Retail Trading Frenzies and Real Investment

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June 2025

Abstract

Using episodes of intense, persistent trade order imbalances to identify retail buying frenzies, we find that frenzies are associated with large contemporaneous stock price increases followed by prolonged anomaly-adjusted underperformance, consistent with price-pressure-based overvaluation. Retail frenzies strongly predict equity issuance and increased investment, with the relation strengthening in the post-zero-commission era. The increased investment is associated with incrementally lower future returns and more negative earnings surprises, and it is concentrated among financially constrained firms led by lower-ability managers. Overall, our findings suggest that retail frenzies adversely impact the real economy by relaxing financial constraints, leading to overinvestment by less-skilled managers.

JEL: G14, G31

Keywords: Retail Trading, Trading Frenzies, Corporate Investment, Real Efficiency

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1. Introduction

Individual investors have assumed a more pivotal role in equity markets in recent years. Commission-free trading and the rise of finance-oriented social media platforms have increased correlated retail trading, often causing large price movements unrelated to fundamentals (e.g., Barber et al., 2022). However, herding among the retail crowd is not new. Research suggests that speculative retail trading has moved markets for decades (e.g., Han and Kumar, 2013; Dorn, Huberman, and Sengmueller, 2008; Barber, Odean, and Zhu, 2008). The significant impact of retail herding on equity markets raises the question of whether retail investors affect corporate strategies. In this article, we introduce an orderflow-based measure of retail buying frenzies and explore the relation between retail buying frenzies and corporate decision-making.

In a frictionless, symmetric information setting, equity markets passively predict future activity (Morck, Shleifer, and Vishny, 1990). However, when stock prices reflect private investor information unknown to capital providers or firm management, markets can influence corporate outcomes. Goldstein, Ozdenoren, and Yuan (2013) model an environment where capital providers learn from prices about investment profitability, which can create an efficient feedback loop between financial markets and real investment (e.g., Luo, 2005; Chen, Goldstein, and Jiang, 2007; Bakke and Whited, 2010; Edmans, Jayaraman, and Schneemeier, 2017; Bennett, Stulz, and Wang, 2020). However, this same mechanism also makes firms susceptible to speculative trading and distorted signals, potentially leading to misallocated capital and suboptimal investment decisions (e.g., Polk and Sapienza, 2009; Hau and Lai, 2013; Lou and Wang, 2018; Dessaint et al., 2019).

Our premise is that retail frenzies reflect speculative trading that creates price pressure unrelated to fundamentals. Barber et al. (2022) find supportive evidence at short horizons, showing that extreme herding events, measured as 99.5 percentile increases in Robinhood ownership, are associated with contemporaneous daily abnormal returns of 14% that revert by roughly a third over the next month. We hypothesize that intense, persistent episodes of retail buying may result in larger price effects that attract attention from firm management.

Our conjecture is exemplified by the frenzy episode of AMC Entertainment Holdings. AMC was severely impacted by the COVID-19 pandemic, leading to significant financial strain and stock price declines. In early 2021, AMC became a popular stock on social media, resulting in a retail-driven buying frenzy that pushed the stock price from $10 per share in January to over $250 by June. Taking advantage of the soaring stock price, AMC issued new equity, increased capital expenditures, and announced the purchase of a significant stake in a gold and silver mining firm. While some investors praised the move to mitigate core business risks, AMC's performance subsequently declined, and its price at the end of 2023 was below $10. While this anecdote highlights that retail investors can impact stock prices and corporate strategies, it is unclear whether this phenomenon extends beyond a few prominent examples discussed in the media.[1]

To systematically analyze the relation between retail trading frenzies and firm outcomes, we construct a measure of retail net trading demand using the algorithm proposed by Barber et al. (2024). Our main approach classifies a stock as experiencing a retail frenzy when its net retail order imbalance over a three-month period exceeds 2% of shares outstanding.[2]

We begin by exploring which firms are likely to experience retail frenzies. Consistent with the price-feedback model proposed by Goldstein, Ozdenoren, and Yuan (2013), we find that frenzies are more likely to occur in stocks where the potential for trader coordination is higher, such as stocks with higher social media coverage. Frenzies are also more common for small stocks, volatile stocks, unprofitable stocks, and those with high short interest, where the impact of

[1] Other examples of retail frenzies influencing corporate decisions include Bed Bath & Beyond, Hertz, and GameStop.
[2] Retail selling frenzies are rare. Our analysis focuses on retail buying frenzies, which we refer to as "retail frenzies."

coordinated trading on prices is likely to be larger. Finally, frenzies are more prevalent when the benefits of changes in stock prices are likely to have a larger impact on firms, specifically financially constrained firms.

We provide strong evidence that retail frenzies distort prices. Abnormal returns are roughly 27% during frenzy quarters, followed by a near-complete reversion in the next 24 months. In contrast, we find no reversals after frenzies measured using aggregate (non-retail) order imbalances, suggesting that retail buying decisions are more influenced by behavioral biases such as attention-based trading than by institutions (e.g., Barber and Odean, 2008).

Frenzy-induced mispricing can impact equity issuance if managers misinterpret market prices or attempt to time the market.[3] Empirically, we find a significant relation between retail frenzies and equity issuance, with frenzy stocks being 69% more likely to issue equity. While issuing firms may accumulate cash or reduce debt, frenzies may also have real effects on corporate investment. We find supportive evidence, with capital expenditures increasing by 1.3% of fixed assets following retail frenzies, reflecting a roughly 20% increase relative to the mean. Additionally, frenzy firms experience significant increases in acquisition expenses. The evidence of increased issuance and investment is robust to alternative frenzy definitions, various matching techniques, and exclusions of unusual time periods such as the Covid pandemic and very small firms.[4]

The advent of zero-commission trading has significantly increased retail trading. Although the shock is not exogenous, it does present clear testable hypotheses. We expect retail frenzies to

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[3] Survey evidence suggests that valuation considerations are an important determinant of equity issuance (Graham and Harvey, 2001; Graham, 2022), and a large empirical literature finds evidence of market timing (e.g., Jenter, 2005; Kim and Weisbach, 2008; Khan, Kogan, and Serafeim, 2012; Dittmar and Field, 2015; Lee, 2021).

[4] One potential concern is reverse causation, with anticipated future investment stimulating retail frenzies. However, we find no rise in investment-related social media posts before frenzies, and the results hold when excluding episodes with prior corporate news activity.

intensify in recent periods, resulting in larger price distortions and stronger effects on corporate decisions. To analyze frenzies across subperiods, we construct a relative frenzy measure that maintains a constant frequency of buying frenzies over time. Our findings indicate that frenzies are associated with larger imbalances, contemporaneous returns, and reversals in the zero-commission era. While retail frenzies predict increased equity issuance and investment in both periods, the relation is significantly stronger in the zero-commission era. Overall, the evidence suggests that intensified retail trading in the zero-commission era coincides with more intense frenzies, larger price distortions, and increased sensitivity of corporate decisions to retail demand.

In feedback models such as Goldstein, Ozdenoren, and Yuan (2013), stock prices guide capital providers and other important stakeholders, shaping firms' investment decisions and producing spillover effects that can alter firm fundamentals. In our setting, speculative retail buying could bolster firm profitability by relaxing financial constraints, enhancing supplier relations, attracting better employees (Gortmaker, Jeffers, and Lee, 2023), or stimulating product demand (Antil and Hunter, 2023). Consistent with these channels, we find that retail frenzies significantly predict improvements in profitability: firms experiencing a recent frenzy are 6.72 percentage points more likely to surpass the consensus I/B/E/S earnings forecast. Moreover, analysts appear to recognize this pattern, as frenzy firms also exhibit higher forecast revisions immediately following the buying episode. The effect is particularly pronounced in the post-2017 period, when heightened retail activity spurs more intense price run-ups and correspondingly stronger cash flow improvements. On the other hand, the sizable stock price reversals following retail frenzies suggest that profitability gains do not fully justify frenzy-level valuations.

The improved fundamentals we observe could be driven, at least in part, by the relaxation of financial constraints that enables firms to undertake value-enhancing investment projects (e.g., Campello and Graham, 2013). However, our findings paint a more cautionary picture. Specifically, we find that frenzy-induced investments are associated with fewer positive earnings surprises and incrementally worse subsequent returns. Furthermore, frenzy firms are significantly more likely to experience downward forecast revisions in the week following a merger announcement, suggesting that these investments are immediately viewed negatively by sophisticated market participants. Using an efficiency-based measure of managerial ability (Demerjian et al., 2012), we find that post-frenzy investments are disproportionately made by less capable managers, particularly in financially constrained firms. Moreover, post-investment underperformance is concentrated among firms led by lower-ability managers. This evidence is consistent with speculative price surges leading to value-destructive investment decisions, highlighting the economic risks associated with retail-driven mispricing. Thus, while retail frenzies can generate real benefits for firm performance, these effects may be attenuated, or even reversed, when frenzies lead to overinvestment, particularly by less capable managers.

The findings are subject to several caveats. While we establish an economically large association between retail frenzies and corporate decision-making, retail trading decisions are not exogenous. We therefore cautiously interpret the findings as providing evidence that is consistent with retail frenzies impacting real investment. Additionally, the poor stock return performance following heavy investments that we document may reflect both existing assets and new investments. However, the fact that analysts revise forecasts downward following merger announcements by frenzy firms, and that investing frenzy firms exhibit fewer positive earnings surprises than non-investing ones, suggests that new investments contribute to long-run underperformance. At a minimum, we conclude that post-frenzy investments are not sufficiently profitable to justify frenzy valuations. Our findings indicate that retail frenzies and subsequent investments provide a valuable signal that can help financial market participants make more informed decisions.

Our study contributes to several strands of research. One area examines the implications of retail investors for market efficiency. Research has found that retail order imbalances positively predict returns at short horizons (e.g., Kaniel, Saar, and Titman, 2008; Kelley and Tetlock, 2013; Barrot, Kaniel, and Sraer, 2016), while others document a negative relation over longer horizons (e.g., Barber, Odean, and Zhu, 2008; McLean, Pontiff, and Reilly, 2022), particularly for stocks with the heaviest retail trading (Barber et al., 2022; Barber, Lin, and Odean, 2024). We provide new evidence that heavy quarterly retail buy imbalances predict significant underperformance over the subsequent 24 months. Our focus is on the relation between retail investors and real investment.[5] We introduce a new retail frenzy measure that permits studying periods before the meme stock era, providing novel evidence of a relation between retail frenzies and real investment.

Our findings also add to the literature on the real effects of financial markets (for a comprehensive review, see Goldstein, 2023). Our work is related to studies analyzing how different financial market participants influence corporate decision-making. For instance, prior research shows that short-sellers and ETFs enhance price informativeness and investment efficiency (Grullon, Michenaud, and Weston, 2015; Antoniou et al., 2023), while commodity indexing and flow-induced mutual fund trading can reduce investment efficiency (Brogaard, Ringgenberg, and Sovich, 2019; Hau and Lai, 2013; Dessaint et al., 2019; Xiao, 2020).

We extend the literature on the real effects of investing clienteles by focusing on the role of retail investors. While institutions are prone to fire sales that create negative price pressure, retail investors are more inclined to engage in buying frenzies. Further, unlike most mutual fund

[5] A large theoretical literature highlights that market efficiency and real efficiency can differ (e.g., Dow and Gorton, 1997; Bond, Goldstein, and Prescott, 2010; Bond, Edmans, and Goldstein, 2012; Goldstein and Yang, 2019).

fire sale measures, which are mechanically related to past returns (Wardlaw, 2020), retail frenzies appear to capture distinct, non-fundamental demand shocks. Moreover, the growth of retail trading in recent years, coupled with technological advancements that may amplify behavioral biases (e.g., Barber et al., 2022; Cookson, Engelberg, and Mullins, 2023), suggests a magnified impact for retail investors, particularly among financially constrained firms with lower-ability managers.

Our findings complement theoretical research on trading frenzies. We find support for the prediction in Goldstein, Ozdenoren, and Yuan (2013) that frenzies are associated with improvements in profitability. However, the evidence of post-frenzy return reversals suggests that profitability gains do not fully justify frenzy-level valuations and that some portion of the frenzy reflects mispricing rather than fundamental strength. Consequently, investors who trade on the assumption of fundamental improvements risk losses. One possibility is that some retail traders believe their purchases can drive lasting firm value, while others aim to profit from short-term coordination (e.g., Abreu and Brunnermeier, 2003; Pedersen, 2022).[6]

Our work complements contemporaneous work by Anderson and Ringgenberg (2024), who focus on coordinated retail trading driven by social media for roughly 75 meme stocks. We analyze retail trading frenzies across more than 1,200 unique firms, extending the sample well before the meme stock era, and explore a diverse set of retail-driven demand shocks. Additionally, by examining earnings surprises and long-horizon reversals, and studying the role of managerial ability and financial constraints, we shed light on whether frenzies spur value-creating or value-destroying investments and under what conditions they have the greatest impact.

2. Data and Descriptive Statistics

[6] For example, Bradley et al. (2024) document that, following the GameStop episode, retail discussions often shift from fundamentals to exploiting price pressure, indicating investor awareness of the fleeting nature of trading spikes.

2.1 Measuring Retail Trading and Other Variable Construction

Our approach for identifying retail trading relies on the methodology of Barber et al. (2024).[7] Specifically, for all trades with TAQ exchange code "D," we classify a trade as a retail buy (retail sell) if the execution price is greater than (less than) the quoted midpoint, but we do not classify trades that execute between 40% and 60% of the National Best Bid or Offer.[8] This algorithm captures marketable orders, which are more likely to reflect liquidity-demanding trades. While the method omits some forms of retail activity (e.g., non-marketable limit orders), it performs well for our purposes by focusing on the segment of retail trading likely to generate price pressure that could affect corporate decisions.

We define daily retail order imbalances for stock *i* on day *t* as the difference between retail purchase volume and retail sell volume, scaled by shares outstanding. We aggregate this measure over three-month rolling windows (*Qtr. Retail Imbalance*) and winsorize *Qtr. Retail Imbalance* at the 0.1 and 99.9 percentiles. We define *Retail Frenzy* as an indicator equal to one if *Qtr. Retail Imbalance* is greater than 2%, which corresponds to roughly 1.3% of all firm-month observations, with 1,224 unique firms experiencing a frenzy.[9]

We merge the data on retail trading with accounting data from *Compustat Fundamental Quarterly* and return data from CRSP. Our primary outcome variables of interest are equity issuance and investment. We measure equity issuance using the Compustat variable SSTK. The SSTK measure includes both firm-initiated equity issuance and employee-initiated issuances (e.g., the exercise of stock options, warrants, employee stock purchase plans, etc.). To isolate firm-

[7] We thank Xing Huang for providing the code to implement the retail trade algorithm.
[8] Barber et al. (2024) finds that relying on quoted midpoints leads to higher accuracy rates than using the sub-penny digit approach of Boehmer, Jones, Zhang, and Zhang (2021) (BJZZ). In robustness tests (Table 6), we also consider signing trades using the BJZZ algorithm and find similar (albeit slightly weaker) results.
[9] We consider various alternative definitions of retail frenzies in robustness tests (see Table 6).

initiated equity issuances, we follow the suggestion of McKeon (2015) and define *Equity Issuance* as an indicator variable equal to one if *SSTK* is greater than 3% of the market capitalization of the firm.[10] Following Dessaint et al. (2019), we measure investment as capital expenditures (Compustat item CAPX) scaled by lagged fixed assets (Compustat item PPENT). We note that the CAPX measure reported in Compustat excludes acquisition expenses, so we also separately examine acquisition expenditures (Compustat item AQC) scaled by lagged fixed assets.

Following Khan, Kogan, and Serafeim (2012), we construct a set of control variables (*Controls)* associated with equity issuance: *ROA*, *Size, Q, Leverage, Dividend Yield, Volatility, Asset Growth,* and returns measured over the prior three months ($Ret_{t-3,t-1}$) and prior four to 12 months ($Ret_{t-12,t-4}$). In addition, following Alti and Sulaeman (2012), we control for the change in institutional ownership (Δ Inst. Ownership), total institutional ownership (*Inst. Ownership*), the total number of common shareholders (*Shareholders*), and short interest (*Short Interest*).

Prior research highlights that mutual fund fire sales can generate mispricing and influence corporate investment (e.g., Lou and Wang, 2018; Dessaint et al., 2019). We follow Edmans, Goldstein, and Jiang (2012) to construct *MFFlow Sales*, a measure of negative price shocks from mutual fund outflows. However, recent work by Wardlaw (2020) raises concerns that *MFFlow Sales* may partly reflect fundamental information rather than purely non-fundamental demand shocks. To address this concern, we also construct *Flow-to-Volume*, a measure designed to better isolate forced selling while avoiding mechanical links to realized returns. We define *Fire Sale MFFlow (Fire Sale Flow-to-Volume)* as indicators equal to one if the respective outflow measure

[10] An alternative way to purge employee-initiated equity issuances is to rely on issuance data from SDC. However, SDC is missing the overwhelming majority of firm-initiated equity issuances (McKeon, 2015), including at-the-market offerings, which have become an increasingly popular method for issuing new equity (Billet, Floros, and Garfinkel, 2019).

falls in the bottom decile (i.e., greatest outflows). For comparison, we also construct analogous measures of *MFFlow Purchases*, to capture price increases triggered by mutual fund inflows.

The model in Goldstein, Ozdenoren, and Yuan (2013) predicts that trading frenzies are more likely when speculators possess more common information, when firms face greater financial constraints, and when capital providers are more sensitive to price changes. Following Da, Fang, and Lin (2025), we proxy for common information using *WSB Coverage*, defined as the number of times a stock is mentioned in Reddit's *WallStreetBets* posts. Due to data limitations, *WSB Coverage* is available only from July 2018 to December 2021. To extend our analysis over a broader sample period, we also use *SA Coverage*, measured as the number of research reports published about a firm on the Seeking Alpha platform. We capture financial constraints using the Kaplan and Zingales (1997) index (*KZ-index*), detailed in Appendix A. Firms are classified as *Constrained* if their KZ-index is in the top quintile within their industry at a given point in time. Similarly, we classify firms as *Capital Sensitive* if the firm's capital-to-price sensitivity is in the top quintile relative to industry peers at the same time. We follow Da, Fang, and Lin (2025) and estimate *Financing Sensitivity* by regressing each firm's net equity issuance in quarter *q,* measured as the change in common equity from *q–1* (net of retained earnings), scaled by book assets on its raw stock return in quarter *q–1*, using a rolling eight-quarter window.

Finally, to control for existing measures of mispricing, we construct 153 firm characteristics based on various market data from CRSP and accounting data from Compustat, following Jensen, Kelly, and Pedersen (2023).[11] The full list of the firm characteristics is available in Table J.1 of JKP (2023). We limit the sample of anomalies to 118 firm characteristics that were significant predictors of returns in the original sample (as defined in JKP). Each month, we sort

[11] We thank the authors for providing detailed code and documentation needed to construct the variables. Interested readers can find more information at https://github.com/bkelly-lab/ReplicationCrisis.

stocks into quintiles based on NYSE breakpoints for each anomaly characteristic. We compute *Net Anomaly* as the number of times the stock appears in the long leg of the anomaly portfolio minus the number of times the stock appears in the short leg. All variables are defined in greater detail in Appendix A. Our final sample includes all common stocks with non-missing data for *Retail Imbalance, Equity Issuance*, *Investment*, and *Controls* from 2007 through 2023.[12]

2.2 Descriptive Statistics

The sample includes 664,269 firm-month observations from January 2007 to December 2023. Table 1 presents summary statistics. *Retail Frenzy* equals one in 8,686 firm-months (1.31% of all firm-months). Panel A of Figure 1 plots the mean of *Retail Frenzy* for each year of the sample. We observe that retail frenzies were less common in the earlier part of the sample. From 2007 through 2014, the mean of *Retail Frenzy* ranged from 0.1% to 1.1%. Consistent with anecdotal evidence, there is a noticeable spike in the frequency of retail frenzies during the COVID period (2020 and 2021). This declines somewhat post-COVID, but the percentage of firms that experience retail frenzies post-COVID (2022 and 2023) is still larger than all the values prior to 2017.

The plot also shows the frequency of *Retail Selling Frenzies* defined as retail order imbalances less than -2%. Since retail investors rarely short-sell, we expect that the impact of behavioral biases, such as attention-based trading, will result in heavy buying pressure rather than heavy selling pressure (Barber and Odean, 2008).[13] Consistent with this prediction, retail *Selling Frenzies* are infrequent throughout the entire sample. Additionally, retail buying frenzies are likely

[12] Retail trading can be identified beginning with the regulation NMS, which was initiated in 2005. However, we observe limited retail trading in 2005 and 2006, possibly because brokerage firms did not immediately adopt the practice of providing fractional cents of price improvement.
[13] Bradley et al. (2024) finds that posts on *Wallstreetbets* are more likely to induce concentrated buying than selling.

to induce more mispricing than selling frenzies, since the risks associated with short-selling overvalued stocks are greater than those of buying underpriced stocks.[14] Accordingly, throughout the remainder of the paper, we focus on retail buying frenzies, which we refer to as "retail frenzies."

Panel B plots retail imbalances during frenzies and reveals a notable increase in frenzy intensity over time. For example, the average imbalance for frenzy stocks from 2007 to 2014 ranged from 2.7% to 3.5%, whereas the corresponding estimates from 2017 to 2023 were 5.5% to 8.5%. Thus, both the frequency and the intensity of retail frenzies have increased over time. Figure 2 plots the event-time dynamics of retail frenzies, demonstrating their persistence. The average retail imbalance for frenzy stocks in quarter *t* (the quarter in which frenzies are measured) is 5.93%. This value remains sizable in both the previous quarter (2.54%) and subsequent quarter (2.27%) and decays slowly over time. After 8 quarters, the value drops to 0.96%, which remains significant both economically and statistically compared to the mean of roughly 0%. The findings support the idea that certain stocks consistently attract retail buying attention.

2.3 Determinants of Retail Frenzies

We explore the determinants of retail frenzies by estimating the following linear probability model:

$$Retail\ Frenzy_{i,t+1} = \alpha + \beta_1 Controls_{i,t} + FE + \varepsilon_{i,t+1}. \quad (1)$$

[14] This is particularly true in the later part of the sample. For example, Qian, Shi, and Yan (2024) find that short-selling hedge funds have significantly reduced their short positions in response to the GME buying frenzy.

Retail Frenzy and *Controls* are defined as in Section 2.1. FE can include fixed effects for month, month × Fama-French 49 industry, and firm.[15] All continuous control variables are standardized to have unit variance, and standard errors are clustered by firm and month.

The price-investment feedback model of Goldstein, Ozdenoren, and Yuan (2013) generates several predictions regarding which firms are likely to experience frenzies. First, frenzies are expected to be more intense when speculators share common signals, as coordinated trading amplifies price pressure and reinforces speculators' incentives to align their trades. Second, frenzies are stronger when feedback effects between prices and real decisions are larger. For example, such effects are amplified in financially constrained firms, where managers depend more heavily on external financing, and capital providers place greater weight on stock prices in deciding how much capital to provide the firm.

We find empirical support for these predictions. Consistent with social media enabling coordination around common signals, we find that retail frenzies are significantly associated with coverage on both WallStreetBets and Seeking Alpha.[16] Additionally, we find that retail frenzies are more prevalent for financially constrained firms (*Constrained)*, and when capital raising is more sensitive to price changes (*Capital Sensitive*). Frenzies are also more common for small stocks and those with high short interest, where the impact of coordinated trading on prices is likely to be larger.

[15] We report estimates from a linear probability model for ease of interpretation. In Table IA1 of the Internet Appendix, we also estimate logit models and find qualitatively similar estimates.

[16] To assess the economic importance of social media, we group stocks by the total number of WSB posts over three months and relate them to contemporaneous retail order imbalances and frenzies. We find an economically large and monotonic relation between posting activity and retail frenzies (Panel A of Table IA2 in the Internet Appendix). For stocks with 0 WSB posts, average retail order imbalances are 0.14%, and frenzies account for 2.4% of firm-quarters. In contrast, stocks with over 100 posts have imbalances of 1.88%, and frenzies comprise 21.01% of observations.

More generally, the evidence that frenzies are more common among smaller firms, those with low profitability, high volatility, significant short interest, lower institutional ownership, and a higher proportion of common shareholders (primarily retail investors) supports existing findings on the preferred habitat of retail investors (Kumar and Lee, 2006; Laarits and Sammon, 2023).

3. Retail Frenzies and Stock Prices

We examine returns around retail frenzies by estimating the following panel regression:

$$Ret_{i,t+x} = \alpha + \beta_1 Retail\ Frenzy_{i,t} + Time_t + \varepsilon_{i,t+x}. \tag{2}$$

The dependent variable is the return on the stock in month *t*+*x*. We let *x* vary from 1 to 24, which allows us to examine monthly returns in each of the 24 months following the frenzy. We also set *x* equal to -1, -2, and -3 to examine returns during the period in which retail buying occurs (hereafter contemporaneous returns). Standard errors are clustered by firm and month. [17]

Columns 1 and 2 of Table 3 report the results. Frenzy stocks experience contemporaneous monthly returns of 9.81%, 9.27%, and 7.69%, respectively, and all three estimates are highly significant. More interestingly, we observe consistently negative estimates in each of the 24 months following the frenzy. The estimates range from -0.86% to -2.21%, and the majority of the estimates are significant at a 5% level. This evidence is consistent with retail buying pressure pushing prices away from their fundamental values during the quarter of the buying frenzy, with the mispricing being gradually corrected over the subsequent 24 months.

Table 2 shows that retail frenzies correlate with stock attributes that are associated with negative returns (e.g., low profitability, high volatility, high short interest, etc.), suggesting that underperformance may be due to retail frenzies concentrating in overvalued stocks. To assess whether the negative returns following retail frenzies differ from existing anomalies, we repeat

[17] We find similar results using Fama-MacBeth regressions (Table IA3 of the Internet Appendix).

Equation (2) using anomaly-adjusted returns. We sort stocks into 50 portfolios based on the *Net Anomaly Score* and compute anomaly-adjusted returns as the stock return minus the average return of stocks in the same *Net Anomaly* portfolio. Columns 3 and 4 report the results for anomaly-adjusted returns. The point estimates decrease, but they remain consistently negative and economically large, indicating that frenzy mispricing is distinct from existing anomalies.

We also implement a calendar-time portfolio strategy to examine the long-term performance of stocks that have experienced frenzies. For each month, a stock's weight in the portfolio is determined by the number of months it has been classified as a retail frenzy stock over the previous 24 months, meaning stocks with more persistent frenzies receive higher weights. We then regress monthly portfolio returns on either the market factor (CAPM alpha) or the Fama and French (2015) five factors plus the Carhart (1997) momentum factor (six-factor alpha). The results, reported in Table IA.4 of the Internet Appendix, indicate that this strategy generates a CAPM alpha of -2.18% and a six-factor alpha of -1.21% per month, both of which are statistically significant. This finding further supports the conclusion that stocks associated with retail buying frenzies experience substantial negative returns in the two years following the frenzy.

Figure 3 displays cumulative market-adjusted and anomaly-adjusted returns from month -3 to +24. We also plot the 95% confidence intervals based on standard errors clustered by firm and month. The figure indicates that retail frenzies are associated with a roughly 27% price run-up. Market-adjusted returns more than fully revert over the 24-month window, while the cumulative anomaly-adjusted returns fall to 4% over the same window.

We investigate whether the findings are specific to retail investors or also occur with large demand shocks from other investor types. We use the Lee and Ready (1991) algorithm to compute aggregate demand shocks from TAQ data. Aggregate order imbalance for stock i on day t is the difference between total buying and selling volume, scaled by shares outstanding, summed over three-month rolling windows (*Qtr. Aggregate Imbalance*). We define *Aggregate Frenzy* as an indicator equal to one if *Qtr. Aggregate Imbalance* exceeds 2%. We contrast the relation between retail frenzies and aggregate frenzies by estimating Equation (2) after including an additional indicator for *Aggregate Frenzy*, and we plot the cumulative anomaly-adjusted returns in Figure IA1. The results indicate that A*ggregate Frenzies* are also associated with large contemporaneous returns of roughly 10%; however, these returns do not reverse over longer horizons. Thus, there is no evidence to suggest *Aggregate Frenzies* push prices beyond their fundamental value.

As a benchmark, we also construct similar plots for measures of mutual fund fire sales, which are known to affect stock prices and corporate actions (Lou and Wang, 2018; Dessaint et al., 2019). We define *Firesale MFFlow* as an indicator equal to one if the mutual fund outflow measure *MFFlow* is in the bottom decile (most outflows). Figure IA2, Panel A plots event-time returns around fire sales. Consistent with prior work, *Firesale MFFlow* is associated with significant negative contemporaneous returns. However, the return decline of roughly -7% is considerably smaller than the 27% return increase associated with retail buying frenzies.

Fire sales are followed by reversals in market-adjusted returns, but the reversal evidence is weaker using anomaly-adjusted returns. This finding aligns with studies suggesting that fire sale stocks differ meaningfully from the broader population (Wardlaw, 2020; Berger, 2021). In Panel B of Figure IA2, we repeat the analysis, replacing the *Fire Sale MFFlow* indicator with *Fire Sale Flow-to-Volume*, defined similarly to *MFFLow* but avoiding the mechanical relation with past returns. Consistent with Wardlaw (2020), we find that *Fire Sale Flow-to-Volume* has a very weak association with contemporaneous returns and is unrelated to future anomaly-adjusted returns. Finally, Panel C of Figure IA2 repeats the analysis for *Fire Purchase Flow-to-Volume.* Consistent with *Fire Sale Flow-to-Volume*, there is little evidence that *Fire Purchase Flow-to-Volume* is related to contemporaneous or future anomaly-adjusted returns. The benchmarking exercise highlights the substantial economic impact of retail frenzies on prices, as their effects are larger and lead to more significant reversals than those associated with mutual fund fire sales.

4. Retail Frenzies, Corporate Decision Making, and Firm Profitability

The results in the previous section indicate that retail buying frenzies are associated with substantial mispricing. In this section, we examine the implications of retail frenzies for corporate decision-making and their spillover effects on firm profitability.

4.1 Equity Issuance

A positive relation between retail frenzies and equity issuance supports the joint hypothesis that 1) managers issue equity when they believe the firm is overvalued, and 2) they recognize this overvaluation following retail frenzies. There is ample evidence for the first part of this hypothesis. For instance, Graham and Harvey (2001) find that two-thirds of CFOs agree that "the amount by which our stock is undervalued or overvalued was an important or very important consideration" in issuing equity.[18] Additionally, literature shows that firms are more likely to issue equity when their stock prices are high (e.g., Jenter, 2005; DeAngelo, DeAngelo, and Stulz, 2010). We conjecture that managers are aware that the price increases from retail frenzies have led to overvaluation. However, the extent to which they exploit this mispricing is an empirical question.

We examine equity issuance and retail frenzies by estimating the following model:

$$Issuance_{i,t+1} = \alpha + \beta_1 Retail\ Frenzy_{i,t} + \beta_2 Controls + FE + \varepsilon_{i,t+1}. \tag{3}$$

[18] The updated survey evidence in Graham (2022) suggests that across survey vintages, 1-5% of CFOs consider their stock to be overvalued.

The dependent variable, *Issuance*, is an indicator equal to one if the firm issued equity in the subsequent quarter, as defined in Appendix A. The key independent variable, *Retail Frenzy*, is an indicator equal to one if the firm experienced a retail frenzy in the current quarter. *Controls* include the same set of controls from Equation (1). FE denotes industry × quarter fixed effects. In some specifications, we also include firm fixed effects. We standardize all continuous control variables to have unit variance, and we cluster standard errors by firm and quarter. We estimate the model using both OLS (i.e., a linear probability model) and logistic regressions.

Specification 1 of Table 4 reports the OLS results for the model with industry × quarter fixed effects. We find that the coefficient on *Retail Frenzy* is positive and highly significant. The result is robust to the inclusion of firm fixed effects (Specification 2) or estimating the model using logistic regressions (Specifications 3 and 4). The estimate from Specification 4 indicates that firms that recently experienced a retail frenzy are 69% more likely to issue equity. As a benchmark, the effect is comparable in magnitude to a 1.5 standard deviation increase in stock price (Q).

4.2 Investment – Hypotheses

The evidence in Table 4 suggests that managers issue new equity following retail buying frenzies. A key question is whether this new equity issuance influences the real economy through increased investment. Rational managers may issue equity in response to overvaluation but recognize that additional investment may not be value-maximizing. In this case, managers would use the equity proceeds to pay off debt or accumulate cash.

Conversely, there are reasons why managers might increase investment after a large stock price increase. They may have positive investment opportunities that were previously inaccessible due to financial constraints (e.g., Campello and Graham, 2013). Alternatively, the easing of financial constraints may lead managers to invest in negative NPV projects due to behavioral biases (e.g., Malmendier and Tate, 2005) or conflicts of interest (Jensen, 1986; 2005). Frenzies could also prompt increased investment in unconstrained managers who misinterpret the price increases as signals of promising opportunities (e.g., Dessaint et al., 2019).

4.3 Investment – Evidence

We examine the relation between investment and retail frenzies by re-estimating Equation (3) with either *CAPX* or *Acquisitions* as the dependent variable. Table 5 presents the results, showing a positive and significant relation between retail frenzies and capital expenditures (Specifications 1 and 2). For example, estimates from Specification 2 indicate that capital expenditures increase by 1.26% of total fixed assets, reflecting a 20% increase relative to the mean capital expenditure of 6.33%. Similarly, there is a positive relation between retail frenzies and acquisition activity (Specifications 3 and 4).

The economic magnitude of the increased investment is substantial. During our sample period, there are 2,604 firm-quarters where the *Retail Frenzy* indicator equals one, with the average retail buy frenzy stock having $768 million in fixed assets. Thus, estimates in Specifications 1 and 3 imply an increase in total capital expenditures of $25.2 billion (1.29% × $768 million × 2,604) or roughly $1.5 billion per year, and a total increase in acquisitions of $37.6 billion.

In addition to increased investment, firms could use proceeds from equity issuance to pay off debt or increase cash holdings. Table IA5 of the Internet Appendix explores the relation between retail frenzies and debt retirement and cash holdings. We define *Debt Retirement* as equal to one if the firm reduced long-term debt (i.e., DLTR − DLTIS) by more than 3% of market capitalization, and *Change in Cash* as the cash change (CHECH) scaled by lagged assets. We then re-estimate Equation (3) with either *Debt Retirement* or *Change in Cash.* We find no robust relation between retail frenzies and debt retirement. In contrast, there is a large and statistically significant increase in cash holdings. Thus, firms appear to use proceeds from equity issuances following retail frenzies to increase investment and cash holdings rather than to pay off existing debt.

4.4 Equity Issuance and Investment – Robustness and Alternative Explanations

We examine whether the equity issuance and investment findings are robust to key research design choices. Table 6 presents the robustness checks, with the baseline results from Tables 4 and 5 in the first row. Rows 2 through 4 consider matched samples based on industry, quarter, and two other matching variables, requiring the matching variables to be in the sample quintile. Thus, these regressions include industry × quarter × first matching variable quintile × second matching variable quintile fixed effects. Following Khan, Kogan, and Serafeim (2012), we match on Q and size (Row 2), past returns and size (Row 3), and asset growth and ROA (Row 4). In Row 5, we match each retail frenzy firm to a non-frenzy firm with the closest propensity score (i.e., nearest neighbor), where propensity scores are the predicted values from Specification 2 of Table 2. The results from these specifications are qualitatively similar to the baseline estimates in Row 1.

Retail frenzies are persistent, as shown in Figure 2, which could lead to biased estimates if the outcome variables also exhibit persistence. To address this, we examine the autocorrelations of our key dependent variables. After including firm fixed effects and controls, we find no evidence of autocorrelation for equity issuance or acquisitions. However, we observe short-term autocorrelations for capital expenditures lasting up to three periods (see Figure IA3). Consequently, we also match on industry × quarter and quintile indicators for each of the first three lags of the dependent variable. The results, reported in Row 6 of Table 6, are similar.

In Rows 7 through 9, we define retail frenzies using imbalance thresholds from 1% (Row 7) to 5% (Row 9). We observe that the estimates increase as the frenzy threshold rises. For instance, the coefficient on capital expenditures is 0.96% for the 1% threshold and 2.43% for the 5%

threshold.[19] However, a higher threshold also reduces the number of buying frenzy observations and typically yields less precise (though still statistically significant) estimates. In Row 10, we consider a relative frenzy measure by comparing retail order imbalances among firms within the same month. The baseline 2% absolute threshold frenzy measure captures frenzies for 1.3% of all firm-months, and we use the top 1.3% percentile threshold each month to obtain a comparable number of frenzy episodes. We find similar estimates for equity issuance and capital expenditures but weaker results for acquisitions.[20] In Row 11, we sign retail trades using the BJZZ (2021) sub-penny price improvement method instead of the quoted midpoint method, as suggested by Barber et al. (2024). We generally find slightly smaller estimates, consistent with the BJZZ (2021) method being less accurate in signing retail trades (Barber et al., 2024).

Our baseline analysis assumes that managers respond in the quarter following the retail frenzy. However, some may react with a delay. To explore this, in Row 12, we replace retail frenzy in the current quarter ($Frenzy_t$), with an indicator if a frenzy occurred in the prior quarters ($Frenzy_{t-1}$). The results remain statistically significant, but the magnitudes are reduced. This suggests that while some firms respond with a delay, more react within one quarter of the retail buying frenzy.

As shown in Figure 1, retail frenzies spiked during COVID (2020-2021). A natural question is whether our results are solely driven by the pandemic. In Row 13, we repeat the analysis excluding the COVID years. The estimates decline, indicating stronger effects during COVID, but remain highly significant, suggesting the results are not confined to that period. Additionally, we

[19] Although the estimated increase in capital expenditures is smaller at lower levels, the aggregate economic effects are larger. For example, at a 1% threshold, *Retail Frenzy* equals one for 5,077 firm quarters, and the average retail frenzy firm has fixed assets of $1.03 billion. Thus, the 0.96% coefficient estimate translates into an aggregate increase in capital expenditures of $50.2 billion compared to $25.2 billion in the baseline estimate.

[20] The conclusions remain unchanged when using 1% or 1.5% percentile thresholds each month. More generally, the frequency and intensity of frenzies significantly increased in the latter part of the sample (see Figures 1 and 2). Thus, the relative frenzy measure emphasizes the earlier sample period. In the next section, we find evidence that frenzies in the later sample period are associated with larger price effects and stronger effects on acquisition activity.

address concerns about very small firms. In Row 14, excluding firms with less than $50 million in assets, we find similar point estimates.

Another potential concern is reverse causation. Anticipated future investment may stimulate retail frenzies. We examine this by analyzing social media posts, specifically Due Diligence reports on WallStreetBets, for the terms "issuance," "capital expenditures" or "CAPX," and "merger" or "acquisition." Panel B of Table IA2 reports the frequency of each term and its variation in posting intensity. We find two main points. First, the terms are infrequent in DD reports, with equity issuance discussed in roughly 0.5% of all reports. Second, there is no clear pattern between posting intensity (the number of DD reports) and issuance or investment discussion. Thus, there is little evidence that anticipation of specific corporate events drives retail frenzies.

We also consider frenzy firms in the news. If frenzy investors are driven by anticipated investment, we would expect stronger findings during episodes with more corporate action-related news. We explore this by tracking articles in Ravenpack labeled "Equity Actions" (including news about equity issuance and investment) or "Acquisitions-Mergers" (including all merger-related news). We find no evidence that the findings are significantly stronger for firms experiencing abnormal corporate action news articles (Table IA6 of the Internet Appendix).

Although our regressions control for stock returns, a concern is that any firm with positive outlier returns over a three-month period may exhibit the observed patterns. We address this issue by constructing pseudo-frenzy firms. For each frenzy firm, we match it with a firm from the same asset size quintile that has the closest return during the frenzy period. In Figure IA4 in the Internet Appendix, we observe no evidence of reversal for pseudo-frenzy firms. While we observe increased issuance for pseudo-frenzy firms (tabulated in Table IA7), the coefficient is less than a third of that for frenzy firms, with a highly significant difference between the two estimates. Additionally, the coefficients on CAPX and acquisitions are economically and statistically insignificant, contrasting sharply with the evidence for frenzy firms.

4.5 Retail Frenzies and Corporate Decisions – Time Series Trends

Figure 1 shows that the frequency and intensity of retail frenzies have increased substantially, with both measures spiking in 2017. This corresponds with the period when zero-commission broker Robinhood experienced significant growth and the subsequent wave of commission cuts by other brokerages.[21] We refer to the 2007-2016 period as the *pre-zero commission period* and the 2017-2023 period as the *post-zero commission period*. Other factors, such as work-from-home orders during the pandemic and increased coordination via social media (Cookson, Engelberg, and Mullins, 2023), may have further amplified retail trading in the post-zero commission era. Regardless of the exact causes, a natural prediction is that increased retail buying pressure will lead to greater mispricing and larger effects on corporate decisions.

We consider the relative frenzy measure introduced in Table 6, which maintains a constant frequency of frenzies over time and allows us to focus on how the impact of frenzies varies with their intensity. We define *Relative Frenzy* as an indicator equal to one if the firm is in the top 1.3% of the retail order imbalance distribution within the same calendar month, yielding roughly the same number of frenzy episodes as the absolute 2% threshold.

Figure 4 plots the average and median buying imbalance for *Relative Frenzy* firms. The average imbalance increases from 1.4% in 2007 to 18.7% in 2021. To examine whether the larger

[21] Over the 2017 calendar year, Robinhood grew from 2 million accounts to 6 million accounts (https://www.businessofapps.com/data/robinhood-statistics/). In February of 2017, Fidelity Investments, Charles Schwab, and TD Ameritrade all reduced trading commissions (https://www.bloomberg.com/news/articles/2017-02-28/fidelity-slashes-commissions-in-the-latest-salvo-in-the-fee-wars?sref=VdHMQbm0).

imbalances correlate with greater mispricing, we plot the cumulative anomaly-adjusted returns from month -3 to +24 associated with *Relative Retail Frenzy* in the pre-period sample (2007-2016) and post-period sample (2017-2023). Figure 5 reports the results. The relation between *Relative Retail Frenzy* and contemporaneous returns is larger in the post period. Specifically, returns from month *t*-3 to *t*-1 are 33.05% in the post period compared to 14.60% in the pre period, with the difference being statistically significant. Larger reversals are also observed in the post period, where retail frenzy stocks earn anomaly-adjusted returns of –26.37% over the subsequent 24 months, compared to -16.39% in the pre period. [22] These findings indicate that retail frenzies induce considerably larger mispricing in the post-zero commission era.

We next repeat the estimates from Equation 3 after replacing *Retail Frenzy* with *Relative Retail Frenzy (Pre-Period)* and *Relative Retail Frenzy (Post-Period)*, and we also test whether the two estimates are significantly different from each other. Specifications 1 and 4 of Table 7 report the results for equity issuance. We find modest evidence that equity issuance is associated with retail frenzies in the pre-period. Specifically, the estimates range from 1.47% to 3.71%, with the latter estimate being significant at a 1% level. However, as expected, *Relative Retail Frenzy (Post Period)* is much larger in magnitude, and the estimate is significantly greater than the estimate on *Relative Retail Frenzy (Pre Period)*.

Specifications 2 and 5 report results for capital expenditures. Estimates in both the pre- and post-period are significant. The post-period estimate is modestly larger, but the difference is not statistically significant. In contrast, Specifications 3 and 6 indicate that the positive relation between retail frenzies and acquisitions is concentrated entirely in the post period. Together,

[22] In Table IA8 of the Internet Appendix, we test whether the magnitude of reversals in the post and pre-periods differ significantly. The difference in means (-9.98%) is not reliably different from zero. However, the fraction of stocks experiencing large negative returns (e.g., returns of -25%, -50%, or -75%) is significantly greater in the post period.

evidence from Figure 5 and Table 7 suggests that the heightened intensity of retail frenzies in the post-zero commission period is associated with greater stock price effects and more pronounced impacts on firms' real decision-making.

4.6 Retail Frenzies and Corporate Profitability

In feedback models such as Goldstein, Ozdenoren, and Yuan (2013), stock prices inform capital providers, influencing firms' investment decisions and creating spillover effects that can impact fundamentals. In our context, speculative retail trading could enhance firm profitability through various channels, such as relaxing financial constraints, improving relationships with suppliers, enabling the firm to hire and retain better employees (Gortmaker, Jeffers, and Lee, 2023), or increasing consumer demand for the product (Antil and Hunter, 2023). In this section, we examine whether retail frenzies are associated with changes in future profitability.

We measure changes in firm profitability around retail frenzies by re-estimating Equation (3) after replacing *Issuance* with *Positive Forecast Error*, which equals one if realized earnings exceed the median I/B/E/S analyst forecasted earnings, where the analyst forecasts are measured in the month prior to the start of the retail frenzy. We consider earnings announcements that occur at least one quarter after the end of the retail frenzy quarter. Our sample includes annual earnings surprises for one-year ahead, two-year ahead, and three-year ahead earnings. Specification 1 of Table 8 reports the regression results. The coefficient on *Retail Frenzy* is positive and significant, indicating that retail frenzies are associated with positive profitability surprises. Firms experiencing a retail frenzy in the prior quarter are 6.79 percentage points more likely to have a positive earnings surprise, reflecting a roughly 16% increase relative to the sample mean of 43%.

We also examine whether sell-side analysts anticipate improvements in profitability for frenzy firms by issuing positive forecast revisions in the period following the frenzy. We repeat

Specification 1 of Table 8 using *Positive Forecast Revision,* defined as an indicator equal to one if the IBES consensus forecast in the quarter after the retail buying frenzy is greater than the consensus forecast in the quarter prior to the frenzy. We find a positive and significant relation between *Retail Frenzy* and *Positive Forecast Revision*, which is consistent with sell-side analysts anticipating that retail buying frenzies are positively associated with future earnings. Finally, as in Table 7, we repeat Specifications 1 and 2 while including *Retail Frenzy* interacted with *Post*, an indicator for the 2017-2023 period. We find that *Retail Frenzy* × *Post* is significantly related to positive earnings surprises and positive earnings revisions. This finding, along with the evidence presented in Figures 4 and 5, suggests that more intense frenzies, which generate more substantial price increases, are associated with greater improvements in cash flow.

The findings from Table 8 support models where trading frenzies create feedback effects that influence firm profitability. However, the significant return reversals in Figure 3 indicate that these profitability gains do not justify the elevated valuations of frenzy firms. Market participants appear to react to stock price movements, but these responses may be driven in part by mispricing rather than true improvements in fundamentals. This raises the question of why retail investors engage in trades that lead to losses. One possibility is that they overestimate their ability to influence fundamentals, expecting larger effects on firm value than actually occur. Another possibility is that traders recognize that their profits depend on the coordinated trading of others (e.g., Abreu and Brunnermeier, 2003). Consistent with this explanation, Bradley et al. (2024) find that after the GameStop frenzy, discussions on Reddit's WallStreetBets focus on exploiting short-term price pressures rather than firm fundamentals, suggesting that some traders understand the transitory nature of frenzies and attempt to time their exits, even if the average trader incurs losses.

Frenzies can also emerge not only from misinterpreting fundamentals or pursuing short-term gains, but also from the complex interplay among very different investor subgroups. In Pedersen's (2022) model, frenzies result from four distinct trader types that shape market dynamics: fanatics, who commit to their view of a firm's fundamentals and anchor market sentiment; naïve investors, who blindly follow the fanatics and amplify price moves; short-term rational investors, who ride bubbles with strategic short-term trading; and patient long-term rational investors. While we cannot provide definitive evidence on the forces driving retail investor decisions, our findings suggest that trading frenzies create profitability improvements. However, subsequent return reversals indicate that these gains are not large enough to justify significant run-ups induced by retail frenzies.

5. What Drives Increased Investment Following Retail Frenzies?

Our analysis uncovers a robust relation between retail frenzies and increased equity issuance and investment. The positive association with increased equity issuance is perhaps not surprising given the abundant anecdotal and empirical evidence that managers choose to time equity issuance (e.g., Graham and Harvey, 2001; Graham, 2022). However, the mechanism driving increased investment is less clear. In this section, we conduct several additional tests to better understand the factors driving the increased investment of retail frenzy firms.

5.1 The Performance of Investment Following Retail Frenzies

Frenzies may relax financial constraints that previously limited managers from investing in positive NPV projects (Campello and Graham, 2013). This suggests that increased investment after retail frenzies could lead to higher future performance compared to other frenzy stocks. On the other hand, easing financial constraints could also lead to overinvestment due to managerial overconfidence (e.g., Malmendier and Tate, 2005) or agency conflicts.

5.1.1 Returns following Retail Frenzy Investments

We expect value-destroying investments to be associated with lower future returns, while value-enhancing investments should be linked to higher return performance. We note that returns after frenzy-induced investments will reflect the performance of new investments as well as the firm's existing assets. However, evidence of negative performance after significant investments made during frenzies would suggest that the heightened investment driven by retail investor enthusiasm failed to support the firm's inflated valuation.

A firm is classified as having made large capital expenditures (*High CAPX)* if its capital expenditures in the previous quarter were in the top quartile across all firms and at least 50% larger than its average capital expenditures in the prior two to four quarters. A firm is classified as having made a large acquisition (*High ACQ*) if the acquisition was at least 1% of total fixed assets in the previous quarter. We define *High Investment* as the maximum of *High CAPX* and *High ACQ*. High investments are classified as *Retail Frenzy - High Investment* if they occurred one or two quarters after a retail frenzy, and all other frenzy stocks are classified as *Retail Frenzy - Low Investment.*

We implement a calendar-time strategy where the weights in the retail frenzy high investment portfolio equal the number of months a stock has been classified as a *Retail Frenzy – High Investment* over the previous 24 months.[23] We compute analogous returns for the retail frenzy low investment portfolio. We then regress the average monthly returns for each strategy on either the market factor (CAPM alpha) or the Fama and French (2015) five factors, along with the Carhart (1997) momentum factor (six-factor alpha). We report the results where monthly observations are weighted by the number of stocks in the portfolio.

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[23] We examine 24-month horizons to account for gradual learning about investment quality, consistent with the corporate-event long-run underperformance evidence (e.g., Loughran and Ritter, 1995; Loughran and Vijh, 1997).

Panel A of Table 9 reports the CAPM alphas. Both the Retail Frenzy – Low Investment and Retail Frenzy – High Investment portfolios significantly underperform, with the high investment portfolio underperforming incrementally by 0.83% per month. Panel B shows that the six-factor alphas are less negative for each portfolio, but the return difference between the two portfolios is virtually identical and remains highly significant. Panels C and D repeat the analysis in Panel B after replacing *High Investment* with either *High CAPX* or *High Acquisition*. Both types of investments are associated with more negative returns, with acquisitions showing a larger magnitude (-1.13% versus -0.65%).

We collect additional detailed information on the timing and characteristics of frenzy mergers from the SDC database. Table IA.9 of the Internet Appendix compares frenzy-induced mergers to non-frenzy mergers. We find that frenzy mergers are more likely to acquire targets outside their primary industry, more likely to acquire private firms, and less likely to finance the merger with cash. Perhaps surprisingly, the day 0 return following frenzy-induced mergers is significantly positive. However, these effects fully reverse within one month and become increasingly negative over longer horizons, and the long-run poor performance of frenzy-induced mergers is robust to controlling for various merger attributes.

5.1.2 Forecast Revisions and Earnings Surprises following Retail Frenzy Investments

The large negative returns following *Retail Frenzy – High Investments* are consistent with the investments destroying value. However, as noted above, this underperformance could also reflect overvaluation of existing assets, as firms making large investments may already have inflated valuations. To help disentangle these effects, we consider two complementary approaches.

First, we examine how sell-side analysts respond to the announcement of new mergers. Although market reactions to frenzy-driven mergers are initially positive—potentially reflecting enthusiasm from retail investors—analyst behavior provides a more informed perspective. If analysts revise earnings forecasts downward following these announcements, it suggests that they view the mergers as value destructive.

We estimate the following panel regression:

$$PosForRev_{i,j,t} = \alpha + \beta_1 Merger_{i,t} + \beta_2 Merger_{i,t} \times Frenzy_{i,t} + \beta_3 Controls + FE + \varepsilon_{i,t+1}. \quad (4)$$

The dependent variable, *Pos ForRev* is a positive forecast revision indicator equal to one if analyst *j*'s forecast at time *t* for stock *i* is greater than their previous forecast for the same stock and fiscal period. We consider forecasts for fiscal years one, two, or three made in days [-30, 30] relative to merger announcement day 0. *Merger* is an indicator that the forecast was issued in the week after a merger announcement (days [0,4]), and the interaction term *Frenzy* is one if the firm experienced a retail frenzy in the quarter ending the month prior to the forecast. Specifications include merger fixed effects (which subsume *Frenzy*), and standard errors are clustered by merger.

The results are presented in Table 10. The coefficient on Merger × Frenzy is negative and statistically significant, indicating that analysts are less likely to issue upward revisions following mergers that occur shortly after a retail frenzy. This suggests that mergers following retail frenzies are viewed more negatively by analysts. In Specification 2, we include leads and lags (Merger Week *t–1* and *t+1*) interacted with Frenzy. The pre-merger interaction term is small and insignificant, reducing concerns about pre-existing downward trends.

In our second test, we compare realized earnings outcomes for firms classified as *Retail Frenzy – High Investment* and *Retail Frenzy – Low Investment* as in Table 9, using the broader Compustat-based measure of investment. Specifically, we assess performance by comparing actual earnings to the I/B/E/S consensus forecasts issued just prior to the investment period. If poor performance stems from weak fundamentals unrelated to the new investment, we would expect these earnings expectations to already be reflected in forecasts prior to the investment announcement. In contrast, if the investments themselves impair profitability, we would expect to observe negative earnings surprises.

We estimate the following panel regression:

$$\underline{Pos\ ForErr_{i,t+1} = \alpha + \beta_1 Retail\ Frenzy_{\square} + \beta_2 Retail\ Frenzy - High\ Inv._{i,t} +} \quad (4)$$

$$\underline{\beta_3 High\ Inv._{i,t} + \beta_4 Controls + FE + \varepsilon_{i,t+1}.}$$

Pos ForErr is an indicator equal to one if the realized earnings exceed the median I/B/E/S analyst forecasted earnings, where the analyst forecasts are measured in the month prior to the start of the investment. *Retail Frenzy*, *Retail Frenzy – High Investment*, and *High Investment* are defined as in the previous section, and the controls are identical to Equation 3. We limit the sample to earnings that are announced at least one quarter after the end of the investment quarter. Our sample includes annual earnings surprises for one-year-ahead, two-year-ahead, and three-year-ahead earnings. Thus, the analysis is similar to Table 8, but we now examine forecast errors centered around the investment decision, rather than the retail buying frenzy.

Table 11 reports the results. Consistent with Table 8, the coefficient on *Retail Frenzy* is positive, indicating that retail frenzy firms that do not make large investments experience improvements in profitability. However, the coefficient on *Retail Frenzy* × *High Investment* is negative and significant, indicating that large investments are associated with declines in future earnings compared to frenzy firms that do not make large investments. In Specification 2, we split *High Investments* into *High Acquisitions* and *High CAPX.* The coefficient estimates for *Retail Frenzy* × *High CAPX* are negative but not reliably different from zero, whereas the coefficient on *Retail Frenzy* × *High Acquisition* is economically large and statistically significant. The pattern suggests that acquisitions following retail frenzies perform particularly poorly.

Specifications 3 and 4 repeat the analysis after replacing *PosForErr* with *PosForRev*, as defined in Table 8. The coefficient on *Retail Frenzy* × *High Investment* is significantly negative. This finding is consistent with the event-time analysis in Table 10 and further suggests that sell-side analysts tend to issue a downward forecast revision following frenzy-induced investments.

5.2 Why Do Managers Invest in Value-Destroying Projects?

The evidence from the previous section is consistent with frenzies inducing managers to engage in value-destroying investments. In this section, we explore several potential explanations for why managers pursue such projects despite their negative expected value.

5.2.1 The Role of Managerial Ability

Poor performance following frenzy-induced investments may stem from managers overestimating investment benefits, a common form of managerial overconfidence (Malmendier and Tate, 2005, 2008). We operationalize this idea by examining how the level and performance of investment vary with managerial ability. Intuitively, lower-ability managers are more likely to initiate value-destroying investments, either due to a weaker ability to distinguish good from bad projects or a lower capacity to efficiently execute potentially valuable projects. By contrast, managers who tend to have better systems for screening investment ideas and more nuanced views of their firms' true growth potential are presumably less prone to over-investment.

We proxy for managerial ability using the measure developed by Demerjian, Lev, and McVay (2012), which gauges a manager's efficiency in generating revenues.[24] A key advantage of this measure is its broad availability across nearly all firms. Moreover, Demerjian, Lev, and McVay (2012) demonstrate that poor performance following equity issuance is more pronounced

[24] We thank Peter Demerjian for the data (https://peterdemerjian.weebly.com/managerialability.html).

in firms with lower-ability managers, suggesting that their measure effectively captures managerial capacity to generate value through investments.

We define *Low Ability* as an indicator equal to one if the managerial ability rank is below the median, and all other managers are classified as *High Ability*. We then repeat the baseline investment tests from Table 5, including *Retail Frenzy* × *Low Ability* and *Low Ability*. The results are reported in Table 12. The coefficient on *Retail Frenzy* × *Low Ability* is positive in all four specifications and statistically significant in three of them. In contrast, the estimates on *Retail Frenzy* are statistically insignificant, suggesting the increase in investment is concentrated among lower-ability managers.

Following Demerjian et al. (2012), we also consider historical industry-adjusted returns as an alternative proxy for managerial ability. Specifically, we measure a firm's industry-adjusted return over the prior two to five years, excluding the most recent year to avoid contamination from the retail frenzy. We define *Low Ability Return* as an indicator variable equal to one if the firm's historical return is below the industry median. The results using this alternative measure, reported in Panel B of Table 12, are qualitatively similar.

We next examine whether the poor performance of frenzy-induced investment is also concentrated in lower-ability managers. We first repeat Panel B of Table 9 after partitioning the *Retail Frenzy - High Investment* portfolio based on whether the manager is classified as high ability or low ability based on the efficiency measure. Figure 6 plots the alphas for each portfolio. We find that the six-factor alpha for high-investment firms is a significant -2.06% per month when led by low-ability managers, compared to an insignificant -0.89% per month for firms led by high-ability managers. Furthermore, the difference of -1.16% is marginally significant (p = 0.06).

We then repeat the earnings tests reported in Specification 1 of Table 11, again partitioning by managerial ability. We find that the estimate on *Retail Frenzy* × *High Investment* is a highly significant -10.03% for firms led by low-ability managers, compared to an insignificant -4.53% for firms led by high-ability managers. Although the difference between the two estimates is not reliably different from zero, the overall evidence suggests that the underperformance following frenzy-induced investment is concentrated in firms with lower-ability managers.

5.2.2 The Joint Role of Managerial Ability and Financial Constraints

We conjecture that the increased investment of low-ability managers following frenzy-induced investments is primarily driven by the relaxation of financial constraints. However, it is possible that even unconstrained, low-ability managers may increase investment if they misinterpret price surges as signals of promising opportunities (Dessaint et al., 2019). To explore the joint role of managerial ability and financial constraints, we repeat the baseline investment analysis from Table 5 after partitioning frenzy firms into 4 groups based on managerial ability (high vs. low) and financial constraints (constrained vs. unconstrained), using the Kaplan and Zingales (1997) measure, as described in Table 2. Table 13 reports the results. Across all four specifications, we find that the increase in investment is economically large and statistically significant only for firms led by low-ability, financially constrained managers. In contrast, the estimates for the other three groups are notably smaller in magnitude and generally statistically insignificant. Taken together, the findings from Sections 5.2.1 and 5.2.2 suggest that retail frenzies relax financial constraints, leading to increased investment—primarily among low-ability managers who overestimate the value of their investment projects.

5.2.3 Retail Frenzies and Investment – Faulty Learning

Another potential explanation for the increased investment is that managers mistakenly interpret price surges as a signal of promising opportunities (hereafter: *faulty learning*) (Dessaint et al., 2019). The evidence that the increased investment is limited to constrained firms (Table 13) is inconsistent with unconstrained managers being fooled into investment by rising stock prices. As an alternative test, we follow Dessaint et al. (2019) and examine whether firms increase investment in response to peer firms experiencing a retail frenzy. Under the faulty learning hypothesis, managers may interpret peer firms' price increases as signals of promising industry-wide opportunities, prompting them to invest more.

To explore this idea, we repeat the baseline investment tests after including *Retail Frenzy – Peer Firm*, defined as the percentage of peer firms experiencing a retail frenzy in the prior quarter. A firm is considered a peer if its product similarity score makes it one of its nearest 25 rivals based on the TNIC-3 classification of Hoberg and Phillips (2015, 2016). Additionally, the product similarity score must exceed 0.01. The results, reported in Table IA.10 of the Internet Appendix, offer no evidence of a significant increase in investment following retail frenzies in peer firms. Thus, we do not find strong evidence in support of the faulty learning hypothesis.

5.2.4 Retail Frenzies and Investment – Catering to Retail Investors

Frenzy firms may view investment as a way to keep their retail investor base enthusiastic about the company and increase the likelihood that it can eventually grow to justify its inflated valuation.[25] This explanation suggests that frenzy firms that conduct large investments are more

[25] Dong, Hirshleifer, and Teoh (2021) find evidence that measures of overvaluation are associated with patent citation counts, consistent with "moon shot" investment, and this type of rationale has been offered to explain movie AMC's frenzy-induced growth strategy. https://www.fool.com/investing/2021/06/03/why-amcs-audacious-growth-strategy-makes-sense/

likely to maintain high levels of retail investor enthusiasm relative to frenzy firms that do not invest.

To test this idea, we revisit the determinants of the retail frenzy analysis from Table 2 after including indicators for *Retail Frenzy, Retail Frenzy × High Investment*, and *High Investment* (as defined in Table 9), and the dependent variable is measured in the quarter after the investment. The results, reported in Table IA.11 of the Internet Appendix, indicate that the coefficient on *Retail Frenzy × High Investment* is insignificantly negative. The negative point estimate is inconsistent with increased investment helping firms sustain higher levels of retail enthusiasm.

5.2.5 Retail Frenzies and Investment – Managerial Career Concerns

The increased investment could be driven by agency problems related to convex managerial payouts. For example, managers of struggling firms, such as unprofitable and distressed firms that are frequently subject to retail frenzies, face significant job loss risks regardless of whether their performance slowly declines or rapidly declines. Thus, managers may have an incentive to pursue investment projects that offer a small probability of success, even if the expected NPV of the project is negative.

This explanation suggests that while frenzy-induced investments are, on average, value-destroying, they may still be associated with better right-tail outcomes. To explore this possibility, we repeat the return analysis in Table 12, but instead of examining the average returns, we examine the likelihood that cumulative returns exceed specific thresholds. Specifically, we consider thresholds of 200%, 100%, 50%, 0%, and -50%. The results, reported in Table IA12 of the Internet Appendix, show that regardless of the return metric used, firms experiencing retail frenzies that invest heavily are less likely to achieve these return thresholds compared to frenzy firms that do not invest heavily. We also find similar results when replacing returns with earnings surprises.

Even if frenzy-induced investments do not lead to extreme right-tail outcomes, they may still benefit managers. For example, increased investment could signal that managers have a strategic vision for the firm, potentially reducing the likelihood of their termination or increasing their compensation. To explore this possibility, we collect information on CEO departures from Audit Analytics and information on changes in CEO total compensation from Execucomp.[26] Table IA.13 reports the results for all CEO departures (Specifications 1 and 2), forced CEO departures, defined as all departures excluding retirements and deaths (Specifications 3 and 4), and changes in total CEO compensation (Specifications 5 and 6). Across all six specifications, we find that the differences between high investment and low investment firms are insignificant, and in four of the six cases, the point estimate is in the "wrong" direction. Thus, there is little evidence that frenzy-induced investments help CEOs improve their career outcomes.

6. Conclusions

We introduce a new proxy for retail trading frenzies based on quarterly retail order imbalances and document a surge in stock prices during these periods, followed by substantial underperformance over the next two years. The poor performance remains significant after adjusting for a broad set of market anomalies, indicating that mispricing associated with retail frenzies is distinct from previously identified return predictors.

We find that retail frenzies strongly correlate with equity issuance and real investment, and this relation has become more pronounced in the post-zero-commission period. This pattern is consistent with reduced trading costs amplifying price distortions and encouraging managers to exploit inflated valuations. Retail frenzy firms also experience improvements in profitability, in

[26] We note that Execucomp coverage is limited primarily to S&P 1500 firms, which reduces our sample by roughly 50%.

line with feedback models (e.g., Goldstein, Ozdenoren, and Yuan, 2013). However, long-run returns lag, suggesting that the boost to fundamentals does not match the scale of the initial price run-up. This pattern is consistent with speculative trading by retail investors, who bid up prices in anticipation of short-term gains rather than basing purchases solely on fundamental values.

Frenzy-induced investments are associated with more negative returns and fewer positive earnings surprises. Investment increases following retail frenzies are significantly larger for firms with lower-ability managers, and the negative relation between investment and future performance is concentrated among these firms. The findings suggest that while retail frenzies can temporarily alleviate financial constraints, they disproportionately empower managers ill-equipped to identify and execute positive NPV projects, ultimately resulting in poor investment outcomes.

Our findings are relevant to both academics and regulators. From a regulatory perspective, the evidence contributes to ongoing policy debates surrounding factors driving coordinated retail trading, such as zero-commission trading, gamification of trading apps, and the proliferation of finance social media platforms. Much of this discussion highlights how these forces contribute to increased volatility and amplify potential losses for small investors. Our research indicates that retail frenzies not only redistribute wealth but also influence real investment decisions and potentially diminish investment efficiency. The estimates suggest that the real economic effects are sizable, providing additional rationale for regulatory scrutiny.

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Appendix A: Variable Definitions

- *Qtr. Retail Imbalance:* Retail buy volume less retail sell volume scaled by total shares outstanding measured over a 3-month window. Retail trades are assigned as buys or sells based on the Barber et al. (2024) algorithm. (Source: TAQ and CRSP).
  - *Retail Frenzy:* An indicator equal to one if *Qtr. Retail Imbalance* is greater than 2% of shares outstanding.
  - *Relative Retail Frenzy:* An indicator equal to one if *Qtr. Retail Imbalance* is in the top 1.3% of the distribution relative to other firms in the same calendar month.
  - *Retail Selling Frenzy:* An indicator equal to one if *Qtr. Retail Imbalance* is less than or equal to -2% of shares outstanding.
- *Qtr. Aggregate Imbalance:* Aggregate TAQ buy volume less aggregate TAQ sell volume scaled by total shares outstanding measured over a 3-month window. Trades are assigned as buys or sells based on the Lee and Ready (1991) algorithm. (Source: TAQ and CRSP).
  - *Aggregate Frenzy:* An indicator equal to one if *Qtr. Aggregate Imbalance* is greater than 2% of shares outstanding.
- *Equity Issuance*: An indicator equal to one if equity issuance (Compustat item SSTK) is greater than 3% of a firm's market capitalization.
- *Capital Expenditures*: Capital expenditures (Compustat item CAPX) scaled by fixed assets (Compustat item PPENT) in the prior quarter.
  - *High CAPX* – An indicator equal to one if the firm's capital expenditures are at least 50% larger than the firm's average capital expenditures in the prior two to four quarters and exceed the top quartile of capital expenditures across all firms.
- *Acquisitions*: Acquisition expenditures (Compustat item AQC) scaled by fixed assets (PPENT) in the prior quarter.
  - *High Acquisitions:* An indicator equal to one if the firm has acquisition expenses that are more than 1% of total fixed effects.
- *High Investment:* An indicator equal to one if either *High CAPX* or *High Acquisitions* is equal to one.
  - *Frenzy × High Investment*: An indicator equal to one if *High Investment* equals one and the firm experienced a retail frenzy in any of the six months prior to the investment.
- *Debt Retirement:* An indicator equal to one if long-term debt reduction (Compustat item DLTR) less long-term debt issuance (Compustat DLTIS) exceeds 3% of market capitalization.
- *Changes in Cash*: The change in cash and cash equivalents (Compustat item CHECH) scaled by total assets in the prior quarter.
- *ROA*: Net Income (Compustat item: NI) scaled by total assets in the prior quarter.
- $Ret_{t-3,\, t-1}$: The return over the prior 1 to 3 months. (Source: CRSP)
- $Ret_{t-12,\, t-4}$: The return over the prior 4 to 12 months. (Source: CRSP)
- *Assets*: Total assets (Compustat item: AT).

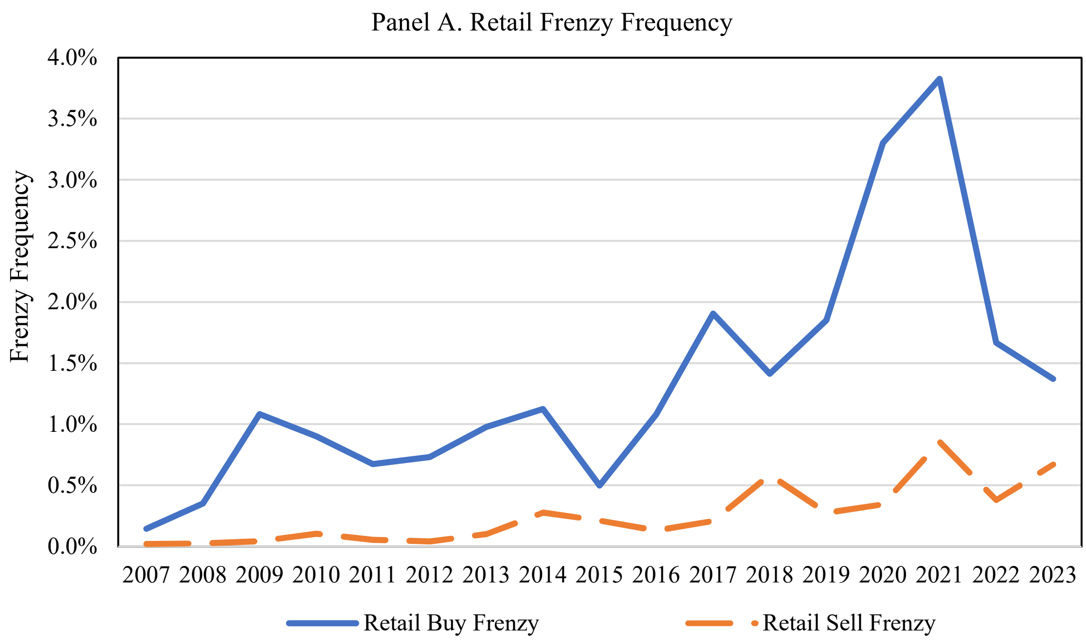
- *Q*: Tobin's Q, defined as book value of assets (Compustat item AT) less book value of equity (Compustat Item: CEQ) plus market value of equity (Compustat: PRCC × CSHO) at the end of the calendar year. Scaled by book value of assets (Compustat item AT).
- *Leverage*: Total assets (AT) scaled by book equity (BE).
- *Div Yield:* Total dividends (Compustat item: DVT) over the prior 12 months scaled by the current price (CRSP item: PRC).
- *Volatility:* The standard deviation of daily returns over the prior month (Source: CRSP).
- *Short Interest:* The total number of shares held short (Compustat item SHORTINT) scaled by shares outstanding.
- *Asset Growth:* The percentage growth in total assets over the prior year (Source: Compustat).
- *Institutional Ownership:* Total ownership by 13F-filing institutional investors, defined as aggregate shares held by institutions scaled by shares outstanding. (Sources: Thomson/Refinitiv S34 Holdings).
- *Δ Institutional Ownership:* The change in institutional ownership relative to the previous quarter (Sources: Thomson/Refinitiv S34 Holdings).
- *MFFlow (Outflow):* A quarterly measure of firm fire sales equal to $(-1)\sum_j^m \frac{\lfloor F_{j,t} \rfloor \times Share_{\ i,j,t-1} \times PRC_{i,t-1}}{TA_{j,t-1} \times Vol_{i,t}}$.
    - $F_{j,t}$: Net dollar flow, defined as the amount of money flowing into or out of a mutual fund in quarter *t*. The sample is restricted to fund quarters where the total net outflow is greater than 5% of total assets. (Source: CRSP Mutual Funds).
    - $Shares_{i,j,t-1}$: The shares held by fund *j* in stock *i* at the end of *quarter t*-1. (Source: CDA Spectrum/Thomson Financial).
    - $PRC_{i,t}$: The share price of stock *i* in quarter *t* (Source: CRSP).
    - $Vol_{i,t}$: Dollar volume traded in stock *i* in quarter *t*, defined as $Share\ Vol_{i,t} \times PRC_{i,t}$ (Source: CRSP).
    - $TA_{j,t-1}$: Total assets of mutual fund *j* in quarter *t-1* (Source: CDA Spectrum/Thomson Financial).
    - *Fire Sale (MFFlow):* An indicator equal to one if *MFFlow* is in the bottom decile.
- *Flow-to-Volume (Outflows*): A measure of mutual fund file sales equal to $(-1)\sum_j^m \frac{\lfloor F_{j,t} \rfloor}{TA_{j,t-1}} \times \frac{Share_{\ j,t-1}}{Share\ Vol_{i,t}}$
    - $Share\ Vol_{i,t}$: Total share volume of stock *i* in quarter *t*. (Source: CRSP).
    - *Fire Sale (Flow to Volume):* An indicator equal to one if *Flow to Volume* is in the bottom decile.
- *Flow-to-Volume* (*Inflows*)*:* Similarly to *Flow-to-Volume*, but the measure is constructed using a restricted sample of fund quarters where the total net inflow is greater than 5% of total assets.
    - *Fire Purchase (Flow to Volume):* An indicator equal to one if *Flow to Volume* (*Inflows*) is in the top decile.

- *Shareholders:* Number of common shareholders (Compustat item: CSHR).
- *Pre-Zero Commission Period:* An indicator equal to one for the 2007-2016 sample period.
- *Post-Zero Commission Period*: An indicator equal to one for the 2017-2023 sample period.
- *Net Anomaly Score:* The number of times the stock appears in the long leg of an anomaly portfolio less the number of times the stock appears in the short leg. The measure considers 118 anomalies that were significant predictors of returns in Jensen, Kelly, and Pedersen (2023). The full list of anomalies is available in Table J.1 of Jensen, Kelley, and Pedersen (2023).
- *WSB Coverage:* The number of WSB posts mentioning the stock during the month.
- *SA Coverage*: The number of single-stock research reports published about the firm on the Seeking Alpha platform during the month.
- *KZ Index*: The KZ index is equal to:

  $-1.002 \times kz\_cf + 0.283 \times kz\_q + 3.139 \times kz\_db + -39.368 \times kz\_dv + -1.315 \times kz\_db$, where
  - $kz\_cf = (NI_{t+} DP_t) / PPENT_{t-12}$
  - $kz\_q = Tobin's\ Q_t$
  - $kz\_db = (DEBT_t) / (DEBT_t + SEQ_t)$
  - $kz\_dv = DIV_t / PPENT_{t-12}$
  - $kz\_cs = CHE_t / PPENT_{t-12}$
- *Constrained:* An indicator equal to one if the *KZ Index* is in the top quintile relative to other firms in the same industry and at the same point in time.
- *Financing Sensitivity:* The estimate from a regression of a firm's net equity issuance in quarter *q,* measured as the change in common equity from *q–1* (net of retained earnings), scaled by book assets on its raw stock return in quarter *q–1*, using a rolling eight-quarter window.
  - *Capital Sensitive:* An indicator equal to one if the firm's *Financing Sensitivity* is in the top quintile relative to industry peers at the same point in time.
- *Anomaly-Adjusted Returns:* The return on the stock less the average return of stocks in the same *Net Anomaly Score* portfolio, where portfolios are created using 50 breakpoints each month.
- *High News:* An indicator equal to one if the firm's news coverage of corporate actions is in the top quartile compared to the number of articles for the same firm over the preceding 12-months. We measure corporate action news articles by counting the number of articles in Ravenpack that are categorized as either "equity actions" or 'acquisitions-mergers."
  - *Low News:* An indicator equal to one if the firm is not classified as *High News*.
- *Positive Forecast Revisions (Pos ForRev) - Mergers:* An indicator equal to one if an analyst's earnings forecast is greater than their previous forecast. Forecasts include all one-year ahead, two-year ahead, and three-year ahead earnings forecasts in the 60 days around merger announcements. (Source: IBES and SDC).
- *Positive Forecast Error (Pos ForErr):* An indicator equal to one if the realized earnings for some horizon after the event (e.g., retail buying frenzy or high investment) is greater than the consensus forecast in the quarter prior to the event. The sample includes all one-year-ahead,

two-year-ahead, and three-year-ahead earnings, but excludes earnings announced within one quarter of the event. (Source: IBES)

- *Positive Forecast Revisions (Pos ForRev):* An indicator equal to one if the IBES consensus forecast in the quarter after the event (e.g., retail buying frenzy or high investment) is greater than the consensus forecast in the quarter prior to the event. The sample includes all one-year-ahead, two-year-ahead, and three-year-ahead earnings, but excludes earnings announced within one quarter of the event. (Source: IBES)
- *Managerial Ability:* We use the variable *MA_SCORE_2022_RANK* available at (https://peterdemerjian.weebly.com/managerialability.html) and described in greater detail in Demerjian, Lev, and McVay (2012).
    - *Low Ability:* An indicator equal to one if *MA_SCORE_2022_RANK* is less than 0.50, and zero otherwise.
- *Low Ability Returns:* An indicator equal to one if the firm's industry-adjusted returns in the prior two to five years are below the median.



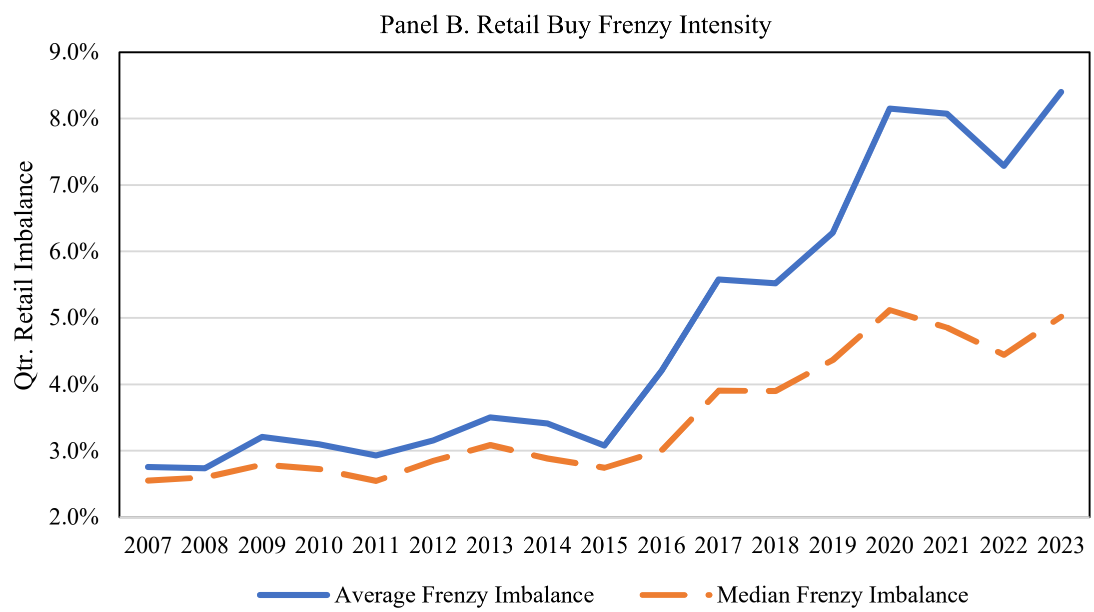


Figure 1. Retail Frenzies by Year

The plot in Panel A shows the mean of *Retail Buy Frenzy* and *Retail Sell Frenzy* for each year of the sample, where *Retail Buy Frenzy* is an indicator equal to one if the quarterly retail imbalance exceeds 2% of shares outstanding, and *Retail Sell Frenzy* is an indicator equal to one when the quarterly retail imbalance is less than -2% of shares outstanding. In Panel B, the plot shows the average and median *Quarterly Retail Imbalance* for each year of the sample for the subset of stocks that experience a *Retail Buy Frenzy*.

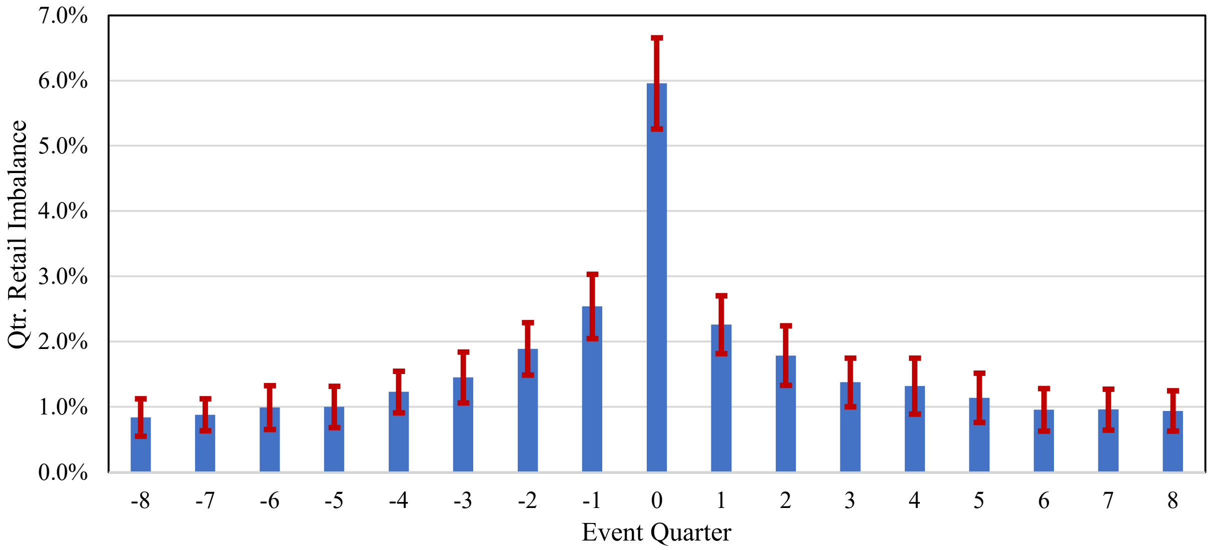


Figure 2. Frenzy Persistence

This figure plots the average *Quarterly Retail Imbalance* in event time, where quarter 0 represents a buying frenzy event. Negative quarters denote periods leading up to the frenzy, while positive quarters represent subsequent periods. Quarter -1 (1) is the quarter immediately preceding (following) the event. The error bars show 95% confidence intervals, with standard errors clustered by firm and quarter.

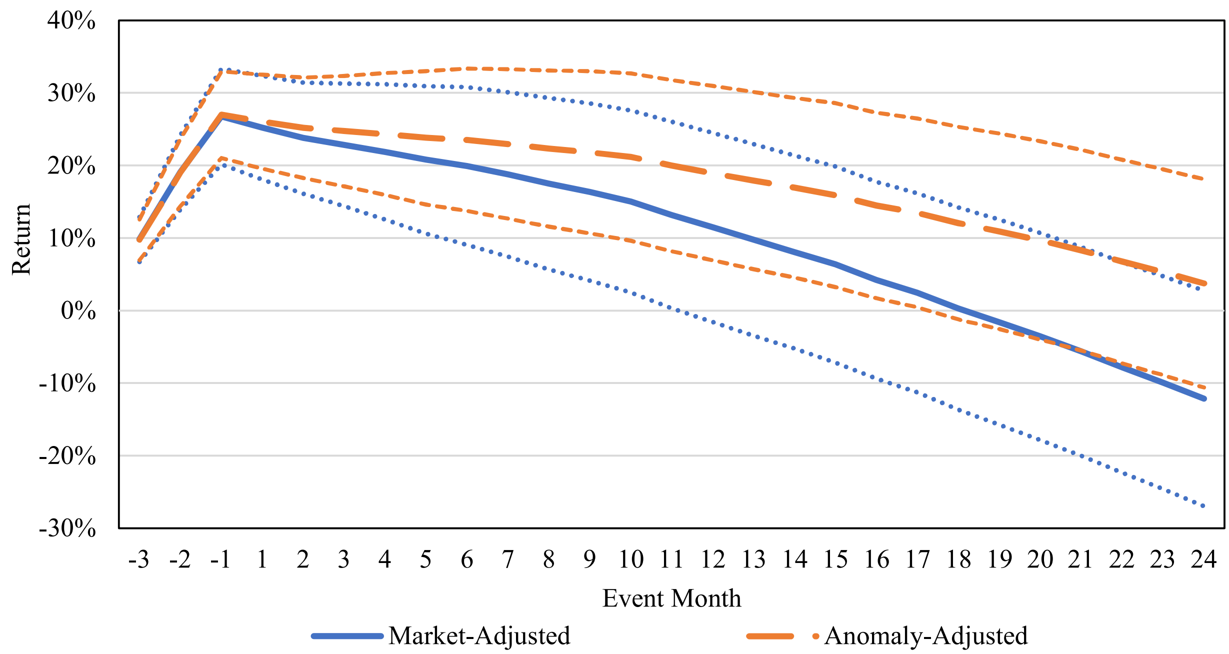


Figure 3. Cumulative Returns around Retail Frenzies

This figure plots the cumulative market-adjusted and anomaly-adjusted returns from month *t-3* to *t+24* following a retail frenzy, where months *t-3* to *t-1* are the returns in the period during which the retail frenzy occurs (i.e., contemporaneous returns). The dotted lines represent 95% confidence intervals computed from standard errors clustered by firm and month.

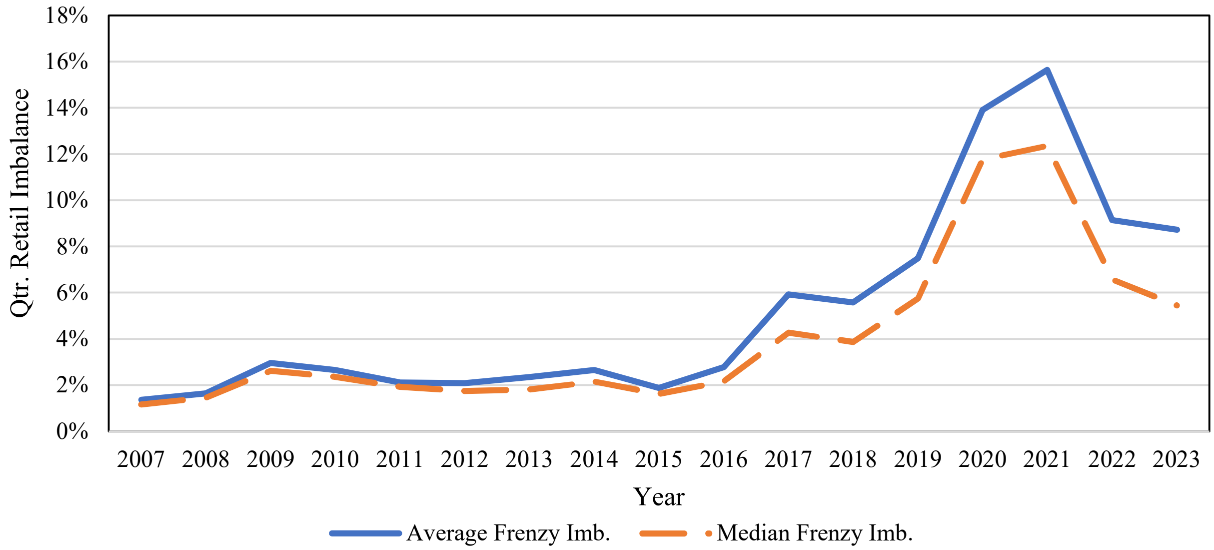


Figure 4. Relative Frenzy Intensity by Year

This figure plots the average and median *Quarterly Retail Imbalance* each year in the sample for the subset of stocks that are classified as having experienced a *Relative Retail Frenzy*, defined as a *Quarterly Retail Imbalance* that is in the top 1.3% of the distribution relative to all firms in that month.

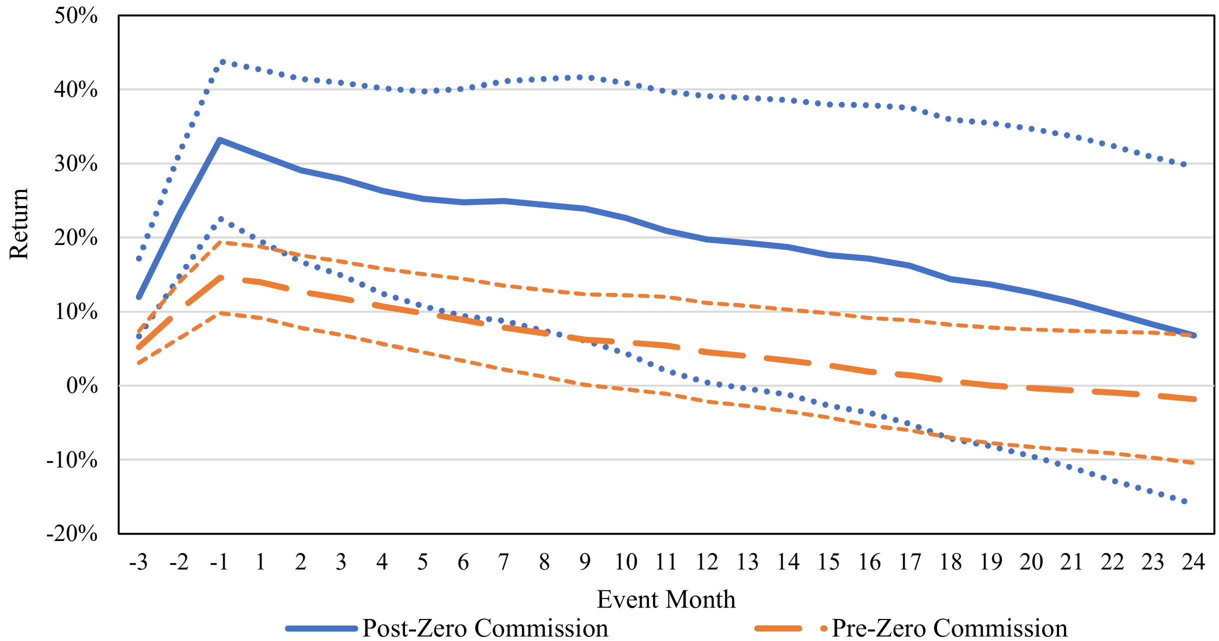
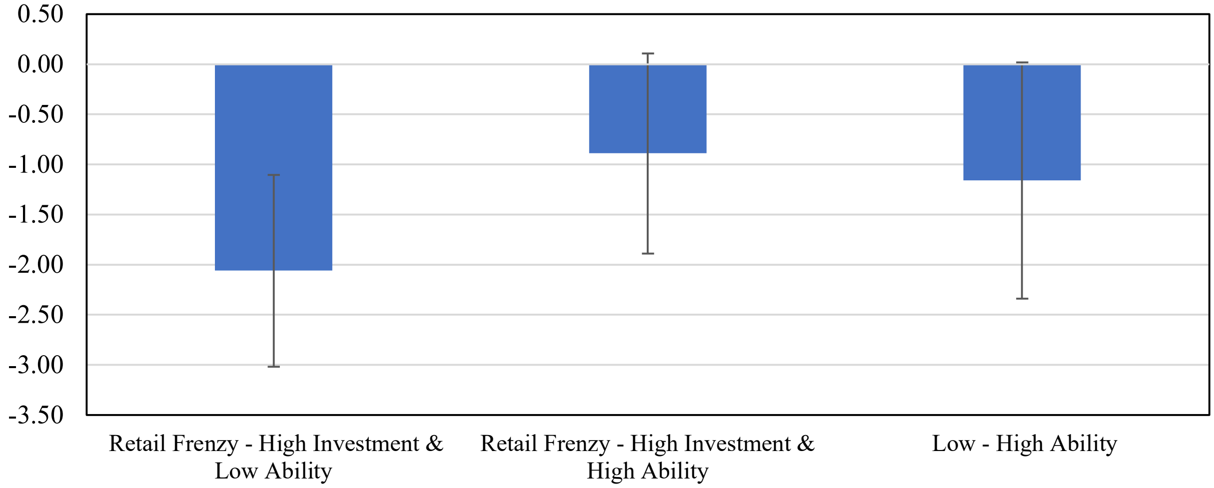


Figure 5. Cumulative Returns around Retail Frenzies: Pre vs. Post Zero Commission Trading
This figure plots the cumulative anomaly-adjusted returns from month *t-3* to *t+24* following a *Relative Retail Frenzy*. We repeat the analysis in Figure 3 after replacing *Retail Frenzy* with *Relative Retail Frenzy* × *Pre*-Zero Commission and *Relative Retail Frenzy* × *Post*-Zero Commission. *Relative Retail Frenzy* is an indicator equal to one if *Quarterly Retail Imbalance* is in the top 1.3% of the distribution relative to all firms in the same calendar month. *Pre-Zero Commission* is an indicator equal to one for the 2007-2016 sample period and zero otherwise, and *Post Zero Commission* is an indicator equal to one for the 2017-2023 sample period and zero otherwise. The dotted lines report the 95% confidence intervals computed from standard errors clustered by firm and month.

Panel A. Calendar Time Returns around Large Investments Preceded by Retail Frenzies by Managerial Ability



Panel B. Earnings Surprises and Large Investment Preceded by Retail Frenzies by Managerial Ability

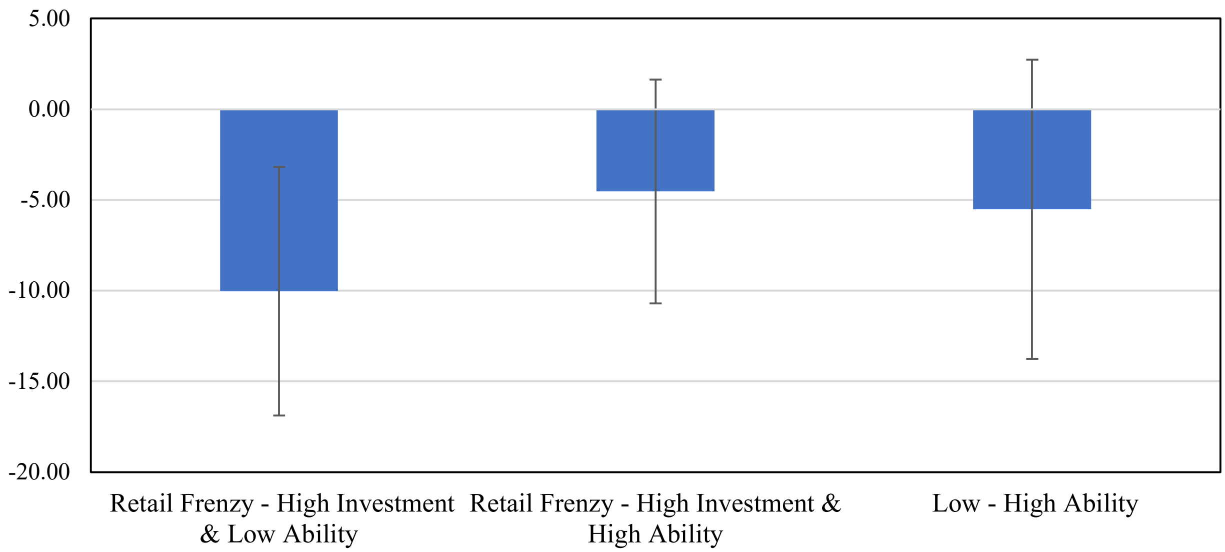


Figure 6. Performance of Large Investments Preceded by Retail Frenzies: The Role of Managerial Ability
Panel A reports the 6-factor alphas from calendar time portfolios for the *Retail Frenzy – High Investment* portfolio (as described in Table 9), after partitioning the sample into firms led by high versus low ability managers. Panel B reports the estimates of earnings surprises from Table 11 after further splitting the *Retail Frenzy* × *High Investment* portfolio into two portfolios based on managerial ability. In both panels, we measure managerial ability using the managerial ability measure of Demerjian, Lev, and McVay (2012), which captures a manager's ability to efficiently generate revenue. The coefficients are reported as blue bars, and the 95% confidence intervals as error bars.

Table 1. Summary Statistics

This table reports summary statistics for the main variables used throughout the analysis. Detailed variable definitions are provided in Appendix A. All firm characteristics without subscripts are computed in the month prior to the start of the construction of *Qtr. Retail Imbalance.* The sample includes 664,229 firm-month observations from January 2007 through December 2023.

Variable	Mean	Std Dev	1%	25%	50%	75%	99%
Qtr. Retail Imbalance	0.05%	1.03%	-1.05%	-0.13%	-0.03%	0.07%	2.51%
Retail Frenzy	1.31%	11.36%	0.00%	0.00%	0.00%	0.00%	100.00%
Q	2.01	1.63	0.61	1.05	1.42	2.26	10.16
ROA	-1.07%	6.54%	-34.31%	-0.86%	0.40%	1.72%	9.94%
$Ret_{t-3\ t-1}$	1.86%	25.27%	-60.82%	-11.57%	0.93%	13.10%	100.45%
$Ret_{t-12,\ t-4}$	6.87%	46.20%	-79.09%	-20.02%	2.52%	24.96%	205.36%
Assets	6,871	21,533	9	198	890	3,599	148,629
Leverage	22.02%	21.85%	0.00%	3.42%	16.45%	34.23%	98.45%
Div Yield	1.11%	1.91%	0.00%	0.00%	0.00%	1.72%	10.39%
Volatility	3.00%	2.10%	0.66%	1.60%	2.40%	3.71%	12.33%
Short Interest	473.47%	540.60%	0.68%	108.93%	281.60%	641.55%	2718.94%
Asset Growth	15.83%	48.60%	-48.62%	-2.83%	5.26%	17.45%	305.51%
Inst Ownership	45.06%	37.89%	0.00%	0.00%	47.09%	82.34%	100.00%
Δ Inst Ownership	0.10%	5.34%	-11.96%	-0.51%	0.00%	0.70%	13.35%
MFFlow (Outflows)	-0.57	0.91	-5.56	-0.68	-0.27	-0.04	0.00
Flow to Volume (Outflows)	-0.55	0.87	-5.27	-0.67	-0.27	-0.04	0.00
Flow to Volume (Inflows)	0.57	0.92	0.00	0.05	0.24	0.66	5.37
Shareholders	7.68	25.39	0.00	0.06	0.37	2.90	185.00
Net Anomaly Score	-3.59	16.30	-44.00	-15.00	-2.00	8.00	31.00
WSB Coverage	0.10	0.73	0.00	0.00	0.00	0.00	3.00
SA Coverage	0.33	1.10	0.00	0.00	0.00	0.00	6.00
KZ Index	-21.51	74.74	-515.99	-13.37	-3.11	0.38	10.19
Financing Sensitivity	0.01	0.10	-0.42	0.00	0.00	0.01	0.50
$Equity\ Issuance_{t+1}$	4.87%	21.52%	0.00%	0.00%	0.00%	0.00%	100.00%
$Capital\ Expenditures_{t+1}$	6.33%	9.71%	-0.01%	1.86%	3.86%	7.35%	45.61%
$Acquisitions_{t+1}$	5.25%	25.82%	-2.70%	0.00%	0.00%	0.00%	196.14%

Table 2. Determinants of Retail Frenzies

This table reports estimates from Equation (1) of the paper. The dependent variable, *Retail Frenzy*, is an indicator equal to one if the quarterly retail imbalance is greater than 2% of shares outstanding. Detailed variable definitions for the controls are available in Appendix A, and all continuous control variables are standardized to have a mean of zero and unit variance. FE denotes either month fixed effects (Specification 1), month × Fama-French 49 industry fixed effects (Specification 2), or month × Fama-French 49 industry fixed effects and firm fixed effects (Specification 3). Standard errors are clustered by firm and month, and *t*-statistics are reported in parentheses.

	[1]	[2]	[3]
Q	-0.48%	-0.47%	-0.15%
	(-7.85)	(-7.10)	(-1.61)
ROA	-1.06%	-1.08%	-0.45%
	(-11.27)	(-10.84)	(-5.40)
$Ret_{t-3\ t-1}$	-0.04%	-0.06%	0.08%
	(-0.70)	(-1.01)	(1.62)
$Ret_{t-12,\ t-4}$	0.05%	0.00%	0.11%
	(0.73)	(0.02)	(2.08)
Log (Assets)	-0.82%	-0.92%	-2.38%
	(-8.81)	(-9.25)	(-8.31)
Leverage	0.08%	0.09%	0.38%
	(1.68)	(1.66)	(3.97)
Div Yield	0.05%	0.03%	-0.02%
	(1.49)	(0.74)	(-0.52)
Log (*Volatility*)	0.74%	0.78%	0.69%
	(11.90)	(13.06)	(12.79)
Short Interest	0.99%	1.03%	1.25%
	(13.77)	(14.18)	(14.01)
Asset Growth	-0.04%	-0.02%	-0.09%
	(-0.70)	(-0.31)	(-1.79)
Inst Ownership	-0.59%	-0.55%	-0.39%
	(-9.33)	(-8.98)	(-6.04)
Δ Inst Ownership	-0.04%	-0.04%	-0.04%
	(-1.44)	(-1.69)	(-1.55)
Fire Sale (Flow-to-Volume)	-0.20%	-0.24%	0.03%
	(-3.97)	(-4.29)	(0.87)
Fire Purchase (Flow-to-Volume)	0.01%	0.01%	(0.00)
	(0.23)	(0.20)	(2.35)
Log (CSHR)	0.33%	0.36%	0.14%
	(7.29)	(7.05)	(1.37)
Net Anomaly Score	-0.02%	0.02%	-0.02%
	(-0.50)	(0.46)	(-0.40)
Log (1+WSB Posts)	0.27%	0.28%	0.22%
	(3.74)	(3.93)	(3.63)
Log (1+SA Coverage)	0.44%	0.50%	0.30%
	(9.75)	(10.60)	(7.16)
Constrained	0.10%	0.08%	0.02%
	(2.52)	(2.17)	(0.51)
Capital Sensitive	0.31%	0.31%	0.05%
	(3.68)	(3.69)	(0.61)
Time FE	Yes	Absorb	Absorbed
Ind × Time FE	No	Yes	Yes
Firm FE	No	No	Yes
Obs. (Firm-Months)	664,229	664,229	664,229
R-squared	5.41%	7.33%	17.34%

Table 3. Event Time Returns around Retail Frenzies

This table reports the estimates from Equation (2):

$$Ret_{i,t+x} = \alpha + \beta_1 \text{Retail Frenzy}_{i,t} + Time_t + \varepsilon_{i,t+x}.$$

The dependent variable is either the market-adjusted return (Specifications [1] and [2]) or the anomaly-adjusted return (Specifications [3] and [4]) on the stock in month t+x, where x varies from -3 to +24. The construction of anomaly-adjusted returns is described in greater detail in Appendix A. The returns from -3 to -1 test the relation between retail frenzies and returns during the period in which the retail buying frenzy occurs (contemporaneous returns), and the returns from +1 to +24 measure the relation between retail frenzies and monthly returns over each of the subsequent 24 months. Time denotes month fixed effects. Standard errors are clustered by firm and month, and *t*-statistics are reported in parentheses next to the estimates.

	Market-Adjusted Returns		Anomaly-Adjusted Returns	
	[1]	[2]	[3]	[4]
Event Month	Estimate	*t*-stat	Estimate	*t*-stat
-3	9.81%	(6.20)	9.76%	(6.79)
-2	9.27%	(5.73)	9.30%	(6.36)
-1	7.69%	(5.07)	7.95%	(5.81)
1	-1.53%	(-1.42)	-1.03%	(-1.06)
2	-1.56%	(-1.54)	-0.97%	(-1.07)
3	-1.42%	(-1.51)	-0.84%	(-1.03)
4	-0.95%	(-0.96)	-0.44%	(-0.52)
5	-0.96%	(-0.98)	-0.42%	(-0.50)
6	-1.08%	(-1.13)	-0.50%	(-0.59)
7	-0.86%	(-0.98)	-0.28%	(-0.37)
8	-1.15%	(-1.35)	-0.58%	(-0.79)
9	-1.31%	(-1.61)	-0.65%	(-0.96)
10	-1.13%	(-1.49)	-0.50%	(-0.79)
11	-1.31%	(-1.76)	-0.66%	(-1.06)
12	-1.86%	(-2.55)	-1.19%	(-1.98)
13	-1.70%	(-2.36)	-1.03%	(-1.76)
14	-1.72%	(-2.27)	-1.02%	(-1.64)
15	-1.69%	(-2.48)	-1.00%	(-1.79)
16	-1.71%	(-2.43)	-1.02%	(-1.78)
17	-2.15%	(-3.47)	-1.43%	(-2.92)
18	-1.97%	(-3.18)	-1.25%	(-2.64)
19	-2.17%	(-3.44)	-1.42%	(-2.75)
20	-1.89%	(-3.17)	-1.15%	(-2.47)
21	-2.04%	(-3.33)	-1.35%	(-2.93)
22	-2.21%	(-4.21)	-1.55%	(-4.07)
23	-2.11%	(-4.07)	-1.49%	(-3.81)
24	-2.18%	(-4.14)	-1.54%	(-3.83)

Table 4. Retail Frenzies and Equity Issuance

This table reports estimates from Equation (3) of the paper. The dependent variable, *Equity Issuance*, is an indicator equal to one if equity issuance exceeds 3% of total market capitalization. *Retail Frenzy* is an indicator equal to one if the firm experienced a retail buying frenzy in the prior quarter. Detailed variable definitions for the controls are available in Appendix A, and continuous control variables are standardized to have a mean of zero and unit variance. We report the regression estimates using either linear probability models ([1] and [2]) or odds ratios from a logistic regression ([3] and [4]). Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

	Equity Issuance (LPM)		Equity Issuance (Logistic)	
	[1]	[2]	[3]	[4]
Retail Frenzy	11.20%	4.47%	1.92	1.69
	(9.89)	(4.94)	(7.50)	(4.33)
Q	1.02%	2.85%	1.07	1.43
	(6.82)	(13.07)	(3.08)	(11.50)
ROA	-3.58%	-1.63%	0.67	0.77
	(-18.51)	(-10.43)	(-24.15)	(-10.95)
$Ret_{t-3\ t-1}$	3.13%	2.56%	1.85	1.69
	(5.90)	(6.76)	(7.90)	(6.15)
$Ret_{t-12,\ t-4}$	0.73%	-0.19%	1.22	1.05
	(3.31)	(-1.01)	(5.76)	(0.97)
Log (Assets)	-0.26%	0.35%	0.94	0.83
	(-1.87)	(0.74)	(-1.88)	(-1.24)
Leverage	0.04%	0.53%	1.03	1.11
	(0.37)	(3.66)	(1.49)	(3.27)
Div Yield	0.32%	0.23%	1.05	1.02
	(4.69)	(2.42)	(2.57)	(0.99)
Log (*Volatility*)	1.41%	1.28%	1.37	1.22
	(11.95)	(10.41)	(13.40)	(6.39)
Short Interest	0.10%	0.35%	1.01	1.08
	(1.03)	(2.66)	(0.66)	(3.10)
Asset Growth	-0.03%	-0.40%	0.96	0.92
	(-0.35)	(-3.64)	(-2.74)	(-3.31)
Inst Ownership	-0.69%	-1.02%	0.84	0.79
	(-6.69)	(-8.78)	(-6.98)	(-8.35)
Δ Inst Ownership	0.01%	-0.09%	1.01	0.99
	(0.14)	(-1.01)	(0.57)	(-0.29)
Fire Sale (Flow-to-Volume)	-0.40%	-0.07%	0.89	0.97
	(-2.88)	(-0.55)	(-2.27)	(-0.77)
Fire Purchase (Flow-to-Volume)	-0.24%	-0.02	0.86	0.96
	(-1.83)	(-0.13)	(-2.92)	(-1.08)
Log (CSHR)	0.27%	-0.54%	1.06	0.93
	(3.34)	(-3.07)	(2.09)	(-1.68)
Net Anomaly Score	-1.61%	-0.79%	0.63	0.83
	(-13.36)	(-9.52)	(-22.81)	(-9.33)
Log (1+WSB Posts)	-0.09%	-0.10%	0.99	0.98
	(-1.78)	(-2.13)	(-0.49)	(-1.14)
Log (1+SA Coverage)	0.09%	0.10%	1.02	1.02
	(1.29)	(1.21)	(0.99)	(1.11)
Constrained	1.26%	2.08%	1.21	1.41
	(6.49)	(8.07)	(4.99)	(7.57)
Capital Sensitive	1.25%	-0.52%	1.30	0.92
	(7.58)	(-2.87)	(7.46)	(-2.08)
Obs. (Firm - Quarter)	209,308	209,308	209,308	209,308
Time × Industry FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes

Table 5. Retail Frenzies and Investment

This table repeats the analysis in Specifications 1 and 2 of Table 4, after replacing *Equity Issuance* with *Investment*. *Investment* is either capital expenditures (CAPX) or acquisitions, with both measures scaled by fixed assets in the prior quarter. *Retail Frenzy* is an indicator equal to one if the firm experienced a retail buy frenzy in the prior quarter. All other variables are defined as in Table 4, and more detailed variable definitions are available in Appendix A. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

	CAPX		Acquisitions	
	[1]	[2]	[3]	[4]
Retail Frenzy	1.29%	1.26%	2.63%	1.88%
	(3.11)	(3.59)	(4.14)	(3.34)
Q	1.03%	1.23%	-0.04%	1.48%
	(8.19)	(11.41)	(-0.35)	(9.05)
ROA	-0.12%	-0.14%	0.67%	0.18%
	(-1.53)	(-1.89)	(5.36)	(1.82)
$Ret_{t-3\ t-1}$	1.20%	0.90%	1.16%	-0.16%
	(7.15)	(6.27)	(3.83)	(-0.61)
$Ret_{t-12,\ t-4}$	1.52%	1.32%	1.88%	0.95%
	(10.36)	(10.76)	(6.33)	(3.74)
Log (Assets)	-0.49%	0.15%	1.55%	6.91%
	(-4.35)	(0.77)	(7.61)	(9.73)
Leverage	-0.28%	-0.90%	-0.03%	-1.71%
	(-3.39)	(-10.07)	(-0.22)	(-9.17)
Div Yield	-0.39%	0.00%	-1.02%	-0.35%
	(-8.97)	(-0.02)	(-9.10)	(-3.68)
Log (*Volatility*)	0.05%	-0.09%	-0.44%	0.21%
	(0.84)	(-2.15)	(-3.55)	(1.67)
Short Interest	0.19%	0.01%	0.29%	0.13%
	(4.60)	(0.30)	(2.36)	(1.12)
Asset Growth	0.78%	0.57%	0.71%	0.04%
	(13.14)	(10.12)	(8.02)	(0.52)
Inst Ownership	-0.07%	-0.18%	0.12%	-0.17%
	(-1.34)	(-2.53)	(0.85)	(-1.08)
Δ Inst Ownership	0.10%	0.10%	0.12%	0.12%
	(4.30)	(4.18)	(1.72)	(1.94)
Fire Sale (Flow-to-Volume)	-0.33%	-0.03%	0.59%	0.14%
	(-4.46)	(-0.59)	(2.34)	(0.55)
Fire Purchase (Flow-to-Volume)	-0.31	-0.02	0.79	0.25
	(-4.06)	(-0.42)	(3.44)	(1.25)
Log (CSHR)	-0.17%	-0.06%	-0.80%	-1.08%
	(-3.44)	(-0.55)	(-5.64)	(-3.67)
Net Anomaly Score	-0.46%	-0.32%	-0.44%	0.43%
	(-7.61)	(-7.38)	(-3.51)	(3.52)
Log (1+WSB Posts)	-0.01%	-0.03%	-0.14%	-0.02%
	(-1.15)	(-1.66)	(-1.77)	(-0.36)
Log (1+SA Coverage)	0.07%	0.00%	-0.27%	0.24%
	(2.00)	(0.13)	(-2.89)	(2.70)
Constrained	-1.83%	-1.35%	-2.92%	-2.30%
	(-15.10)	(-14.86)	(-13.83)	(-11.47)
Capital Sensitive	0.44%	0.20%	0.99%	0.39%
	(4.71)	(2.42)	(4.90)	(2.32)
Obs. (Firm - Quarter)	209,308	209,308	209,308	209,308
Time × Industry FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes

Table 6. Retail Frenzies: Equity Issuance and Investment – Robustness

This table reports the sensitivity of our baseline estimates from Tables 4 and 5 to different research design choices. For reference, Row 1 reports the baseline estimate for equity issuance (Specifications 1 and 2 of Table 4), capital expenditures (Specifications 1 and 2 of Table 5), and acquisitions (Specifications 3 and 4 of Table 5). Rows 2 through 4 report the results from matched samples where we match on industry, quarter, and two other matching variables, requiring the matched variables to be in the same quintile. Thus, these regressions include industry × quarter × first matching variable quintile × second matching variable quintile fixed effects. Row 5 reports the results after matching retail frenzy firms to a non-frenzy firm with the closest propensity score (i.e., nearest neighbor matching), where the propensity scores are the predicted values from Specification 2 of Table 2, and Row 6 reports the results after matching by industry, quarter, and quintile indicators for each of the first three lags of the dependent variable. In Rows 7-9, we define retail frenzy as an indicator equal to one if the quarterly retail imbalance is greater than 1%, 3%, or 5% of shares outstanding, respectively. In Row 10, we define retail frenzy as an indicator if the retail imbalance in the prior quarter is in the top 1.3% of the distribution relative to other firms in the same month. In Row 11, we sign retail trades using the methodology of Boehmer, Jones, Zhang, and Zhang (2021), and Row 12 defines retail frenzies based on retail imbalances over the prior four to six months. In Rows 13 and 14, we repeat the analysis after excluding the COVID period (2020 and 2021) or excluding small firms (assets < 50 million). Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

	Exclude Firm FE			Include Firm FE		
	Equity Issuance	CAPX	Acquisitions	Equity Issuance	CAPX	Acquisitions
	[1]	[2]	[3]	[4]	[5]	[6]
1. Baseline Results	11.20%	1.29%	2.63%	4.47%	1.26%	1.88%
	(9.89)	(3.11)	(4.14)	(4.94)	(3.59)	(3.34)
Panel A: Alternative Fixed Effects/Matching						
2. Match on Time - Ind - Size - Q	10.39%	1.23%	1.84%	6.13%	1.20%	1.59%
	(8.56)	(2.87)	(2.90)	(6.09)	(2.88)	(2.46)
3. Match on Time - Ind - Size - Past Return	9.65%	1.60%	2.32%	5.30%	1.31%	2.01%
	(8.99)	(3.47)	(3.73)	(5.91)	(3.08)	(3.25)
4. Match on Time - Ind -ROA- Asset Growth	11.10%	0.95%	1.74%	6.29%	0.81%	1.64%
	(9.02)	(2.34)	(3.03)	(6.02)	(1.99)	(2.88)
5. Match on Time - Ind -Propensity Score	10.04%	1.77%	2.36%	5.22%	1.31%	1.99%
	(9.08)	(4.01)	(3.47)	(5.49)	(3.39)	(2.92)
6 Match on Time - Ind -Lag Y (3 Lags)	10.70%	1.26%	2.20%	7.22%	1.11%	1.96%
	(7.60)	(2.70)	(2.55)	(6.10)	(2.42)	(2.51)
Panel B: Alternative Frenzy Definitions						
7. >1% Imbalance	7.64%	0.96%	1.05%	2.72%	0.85%	0.83%
	(9.90)	(4.07)	(2.83)	(4.41)	(3.78)	(2.22)
8. >3% Imbalance	14.14%	1.92%	2.77%	6.06%	1.97%	1.35%
	(9.25)	(2.81)	(3.32)	(4.84)	(3.88)	(1.76)
9. >5% Imbalance	16.34%	2.43%	3.75%	6.72%	2.51%	1.95%
	(6.35)	(2.21)	(2.97)	(3.14)	(2.83)	(1.69)
10. Relative Frenzy	8.38%	1.49%	0.97%	3.07%	1.40%	0.61%

	(6.98)	(3.81)	(1.40)	(3.57)	(4.38)	(0.98)
11. BJZZ Measure	10.64%	0.88%	1.72%	4.35%	0.87%	1.03%
	(8.24)	(2.12)	(2.64)	(4.70)	(2.54)	(2.02)
12. Lag Frenzy	8.36%	0.69%	1.31%	2.33%	0.70%	1.08%
	(7.84)	(2.05)	(2.22)	(2.64)	(2.10)	(1.98)
Panel C: Alternative Samples						
13. Exclude Covid (2020 & 2021)	9.41%	0.92%	1.90%	3.03%	1.18%	1.39%
	(7.17)	(2.30)	(3.18)	(2.80)	(3.22)	(2.66)
14. Exclude small firms (assets < 50 billion)	11.61%	1.40%	2.69%	4.91%	1.00%	2.11%
	(6.86)	(2.99)	(2.61)	(3.86)	(2.31)	(2.40)

Table 7. Retail Frenzies and Corporate Decisions – Pre vs. Post Zero Commission Trading

We repeat the equity issuance regressions (Table 4) and investment regressions (Table 5) after replacing *Retail Frenzy* with *Relative Retail Frenzy × Pre Zero Commissions* and *Relative Retail Frenzy × Post Zero Commissions*. *Relative Retail Frenzy* is an indicator equal to one if retail imbalances in the prior quarter are in the top 1.3% of the distribution relative to all firms in the same calendar month. *Pre-Zero Commissions* is an indicator equal to one for the 2007-2016 sample period and zero otherwise, while *Post Zero Commissions* is an indicator equal to one for the 2017-2023 sample period and zero otherwise. All other details are identical to Tables 4 and 5. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses. Below the regression estimates, we also test whether the estimates on the *Retail Frenzy × Post Zero Commissions* and *Retail Frenzy × Pre Zero Commissions* are significantly different from each other.

	Equity Issuance	CAPX	Acquisitions	Equity Issuance	CAPX	Acquisitions
	[1]	[2]	[3]	[4]	[5]	[6]
Relative Frenzy × Post Zero Commission	15.25%	1.71%	4.08%	5.66%	1.51%	2.31%
	(6.93)	(2.11)	(3.36)	(3.30)	(2.36)	(1.97)
Relative Frenzy × Pre Zero Commission	3.61%	1.35%	-1.10%	1.40%	1.34%	-0.45%
	(3.46)	(3.45)	(-1.61)	(1.46)	(3.72)	(-0.67)
Difference	11.63%	0.36%	5.18%	4.25%	0.17%	2.76%
	(4.71)	(0.39)	(3.65)	(2.12)	(0.23)	(2.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
Obs. (Firm-Quarters)	209,308	209,308	209,308	209,308	209,308	209,308

Table 8. Retail Frenzies and Profitability

This table reports estimates of earnings surprises or earnings revisions on the retail frenzy indicator and other controls. In Specification 1 the dependent variable is *Positive Forecast Error (Pos ForErr),* an indicator equal to one if the realized earnings exceed the median I/B/E/S analyst forecasted earnings. Analyst forecasts are measured in the month prior to the start of the retail buying frenzy, and realized earnings are measured at least one quarter after the end of the retail frenzy. Specifications 2 replaces *Pos ForErr* with *Positive Forecast Revision* (*Pos ForRev*), an indicator equal to one if the IBES consensus forecast in the quarter after the retail frenzy is greater than the consensus forecast in the quarter prior to the retail frenzy. Specifications 3 and 4 repeat the analysis after interacting *Retail Frenzy* with *Post Zero Commission* (*Post*), an indicator equal to one if the frenzy occurred in the post-zero commission era (2017-2023). The regression includes all the controls from Table 4, but in the interest of brevity, we omit the estimates on the coefficients of seven control variables that were insignificant in all four specifications: *Leverage, Fire Sale (Flow-to-Volume)*, *Fire Purchase (Flow-to-Volume), CSHR, WSB Posts*, *SA Coverage*, and *Capital Sensitive*. All independent variables are defined as in Table 4, and more detailed variable definitions are available in Appendix A. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses. The sample is limited to earnings surprises for one-year-ahead, two-year-ahead, and three-year-ahead earnings that are announced at least one quarter after the end of the retail frenzy quarter.

	Pos ForErr [1]	*Pos ForRev* [2]	*Pos ForErr* [3]	*Pos ForRev* [4]
Retail Frenzy	6.79%	6.78%	0.64%	0.99%
	(4.08)	(4.08)	(0.28)	(0.35)
Retail Frenzy × Post			9.97%	9.38%
			(2.77)	(2.47)
Q	0.10%	1.81%	0.12%	1.83%
	(0.26)	(4.67)	(0.30)	(4.69)
ROA	-1.80%	-1.45%	-1.78%	-1.43%
	(-5.27)	(-4.91)	(-5.22)	(-4.88)
$Ret_{t-3\ t-1}$	6.45%	9.40%	6.44%	9.39%
	(13.22)	(16.40)	(13.22)	(16.39)
$Ret_{t-12,\ t-4}$	2.59%	4.78%	2.60%	4.78%
	(5.36)	(9.83)	(5.37)	(9.84)
Log (Assets)	2.90%	4.49%	2.92%	4.51%
	(5.66)	(7.79)	(5.68)	(7.81)
Div Yield	-2.27%	-2.80%	-2.27%	-2.79%
	(-8.55)	(-13.95)	(-8.52)	(-13.85)
Log (*Volatility*)	-2.54%	-4.28%	-2.53%	-4.28%
	(-5.97)	(-10.33)	(-5.96)	(-10.33)
Short Interest	-2.04%	-1.74%	-2.02%	-1.72%
	(-6.40)	(-7.38)	(-6.34)	(-7.28)
Asset Growth	-1.10%	-1.02%	-1.10%	-1.02%
	(-5.93)	(-5.21)	(-5.91)	(-5.19)
Inst Ownership	1.38%	1.71%	1.38%	1.71%
	(4.82)	(6.81)	(4.83)	(6.81)
Δ Inst Ownership	-0.80%	-0.54%	-0.81%	-0.54%
	(-5.89)	(-3.44)	(-5.91)	(-3.45)
Net Anomaly Score	3.27%	0.83%	3.26%	0.82%
	(10.30)	(2.55)	(10.24)	(2.53)
Constrained	-1.44%	-1.02%	-1.44%	-1.01%
	(-2.29)	(-2.75)	(-2.28)	(-2.74)
Obs. (Firm – Quarter-Earnings Period)	350,192	350,192	350,192	350,192
Time × Industry FE	Yes	Yes	Yes	Yes

Table 9. Calendar Time Returns around Large Investments Preceded by Retail Frenzies

Panels A and B report the alphas and factor loadings for calendar-time strategies for three portfolios: *Retail Frenzy – Low Investment*, *Retail Frenzy – High Investment*, and the difference between the two portfolios (*High – Low Investment*). We classify a firm as *High Investment* if it had a large capital expenditure (*High CAPX*), defined as capital expenditures in the previous quarter that are in the top quartile across all firms and at least 50% larger than its average capital expenditures over the prior two to four quarters, or a large acquisition (*High AQC)*, defined as an acquisition that was at least 1% of total assets in the previous quarter. We classify a firm as *Retail Frenzy - High Investment* if it is classified as *High Investment* in the first quarter or second quarter after a retail frenzy, and all other retail frenzy stocks are classified as *Retail Frenzy – Low Investment*. We implement a calendar-time strategy where the weights in the *Retail Frenzy – High Investment* portfolio are equal to the number of months a stock has been classified as *Retail Frenzy – High Investment* over the previous 24 months, and we compute analogous returns for the *Retail Frenzy – Low Investment* portfolio. *High – Low* Investment reports the returns to going long the *Retail Frenzy - High Investment* and short *Retail Frenzy – Low Investment.* In Panels C and D, we replace *High Investment* with *High CAPX* and *High AQC,* respectively. Standard errors are computed from the time-series standard deviation, and *t*-statistics are reported in parentheses.

	Alpha	MKTRF	SMB	HML	UMD	CMA	RMW
Panel A: CAPM Alphas - All Investments							
Retail Frenzy – Low Investment	-1.55	1.56					
	(-2.19)	(12.35)					
Retail Frenzy – High Investment	-2.38	1.59					
	(-3.45)	(10.69)					
High - Low Investment	-0.83	0.03					
	(-2.69)	(0.46)					
Panel B: Six-Factor Alphas - All Investments							
Retail Frenzy – Low Investment	-0.61	1.28	1.34	-0.62	-0.29	1.02	-1.63
	(-1.28)	(11.98)	(3.75)	(-3.21)	(-2.07)	(2.42)	(-6.57)
Retail Frenzy – High Investment	-1.45	1.32	1.17	-0.81	-0.33	0.79	-1.60
	(-2.91)	(13.09)	(3.63)	(-3.69)	(-1.96)	(2.27)	(-6.56)
High - Low Investment	-0.84	0.04	-0.17	-0.19	-0.04	-0.23	0.03
	(-2.73)	(0.70)	(-0.93)	(-1.40)	(-0.33)	(1.05)	(0.25)
Panel C: Six-Factor Alphas - Capital Expenditures							
Retail Frenzy – Low CAPX	-0.67	1.29	1.34	-0.63	-0.30	1.02	-1.62
	(-1.44)	(12.04)	(3.80)	(-3.22)	(-2.15)	(2.46)	(-6.62)
Retail Frenzy – High CAPX	-1.33	1.32	1.17	-0.82	-0.22	0.78	-1.59
	(-2.27)	(12.29)	(3.02)	(-3.14)	(-1.01)	(1.98)	(-5.59)
High - Low CAPX	-0.65	0.04	-0.17	-0.19	0.08	-0.24	0.04
	(-1.70)	(0.53)	(-0.73)	(-1.08)	(0.49)	(-1.06)	(0.19)
Panel D: Six-Factor Alphas - Acquisitions							
Retail Frenzy – Low Acquisition	-0.63	1.29	1.32	-0.63	-0.28	0.98	-1.63
	(-1.33)	(12.12)	(3.70)	(-3.26)	(-1.98)	(2.37)	(-6.60)
Retail Frenzy – High Acquisition	-1.77	1.32	1.13	-0.82	-0.57	-0.86	-1.66
	(-3.55)	(11.44)	(4.03)	(-3.63)	(-3.26)	(2.34)	(-6.18)
High - Low Acquisition	-1.13	0.03	-0.20	-0.18	-0.29	-0.12	-0.03
	(-2.67)	(0.38)	(-0.78)	(-0.95)	(-2.00)	(-0.38)	(-0.12)

Table 10. Analyst Forecast Revisions around Frenzy Mergers

This table reports the results of regressing analyst-level earnings forecast revisions on merger and frenzy indicators. The dependent variable, *Positive Forecast Revision*, equals one if an analyst's earnings forecast is higher than the analyst's previous forecast for the same firm and fiscal period. The sample includes analyst forecasts for earnings announced one, two, and three fiscal years ahead, made within days [-30, +30] relative to the merger announcement (day 0). The primary independent variables are indicators for timing relative to the merger announcement: *Merger Week*: equals one if the forecast revision occurs in the five trading days following the merger announcement (days [0, +4]). *Frenzy* equals one if the merger follows a retail frenzy in the preceding quarter. Column (2) also includes indicator variables for forecasts made in the week before (*Merger Week* (–1)) and the week after (*Merger Week* (+1)) the merger, as well as their interactions with the Frenzy indicator. All regressions include merger fixed effects. Standard errors are clustered by merger, and *t*-statistics are reported in parentheses.

	[1]	[2]
Merger Week	5.97	6.31
	(14.84)	(14.88)
Merger Week × Frenzy	-11.84	-12.34
	(-3.17)	(-3.10)
Merger Week $_{t-1}$		0.09
		(0.20)
Merger Week $_{t-1}$ × *Frenzy*		-0.35
		(-0.07)
Merger Week $_{t+1}$		2.60
		(5.43)
Merger Week $_{t+1}$ × *Frenzy*		-3.82
		(-0.85)
Merger FE	Yes	Yes
Observation	438,079	438,079

Table 11. Earnings Surprises around Large Investments Preceded by Retail Frenzies

Specifications 1 reports the estimates from the following panel regression:

$$Pos\ ForErr_{i,t+x} = \alpha + \beta_1 Retail\ Frenzy_{i,t-1,t-2} + \beta_2 Retail\ Frenzy_{i,t-1,t-2} \times High\ Inv._{i,t} + \beta_3 Controls + FE + \varepsilon_{i,t+x}.$$

Positive Forecast Error (Pos ForErr) is an indicator equal to one if the realized earnings exceed the median I/B/E/S analyst forecasted earnings, where the analyst forecasts are measured in the month prior to the start of the investment and the realized earnings are measured at least one quarter after the investment. *Retail Frenzy × High Investment* and *High Investment* are defined as in Table 9. Specification 2 replaces *High Investment* with *High CAPX* and *High Acquisition*, as defined in Table 9. Specifications 3 and 4 repeat the analysis after replacing *Positive Forecast Error* with *Positive Forecast Revision (Pos ForRev*), an indicator equal to one if the IBES consensus forecast in the quarter after the investment is greater than the consensus forecast in the quarter prior to the investment. Controls include the same set of controls as Table 4. All independent variables are defined as in Table 4, and more detailed variable definitions are available in Appendix A. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses. The sample is limited to earnings surprises for one-year-ahead, two-year-ahead, and three-year-ahead earnings that are announced at least one quarter after the end of the investment quarter.

	Pos ForErr	*Pos ForErr*	*Pos ForRev*	*Pos ForRev*
	[1]	[2]	[3]	[4]
Retail Frenzy	5.56%	5.54%	5.66%	5.49%
	(3.56)	(3.59)	(4.54)	(4.46)
Retail Frenzy × High Investment	-6.12%		-7.45%	
	(-2.87)		(-3.67)	
High Investment	-0.89%		1.33%	
	(-2.39)		(4.26)	
Retail Frenzy × High Acquisition		-10.78%		-5.06%
		(-3.40)		(-1.67)
Retail Frenzy × High CAPX		-3.43%		-6.68%
		(-1.29)		(-2.82)
High Acquisition		-0.13%		2.10%
		(-0.28)		(5.14)
High CAPX		-1.82%		-0.09%
		(-4.10)		(-0.24)
Controls	Yes	Yes	Yes	Yes
Obs. (Firm - Quarter - Earnings Period)	350,192	350,192	350,192	350,192
Time × Industry FE	Yes	Yes	Yes	Yes

Table 12. Retail Frenzies and Investment – The Role of Managerial Ability

This table repeats the analysis in Table 5, after interacting *Retail Frenzy* with a *Low Ability* indicator. In Panel A, ability is measured using the managerial ability measure of Demerjian, Lev, and McVay (2012), which captures a manager's ability to efficiently generate revenue. In Panel B, we measure ability using the firm's industry adjusted returns over the prior two to five years. For both measures, we classify a manager as *Low Ability* if the manager is below the median. *Controls* include the full set of controls from Table 5 plus the *Low Ability* indicator, and FE denotes fixed effects listed below the regression estimates. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

Panel A: Revenue Efficiency Ability Measure				
	CAPX	Acquisitions	CAPX	Acquisitions
	[1]	[2]	[3]	[4]
Retail Frenzy	0.25%	0.79%	0.54%	-0.47%
	(0.41)	(0.93)	(0.98)	(-0.41)
Retail Frenzy × Low Ability	1.77%	4.89%	0.91%	5.37%
	(2.31)	(3.05)	(1.32)	(3.08)
Controls	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
Obs. (Firm-Quarters)	150,291	150,291	150,291	150,291

Panel B: Industry-Adjusted Performance Ability Measure				
	CAPX	Acquisitions	CAPX	Acquisitions
	[1]	[2]	[3]	[4]
Retail Frenzy	-0.15%	-0.88%	0.17%	-0.12%
	(-0.22)	(-0.82)	(0.25)	(-0.12)
Retail Frenzy × Low Ability	2.06%	4.57%	1.46%	2.68%
	(2.30)	(3.39)	(1.87)	(2.23)
Controls	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
Obs. (Firm-Quarters)	182,160	182,160	182,160	182,160

Table 13. Retail Frenzies and Investment – The Joint Role of Managerial Ability & Financial Constraints

This table repeats the analysis in Table 5, after interacting *Retail Frenzy* with measures of managerial ability and financial constraints. We define a manager as *Low Ability* if the manager is below the median in the managerial ability measure of Demerjian, Lev, and McVay (2012), and *High Ability* otherwise. We define a firm as constrained if it is in the top quintile of the KZ index relative to other firms in the same industry at the same point in time, and all other firms are classified as unconstrained. Thus, each firm is placed into one of four groups based on managerial ability (High vs. Low) and financial constraints (Constrained vs. Unconstrained), and we interact *Retail Frenzy* with indicators for each of the four groups. *Controls* include the full set of controls from Table 5 plus three of four indicators for ability and constraints (with *High Ability & Unconstrained* omitted), and FE denotes fixed effects listed below the regression estimates. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

	CAPX [1]	Acquisitions [2]	CAPX [3]	Acquisitions [4]
Retail Frenzy × Low Ability & Constrained	3.97%	9.16%	3.09%	7.78%
	(3.19)	(4.28)	(2.90)	(3.81)
Retail Frenzy × Low Ability & Unconstrained	0.52%	3.26%	0.27%	2.90%
	(0.95)	(1.67)	(0.44)	(1.83)
Retail Frenzy × High Ability & Constrained	0.87%	3.40%	1.16%	1.14%
	(0.70)	(2.18)	(1.06)	(0.56)
Retail Frenzy × High Ability & Unconstrained	0.04%	-0.52%	0.31%	-1.24%
	(0.06)	(-0.50)	(0.43)	(-1.01)
Controls	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
Obs. (Firm-Quarters)	150,291	150,291	150,291	150,291

Internet Appendix for:

Retail Trading Frenzies and Real Investment

In this appendix, we tabulate the results of robustness and supplementary analyses referenced in the paper. The set of figures and tables is as follows:

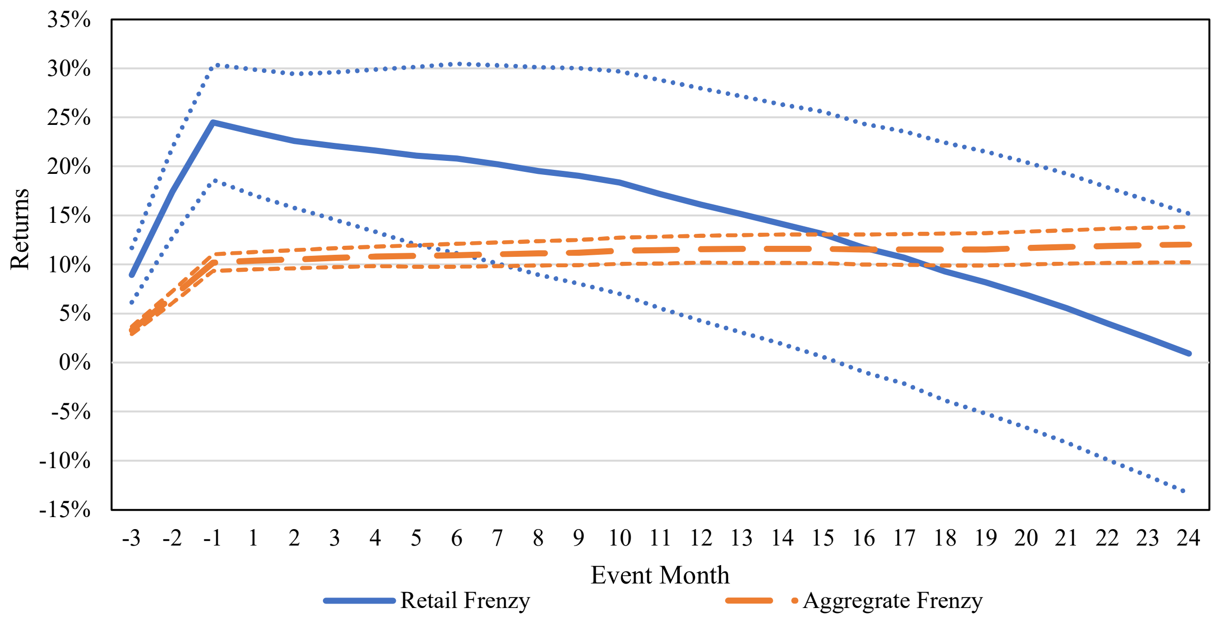


Figure IA1. Cumulative Returns around Retail and Aggregate Frenzies
This figure plots estimates from the following panel regression:

$$Ret_{i,t-3,t+x} = \alpha + \beta_1 Retail\ Frenzy_{i,t} + +\beta_2 Aggregate\ Frenzy_{\mathrm{i,t}} + Time_t + \varepsilon_{i,t}.$$

The dependent variable is the cumulative anomaly-adjusted return on the stock from month *t*-3 to month *t*+*x*, where *x* varies from -3 to +24. *Retail (Aggregate) Frenzy* is an indicator equal to one if quarterly retail (aggregate) imbalance is greater than 2% of shares outstanding. The dotted lines represent the 95% confidence intervals computed from standard errors clustered by firm and month.

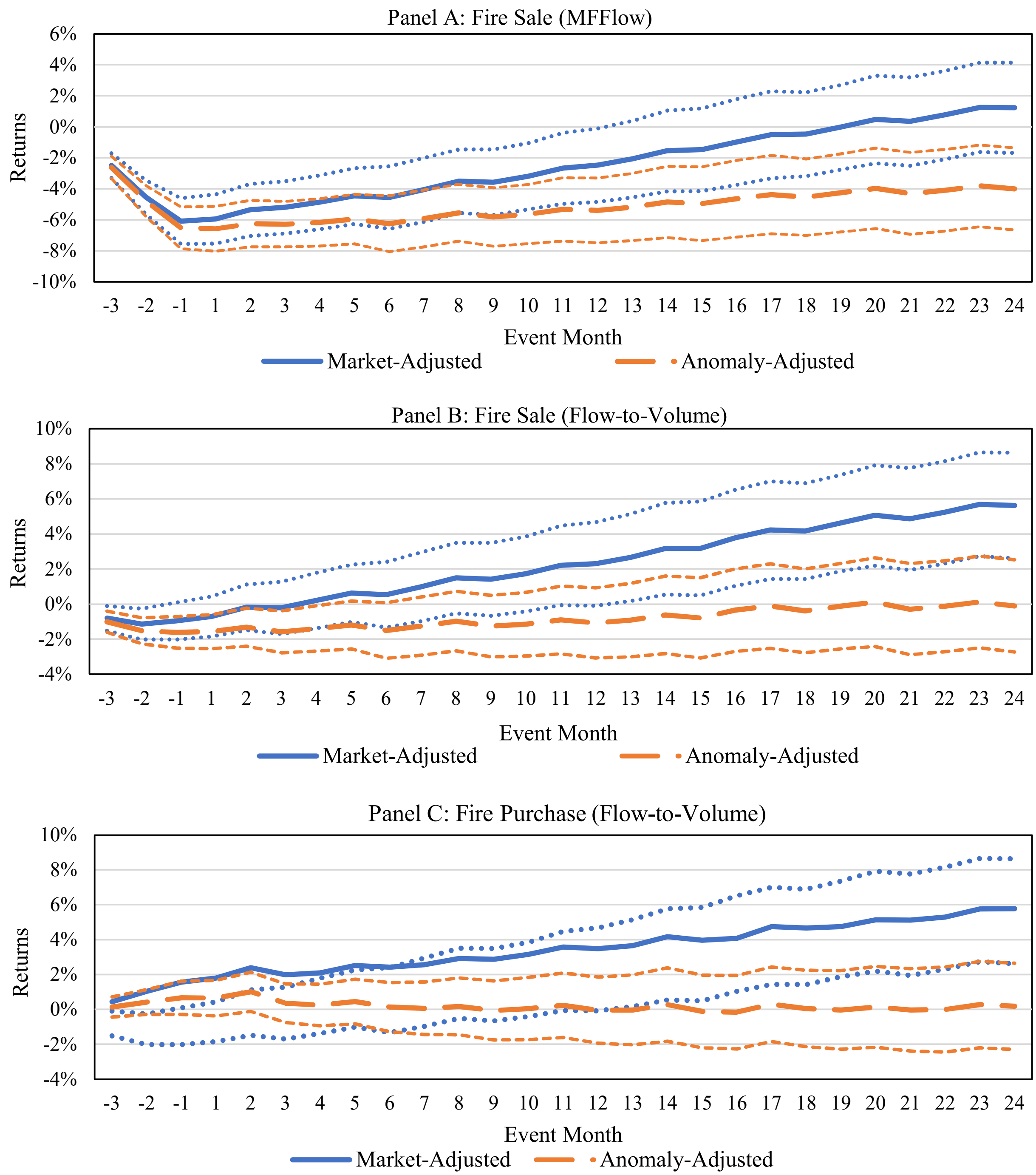


Figure IA2. Cumulative Returns around Mutual Fund Fire Sales and Fire Purchases

Panels A and B plot the cumulative market-adjusted and anomaly-adjusted returns from month *t-3* to *t+24* following mutual fund fire sales, where fire sales are measured from months *t-3* to *t*-1. We classify a firm as having experienced a fire sale if it is in the bottom decile of either *MFFlow* (Panel A) or *Flow-to-Volume* (Panel B). Panel C repeats Panel B after replacing fire sales with fire purchases. All measures are defined in more detail in Appendix A. The dotted lines report the 95% confidence intervals computed from standard errors clustered by firm and month.

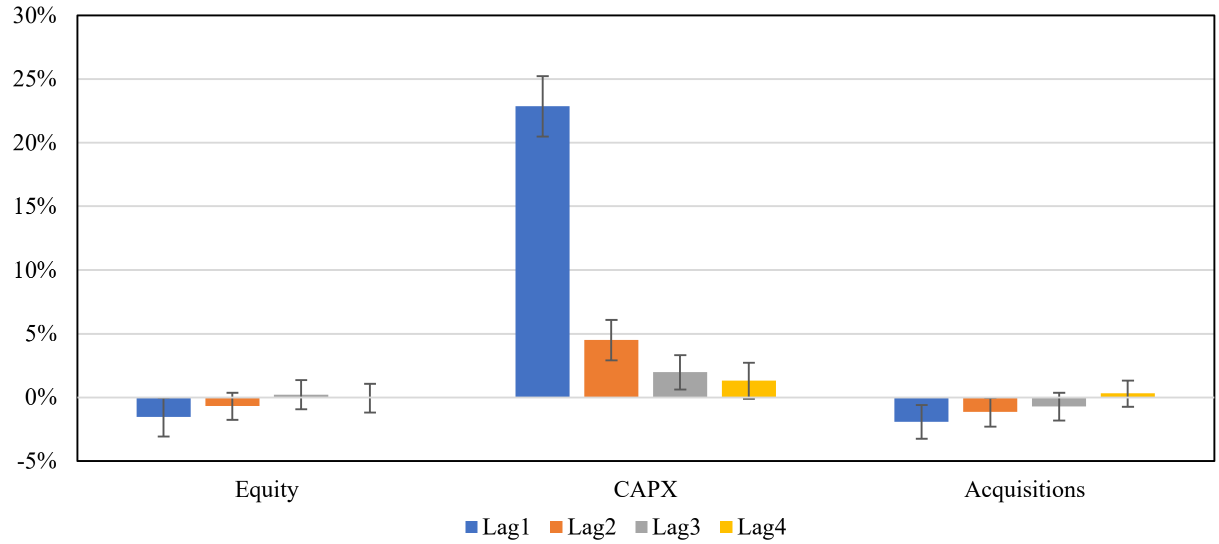


Figure IA3. Autocorrelation of Equity Issuance and Investment
This table reports the estimates β_3-β_6 from the following regression:

$$Y_{i,t+1} = \alpha + \beta_1 Retail\ Frenzy_{i,t} + \beta_2 Controls + \beta_3 Y_{i,t} + \beta_4 Y_{i,t-1} + \beta_5 Y_{i,t-2} + \beta_6 Y_{i,t-3} + FE + \varepsilon_{i,t+1},$$

where *Y* is either equal to equity issuance, capital expenditures, or acquisitions (as defined in Tables 4 and 5). *Retail Frenzy* and *Controls* are defined as in Table 4, and *FE* denotes industry × time fixed effects and firm fixed effects. The coefficients for each lag are reported as colored bars, and their 95% confidence intervals are shown as error bars.

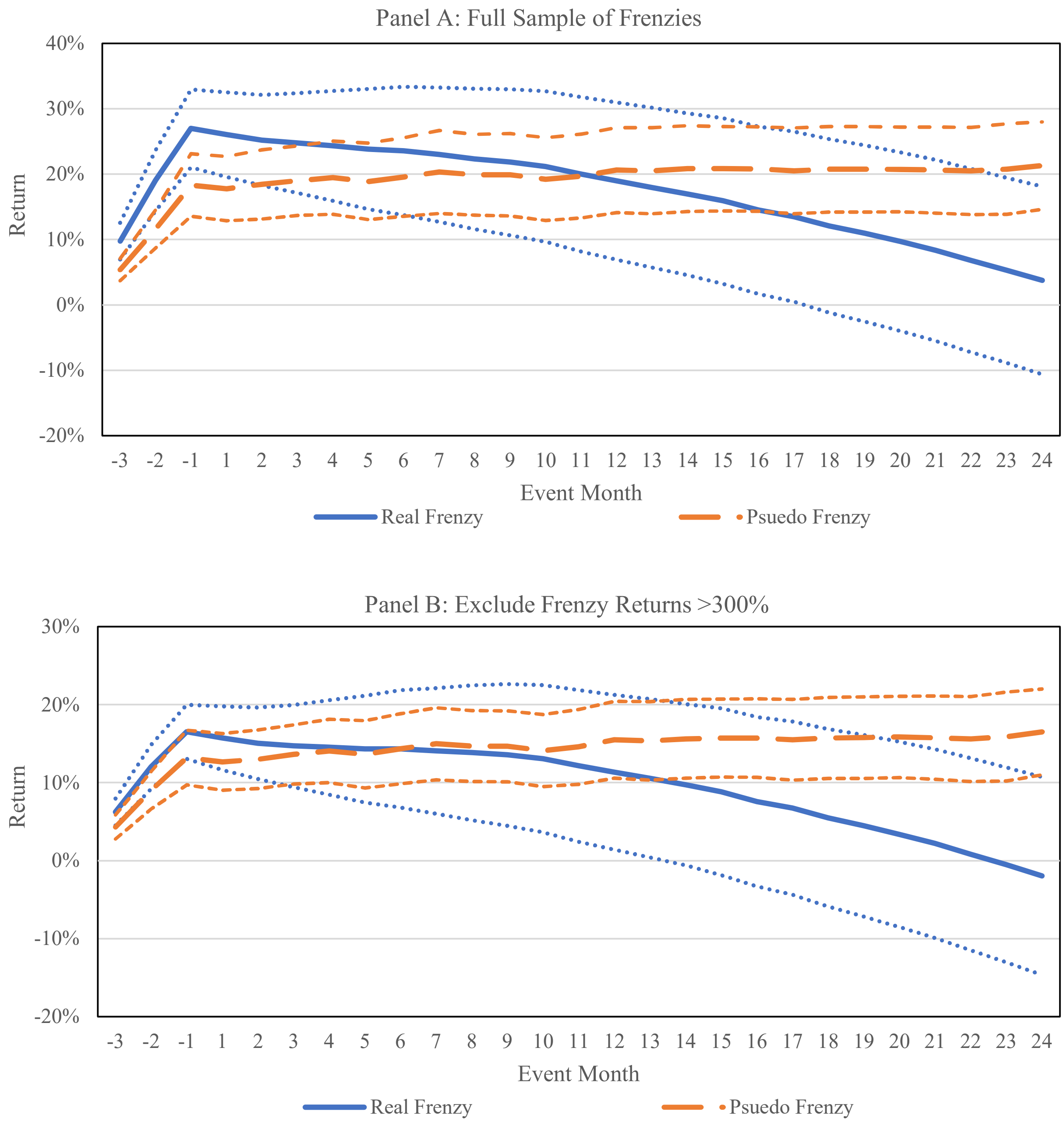


Figure IA4. Cumulative Returns around Real vs. Pseudo Frenzies

Similar to Figure 3 in the text, these plots show the cumulative anomaly-adjusted returns from month *t*-3 to *t*+24 following a retail frenzy or pseudo frenzy, where frenzies are measured from month *t*-3 to *t*-1. Pseudo frenzy firms are chosen as the stocks in the same asset size quintile with the closest returns to the frenzy stock during the frenzy period. In the lower panel, we exclude frenzies with frenzy period returns that are greater than 300% (2.2% of frenzy observations). The dotted lines report the 95% confidence intervals computed from standard errors clustered by firm and month.

Table IA1. Determinants of Retail Frenzies - Logistic Regressions

This table repeats the analysis in Table 2, except that we replace the linear probability model with a logistic regression. The table reports the odds ratios from the logistic regressions.

	[1]	[2]	[3]
Q	0.69	0.66	0.86
	(-10.59)	(-10.69)	(-3.21)
ROA	0.89	0.82	0.93
	(-5.84)	(-9.01)	(-2.58)
$Ret_{t-3\ t-1}$	0.97	0.97	1.00
	(-1.56)	(-1.67)	(0.21)
$Ret_{t-12,\ t-4}$	1.06	1.04	1.05
	(2.54)	(1.80)	(1.71)
Log (Assets)	0.36	0.36	0.21
	(-12.46)	(-13.66)	(-10.59)
Leverage	1.12	1.11	1.21
	(4.55)	(3.64)	(4.35)
Div Yield	1.02	1.06	1.01
	(0.53)	(1.73)	(0.29)
Log (*Volatility*)	1.93	1.85	1.74
	(21.93)	(19.74)	(15.25)
Short Interest	1.82	1.85	1.98
	(26.09)	(25.93)	(24.17)
Asset Growth	0.98	0.98	0.96
	(-1.36)	(-1.23)	(-1.57)
Inst Ownership	0.54	0.53	0.69
	(-10.50)	(-11.00)	(-6.43)
Δ Inst Ownership	0.99	0.98	0.99
	(-0.86)	(-1.31)	(-0.41)
Fire Sale (Flow-to-Volume)	0.47	0.71	0.99
	(-4.79)	(-3.17)	(-0.11)
Fire Purchase (Flow-to-Volume)	0.30	0.67	0.95
	(-5.80)	(-3.84)	(-0.79)
Log (CSHR)	1.11	1.13	1.03
	(2.26)	(2.83)	(0.33)
Net Anomaly Score	0.85	0.89	0.96
	(-5.30)	(-3.98)	(-1.05)
Log (1+WSB Posts)	1.07	1.08	1.06
	(4.02)	(4.25)	(3.85)
Log (1+SA Coverage)	1.38	1.42	1.25
	(11.19)	(11.92)	(7.51)
Constrained	1.16	1.14	1.07
	(2.85)	(2.35)	(0.97)
Capital Sensitive	1.07	1.11	0.00
	(1.17)	(1.61)	(0.61)
Time FE	Yes	Absorb	Absorbed
Ind × Time FE	No	Yes	Yes
Firm FE	No	No	Yes
Obs. (Firm-Months)	664,229	664,229	664,229

Table IA2. WallStreetBets Posting and Retail Frenzies

Panel A sorts all stocks into groups based on the total number of WSB posts over the prior three months. For each group, we report the total number of observations (i.e., firm-months), the average *Qtr. Retail Imbalance*, and the percentage of firm-months classified as having experienced a retail buy frenzy (i.e., *Qtr. Retail Imbalance > 2%*). In Panel B, we report the total number of Due Diligence (DD) reports for the stock and the fraction of DD reports that mention words related to issuance, capital expenditures, and acquisitions. We search posts for the corporate investment-related terms "issuance," "capital expenditures" or "CAPX," and "merger" or "acquisition." In the last column, we also report the fraction of reports that have an M&A term and are followed in quarter t+1 with Compustat acquisition expenses greater than zero. The sample period is based on the availability of WSB data and spans July 2018 to June 2021.

Panel A: WallStreetBets Posting and Retail Order Imbalances

Total WSB Posts	Observations	Average Retail Imbalance	% Frenzy
0	143,762	0.14%	2.44%
1	3,784	0.49%	5.84%
[2, 5]	3,287	0.54%	6.56%
[6, 20]	1,254	0.93%	10.38%
[21, 100]	433	1.08%	17.05%
>100	117	1.88%	21.01%

Panel B: WallStreetBets Due Diligence Report Contents

Total WSB Posts	DD Reports	Issuance	CAPX	M&A	M&A & Future Acquisition
Any	4,764	0.52%	0.42%	11.29%	0.97%
1	1,839	0.49%	0.50%	14.13%	1.31%
[2,5]	598	0.84%	0.33%	12.04%	1.62%
[6,20]	620	0.16%	0.48%	12.74%	0.87%
[21,100]	674	0.45%	0.59%	12.31%	1.22%
>100	1,033	0.68%	0.19%	4.26%	0.00%

Table IA3. Event Time Returns around Retail Frenzies – Fama-MacBeth Estimates

This table repeats the analysis in Table 3, but we now estimate the regression month by month, and we report the average of the monthly estimates (i.e., Fama-MacBeth estimates). Standard errors are computed from the time-series standard deviation of the estimates, and *t*-statistics are reported in parentheses.

	Market-Adjusted Returns		Anomaly-Adjusted Returns	
	[1]	[2]	[3]	[4]
Event Month	Estimate	*t*-stat	Estimate	*t*-stat
-3	8.22%	(5.81)	8.55%	(6.38)
-2	7.39%	(5.63)	7.76%	(6.31)
-1	7.20%	(5.79)	7.56%	(6.53)
1	-1.68%	(-1.58)	-1.26%	(-1.27)
2	-2.10%	(-2.29)	-1.67%	(-1.93)
3	-2.09%	(-2.31)	-1.64%	(-1.95)
4	-2.05%	(-3.32)	-1.65%	(-2.96)
5	-2.08%	(-3.35)	-1.74%	(-3.04)
6	-1.34%	(-2.06)	-0.95%	(-1.58)
7	-1.25%	(-1.98)	-0.79%	(-1.37)
8	-1.05%	(-1.52)	-0.61%	(-0.95)
9	-1.39%	(-2.21)	-0.96%	(-1.66)
10	-1.51%	(-2.63)	-1.08%	(-2.07)
11	-1.56%	(-3.04)	-1.12%	(-2.46)
12	-1.51%	(-2.73)	-1.11%	(-2.25)
13	-1.71%	(-3.05)	-1.32%	(-2.70)
14	-1.34%	(-2.39)	-0.91%	(-1.81)
15	-1.29%	(-2.31)	-0.87%	(-1.78)
16	-1.25%	(-2.44)	-0.74%	(-1.64)
17	-0.94%	(-1.68)	-0.44%	(-0.86)
18	-1.41%	(-2.77)	-1.03%	(-2.32)
19	-1.96%	(-3.74)	-1.46%	(-3.07)
20	-1.38%	(-2.71)	-0.94%	(-2.09)
21	-1.36%	(-2.92)	-0.93%	(-2.27)
22	-1.46%	(-3.42)	-1.03%	(-2.68)
23	-1.58%	(-3.59)	-1.17%	(-3.04)
24	-1.27%	(-2.57)	-0.90%	(-2.08)

Table IA4. Calendar Time Returns around Retail Frenzies

This table reports the alphas and factor loadings for a calendar-time trading strategy where the stock's weight in the portfolio is equal to the number of times a stock has been classified as a retail frenzy (as defined in Table 1) over the previous 24 months. We then regress the average monthly excess returns for this strategy on either the market factor (CAPM alpha) or the Fama and French (2015) five factors, along with the Carhart (1997) momentum factor (six-factor alpha). Panel A reports the equal-weighted time-series average. Panel B reports the time-series average where each month is weighted by the total number of stocks in the portfolio. Standard errors are computed from the time-series standard deviation, and *t*-statistics are reported in parentheses.

Panel A: Equal-Weight by Month

	Alpha	MKTRF	SMB	HML	UMD	CMA	RMW
(1) CAPM Alpha	-1.86	1.68					
	(-3.35)	(14.37)					
(2) Six-Factor Alpha	-1.17	1.30	1.20	-0.68	-0.37	0.86	-1.48
	(-2.53)	(12.93)	(3.94)	(-3.78)	(-2.53)	(2.06)	(-5.09)

Panel B: Observation-Weight Months by Portfolio Size

	Alpha	MKTRF	SMB	HML	UMD	CMA	RMW
(1) CAPM Alpha	-2.18	1.61					
	(-3.09)	(12.18)					
(2) Six-Factor Alpha	-1.21	1.31	1.36	-0.73	-0.31	1.13	-1.67
	(-2.55)	(13.14)	(3.49)	(-3.43)	(-2.14)	(2.34)	(-6.26)

Table IA5. Retail Frenzies and Other Corporate Decisions

This table repeats the analysis from Table 5 after replacing the investment measures with either *Debt Retirement*, defined as an indicator equal to one if the firm reduced long-term debt (i.e., long-term debt reduction less long-term debt issuance) by more than 3% of its market capitalization, or *Change in Cash*, defined as the change in cash and cash equivalents scaled by lagged assets. Standard errors are clustered by firm and quarter, and t-statistics are reported in parentheses.

	Debt Retirement		Change in Cash	
	[1]	[2]	[3]	[4]
Retail Frenzy	0.43%	0.26%	6.57%	6.27%
	(0.45)	(0.31)	(5.61)	(7.16)
Q	-2.65%	-1.29%	1.37%	2.88%
	(-19.08)	(-8.66)	(9.14)	(12.07)
ROA	0.05%	-0.27%	-0.42%	-1.31%
	(0.44)	(-2.51)	(-1.77)	(-6.89)
$Ret_{t-3\ t-1}$	-2.65%	-2.75%	4.63%	3.28%
	(-4.34)	(-4.90)	(10.19)	(7.65)
$Ret_{t-12,\ t-4}$	-1.81%	-2.06%	2.40%	1.54%
	(-4.92)	(-6.17)	(7.70)	(5.30)
Log (Assets)	0.65%	0.43%	1.40%	8.43%
	(2.73)	(0.96)	(12.45)	(13.64)
Leverage	5.67%	5.72%	-0.36%	-0.57%
	(19.24)	(19.83)	(-4.72)	(-4.41)
Div Yield	0.14%	0.59%	0.03%	-0.07%
	(0.74)	(3.17)	(0.64)	(-1.08)
Log (*Volatility*)	3.34%	2.10%	0.46%	0.66%
	(12.83)	(9.32)	(5.00)	(6.13)
Short Interest	0.35%	0.36%	-0.10%	-0.16%
	(2.90)	(2.60)	(-1.71)	(-1.78)
Asset Growth	0.08%	0.04%	-0.36%	-0.82%
	(0.99)	(0.56)	(-3.78)	(-6.66)
Inst Ownership	-0.60%	-0.37%	-0.21%	-0.65%
	(-4.32)	(-2.13)	(-2.96)	(-5.72)
Δ Inst Ownership	-0.08%	-0.02%	0.36%	0.33%
	(-0.99)	(-0.27)	(4.93)	(5.14)
Fire Sale (Flow-to-Volume)	0.76%	0.19%	0.35%	0.07%
	(2.56)	(0.73)	(3.90)	(0.78)
Fire Purchase (Flow-to-Volume)	(-0.00)	(-0.01)	(0.00)	(-0.00)
	(-1.99)	(-2.45)	(1.04)	(-1.09)
Log (CSHR)	-0.03%	-0.03%	-0.38%	-0.97%
	(-0.22)	(-0.12)	(-7.10)	(-5.97)
Net Anomaly Score	1.23%	0.27%	-0.26%	-0.15%
	(9.76)	(2.02)	(-3.72)	(-1.93)
Log (1+WSB Posts)	-0.09%	-0.04%	-0.02%	0.00%
	(-1.31)	(-0.62)	(-0.34)	(-0.02)
Log (1+SA Coverage)	-0.18%	0.14%	-0.20%	-0.03%
	(-1.64)	(1.45)	(-4.89)	(-0.69)
Constrained	3.55%	2.59%	0.68%	1.06%
	(9.53)	(7.99)	(4.82)	(5.53)
Capital Sensitive	-0.91%	-0.20%	-0.26%	-0.66%
	(-4.06)	(-0.95)	(-1.72)	(-4.53)
Obs. (Firm - Quarter)	209,308	209,308	209,308	209,308
Time × Industry FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes

Table IA6. Retail Frenzies and Corporate Decisions – The Role of News

We repeat the baseline regressions for equity issuance, capital expenditures, and acquisitions after replacing *Retail Frenzy* with *Retail Frenzy × Low News* and *Retail Frenzy × High News.* We also include a *High News* indicator (unreported). *High News* equals one if the total number of Ravenpack articles in the "Equity Actions" or "Acquisitions-Mergers" news groups for a firm during the frenzy quarter is in the top quartile compared to the number of articles for the same firm over the preceding 12 quarters. All other quarters are classified as *Low News.* All other details are identical to the baseline regressions. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses. We also report a statistical test for the difference in coefficients.

	Equity Issuance	CAPX	Acquisitions	Equity Issuance	CAPX	Acquisitions
	[1]	[2]	[3]	[4]	[5]	[6]
Retail Frenzy × High News	7.61%	1.71%	2.33%	0.81%	1.67%	1.72%
	(4.96)	(2.59)	(2.16)	(0.62)	(2.89)	(1.78)
Retail Frenzy × Low News	13.22%	1.10%	2.25%	6.62%	1.07%	1.39%
	(10.06)	(2.34)	(3.16)	(5.85)	(2.47)	(2.07)
Difference	-5.61%	0.61%	0.08%	-5.81%	0.60%	0.33%
	(-3.42)	(0.83)	(0.06)	(-3.65)	(0.84)	(0.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
Obs. (Firm-Quarters)	209,308	209,308	209,308	209,308	209,308	209,308

Table IA7. Retail Frenzies and Corporate Decisions – Pseudo Frenzy Firms

We repeat the baseline regressions for equity issuance, capital expenditures, and acquisitions after including an indicator for pseudo frenzy firms (*Pseudo Frenzy*), where pseudo frenzy firms are defined as in Figure IA4. All other details are identical to the baseline regressions. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses. We also report a statistical test for the difference in coefficients.

	Equity Issuance	CAPX	Acquisitions	Equity Issuance	CAPX	Acquisitions
	[1]	[2]	[3]	[4]	[5]	[6]
Retail Frenzy	11.30%	1.31%	2.62%	4.51%	1.28%	1.92%
	(9.99)	(3.13)	(4.10)	(5.05)	(3.62)	(3.37)
Pseudo Frenzy	2.96%	-0.20%	0.11%	1.52%	-0.30%	0.07%
	(3.52)	(-0.78)	(0.17)	(2.07)	(-1.29)	(0.11)
Difference	8.34%	1.51%	2.51%	2.99%	1.58%	1.85%
	(6.77)	(3.28)	(2.90)	(2.50)	(3.83)	(2.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
Obs. (Firm-Quarters)	209,308	209,308	209,308	209,308	209,308	209,308

Table IA8. Returns around Retail Frenzies: Pre vs. Post-Zero Commissions

This table reports estimates from the following panel regression:

$$Ret_{i,t+x} = \alpha + \beta_1 \text{Relatve Frenzy}_{i,t} \times Post + \beta_2 \text{Relatve Frenzy}_{i,t} \times Pre \ + Time_t + \varepsilon_{i,t+x}.$$

The dependent variable, *Ret,* is a measure of cumulative returns that varies across specifications. In Specification 1, *Ret* equals *Event Ret*, defined as the cumulative return during the quarter of the retail buying frenzy (i.e., months *t*-3 to *t*-1). In Specification 2, *Ret* equals *Post-Event Ret*, defined as the cumulative return during the two years following the retail buying frenzy (i.e., months *t*+1 to *t*+24). In Specification 3, *Ret* equals *Total Ret*, defined as *Event Ret* + *Post-Event Ret.* In Specifications 4-6, *Ret* is an indicator equal to one if *Post-Event Ret* is less than -25%, -50%, or -75%, respectively. *Relative Retail Frenzy* is an indicator equal to one if retail imbalances in the prior quarter are in the top 1.3% of the distribution relative to all firms in the same calendar month. *Pre-Zero Commissions* is an indicator equal to one for the 2007-2016 sample period and zero otherwise, and *Post Zero Commissions* is an indicator equal to one for the 2017-2023 sample period and zero otherwise. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses. Below the regression estimates, we also test whether the estimates on the *Relative Frenzy* × *Post* and *Relative Frenzy* × *Pre* are significantly different from each other.

	Event Ret	Post-Event Ret	Total Ret	Post Event < -25%	Post Event < -50%	Post Event < -75%
	[1]	[2]	[3]	[4]	[6]	[6]
Relative Frenzy × Post	33.19%	-26.37%	6.82%	24.10%	27.06%	26.97%
	(6.15)	(-2.84)	(0.59)	(9.28)	(11.51)	(12.58)
Relative Frenzy × Pre	14.60%	-16.39%	-1.79%	17.32%	19.77%	16.93%
	(6.00)	(-4.12)	(-0.41)	(9.99)	(13.38)	(11.98)
Difference	18.59%	-9.98%	8.61%	6.78%	7.30%	10.03%
	(3.15)	(-0.98)	(0.70)	(2.17)	(2.58)	(3.94)
Obs. (Firm-months)	662,911	662,911	662,911	662,911	662,911	662,911
Fixed Effects	Month	Month	Month	Month	Month	Month

Table IA9. Retail Frenzies and Acquisitions – Characteristics & Event-Time Returns

We identify all mergers in the SDC database from 2007-2023. We limit the sample to firms-months that appear in our main analysis (i.e., firm-months included in Table 1). We classify a merger as *Frenzy* if it occurred within six months after a retail frenzy, and all other mergers are classified as non-frenzy. Panel A provides descriptive statistics for Frenzy and Non-Frenzy mergers. *Pct Cash* is the percentage of consideration paid in cash; *Same Industry* and *Same Macro* are indicators equal to one if the acquirer and target belong to the same industry (85 categories) or macro industry (14 broader categories), and *Public* and *International* are indicators equal to one if the target is a public company or international company, respectively. Panels B and C report market-adjusted and anomaly-adjusted event-time returns around mergers based on the reported merger announcement date in SDC. We explore returns for horizons ranging from the day of the announcement ([0]) to up to two years following the day of the announcement ([1,504]). We report returns for acquisitions made by non-frenzy firms (Non-Frenzy Acquisitions), acquisitions made by Frenzy Firms (Frenzy Acquisitions), and the difference between the two returns. Panel D regresses the anomaly-adjusted return on the *Frenzy* indicator and the other merger attributes reported in Panel A. Standard errors are clustered by firm and month, and t-statistics are reported below the return estimates.

Panel A: Merger Characteristics

	Obs.	Pct Cash	Same Ind.	Same Macro	Public	International
Frenzy	445	70.55%	44.40%	65.09%	21.55%	19.78%
Non-Frenzy	35,787	91.81%	57.17%	74.64%	30.20%	21.40%
Difference		-21.26%	-12.78%	-9.55%	-8.65%	-1.62%
t (difference)		(-7.34)	(-3.32)	(-2.38)	(-3.25)	(-0.77)

Panel B: Market-Adjusted Returns

	[0]	[1]	[1,5]	[1,21]	[1,63]	[1,252]	[1,504]
Non-Frenzy Acquisitions	0.57%	0.40%	0.55%	0.74%	0.59%	1.10%	2.92%
	(16.62)	(13.83)	(11.20)	(6.49)	(2.58)	(2.28)	(4.07)
Frenzy Acquisitions	2.68%	-0.08%	-1.46%	-4.38%	-8.54%	-22.96%	-33.82%
	(4.01)	(-0.17)	(-1.98)	(-2.51)	(-3.08)	(-4.41)	(-6.19)
Difference	2.12%	-0.48%	-2.01%	-5.11%	-9.13%	-24.06%	-36.74%
	(3.18)	(-1.07)	(-2.72)	(-2.97)	(-3.38)	(-4.70)	(-6.80)

Panel C: Anomaly-Adjusted Returns

	[0]	[1]	[1,5]	[1,21]	[1,63]	[1,252]	[1,504]
Non-Frenzy Acquisitions	0.54%	0.39%	0.50%	0.50%	-0.16%	-2.45%	-5.91%
	(14.56)	(12.99)	(9.59)	(4.69)	(-0.71)	(-3.42)	(-5.22)
Frenzy Acquisitions	2.30%	0.00%	-1.09%	-4.13%	-7.70%	-21.47%	-28.83%
	(4.02)	(0.01)	(-1.54)	(-2.42)	(-3.01)	(-4.79)	(-5.31)
Difference	1.76%	-0.39%	-1.58%	-4.63%	-7.54%	-19.03%	-22.92%
	(3.08)	(-0.89)	(-2.24)	(-2.73)	(-2.95)	(-4.22)	(-4.15)

Panel D: Regression Estimates of Anomaly-Adj. Returns on Frenzy and Controls

	[0]	[1]	[1,5]	[1,21]	[1,63]	[1,252]	[1,504]
Frenzy	1.86%	-0.29%	-1.46%	-4.41%	-7.15%	-18.57%	-22.82%
	(3.26)	(-0.68)	(-2.07)	(-2.60)	(-2.79)	(-4.13)	(-4.15)
Pct Cash	0.99%	0.60%	0.63%	1.77%	3.61%	5.32%	14.33%
	(3.49)	(2.36)	(1.71)	(3.25)	(4.19)	(2.95)	(1.66)
Same Ind.	0.31%	1.25%	0.14%	0.20%	0.37%	0.31%	-1.49%
	(4.11)	(2.31)	(1.67)	(1.23)	(1.35)	(0.45)	(-1.36)
Public	-0.61%	0.08%	0.24%	0.27%	0.25%	-0.43%	-1.41%
	(-4.48)	(0.85)	(1.73)	(1.30)	(0.76)	(-0.56)	(-1.33)
International	-0.27%	-0.19%	-0.17%	-0.06%	0.33%	0.58%	0.39%
	(-3.57)	(-3.73)	(-2.05)	(-0.36)	(1.19)	(0.96)	(0.43)

Table IA10. Retail Frenzies in Peer Firms and Investment

This table repeats the baseline investment analysis in Table 5 after including an additional variable, *Retail Frenzy – Peer Firm*, defined as the percentage of peer firms experiencing a retail frenzy in the prior quarter. A firm is considered a peer if its product similarity score makes it one of its nearest 25 rivals based on the TNIC-3 classification of Hoberg and Phillips (2015, 2016). We also require that the product similarity score exceed 0.01. All other details are identical to those in Table 5. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

	CAPX [1]	Acquisitions [2]	CAPX [3]	Acquisitions [4]
Retail Frenzy	1.27%	2.65%	1.25%	1.86%
	(3.08)	(4.18)	(3.55)	(3.32)
Retail Frenzy - Peer Firms	0.79%	-0.70%	0.52%	0.86%
	(1.29)	(-0.85)	(1.14)	(1.21)
Controls	Yes	Yes	Yes	Yes
Time × Industry Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
Obs. (Firm-Quarters)	164,858	164,858	164,858	164,858

Table IA.11: Investment and the Determinants of Retail Buying Frenzies

This table repeats the determinants analysis of Table 2 after including three additional explanatory variables: Retail Frenzy, High Investment, and their interaction (Retail Frenzy × High Investment). The dependent variable, *Retail Frenzy*, indicates whether a firm experiences a retail frenzy in quarter *t*. The independent variable *High Investment* is measured in the quarter immediately preceding (quarter $t-1$), and *Retail Frenzy* as an explanatory variable captures whether a retail frenzy occurred in the six months prior to the investment). The regression includes all the controls from Table 2, but in the interest of brevity, we omit the estimates on the coefficients of eight control variables that were insignificant (at a 5% level) in all three specifications: $Ret_{t-3\ t-1}$, $Ret_{t-12,\ t-4}$, *Div Yield, Asset Growth, Δ Inst Ownership*, *Fire Purchase (Flow to Volume)*, *Net Anomaly Score*, and *Capital Sensitive*. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses**.**

	[1]	[2]	[3]
Retail Frenzy	12.76%	12.60%	4.41%
	(15.11)	(15.18)	(6.82)
Retail Frenzy × High Investment	-0.56%	-0.68%	-1.18%
	(-0.43)	(-0.53)	(-0.99)
High Investment	0.18%	0.22%	0.21%
	(4.11)	(4.93)	(4.55)
Q	-0.25%	-0.24%	-0.06%
	(-5.78)	(-4.85)	(-0.73)
ROA	-0.59%	-0.62%	-0.34%
	(-8.46)	(-8.38)	(-4.71)
Log (Assets)	-0.43%	-0.51%	-1.86%
	(-6.22)	(-6.96)	(-7.21)
Leverage	0.05%	0.06%	0.31%
	(1.47)	(1.53)	(3.71)
Log (*Volatility*)	0.53%	0.58%	0.58%
	(10.17)	(11.66)	(11.86)
Short Interest	0.65%	0.68%	0.93%
	(11.43)	(11.86)	(12.04)
Inst Ownership	-0.38%	-0.36%	-0.27%
	(-9.13)	(-8.83)	(-4.97)
Fire Sale (Flow-to-Volume)	-0.06%	-0.11%	0.02%
	(-1.43)	(-2.34)	(0.58)
Log (CSHR)	0.18%	0.21%	0.02%
	(5.56)	(5.66)	(0.17)
Log (1+WSB Posts)	0.23%	0.23%	0.20%
	(3.42)	(3.55)	(3.32)
Log (1+SA Coverage)	0.30%	0.35%	0.25%
	(8.29)	(9.19)	(6.50)
Constrained	0.08%	0.07%	0.03%
	(2.44)	(2.06)	(0.64)
Time FE	Yes	Absorb	Absorbed
Ind × Time FE	No	Yes	Yes
Firm FE	No	No	Yes
Obs. (Firm-Months)	595,663	595,663	595,663
R-squared	8.47%	10.32%	18.05%

Table IA12: Retail Frenzies and Investment – the Distribution of Future Performance

This table reports the probability that a firm exceeds a performance threshold. The performance measures in Panels A and B are the two-year cumulative event-time market-adjusted or anomaly-adjusted return. The performance measure in Panel C is the earnings surprise, defined as the realized earnings less the IBES forecasted earnings, scaled by the stock price, where the analyst forecasts and stock price are measured in the quarter prior to the start of the investment, and the realized earnings are measured at least one quarter after the investment. For each measure, we estimate a regression of the performance threshold (e.g., that the return exceeds 200%) on indicators for *Retail Frenzy – High Investment* and *Retail Frenzy – Low Investment* as defined in Table 9. We also report the difference between the two estimates. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

Panel A: Market-Adjusted Returns

	[1]	[2]	[3]	[4]	[5]
	Return > 200%	Return > 100%	Return >50%	Return >0	Return > -50%
Retail Frenzy – High Investment	4.29%	11.66%	19.63%	32.00%	50.31%
Retail Frenzy – Low Investment	5.46%	14.46%	23.31%	38.06%	55.33%
Difference	-1.17%	-2.80%	-3.68%	-6.06%	-5.02%
	(-1.39)	(-2.12)	(-2.25)	(-3.17)	(-2.31)

Panel B: Anomaly-Adjusted Returns

	[1]	[2]	[3]	[4]	[5]
	Return > 200%	Return > 100%	Return >50%	Return >0	Return > -50%
Retail Frenzy – High Investment	4.81%	13.29%	23.21%	39.16%	57.77%
Retail Frenzy – Low Investment	5.76%	15.50%	25.58%	42.96%	61.74%
Difference	-0.95%	-2.21%	-2.37%	-3.79%	-3.97%
	(-1.07)	(-1.60)	(-1.39)	(-1.91)	(-1.94)

Panel C: Earnings Surprise (Surprise/Price)

	[1]	[2]	[3]	[4]	[5]
	>100	>5	>0	>-5	>-100
Retail Frenzy – High Investment	3.54%	8.91%	38.99%	90.56%	97.18%
Retail Frenzy – Low Investment	4.35%	11.77%	45.40%	91.51%	97.48%
Difference	-0.81%	-2.86%	-6.41%	-0.95%	-0.30%
	(-1.14)	(-2.05)	(-3.21)	(-0.73)	(-0.47)

Table IA13. Retail Frenzies and Investment – Career Outcomes

This table reports the estimates from regressions of CEO career outcomes on indicators for *Retail Frenzy – High Investment, Retail Frenzy – Low Investment, Controls*, and FE. In Specifications 1 and 2, the career outcome is *CEO Turnover* which is an indicator equal to one if the CEO is no longer in office in the year following the retail frenzy (as reported by Audit Analytics). The outcome in Specifications 3 and 4 is *Forced CEO Turnover* which includes all CEO turnover except turnovers that are reported in Audit Analytics as being attributed to either retirement or death. In Specifications 5 and 6, the career outcome is the change in total compensation as reported in Execucomp. *Retail Frenzy – High Investment and Retail Frenzy – Low Investment* are defined as in Table 9. *Controls* include the controls from Table 4, and fixed effects denote industry × year fixed effects, and in some specifications, firm fixed effects. Standard errors are clustered by firm and year, and t-statistics are reported in parentheses. Below the regression estimates, we also test whether the estimates on the *Retail Frenzy – High Investment* and *Retail Frenzy – Low Investment* are significantly different from each other.

	CEO Turnover		*Forced CEO Turnover*		*Δ CEO Compensation*	
	[1]	[2]	[3]	[4]	[5]	[6]
Retail Frenzy – Low Investment	-2.19%	-1.13%	-1.70%	-0.94%	4.08%	3.26%
	(-2.00)	(-0.89)	(-1.41)	(-0.74)	(0.97)	(0.69)
Retail Frenzy – High Investment	0.11%	0.41%	1.01%	1.30%	5.47%	7.24%
	(0.06)	(0.22)	(0.64)	(0.87)	(0.86)	(1.17)
High - Low Investment	2.30%	1.53%	2.71%	2.24%	1.39%	3.98%
	(1.22)	(1.17)	(1.50)	(1.66)	(0.17)	(0.51)
Observations (Firm-Years)	59,969	59,969	59,969	59,969	23,945	23,945
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes