Anomalies Never Disappeared:

The Case of Stubborn Retail Investors*

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Abstract

Defying conventional beliefs, our analysis of 260 anomalies over the last half-century reveals that they have not vanished as market efficiency improves, because their alphas predominantly materialize over the long haul—an overlooked timeframe with far-reaching financial and real implications. The enduring long-run alphas in recent years are driven by the anomalies that retail investors trade against, yielding staggering value-weighted two-year alphas of 23%. Incorporating retail trading, we develop asset pricing models that surpass existing prominent models in explaining these long-run alphas. We propose and validate a hypothesis: the stubbornness of retail investors underpins long-run alphas, inflicting long-horizon risks on arbitrageurs. Our findings imply that as society advances and other frictions fade, the unyielding nature of financially naive individuals will remain an enduring impediment to market efficiency.

JEL: G10, G11, G14

Keywords: Anomalies, Retail investors, Horizon, Noise Trading Risk, Limits to Arbitrage, Return Predictability

Introduction

Over the last five decades, academic research has uncovered numerous patterns of anomalous cross-sectional return predictability that are unexplained by standard asset pricing theories.[1] Many studies suggest that these anomaly returns are disappearing in recent years,[2] attributed to increased arbitrage following anomaly publication, improved fund performance measurement, and better information disclosure and liquidity.[3] These explanations align with the conventional belief that market efficiency naturally improves as societal and market frictions diminish. However, prior literature focuses on the formation-month returns, overlooking long-run alpha of anomalies, which recent studies argue to have far-reaching implications. On the financial side, they are crucial for understanding asset pricing, market efficiency, and the genuine profitability of trading strategies. After all, a good asset pricing theory should be able to explain long-horizon moments.[4] On the real side, they are vital for understanding real inefficiencies as investment decisions are not based on monthly outcomes.[5] Separately, while mixed meta-analysis evidence exists regarding the role of institutions in anomalies,[6] how retail investors shape anomalies systematically is

[1] The *Journal of Financial Economics* published a special issue on return anomalies as early as 1978. Since that time, hundreds of cross-sectional return anomalies have been documented (e.g. Harvey et al., 2015).

[2] Green, Hand and Zhang (2017) conduct a meta-analysis of 97 anomalies and find that only two anomalies are independently significant return predictors since 2003, and, outside microcaps, the long-short returns have also become insignificant since then. Other studies document the declining trend for a subset of anomalies, e.g., Chordia, Subrahmanyam, and Tong (2014), Fama and French (2021), Ben-David, Li, Rossi, and Song (forthcoming), Smith and Timmermann (2022), and Bowles, Reed, Ringgenberg, and Thornock (forthcoming).

[3] McLean and Pontiff (2015) show that short interest increases in the direction of exploiting anomalies following anomaly publication. Dong et al. (forthcoming) provides systematic evidence that hedge funds and short sellers increase their trading intensity in 99 anomalies following anomaly publication, while Calluzzo et al. (2019) provide similar hedge fund evidence for a handful of anomalies. Ben-David, Li, Rossi, and Song (forthcoming) shows that Morningstar's 2003 reform on fund performance rating reduces momentum anomaly profits. Bowles, Reed, Ringgenberg, and Thornock (forthcoming) show that 10K statements are released increasingly earlier, allowing arbitrageurs to quickly correct the mispricing in accounting-based anomalies. Kim, Ivkovich, and Muravyev (2021) shows similar effects after the introduction of Edgar. Chordia, Subrahmanyam, and Tong (2014) shows that increased liquidity in recent years is associated with the disappearance of a handful of anomalies.

[4] See, e.g., Baba-Yara, Boons, and Tamoni (2020), Chernov, Lochstoer, and Lundeby (2022), Gormsen and Lazarus (2023), van Binsbergen, Boons, Opp, and Tamoni (2023), Cho and Polk (forthcoming).

[5] Van Binsbergen and Opp (2019) shows that it is not the magnitude of alphas but the persistence of alphas of anomalies that are important for causing real outcomes.

[6] In contrast to the hedge fund and short seller evidence in Footnote 3, institutions, most of which are mutual and pension funds, tend to trade against anomalies implying they may exacerbate anomalies (Edelen, Ince, and Kadlec, 2016). Akbas et al. (2015) shows correlation-based evidence that flows to mutual and hedge funds induce fund managers to exacerbate and correct a few noninvestment-based anomalies, respectively. Dong, Kang, and Peress (2023) provide direct trading and causal evidence for this argument. These results point towards individual investors as a potential underlying cause of at least some anomalies.

largely unexplored. The gap is critical to understand the complete picture of market participants in anomalies. The answer to the question is also a priori unclear, given the ongoing debate on whether retail trading is strategically savvy or fundamentally unsound.[7]

In this article, we contrast the long vs. short-run alphas of up to 260 established cross-sectional anomalies and explore the role of retail trading in these alphas. We focus on the CAPM alpha because as argued by Jensen, Kelly, and Pedersen (2022), economic theory dictates that the truly anomalous return is the one unexplained by the standard asset pricing theory if we wish to learn about "anomalies."

We start by examining the value-weighted long-short anomaly portfolio alphas over the portfolio formation month (t+1) and the subsequent 23 months (t+2 to t+24). During this two-year event time, the anomaly ranking for each stock, established in month t, is held constant. To examine the evolution of alphas over time, we break the last 50 years into three intervals: 2009-2022, 1989-2008, and 1969-1988, and compute alphas separately for each. We refer to 2009-2022 as the recent years, where direct retail trading data are available (in some tests, we reserve the post-COVID period March 2020-December 2022 as a case study). We find that the formation-month alpha indeed gradually declines over time, with the percentage of significant anomalies (t>1.96) more than halved from 55% to 24% in the recent years and the magnitude of alphas nearly halved to 0.36% per month. This pattern aligns with the conventional belief that anomalies are disappearing. However, the subsequent 23-month alphas reveal a sharply different picture. These alphas remain similarly strong across all three intervals. Furthermore, the total two-year alphas of anomalies predominantly materialize not in the formation month but over the long haul, suggesting that this overlooked timeframe is an economically much more relevant timeframe to understand anomalies than the formation month. Since we deal with long-horizon returns, we ensure the significance of our findings by using various methods throughout the paper, including the Newy-West standard error adjustment, the Jagadeesh-Titman nonoverlapping return approach, or double-clustered standard errors.

[7] On the one hand, individual investors have been shown to exhibit behavioral biases or are uninformed (e.g., Kumar and Lee 2006; Barber, Odean, and Zhu 2009; Barber, Lin, and Odean 2021; Bryzgalova, Pavlova, and Sikorskaya 2022). On the other hand, other work finds that aggregate retail order flows correctly predict returns (e.g. Kaniel, et al. 2012; Kelley and Tetlock 2013; Boehmer et al. 2021), suggesting that retail investors in aggregate appear informed.

We then explore the alpha pattern by separating anomalies based on abnormal retail trading intensity in individual anomalies (ATI) during the quarter before the formation month (month t-2 to t). Our approach relies on the retail trade algorithm developed by Boehmer, Jones, Zhang, and Zhang (2021) (BJZZ), and we track how retail trading evolves as stocks acquire their anomaly-defining characteristics. We construct the anomalies so that their average long-short returns deliver positive alphas in the formation month. Therefore, if ATI is negative (positive) in an anomaly, we categorize this anomaly into the anomalies that retail investors trade against (with). We find that retail investors trade against 60% of anomalies, while trading with the remaining 40%. In the latter group, the significance and magnitude of alphas indeed drop to nonexistence in the recent years regardless of return horizons. In contrast, in the group that retail investors trade against, while the percentage of significant formation-month alphas drops from 56% to 34%, that of significant 24-month alphas increases from 40% to almost 60% over the past 50 years. In terms of magnitude, while the average formation-month alphas drop modestly from 0.6% per month to 0.5%, the average 24-month alphas increase from 10.29% to 14.44%. Therefore, the improvement of market efficiency over time appears to have only diminished the alphas of the anomalies that retail investors trade with but not the ones that they trade against, especially concerning the long run alphas. It is the latter anomalies that are responsible for the enduring long-run alphas we documented earlier for all anomalies.

We next evaluate whether anomaly alphas vary with ATI. We sort anomalies based on their pre-formation (t-2 to t) ATI into five groups from R1 to R5, with R1 being the anomalies with the most positive ATI and R5 the most negative. We compute the average ATI and return across anomalies within each group. Retail investors trade against three groups of anomalies R3-R5 and trade with two R1-R2, consistent with the 60%/40% with/against ratio documented earlier. The pre-formation alphas are negative for R3-R5 but positive for R1-R2, matching the sign of pre-formation ATI. Moving from R3 to R5, as ATI becomes more negative, alphas also turn more negative, from -0.13% in R3 to -3.33% in R4 and to -4.25% in R5 per quarter. However, the sign of alphas of R3-R5 reverses post -formation, turning significantly positive across return horizons. The magnitude of alphas dramatically increases as the horizon lengthens. Remarkably, R5 anomalies can achieve a substantial 23.36% 24-month *value-weighted* alpha. In stark contrast, for R1-R2, although the pre-formation alphas are economically and statistically significantly positive, they are insignificant across all event horizons. Overall, the results suggest that the more retail investors trade against an anomaly before portfolio formation, the higher the anomaly alpha will be after portfolio formation, especially in the long term. In contrast, when retail investors trade with an anomaly, any mispricing associated with the anomaly appears to have largely been corrected before portfolio formation.[8]

To understand what anomaly characteristics retail investors trade against/with and rule out that their trading tendency is arbitrary, we group anomalies according to different economic concepts identified in prior literature. We find that retail investors do not trade against characteristics in a random way but in a fashion consistent with prior considerations of retail preferences/beliefs. For example, they trade against profitability, trading frictions, and value vs. growth anomalies (Hou, Xue, and Zhang 2020); lottery anomalies (Kumar 2009); and anomalies having speculative short legs (Birru 2018).

Why do the alphas of the anomalies that retail investors trade against survive in the recent years while those they trade with disappear? Based on our findings so far, we hypothesize one underlying cause is that retail investors often have entrenched preferences or beliefs, inflicting long-horizon risks on arbitrageurs who take the opposite side in those anomalies traded against by retail investors. This long-horizon risk can persist due to the inherent irrationality of noise traders' preferences and beliefs, which need not change with the rational measures developed to improve market efficiency over the past fifty years.

Additionally, retail investors' influence on stock prices is an ongoing concern. They may even intensify over time, propelled by easier coordination via social media (Barber, Huang, Odean, and Schwarz, 2022), and the convenience from fintech advancement such as zero-commission and fractional trading. In the pre-social media and fintech era, the smaller, disparate trades of retail investors often neutralized each other, minimizing their collective market impact. However, this dynamic has shifted significantly. This view is echoed in popular media. For instance, the Hollywood biopic 'Dumb Money', centered on the GameStop saga, reflects a growing consensus: 'There was no hope for the little guy. Maybe now there is.' Indeed, our

[8] We interpret anomalies as mispricing-based for expositional purposes. Our paper's conclusion could also be consistent with some risk-based interpretations.

results show that retail trading volume and the net trading intensity in the anomalies that retail investors trade against have both tripled over the recent years.

Based on our hypothesis, retail investors pose, and are likely to continue posing, a significant horizon risk, enabling the longevity of anomalous returns in financial markets. To highlight the significance of retail investors' role in understanding asset pricing, we develop factor models incorporating retail trading information. We employ two approaches to build a retail factor. The first method, statistically motivated, takes the average returns across the quintile of anomalies most negatively traded by retail investors. The second method, motivated by theory, accounts for the marginal utility of arbitrageurs opposing retail investors. The resulting asset pricing models considerably outperform existing prominent models in explaining the long-run alphas of the surviving anomalies in the recent years—those that are still relevant for asset pricing models to explain.

Having established the importance of retail trading for understanding asset pricing, we next further support our hypothesis. We argue that the persistent misactions of retail investors, potentially sometimes exacerbated by an intensifying sentiment post formation, multiply the risk exposure of arbitrageurs, who therefore demand higher returns anticipating such long-horizon risk. This argument is based on three key considerations. First, a critical element of arbitrage holding costs is the return variation of the arbitrage position (e.g., Pontiff 2006), driven by both the fundamental risk and the noise trader risk in the underlying stock. We argue that the effective holding costs of an arbitrage position are encapsulated by its lifetime risk exposure: with an increase in holding duration, the variance of *the cumulative return* proportionately increases. Second, contrary to common beliefs, the risk-reward tradeoff does not necessarily improve as the holding period lengthens. For fund managers concerned with outflows from poor performance, metrics like Value at Risk (VaR), indicating the size of potential loss for a given probability, become crucial. Indeed, the size of rare losses can increase several times faster with holding horizon than does volatility. Many hedge funds (e.g., LTCM, Melvin Capital) collapsed following rare, significant losses, exacerbated by resultant outflows. Third, most anomalies are driven by their short legs (e.g., Stambaugh, Yu, and Yuan 2012, 2015; Dong, Li, Rapach, and Zhou 2022)—a fact we confirm in our sample. This means short sellers are the most relevant arbitrageurs for exploiting anomalies. Their holding costs, like fees and fee risk, also increase proportionally with the holding horizon (Engelberg, Reed, and Ringgenberg 2018).

We conduct several tests to substantiate the above argument. First, we examine the abnormal holding positions of retail investors and short sellers in anomaly strategies that retail investors trade against, spanning 24 months pre- and post-portfolio formation in event time. Our findings reveal a mirror movement between retail investors and short sellers: as retail investors gradually accumulate incorrect positions in anomalies, such as purchasing overvalued short-leg stocks pre-formation, short sellers simultaneously establish correct positions by shorting these stocks. Both reach their peak position just before portfolio formation, followed by a slow reduction phase. Retail positions evolve fairly slowly: after a long 4 years, they go back to where they started, which is still half their peak! The monthly changes in retail positions are comparable in magnitude to those in short positions, underscoring that the risk posed by retail trading is an economically relevant concern for short sellers. Overall, the pattern aligns with a general equilibrium model where short sellers take the opposite side of retail investors over a long spell of time. However, maintaining such risky positions is a daunting task for short sellers as we find that the tenure of short positions for an *average* stock is merely 4 (2) months on an equal-(value-) weighted basis. This short tenure suggests that short sellers should prefer strategies with shorter-term profitability. Such preference would notably amplify the discounting of strategies that only yield the bulk of their profits in the long run.

Second, we establish a linkage between the persistence of retail holding of anomaly portfolios post formation with the degree of their trading mistakes before formation. This analysis yields two findings. The first finding is that moving from R1 (the least negatively traded anomalies by retail investors) to R5 (the most negatively traded ones), the percentage of months in which retail ATI is negative monotonically increases from 29% to 77%, suggesting that retail misactions in the anomalies that they trade against are fairly persistent before formation. The second finding is that the more retail investors misact before formation, the more persistent their holdings in the anomaly portfolio will be post formation. The pattern is only significant among the anomalies that retail investors trade against. This result suggests that retail investors tend to stick to their misactions even after disconfirming evidence starts piling in post formation as anomalies start realizing positive alphas. This stubbornness implies that the more retail investors trade against an anomaly, the longer the short-selling duration, thereby increasing the expected long-run alpha.

Third, we examine the risk measures of anomaly strategies. For the long-run alphas of anomalies traded against by retail investors to survive, the risk-reward tradeoff of these strategies must be not as attractive as the apparent value of the alphas implies. We find two patterns supporting this prediction. The first pattern is that the 24-month 1% VaR and 0.1% VaR of the quintile of the anomalies most negatively traded by retail investors (R5) is -42% and -62%, respectively. Such substantial losses could readily precipitate the closure of a hedge fund due to investor outflows. The 1% and 0.1% VaR thresholds we employ are conservative, considering, for example, that the event leading to the collapse of LTCM was a rare 10-sigma event.[9] Furthermore, the VaR of R5 anomalies are similar to that of R1 anomalies, which do not generate long-run alphas. Therefore, holding R5 anomaly portfolios for 24 months is not necessarily more attractive than holding an anomaly portfolio amounting to pure noise, provided that VaR is an important determinant of arbitrageurs' risk management practice. This result obtains largely because the size of monthly anomaly alpha is an order of magnitude smaller than that of its volatility. The second pattern is that the *t* value of the monthly alphas of individual anomalies in R5 only infrequently cross the 1.96 bar over the 24 months post formation. The *t* value of the 24-month cumulative alpha is, however, considerably higher than 1.96. This difference is caused by the noise in alpha in each event month. The 24-month alpha, resembling a simple average alpha measure, effectively neutralizes the monthly noise, akin to the principle of diversification. Therefore, to achieve the substantial 24-month alpha with a high signal-to-noise ratio, arbitrageurs must sustain long-term positions. However, such time diversification need not be attractive in light of the VaR issue we documented earlier.

Finally, for retail trading to be a credible threat to arbitrageurs, there at least needs to be some evidence *suggesting* that retail trading can exacerbate anomalies. Such evidence includes two aspects. First, retail

[9] See p. 127 of Lowenstein, Roger. When Genius Failed. Random House, Inc. New York, NY. 2000. Furthermore, the case of LTCM is widely taught in business schools and known on Wall Street. The hedge fund industry's awareness of the critical need to safeguard against black-swan events has notably heightened in the post-LTCM era.

trading is potent enough to exacerbate mispricing, realizing negative anomaly alpha, before formation. Such evidence helps explain why anomalies realize positive alpha after formation. Second, retail investors may intensify trading against anomalies post formation, as the noise trader sentiment may increase for exogenous reasons (Shleifer and Vishny 1997). This would present another threat to arbitrageurs who build positions to the peak level in the anomaly ranking month, implying an even longer holding horizon. We document four sets of findings supporting these conjectures.

The first set of findings pertains to our earlier results. In sorting anomalies, we use ATI, constructed from detrended stock-level trading, to serve as an unexpected shock that removes firm and anomaly fixed effects. Additionally, our focus on a brief three-month pre-formation period helps to mitigate the influence of persistent, economy-wide variables that might simultaneously drive ATI and returns. Therefore, for the anomalies traded against by retail investors (R3-R5), the finding that retail ATI and anomaly returns is negative before formation and turn positive after formation aligns with the interpretation that the pre-formation retail trading exacerbates mispricing, which is then gradually corrected by various forces post formation. However, this evidence is still correlation-based.

Our second set of findings are based on a difference-in-difference (DiD) test. We utilize the COVID stay-at-home period (March 2020 to December 2020) as a shock to retail trading. The dramatic rise in retail trading during this period helps shed light on the causal effect of retail investors (e.g., Ozik, Sadka, and Shen 2021). Several factors contributed to this rise: First, the pandemic-induced lockdown placed a hold on many other activities, such as sports and travel, and with people working from home, there was greater flexibility to trade during market hours. Second, the emergence of zero-commission brokers, user-friendly trading apps, fractional trading, and immediate access to capital made investing more accessible (Welch, 2022). Third, social media platforms, particularly forums like Reddit's WallStreetBets, became influential in guiding individual investors, leading to coordinated trading (Barber, Huang, Odean, and Schwarz, 2022). Finally, stimulus checks provide additional capital for retail trading.

To more cleanly support retail investors exacerbate anomalies, we use the pre-pandemic persistent retail trading behavior as an instrument and focus on treated anomalies (104 anomalies) defined as the ones that retail investors persistently trade against at least 60% of the months pre pandemic. Since they always tend to trade against these anomalies pre pandemic, any increase in ATI due to the stay-at-home shock can be considered as an exogenous increase unrelated to the COVID-triggered economic conditions. In the remaining anomalies, we remove those persistently traded with by retail investors in at least 60% of the months pre pandemic and define the rest as the control anomalies.

We then proceed to the DiD test. We find that the treatment anomalies experience striking effects. First, as retail trading volume triples for an average stock, the pre-formation ATI of treated anomalies turn three times more negative during the pandemic, confirming the relevance of the shock. Second, the pre-formation alpha also turns three times more negative. This pattern survives the parallel trend test. Third, the ATI remains significantly negative for the first quarter post formation, suggesting that the level of retail sentiment (of holding overpriced stocks) does not abate but intensifies after anomaly ranking information is publicly available. Correspondingly, treated anomalies' alphas become absolutely negative, yielding -5.4%, for the first quarter post formation. The bulk of the correction and hence positive alphas only start realizing from quarter 4, suggesting that retail sentiment can significantly impair the short-term profitability of arbitrageurs. Fifth, the long-term alpha, however, is much larger than the baseline period, consistent with our hypothesis that a longer-term risk exposure comes with a higher required rate of return.

In our third set of findings, we further exploit the stimulus check event during the COVID period to further reduce endogeneity concerns. The first paycheck was disbursed on April 9th, 2020 (Zimmerman and Divakaruni 2021) and shown to be the most effective one to affect prices (Greenwood, Laarits, and Wurgler 2023). Every single person receives $1,200. Based on a regression-discontinuation design (RDD), we calculate two stock level ATI based on whether the dollar amount of a retail order falls into the range of [1150,1200) and (1200, 1250], respectively. We hypothesize that after the disbursement, as retail investors' wealth increases, they are more likely to increase trading in the dollar-cost range of [1150,1200] because the check payment cannot be used to put a buy order of more than $1200. Therefore, the difference in ATI between treatment and control anomalies should be more pronounced in the lower range and driven by the ATI change computed from buy trades. We find that this is indeed the case. Furthermore, the DiD test reveals that the pre-formation month treatment anomaly return indeed becomes significantly more negative at the daily level between April 9 and June 12 when the stimulus check is most likely to affect the stock market. Therefore, the results sharpen the evidence that retail trading can exacerbate anomalies over a subperiod where the increase in retail ATI in treated anomalies is likely more exogenous.

In our fourth set of findings, we show that the treated anomaly alphas during the formation month, which is usually positive, turn significantly negative to up to -4% *per month* during not only the COVID period, but also the tech bubble period. Since both periods are characterized by retail frenzy, these results suggest that retail sentiment increases, exacerbating mispricing, after formation, inflicting more risk on performance-sensitive arbitrageurs.

Our study provides food for thought not only for understanding asset pricing, but also extending its relevance to policy frameworks and regulatory considerations in retail trading. The dynamics observed during events such as the GameStop saga provoke pivotal questions within the regulatory sphere: the appropriateness of restrictions on retail trading, the governance of coordinated trading activities via social media and their adverse impact to arbitrageurs, and the societal impacts of fintech innovations like zero-commission trading. Our empirical findings suggest a nuanced approach may be warranted, incorporating targeted regulatory measures or enhanced financial literacy initiatives for retail market participation. After all, the persistence of non-professional investors in adhering to their beliefs/preferences, absent sophisticated financial acumen, adversely affect the financial market and broader economy, as short sellers can hardly engage in prolonged risky arbitrage and the corporate investment planning hinges on long-run cost of capital. Furthermore, our research underscores the potential of private markets as an alternative in jurisdictions where retail investor behavior education modification presents significant challenges, potentially providing one rationale why in less developed countries, private markets often play a more significant role than public markets. However, our results also imply that retail trading plays a dual role in the financial market. If retail view coincides with arbitrageurs' view such as in anomalies traded with by retail investors, regulatory changes aimed at mitigating other limits to arbitrage may be particularly effective in recent years.

Literature and Contribution

We contribute to understanding anomalies, retail trading, and their relation in several aspects. First, we document novel patterns of anomaly returns. Anomaly alphas predominantly materialize in the long term rather than in the portfolio formation month that the prior literature focuses on. These long-run alphas stay stable over time even as the formation-month alphas disappear. These findings call for a fundamental re-focus of the anomaly literature on the long-run alphas of anomalies going forward, given the implications of long runs alphas and the diminishing formation-month returns. Second, we propose a retail-based factor model that outperforms prominent factor models in explaining the anomalies that remain significant in recent years. Our best performed model is the one that adds the retail factor to the mispricing factor model of Daniel, Hirshleifer, and Sun (2020), whose explanation power is largely due to a firm trading factor. To the extent that the stochastic discount factor is determined by market participants, our findings suggest that a future direction of developing asset pricing models could be aggregating information from the market actions of important traders. This direction differs from the traditional way of building factors from fundamental variables (e.g., Fama and French 2015; Hou, Xue, and Zhang 2020). Third, we advance a horizon-based risk that retail trading imposes on arbitrageurs at the anomaly level. Fourth, our evidence suggests that retail trading plays a crucial role in shaping anomaly returns. The anomalies that retail investors trade against are entirely responsible for the alphas of anomalies in the recent years, especially for long-run alphas.

Existing evidence systematically connecting retail trading with anomalies is scarce. The first study exploring this relation is McLean, Pontiff, and Reilly (2021 MPR), which finds that retail trading is negatively associated with an aggregate anomaly signal. MPR study how well anomaly characteristics explain retail trading performance. We focus on the recent trend in anomaly alphas and their relation to retail trading, propose a new factor model, and introduce a horizon-based risk for arbitrageurs. We consider individual anomalies and find that retail investors trade with some anomalies and against others. We shed light on the causal effect of retail trading by characterizing which anomalies are exacerbated by retail investors (and which ones aren't).

There is an ongoing debate on whether retail trading is smart or dumb. The retail trading measure we use has been shown to positively predict short-term returns. We shed light on this debate by examining short-run and very long-run *risk-adjusted* returns. We find retail investors trade with and against 40% and 60% of the anomalies, respectively, providing evidence of them being smart and dumb under different circumstances. Since individual anomalies account for a small portion of the return variance, combining all evidence across anomalies may not significantly affect the aggregate retail trading smartness. However, our findings shed light on how retail trading can be smart or dumb w.r.t different anomaly characteristics.

1. Sample Construction and Descriptive Statistics

1.1. Anomaly Sample

We consolidate a dataset of 260 anomalies sourcing from those studied by Stambaugh, Yu, and Yuan (SYY, 2012, 2015), Green, Hand, and Zhang (2017), Jensen, Kelly, and Pedersen (2023), and Dong, Li, Rapach, and Zhou (2022),[10] by removing duplicates with similar construction methods. We replicate anomaly portfolio returns using publicly available data from CRSP (Center for Research for Security Prices), Compustat, and I/B/E/S. We focus on common stocks listed on the NYSE, AMEX, and Nasdaq and, following BJZZ, exclude stocks priced below $1 in the preceding month. Monthly stock returns are adjusted for delisting. The long-short anomaly portfolio goes long on the tenth decile and short on the first decile, with the expectation that the long leg will generate relatively high returns and the short leg low returns in the formation month.

To characterize the return dynamics of anomalies both before and after portfolio formation, our tests are based on an event-time approach where we maintain a constant anomaly portfolio composition a quarter before the portfolio formation month (t+1) and two years after. The portfolio composition is determined by the anomaly characteristic ranking in month t, referred to as the ranking month. We calculate the characteristics based on the information available at the end of month t. We assume the annual accounting

[10] Our findings are insensitive to the anomaly sets. Except SYY, which consists too few (11) anomalies for testing, tests based on Green, Hand, and Zhang (2017), Jensen, Kelly, and Pedersen (2023), and Dong, Li, Rapach, and Zhou (2022) yield qualitatively similar results.

data become available four months after a firm's fiscal year end, and quarterly accounting data is available upon the issuance of the quarterly earnings report.[11]

The anomaly alphas in our main tables are risk-adjusted by the CAPM model following Jensen, Kelly, and Pedersen (2022). For each event-time h-period monthly anomaly return $\mathrm{Ret}_{\mathrm{t+h}}$, we regress the raw anomaly portfolio return on the excess market return $Mkt_{\mathrm{t+h}}$ to get the risk loading on the market factor β_{h}. The alpha is calculated as the difference between raw return and its market risk premium $\alpha_{\mathrm{t+h}} = \mathrm{Ret}_{\mathrm{t+h}} - \beta_{\mathrm{h}} \times \mathrm{MktRf}_{\mathrm{t+h}}$. Cumulative monthly risk-adjusted returns are obtained by the following formula: $\alpha_{\mathrm{t+1tot+h}} = \prod_{\mathrm{j=1}}^{\mathrm{h}}(1 + \alpha_{\mathrm{t+j}})$. The alphas we consider include the quarterly cumulative alphas before formation (α_{t-2tot}), the formation-month alpha (α_{t+1}), and the six-month ($\alpha_{t+1tot+6}$), 12-month ($\alpha_{t+1tot+12}$), and 24-month ($\alpha_{t+1tot+24}$) alphas post formation. As will be explained in the subsequent section, quality retail trading data starts from January 2009. Therefore, we focus on examining anomaly returns in the recent years where the first ranking month of anomalies starts from January 2009. Our event study, discussed later in the paper, examines anomaly portfolio performance during the post COVID period. To this end, we consider two samples to examine anomaly returns. The first sample, referred to as the pre-pandemic sample, excludes the post COVID period, focusing on portfolio returns from October 2008 to February 2020. The second sample, referred to as the full sample, is more comprehensive, with anomaly returns covering from October 2008—three months before the first portfolio formation month—to December 2022, 24 months after the last ranking month.

Table 1, Panel A presents summary statistics for anomaly portfolio returns for these two samples. For the pre-pandemic sample, the one-month formation-month alpha (α_{t+1}) is 0.33%, consistent with the immediate positive performance post formation reported by the literature. For longer holding horizons, the alphas generally increase, with $\alpha_{t+1tot+6}$, $\alpha_{t+1tot+12}$, and $\alpha_{t+1tot+24}$ at 1.92%, 4.02%, and 8.40%, respectively. In the full sample, the post formation alphas exhibit a similar pattern.

[11] Bowles, Reed, Ringgenber, and Thornock (2023) shows that some accounting information is available during earnings announcement, which usually happens before the 10-K report.

1.2. Retail Trading and Holding at the Stock Level

Retail trading data is obtained from TAQ (Trade and Quote). According to BJZZ, Regulation National Market System (Reg NMS) requires a broker/dealer to give a slight price improvement relative to the National Best Bid or Offer (NBBO) to retail orders. We follow the method of price improvement to isolate retail investors' marketable orders from institutional orders. Specifically, we identify a transaction as a retail buy if the sub-penny price is between 60 and 100 basis points and a retail sale if the sub-penny price is between 0 and 40 basis points. We then take the difference between buy and sell volumes to obtain retail net buy, denoted as NB_t. Given retail trading displays a trend in the recent years, we focus on a detrended, abnormal retail trading measure, which takes the difference between the current month NB and the average NB in the past 12 months and is scaled by shares outstanding as follows:

$$RetailTrading_t = \frac{NB_t - \sum_{j=t-1}^{j=t-12} NB_j/12}{ShrOut_t}.$$

We winsorize stock level trading at 0.5% and 99.5%. Our retail trading data covers the period from January 2009 as BJZZ's evidence shows that it may have taken the market some time to fully comply with Reg NMS so that good quality retail trading data starts roughly from 2009.

Table 1, Panel B, reports that the average monthly stock-level retail trading is 0.003%, suggesting that retail investors tend to purchase stocks.

We also introduce a detrended, abnormal retail holding measure to proxy for the level of retail demand rather than the changes of demand, in line with the noise trader models that relate the level of demand to noise trader sentiment (e.g., De Long, Shleifer, Summers, and Waldmann 1990; Shleifer and Vishny 1997). This detrended holding measure can be backed out from the retail net buy measure. Specifically, let H_t denote the retail holding (scaled by share outstanding) of a stock in time t, and NB_t denote retail net buy. The abnormal retail holding measure, defined as the holding detrended by its 12-month moving average can be expressed as follows:

$$RetailHolding_t = H_t - \frac{(H_{t-1} + H_{t-2} + \cdots + H_{t-12})}{12}$$

$$= H_t - H_{t-1} + \left(\frac{11}{12}H_{t-1} - \frac{11}{12}H_{t-2}\right) + \left(\frac{10}{12}H_{t-2} - \frac{10}{12}H_{t-3}\right) + \cdots + (\frac{1}{12}H_{t-11} - \frac{1}{12}H_{t-12})$$

$$= NB_t + \tfrac{11}{12}NB_{t-1} + \tfrac{10}{12}NB_{t-2} + \cdots + \tfrac{1}{12}NB_{t-11},$$

where the last row of the formula provides a way to use retail net buy to compute retail holding.

Table 1, Panel B summarizes monthly stock-level retail holding. On average, retail investors have a positive abnormal holding position of 0.098%.

1.3. Retail Trading and Holding at the Anomaly Level

We then construct retail anomaly-level trading and holding intensity, defined as the average trading or holding in decile-10 (underpriced) stocks of the anomaly minus that of decile-1 (overpriced) stocks. Specifically, for each anomaly, retail anomaly-level trading or holding intensity are constructed as below:

$$ATI_{it}(or\ AHI_{it}) = L_{it} - S_{it}$$

where L_{it} and S_{it} are the average $RetailTrading$ or $RetailHolding$ in the long- and short-leg stocks. Negative ATI_{it} suggests that retail investors buy or hold more (or sell less) decile-1 stocks than decile-10 stocks. In other words, Retail investors appear to trade in the "wrong" direction that may exacerbate anomaly-based mispricing. Similarly, positive ATI_{it} suggests retail investors trade in the "right" direction.

Table 1, Panel C, summarizes the total retail ATI and AHI the quarter before formation. For the pre-pandemic sample, the average ATI is negative, at -0.01%, suggesting that retail investors trade against anomalies before anomaly portfolio formation. Similarly, the average AHI is -0.43%, indicating that retail investors hold more stocks in the short leg than in the long leg. In the full sample, retail ATI further declines to -0.03% and AHI decreases to -0.52%, suggesting that retail investors increase their intensity to buy and hold overpriced stocks in more recent years.

1.4. Short Seller Holding at the Stock and Anomaly Level

We construct short-seller anomaly-level holding intensity using Compustat short interest data. First, at the stock level, the detrended, abnormal short-seller holding is calculated using the difference between current mid-month short interest and average short interest in the past 12 months and is scaled by shares outstanding. We then switch the sign of this difference so that a more negative short seller holding measure indicates higher short interest:

$$ShortSellerHolding_t = -\frac{Short\ Interest_t - \sum_{j=t-1}^{j=t-12} Short\ Interest_j/12}{ShrOut_t}.$$

The short-seller anomaly-level holding intensity is then constructed in the same way as retail *AHI*:

$$AHI_{it} = L_{it} - S_{it},$$

where L_{it} and S_{it} are the average $ShortSellerHolding$ in the long and short leg stocks. Positive short-seller AHI_{it} suggests that short sellers hold more decile-10 (underpriced) stocks than decile-1 (overpriced) stocks. In other words, short sellers exploit the anomaly in the "right" direction by shorting overpriced stocks more than underpriced stocks. Conversely, negative short seller AHI_{it} implies that their holding in the anomaly portfolio is in the "wrong" direction.

Table 1, Panels B, reports that the average short-seller stock-level holding is -0.14% with a standard deviation of 2.34% in the full sample. Panel C shows that short sellers tend to exploit anomalies in the "right" direction. The average short-seller AHI is 0.89% in the pre-pandemic sample. This figure increases to 0.97% in the full sample, suggesting an increase in short-seller positions potentially responding to the increase in retail holding in more recent years.

2. Anomaly Alphas and Retail Anomaly Trading Intensity

In this section, we first examine the anomaly alphas over the past half-century in Section 2.1. In Section 2.2, we then examine the role of retail trading in anomaly alphas. In Section 2.3, we introduce an anomaly aggregation approach to sharpen our understanding of the relation between retail trading and anomaly alphas. Finally, in Section 2.4, we examine the relation between retail trading and different subgroups of anomalies. In all subsections, to account for serial correlation, we either adjust the t-statistics of the cumulative return $\alpha_{t+1tot+h}$ using the Newey-West method, with adjustments for 6, 12, and 24 lags for $\alpha_{t+1tot+6}$, $\alpha_{t+1tot+12}$, and $\alpha_{t+1tot+24}$, respectively, or using a non-overlapping return approach from Jagadeesh and Titman (1993).

2.1. Short and Long-Run Anomaly Alphas Over the Past Half-Century

We examine the value-weighted CAPM alpha of 260 anomalies, dividing the sample period into three distinct intervals based on the ranking months of anomaly signals. The first two intervals are a 20-year period from 1969 to 1988 and from 1989 to 2008, respectively. The final interval starts from 2009. As explained in Section 1.1, we consider two samples of the final interval. Section 2 primarily discusses findings from the pre-pandemic sample, while a similar pattern for the full sample is reported in Figure IA1 and IA2 of the Internet Appendix.

Figure 1, Panel A, shows that the formation-month alpha α_{t+1} monotonically declines over time with the percentage of significant anomalies (t>1.96) being more than halved from 55% to 23%. Furthermore, Figure 1, Panel B, shows that the magnitude of alpha nearly halved to 0.35% per month. In stark contrast, the long-run alpha ($\alpha_{\mathrm{t+2tot+24}}$) maintains a stable presence both in terms of number of significant anomalies and magnitude across all intervals. Approximately 40% of anomalies exhibit a significant long-run alpha, with its average magnitude around 9%. This considerable difference between the long-run and the diminished formation-month alphas underscores that anomaly alphas are predominantly realized in the long run—post portfolio formation.

Overall, these results highlight a surprising resilience of the long-run alphas of anomalies over the past half-century. Given that long-run alphas constitute the majority of total anomaly profits, they warrant critical attention for evaluating the profitability of anomalies.

2.2. Anomaly Alphas and Retail Anomaly Trading

We then separate anomalies based on the retail ATI over the quarter prior to the formation month to examine the relationship between retail trading and anomaly returns. If retail investors buy more stocks in the short leg than in the long leg of an anomaly, indicating a negative ATI, we classify this anomaly into the group where retail investors trade against. Conversely, if ATI is positive, we classify the anomaly into the group that they trade with. We find that retail investors trade against (with) 60% (40%) of all anomalies.

Figure 2, Panel A1, shows that among the 40% of anomalies that retail investors trade with, there is a marked decrease in the number of anomalies with significant formation-month alpha α_{t+1}, falling sharply from 52% to 9%. A similar trend is observed for alphas in the long run; the number of anomalies with significant $\alpha_{t+2tot+24}$ drops from 41% to 13%. In contrast, Panel A2 indicates a more modest reduction in the formation-month alpha for anomalies traded against by retail investors, declining from 57% to 33% between 1969-1988 and 2009-2018. More strikingly, there is an increase in the percentage of significant long-run alpha $\alpha_{t+2tot+24}$, rising from 40% to 59% during the same periods.

Turning to magnitude, Panel B1 reveals that the formation-month alpha α_{t+1} for the anomalies traded with by retail investors drop dramatically from 0.53% to 0.10%, consistent with disappearing profits. The long-run alpha $\alpha_{t+2tot+24}$ similarly diminishes, falling from 6% to a negative number of -0.62%. In sharp contrast, Panel B2 shows that for the anomalies traded against by retail investors, while the average formation-month alpha α_{t+1} only experiences a small decline from 0.60% to 0.51%, the long-run alpha $\alpha_{t+2tot+24}$ increases from 10.26% to 14.44%.

These findings suggest that the improving market efficiency over time appears to have significantly weakened the short- and long-term alphas of anomalies traded with by retail investors. However, it has little weakening effect, especially on the long-term profitability of the anomalies that retail investors trade against. It is these anomalies, which represent the majority of anomalies, that are responsible for the enduring long-run alphas we documented earlier for all anomalies.

2.3. An Anomaly Aggregation Approach

To enhance our understanding of the patterns documented in the previous two subsections, we introduce an anomaly aggregation approach. We first calculate t-statistics from the time-series retail ATI over the quarter before anomaly formation for each anomaly. We then sort anomalies into 5 groups, labeled R1 through R5, according to their respective t-statistics of ATI. For each group, we compute the average returns across anomalies on a monthly basis. We then examine the group-based alphas from a quarter before to two years after portfolio formation. This aggregation approach effectively allows us to abstract away from the anomaly-level specific noise and extract the common feature of alphas from anomalies with comparable levels of retail ATI. Notably, the simple 1/N average has been theoretically and empirically validated as the most robust method to diversify away idiosyncratic noise in returns (see, e.g., DeMiguel, Garlappi, and Uppal 2009; Yuan and Zhou (forthcoming); Dong, Li, Li, Rapach, and Zhou 2023).

Table 2, Panel A Column (2**),** shows the average ATI over the quarter before formation for each group. From R1 to R5, ATI decreases monotonically. Retail investors trade with anomalies in R1 and R2 and against those in R3 to R5. Column (1) sheds light on the persistence of retail anomaly trading by counting the percentage of calendar months with negative retail trading over the sample period. For instance, in R5, where ATI is the most negative, retail investors trade against the anomalies 77% of the time on average, indicating a very high level of persistence. Additionally, Column (1) reveals that, moving from R1 to R5, as ATI turns more negative, it also becomes more persistently negative. The result suggests that the more retail investors misact, the more they stick to their misactions—a pattern that we will revisit with further evidence in Section 4.

Table 2, Panel A Column (3), shows that the cumulative alpha over the quarter before formation decreases monotonically as retail ATI becomes negative. For anomalies in R1 and R2 groups, α_{t-2tot} is significantly positive at 4.03% and 3.93%. In contrast, for R4 and R5 groups, α_{t-2tot} are significantly negative at -3.54% and -3.68%.

Columns (4) to (8) of Table 2 detail the alphas for various holding horizons post formation, including short-term (defined as those with holding horizons shorter than one year) and long-term ones (defined as those with holding horizons equal to or longer than one year). For anomalies in R3 to R5, where retail investors trade against, we observe an immediate reversal in anomaly portfolio alphas following ranking. Moreover strikingly, post-formation alphas are positively significant for those anomalies that retail investors trade against, namely R3-R5 anomalies. For instance, the formation-month alpha for R5 anomalies stands at 0.83%, compared to an insignificant 0.07% for R1 anomalies. Moreover, the 24-month alpha exhibits a monotonic pattern: the more negative the retail $\mathrm{ATI}_{\mathrm{t-2tot}}$ before formation, the higher the long run alpha post formation. The 24-month alpha can reach as high as 23.49% for R5 anomalies.

In addition to Newey-West adjustments for serial correlation, we also incorporate a non-overlapping return method from Jagadeesh and Titman (1993). In this alternative method, for any given month t, the h

holding-horizon monthly return is calculated as the average monthly risk-adjusted return at month t from ranking date t-h to the ranking date t-1. The *h*-holding monthly return is constructed from *h* long/short portfolios. We then compound *h*-holding monthly returns by *h* months to get the cumulative holding period return and t-statistics are derived from monthly alpha. Panel B reports the results, which align closely with those in Panel A. This consistency reinforces the robustness of our findings against potential biases in statistical inferences from overlapping holding periods.

Jointly considering the pre- and post-formation alpha patterns, we conclude that retail traders may contribute to anomaly-based mispricing before formation, driving down the returns of R3-R5 anomalies that they trade against before formation; this exacerbation is followed by a pronounced and sustained correction post formation. In contrast, for R1-R2 anomalies that retail investors trade with before formation, anomalies realize positive alphas before formation, leaving little profits post formation, suggesting that retail trading may help expedite the mispricing correction in these anomalies.

2.4. Retail Anomaly Trading Group Characteristics

To understand what anomaly characteristics that retail investors tend to trade against/with, and to address the concern that their trading might be arbitrary, we group anomalies according to different economic concepts identified in previous studies. This involves computing the group-level retail ATI by averaging the ATI over the quarter before formation across anomalies within each group. Table 3 reports the results.

We consider several group concepts. First, we segregate all anomalies into subgroups following the categorization of Hou, Xue, and Zhang (2020). Our analysis reveals that retail investors strongly trade against anomalies related to profitability, trading frictions, and value vs. growth, while their engagement with momentum, investment, and intangible-related anomalies appears comparatively weaker. These results are consistent with several theories on unsophisticated investors' preferences/belief. First, the tendency to trade again profitability anomalies are consistent with the theory that uninformed investors may have biased beliefs toward profitability (Bouchaud, Krueger, Landier, and Thesmar 2019). Second, the tendency to trade against frictions-based anomalies or favor growth, rather than value, stocks is consistent with theories of retail preferences for gambling, skewness or lottery-like features (Han and Kumar 2013). Friction-based anomalies are also inherently challenging for arbitrageurs to correct.

Daniel, Hirshleifer, and Sun (2020) argue that the mispricing of some anomalies is more persistent than others, categorizing anomalies into short- and long-horizon types. The typical short-horizon anomalies are the earnings surprise-based anomalies, whereas the long-horizon exploits the information in the manager's decisions to issue or repurchase equity. Our results indicate that retail investors trade with short-horizon anomalies, consistent with the evidence that retail investors tend to trade in the right direction *ahead of* earnings surprises (Kaniel, Liu, Saar, and Titman 2012). We also find that retail investors trade against the long-horizon anomalies, consistent with the stubborn nature of retail misactions.

We also divide our anomalies into those identified as lottery-demand-driven anomalies (e.g., Kumar 2009) and the rest, which we label as non-lottery anomalies. Retail investors trade against both groups of anomalies but more strongly against lottery anomalies, more cleanly supporting the relation between retail trading and the lottery preference theories in literature.

For anomalies that Akbas et al. (2015) identifies as investment and non-investment anomalies in the 11 anomalies from SYY (2012, 2015), retail investors strongly trade against non-investment anomalies while trading with investment anomalies. This suggests that retail trading resembles mutual fund flow-induced trading, which also shows a tendency of trading against noninvestment anomalies (Akbas et al. 2015; Dong, Kang, and Peress 2023).

Finally, we find that among the anomalies that Birru (2018) identifies as having clear speculative short and long legs, retail investors strongly trade against the anomalies having speculative short legs, such as idiosyncratic and profitability anomalies. In contrast, they trade with those having speculative long legs, like size and illiquidity anomalies. The results suggest that retail investors have preferences for or (mis)beliefs in buying speculative stocks, especially for those overpriced ones in anomaly short legs.

In summary, our findings suggest that retail investors engage in trading against and with various dimensions of characteristic concepts, with no single concept predominantly drives their trading behavior. The trading patterns appear not arbitrary but instead are consistent with existing theories.

3. Explaining Long-Horizon Returns: Two Retail Factor Models

Our previous findings suggest that the influence of retail trading on the long-term returns of anomalies is crucial. Building on this insight, we develop asset pricing models, incorporating retail trading information, to explain the long-run alphas of the anomalies that have remained significant in recent years. In Section 3.1 and 3.2, we propose statistically and theoretically motivated retail factors, respectively. In Section 3.3, we build asset pricing models by including one of these two factors and evaluate these models' performance relative to other prominent models.

3.1. R5F Retail Factor Construction

The first retail factor, labeled R5F, is derived from the formation-month returns of R5 anomalies, predominantly traded against by retail investors. To construct this factor, we first compute the average anomaly rankings within R5 anomalies. To control for the size effect, we employ a double sorting method following Fama and French (1993). Specifically, we independently sort size into 2 groups—small (S) and big (B)—based on the NYSE breakpoint and sort the average rankings from R5 anomalies into low (L), middle (M), and high (H) groups. A size-controlled, value-weighted factor return is obtained as the average return of the high-ranking portfolio minus that of the low- ranking portfolio:

$$\mathrm{R5F} = (\mathrm{r_{SH}} + \mathrm{r_{BH}})/2 - (\mathrm{r_{SL}} + \mathrm{r_{BL}})/2$$

The intuition is straightforward. The R5 anomalies experience the most persistent and negative retail trading among all anomalies. Consequently, we expect these anomalies to capture the long-horizon risk imposed by retail trading with the highest signal-to-noise ratio. By averaging across anomalies, we effectively cancel out anomaly-specific noise.

3.2. TF Retail Factor Construction

The second retail factor, denoted TF, is derived using market-wide retail trading, following the methodology similar to the construction of the liquidity risk factor in Pastor and Stambaugh (2003). We construct the TF factor using daily trading data. Consistent with our approach for detrending the monthly retail trading, we detrend daily trading. This involves detrending the current day's trading—quantified as the difference between the number of shares bought and sold—against the prior 252-day moving average and scaling it by number of shares outstanding. Additionally, we winsorize the cross-section at 0.5% and

99.5% levels to avoid outliers. We then proceed with the following steps. First, we calculate daily market-wide average retail trading (MWRT) across all stocks i:

$$MWRT_t = \sum_i RetailTrading_{it}$$

We then derive the market-wide trading shock using the residual from an AR(1) model, denoted by η:

$$MWRT_t = \gamma MWRT_{t-1} + \eta_t$$

Utilizing daily data within a month, we compute the monthly sensitivity of each stock's return to the market-wide trading shock, denoted as β. This involves running a regression for each stock as follows:

$$R_t = \beta_{0t} Mkt_t + \beta_t \eta_t + \epsilon_t$$

Next, in each ranking month, we sort on the retail trading β and form monthly long-short portfolio and keep the ranking fixed for 24 months after ranking. In each factor return date t, the TF factor is calculated as the average monthly return across 24 long-short portfolios formed, respectively, over ranking months t+1 to t-24, following the non-overlapping return approach of Jagadeesh and Titman (1993). The TF factor is a proxy for the risk in the long-run return of the portfolio exposed to retail trading risk.

The TF factor is theoretically motivated by an equilibrium featuring the interplay between retail investors and short sellers (see, e.g., Daniel, Hirshleifer, and Sun 2020), considering our results are driven by anomaly short legs. In this framework, retail investors buy overpriced short-leg stocks, while short sellers take the opposite side by shorting the stocks. Stocks with high retail beta are more susceptible to fluctuations in retail sentiment. In the scenario where retail investors become more optimistic, the prices of the stocks that retail investors hold are likely to escalate due to intensified buying activity, and arbitragers—who short the stocks—experience more losses. This increase in losses leads to a rise in short sellers' marginal utility. Thus, stocks with higher retail beta bring larger losses to short sellers when their marginal utility is high. Consequently, short sellers demand higher compensation for shorting high retail-beta stocks, leading to higher retail-beta stocks yielding a lower expected return.

3.3. Spanning Tests and Factor Models Performance

We first run a spanning test to examine how well other commonly used factor models explain our two retail factors, R5F and TF, and vice versa. Since we aim to explain the long-run (i.e., 24-month) returns, our return sample period starts from 2011 and ends in 2022. We run a time-series regression of R5F and TF on different factor models: CAPM; the three- and five-factor model of Fama and French (1993) and Fama and French (2015), denoted FF3 and FF5; the four-factor model of Carhart (1997), denoted Carhart4; the short and long-horizon mispricing factor model (DHS); and our two retail factor models. Since the FIN factor in the three-factor model of Daniel, Hershleifer, and Sun (2020) also aims to capture long-horizon mispricing, we include the FIN factor as another dependent variable in our spanning test as a contrast.[12]

Table 4, Panel A, reports the alphas from the spanning test. Columns (6) and (7) reveal that our two retail models, R5F and TF, effectively explain the FIN factor, as indicated by their insignificant alphas. In contrast, Column (5) shows that the long and short-term mispricing model of DHS fails to account for these two retail factors. Furthermore, Columns (1)-(4) shows that the standard models, including CAPM, FF3, Carhart4, and FF5, fail to explain the R5F factor. The only exception is our TF model, as shown in Column (7). This suggests that our theoretically motivated retail factor can fully explain the statistically motivated retail factor R5F. Notably, none of the factor models can explain the theoretically motivated TF factor. This finding underscores the unique information captured by our two retail factors.

Next, we evaluate whether the proposed retail two factor models can price long-horizon anomaly portfolio returns, especially in the R4 and R5 groups of anomalies that retail investors significantly trade against, as shown in Table 2 (retail investors also trade against R3, albeit insignificantly). In total, 104 testing anomaly portfolios are used. Table 4 Panel B reports the average absolute alphas, average t-statistics, and number of anomalies with significant alphas (*$t \geq 1.96$*) from each model under consideration.

[12] Since the FIN factor in DHS is only available up to 2018, we constructed a size-controlled FIN factor following the DHS methodology. This process entails averaging the rankings of two anomalies: the 1-year net share issuance and the 5-year composite share issuance; and applying a double sort based on size, using the NYSE breakpoint and the average rankings. Monthly returns for the FIN factor are determined by calculating the difference between the average returns of portfolios with low and high share issuance. We verify that the FIN factor we build delivers the same performance as the original FIN factor in the DHS model in the original sample period in DHS paper.

The results show that pricing errors of the existing prominent models are: CAPM (0.74%), FF3 (0.53%), Carhart (0.46%), FF5 (0.38%), and DHS (0.38%). Although the pricing error of DHS is the same as that of FF5, it appears to be the best performing one as the number of significant anomalies of DHS is more than halved compared to FF5. However, our two retail factor models obtain considerably better performance than any of these prominent models, evident in the lowest pricing errors, average t-statistics, and the fewest anomalies with significant alphas. In comparison, the pricing errors for FF5 and DHS are nearly 50% higher than those for our retail models.

Given that the mispricing-based DHS model performs the best among the existing prominent models considered, and the FIN factor originates from firm trading. We consider a model that includes R5F or TF into DHS. The resulting four-factor model, reported in the last two rows of Panel B, generate a marked improvement of performance over DHS, with a notable reduction of the pricing error by 50%, from 0.38% to 0.19%. This improvement underscores a key insight: factors derived from retail trading contain distinct information from the long-horizon factor based on firm trading. The four-factor model, which combines these diverse sources of trading information, outperforms all other factor models.

To the extent that the stochastic discount factor is based on market participants' views, our results suggest a future avenue for the development of asset pricing models: incorporating the market actions of important market participants. This approach departs from the traditional methodologies that primarily rely on fundamental variables sourced from databases like Compustat. The growing relevance of action-based information is supported by the increasing availability of high-frequency trading data, which, until recently, was largely inaccessible. The FIN factor, as motivated by DHS, is based on the idea that firm trading encapsulates a comprehensive range of mispricing identified by firms. Analogously, retail trading can be viewed as a "catch-all" for mispricing influenced by retail investors—the sharpest proxy for the views of unsophisticated, noise traders. Therefore, these two types of factors are likely to complement each other in the attempt to build a comprehensive action-based asset pricing model.

4. Stubborn Retail Trading and the Long-Horizon Risk

Why do the long-horizon alphas of the anomalies that retail investors trade against thrive? Based on our findings so far, we hypothesize that retail investors have stubborn preferences/beliefs, inflicting long-horizon risks on arbitragers. In Section 4.1, we investigate whether retail investors are inclined to persist in their investment errors by analyzing their holding patterns 24 months before and after formation. To further understand the risks faced by arbitragers, we also examine short-seller holdings in the meantime. We focus on holdings in this section because equilibrium noise trading models are usually based on demand rather than change in demand (e.g., De Long, Shleifer, Summers, and Waldmann 1990; Shleifer and Vishny 1997). In Section 4.2, we show that long-horizon holding costs such as VaR are likely to be the relevant long-horizon risk that limits arbitrage.

4.1. Persistent Retail Anomaly Holding and Short Selling

Figure 3, Panel A plots retail anomaly holding intensity (AHI) for the 60% of anomalies that retail investors trade against. In the 24-month periods leading up to the anomaly formation, there is a noticeable buildup of negative retail AHI. This buildup suggests a continuing acquisition of stocks in the short leg by retail investors. After the anomaly formation, the AHI slowly reverts, indicating a gradual divestment from the previously accumulated positions. However, even 24 months after the ranking month, retail AHI is still half the size of its peak value reached in the ranking month. The protracted nature of the unwinding process post formation emphasizes retail investors' reluctance to swiftly rectify their positions, highlighting a potential hesitancy to acknowledge and act upon signals that contradict their initial actions. Such a level of stubbornness is striking, given the huge amount of alpha we observe post formation.

We further explore the notion of retail investors' misguided persistence by examining the direct correlation between their pre-formation misactions and the adherence to their erroneous positions following formation. Specifically, we regress the post-formation retail holding persistence on the cross-sectional standardized retail ATI over the quarter before formation (ATI_{t-2tot}), where holding persistence is computed as the AR(1) coefficient of the monthly retail holding AHIs over the event window of 24 months post formation.

Table 5 Column (1) shows across anomalies that retail investors trade against, the more negative the ATI_{t-2tot} is, the more persistent the post-formation AHI becomes. A one standard deviation decrease in ATI is associated with a 0.01 increase in AHI persistence. To put this number into perspective, we consider the half-life measure of a time series, which measures half of the time needed for a variable to revert back to its mean given a shock.[13] The half-life increases at an increasing rate for more persistent series. For example, while an autocorrelation increase of 0.01 would increase the half-life of an average anomaly that retail investors trade against (AR(1)=0.92) by one month, it increases R5 anomalies (AR(1)=0.95) by 4 months because retail holding in the latter group is more persistent to begin with. This contrast suggests that the more an anomaly is traded against by retail investors, the more risky it may be for arbitrageurs. In contrast, Column (2), focusing on anomalies that retail investors trade with, shows no significant result. This result suggests that retail investors mainly tend to persist only if such actions are wrong.

Overall, the persistent holding patterns of retail investors, despite potential losses or contradictory public signals, can lead to sustained mispricing in the market, elevating the risks for arbitragers targeting these anomalies. Arbitragers not only face fundamental risks but also prolonged noise trader risks, as they navigate the protracted price correction delayed by retail stubbornness.

Figure 3, Panel B, shows short seller anomaly holding in anomalies that are traded against by retail investors. We find that short sellers appear to be exactly on the opposite side of retail investors in these anomalies. Prior to the anomaly formation, short sellers progressively accumulate short positions, as retail investors push up asset prices above fundamental values in the short-leg stocks. Following anomaly formation, while short sellers' AHI exhibit a gradual decline, it remains markedly elevated, even two years post formation. This sustained holding accentuates the long-horizon risks undertaken by short sellers, as fundamental risk, noise trader risk, and transaction costs all accumulate as holding horizon lengthens. Furthermore, using Markit data, we find that the tenure of short positions for an average stock is merely 4 (2) months on an equal-(value-) weighted basis. This result suggests that maintaining long-term risky

[13] the half-life calculation is from half-life = $-\frac{\ln(2)}{\ln(|\emptyset|)}$, where $\emptyset$ is the AR(1) coefficient.

positions is challenging for short sellers; it may also imply that short sellers' maybe particularly average to strategies that realize profits in the long run.

4.2. The Long-Horizon Risk

In this section, we consider some more tangible metrics to gauge the potential long-horizon risk arbitrageurs may encounter, had they taken the opposite side of retail investors by establishing a holding position for 24 months. We know that while variance proportionately increases with horizon, volatility does not grow as fast. This usually gives investors a misleading impression that buy-and-hold must be safer. However, such time diversification illusion ignores the size of potential losses based on the cumulative return. Such concept is captured by the Value at Risk (VaR) concept, which quantifies the potential size of loss at a given probability after accounting for the effect of the expected return. It is defined as the difference between the time-series mean of alphas and the product of z-score for the designated confidence level and standard deviation of anomaly portfolio alphas. The formula for VaR is $VaR = \overline{\alpha} - z \times \sigma_{\alpha}$, where z is the z-score that takes the values of 2.33 and 3.09 for 1% and 0.1% VaR, respectively. The first term $\overline{\alpha}$ captures the potential gains of holding the anomaly portfolio, while the second term $z \times \sigma_{\alpha}$ captures the potential losses for a given probability. Conventional belief is that as the holding horizon lengthens, the first term is scaled up by the number of periods n, while the second term is scaled up by $z \times \sqrt{\text{n}}$. It appears that the alpha term is scaled up by a bigger number than the volatility term as long as the z-score used is not too large. However, this intuition does not account for the fact that the volatility of monthly anomaly alpha is usually an order of magnitude larger than the magnitude of the monthly alpha (see α_{t+1} in Table 1), due to the weak signal-to-noise ratio of monthly anomaly profits. As a result, the *magnitude* of potential losses can escalate as the holding period extends. For example, an alpha of 0.1 scaled by a factor of 10 would increase by a magnitude of 0.9 (=0.1×10-0.1); however, a volatility of 1 scaled by 5 would still increase by a much larger magnitude of 4 (=1×5-1). This means that the magnitude of losses can also increase faster than that of gains as the horizon lengthens, depending on the balance of several considerations.

Since fund managers are particularly sensitive to the risk of outflows stemming from poor performance, VaR is a critical metric, informing their decision-making processes. We compute 1% and 0.1% VaR for the long-term alpha ($\alpha_{t+2tot+24}$), using parametric method. Table 6 columns (4) and (5) show that the estimated 1% and 0.1% VaR for the long-term alpha of an average anomaly within the R5 group can reach a staggering -42% and -62%, respectively. Intriguingly, these figures are similar to those of R1 anomalies, even though the monthly alpha of R1 is much smaller than that of R5. This implies that arbitrageurs engaging in R5 strategies would be subject to a level of VaR-based risk comparable to that of anomalies that do not yield long-run alphas at all like R1 anomalies.

The next pertinent question arising from our analysis is whether arbitrageurs can circumvent the risks associated with holding R4 or R5 anomalies for extended periods by engaging in a random selection of anomalies in a random post-formation month. We examine the t-values of the monthly alphas for each anomaly during each event month post formation. Figure 4 shows that these t values barely cross the 1.96 bar in any of the 24 months post formation. The best performed anomalies are in the R5 group, whose t-values cross the 1.96 bar starting month 12 after ranking. In other words, arbitrageurs really need to buy and hold an anomaly portfolio for sufficiently long time in order to earn the long-run alphas with sufficiently high signal-to-noise ratio. The intuition is that longer holding horizon can diversify away the noise in individual monthly alphas.

Finally, although short selling fees are important for short sellers, we find that this simple concern is far from being able to explain the long-run alpha of anomalies. Specifically, Muravyev, Pearson, and Pollet (2022) shows that anomaly alphas disappear after excluding the 12% observations with high short fees. In Table IA2 of the Internet Appendix, we remove the 12% observations used in their study, which leave stocks with low short-selling fees based on Markit data. However, we find that the 24-month alphas of our R4 or R5 anomalies remain large. For example, the alphas of R5 reduces by 6% to 17%, suggesting some form of long-horizon risk akin to VaR remains an important candidate for explaining anomaly returns.

These findings illuminate the stark reality that the risk-reward tradeoff inherent in the R5 anomaly strategies may not be as compelling as what their long-term alpha values suggest. This substantial VaR underscores the severe risk arbitrageurs assume when opposing retail investors over extended investment horizons.

5. Three Event Studies on Retail Anomaly Trading

In section 5, we provide two exogenous shocks to retail anomaly trading to shed light on the causal inference of retail trading on anomalies. The first (Section 5.1) pertains to the COVID-induced stay-at-home mandates, which precipitated an unparalleled surge in retail trading. The second (Section 5.2) pertains to the 1st economic impact payment. Following the methodology of Divakaruni and Zimmerman (2021), we implement a regression discontinuity design to capture the effects of this sudden wealth increase on retail anomaly trading. Finally, in Section 5.3, using the Tech Bubble as an out of sample test, we evaluate the performance of treatment and control group based on retail trading data from the 2010s.

Throughout this section, we classify anomalies into treatment and control groups based on pre-pandemic retail ATI_{t-2tot}. The treatment group, with ATI_{t-2tot} t-statistics (Table 2 Panel A) below the 40th percentile, contains anomalies facing consistent negative retail trading from January 2015 to February 2020. We find that retail investors also persistently trade against these anomalies at least 60% of the months pre pandemic. The control group consists of anomalies with ATI_{t-2tot} t-statistics in the 50th to 80th percentiles, which reflects a neutral retail stance—typically trading against these anomalies 40% to 50% of the time pre pandemic. The anomalies with ATI_{t-2tot} t-statistics above 80th percentiles are removed from the control group, as they are traded with by retail investors at least 60% of the months pre pandemic. Furthermore, in some of our tests, we use anomalies in the 40th to 50th percentile for robustness tests. The study considers 104 anomalies in the treatment group and 78 in the control group.

5.1. The Pandemic Induced Stay-at-Home Shock

5.1.1. Diff-in-Diff Design

For the analysis of the first exogenous shock to retail investor trading, induced by the pandemic stay-at-home orders, we narrowed our sample period to January 2015 through December 2020. We define during the pandemic as the period from March 2020 to December 2020, and before the pandemic as from January 2015 to February 2020. Figure 5 shows that the retail monthly volume dramatically increases during the pandemic. This finding is quantified by the regression results shown in Table 7, Panel A. Following the onset of stay-at-home orders, there is a significant upsurge in retail trading volume. It effectively doubled from a pre-pandemic average of 2.13% to an average of 4.62% during the pandemic period.

5.1.2. Empirical Results

Table 7, Panel B illustrates the differences in Anomaly Trading Intensity (ATI) between treatment and control group anomalies, both a quarter before and after anomaly formation. Column (1) details the regression outcomes for retail ATI prior to anomaly formation. The findings indicate that, on average, the retail ATI in the treatment group is 0.12% lower than in the control group before the pandemic. This disparity is accentuated during the pandemic, as evidenced by the significantly negative coefficient of -0.37% for the interaction term *Treat×Post*. This signifies that the difference in ATI between the treatment and control groups quadruples in comparison to the pre-pandemic period.[14] Columns (3) and (4) reveal that this heightened negative difference in ATI between treatment and control groups persists beyond the anomaly ranking month during the pandemic posing a credible threat to arbitrageurs countering retail investors.

Previously, we documented that pre-pandemic, for the anomalies traded against by retail investors, the risk-adjusted return of the anomaly portfolio a quarter before formation could be as low as nearly -4%, with a quick reversal occurring post formation. During the pandemic, retail investors traded even more strongly against anomalies in the treatment group and for extended periods. Consequently, we hypothesized that during the pandemic, the negative cross-sectional impact of retail trading on anomaly portfolio returns could extend beyond the anomaly ranking. Table 8 confirms this hypothesis. Column (1) reveals that a quarter before formation and before the pandemic, the treatment group anomalies' portfolio returns were 5.27% lower than those of the control group anomalies. During the pandemic, this difference more than tripled, with treatment group anomaly portfolio returns being 17.56% lower than those of the control group. Column (3) examines the formation month alpha. Before the pandemic, treatment group anomalies outperformed the control group, with the *Treat* variable coefficient for the value-weighted anomaly returns being significantly positive at 0.63%. However, during the pandemic, the alpha for the treatment group anomalies,

[14] Table IA3 of the Internet Appendix further indicates that the change in the ATI difference between treatment and control during the pandemic is mainly attributed to the ATI change in the short leg.

on average, was 2.16% lower than that of the control group anomalies. [15] [16] This is consistent with more negative Anomaly Trading Intensity (ATI) following the ranking month, suggesting that the intensified negative retail trading indeed caused arbitrageurs to suffer greater losses.

Figure 6 presents detailed plots of the return differences between treatment and control group anomalies, both before and during the pandemic, extending from a quarter before anomaly formation up to 24 months afterward. For this analysis, we employed a regression model of $\alpha = \beta_1 Treat + \beta_2 Treat \times Post$ with double clustered standard errors. The light green bars show the estimate of β_1 together with a 5% confidence interval, i.e., the difference in anomaly portfolio performance between the treatment and control groups before the pandemic. The dark green shaded bars show the estimate of $\beta_1 + \beta_2$ and 5% confidence interval, i.e., the performance difference between the treatment and the control group anomalies during the pandemic. Before the pandemic, anomaly portfolio returns of treatment anomalies are significantly lower than those of the control group anomalies. Such difference disappears right after the anomaly ranking month. However, during the pandemic and before anomaly formation, the anomaly portfolio returns for the treatment group anomalies are even more negative compared to those of the control group, and this trend continues even after the anomaly signal formation. The difference in anomaly portfolio returns remains significantly negative up to one quarter after anomaly formation, followed by a more pronounced reversal from the 7th to the 24th month. This outcome is consistent with the retail anomaly trading intensity difference remaining negative for a quarter after the anomaly signal formation, posing a credible risk to arbitrageurs.

Finally, using the panel regression of $\alpha_{i,t+1} = \sum_{t=2015}^{2020} \beta_t Treat_i \times Year_t + \mu_i + \gamma_t + \epsilon_{it}$, Figure 7 shows parallel trend interaction term coefficients β_t for the formation-month alpha. $Year_t$ is a pseudo-post-event dummy, assigned a value of 1 for the sample range from March in year t to March in the subsequent

[15] Table IA4, Panel A of the Internet Appendix shows 72% of the during pandemic formation-month alpha difference between treatment and control is due to increased alpha in the short leg.
[16] Table IA4, Panel C of the Internet Appendix further reveals that as the ATI of the treatment group becomes more negative (from the bottom 50th to bottom 30th percentile), the formation-month alpha difference between treatment and control group anomalies during the pandemic becomes more negative.

year, t+1. Both firm and date-fixed effects are included in the analysis. The year 2015 serves as the reference period and its interaction term is omitted to avoid multicollinearity. The parallel trend test suggests that using the sample period of 6 years, for α_{t+1} , it is only in 2020 that the difference between treatment and control group anomaly portfolio returns is significantly lower than that in 2015. This finding highlights a distinct shift in the relationship between treatment and control group anomalies specifically during the surge in retail trading.

5.2. The First Stimulus Check

5.2.1. Regression Discontinuity Design

The first Economic Impact Payment (EIP) in the U.S., part of the response to the COVID pandemic, was announced on March 30, 2020. It provided up to $1,200 for individuals. The payments, which began distribution shortly after the announcement, were aimed at offering financial relief to households and stimulating economic activity. Starting from April 2020, the US government sent these payments directly to households. Figure 8 from Divakaruni and Zimmerman (2021) shows the accumulative distribution in terms of the number of paychecks and the total amount paid. The first paycheck starts to distribute on April 9 and the distribution continues beyond June 8.[17] Thus, we use daily retail anomaly trading intensity from Jan 2, 2020, to Jun 12, 2020, and define the post-disbursement period from April 9 to June 12.

The key idea of regression discontinuity design is that we examine retail ATI within a $100 window centered on the $1,200 EIP—$50 above and $50 below this threshold. With the wealth constraint relaxed post-disbursement, a change in retail trading activity should only be observed in the lower cost range. To do so, we form daily retail ATI in the pre-formation month (ranking month) by dollar amount traded. Specifically, we calculate two stock level ATI based on whether the dollar amount of a retail order falls into the range of [1150,1200] or (1200, 1250]. Then, we detrend the stock level trading intensity using 2019's average daily trading intensity in each dollar range. Consistent with monthly retail stock level trading methodology, daily trading is winsorized at 0.5% and 99.5% levels by different dollar ranges. The

[17] CNBC reports on June 8, 2020: 35 million checks are yet to be disbursed *https://www.cnbc.com/2020/06/08/35-million-stimulus-checks-havent-been-sent-out-who-is-waiting-for-money.html*.

resultant daily anomaly trading intensity was derived from the average stock level trading intensity in the long leg subtracted by that of the short leg. A negative retail ATI indicates that retail investors traded in a manner that exacerbated anomaly mispricing- buying more stocks in the short leg.

Figure 9 shows a descriptive analysis of daily trading volume and the number of trades by dollar amount trade, using the pre-EIP sample from Jan 2 to Apr 9, 2020. As the dollar costs increase, the number of trades and volume placed by retail investors decrease. Within the [1150,1200) and (1200, 1250] cost brackets, an average of approximately 15 trades per stock per day was made by retail investors.

We first run diff-and-diff regressions for treatment and control group anomalies separately:

$$ATI_{it} = \beta_1 \mathrm{I}(< 1200)_i + \beta_2 \mathrm{I}(< 1200)_\mathrm{i} \times \mathrm{Post_t} + \gamma_t + \epsilon_{it}$$

Here, ATI_{it} is the anomaly retail trading intensity at one month prior to formation month, $\mathrm{I_i}(< 1200)$ is an indicator and takes on the value of 1 if the retail order falls within the lower cost range [1150,1200), and 0 otherwise, and γ_t is the time-fixed effect. We hypothesize that before disbursement, we should observe no difference in ATI in the two dollar cost ranges both for treatment and control group anomalies, i.e., β_1 is insignificant from 0. Post-disbursement, retail investors place more buy orders in the range [1150, 1200) for short-leg stocks in the treatment group anomalies, resulting in a more negative ATI_{it} , thus, a significant negative β_2. Control group anomalies, where retail investors are expected to maintain neutrality, should exhibit an insignificant β_2. Moreover, since the EIP acts as an exogenous shock to individuals' wealth, we expect the observed differences to arise predominantly from changes in the buy-side anomaly trading intensity. Therefore, we decompose the retail ATI into buy-side and sell-side components: the buy-side ATI is the difference in the average number of shares bought in the long and short legs of an anomaly, while the sell-side ATI is the corresponding difference in shares sold.

To facilitate the incorporation of additional variables, such as an announcement and crash dummies, we have developed a triple interaction regression model. The model is specified as:

$$ATI_{it} = \beta_1 Treat_i + \beta_2 I\ (< 1200)_i + \beta_3 Treat_i \times Post_t$$

$$+\boldsymbol{\beta_4} Treat_i \times I\ (< 1200)_i + \beta_5 I\ (< 1200)_i \times Post_t$$

$$+\boldsymbol{\beta_6} Treat_i \times Post_t \times I\,(< 1200)_i + \gamma_t + \epsilon_{it}$$

In line with the difference-in-differences design, we hypothesize that, prior to the disbursement, there is a distinguishable difference in trading intensities between treatment and control group anomalies within each dollar cost range. Specifically, $\beta_1 + \beta_4$ should be significantly negative for the lower cost range, while β_1 alone should be significantly negative for the higher cost range. However, the difference between the treatment and control groups should remain consistent across both dollar cost ranges, implying that $\boldsymbol{\beta_4}$ should not be significantly different from zero. After the disbursement, we anticipate retail investors are more likely to increase trading in the dollar range of [1150,1200), and the difference between treatment and control group trading is more pronounced in the lower cost than the higher cost range. As a result, $\boldsymbol{\beta_6}$ should be significantly negative.

5.2.2. Empirical Results

Table 9, Panel A represents results for diff-and-diff design. Columns (1) and (2) show treatment group anomalies. In Column (1), focusing on the period before the paycheck disbursement, we observe no significant difference in retail trading between the low-cost and high-cost dollar ranges for the buy-side ATI. After the disbursement, retail investors buy more of the short-leg stock within the lower cost range, leading to a negative difference between the buy-side ATI in the lower cost range and the high cost range. Column (2), in contrast, indicates that there are no significant findings from the sell-side ATI, confirming our hypothesis that the sell-side trading behavior should not exhibit noticeable changes in response to the disbursement. Furthermore, columns (3) and (4) reveal that there is no change in the retail ATI in control group anomalies. This observation further confirms our hypothesis that control group anomalies are those where retail investors take a neutral stance.

After identifying the retail anomaly trading intensity change in the treatment group anomalies, we further decompose retail trading within treatment group anomalies into short-leg and long-leg trading. Column (2) of Table IA5 of the Internet Appendix suggests that, after the disbursement, retail investors tend to buy stocks in the short leg of treatment group anomalies, and it’s the primary driver behind the observed changes in the treatment group's anomaly trading intensity.

Table 9, Panel B represents the results of the triple difference analysis. Column (1) reveals that retail investors generally exhibit more negative trading towards treatment group anomalies compared to control group anomalies, with an average difference of approximately 0.057 basis points (bp) per day within each dollar cost range. Furthermore, the trading difference between treatment and control group anomalies across the [1150,1200) and (1200, 1250] ranges is initially insignificant at 0.002bp before the disbursement, but becomes more negative, reaching -0.010bp, after the disbursement. Consistent with the findings in Panel A, there are no significant results from the sell-side ATI.

To account for potential influences beyond the exogenous shock to household wealth, we introduce an announcement dummy into the regression. This dummy, denoted as 'Ann', takes the value of 1 for ATI during the first stimulus check announcement week, specifically from -9 to -6 days relative to the event day. Columns (2) and (4) demonstrate that our results remain robust after including the announcement dummy. Additionally, we consider the possibility that the results could be influenced by retail investors providing liquidity during the market crash. To address this, we include a 'crash' dummy in our analysis. The S&P 500 index experienced a significant drop of 29% from March 2 to March 16, 2020. We define 'Crash=1' for trading intensities falling within the event days of -26 to -13. Columns (3) and (6) confirm the robustness of our results.

Finally, to gain cleaner evidence of retail trading effect on anomaly performance, we also refine the DiD test in Section 5.1. Specifically, we redefine the post period as the post check disbursement period, which includes April, May, and June of 2020, while the definition of the pre period remains the same. Given the potential deterioration in economic fundamentals during the COVID sample, the three-month period following the disbursement provides a sharper identification of the impact of exogenous retail trading, influenced both by stay-at-home mandates and an increase in retail wealth. Table 9 Panel C shows that the ranking month alpha difference between treatment and control group during the post period becomes more negative from the pre period of -3.53% to -10.25%, suggesting the heightened retail trading activity contributes to a greater underperformance of anomalies in the treatment group.

5.3. The Tech Bubble: An Out-Of-Sample Test of Anomaly Performance

The latter half of the 1990s witnessed a remarkable escalation in technology stock values, leading to the phenomenon known as the 'tech bubble.' It is commonly believed that retail frenzy played an important role in this bubble. Our analysis focuses on the treatment and control groups' anomaly performance during the formation month within the tech bubble, using a sample timeframe from January 1993 to January 2000. The commencement of the tech bubble, as identified by Baker and Wurgler's (2006) initial public offering (IPO) returns, extends from September 1998 to January 2000. Figure 10 elucidates the comparative performance trajectories of the treatment and control group anomalies during two significant market upheavals: the tech bubble and the COVID pandemic. In both instances, outside the bubble period, with an immediate correction occurring at the formation month, the anomalies within the treatment group initially outperform those in the control group. However, amidst the bubble period, the treatment group's anomalies tend to underperform substantially, potentially attributed to retail investors' increased purchase of short-leg stocks within the treatment group anomalies. The formation-month anomaly alpha of treatment anomalies can drop to as low as -4% per month, while the alphas of control anomalies remain stable throughout the period.

The empirical robustness of our findings is further solidified when viewed through the lens of the technology bubble of the late 1990s—an out-of-sample event when considering our initial selection of treatment and control group anomalies based on retail trading data from the 2010s. Despite the temporal and contextual disparities, Figure 10 demonstrates a strikingly similar anomaly performance pattern during the tech bubble, mirroring the trends observed amidst the COVID pandemic. This congruence suggests that the retail trading behaviors influencing anomalies need not be confined to recent market conditions but also extend to earlier periods of significant market exuberance.

Overall, these results provide vivid examples that retail sentiment can intensify even after the ranking month, further endangering arbitrageurs who have built up their positions to the peak level (Figure 3) during the ranking month.

6. Conclusion

Our examination of 260 anomalies challenges the prevailing notion that market efficiency erodes anomaly-based profits, these anomalies continue to thrive, especially over longer timeframes. We demonstrate that retail investors play a pivotal role in the persistence of these anomalies. Their stubborn trading patterns, especially against anomalies, not only contribute to initial mispricing but also lead to delayed price corrections. This behavior imposes long-horizon risks on arbitrageurs, complicating the market's return to equilibrium and underscoring the complexity of market dynamics in the presence of retail trading. Our study makes significant contributions to the understanding of long-horizon returns through the two novel retail factor models. Additionally, our analysis of the pandemic-induced stay-at-home orders, EIP, and the tech bubble era reveals the intensified impact of retail trading on anomaly performance, exacerbating mispricing for an extended periods and presenting a substantial challenge to arbitrage strategies.

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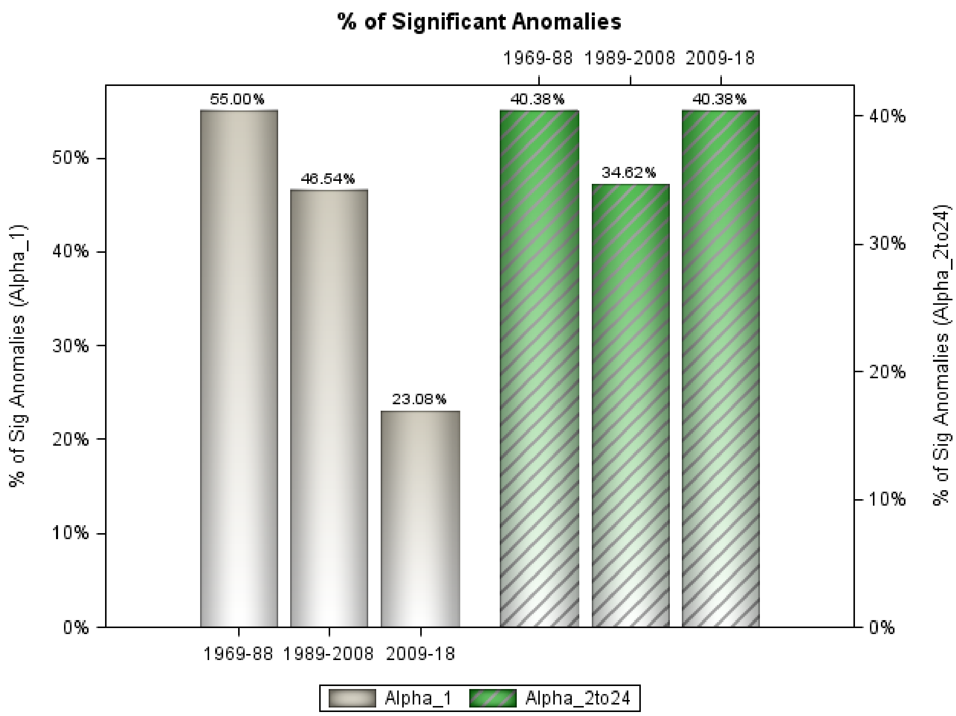
Figure 1 Short and Long-term Anomaly Portfolios

Figure 1 panel A and panel B show the percentage of significant anomaly portfolios and return magnitude using CAPM-alpha over three distinct intervals spanning the past half-century. For each event-time h-period monthly anomaly return Ret_{t+h}, we regress the raw anomaly portfolio return on the excess market return Mkt_{t+h} to get the risk loading on the market factor β_h. The alpha is calculated as the difference between raw return and its market risk premium $\alpha_{t+h} = \mathrm{Ret}_{t+h} - \beta_h \times \mathrm{MktRf}_{t+h}$. Cumulative monthly risk-adjusted returns are obtained by the following formula: $\alpha_{t+1tot+h} = \prod_{j=1}^{h}(1 + \alpha_{t+j})$. Alphas are calculated using in-sample method. For example, the formation-month α_{t+1} (Alpha_1) from 1969 to 1988, is calculated using the sample period from Jan 1969 to Dec 1988, defined as anomaly ranking months. The long-term $\alpha_{t+2tot+24}$ is the cumulative CAPM-adjusted return over the event periods from 2 to 24 months after anomaly formation. T-stats are adjusted for serial correlation using Newey-West method. $\alpha_{t+2tot+24}$ is adjusted for 23 lags. An anomaly portfolio return is significant when t-stats are higher than 1.96.

Panel A: Short and Long-term Percentage of Significant Anomalies



Panel B: Short and Long-term Anomaly Performance

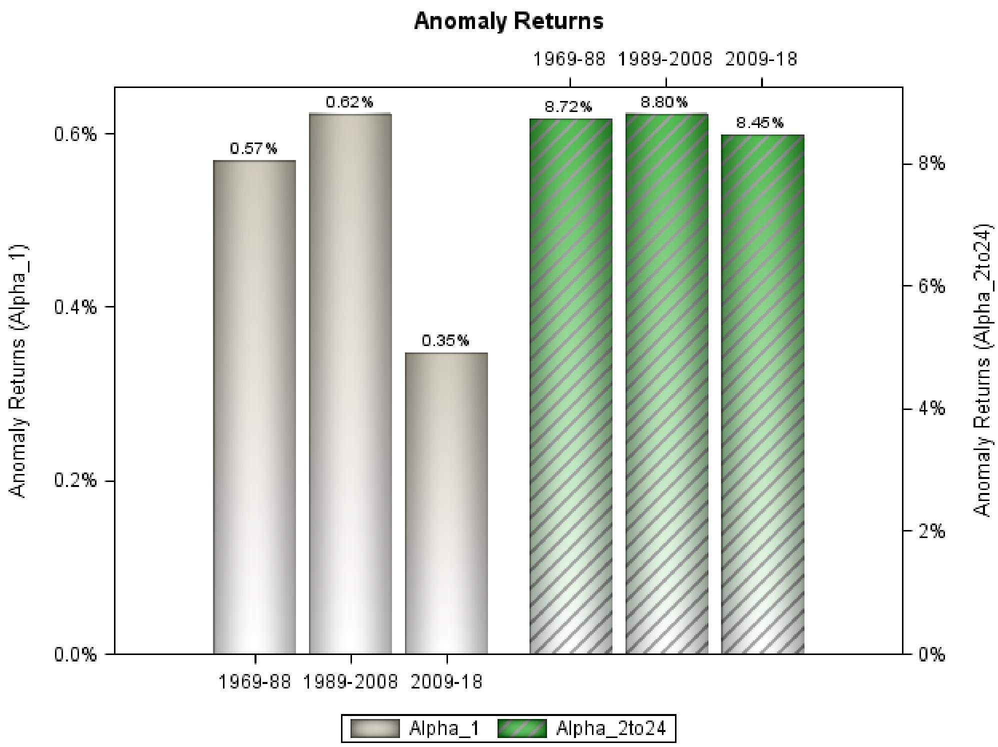
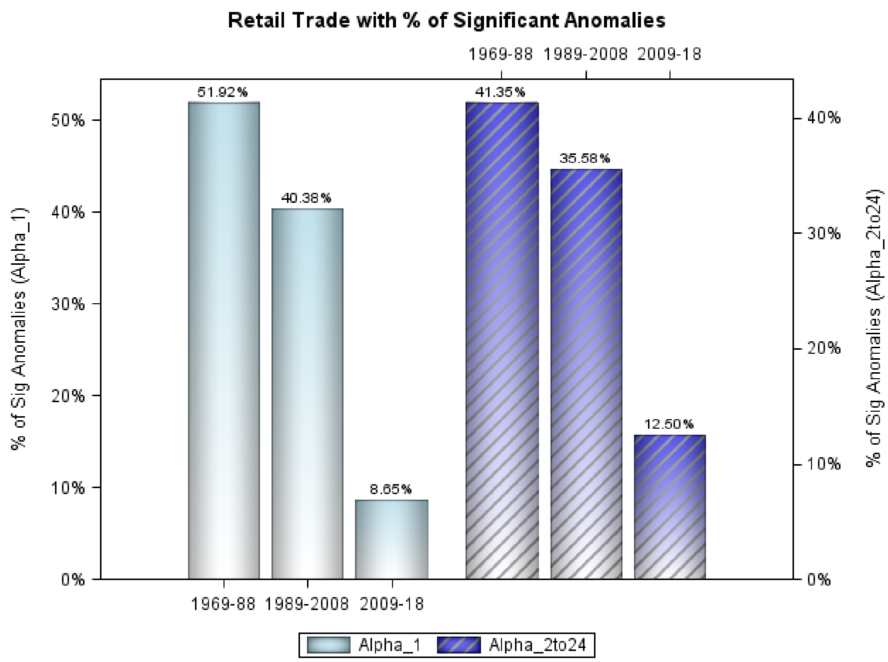


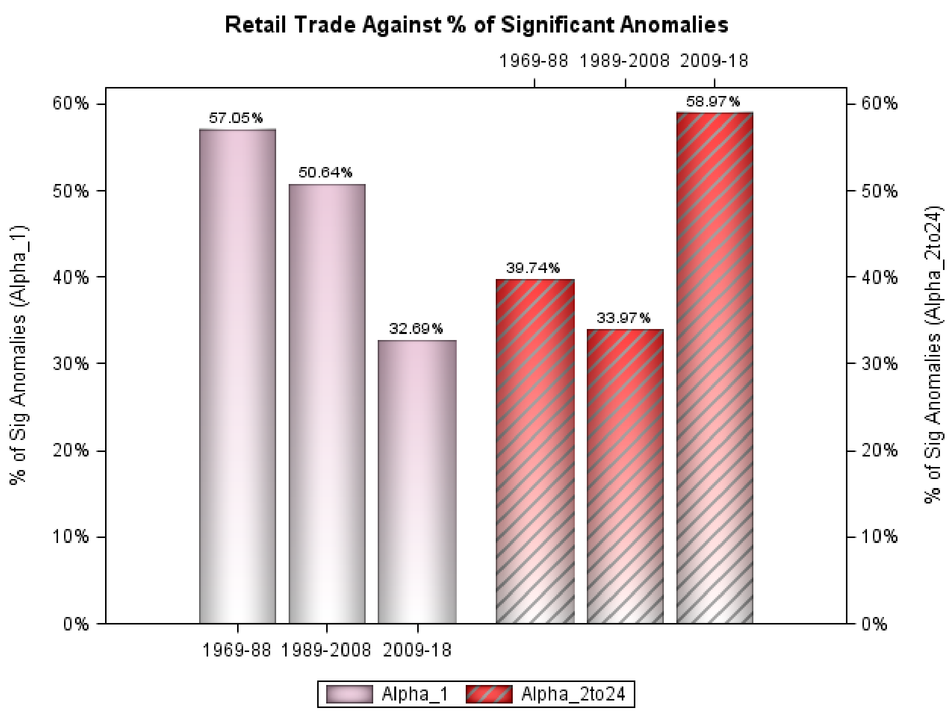
Figure 2 Short and Long-term Anomaly Portfolio by Retail Trading Direction

Figure 2 divides anomalies into retail investors trade with versus trade against and examines short and long-term anomaly portfolio alphas. If retail investors buy more (less) stocks in the short leg than in the long leg of an anomaly, the anomaly is classified into the group where retail investors trade against (with). Panel A1 and A2 show the percentage of significant anomaly portfolios. Panel B1 and B2 show the alpha magnitude.

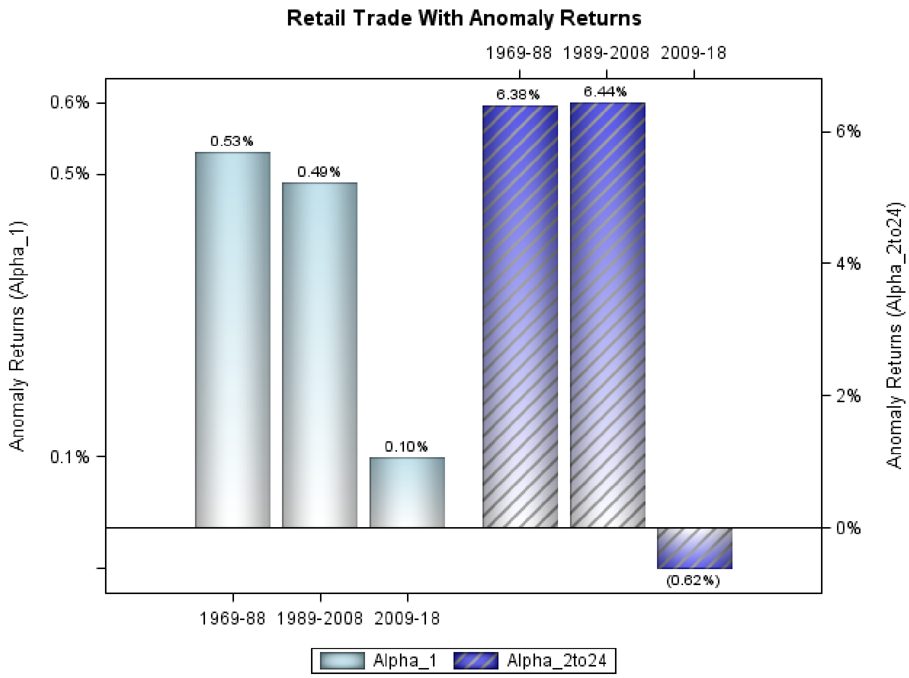
Panel A1: Retail Trade with Percentage of Significant Anomalies



Panel A2: Retail Trade Against Percentage of Significant Anomalies



Panel B1: Retail Trade with Anomaly Alphas



Panel B2: Retail Trade Against Anomaly Alphas

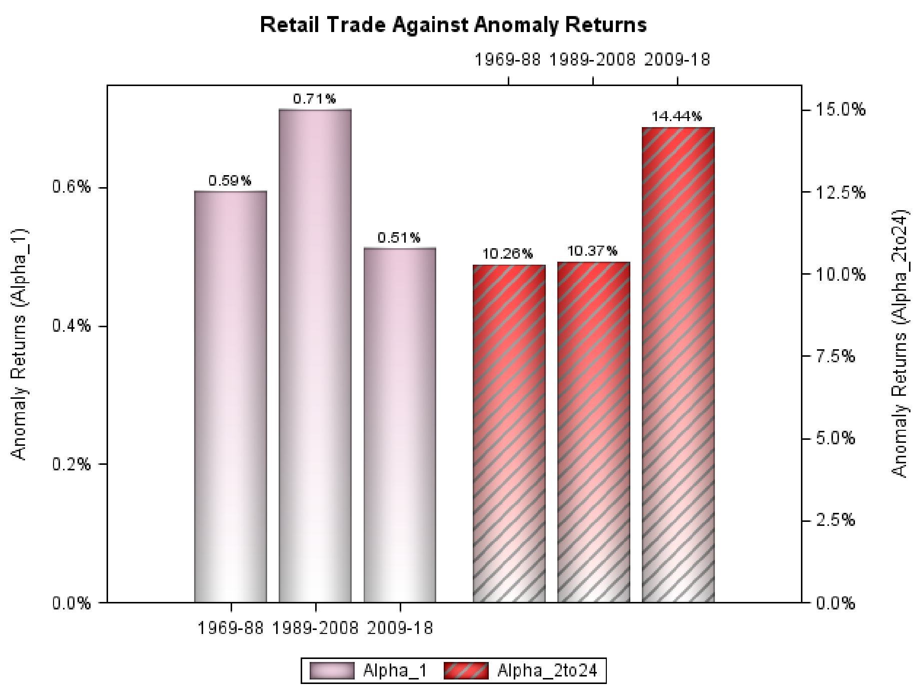
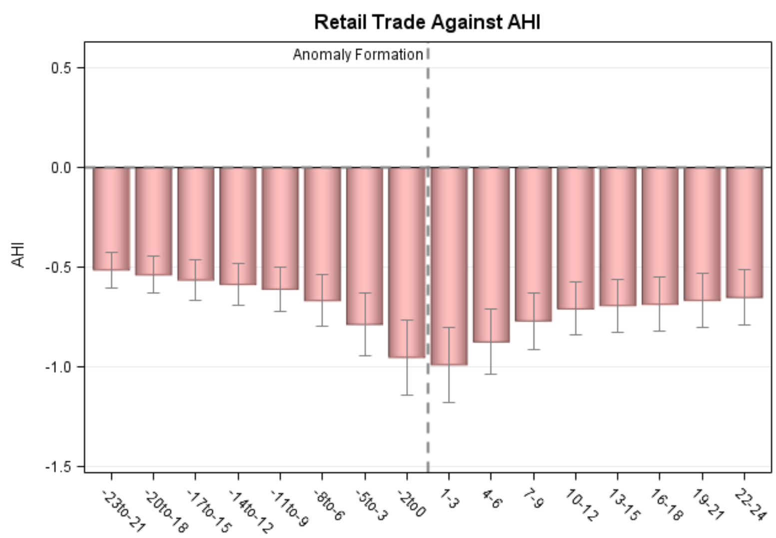


Figure 3 Retail and Short-Seller Anomaly Holding Intensity

Figure 3 shows retail and short seller anomaly holding intensity (AHI) in percent for the anomalies that retail investor trade against. Figure 3 plots AHI 24 event-month before anomaly formation and 24-month after. Sample period is from 2009 to 2020, defined as anomaly ranking months. Panel A shows retail AHI. Panel B shows short seller AHI.

Panel A: Retail AHI



Panel B: Short-Seller AHI

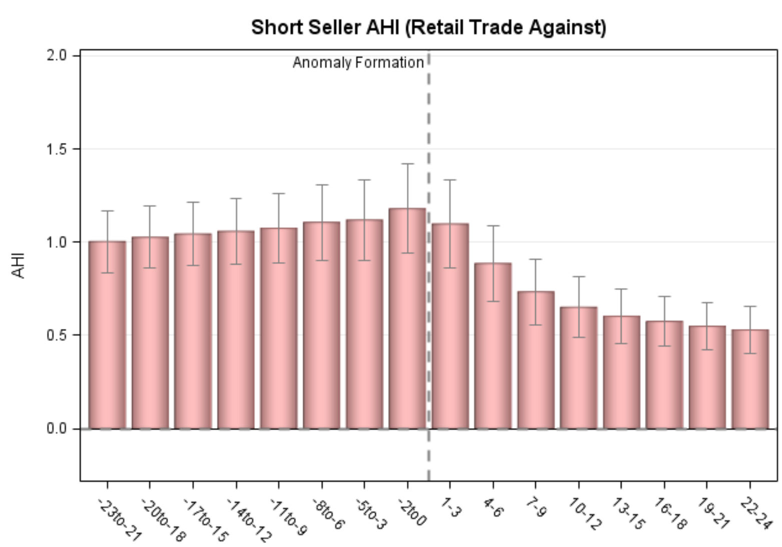


Figure 4 Monthly Average Anomaly Alpha T-stats

Figure 4 shows average anomaly portfolio alpha t-statistics within each R1 to R5 group using the return data from October 2008 to February 2020, corresponding to ranking months from January 2009 to December 2020. Retail investors trade with R1 and R2 group of anomalies, and trade against R3 to R5 group of anomalies.

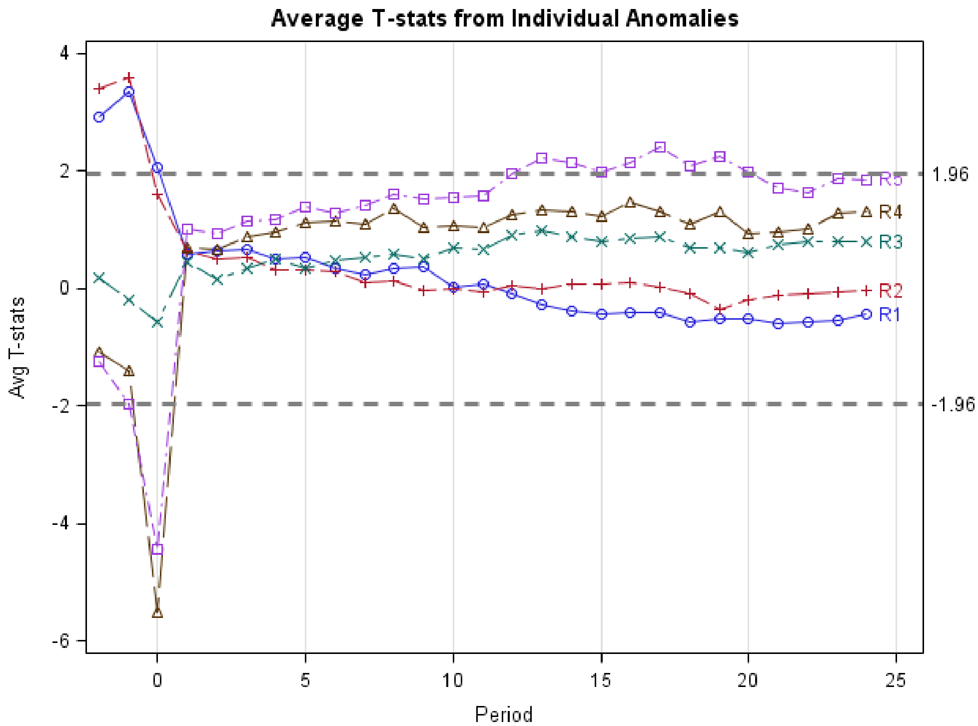


Figure 5 Retail Trading Volume

Figure 5 plots the retail time series monthly average stock level trading volume (in percent). Monthly average retail trading is calculated as the average retail trading of both shares bought and sold scaled by shares outstanding across all companies that are used in anomaly portfolio construction.

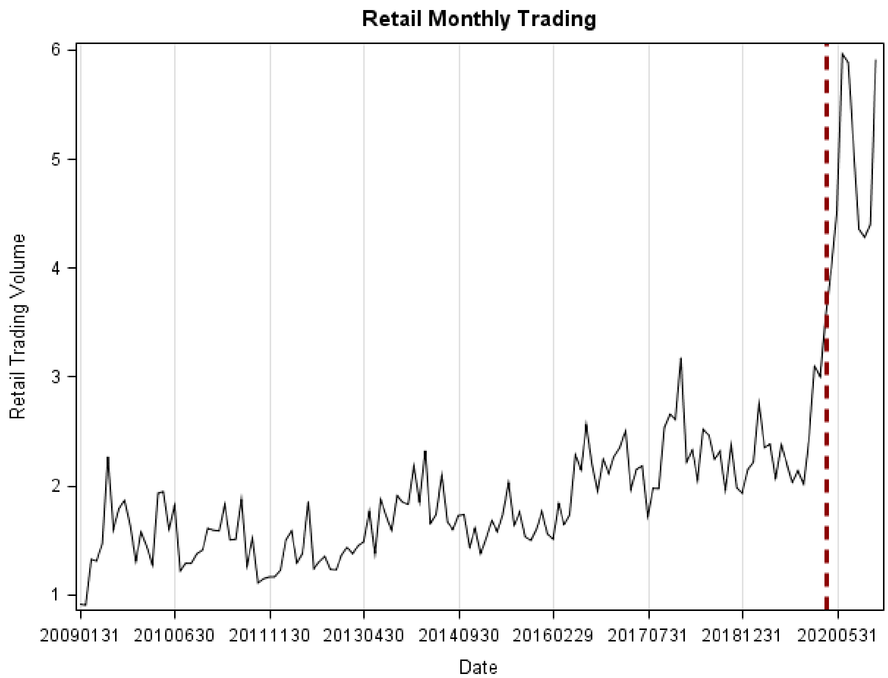


Figure 6 Anomaly Performance Plot

Figure 6 plots the anomaly portfolio alpha difference between treatment and control group anomalies five years before and during the pandemic, extending from one quarter before anomaly formation to several quarters after. The light green bars show the difference before the pandemic and the dark green shaded bars show the difference during the pandemic. The lines indicate 95% confidence interval. Sample period is from 2015 to 2020, defined as anomaly ranking months. Treatment and control group anomalies are defined using pre-pandemic t-stats of ATI a quarter before anomaly formation. The treatment anomalies are those in the lower 40th percentile (104 anomalies). Control group anomalies are those in the 50^{th} to 80^{th} percentile and there are 78 anomalies in the control group. Standard errors are double clustered by date and anomaly.

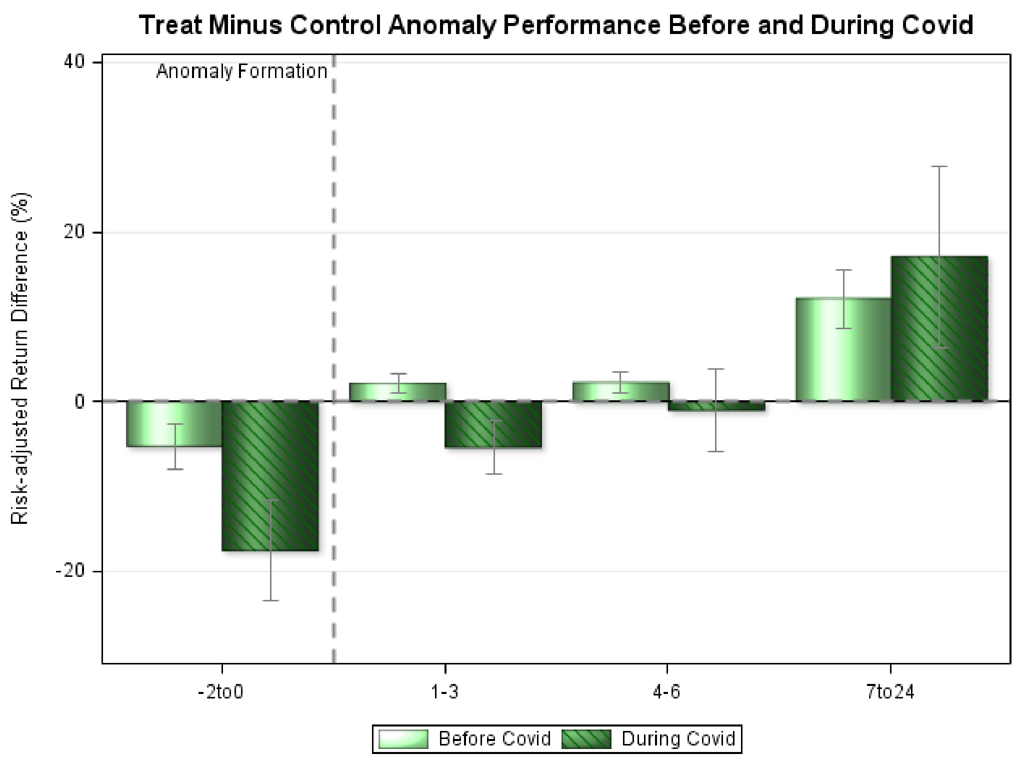


Figure 7 Parallel Trend

Figure 7 plots the estimated coefficient β_t for the interaction terms from the parallel trends analysis using the panel regression. The dependent variables is anomaly portfolio alphas at the formation month α_{t+1} . Independent variables include a series of interaction terms between the treatment indicator (*Treat*) and pseudo-post-event yearly dummies ($Year$) from 2015 to 2020. The year 2015 serves as the reference period and its interaction term is omitted to avoid multicollinearity. The plotted β_t coefficients indicate the change in the difference in α_{t+1} between the treatment and control groups over time compared to that of the base year 2015.

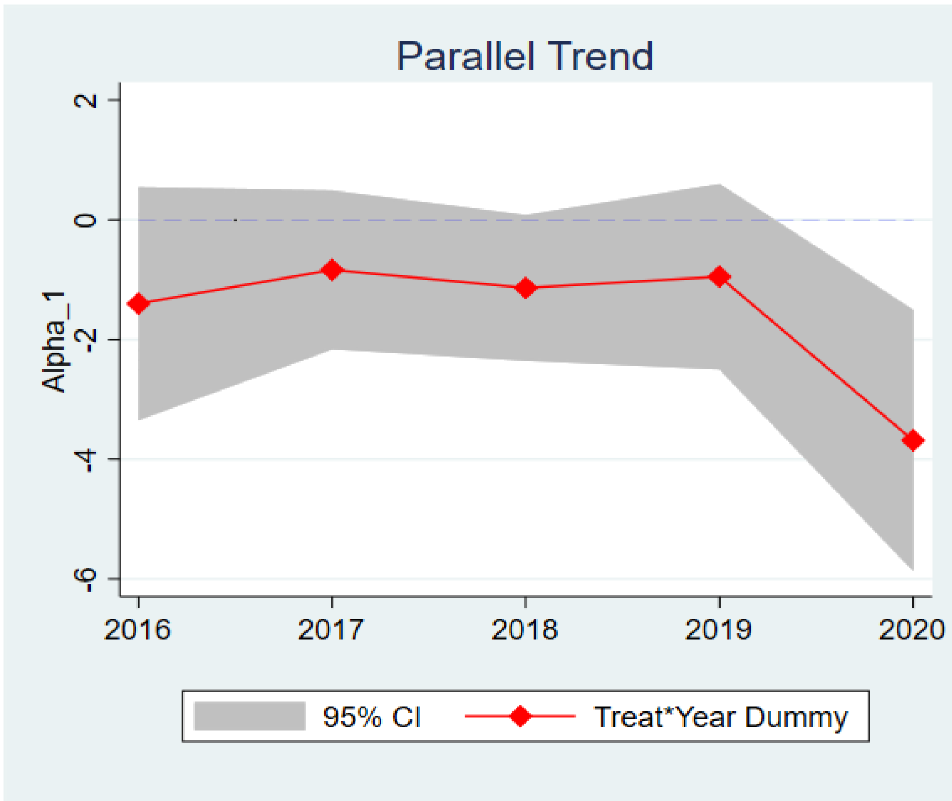


Figure 8 EIP Distribution Schedule

Figure 8 shows the Economic Impact Payment distribution Schedule (Divakaruni and Zimmerman (2021)). The dashed line shows the cumulative number of EIPs and the solid line shows the cumulative amount paid.

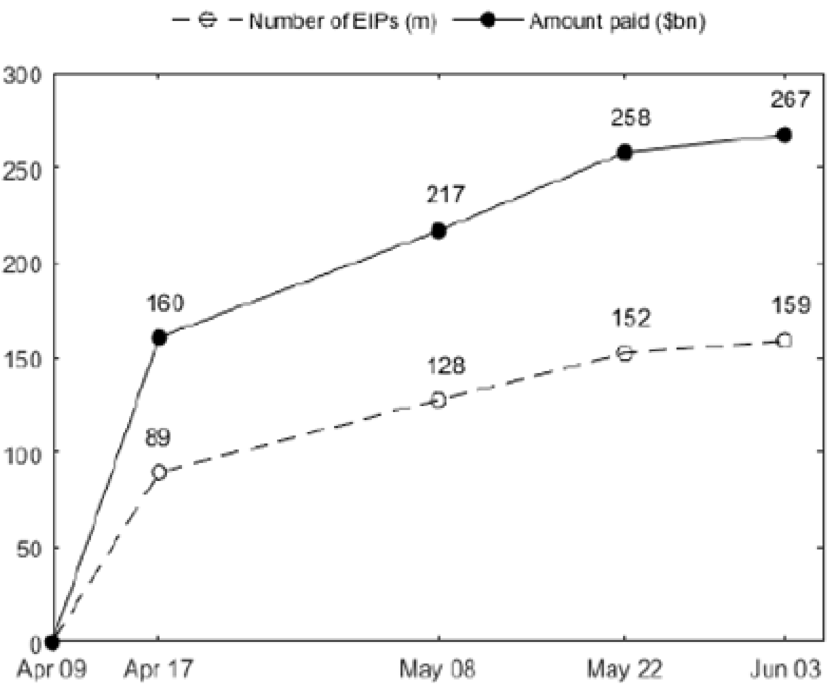


Figure 9 RDD Design

Figure 9 shows daily retail trading volume and the number of trades by dollar amount traded. Retail trading by dollar amount is identified using the algorithm proposed by Boehmer, Jones, Zhang, and Zhang (2021). We calculate retail trading volume as shares bought and sold scaled by shares outstanding across all companies that are used in anomaly portfolio construction.

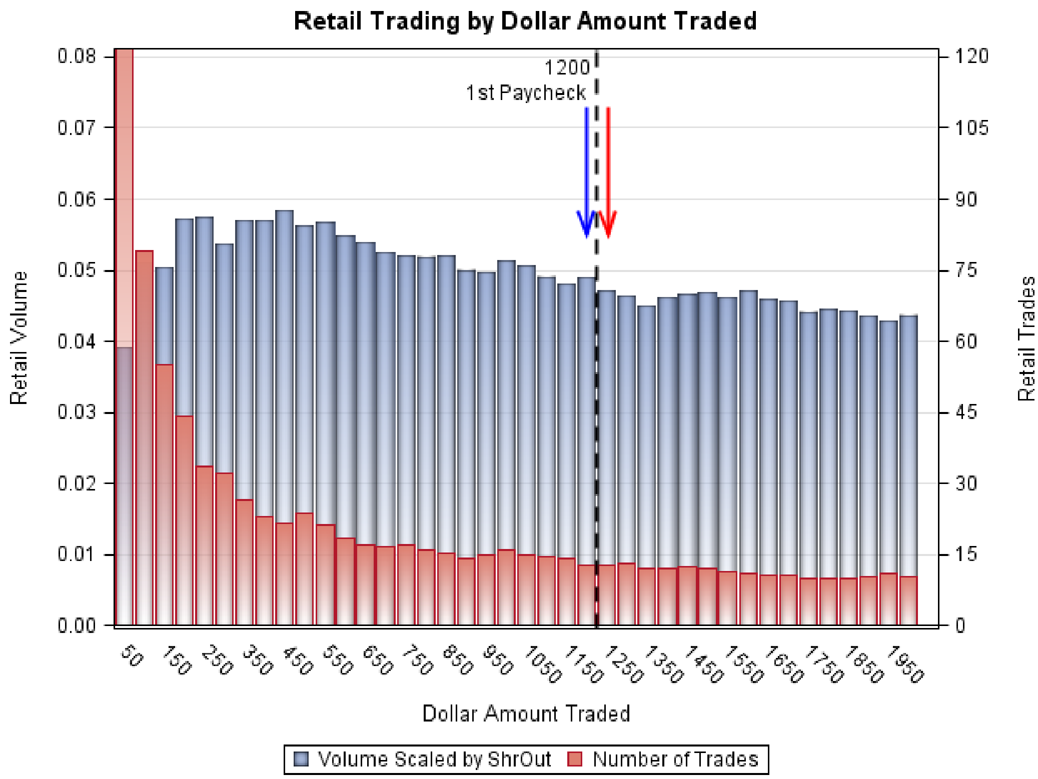


Figure 10 During the Tech Bubble and COVID Anomaly Performance Comparison

Figure 10 contrasts the anomaly performance at formation months across two distinct market events characterized by heightened retail investor trading: the Tech Bubble and the COVID pandemic. The red line represents the treatment group alpha, while the blue line depicts the control group alpha.

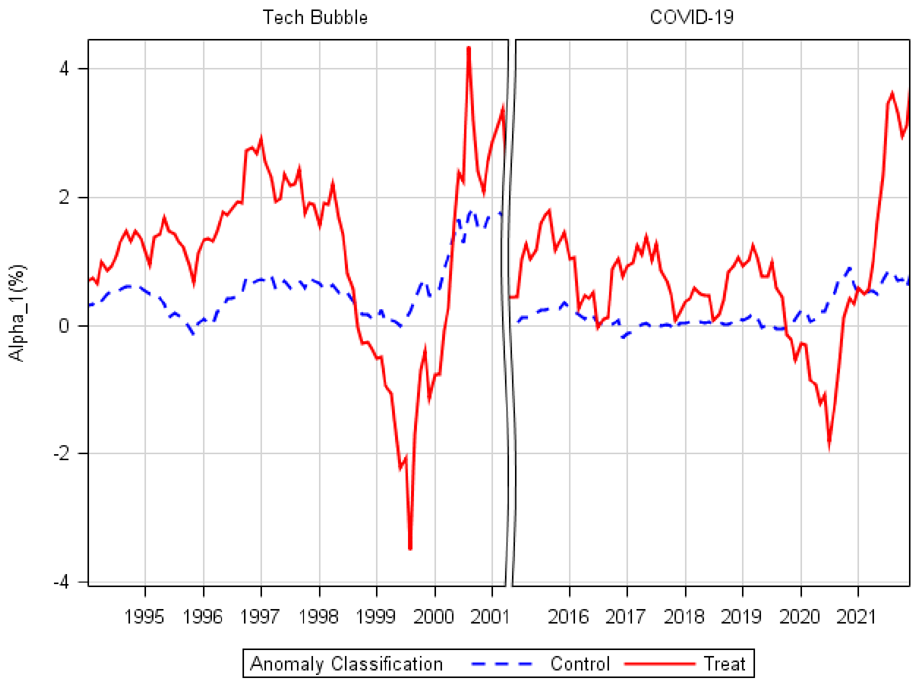


Table 1 Summary Statistics

Panel A shows summary statistics for the 260 anomaly portfolios CAPM-adjusted returns. For each event-time h-period monthly anomaly return $\mathrm{Ret}_{\mathrm{t+h}}$, we regress the raw anomaly portfolio return on the excess market return $Mkt_{\mathrm{t+h}}$ to get the risk loading on the market factor β_{h}. The alpha is calculated as the difference between raw return and its market risk premium $\alpha_{\mathrm{t+h}} = \mathrm{Ret}_{\mathrm{t+h}} - \beta_{\mathrm{h}} \times \mathrm{MktRf}_{\mathrm{t+h}}$. Cumulative monthly risk-adjusted returns are obtained by the following formula: $\alpha_{\mathrm{t+1tot+h}} = \prod_{\mathrm{j=1}}^{\mathrm{h}}(1 + \alpha_{\mathrm{t+j}})$.The return data covers from October 2008 to December 2022, corresponding to ranking months from January 2009 to December 2020. $\alpha_{\mathrm{t-2tot0}}$ is the cumulative CAPM-adjusted anomaly return from period t-2 to t (one quarter before anomaly formation). $\alpha_{\mathrm{t+1}}$ is the formation month anomaly portfolio alpha. $\alpha_{\mathrm{t+1tot+12}}$ is the cumulative anomaly portfolio alphas one year after anomaly formation. Panel B shows stock level monthly trading and holding intensity summary statistics for retail investors and short sellers. We invert the sign of short interest directly from Compustat. A more negative trading intensity is interpreted as high short interest. Panel C shows summary statistics for anomaly trading and holding intensity for retail investors and short sellers one quarter before anomaly formation.

Panel A: Anomaly Portfolio CAPM-adjusted Returns

	N	Mean	Std.Dev.	25th%ile	Median	75th%ile
			Oct 2008 to Feb 2020			
$\alpha_{\mathrm{t-2tot}}$	28,462	0.18	12.11	-4.96	0.09	5.02
$\alpha_{\mathrm{t+1}}$	28,462	0.33	4.19	-1.79	0.30	2.44
$\alpha_{\mathrm{t+1to\ t+6}}$	28,456	1.92	10.52	-3.77	1.38	6.93
$\alpha_{\mathrm{t+1to\ t+12}}$	28,452	4.02	15.09	-4.88	2.71	11.33
$\alpha_{\mathrm{t+1to\ t+24}}$	28,452	8.40	24.56	-6.29	4.97	19.81
			Oct 2008 to Dec 2022			
$\alpha_{\mathrm{t-2tot}}$	37,251	-0.12	15.01	-5.47	-0.09	5.05
$\alpha_{\mathrm{t+1}}$	37,251	0.24	4.49	-1.96	0.24	2.49
$\alpha_{\mathrm{t+1to\ t+6}}$	37,245	1.56	11.50	-4.37	1.20	7.14
$\alpha_{\mathrm{t+1to\ t+12}}$	37,241	3.30	16.36	-6.06	2.25	11.37
$\alpha_{\mathrm{t+1to\ t+24}}$	37,241	7.38	26.53	-8.28	4.12	19.75

Panel B: Stock-Level Monthly Trading and Holding Intensity (in percent)

	N	Mean	Std.Dev.	25^{th}%ile	Median	75^{th}%ile
			Oct 2008 to Feb 2020			
Retail Trading (Detrended)	387,669	0.001	0.411	-0.074	-0.001	0.067
Retail Holding (Detrended)	384,415	0.059	1.057	-0.234	-0.022	0.199
Short Seller Holding (Detrended)	381,944	-0.120	2.328	-0.640	0.015	0.669
			Oct 2008 to Dec 2022			
Retail Trading (Detrended)	500,539	0.003	0.447	-0.070	-0.002	0.062
Retail Holding (Detrended)	496,145	0.098	1.253	-0.210	-0.014	0.191
Short Seller Holding (Detrended)	492,999	-0.141	2.340	-0.662	0.015	0.652

Panel C: Anomaly-Level Monthly Trading and Holding intensity (in percent)

	N	Mean	Std.Dev.	25^{th}%ile	Median	75^{th}%ile
			Oct 2008 to Feb 2018			
Retail ATI_{t-2tot}	28,462	-0.010	0.177	-0.079	-0.004	0.064
Retail AHI_{t-2tot}	28,462	-0.434	1.055	-0.860	-0.302	0.109
Short Seller AHI_{t-2tot}	28,462	0.878	1.750	-0.186	0.733	1.854
			Oct 2008 to Dec 2022			
Retail ATI_{t-2tot}	37,243	-0.026	0.233	-0.094	-0.008	0.065
Retail AHI_{t-2tot}	37,251	-0.516	1.512	-0.980	-0.307	0.167
Short Seller AHI_{t-2tot}	37,251	0.967	1.906	-0.186	0.797	1.985

Table 2 Retail Anomaly Trading Intensity and Anomaly Performance

Panel A of Table 2 shows cross-sectional evidence of retail anomaly trading and anomaly performance (in percent). This analysis uses the return data from October 2008 to February 2020, omitting the COVID period for a dedicated event study. Anomaly portfolios are sorted into 5 groups according to average retail ATI (in percent) a quarter before anomaly formation. Column (1) shows the average percentage of the time that retail investors trade against anomalies within each group. Column (2) shows the average ATI a quarter before anomaly formation. Column (3) to column (8) shows cumulative anomaly portfolio alphas. T-stats are adjusted for serial correlation using Newey-West approach. α_{1to6}, α_{1to12} , and α_{1to24} are adjusted for 6, 12, and 24 lags. *Panel B* shows the panel A result using the Jagadeesh-and-Titman-approach to address the overlapping issue. Monthly returns are compounded to get the holding period return. T-stats in panel B are on monthly alphas a. The alphas of the anomaly portfolios that retail investors trade against are highlighted in bold.

Panel A: Newey West Approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Pre-Formation (%)		**Post-Formation** (%)				
	%Month w/ Neg ATI	Trading	Return	Short-term Return		Long-term Return		
		ATI_{t-2tot}	α_{t-2tot}	α_{t+1}	$\alpha_{t+1tot+6}$	$\alpha_{t+1tot+12}$	$\alpha_{t+1tot+24}$	$\alpha_{t+2tot+24}$
R1 (Pos)	28	0.063***	4.03***	0.07	0.26	0.17	-1.31	-1.38
		(6.59)	*(8.29)*	*(0.66)*	*(0.45)*	*(0.16)*	*(-0.85)*	*(-1.36)*
R2	43	0.025***	3.93***	0.13	0.41	0.55	0.32	0.14
		(5.36)	*(8.29)*	*(1.51)*	*(1.10)*	*(1.00)*	*(0.48)*	*(0.27)*
R3	52	-0.009	0.19	**0.28*** **	**1.46*** **	**3.33*** **	**8.35*** **	**7.95*** **
		(-1.61)	*(0.62)*	*(2.76)*	*(4.21)*	*(5.37)*	*(8.99)*	*(9.99)*
R4	61	-0.030***	-3.54***	**0.43*** **	**2.69*** **	**5.86*** **	**13.23*** **	**12.69*** **
		(-2.90)	*(-6.97)*	*(2.84)*	*(4.47)*	*(7.09)*	*(12.67)*	*(13.57)*
R5 (Neg)	77	-0.096***	-3.68***	**0.83*** **	**4.57*** **	**10.17*** **	**23.49*** **	**22.48*** **
		(-5.43)	*(-3.99)*	*(2.80)*	*(3.88)*	*(5.01)*	*(10.25)*	*(10.95)*

Panel B: Jagadeesh and Titman Approach

	(1)	(2)	(3)	(4)	(5)
	Post-Formation (%)				
	Short-term Return (%)		Long-term Return (%)		
	α_{t+1}	$\alpha_{t+1tot+6}$	$\alpha_{t+1tot+12}$	$\alpha_{t+1tot+24}$	$\alpha_{t+2tot+24}$
R1 (Pos)	0.00	-0.17	-0.93	-2.25	-2.25
	(0.01)	*(-0.31)*	*(-0.87)*	*(-1.23)*	*(-1.28)*
R2	0.11	0.38	0.76	1.03	0.92
	(1.45)	*(1.11)*	*(1.34)*	*(1.03)*	*(0.98)*
R3	**0.43*** **	**2.37*** **	**4.89*** **	**10.45*** **	**9.98*** **
	(3.31)	***(3.17)***	***(3.32)***	***(3.57)***	***(3.57)***
R4	**0.59*** **	**3.63*** **	**7.31*** **	**14.95*** **	**14.28*** **
	(2.84)	***(2.97)***	***(3.05)***	***(3.16)***	***(3.17)***
R5 (Neg)	**1.06*** **	**5.31*** **	**10.69*** **	**23.05*** **	**21.76*** **
	(4.04)	***(3.48)***	**(3.50)**	**(3.80)**	***(3.78)***

Table 3 Retail Anomaly Trading Intensity Groups

Table 3 groups retail anomaly portfolio trading intensity a quarter before anomaly formation according to group classification by Hou, Xue, and Zhang. (2020), Daniel, Hirshleifer, and Sun (2020), Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), Kumar (2009), and Birru (2018) and report average retail ATI within a group (in percent). Column (1) lists related literature. Column (2) lists anomaly group names in the corresponding literature. Column (3) shows the retail ATI a quarter before anomaly formation within the group and column (4) shows t-stats calculated from time series grouped retail ATI. Column (5) shows the average percentage of the time that retail investors trade against each group classification.

(1) Literature	(2) Group Name	(3) ATI_{t-2tot}	(4) T-Stats	(5) %Month w/ Neg ATI
HXZ(2020)	Intangible	0.007***	(4.80)	36
	Investment	0.023***	(6.29)	24
	Momentum	0.020**	(2.32)	51
	Profitability	-0.049***	(-6.78)	76
	TradingFriction	-0.056***	(-8.69)	77
	VvsG	-0.025***	(-3.27)	65
DHS(2020)	Long-Horizon	-0.017	(-1.37)	47
	Short-Horizon	0.016**	(2.19)	46
AASS(2015)	Investment	0.058***	(7.28)	27
	Non-Investment	-0.035***	(-4.99)	70
Kumar (2009)	Lottery	-0.083***	(-8.94)	78
	Non-Lottery	-0.013***	(-4.25)	60
Birru(2018)	Long Leg	0.007**	(2.01)	46
	Short Leg	-0.080***	(-8.36)	78

Table 4 Retail-Related Factor Models to Explain Long-horizon Anomaly Performance

Table 4 Panel A reports alphas from the regression of FIN factor (Daniel et al. 2020), the retail factor formed from the group of anomalies that retail investor trade the mostly negative, denoted R5F, and the retail factor directly related to trading, denoted TF, on other set of factor models: capital asset pricing model, denoted CAPM; the three- and five-factor model of Fama and French (1993) and Fama and French (2015), denoted FF3 and FF5; the four-factor model of Carhart (1997); the behavioral model introduced by Daniel, Hershleifer, and Sun (2020); and the two retail-related models introduced in this study. Panel B shows the average absolute alphas, average t-statistics, and number of anomalies with significant alphas (t-statistics >= 1.96) from the time-series regression of R4 and R5 group anomaly Jagadeesh-Titman type 24-month monthly portfolio returns on different factor models. The 24-month monthly return sample covers from 2011 to 2022. Standard errors are adjusted for serial correlation with Newey-West method of 6 lags.

Panel A Spanning test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	CAPM	FF3	Carhart4	FF5	DHS	MKT + R5F	MKT + TF
FIN	0.43	0.36**	0.38**	0.12		-0.19	-0.19
	(1.38)	(2.41)	(2.46)	(1.15)		(-1.05)	(-0.80)
R5F	1.14***	0.90***	0.82***	0.63***	0.50**		0.24
	(2.84)	(3.24)	(2.89)	(3.50)	(2.27)		(0.86)
TF	-0.61***	-0.54***	-0.57***	-0.46***	-0.50***	-0.35***	
	(-4.08)	(-4.90)	(-4.60)	(-5.69)	(-6.69)	(-3.51)	

Panel B Model Performance Comparison

(1)	(2)	(3)	(4)
Model	Average Alpha	Average T-stats	# Anomalies with α**
CAPM	0.74%	1.87	47
FF3	0.53%	1.82	41
Carhart4	0.46%	1.58	32
FF5	0.38%	1.64	37
DHS	0.38%	1.16	16
MKT + R5F	0.21%	0.75	6
MKT + TF	0.23%	0.78	6
DHS + R5F	0.18%	0.69	6
DHS + TF	0.19%	0.66	6

Table 5 Retail Trading Persistence

Table 5 shows the results of retail ATI magnitude and persistence correlation. Using an event window of 24 months after anomaly ranking month, anomaly retail holding persistence measure is calculated by regressing current event time AHI on lagged event time AHI and taking the AR(1) coefficient. Retail ATI is standardized between 0 and 1 using the cross-sectional retail ATI at each month. The sample period is from 2009 to 2020, defined as anomaly ranking months. Standard errors are clustered by anomaly and date.

	(1) Holding Persistence (Against)	(2) Holding Persistence (With)
$\mathrm{ATI}_{\mathrm{t-2tot}}$ (%)	-0.01***	0.00
	(-3.78)	(1.18)
Date FE	YES	YES
Observations	22,556	14,544
Adjusted R-squared	0.095	0.050

Table 6 Risk Management Measures

Table 6 shows average standard deviation and 1% Value-at-Risk for anomaly portfolios within each R1 to R5 group. Retail investors trade with R1 and R2 group of anomalies, and trade against R3 to R5 group of anomalies. For an anomaly portfolio, 1% VaR is calculated as the difference between the times-series mean of alphas and the product of 1% z-score (2.33) and standard deviation of anomaly portfolio alphas, that is, $1\%VaR = \overline{\alpha} - 2.33 \times \sigma_{\alpha}$. Similarly, $0.1\%VaR = \overline{\alpha} - 3.09 \times \sigma_{\alpha}$.

	(1)	(2)	(3)	(4)	(5)
			Std	1%VaR(%)	0.1%VaR(%)
Short-term	R1 (Pos)	α_{t+1}	4.28	-9.85	-12.73
	R2	α_{t+1}	4.01	-9.1	-11.98
	R3	α_{t+1}	4.33	-9.79	-12.90
	R4	α_{t+1}	4.62	-10.33	-13.64
	R5 (Neg)	α_{t+1}	5.46	-11.89	-15.76
Long-term	R1 (Pos)	$\alpha_{t+2tot+24}$	18.99	-44.1	-58.53
	R2	$\alpha_{t+2tot+24}$	18.36	-42.14	-56.10
	R3	$\alpha_{t+2tot+24}$	21.64	-43.65	-60.10
	R4	$\alpha_{t+2tot+24}$	21.31	-38.39	-54.59
	R5 (Neg)	$\alpha_{t+2tot+24}$	26.11	-42.02	-61.86

Table 7 Retail Trading Before and During the Pandemic

Table 7 shows retail trading volume and ATI results using the sample period from 2015 to 2020, defined as anomaly ranking months. Panel A shows the regression result of retail trading volume (in percent) at the stock level to a *Post* dummy, where the post dummy is equal to 1 if the sample is from March 2020 to December 2020, and is equal to 0 if otherwise. Panel B reports regression results of retail ATI (in percent) on *Treat* and *Treat*×*Post* interaction term. Standard errors are clustered by date and anomaly.

Panel A: Retail Trading Volume

	(1)
	Retail Volume (%)
Post	2.49***
	(9.16)
Constant	2.13***
	(46.42)
Firm FE	YES
Observations	250,113
Adjusted R-squared	0.342

Panel B: Retail ATI

	(1)	(2)	(3)	(4)
	Pre-Formation		Post-Formation	
	ATI_{t-2tot}	ATI_{t}	ATI_{t+1}	$\mathrm{ATI}_{t+1tot+3}$
Post x Treat	-0.37***	-0.13***	-0.07***	-0.16***
	(-3.57)	(-3.54)	(-2.82)	(-2.86)
Treat	-0.12***	-0.05***	-0.00	0.02
	(-6.73)	(-6.20)	(-0.67)	(1.03)
Post	0.01	-0.00	-0.00	-0.02
	(0.17)	(-0.12)	(-0.16)	(-0.48)
Anomaly FE	NO	NO	NO	NO
Observations	12,717	13,079	12,898	12,717
Adjusted R-squared	0.153	0.130	0.025	0.027

Table 8 Diff-in-Diff Results for Anomalies Portfolio Returns

Table 8 shows diff-in-diff regression results of anomaly portfolio alphas (in percent) a quarter before and after formation on the treat dummy and Treat×Post interaction term. Standard errors are clustered by date and anomaly.

	(1)	(2)	(3)	(4)
	Pre-Formation		Post-Formation	
	α_{t-2ot}	α_t	α_{t+1}	$\alpha_{t+1ot+3}$
Treat x Post	-12.29***	-4.40***	-2.79**	-7.54***
	(-5.49)	(-3.34)	(-2.39)	(-4.53)
Treat	-5.27***	-3.53***	0.63**	2.14***
	(-3.89)	(-4.19)	(2.07)	(4.02)
Date FE	YES	YES	YES	YES
Observations	12,717	13,079	12,898	12,536
Adjusted R-squared	0.109	0.078	0.114	0.122

Table 9 Retail Anomaly Trading During the 1st Stimulus Check

Table 9 panel A show DID results for treatment and control group anomaly portfolios separately using the 1st stimulus check payment schedule. The sample period is Jan 2, 2020, to Jun 12, 2020. The post-disbursement period is from April 9 to June 12. The daily abnormal retail ATI are formed by dollar amount traded, [1150,1200) and (1200, 1250]. $\mathrm{I}(< 1200)$ is an indicator and takes on the value of 1 if the retail order falls within the lower cost range [1150,1200), and 0 otherwise. Panel B shows triple difference results by adding an announcement and crash dummy. Panel C shows monthly DID test result using monthly alpha. The post period is defined for April, May, and June of 2020 (post = 1), compared to the monthly pre-stimulus period from 2015 to February 2020 (post = 0). Congress passed the CARES Act on Mar 27, 2020. Ann is a dummy that takes the value of 1 for ATI during the first stimulus check announcement week, specifically from -9 to -6 days relative to the event day. The S&P 500 index dropped by 29% from March 2 to March 16, 2020. We define *Crash=1* if trading intensity falls into the event day of -26 to -13. Standard errors are clustered by date and anomaly.

Panel A: Diff-in-Diff

	(1)	(2)	(3)	(4)
	Treat		Control	
	$BuyATI_t$	$SellATI_t$	$BuyATI_t$	$SellATI_t$
I (<$1200) x Post	**-0.009*** **	**-0.001**	0.001	0.001
	(-2.76)	(-0.32)	(0.95)	(0.42)
I (<$1200)	0.001	-0.001	0.000	0.000
	(0.73)	(-0.27)	(-0.60)	(-0.67)
Date FE	YES	YES	YES	YES
Observations	22,826	22,826	17,402	17,402
Adjusted R-squared	0.24	0.239	0.006	0.005

Panel B: Triple Difference

	(1)	(2)	(3)	(4)	(5)	(6)
		$BuyATI_t$			$SellATI_t$	
Treat	-0.057***	-0.057***	-0.059***	-0.056***	-0.056***	-0.057***
	(-9.54)	(-9.70)	(-10.32)	(-9.54)	(-9.64)	(-9.96)
I (<$1200)	-0.000	-0.000	-0.000	-0.000	-0.001	-0.000
	(-0.61)	(-0.82)	(-0.43)	(-0.67)	(-1.06)	(-0.39)
Treat x Post	-0.074***	-0.074***	-0.072***	-0.076***	-0.076***	-0.075***
	(-9.00)	(-8.90)	(-8.60)	(-8.87)	(-8.79)	(-8.54)
Treat x I (<$1200)	**0.002**	**0.002**	**0.003**	**-0.000**	**0.000**	**0.000**
	(0.90)	(1.09)	(1.58)	(-0.07)	(0.16)	(0.10)
I (<$1200) x Post	0.001	0.001	0.001	0.001	0.001	0.000
	(0.96)	(1.02)	(0.80)	(0.42)	(0.60)	(0.31)
Treat x Ann		0.000			-0.001	
		(0.01)			(-0.19)	
I (<$1200) x Ann		0.002			0.004*	
		(0.71)			(1.78)	
Treat x I (<$1200) x Post	**-0.010*** **	**-0.010*** **	**-0.011*** **	**-0.002**	**-0.002**	**-0.002**
	(-2.75)	(-2.82)	(-3.09)	(-0.45)	(-0.57)	(-0.52)
Treat x I (<$1200) x Ann		-0.008*			-0.008	
		(-1.90)			(-1.15)	
Treat x Crash			0.009			0.005
			(1.09)			(0.76)
Doldum x Crash			-0.000			-0.000
			(-0.32)			(-0.27)
Treat x Doldum x Crash			-0.007			-0.002
			(-1.22)			(-0.36)
			-0.059***			-0.057***
Date FE	YES	YES	YES	YES	YES	YES
Observations	40,228	40,228	40,228	40,228	40,228	40,228
Adjusted R-squared	0.342	0.342	0.343	0.345	0.345	0.345

Panel C: Monthly DID Test

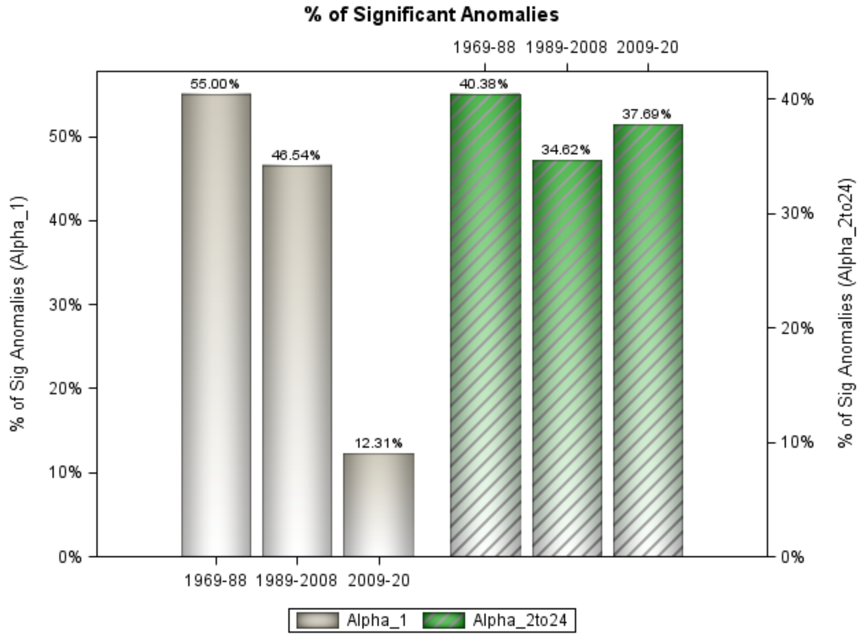
	α_t
Treat x Post	-6.72***
	(-4.79)
Treat	-3.53***
	(-4.19)
Date FE	YES
Observations	11,814
Adjusted R-squared	0.072

Internet Appendix

Figure IA1 Short and Long-term Anomaly Portfolios–The Full Sample

Figure 1 panel A and panel B show the percentage of significant anomaly portfolios and return magnitude using CAPM-alpha over the past half-century, with the recent years including COVID periods.

Panel A: Short and Long-term Percentage of Significant Anomalies



Panel B: Short and Long-term Anomaly Performance

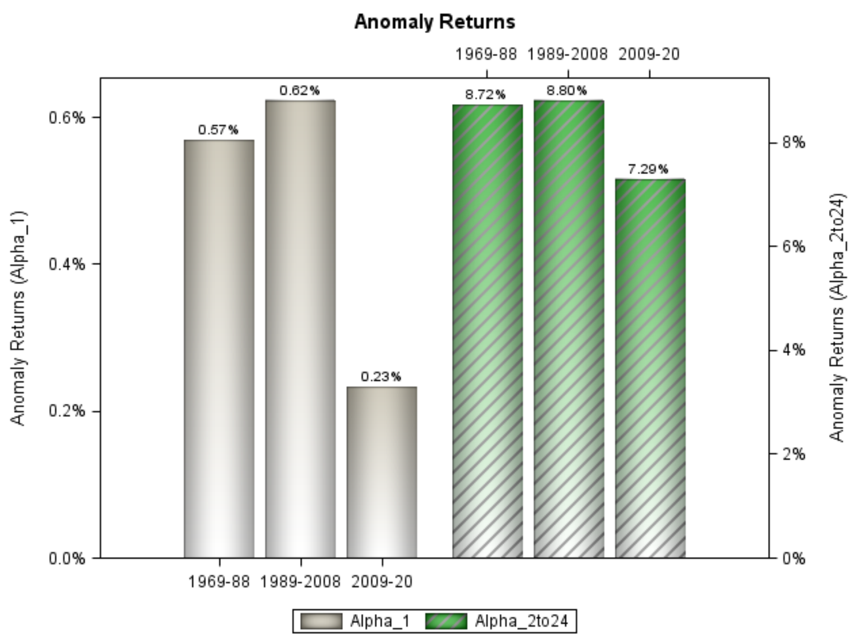
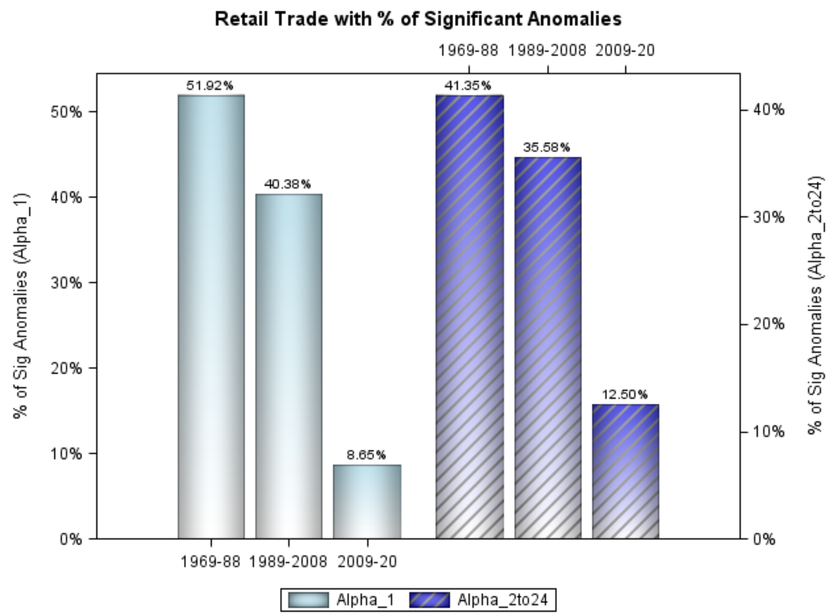


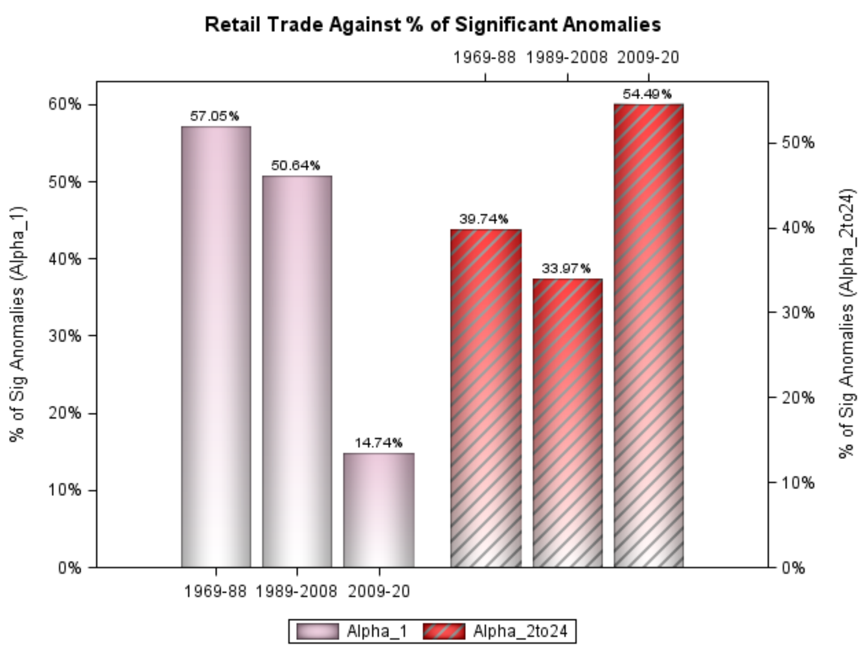
Figure IA2 Short and Long-term Anomaly Portfolio by Retail Trading Direction–The Full Sample

Figure 2 divides anomalies into retail investors trade with versus trade against and examines short and long-term anomaly portfolio alphas. Panel A1 and A2 show the percentage of significant anomaly portfolios. Panel B1 and B2 show the alpha magnitude.

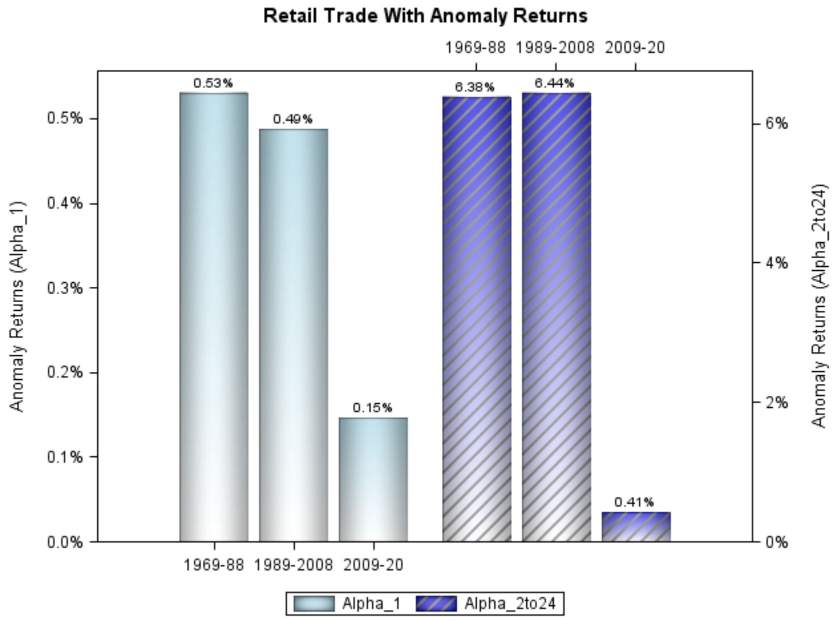
Panel A1: Retail Trade with Percentage of Significant Anomalies



Panel A2: Retail Trade Against Percentage of Significant Anomalies



Panel B1: Retail Trade with Anomaly Alphas



Panel B2: Retail Trade Against Anomaly Alphas

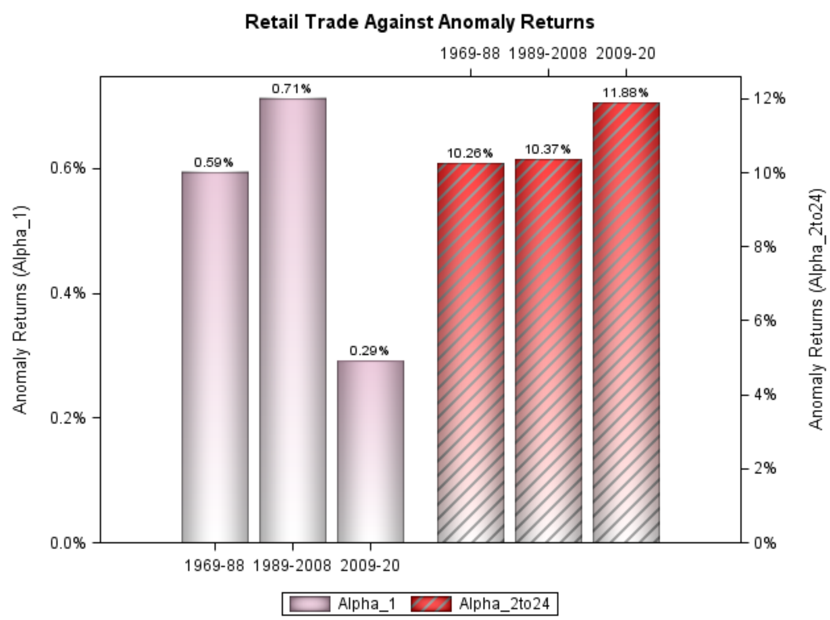


Figure IA3 Retail Before Ranking ATI Time-Series

Figure IA3 plots retail ATI_{t-2tot} from R1(retail investors trade the most positively) to R5(retail investors trade the most negatively) over time.

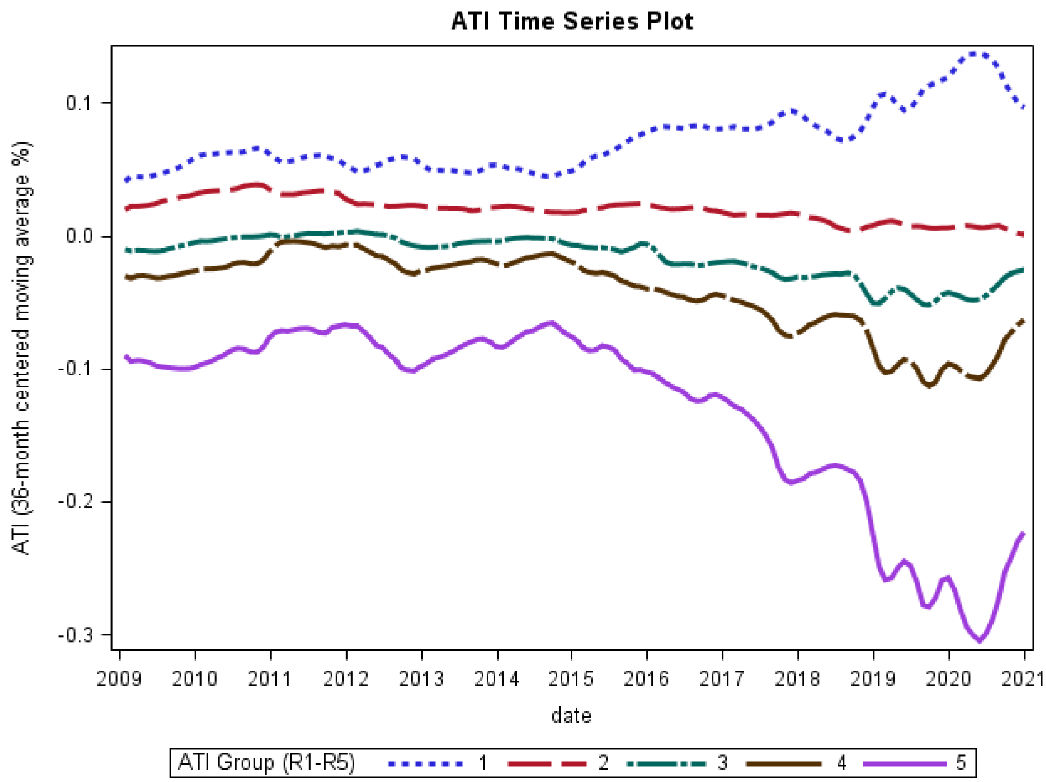


Table IA1 Retail Anomaly Trading Intensity and Anomaly Performance–The Full Sample

Table IA1 shows cross-sectional evidence of retail anomaly trading and anomaly performance. This analysis uses the return data from October 2008 to December 2022. Anomaly portfolios are sorted into 5 groups according to average retail ATI (in percent) a quarter before anomaly formation. Column (1) to column (6) shows cumulative anomaly portfolio alphas. T-stats are adjusted for serial correlation using Newey-West. α_{1to6}, α_{1to12} , and α_{1to24} are adjusted for 6, 12, and 24 lags. The alphas of the anomaly portfolios that retail investors trade against are highlighted in bold.

	Pre-Formation	Post-Formation				
	(1)	(2)	(3)	(4)	(5)	(6)
	Return (%)	Short-term Return (%)		Long-term Return (%)		
	$\alpha_{\mathrm{t-2tot}}$	α_{t+1}	$\alpha_{t+1tot+6}$	$\alpha_{t+1tot+12}$	$\alpha_{t+1tot+24}$	$\alpha_{t+2tot+24}$
R1 (Pos)	5.04***	0.15	0.89	1.09	-0.44	-0.58
	(8.38)	*(1.47)*	*(1.53)*	*(1.06)*	*(-0.25)*	*(-0.53)*
R2	4.21***	0.20***	0.77**	0.86*	0.86	0.65
	(21.12)	*(2.59)*	*(2.50)*	*(1.66)*	*(1.26)*	*(1.21)*
R3	**-0.19**	**0.14**	**0.84****	**2.31*****	**6.62*****	**6.42*****
	(-0.65)	*(1.49)*	*(1.97)*	*(2.81)*	*(5.92)*	*(6.00)*
R4	**-4.25*****	**0.24***	**2.02*****	**4.70*****	**11.17*****	**10.94*****
	(-8.22)	*(1.49)*	*(2.91)*	*(4.19)*	*(7.78)*	*(9.00)*
R5 (Neg)	**-5.35*****	**0.48***	**3.23*****	**7.46*****	**18.56*****	**18.14*****
	(-5.39)	*(1.72)*	*(2.65)*	*(3.28)*	*(6.13)*	*(7.22)*

Table IA2 Retail Anomaly Trading Intensity and Anomaly Performance–Drop High Fee Stocks

Table IA2 shows cross-sectional evidence of retail anomaly trading and anomaly performance by excluding high fee stocks. Following Muravyev, Pearson, and Pollet (2023), we use the 'Indicative Fee' from the Makit short-selling dataset for short-selling costs and filter out stocks whose fee exceeds 1% per annum as of the end of the previous month. Anomaly portfolios are sorted into 5 groups according to average retail anomaly trading intensity (ATI) in percent a quarter before anomaly formation. Column (1) to column (6) shows cumulative anomaly portfolio alphas. T-stats are adjusted for serial correlation using Newey-West. α_{1to6}, α_{1to12} , and α_{1to24} are adjusted for 6, 12, and 24 lags. The alphas of the anomaly portfolios that retail investors trade against are highlighted in bold.

	Pre-Formation	Post-Formation				
	(1)	(2)	(3)	(4)	(5)	(6)
	Return (%)	Short-term Return (%)		Long-term Return (%)		
	α_{t-2tot}	α_{t+1}	$\alpha_{t+1tot+6}$	$\alpha_{t+1tot+12}$	$\alpha_{t+1tot+24}$	$\alpha_{t+2tot+24}$
R1 (Pos)	3.41***	0.14	0.55	0.65	-0.43	-0.58
	(7.90)	*(1.46)*	*(0.98)*	*(0.62)*	*(-0.28)*	*(-0.39)*
R2	3.82***	0.11	0.42	0.58	0.18	0.02
	(21.57)	*(1.22)*	*(1.13)*	*(1.07)*	*(0.28)*	*(0.03)*
R3	**0.19**	**0.22****	**1.17*****	**2.70*****	**6.84*****	**6.56*****
	(0.65)	*(2.47)*	*(3.25)*	*(4.46)*	*(9.46)*	*(9.11)*
R4	**-3.38*****	**0.30****	**2.09*****	**4.71*****	**10.81*****	**10.43*****
	(-7.09)	*(2.08)*	*(3.59)*	*(6.17)*	*(13.08)*	*(12.61)*
R5 (Neg)	**-3.56*****	**0.53***	**2.90****	**7.17*****	**17.29*****	**16.72*****
	(-4.17)	*(1.87)*	*(2.55)*	*(3.81)*	*(7.86)*	*(7.63)*

Table IA3 DID Retail Anomaly Trading by Long and Short Leg

Table IA3 shows retail anomaly trading results using the diff-in-diff sample period from January 2015. The table reports regression results of retail anomaly long-short ATI_{t-2tot} (in %), together with short and long leg ATI_{t-2tot} on *Treat* and *Treat×Post* interaction term, where the post dummy is equal to 1 if in the pandemic, from March 2020 and onwards, and is equal to 0 if otherwise. Standard errors are clustered by date and anomaly.

	(1)	(2)	(3)
	Long-Short Leg	Short Leg	Long Leg
	ATI_{t-2tot}	ATI_{t-2tot}	ATI_{t-2tot}
Treat x Post	-0.37***	0.29***	-0.09***
	(-3.57)	(3.46)	(-3.57)
Treat	-0.12***	0.09***	-0.03***
	(-6.73)	(6.29)	(-6.27)
Post	0.01	0.12*	0.12**
	(0.17)	(1.82)	(2.35)
constant	0.01*	0.02**	0.02***
	(1.68)	(2.16)	(3.17)
Anomaly FE	NO	NO	NO
Adj R-squared	0.153	0.153	0.089
Observations	12,717	12,717	12,718

Table IA4 DID Anomaly Performance by Long and Short Leg

Panel A: Anomaly Performance

	(1) Long-Short α_{t+1}	(2) Short-Leg α_{t+1}	(3) Long-Leg α_{t+1}
Treat x Post	-2.79**	2.00**	-0.79**
	(-2.39)	(2.15)	(-2.44)
Treat	0.63**	-0.45*	0.18**
	(2.07)	(-1.83)	(2.25)
Date FE	YES	YES	YES
Observations	12,898	12,898	12,899
Adjusted R-squared	0.114	0.212	0.028

Panel B: Parallel Trend

	(1) Long-Short α_{t+1}	(2) Short-Leg α_{t+1}	(3) Long-Leg α_{t+1}
Treat x Post(2016)	-1.40	1.26	-0.14
	(-1.20)	(1.36)	(-0.51)
Treat x Post(2017)	-0.84	1.02	0.19
	(-1.05)	(1.62)	(0.82)
Treat x Post(2018)	-1.14	0.97	-0.16
	(-1.56)	(1.53)	(-1.23)
Treat x Post(2019)	-0.95	1.03	0.08
	(-1.02)	(1.33)	(0.42)
Treat x Post(2020)	**-3.68*** **	**2.86*** **	**-0.82** **
	(-2.82)	(2.72)	(-2.31)
Date FE	YES	YES	YES
Anomaly FE	YES	YES	YES
Observations	12,534	12,534	12,535
Adjusted R-squared	0.120	0.216	0.039

Panel C Anomalies that Retail Investors Trade More Against

	(4)	(5)	(6)
	<50%	<40%	<30%
	α_{t+1}	α_{t+1}	α_{t+1}
Treat x Post	**-2.60****	**-2.79****	**-3.11****
	(-2.45)	(-2.39)	(-2.32)
Treat	0.57**	0.63**	0.72**
	(2.12)	(2.07)	(2.13)
Date FE	YES	YES	YES
Observations	14,743	12,898	11,073
Adjusted R-squared	0.114	0.114	0.111

Table IA5 RD Retail Anomaly Trading Intensity within Treatment Group by Long and Short Leg

	(1)	(2)	(3)	(4)	(5)	(6)
	$BuyATI_t$			$SellATI_t$		
	Long-Short	Short-Leg	Long-Leg	Long-Short	Short-Leg	Long-Leg
I (<$1200) x Post	-0.009***	0.010***	0.002**	-0.001	0.001	-0.000
	(-2.76)	(2.89)	(2.29)	(-0.32)	(0.21)	(-0.38)
I (<$1200)	0.001	-0.002	-0.001	-0.001	-0.000	-0.001*
	(0.73)	(-0.90)	(-1.16)	(-0.27)	(-0.13)	(-1.91)
Date FE	YES	YES	YES	YES	YES	YES
Observations	22,826	22,826	22,826	22,826	22,826	22,826
AdjustedR-squared	0.240	0.411	0.179	0.239	0.407	0.178