low RPSIM, then investors could be rationally trading on such mispricing. If this is the case, however, one should expect a stronger response for large orders, where institutional investors dominate. Figure 7 shows that the pattern based on large, potentially institutional, order imbalance is minimal. This stronger post-formation retail demand response suggests that our evidence is more consistent with the continued overreaction channel.

Beyond retail trading, we also examine trading volume. Short-sale constraints imply that price-based return predictability is driven primarily by buy-side pressure. As such, stocks whose price-comparable peers earned high returns in the past should exhibit abnormally elevated trading volume. Appendix Table A2 confirms our hypothesis. We find that higher RPSIM is indeed associated with higher abnormal turnover in the next month.

4.3 Price-Based Return Predictability over the Long Horizon

Analogous to other return predictability patterns such as momentum (Jegadeesh and Titman, 1993), our price-based return predictability has several potential explanations.

[17] The calculation details are provided in Appendix A.

More specifically, two prevailing channels exist: (1) continued overreaction after portfolio formation and (2) initial underreaction at the portfolio construction date. Under the continued overreaction channel, recent returns might shift investor attention toward other stocks within the same nominal price category, thereby generating excess trading. As a result of such price pressure, stocks whose price-comparable peers earned high recent returns subsequently deliver higher returns.

For the underreaction story, predictability emerges because of slowly diffused fundamental news. If similarly priced stocks share correlated fundamentals and investors overlook this information, then the focal stock tends to be undervalued (overvalued) when peer stocks have recently realized high (low) returns. Abnormal returns result as focal stocks' prices converge to fundamental values. However, this case appears less plausible since the nominal price level itself provides little justification of firm fundamentals. To distinguish alternative channels underlying price-based return predictability, we examine strategy returns over longer horizons.

Figure 8 presents price-based return predictability over long horizons. We form portfolios with long-term holding periods following the method of Jegadeesh and Titman (1993). The RPSIM strategy return increases gradually over the first 16 months and then begins to decline. The effect fully reverses and even becomes negative after about 30 months. Since the standard momentum also exhibits long-term reversal, we account for this potential confounding factor by estimating six-factor alphas. The lower graph of Figure 8 shows that price-based predictability still diminishes and reverses over the long run. Controlling for the five-factor model yields the same conclusion. This long-run reversal pattern makes it less likely that our results reflect initial underreaction to fundamental news.

5 Further Robustness Checks

This section provides heterogeneity analysis based on sample period, firm size, idiosyncratic volatility, and institutional ownership. We also extend the analysis to show that price-based return predictability is an international phenomenon.

5.1 Subsample Analysis

Panel A of Table 6 reports a subsample analysis in which we split the full sample into an early and a recent period. Price-based return predictability is more evident in the early sample period. For instance, the Fama-French three-factor alpha equals 1.35% (t = 7.19) per month in the early period and 0.85% (t = 3.88) in the recent period. This pattern is consistent with the view that the mechanism underlying price-based predictability operates primarily through retail trading. To the extent that direct retail participation in individual stocks declines in the more recent period, the resulting attenuation in retail-driven demand spillovers would weaken the predictability pattern. This time-series pattern contrasts with the evidence on traditional style investing. Wahal and Yavuz (2013) show that style returns display predictive power primarily in the post-1988 period, whereas the effect is largely indistinguishable from zero earlier. They ascribe the stronger predictability in the later period to the expanded adoption of size and value styles in institutional portfolio construction.[18]

Panel B of Table 6 reports subsamples by firm size. We classify firms as large if their market capitalization exceeds the NYSE median and as small otherwise. Price-based return predictability remains statistically significant in both groups. For example, the high-minus-low RPSIM portfolio among large firms continues to deliver a monthly three-factor alpha of 0.38% (t = 4.06), although the magnitude is smaller than among small firms. This evidence is informative since Wahal and Yavuz (2013) find little cross-sectional predictive power of past style returns among large stocks, suggesting that value-growth style returns alone do not account for the return variation among large stocks.

We also split the sample into two groups based on idiosyncratic volatility in Panel C. The price-based predictability is again present in both subsamples. As expected, the effect is weaker among low-IVol firms but remains economically meaningful and statistically significant, with a monthly three-factor alpha of 0.62% (t = 5.41). Overall, the evidence indicates that price-based return predictability is not confined to small or difficult-to-arbitrage stocks, although it is stronger in those segments, consistent with limits to arbitrage slowing the correction of mispricing. At the same time, the persistence of the effect among

[18] A potential reconciliation is that retail investors are the primary providers of mutual fund capital. Accordingly, even if the stronger style-based return predictability in the later period reflects capital allocation by delegated asset management, it remains consistent with a retail origin of style-level flows. Under this interpretation, greater retail participation through style-oriented mutual funds could amplify return predictability in the recent period, while reduced direct retail participation in individual stocks would dampen the predictive power of price-comparable peers' returns.

large and low-IVol firms suggests that arbitrage activity does not fully eliminate the demand spillovers induced by the interaction between categorical thinking and the experience effect, potentially because such bias is not immediately salient to sophisticated traders.

If retail investors are more prone to categorical thinking and susceptible to the experience effect, price-based return predictability should be stronger among firms with lower institutional ownership. We split stocks into high and low institutional ownership subsamples using size-adjusted institutional ownership following Nagel (2005). Panel D of Table 6 reports portfolio performance from sequential sorts on institutional ownership and RPSIM. We find that price-based predictability persists in both groups and is indeed more pronounced among stocks with low institutional ownership. Prior work, such as Teo and Woo (2004) and Froot and Teo (2008), documents style-level trading by institutions and often attributes style-return predictability to institutional trading activity. In contrast, our results point to a primarily retail-driven mechanism.

5.2 Evidence from International Markets

Lastly, we examine price-based return predictability using international data to further assess the external validity of our findings. Since trading intensity varies substantially across markets, a fixed calendar horizon may correspond to different volume-time horizons. For example, in high-turnover markets, one week of trading can be comparable (in terms of trading activity) to a month in low-turnover markets. In extremely high-turnover markets (e.g., China), investors may therefore respond more strongly to weekly, rather than monthly, past returns. Motivated by this heterogeneity, we classify markets using aggregate turnover, defined as the average annual turnover for each country/area across all sample years. In above-median-turnover markets, we sort on the prior-week residual average return of price-comparable peers and hold portfolios for one week. For markets with aggregate turnover below the median, we continue to use monthly RPSIM as the predictor and hold portfolios for one month. More broadly, aggregate turnover may proxy for retail participation, as individual investors tend to trade more actively.

We implement this procedure for the 38 markets reported in Table 7. Given limited cross-sectional coverage in some markets, we compute RPSIM using the average returns of the 30 most similarly priced peers. In high-turnover markets, price-based return predictability is positive in 17 of 19 cases, with 11 estimates reaching conventional significance levels. Given the shorter sample length and smaller cross-sectional coverage outside the U.S. market,

statistical power at the individual-market level is generally weaker. Nevertheless, the effect remains economically large in the aggregate, with the average high-minus-low spread in high-turnover markets being 7.85% ($t = 7.71$) per year. Moreover, only two of the 19 high-turnover markets display negative spreads, and none is statistically significant. By contrast, the low-turnover group exhibits a smaller and statistically insignificant average spread, with an annualized return spread of 2.89% ($t = 2.95$). Balasubramaniam et al. (2023) document strong price-related investor clienteles in India, while Liu and Shi (2021) show that Chinese retail investors substantially segment their choices by stock price. Consistent with these findings, Table 7 shows that both India (IND) and Mainland China (CHN) markets exhibit significant price-based return predictability. These results align with the interpretation that greater retail participation amplifies price-based return predictability.

6 Conclusion

In this study, we investigate the asset pricing implications of the interaction between price-based categorical thinking and experience effects. We find that the recent performance of a stock's price-comparable peers positively predicts its subsequent return. This pattern accords with the story that favorable return experiences direct investor attention and capital toward price-proximate stocks. We also show that our price-based return predictability is not completely driven by traditional size and value style investing and other well-known anomalies. Moreover, price-based return predictability attenuates markedly after stock splits, providing clean evidence on the joint role of price-based categorization and experience effects.

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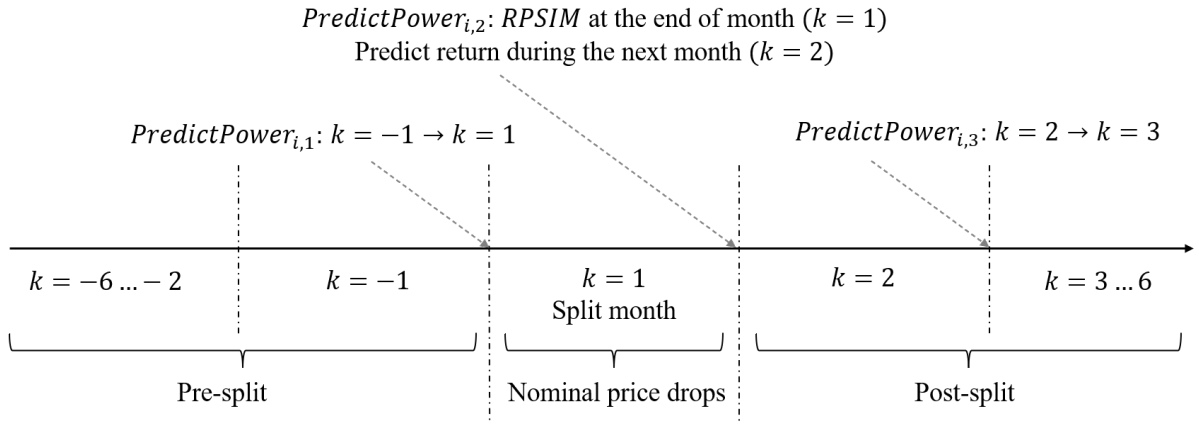


Figure 1: Timeline of Split Tests

This figure shows the timeline of stock split-related tests. We consider an event window spanning six months before and six months after a split. We define dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ for $k = -6, \ldots, -1, 1, \ldots, 6$, which equals one if month t is k months relative to the split event month. The month in which the split occurs is labeled $k = 1$. The main dependent variable of interest is $\text{PredictPower}_{i,t+1}$, the predictive power of month-t RPSIM for returns in month $t+1$. We compute RPSIM at the end of each month. Thus, for $k \geq 1$, RPSIM is calculated using month-end post-split prices, whereas for $k \leq -1$, RPSIM is calculated using month-end pre-split prices.

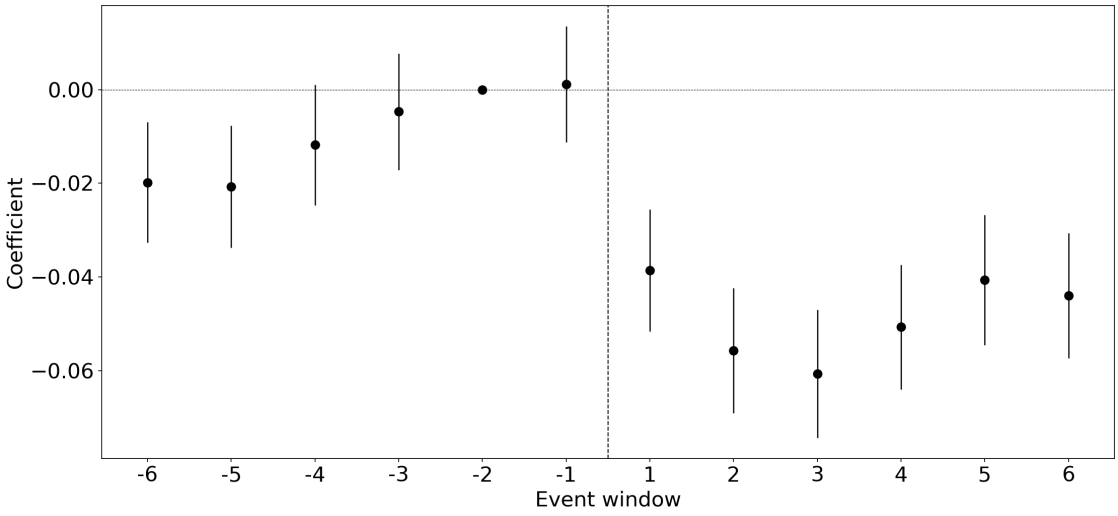


Figure 2: Price-Based Return Predictability and Stock Splits

This figure shows changes in the price-based predictability around stock splits by presenting the regression coefficients (β_k) from equation (4):

$$\text{PredictPower}_{i,t+1} = \alpha + \sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} + \tau_t + \eta_i + \varepsilon_{i,t+1},$$

where $k = -1$ serves as the estimation benchmark. The dependent variable $\text{PredictPower}_{i,t+1}$ is an indicator variable that equals one if both stock i's current monthly return $(t+1)$ and its lagged RPSIM (t) fall within either the top or bottom quintile, and zero otherwise. Dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ equals one if month t is k months before or after a split event for stock i, with $k = 1$ denoting the split event month. The regression includes year-month fixed effects (τ_t) and firm fixed effects (η_i). Standard errors are clustered by stock and month. The sample period is from 1964 to 2024.

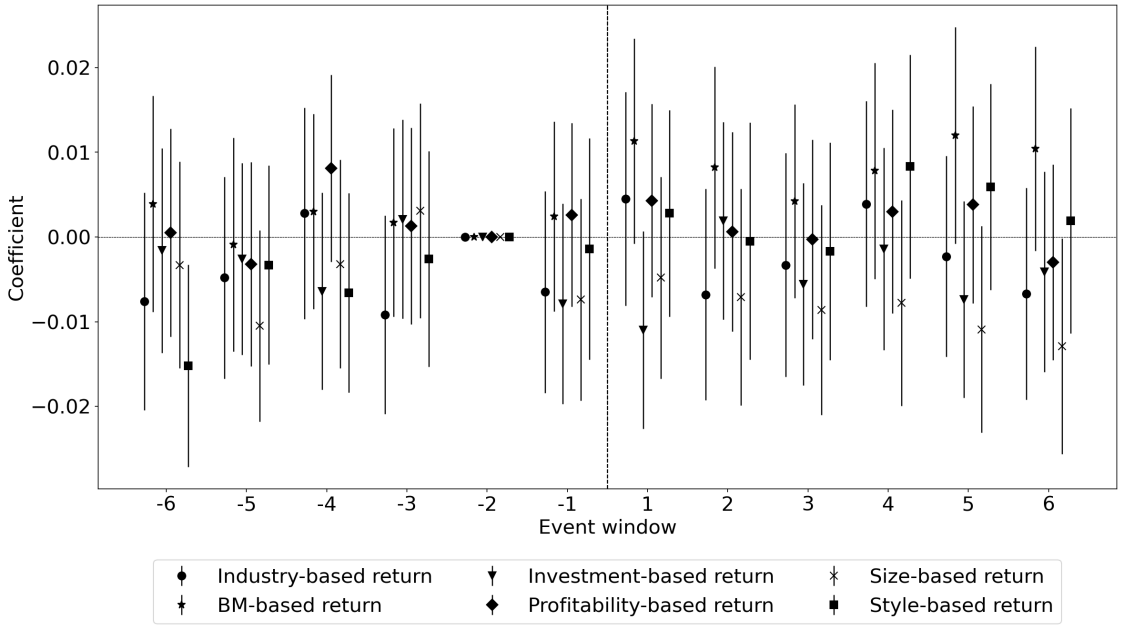


Figure 3: Splits and Predictability Based on Alternative Characteristics

This figure presents changes in the alternative predictability pattern around stock splits. We consider six specifications: industry-based return (Moskowitz and Grinblatt, 1999), style-based return (Wahal and Yavuz, 2013), and four characteristic-based returns (size, book-to-market ratio, profitability, and investment). For each characteristic, we define peer stocks analogously as when defining price-based peers, and then we calculate the value-weighted average monthly return of the focal stocks' characteristic-based peer stocks. For each specification, the figure shows coefficients (β_k) from regression (4):

$$\text{PredictPower}_{i,t+1} = \alpha + \sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} + \tau_t + \eta_i + \varepsilon_{i,t+1},$$

where $k = -1$ serves as the estimation benchmark. The dependent variable $\text{PredictPower}_{i,t+1}$ is an indicator variable that equals one if both stock i's current monthly return $(t+1)$ and its lagged return-based predictor value (t) fall within either the top or bottom quintile, and zero otherwise. Dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ equals one if month t is k months before or after a split event for stock i, with $k = 1$ denoting the split event month. Regressions include year-month fixed effects (τ_t) and firm fixed effects (η_i). Standard errors are clustered by stock and month. The sample period is from 1964 to 2024.

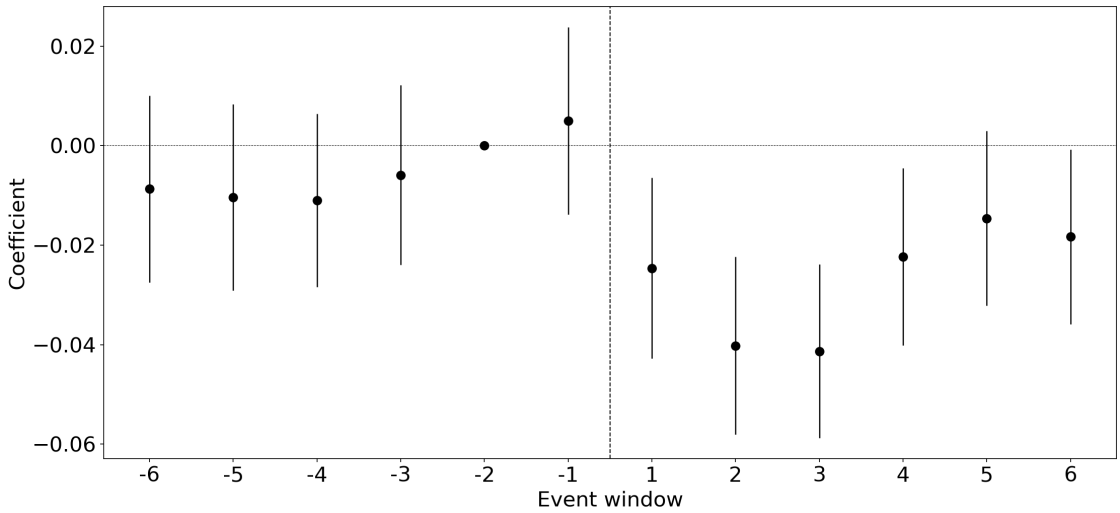


Figure 4: Comparison Between 2-for-1 and Moderate-Factor Splits

This figure presents the difference between 2-for-1 and moderate-factor (3-for-2 and 5-for-4) splits by showing regression coefficients (γ_k) from regression (5):

$$\begin{aligned}\text{PredictPower}_{i,t+1} = &\sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} \\ &+ \sum_{k=-6}^{6} \gamma_k \mathbb{I}\{EventMonth_{i,t} = k\} \times \mathbb{I}\{TwoForOne_{i,t}\} \\ &+ \mathbb{I}\{TwoForOne_{i,t}\} + \alpha + \tau_t + \eta_i + \varepsilon_{i,t+1},\end{aligned}$$

where $k = -1$ serves as the estimation benchmark. The dependent variable $\text{PredictPower}_{i,t+1}$ is an indicator variable that equals one if both stock i's current monthly return $(t+1)$ and its lagged RPSIM (t) fall within either the top or bottom quintile, and zero otherwise. Dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ equals one if month t is k months before or after a split event for stock i, with $k = 1$ denoting the split event month. $\mathbb{I}\{TwoForOne_{i,t}\}$ is an indicator variable that takes a value of one if the split event for stock i in month t is a 2-for-1 split, and zero if it is a 3-for-2 split or 5-for-4 split. The regression includes year-month fixed effects (τ_t) and firm fixed effects (η_i). Standard errors are clustered by stock and month. The sample period is from 1964 to 2024.

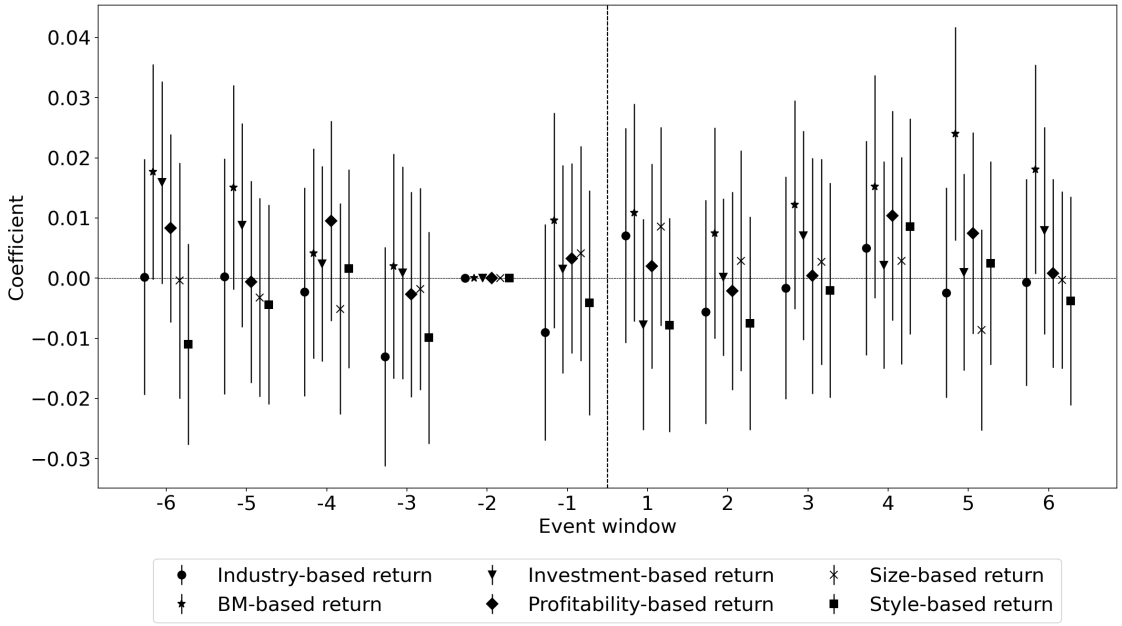


Figure 5: 2-for-1 and Moderate-Factor Splits: Alternative Characteristics
This figure presents the difference between 2-for-1 and 3-for-2 splits under six specifications: industry-based return (Moskowitz and Grinblatt, 1999), style-based return (Wahal and Yavuz, 2013), and four characteristic-based returns (size, book-to-market ratio, profitability, and investment). For each characteristic, we define peer stocks analogously as when defining price-based peers, and then we calculate the value-weighted average monthly return of the focal stocks' characteristic-based peer stocks. For each specification, the figure shows coefficients (γ_k) from regression (5):

$$\begin{aligned}\text{PredictPower}_{i,t+1} = &\sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} \\ &+ \sum_{k=-6}^{6} \gamma_k \mathbb{I}\{EventMonth_{i,t} = k\} \times \mathbb{I}\{TwoForOne_{i,t}\} \\ &+ \mathbb{I}\{TwoForOne_{i,t}\} + \alpha + \tau_t + \eta_i + \varepsilon_{i,t+1},\end{aligned}$$

where $k = -1$ serves as the estimation benchmark. The dependent variable $\text{PredictPower}_{i,t+1}$ is an indicator variable that equals one if both stock i's current monthly return $(t+1)$ and its lagged predictor (t) fall within either the top or bottom quintile, and zero otherwise. Dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ equals one if month t is k months before or after a split event for stock i, with $k = 1$ denoting the split event month. $\mathbb{I}\{TwoForOne_{i,t}\}$ is an indicator variable that takes a value of one if the split event for stock i in month t is a 2-for-1 split, and zero if it is a 3-for-2 split or 5-for-4 split. The regression includes year-month fixed effects (τ_t) and firm fixed effects (η_i). Standard errors are clustered by stock and month. The sample period is from 1964 to 2024.

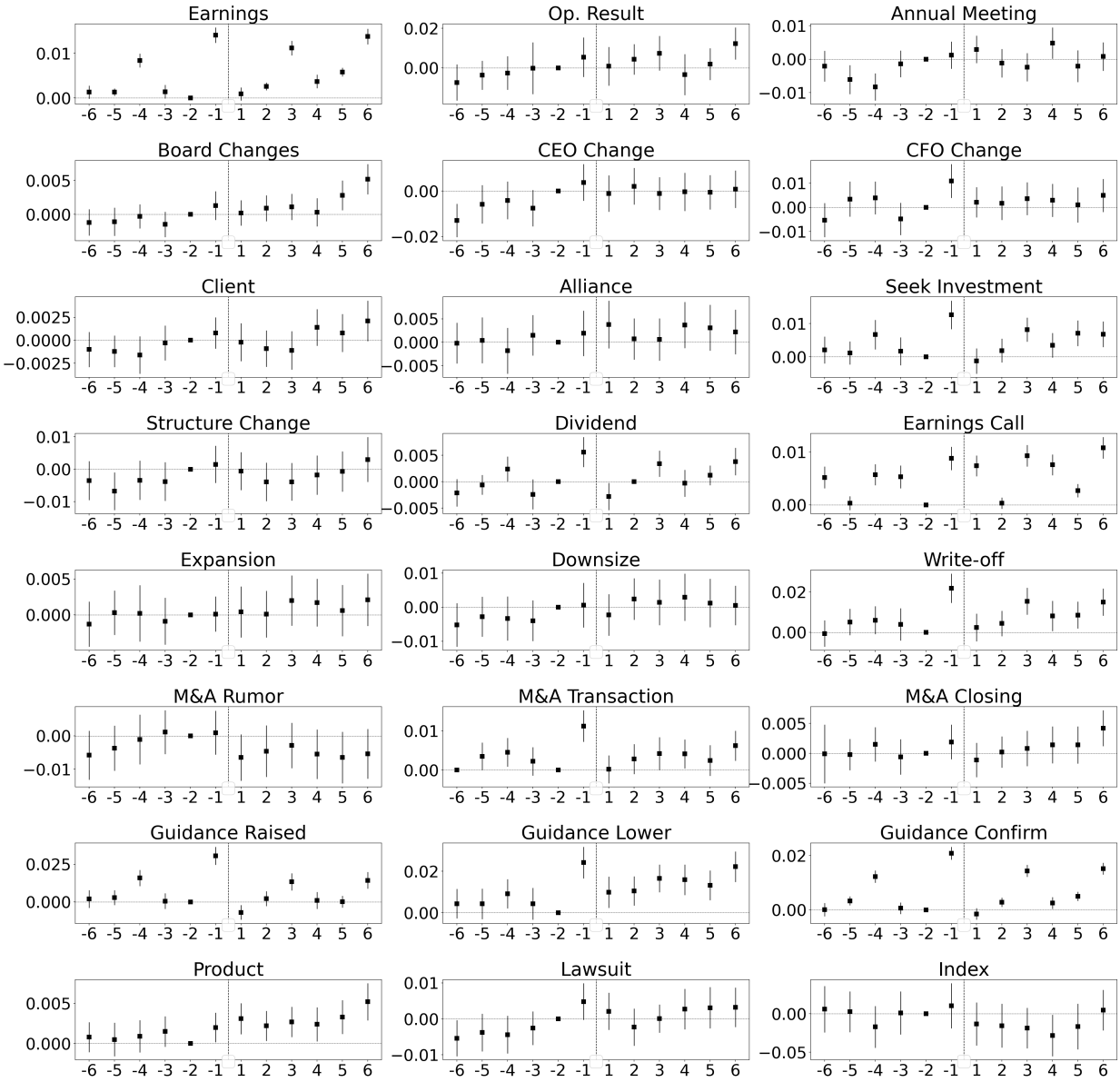


Figure 6: Placebo Events

This figure shows changes in price-based return predictability around corporate events by presenting the regression coefficients (β_k) from equation (4):

$$\text{PredictPower}_{i,t+1} = \alpha + \sum_{k=-6}^{6} \beta_k \mathbb{I}\{EventMonth_{i,t} = k\} + \tau_t + \eta_i + \varepsilon_{i,t+1},$$

where $k = -1$ serves as the estimation benchmark. The dependent variable $\text{PredictPower}_{i,t+1}$ is an indicator variable that equals one if both stock i's current monthly return $(t+1)$ and its lagged RPSIM (t) fall within either the top or bottom quintile, and zero otherwise. Dummy variable $\mathbb{I}\{EventMonth_{i,t} = k\}$ equals one if month t is k months before or after a corporate event for stock i, with $k = 1$ denoting the event month. The regression includes year-month fixed effects (τ_t) and firm fixed effects (η_i). Standard errors are clustered by stock and month.

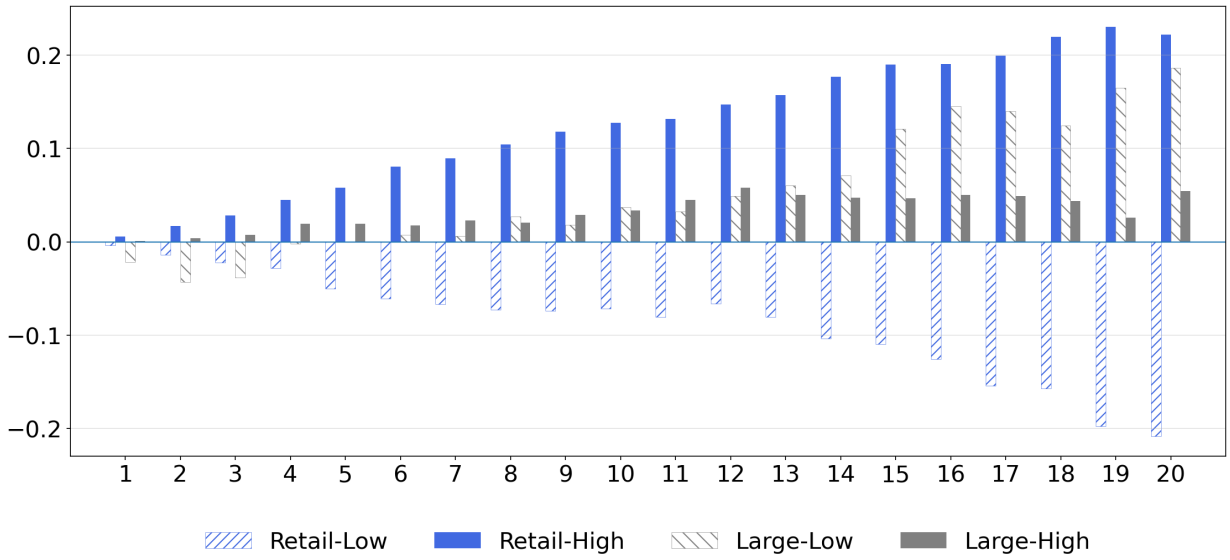


Figure 7: Subsequent Order Imbalance

This figure plots the detrended cumulative order imbalance in the subsequent trading month. At the end of each month t, we form decile portfolios based on RPSIM. For each stock, we measure the change in the retail (large) order imbalance by taking the difference between the daily imbalance in month $t+1$ and the average daily imbalance of the six-month window from month $t-7$ to month $t-2$. Then we calculate the cumulative retail order imbalance. To better demonstrate the results, we subtract the average order imbalance from the order imbalance of decile groups in each trading day to detrend. For example, Retail-Low represents the average cumulative retail order imbalance for the bottom RPSIM decile portfolio. The sample period is from 1983 to 2000.

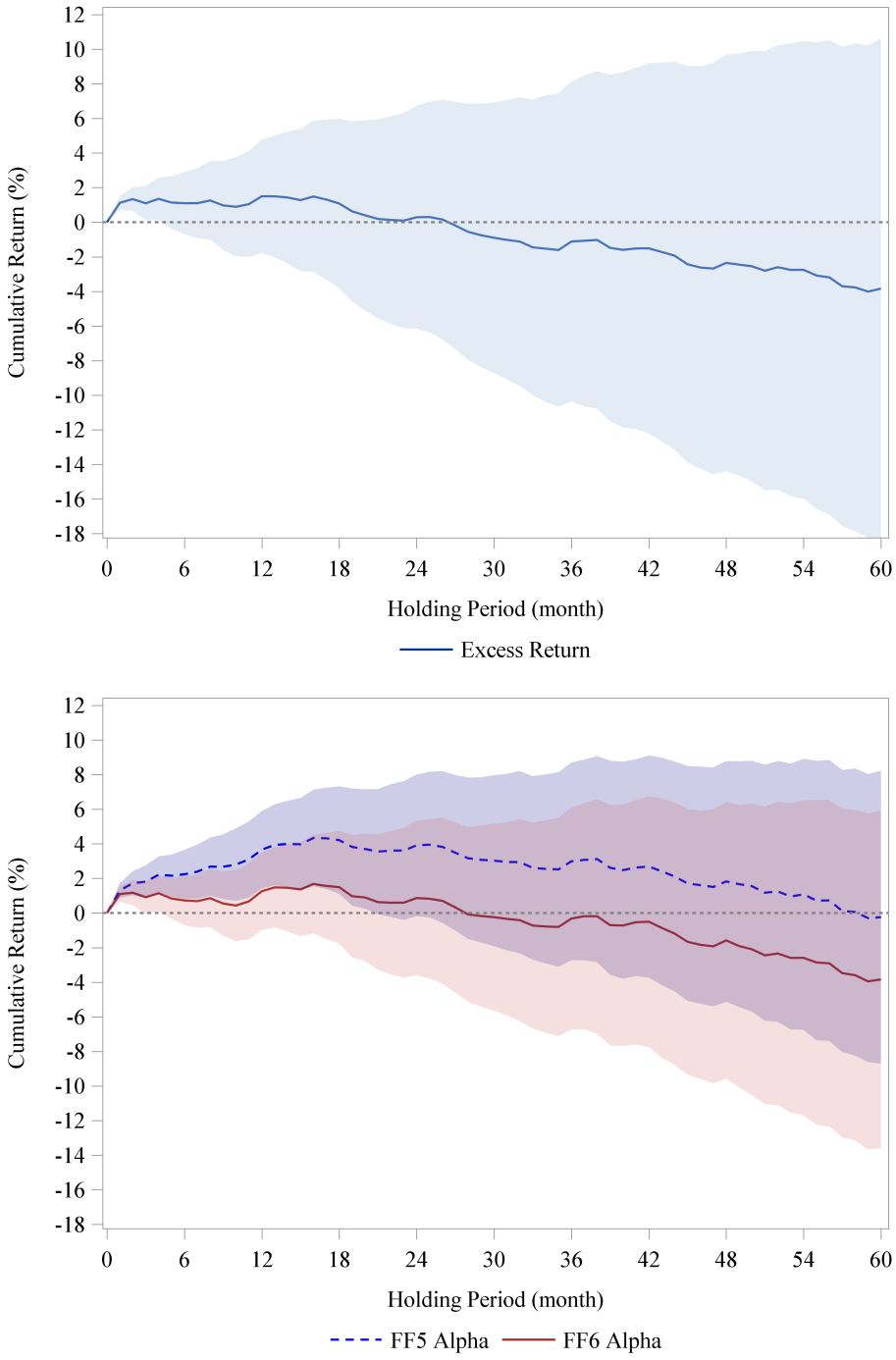


Figure 8: Price-Based Return Predictability over the Long Run

This figure plots price-based return predictability over long horizons using the method of Jegadeesh and Titman (1993). For the strategy with a holding period of K months, each RPSIM decile consists of K subgroups, which are separately initiated in the previous K months. Portfolios are formed that equally weigh the subgroups. Then, the long-short strategy buys the top decile portfolio and sells the bottom decile portfolio. The lower graph reports abnormal returns adjusted by the Fama and French (2015) five-factor model and the six-factor model augmented by momentum. The shadow areas represent 95% confidence intervals. The sample period is from July 1963 to December 2024.

Table 1: Summary Statistics of RPSIM Portfolios

This table reports the time-series average of firm-level characteristics. Each month, we sort stocks into deciles based on RPSIM and compute the mean values of the characteristics listed in the top row of the table across all stocks in the decile for each portfolio. For each stock, we define PSIM as the value-weighted average monthly return of the 100 nearest price-comparable stocks, where the distance between stocks is calculated using nominal share prices. RPSIM is the residual of cross-sectional regressions of PSIM on the focal stock's contemporaneous monthly return. Reported characteristics include the sorting variable RPSIM, RPSIM in the subsequent month (RPSIM_{t+1}), market beta (Beta), share price (Prc), the natural logarithm of market capitalization (Size), book-to-market ratio (BM), operating profit (Profit), asset growth (Invest), past 1-month return (R1m), past 12-month return skipping the most recent month (Mom), idiosyncratic volatility (IVol) of Ang et al. (2006), and the Amihud (2002) illiquidity measure (Illiq). The last row reports time-series averages of cross-sectional correlations between RPSIM and various characteristics. All variables are winsorized each month at the 1% and 99% levels. The sample period is from June 1963 to December 2024.

Decile	RPSIM	RPSIM_{t+1}	Beta	Prc	Size	BM	Profit	Invest	R1m	Mom	IVol	Illiq
High	5.772	1.050	1.143	37.305	12.872	0.707	0.367	0.177	0.641	17.966	0.025	2.442
9	3.641	1.067	1.135	33.858	12.919	0.704	0.366	0.175	1.355	17.431	0.023	1.856
8	2.510	0.865	1.140	30.212	12.795	0.717	0.364	0.176	1.300	16.297	0.024	1.774
7	1.577	0.660	1.150	27.297	12.627	0.730	0.364	0.177	1.303	15.380	0.024	1.887
6	0.690	0.387	1.162	25.129	12.455	0.748	0.363	0.178	1.174	14.300	0.025	2.140
5	-0.215	0.114	1.174	22.603	12.242	0.765	0.361	0.181	0.939	12.559	0.027	2.678
4	-1.184	-0.221	1.185	20.316	12.002	0.791	0.358	0.177	0.781	11.163	0.029	3.423
3	-2.305	-0.646	1.201	17.775	11.713	0.821	0.352	0.174	0.551	8.652	0.031	4.695
2	-3.781	-1.184	1.210	14.653	11.334	0.863	0.345	0.164	0.402	4.900	0.035	6.706
Low	-6.691	-1.938	1.217	9.891	10.763	0.922	0.328	0.148	1.468	-1.973	0.042	10.972
Corr. RPSIM	1.000	0.232	-0.039	0.241	0.314	-0.110	0.039	0.010	0.009	0.109	-0.228	-0.126

Table 2: Portfolio Returns by Sorting on RPSIM

This table reports the monthly returns and alphas of portfolios sorted on RPSIM. For each stock i at the end of each month t, we measure nominal price proximity relative to every other stock j as $\text{Distance}_{i,j,t} = |\text{Price}_{i,t} - \text{Price}_{j,t}|$, where $\text{Price}_{i,t}$ and $\text{Price}_{i,t}$ denote the standardized nominal prices of stocks i and j, respectively. We then define PSIM as the value-weighted average excess return (over the risk-free rate) of the 100 nearest price-comparable stocks over the previous month. RPSIM is the residual from cross-sectional regressions of PSIM on the focal stock's own monthly return. Each month, we sort stocks into decile portfolios based on RPSIM; portfolios are value-weighted and held for one month. Panel A reports the average excess returns and alphas of the top and bottom decile portfolios and the corresponding long-short strategy. In Panel B, RPSIM is calculated based on the value-weighted average excess return of the past year or the past week; portfolios are value-weighted. Panel C considers alternative specifications of price-comparable stocks, including price-based peers within the same Fama-French industry classification and price-based peers from different industries, price-based peers excluding shared analyst coverage (Ali and Hirshleifer, 2020), and randomly matched peer stocks; returns are value-weighted throughout Panel C. Panel D reports portfolio performance based on the original PSIM variable. To calculate alpha, we consider the capital asset pricing model (CAPM), the Fama and French (1996) three-factor model (FF3), the Carhart (1997) four-factor model (Carhart), the Fama and French (2015) five-factor model (FF5), and the momentum-augmented Fama and French (2015) model (FF6). Returns are reported in percentages. The sample period is from July 1963 to December 2024. Newey-West three-lag adjusted t-statistics are reported in parentheses.

Panel A. Baseline: portfolios based on RPSIM

	Excess Return	CAPM Alpha	FF3 Alpha	Carhart Alpha	FF5 Alpha	FF6 Alpha
High	1.08	0.46	0.48	0.51	0.55	0.58
	(5.18)	(4.69)	(5.53)	(5.44)	(5.93)	(5.86)
Low	-0.05	-0.81	-0.90	-0.62	-0.75	-0.52
	(-0.16)	(-4.74)	(-6.22)	(-3.69)	(-4.53)	(-3.09)
High-Low	1.13	1.27	1.38	1.13	1.31	1.10
	(5.52)	(6.58)	(7.56)	(5.21)	(5.91)	(4.84)

Panel B. Alternative reference periods when constructing RPSIM

	Yearly return-based RPSIM			Weekly return-based RPSIM		
	FF3 Alpha	FF5 Alpha	FF6 Alpha	FF3 Alpha	FF5 Alpha	FF6 Alpha
High	0.12	0.12	-0.02	0.38	0.47	0.65
	(1.25)	(1.15)	(-0.21)	(3.24)	(3.64)	(4.73)
Low	-0.70	-0.50	-0.16	-0.84	-0.77	-0.64
	(-4.30)	(-2.94)	(-1.01)	(-6.60)	(-6.30)	(-5.14)
High-Low	0.82	0.62	0.14	1.22	1.24	1.29
	(3.86)	(2.73)	(0.67)	(6.80)	(6.76)	(6.11)

Panel C. Alternative specifications of price-comparable stocks

	Same Industry			Different Industry		
	FF3 Alpha	FF5 Alpha	FF6 Alpha	FF3 Alpha	FF5 Alpha	FF6 Alpha
High	0.36	0.39	0.30	0.29	0.34	0.40
	(3.64)	(3.43)	(2.93)	(3.20)	(3.40)	(4.11)
Low	-0.93	-0.87	-0.81	-0.68	-0.53	-0.33
	(-7.92)	(-7.28)	(-6.56)	(-4.69)	(-3.12)	(-1.87)
High-Low	1.28	1.27	1.11	0.97	0.87	0.73
	(7.66)	(6.73)	(6.23)	(5.34)	(4.43)	(3.43)
	Exclude common analyst			Randomly matched peers		
	FF3 Alpha	FF5 Alpha	FF6 Alpha	FF3 Alpha	FF5 Alpha	FF6 Alpha
High	0.36	0.40	0.44	-0.05	-0.06	-0.05
	(4.03)	(4.15)	(4.63)	(-0.80)	(-0.96)	(-0.74)
Low	-0.89	-0.76	-0.53	0.06	0.05	0.06
	(-6.30)	(-4.60)	(-3.12)	(1.04)	(0.82)	(1.01)
High-Low	1.25	1.16	0.97	-0.11	-0.11	-0.11
	(7.11)	(5.99)	(4.58)	(-1.31)	(-1.27)	(-1.21)

Panel D. Original PSIM without orthogonalization

	Excess Return	CAPM Alpha	FF3 Alpha	Carhart Alpha	FF5 Alpha	FF6 Alpha
High	1.05	0.44	0.46	0.48	0.55	0.56
	(5.08)	(4.31)	(4.81)	(4.99)	(5.04)	(5.24)
Low	0.13	-0.66	-0.76	-0.44	-0.59	-0.33
	(0.42)	(-3.67)	(-4.90)	(-2.29)	(-3.23)	(-1.67)
High-Low	0.92	1.10	1.21	0.92	1.13	0.89
	(4.22)	(5.30)	(6.13)	(3.83)	(4.52)	(3.46)

Table 3: Double-Sorted Portfolio Returns

This table reports double-sorted portfolio returns based on RPSIM and confounding factors. Size is the natural logarithm of market capitalization. BM is the book-to-market ratio. Profit is the operating profitability (Fama and French, 2015). Invest is asset growth (Fama and French, 2015). R1m is the past one-month return of the focal stock. Mom is the cumulative return from month $t-12$ to month $t-2$. Ltrev is the cumulative return from month $t-60$ to month $t-13$. IVol is idiosyncratic volatility (Ang et al., 2006). MAX is the maximum daily return in month $t-1$ (Bali et al., 2011). Skew is the skewness of monthly returns over the previous five years. Coskew is coskewness (Harvey and Siddique, 2000) using five years of monthly returns. IndRet represents industry return over the past six months (Moskowitz and Grinblatt, 1999). Each month, stocks are sorted into quintiles based on a confounding factor; within each quintile, stocks are then further sorted into deciles based on RPSIM. The returns of the decile portfolios over the next month are averaged across the five control variable quintiles. We report the five-factor model (Fama and French, 2015) alphas, on a value-weighted basis, of the decile RPSIM portfolios and of the high-RPSIM minus low-RPSIM long-short portfolio. The sample period runs from July 1963 to December 2024. Newey-West three-lag adjusted t-statistics are reported in parentheses.

	Size	BM	Profit	Invest	R1m	Mom	Ltrev	IVol	MAX	Skew	Coskew	IndRet
High	0.24	0.32	0.46	0.52	0.51	0.34	0.39	0.34	0.44	0.45	0.47	0.56
	(4.56)	(4.31)	(5.34)	(4.80)	(5.29)	(4.00)	(4.99)	(3.74)	(4.73)	(5.34)	(4.79)	(6.23)
9	0.15	0.14	0.19	0.13	0.16	0.11	0.14	0.02	0.18	0.12	0.23	0.18
	(3.25)	(2.20)	(2.56)	(2.08)	(2.32)	(1.52)	(2.05)	(0.23)	(2.23)	(1.66)	(3.22)	(2.44)
8	0.12	0.04	0.09	0.05	0.04	-0.02	0.06	-0.04	-0.00	0.08	0.08	0.14
	(2.45)	(0.70)	(1.49)	(0.75)	(0.67)	(-0.24)	(1.10)	(-0.58)	(-0.03)	(1.39)	(1.56)	(2.27)
7	0.00	0.04	-0.05	0.06	0.16	-0.16	0.06	-0.12	-0.05	-0.02	0.10	-0.02
	(0.03)	(0.69)	(-0.80)	(0.88)	(2.22)	(-2.51)	(0.94)	(-1.61)	(-0.68)	(-0.40)	(1.48)	(-0.30)
6	0.09	-0.02	-0.08	-0.11	-0.16	-0.17	-0.04	-0.22	-0.14	0.00	-0.14	-0.15
	(1.87)	(-0.39)	(-1.15)	(-1.87)	(-2.50)	(-2.36)	(-0.72)	(-2.82)	(-1.86)	(0.03)	(-2.02)	(-2.46)
5	-0.05	-0.22	-0.13	-0.17	-0.09	-0.23	-0.17	-0.11	-0.24	-0.18	-0.12	-0.21
	(-0.87)	(-3.40)	(-2.00)	(-2.41)	(-1.22)	(-3.27)	(-2.75)	(-1.35)	(-3.25)	(-2.53)	(-1.82)	(-3.30)
4	-0.14	-0.27	-0.30	-0.15	-0.18	-0.29	-0.23	-0.24	-0.22	-0.28	-0.24	-0.30
	(-2.13)	(-4.00)	(-3.74)	(-2.19)	(-1.93)	(-4.04)	(-3.58)	(-3.29)	(-2.91)	(-3.89)	(-3.20)	(-4.11)
3	-0.08	-0.32	-0.47	-0.48	-0.33	-0.36	-0.36	-0.42	-0.41	-0.37	-0.44	-0.42
	(-1.22)	(-3.77)	(-4.88)	(-4.97)	(-3.43)	(-4.06)	(-5.18)	(-5.03)	(-4.89)	(-4.64)	(-4.39)	(-4.24)
2	-0.16	-0.40	-0.41	-0.40	-0.41	-0.46	-0.40	-0.42	-0.39	-0.44	-0.33	-0.44
	(-2.08)	(-3.72)	(-3.28)	(-3.48)	(-3.81)	(-5.11)	(-4.44)	(-4.23)	(-3.93)	(-4.80)	(-3.43)	(-4.16)
Low	-0.31	-0.56	-0.56	-0.49	-0.57	-0.41	-0.42	-0.44	-0.37	-0.43	-0.58	-0.71
	(-3.58)	(-3.67)	(-3.47)	(-2.95)	(-3.46)	(-3.14)	(-2.66)	(-3.69)	(-2.86)	(-3.11)	(-3.53)	(-4.71)
High-Low	0.55	0.88	1.02	1.00	1.08	0.75	0.80	0.77	0.81	0.88	1.05	1.27
	(5.74)	(5.02)	(4.93)	(4.37)	(5.09)	(4.63)	(4.35)	(5.07)	(4.86)	(5.02)	(4.82)	(6.20)

Table 4: Fama-MacBeth Regressions

This table reports time-series averages of coefficients from monthly cross-sectional regressions, where the dependent variable is the one-month-ahead stock return (in percentages). The main independent variable of interest, RPSIM, is the residual average return of the focal stock's price-based peers. In column (1), only RPSIM is included. In column (2), we control for one-month style and industry returns (Style 1M and Industry 1M). In column (3), we control for six-month style and industry returns (Style 6M and Industry 6M). In column (4), we control for 12-month style and industry returns (Style 12M and Industry 12M). Column (5) includes style and industry returns across all horizons. Other firm-level characteristics include size, book-to-market ratio, operating profitability, asset growth, idiosyncratic volatility (Ang et al., 2006), cumulative return from month $t-12$ to month $t-2$, illiquidity (Amihud, 2002), and the focal stock's share price. Independent variables are standardized each month to have zero mean and unit variance. The sample period is from June 1963 to December 2024. The last three rows in the table report the average R^2 for cross-sectional regressions, the average number of observations each month, and the number of months. Newey-West three-lag adjusted t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
RPSIM	0.156	0.166	0.168	0.167	0.163
	(5.65)	(5.75)	(5.84)	(5.83)	(5.76)
StyleRet 1m		0.042			-0.043
		(1.48)			(-1.56)
IndRet 1m		0.259			0.195
		(7.11)			(5.84)
StyleRet 6m			0.072		-0.004
			(2.14)		(-0.09)
IndRet 6m			0.240		0.103
			(6.08)		(1.74)
StyleRet 12m				0.090	0.158
				(2.49)	(3.02)
IndRet 12m				0.239	0.102
				(6.02)	(1.98)
Controls	Yes	Yes	Yes	Yes	Yes
Intercept	0.782	0.785	0.784	0.786	0.785
	(3.28)	(3.30)	(3.30)	(3.30)	(3.30)
Avg. R^2(%)	4.782	5.332	5.349	5.354	5.971
Avg. Obs.	2535	2431	2431	2431	2431
# Months	738	738	738	738	738

Table 5: Comovement and Predictability in the Green and Hwang (2009) Setting

This table reports average slope coefficients before and after stock splits, along with the corresponding changes. For each split event, Panel A estimates comovement regressions as follows:

$$R_{i,d} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,d} + \beta_{HighPrc,i} R_{HighPrc,i,d} + \varepsilon_{i,d},$$

where $R_{i,d}$ is the return of stock i on day d and $R_{LowPrc,i,d}$ ($R_{HighPrc,i,d}$) is stock i's respective low (high) price index on day d. Panel B estimates predictive regressions as follows:

$$R_{i,d+1} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,d} + \beta_{HighPrc,i} R_{HighPrc,i,d} + \beta_{Focal,i} R_{i,d} + \varepsilon_{i,d+1},$$

where the focal stock's lagged return $R_{i,d}$ is included to control for the short-term reversal effect. In each regression, the low-price index comprises stocks with prices in $[\frac{1}{4}P_{pre}, \frac{3}{4}P_{pre}]$, and the high-price index consists of stocks with prices in $[\frac{3}{4}P_{pre}, \frac{5}{4}P_{pre}]$, where P_{pre} is the pre-split price measured one day before the split. The sample includes 2-for-1 split events from 1964 to 2024. The table reports the average $\beta_{LowPrc,i}$, the average $\beta_{HighPrc,i}$, and the average difference $\beta_{HighPrc,i} - \beta_{LowPrc,i}$ in the pre- and post-split periods, as well as the change between the two periods. Standard errors are clustered by month, and t-statistics are reported in parentheses.

Panel A. Contemporaneous comovement			
	Before splits	After splits	Difference: After−Before
LowPrc	0.812	1.018	0.206
	(42.54)	(50.29)	(9.01)
HighPrc	0.213	0.127	-0.085
	(10.59)	(6.60)	(-4.39)
Difference:	-0.599	-0.891	-0.291
HighPrc−LowPrc	(-16.34)	(-24.25)	(-7.11)
Panel B. Predictive regressions			
	Before splits	After splits	Difference: After−Before
LowPrc	0.063	0.144	0.081
	(3.90)	(9.24)	(3.68)
HighPrc	0.168	0.117	-0.051
	(10.87)	(7.33)	(-2.35)
Difference:	0.105	-0.027	-0.132
HighPrc−LowPrc	(3.43)	(-0.89)	(-3.10)

Table 6: Subsample Analysis

This table reports the monthly alphas on value-weighted quintile portfolios sorted on RPSIM. In Panel A, we divide the whole sample into two subperiods: 1963 to 1989, and 1990 to 2024. In Panel B, we split the sample based on the median market size breakpoint of NYSE stocks. In Panel C, subsamples are defined based on the median idiosyncratic volatility (IVol). In Panel D, we split the sample into two groups based on institutional ownership (IO). We use the size-adjusted institutional ownership following the method of Nagel (2005). Newey-West three-lag adjusted t-statistics are reported in parentheses. The sample period in Panel B, Panel C, and Panel D is from July 1963 to December 2024.

		Low	2	3	4	High	High-Low
Panel A. Earlier and recent sample periods							
1963-1989	Excess Return	-0.30	0.19	0.27	0.56	0.86	1.16
		(-0.81)	(0.59)	(0.97)	(1.97)	(2.98)	(5.07)
	FF3 Alpha	-0.95	-0.41	-0.24	0.07	0.40	1.35
		(-6.70)	(-4.09)	(-3.26)	(1.01)	(4.20)	(7.19)
	FF6 Alpha	-0.64	-0.14	-0.10	0.10	0.35	0.99
		(-3.72)	(-1.23)	(-1.35)	(1.38)	(3.43)	(4.27)
1990-2024	Excess Return	0.33	0.44	0.60	0.80	0.97	0.64
		(0.93)	(1.65)	(2.41)	(3.41)	(3.72)	(2.66)
	FF3 Alpha	-0.63	-0.37	-0.17	0.06	0.22	0.85
		(-3.62)	(-3.51)	(-2.17)	(0.81)	(2.27)	(3.88)
	FF6 Alpha	-0.32	-0.30	-0.09	0.06	0.30	0.62
		(-1.67)	(-2.93)	(-1.20)	(0.77)	(2.74)	(2.33)
Panel B. Small and large subsamples							
Size<NYSE p50	Excess Return	0.18	0.46	0.68	0.82	1.02	0.85
		(0.58)	(1.69)	(2.62)	(3.25)	(3.99)	(6.50)
	FF3 Alpha	-0.72	-0.41	-0.17	0.00	0.21	0.93
		(-6.79)	(-6.20)	(-3.47)	(0.07)	(3.66)	(7.76)
	FF6 Alpha	-0.35	-0.18	-0.03	0.12	0.32	0.68
		(-2.93)	(-2.16)	(-0.52)	(2.78)	(4.83)	(4.60)
Size>NYSE p50	Excess Return	0.39	0.53	0.55	0.63	0.71	0.32
		(2.15)	(3.14)	(3.31)	(3.94)	(4.06)	(3.26)
	FF3 Alpha	-0.22	-0.04	0.00	0.12	0.17	0.38
		(-3.39)	(-0.83)	(0.04)	(2.42)	(3.17)	(4.06)
	FF6 Alpha	-0.14	-0.06	-0.02	0.11	0.20	0.34
		(-2.04)	(-1.08)	(-0.35)	(2.08)	(3.63)	(3.34)

		Low	2	3	4	High	High-Low
Panel C. High and low idiosyncratic volatility subsamples							
High IVol	Excess Return	-0.04	0.18	0.49	0.64	0.84	0.88
		(-0.14)	(0.63)	(1.69)	(2.22)	(2.93)	(4.88)
	FF3 Alpha	-0.98	-0.70	-0.37	-0.17	0.05	1.03
		(-6.70)	(-5.46)	(-2.95)	(-1.42)	(0.39)	(5.98)
	FF6 Alpha	-0.52	-0.29	-0.02	0.13	0.28	0.80
		(-3.21)	(-1.78)	(-0.18)	(1.09)	(2.15)	(3.70)
Low IVol	Excess Return	0.35	0.59	0.55	0.66	0.87	0.52
		(1.85)	(3.62)	(3.48)	(4.19)	(5.36)	(4.51)
	FF3 Alpha	-0.29	-0.01	-0.01	0.11	0.33	0.62
		(-3.36)	(-0.13)	(-0.13)	(2.00)	(6.07)	(5.41)
	FF6 Alpha	-0.23	-0.01	-0.05	0.04	0.30	0.52
		(-2.56)	(-0.20)	(-0.89)	(0.64)	(5.39)	(4.41)
Panel D. High and low institutional ownership subsamples							
High IO	Excess Return	0.18	0.46	0.59	0.77	0.90	0.72
		(0.64)	(2.04)	(2.79)	(3.82)	(4.22)	(4.36)
	FF3 Alpha	-0.65	-0.28	-0.15	0.05	0.20	0.85
		(-4.83)	(-3.14)	(-1.88)	(0.85)	(2.86)	(5.20)
	FF6 Alpha	-0.54	-0.28	-0.15	0.03	0.21	0.75
		(-4.09)	(-3.24)	(-2.08)	(0.36)	(2.96)	(4.40)
Low IO	Excess Return	0.06	0.37	0.63	0.90	1.04	0.98
		(0.18)	(1.25)	(2.36)	(3.39)	(3.48)	(4.20)
	FF3 Alpha	-0.78	-0.46	-0.14	0.21	0.32	1.10
		(-4.37)	(-3.14)	(-1.25)	(1.74)	(1.89)	(4.86)
	FF6 Alpha	-0.30	-0.04	0.15	0.43	0.56	0.86
		(-1.63)	(-0.21)	(1.33)	(3.73)	(3.41)	(3.19)

Table 7: International Evidence on Price-Based Return Predictability

This table reports the average returns of portfolios formed on RPSIM in 38 markets. Considering the limited availability of stocks in certain countries, we calculate the RPSIM by uniformly utilizing the residual average returns of the 30 nearest price-comparable stocks. We divide the sample into two groups based on aggregate turnover, which is the average annual turnover across all the years for which we have data for the market. For turnover higher than the cross-sectional median level, we use the past one-week residual average return of peer stocks as our predictive variable RPSIM, whereas for turnover below the median, we still use the monthly returns. Also reported are returns on a strategy that equally combines the strategies available within a given week or month (Comb).

	High turnover				Low turnover		
Market	Low	High	High-Low	Market	Low	High	High-Low
AUS	-0.021	0.284	**0.305**	ARG	1.426	0.785	-0.642
	(-0.22)	(3.39)	(5.30)		(2.20)	(1.20)	(-1.16)
BRA	0.325	0.292	-0.032	AUT	0.467	0.870	0.402
	(1.86)	(1.96)	(-0.20)		(1.03)	(1.77)	(0.94)
CHE	0.187	0.199	0.012	BEL	0.059	0.544	0.485
	(2.62)	(2.81)	(0.19)		(0.17)	(1.62)	(1.50)
CHN	-0.035	0.237	**0.271**	CAN	0.749	1.464	**0.716**
	(-0.33)	(2.34)	(4.06)		(1.55)	(3.60)	(1.85)
DEU	0.060	0.109	0.049	CHL	0.645	0.778	0.133
	(0.59)	(1.35)	(0.48)		(1.74)	(2.07)	(0.63)
GBR	0.117	0.059	-0.058	DNK	0.575	0.599	0.024
	(1.54)	(0.84)	(-0.95)		(1.60)	(1.62)	(0.07)
HKG	-0.013	0.182	**0.195**	ESP	0.180	0.661	0.481
	(-0.14)	(1.87)	(2.61)		(0.52)	(2.01)	(1.58)
IND	0.156	0.441	**0.284**	FIN	0.792	1.110	0.318
	(1.47)	(4.23)	(3.82)		(1.90)	(2.61)	(0.90)
ISR	0.226	0.243	0.017	FRA	0.371	0.519	0.148
	(2.50)	(2.85)	(0.29)		(1.09)	(1.58)	(0.61)
ITA	0.082	0.179	0.097	GRC	0.381	0.490	0.108
	(0.99)	(2.29)	(1.60)		(0.63)	(0.90)	(0.24)
JPN	0.059	0.154	**0.096**	IDN	0.944	0.829	-0.115
	(0.79)	(2.13)	(2.71)		(1.31)	(1.26)	(-0.29)
KOR	0.018	0.086	0.067	MEX	0.448	1.137	**0.689**
	(0.14)	(0.68)	(0.86)		(1.10)	(2.72)	(2.12)
NLD	0.037	0.226	**0.190**	MYS	0.359	0.449	0.090
	(0.42)	(2.78)	(2.33)		(0.65)	(0.98)	(0.32)
NOR	0.022	0.281	**0.259**	NZL	0.213	0.699	**0.486**
	(0.21)	(2.69)	(2.96)		(0.59)	(2.15)	(1.94)
PAK	0.059	0.363	**0.304**	PHL	0.715	0.570	-0.145
	(0.55)	(3.39)	(3.41)		(1.21)	(1.24)	(-0.42)
RUS	-0.007	0.293	**0.300**	POL	0.440	1.263	**0.823**
	(-0.05)	(1.64)	(1.73)		(0.88)	(2.54)	(2.44)
SWE	0.090	0.325	**0.235**	PRT	1.239	0.377	-0.862
	(0.91)	(3.48)	(3.23)		(1.17)	(0.40)	(-0.93)
THA	0.113	0.240	**0.127**	SGP	0.448	0.722	0.273
	(0.98)	(2.28)	(1.77)		(0.95)	(1.60)	(0.83)
TUR	0.173	0.285	0.112	ZAF	0.570	0.875	0.305
	(1.11)	(1.82)	(1.35)		(1.26)	(1.93)	(0.99)
Comb	0.084	0.235	**0.151**	Comb	0.552	0.792	**0.241**
	(1.43)	(4.03)	(7.71)		(1.84)	(2.77)	(2.95)

Appendix

A Order Imbalance

We infer retail order imbalance (RIMB) from trade-level data in ISSM and TAQ. Following Hvidkjaer (2006), we restrict the sample to NYSE and AMEX common stocks from 1983 to 2000.[19] We exclude trades and quotes with irregular condition codes and filter out likely data errors using a simple price-based screen.

Step 1: Classify trades by size. We follow Lee (1992) to classify trades by size using dollar-value cutoffs that vary with firm size. Specifically, at the end of month $t-1$, we sort stocks into size quintiles. We then classify each trade in month t as small, medium, or large using the size-quintile-specific dollar cutoffs reported below:

Firm-size quintile	Small	2	3	4	Large
Small trade cutoff, in $	3400	4800	7300	10300	16400
Large trade cutoff, in $	6800	9600	14600	20600	32800

Step 2: Infer trade direction. We then classify each trade as buyer initiated or seller initiated using the Lee and Ready (1991) algorithm, which compares the trade price to bid-ask quotes. A trade is buyer initiated (seller initiated) if it executes above (below) the quote midpoint. If the trade occurs at the midpoint, we apply the tick test, which classifies it as buyer initiated (seller initiated) if the trade price is above (below) the most recent transaction price.

Using the trade-size and trade-direction classifications, we compute retail order imbalance as

$$RIMB_{i,d} = \frac{BUYVOL_{i,d} - SELLVOL_{i,d}}{BUYVOL_{i,d} + SELLVOL_{i,d}},$$

where $BUYVOL_{i,d}$ and $SELLVOL_{i,d}$ denote buyer-initiated and seller-initiated volume for stock i on day d within the small-trade category. We construct an analogous imbalance measure for large trades to proxy for institutional order imbalance.

[19] Following Barber et al. (2008), our retail order imbalance sample ends in 2000 since the widespread introduction of decimalization in 2001 significantly impacts the distribution of trade size.

For each stock, we compute the change in retail (and large) order imbalance as the difference between the daily imbalance and its trailing six-month baseline. Specifically, we subtract the stock's average daily imbalance over months $t-7$ through $t-2$ from the daily imbalance. We then cumulate these abnormal daily imbalances within a month. For presentation, we detrend the series by subtracting, on each trading day (or month), the average order imbalance from the order imbalance of each portfolio.

B Additional Empirical Results

Table A1: Portfolio Returns by Sorting on RPSIM: Alternative Factor Models

This table reports the monthly returns and alphas of portfolios sorted on RPSIM. For each stock i at the end of each month t, we measure nominal price proximity relative to every other stock j as $\text{Distance}_{i,j,t} = |\text{Price}_{i,t} - \text{Price}_{j,t}|$, where $\text{Price}_{i,t}$ and $\text{Price}_{i,t}$ denote the standardized nominal prices of stocks i and j, respectively. We then define PSIM as the value-weighted average excess return (over the risk-free rate) of the 100 nearest price-comparable stocks over the previous month. RPSIM is the residual from cross-sectional regressions of PSIM on the focal stock's own monthly return. The table reports alphas of the top and bottom decile portfolios and the long-short strategy. We consider the Hou et al. (2015) Q-factor model (Q4), the Stambaugh and Yuan (2017) mispricing factor model (SY4), the Daniel et al. (2020) behavioral factor model (DHS3), and the Fama and French (2015) model augmented by the momentum factor and the short-term reversal factor (FF7). Returns are reported in percentages. The sample period is from July 1963 to December 2024. Newey-West three-lag adjusted t-statistics are reported in parentheses.

	Value Weighted			Equal Weighted		
	High	Low	High-Low	High	Low	High-Low
Q4 Alpha	0.63	-0.46	1.09	0.56	-0.06	0.61
	(5.95)	(-2.29)	(4.15)	(6.18)	(-0.34)	(3.27)
SY4 Alpha	0.40	-0.39	0.79	0.44	-0.13	0.58
	(3.66)	(-1.95)	(3.11)	(4.22)	(-0.70)	(2.95)
DHS3 Alpha	0.68	-0.12	0.80	1.02	0.44	0.58
	(5.77)	(-0.55)	(3.08)	(6.90)	(1.78)	(2.68)
FF7 Alpha	0.68	-0.68	1.36	0.54	-0.28	0.82
	(6.59)	(-4.13)	(6.01)	(5.28)	(-2.04)	(5.09)

Table A2: Portfolios by Sorting on RPSIM: Predicting Turnover

This table reports next-month average abnormal turnover for decile portfolios formed on RPSIM. For each stock i at the end of each month t, we measure nominal price proximity relative to every other stock j as $\text{Distance}_{i,j,t} = |\text{Price}_{i,t} - \text{Price}_{j,t}|$, where $\text{Price}_{i,t}$ and $\text{Price}_{i,t}$ denote the standardized nominal prices of stocks i and j, respectively. We then define PSIM as the value-weighted average excess return (over the risk-free rate) of the 100 nearest price-comparable stocks over the previous month. RPSIM is the residual from cross-sectional regressions of PSIM on the focal stock's own monthly return. Each month, we sort stocks into deciles by RPSIM and compute the value-weighted average abnormal turnover of each portfolio in the next month. Abnormal turnover is defined as monthly turnover minus the average turnover over the prior 3, 6, or 12 months. Turnovers are multiplied by 100. The sample period is from July 1963 to December 2024. Newey-West adjusted t-statistics are reported in parentheses.

	Abnormal Turnover (3m)	Abnormal Turnover (6m)	Abnormal Turnover (12m)
Low	-0.59	-1.90	-0.73
2	-0.49	-4.87	-0.41
3	-0.15	-2.17	-0.14
4	-0.19	-1.69	-0.16
5	-0.09	-1.48	-0.06
6	-0.05	-0.54	0.02
7	-0.02	-0.84	0.04
8	0.03	-0.64	0.10
9	0.10	-0.50	0.20
High	0.13	-0.69	0.32
High-Low	0.72	1.21	1.05
	(3.37)	(1.83)	(4.04)