Swimming Against the Current:
Contrarian Retail Trading

Brad Cannon Hannes Mohrschladt*

Abstract: Retail investor contrarian selling depends on whether a position is at a gain or loss. Selling propensity increases in daily returns for positions with unrealized gains (contrarian selling) and decreases in returns for loss positions (trend-following selling). This pattern is consistent with behavioral arguments that investors update beliefs when stock prices move away from their purchase prices. In line with increased liquidity from contrarian selling, illiquid stocks exhibit weaker short-term reversals when investors have higher unrealized capital gains. Our findings diminish following stock splits, suggesting that unrealized capital gains are central to contrarian behavior, particularly when investors perceive them clearly.

Keywords: Individual Investors, Contrarian Behavior, Liquidity, Short-Term Reversals

JEL: G11, G12, G41

*Cannon, bcannon@binghamton.edu, Binghamton University School of Management; Mohrschladt, hannes.mohrschladt@uni-potsdam.de, University of Potsdam Faculty of Economics and Social Sciences and University of Münster Finance Center Münster.

We thank Stephan Siegel (the Editor) and an anonymous referee for helpful comments. We also thank Zahi Ben-David, Justin Birru, Rawley Heimer, Brian Roseman, Simon Rottke, participants at the Research in Behavioral Finance Conference, the Annual Meeting of the German Finance Association, the Annual Meeting of the Southwestern Finance Association, the Behavioural Finance Working Group Conference, and seminar participants at the University of Kansas and the University of Münster for their valuable comments and suggestions.

I. Introduction

Retail investors are often viewed as uninformed traders who make suboptimal decisions (Barber and Odean (2013)). However, their tendency to sell following short-term price increases—contrarian selling—has been argued to be a bright point. When pressure from institutional demand moves up prices, retail traders can earn liquidity premiums from contrarian selling because they are able to sell at a comparably high price. This contrarian behavior in response to daily returns has been shown to improve market efficiency and reward retail traders with abnormal returns in the short run (Kaniel, Saar, and Titman (2008), Kelley and Tetlock (2013)).

Despite widespread evidence of contrarian retail selling, little is known about what explains this puzzling behavior. Are retail investors good market makers who collect liquidity premiums, as existing evidence might suggest? Or does a behavioral theory explain why retail investors might look like liquidity providers? In this paper, we provide evidence in support of a behavioral belief updating mechanism (Ben-David and Hirshleifer (2012)) that generates variation in contrarian selling.

Under the framework of Ben-David and Hirshleifer (2012), selling propensity is V-shaped in capital gains because investors update their beliefs in response to price movements. As a stock's price moves further from the price at which it was purchased, investors are more likely to decide that their original investment thesis was flawed or that information has already been priced in. This process results in selling that is least likely near the purchase price and becomes increasingly likely as unrealized gains or losses become larger.

Our primary hypothesis is that this belief-driven behavior has important implications for contrarian selling. For positions with unrealized gains, a *positive* return moves an investor further from the purchase price, increasing the likelihood of selling (contrarian behavior). In contrast, when at a loss, a *negative* return moves an investor further from the purchase price, also increasing the likelihood of selling (trend-following behavior). We refer to this opposite response to recent returns as domain-based contrarian selling. In this paper, we provide evidence in support of domain-based contrarian selling and examine its implications for asset prices.

We begin our analysis with a sample of individual investor transactions from a large discount broker as introduced by Barber and Odean (2000). To study retail contrarian selling, we estimate investor-stock-date panel regressions and examine how selling is related to a stock's most recent daily return. We additionally construct an indicator variable equal to one if a position is trading at a gain, which allows us to test whether contrarian retail selling depends on the trading domain. We find that contrarian selling strongly differs between domains. For positions at a gain, a positive 5% daily return is associated with a 2.1 percentage points *higher* propensity to sell. In contrast, for positions at a loss, the same 5% return is associated with a 1.0 percentage point *lower* propensity to sell.

The domain dependence of contrarian selling remains highly significant after controlling for other variables that have been shown to predict investor selling propensity as well as including a host of fixed effects (Odean (1998), Hartzmark (2015)). Using stock-date fixed effects, we show that even among investors holding the same stock on the same day, those with unrealized gains are more likely to sell in a contrarian way. Moreover, we show that our findings are inconsistent with alternative explanations such as portfolio rebalancing and tax loss selling.

We then consider whether these domain-based contrarian patterns at the individual level scale up to affect stock market prices (Barber, Odean, and Zhu (2009)). Because contrarian trades are executed in the opposite direction of returns, they have the potential to reduce temporary price pressures, dampening subsequent return reversals. To examine this hypothesis, the timing of contrarian selling requires further investigation. For example, if a positive return on day *t* leads to contrarian selling on day *t* only, the return on day *t* is attenuated leading to weaker reversals on day *t+1* and onward. In contrast, if a positive return on day *t* leads to more selling on day *t+1* only, this implies a stronger reversal on day *t+1* and reduced reversals for longer horizons since the price pressure from day *t* is partially offset on day *t+1*.

To better understand the dynamics of contrarian trading, and sharpen our reversal predictions, we examine how domain-dependent contrarian trading evolves over the course of one month. We find that the difference in contrarian selling between the gain and loss domains (domain-based contrarian selling) is strongest on day *t* and exhibits exponential decay over a month. Though we observe an economically meaningful domain-based contrarian effect for several days, the effect magnitude declines by more than 90% over the next two weeks and becomes statistically insignificant after about three weeks. Hence, while predictions for *daily* short-term return reversals are unclear due to persistent domain-based contrarian behavior, we expect reversals to be affected across longer horizons as the persistence wears off. As such, we hypothesize that *monthly* short-term reversals weaken when investors have larger average unrealized capital gains.[1]

To test this hypothesis, we use the stock-level capital gains overhang measure CGO (Grinblatt and Han (2005)), which estimates the average unrealized capital gain of a stock's

[1]Our main individual investor analyses examine daily patterns because this procedure allows clearer identification of investors' response to returns. However, we also run all our analyses at the *monthly* frequency and introduce RobinTrack data on retail investor holdings (Barber, Huang, Odean, and Schwarz (2022)). Across both datasets, we find consistent evidence of more contrarian behavior in the gain domain over a monthly horizon. Moreover, these additional analyses provide evidence that our findings on selling behavior are not offset by retail buying.

investors based on price and trading volume dynamics.[2] In line with our retail evidence, the returns from a value-weighted monthly short-term reversal strategy are substantially lower among high-CGO stocks. Specifically, the average monthly return from a short-term reversal strategy is 1.25% lower among the highest CGO quintile compared to the lowest. This finding persists after controlling for standard asset pricing factors (Fama and French (1993), Fama and French (2015), Fama and French (2018), Hou, Xue, and Zhang (2015), Hou, Mo, Xue, and Zhang (2021)) and goes beyond bid-ask bounce effects (Jegadeesh and Titman (1995)). Furthermore, the short-term reversal patterns we find are driven by illiquid stocks, consistent with our arguments on contrarian retail selling and liquidity provision.

We conclude our analysis by examining how our results change following stock splits. Birru (2015) shows that stock splits confuse investors about the purchase price of a stock, causing the disposition effect to disappear. Applying this argument to our setting, we expect domain-based contrarian selling and its pricing effects to weaken following stock splits if investor perception of capital gains plays an important role. This is precisely what we find: the domain dependence of contrarian retail selling vanishes for positions that have experienced a stock split. Moreover, the difference in short-term reversal returns between high- and low-CGO stocks is substantially reduced post-split, providing further evidence that unrealized capital gains are central to understanding retail contrarian behavior and its implications for asset prices.

Our paper contributes to the existing literature in three ways. First, we offer new evidence on individual investor behavior. Prior work by Ben-David and Hirshleifer (2012) presents evidence that investor belief updating results in a selling propensity that is V-shaped in unrealized

[2] Our construction of CGO reflects the trading dynamics of all investors, not just retail investors. Importantly, we validate this measure as a proxy for *retail* behavior in the Online Appendix by showing that CGO closely tracks the share of retail investors trading at a gain.

capital gains. We extend these arguments and provide empirical tests to understand investor contrarian selling. In addition, among the extensive evidence on contrarian trading, Grinblatt, Keloharju, and Linnainmaa (2012) show that contrarian strategies are more often followed by high-IQ investors.[3] In general, this body of work paints retail contrarian trading in a positive light. Our paper offers a new perspective by showing that contrarian retail trading patterns are consistent with a behavioral belief updating mechanism. In particular, we find that retail investors are most likely to provide liquidity when unrealized capital gains are high despite evidence that return premiums for providing liquidity (i.e., short-term return reversals) are lowest for such stocks.

Second, we contribute to the growing literature that connects retail investor behavior to asset prices. De Long, Shleifer, Summers, and Waldmann (1990) and Barber et al. (2009) argue that systematic noise trading can move asset prices.[4] Closely related to our study, Kaniel et al. (2008), Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock (2013), and Barrot et al. (2016) show that individual investors are contrarian and thereby provide liquidity that could mitigate short-term return reversals. Our results suggest that these observations strongly depend on unrealized capital gains.

Third, we contribute to the literature on short-term return reversals (Jegadeesh (1990)). Prior work finds that short-term return reversals are strongest among stocks with low returns during the previous months (Zhu and Yung (2016), Cheng, Hameed, Subrahmanyam, and Titman (2017)), distressed firms (Da and Gao (2010)), stocks with high idiosyncratic volatility (Da, Liu,

[3]Evidence of contrarian retail trading has been documented in the US based on NYSE's Consolidated Equity Audit Trail Data (Kaniel et al. (2008)) and based on TAQ data (Boehmer, Jones, Zhang, and Zhang (2021)), in Korea (Choe, Kho, and Stulz (1999)), in Finland (Grinblatt and Keloharju (2001)), in six Asian markets (Richards (2005)), and in France (Barrot, Kaniel, and Sraer (2016)).

[4]For evidence on the disposition effect, attention-grabbing stocks, and V-shaped selling propensity, see Odean (1998), Grinblatt and Han (2005), Barber and Odean (2008), Da, Engelberg, and Gao (2011), Ben-David and Hirshleifer (2012), and An (2016).

and Schaumburg (2014)), and low-turnover stocks (Medhat and Schmeling (2022)). We show that CGO negatively predicts short-term reversals after controlling for these variables. Moreover, we provide further evidence of the importance of unrealized capital gains by showing that domain-dependent short-term reversals weaken following stock splits.

II. Contrarian Trading of Retail Investors

A. Hypothesis Development

In the first portion of our paper, we test our primary hypothesis: retail investors' contrarian selling depends on whether a position is at a gain or a loss—a behavior we refer to as domain-based contrarian selling. This hypothesis is motivated by the belief updating mechanism in Ben-David and Hirshleifer (2012), who show that selling propensity is increasing in both capital gains *and* capital losses (V-shaped selling).

Ben-David and Hirshleifer (2012) explain the V-shape through a belief-updating mechanism. As the price of a stock moves further from the purchase price—whether higher or lower—investors are more likely to revise their initial belief. When the revised belief suggests that the investor's original investment thesis was flawed or that information has now been priced in, investors are more likely to sell. This process results in a selling propensity that is V-shaped in capital gains. In other words, selling is least likely near the purchase price and becomes more likely as gains or losses become larger.

We hypothesize that this belief updating mechanism has important implications for how investors respond to short-term returns. When at a gain, a positive daily return moves an investor further from their purchase price, increasing the likelihood of selling—a contrarian response. In contrast, when at a loss, a *negative* return moves an investor further from their purchase price, increasing the likelihood of selling—a trend-following response.

In this section, we first test our hypothesis using individual investor transaction data and daily returns. The detailed transaction records allow us to accurately measure each investor's purchase price and unrealized capital gains, while the use of daily returns aligns with prior studies on retail contrarian trading (e.g., Kaniel et al. (2008); Kelley and Tetlock (2013). We then extend the analysis to monthly returns and bring in data from RobinTrack. The monthly setting follows from patterns we observe about the persistence of daily contrarian behavior and links our findings to asset pricing work on short-term return reversals (e.g., Jegadeesh (1990)). Including RobinTrack allows us to analyze retail trading on a broader scale and corroborates our findings with alternative retail trading data.

B. Data and Variables

For our initial tests, we track retail trading using transactions data from a large discount broker covering January 1991 to November 1996.[5] We merge the trading data with CRSP for split-adjusted stock prices and apply standard filters following Ben-David and Hirshleifer (2012) and Hartzmark (2015). We retain only trades of common ordinary shares and drop transactions with negative commissions. We assume net positions of zero at the beginning of the sample period and reconstruct investor holdings by netting purchases and sales, adjusted for stock splits. We remove investor-stock pairings where the net position becomes negative; this excludes all pre-sample purchases and short selling.

[5]We thank Terrance Odean for sharing the data.

An investor's purchase date is defined as the date when a net position in a stock moves from zero to a positive value. If an investor makes purchases of a stock on multiple dates, without closing the position, we use the first purchase price to determine unrealized capital gains.[6] A position is closed when its net position moves from a positive value to zero. Finally, we create a sample of sell dates, days where an investor decreases holdings in at least one stock. For these dates, we create an observation for each position held by an investor to construct the full choice set.[7]

The primary dependent variable for our analysis is $SELL$, which is an indicator variable equal to one if investor *i* sells stock *j* on day *t*. To study contrarian behavior, we estimate the relation between $SELL$ and RET, the return of stock *j* on day *t-1*. For each investor's position, we also compute the relative change in price between the purchase date and day *t-1*. If the price has appreciated, we classify the position as being at a gain, $GAIN$.

We follow the previous literature and control for explanatory variables known to affect investor selling. This includes the holding period HP, the stock's return volatility VOL, and indicator variables for the best and the worst stock in an investor's portfolio ($BEST$ and $WORST$, Hartzmark (2015)). These variables are defined in the Appendix. All variables are winsorized at 1% and 99% quantiles. We restrict our sample to observations with values for all the variables, which adds the additional requirement of having at least 5 stocks in a portfolio, resulting in 2,434,072 investor-stock-date observations.[8]

---

[6] In the Online Appendix, we show that our evidence of domain-based contrarian selling holds (and even slightly strengthens) if we define capital gains based on share-weighted purchase prices for positions with multiple purchases.

[7] Restricting our sample to sell dates follows much of the literature on individual investors (e.g., Hartzmark (2015)) and ensures that investors are attentive to their portfolios. In the Online Appendix, we show that our findings are robust to a sample that includes all investor-stock-dates.

[8] In the Online Appendix, we show that our results hold without requiring $BEST$ and $WORST$, which are only constructed for portfolios with at least 5 stocks.

[Insert Table 1 approximately here]

In Table 1, we report summary statistics and correlation coefficients for the variables of interest. On average, investors sell 11% of their positions on potential sell dates. The mean daily return is approximately zero and just over half of the observations are trading at a gain (53%). We observe some evidence of contrarian retail trading as indicated by the slightly positive correlation between $SELL$ and RET. The positive correlation of $SELL$ with $GAIN$, $BEST$, and $WORST$ is in line with Odean (1998) and Hartzmark (2015).

C. Main Results of Contrarian Retail Selling

Using our sample of transaction data and prices, we test whether investors' propensity to sell in response to recent returns depends on whether a position is at a gain or a loss—domain-dependent contrarian selling. To do so, we estimate the following panel regression:

$$(1) \qquad SELL_{i,j,t} = \alpha + \beta_1 RET_{j,t-1} + \beta_2 GAIN_{i,j,t-1} + \beta_3 RET_{j,t-1} \times GAIN_{i,j,t-1} + \epsilon_{i,j,t}$$

where j refers to the stock held by investor i and *t* is the potential sell date. β_1 is the coefficient on the return from day *t-1* and indicates how investor selling responds to returns. A positive coefficient indicates contrarian selling, whereas a negative coefficient is trend-following. The coefficient of interest is β_3, the interaction of returns from day *t-1* with $GAIN$. If β_3 is positive, this indicates that investor sells are more contrarian when trading at a gain, consistent with domain-dependent contrarian selling.[9]

[9] Note that our behavioral arguments do not prescribe whether returns on day *t-1* influence selling on day *t-1*, day *t*, or later. We examine different timing specifications in Subsection D. In our main analyses, we use a one-day lag

In the first column in Table 2, there is a positive unconditional relation between RET and $SELL$ (0.102, t-stat=3.88), indicating that, on average, retail investor selling increases in returns—contrarian selling. In column 2, we test whether this response depends on the investor's capital gain by interacting RET with $GAIN$. We find strong evidence of domain-dependent contrarian selling. When accounting for trading domain, the coefficient on RET becomes negative (-0.206, t-stat=-8.41), indicating that investors are *trend-following* when the position is at a loss. In contrast, when the position is at a gain, contrarian selling prevails. Our coefficient estimate (0.632, t-stat=19.71) indicates that following a 3% return (one standard deviation), investors are 1.9 percentage points more likely to sell at a gain compared to a loss—nearly 20% of the mean selling propensity.

[Insert Table 2 approximately here]

In the third column, we test the robustness of our findings by including $GAIN$, HP, VOL, $BEST$, and $WORST$—variables shown to influence selling behavior. Additionally, we control for investor and date fixed effects. Despite including this set of controls, contrarian selling is substantial in the gain domain and trend-following selling persists in the loss domain. Moreover, the difference in contrarian selling remains statistically significant and economically meaningful (0.455, t-stat=15.26).

In column 4, we provide tighter identification of domain-based contrarian selling by including stock-date fixed effects. Stock-date fixed effects essentially compare investors holding the same stock on the same date, who differ only in the timing of their purchase. This means our identification comes from comparing investors trading at a gain to those at a loss, based solely on

because this rules out endogeneity concerns that apply to contemporaneous regressions (e.g., selling affecting returns).

when they purchased the stock. After including stock-date fixed effects, the interaction between RET and $GAIN$ remains positive and significant (0.265, t-stat=6.99).

We next decompose the interaction between RET and $GAIN$. Under the belief updating hypothesis, selling should be especially responsive to *positive* returns in the *gain* domain and to *negative* returns in the *loss* domain. In column 5, we estimate a regression that includes RET, along with two interactions: $RET \times GAIN \times POS$ and $RET \times LOSS \times NEG$. The baseline coefficient on RET captures return sensitivity when the return direction and capital gains are not aligned. The interaction terms isolate cases where the return direction and domain have the same sign. These are cases where the belief-updating mechanism predicts stronger return sensitivities.

The results show that selling propensity has a pronounced positive return sensitivity when the return is positive and the investor is trading at a gain (1.062, t-stat=24.39). Similarly, selling propensity has a pronounced negative return sensitivity when the return is negative and the investor is at a loss (-0.297, t-stat=-7.47). This evidence is in line with belief updating and a higher selling propensity when a stock's price moves further away from the purchase price. Moreover, the last column in Table 2 suggests that this effect magnitude is asymmetric—the effect in the gain domain is larger in magnitude compared to the effect in the loss domain.

In the Online Appendix, we provide additional tests of the belief updating mechanism and examine the robustness of our domain-based contrarian selling evidence. Consistent with belief-updating, we find that more salient positions exhibit stronger domain dependence. We further show that our results are inconsistent with alternative explanations such as portfolio rebalancing and tax-loss selling. Importantly, while retail investor trades are more contrarian in the gain domain, portfolio tests show that retail contrarian selling is more profitable in the loss domain. This evidence questions rational motives as the driving force of domain-based contrarian selling. Finally, we document domain-based contrarian selling in other sample specifications and when we use a positive return indicator to infer contrarian behavior.

D. Timing of Contrarian Selling

We next investigate *when* retail investors sell in a domain-based contrarian way. These analyses have important implications for asset pricing tests as they determine the horizon at which we should expect return reversals to be affected by contrarian selling. For these tests, we examine how domain-dependent contrarian selling evolves over the course of one month. Specifically, we estimate regression (1) and measure RET and $GAIN$ for days *t* through *t-20* while the sell indicator for day *t* remains the dependent variable. We include stock and date fixed effects as well as the controls described earlier. The regression coefficients and 90% confidence intervals are plotted in Figure 1 and are also reported in the Online Appendix.

[Insert Figure 1 approximately here]

In Figure 1, we see that domain-based contrarian selling is strongest on the same day and declines over the course of a month. Examining the point estimates, the initial coefficient estimate on $GAIN_t \times RET_t$ is 0.694. This return sensitivity reduces to 0.455 for $GAIN_{t-1} \times RET_{t-1}$, 0.275 for $GAIN_{t-2} \times RET_{t-2}$, and declines steadily to 0.039 for $GAIN_{t-20} \times RET_{t-20}$. The $RET \times GAIN$ coefficient is significantly positive for about three weeks, as indicated by the confidence interval bands in Figure 1. The economic magnitude, by comparison, is essentially zero by the end of week two.

These patterns yield an unclear prediction for the relation between domain-dependent contrarian selling and *daily* return reversals. Specifically, strong domain-based contrarian selling on day *t* suggests that prices should be affected on day *t*, the day of the initial price pressure. Attenuated price pressure on day *t* should dampen return reversals on day *t+1*. However, the continued domain-based contrarian selling on day *t+1* should also affect prices on day *t+1*, which strengthens reversals due to the added correction on day *t+1* prices.

Although these forces distort predictions for daily reversals, they complement one another over a longer horizon. For example, with monthly reversals, the daily timing of contrarian trading is far less consequential. As long as contrarian trades to daily returns occur during the month, the monthly return magnitude from price pressure is reduced, implying a smaller return reversal in the following month. As such, we focus on *monthly* short-term reversals for our asset pricing tests in Section III.[10]

E. Monthly Retail Trading Analysis

Given the monthly horizon in our asset pricing tests, we also provide tests of *monthly* retail trading using the transaction data from earlier and introduce data from RobinTrack. The transaction data allow us to test whether monthly returns experience domain-based contrarian selling that could reduce price pressure. RobinTrack provides stock-level data of retail trading, which allows us to analyze retail trading on a broader scale and corroborate our findings with alternative retail trading data.

For our analysis with transaction data, we follow the empirical setup described before, with a few exceptions. Because persistent daily contrarian trading can reduce price pressure

[10] Though our asset pricing tests focus on monthly reversals, we also examine daily reversals in the Online Appendix. In this daily reversal analysis, we find qualitatively similar results compared to our monthly tests. However, given our evidence on the timing of retail trades, we do not interpret this observation as a direct result of domain-based contrarian retail selling.

during a month, we now focus on monthly returns and retail selling from that same month. Therefore, our observations include all positions held by investors entering a new month and the dependent variable $SELL$ is an indicator variable equal to one if investor *i* sells stock *j* during month *t*. The return variable RET is likewise the return of stock *j* during the same month *t*. Lastly, if the price of stock *j* has appreciated since it was purchased by investor *i*, based on its price on the last day of month *t-1*, we define the position as at a gain, $GAIN$.

While RobinTrack does not contain account-level details, it offers broad stock-level coverage over a more recent time period. RobinTrack reports the number of Robinhood investors holding a stock from May 2018 through August 2020. Following Barber et al. (2022), we construct two variables to measure retail activity with this data: CHG and $RATIO$. CHG is the monthly change in retail investors holding a stock based on the number of Robinhood users holding the stock on the last day of month *t-1* and the last day of month *t*; $RATIO$ is constructed the same way, except in percent changes. In line with Barber et al. (2022), we focus on stocks with over 100 Robinhood investors at the end of month *t-1*.

Because RobinTrack is not account-level data, we cannot directly observe investors' capital gains. To address this concern, we construct a stock-level proxy for the average unrealized capital gains of a stock's investors, similar to the work of Grinblatt and Han (2005). The estimation uses weekly price and trading volume data from the previous five years. For a given stock j, we estimate the average unrealized capital gain for the stock's investors in week w as

(2) $$CGO_{j,w} = \ln\left(\frac{P_{j,w}}{k_{j,w}\sum_{n=1}^{260}(V_{j,w-n}\prod_{\tau=1}^{n-1}[1-V_{j,w-n+\tau}])P_{j,w-n}}\right),$$

where V_w and P_w are the stock's turnover and split-adjusted stock price in week w, respectively.

We truncate the weekly turnover at 1, making the previous prices $P_{j,w-n}$ weighted by the probability that a current investor bought the share in week $w - n$. We scale the weights with a factor k such that they add up to 1 and require at least 100 weekly observations. We merge the last weekly CGO estimate from month *t-1* with our RobinTrack retail trading measures in month *t*.[11]

Following the setup of our daily analysis, we estimate the following monthly panel regression using the brokerage data:

$$(3) \qquad SELL_{i,j,t} = \alpha + \beta_1 RET_{j,t} + \beta_2 GAIN_{i,j,t-1} + \beta_3 RET_{j,t} \times GAIN_{i,j,t-1} + \epsilon_{i,j,t}$$

where j refers to the stock held by investor i and *t* is the potential sell month. We further include and require the same set of control variables as before.

We, likewise, estimate the following panel regression for the RobinTrack data:

$$(4) \qquad Retail\ Activity_{j,t} = \alpha + \beta_1 RET_{j,t} + \beta_2 CGO_{j,t-1} + \beta_3 RET_{j,t} \times CGO_{j,t-1} + \epsilon_{j,t},$$

where $Retail\ Activity_{j,t}$ is the monthly change in the number of Robinhood investors. For these tests, we include and require controls for $BETA$, $SIZE$, BM,MOM, $ltREV$, OP, AG, LEV, $IVOL$, PRC, $ILLIQ$, and TO. Detailed definitions for these variables are available in the Appendix.

The variable of interest is β_3, the coefficient of the interaction of contemporaneous returns and unrealized capital gains. Because the dependent variable $Retail\ Activity_{j,t}$ reflects buys

[11] Our proxy for the average unrealized capital gain of a stock's investors, CGO, is constructed using the trading information of *all* investors, not only retail investors. Though non-retail investors could exhibit similar domain-dependent contrarian tendencies, we validate this measure as a proxy for *retail* behavior in the Online Appendix. In these tests, we show that CGO closely tracks the fraction of retail investors trading at a gain from the brokerage data, where we can precisely identify retail investor gains.

minus sells in equation (4), a positive value indicates net buying. This moves in the opposite direction of the sell dummy we use for the transaction data. Hence, if retail investors are more contrarian when at a gain, we expect the regression coefficient β_3 to have a negative sign in equation (4) and a positive sign in equation (3).

[Insert Table 3 approximately here]

Table 3 provides evidence that the degree of contrarian trading significantly depends on capital gains across both datasets. In Panel A, we report the findings from the brokerage transaction data. Among brokerage investors, selling increases with returns, and this contrarian behavior is twice as large when the position is at a gain compared to a loss.[12] For Robinhood investors, Panel B shows a significantly negative coefficient for the interaction of CGO and RET, indicating that contrarian trading increases in unrealized capital gains. This further indicates that our findings also hold if we consider the net effect of sells and buys. We find similar evidence as we add control variables as well as date and stock fixed effects.

III. Asset Pricing Implications

We next investigate whether domain-dependent contrarian selling by retail investors is consistent with empirical evidence on asset prices. If contrarian trades dampen price pressures, they should weaken short-term return reversals (Kaniel et al. (2008), Kelley and Tetlock (2013)).

[12] In the Online Appendix, we repeat all our tests from Table 2 with the monthly brokerage specification. In these tests, we find a robust positive interaction between $RET \times GAIN$. However, we do not find trend-following selling in the loss domain. In this sense, the *presence* of contrarian trading is not domain-dependent for our monthly specification. However, the *degree* of contrarian trading remains domain-dependent.

Consequently, we expect short-term reversals to be smaller among stocks where the average investor has higher unrealized capital gains.

A. Data and Variables

Our sample for this section is based on common ordinary US stocks traded on NYSE, AMEX, or NASDAQ for a sample period from January 1962 to December 2024. Stock market and accounting data are retrieved from CRSP and COMPUSTAT, respectively. Risk-free rate data and return factors are obtained from Kenneth French's homepage. Stock returns are adjusted for delisting following Shumway (1997).

Following Jegadeesh (1990), we study short-term return reversals based on the cross-sectional relationship between stock returns in month *t* (RET) and subsequent returns in month *t+1* ($SRET$). As described in Section II, we use a methodology similar to Grinblatt and Han (2005) to estimate the average unrealized capital gain (CGO) for investors in a given stock. Since our monthly retail investor analyses use the last weekly CGO-estimate in month *t-1* to predict contrarian trading in month *t*, we examine whether the CGO-estimate from month *t-1* moderates the relationship between RET and $SRET$.

For our analysis, we again include controls for $BETA$, $SIZE$, BM,MOM, $ltREV$, OP, AG, LEV, $IVOL$, PRC, $ILLIQ$, and TO. We restrict our sample to stock-month observations with non-missing values for CGO, RET, and these control variables. All of these variables are available at the end of month *t* and winsorized at 1% and 99% quantiles. The subsequent returns $SRET$ refer to month *t+1* and are based on a sample period from January

1962 through December 2024. This procedure results in 1,772,736 stock-month observations with data for CGO, RET, control variables, and $SRET$.

[Insert Table 4 approximately here]

We report summary statistics and correlation coefficients for the variables of interest in Table 4. Our main explanatory variable CGO is, by construction, strongly correlated with explicit (MOM and $ltREV$) and implicit ($SIZE$ and PRC) measures of previous stock performance. Consequently, we carefully control for these characteristics in regressions.

B. CGO-Dependent Short-Term Return Reversal

We begin our return reversal analysis by conducting independent portfolio double sorts based on CGO and RET. At the end of each month, stocks are allocated to one quintile portfolio based on CGO and one quintile portfolio based on RET. We compute the value-weighted average returns in the subsequent month for each of the resulting 25 portfolios. If domain-dependent contrarian trading affects short-term return reversals, we expect to see weaker return reversals when the average investor has a larger capital gain—instances where contrarian retail selling was more prevalent.

Table 5 shows that, among low-CGO stocks, the low-RET portfolio strongly outperforms the high-RET portfolio by 1.54% per month. In contrast, the magnitude of short-term reversals is small for high-CGO stocks (0.29%), the difference in returns being statistically significant (1.25%, t-stat=4.37). This pattern aligns with our evidence of domain-based contrarian trading; since retail investors provide greater liquidity when at a gain, we expect weaker short-term reversals for high-CGO stocks. This difference in short-term return reversals is robust to adjusting portfolio returns with respect to the three-factor model of Fama and French (1993), see right side of Table 5.

[Insert Table 5 approximately here]

The Online Appendix documents similar findings for other standard factor models, equal-weighted portfolio returns, and alternative versions of CGO. Moreover, we show that a market-wide measure of CGO predicts short-term reversal profits in the time-series. Our tests in the Online Appendix are also in line with a more nuanced implication of our retail trading evidence: Table 2 shows that domain-dependent contrarian selling is stronger if RET is positive. In line with this asymmetry, the moderating effect of CGO on short-term reversals is stronger when recent returns are positive.

In Table 6, we use Fama-MacBeth regressions as a secondary method to test whether CGO influences short-term return reversals. This allows us to control for a host of variables while examining the relation between subsequent stock returns and the interaction term $CGO \times RET$. Table 6 presents the time-series averages of the cross-sectional regression coefficients. Column 1 shows that CGO significantly moderates short-term return reversals (7.923, t-stat=10.66). When $CGO = 0$, a 1% monthly return reverses by 2.912 basis points the following month. If CGO decreases by one standard deviation, this reversal strengthens by an additional 2.615 basis points. These effects remain statistically and economically significant as we add controls.

[Insert Table 6 approximately here]

Table 4 shows that CGO is correlated with illiquidity proxies such as $ILLIQ$. Because these illiquidity proxies might influence the magnitude of short-term reversals, we also consider the interaction term $ILLIQ \times RET$ as a control variable and continue to find a robust relationship between $RET \times CGO$ and subsequent returns. In the Online Appendix, we consider additional liquidity-related interaction terms and find similar results.

In the last column, we follow the arguments of Green, Hand, and Zhang (2017) and exclude microcaps from the analysis. That is, each month, we exclude all stocks that fall below the 20%-NYSE size threshold. Column 6 shows that the moderating effect of CGO for short-term reversals is substantially smaller for non-microcaps, yet remains significant. This result is consistent with the intuition that retail trading, especially trading that is liquidity-related, should have a smaller impact among larger and more liquid stocks.

C. Liquidity

For large liquid stocks, there are ample investors and professional market makers willing to facilitate trades. Because of this, it is challenging for variation in contrarian retail trading to have a material effect on prices. For less liquid stocks, however, there are limited potential counterparties, allowing retail traders to play a greater role. As such, we hypothesize that our asset pricing results are strongest for less liquid stocks.

We first examine this hypothesis following the method proposed by Amihud (2002) to measure stock liquidity. Specifically, we construct samples of below-median Amihud (2002) illiquidity stocks and above-median Amihud (2002) illiquidity stocks. For both groups, we conduct conditional double sorts on CGO and RET and report the subsequent portfolio returns. We expect our results to be strongest among the less liquid sample if retail trading helps explain our short-term return reversal findings.

[Insert Table 7 approximately here]

Table 7 shows that short-term reversals are weakly related to CGO in the liquid half of stocks: a reversal strategy only earns an average return 0.31% (t-stat=1.31) higher for low-CGO stocks, relative to high-CGO stocks. In contrast, CGO has a substantial moderating effect on short-term return reversals for illiquid stocks. Short-term return reversals are 2.38% (t-stat=6.44) stronger among low-CGO stocks compared to high-CGO stocks. The difference between these two return figures is also highly significant (untabulated t-stat of 4.22). These findings are consistent with our hypothesis that domain-dependent contrarian retail selling among high-CGO stocks can reduce the magnitude of illiquidity-induced short-term reversals.

While the Amihud (2002) illiquidity measure helps us to understand how our findings vary based on potential price impact, there are other stock characteristics related to liquidity where we also expect our asset pricing findings to be strongest. In particular, high-low spreads (Corwin and Schultz (2012)) and relative bid-ask spreads (Copeland and Galai (1983)) also reflect liquidity and should moderate illiquidity-related short-term reversals (Jegadeesh and Titman (1995)). Additionally, market makers' capacity to provide liquidity should be reduced among high-$IVOL$ firms due to arbitrage risk (Benston and Hagerman (1974)). Lastly, small firms are typically assumed to be comparably illiquid. For these alternative proxies, our Online Appendix provides evidence comparable to Table 7: CGO has a substantially stronger impact on the magnitude of reversals among illiquid, high-$IVOL$, and small stocks.

D. Transmission Mechanism

We next examine the transmission mechanism for CGO-dependent short-term reversals (Jegadeesh and Titman (1995)). In many microstructure models, reversals arise from bid-ask bounce (see, for example, Roll (1984)). For example, institutional demand can generate a positive return by moving a stock's closing price to the ask quote. This positive return can be followed by a negative return when there are future market sell orders, which move the stock's price down to the bid quote. This bid-ask bounce reversal can happen although market makers do not change quotes. If retail investors take the opposite side of the institution's trade, the initial price increase (and subsequent reversal) could potentially be eliminated.[13]

In other models such as Ho and Stoll (1981) and Hendershott and Menkveld (2014), reversals can arise without bid-ask bounce effects because risk-averse market makers adjust midquotes to manage inventory. For example, when a market maker receives a large buy order, this leaves her below target inventory (short position for the market maker). Consequently, she raises both bid and ask quotes (a midquote increase) to make selling more attractive and further buying less so. The elevated midquote tilts incoming orders toward selling, which moves inventory toward its target and allows the market maker to adjust her midquote back to its inventory-neutral level—generating a reversal in midquote returns. When retail investors provide contrarian sells in response to buying pressure, this can reduce the initial increase in quotes and

[13]Our arguments follow Kaniel et al. (2008) and Kelley and Tetlock (2013) in assuming that retail investors attenuate *institutional* price pressure. However, our behavioral arguments do not imply that retail investors' domain-based contrarian trading depends on a specific source of price pressure. Notwithstanding, two empirical observations support the institutional framing of our arguments. First, the Online Appendix shows that the CGO-dependence of short-term reversals is particularly strong for stocks with high residual institutional ownership (Nagel (2005)). Second, untabulated analyses show that the CGO-dependence of short-term reversals negatively, though insignificantly (t-statistic of -1.72), depends on the one-month lagged investor sentiment index of Baker and Wurgler (2006). If the price pressure that is mitigated by contrarian selling was due to sentiment-driven retail purchases, we would expect a positive sign.

can help market makers unwind their short positions such that the price pressure is corrected more quickly.

Based on these competing theories, we examine the role of bid-ask bounce in our findings. For our sample of illiquid stocks (above-median Amihud (2002) illiquidity), we conduct conditional portfolio double sorts using closing prices and bid-ask midpoints separately. Each month, we assign stocks to quintiles based on CGO. Within each CGO group, stocks are then allocated to a portfolio based on RET, the stock's log return in month *t*. We report value-weighted returns in month *t+1* for each of the 25 portfolios in Table 8. On the left side of Table 8, RET and subsequent returns are computed based on closing prices at the end of month *t*. This makes the portfolio returns in month *t* susceptible to bid-ask bounce. In this setting, we observe that short-term reversals are strongly related to CGO. A short-term reversal strategy among low-CGO stocks generates an average monthly return that is 1.68% higher compared to high-CGO stocks.

[Insert Table 8 approximately here]

On the right side of Table 8, we run the same analyses but calculate RET and subsequent returns based on the bid-ask midpoint at the end of month *t*, removing bid-ask bounce effects. We find that the difference in short-term return reversals between low and high CGO-quintile is quite similar (1.44%). As such, CGO-dependent reversals appear to extend beyond bid-ask bounce effects.[14]

These observations align well with our previous arguments and findings: Retail investors do not only provide direct liquidity by being the counterparty for institutional trades. Instead they respond to price movements on the same day and on subsequent days (see Figure 1). Hence, their

[14]The Online Appendix shows that removing the last trading day of the month from the calculation of RET also does not eliminate the CGO-dependence of short-term reversals.

contrarian sells appear to help (market makers) reduce quotes and lead to weaker short-term reversals at a monthly horizon. These arguments also imply that more retail investor contrarian selling corresponds to lower return volatility and reduced market maker inventory risk. Additional Online Appendix analyses support these predictions.

IV. Evidence from Stock Splits

We conclude our analysis by examining how our results are affected by stock splits. Our evidence shows that retail investors are more contrarian when trading at a gain. This suggests that the relationship between a stock's current price and an investor's purchase price is central to retail contrarian selling. In related work, Birru (2015) argues that stock splits confuse investors about the purchase price of a stock, weakening the disposition effect. Applying this logic to our setting, if differences between the current price and purchase price trigger belief updating and domain-dependent contrarian selling, then stock splits and blurred purchase prices should weaken this channel. As such, we expect the relationship between capital gains and contrarian behavior, and its resulting effect on return reversals, to diminish following stock splits.

We first investigate the effect of stock splits on domain-based contrarian selling. Using our daily brokerage transaction sample, we classify each investor-stock-date into one of two subsamples: positions affected by a stock split during the holding period ($SPLIT$) and those unaffected ($NON\text{-}SPLIT$). We re-estimate the regression from our main analysis within each group and report the results in Table 9.

[Insert Table 9 approximately here]

Consistent with our earlier findings, we observe strong domain-based contrarian selling for the non-split subsample—$RET \times GAIN$ is highly significant. In contrast, for the split subsample, the interaction is insignificant. Moreover, the difference in coefficients between the split and non-split subsamples is significant. In line with our hypothesis, domain-based contrarian selling weakens following stock splits.[15]

We next test whether our short-term return reversal findings are affected by stock splits. Since stock splits seem to reduce domain-based contrarian selling, we expect CGO to have a weaker moderating effect on short-term return reversals following splits. For this test, we assign each stock-month observation to a subsample, depending on whether the stock experienced a split in the previous year or not. We re-estimate our portfolio tests separately within each group.

[Insert Table 10 approximately here]

Consistent with our hypothesis, Table 10 shows that CGO has a substantially weaker effect on short-term reversals following stock splits. In the non-split subsample, the average monthly return to a short-term reversal strategy is 1.78% higher per month among low-CGO stocks compared to high-CGO stocks. In contrast, this portfolio return difference is only 0.92% and insignificant in the split sample. Fama-MacBeth regressions in the Online Appendix yield the same conclusion. Overall, our evidence from stock splits highlights the role of capital gains for domain-based contrarian selling and short-term return reversals.

[15]In the Online Appendix, we examine whether domain-based trading weakens after stock splits in the monthly data. For both the brokerage and RobinTrack samples, we find reduced domain-dependent contrarian behavior following stock splits, consistent with the important role of unrealized capital gains.

V. Conclusion

In this paper, we study whether contrarian retail trading reflects informed market-making or behavioral tendencies. Given prior work showing that contrarian retail trades can attenuate return reversals and improve market efficiency (Kaniel et al. (2008), Kelley and Tetlock (2013)), one might expect contrarian trading to be an area where retail investors exhibit intentional skill. However, using transaction data from discount broker customers, we find strong evidence in favor of a behavioral belief-updating mechanism: investors re-evaluate their positions as a stock's price moves further from its purchase price, leading to predictable patterns in contrarian selling.

In support of this behavioral interpretation, we show that retail selling is contrarian for positions at a gain and trend-following for those at a loss. This domain dependence is robust across various samples, persists after accounting for time-varying stock fixed effects, and is not explained by other known predictors of retail selling. Moreover, we show that measures of retail trading activity derived from RobinTrack also exhibit heightened contrarian behavior when more investors are trading at a gain.

We then explore the potential asset pricing implications of this behavior. Since contrarian trades are in the opposite direction of price movements, they can dampen temporary price pressures. Consistent with this idea, we find that monthly short-term return reversals are weaker for stocks where the average investor has a greater capital gain. This result persists after adjusting returns for standard factor models, extends beyond bid-ask bounce, and is driven by illiquid stocks—those where retail trades should have the largest effect.

We conclude our analysis by examining how our findings change around stock splits. Birru (2015) argues that stock splits make it more difficult for investors to know their purchase price of a stock, reducing its influence on trading behavior. Based on this logic, if capital gains are central to domain-based contrarian selling, then both the behavioral patterns and the associated asset pricing effects should diminish post-split. Consistent with this view, we find that the trading domain matters much less for contrarian trading after stock splits. Likewise, the average unrealized capital gain of investors exhibits a much weaker moderating effect on short-term return reversals post-split.

Taken together, our results suggest that contrarian retail trading is more likely driven by behavioral tendencies than by sophisticated market-making. While liquidity premiums are *lower* for stocks where investors have larger unrealized capital gains, retail investors supply *more* liquidity in precisely those settings. Our evidence indicates that contrarian retail selling varies systematically based on trading domain which spills over into stock market liquidity. These findings have implications not only for our understanding of retail trading, but also for the execution of large institutional orders.

FIGURE 1

Domain-Based Contrarian Selling Dynamics

In this figure, we illustrate how domain-based contrarian selling evolves over the course of a month by estimating the following regression:

$$SELL_{i,j,t} = \alpha + \beta_1 RET_{j,t-T} + \beta_2 GAIN_{i,j,t-T} + \beta_3 RET_{j,t-T} \times GAIN_{i,j,t-T} + \epsilon_{i,j,t}$$

where $SELL_{i,j,t}$ is an investor-stock-date indicator variable equal to one if investor *i* sells stock *j* on day *t*. $RET_{j,t-T}$ is the return for stock *j* on day *t-T*. $GAIN_{i,j,t-T}$ is an indicator variable equal to one if investor *i*'s position in stock *j* on day *t-T* is trading in the gain domain. We plot the estimates and 90% confidence interval bands for β_3, the regression coefficient for $RET_{j,t-T} \times GAIN_{i,j,t-T}$ where $T \in \{0, 1, \ldots, 20\}$ determines the x-axis. For all specifications, we include the control variables HP, VOL, $BEST$, and $WORST$ as well as investor and date fixed effects. Confidence intervals are created using standard errors that are double-clustered by investor and date.

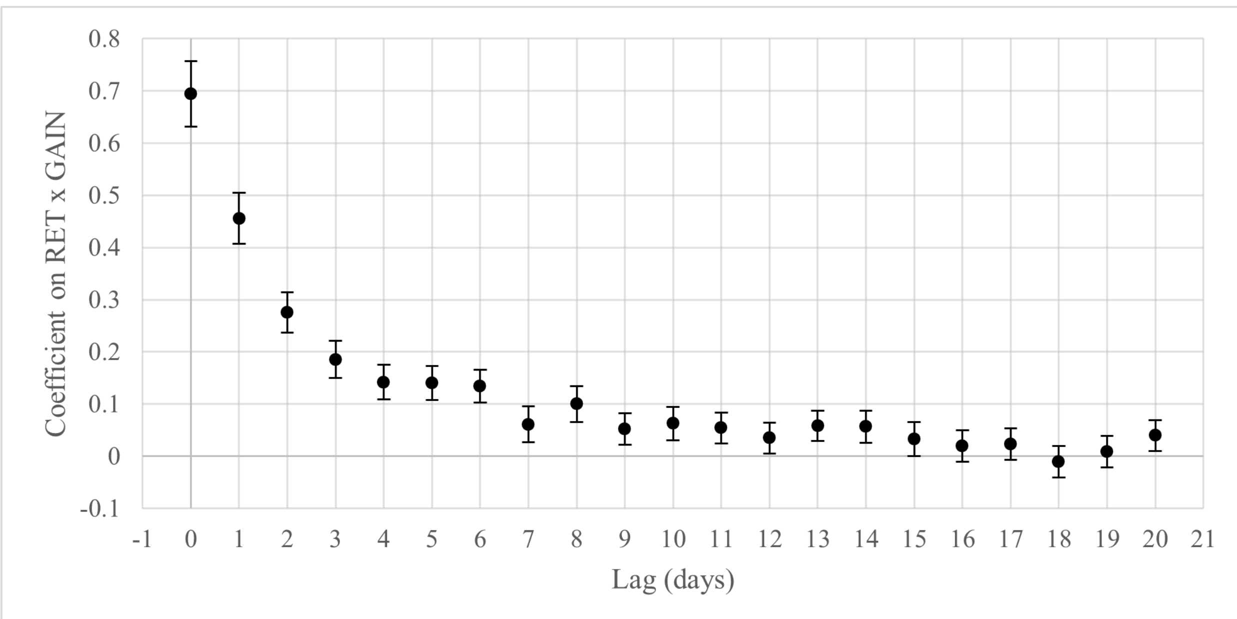


TABLE 1

Individual Investor Summary Statistics

This table reports summary statistics (mean, standard deviation, minimum, 0.1-quantile, median, 0.9-quantile, maximum) and correlation coefficients for retail investors' stock holdings on days when the respective investor sells at least one stock. $SELL$ is an indicator variable equal to one if an investor sells the stock on day *t*. RET is the stock return on day *t-1*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. The holding period HP is the square root of the number of days the investor has held the stock as of day *t-1*. VOL is the standard deviation of daily stock returns over the previous year through day *t-1*. $BEST$ is an indicator variable equal to one if the stock has the highest return, relative to its purchase price, in the investor's portfolio as of day *t-1*. $WORST$ is an indicator variable equal to one if the stock has the lowest return, relative to its purchase price, in the investor's portfolio as of day *t-1*. The sample period is from January 1991 to November 1996.

Summary Statistics

	$SELL$	RET	$GAIN$	HP	VOL	$BEST$	$WORST$
mean	0.11	0.00	0.53	16.20	0.03	0.08	0.08
SD	0.32	0.03	0.50	9.89	0.02	0.28	0.28
min	0.00	-0.10	0.00	1.00	0.01	0.00	0.00
$q_{0.1}$	0.00	-0.03	0.00	4.58	0.01	0.00	0.00
med	0.00	0.00	1.00	14.39	0.03	0.00	0.00
$q_{0.9}$	1.00	0.04	1.00	30.85	0.05	0.00	0.00
max	1.00	0.12	1.00	42.07	0.10	1.00	1.00

Correlation Coefficients

	$SELL$	RET	$GAIN$	HP	VOL	$BEST$	$WORST$
$SELL$	1.00						
RET	0.01	1.00					
$GAIN$	0.05	0.09	1.00				
HP	-0.07	-0.00	0.07	1.00			
VOL	0.02	0.01	-0.24	-0.15	1.00		
$BEST$	0.11	0.04	0.27	0.11	-0.00	1.00	
$WORST$	0.03	-0.05	-0.30	0.07	0.21	-0.09	1.00

TABLE 2

Domain-Based Contrarian Selling

This table tests whether retail investor contrarian selling is influenced by the domain in which a position is trading. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day t. RET is the stock return on day *t-1*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. POS is an indicator variable equal to one if the stock return on day *t-1* is positive. NEG is an indicator variable equal to one if POS is zero. $LOSS$ is an indicator variable equal to one if $GAIN$ is zero. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SELL$	$SELL$	$SELL$	$SELL$	$SELL$
RET	0.102***	-0.206***	-0.115***		-0.128***
	(3.88)	(-8.41)	(-5.41)		(-4.27)
$RET \times GAIN$		0.632***	0.455***	0.265***	
		(19.71)	(15.26)	(6.99)	
$RET \times POS \times GAIN$					1.062***
					(24.39)
$RET \times NEG \times LOSS$					-0.297***
					(-7.47)
$GAIN$		0.030***	0.032***	0.035***	0.026***
		(11.17)	(19.70)	(25.56)	(16.91)
Controls			x	x	x
Investor FE			x	x	x
Date FE			x		x
Stock-Date FE				x	
Observations	2,434,072	2,434,072	2,434,072	2,434,072	2,434,072
R^2	0.000	0.003	0.067	0.417	0.084

TABLE 3

Monthly Domain-Based Contrarian Trading

This table examines whether contrarian trading over the course of a month depends on the capital gains of retail investors. Panel A uses brokerage trade data. Panel B uses RobinTrack data. In Panel A, we estimate investor-position regressions where our dependent variable $SELL$ is an indicator variable equal to one if an investor sells the stock during month *t*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price at the end of month *t-1*. Control variables for Panel A are based on the end of month *t-1* and include HP, VOL, $BEST$, and $WORST$. RET is the stock return during month *t* for both Panels A and B. In Panel B, we estimate stock-level regressions. In columns 1-3, the dependent variable is CHG, the change in the number of Robinhood investors holding the stock between the end of month *t-1* and the end of month *t*. In columns 4-6, the dependent variable is $RATIO$, the percent change in the number of Robinhood investors holding the stock between the end of month *t-1* and the end of month *t*. CGO is the stock-level capital gains overhang measure from month *t-1*. Control variables for Panel B are based on the end of month *t-1* and include $BETA$, $SIZE$, MOM, $ltREV$, OP, AG, LEV, $IVOL$, PRC, TO, and $ILLIQ$. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and month in Panel A and robust standard errors in Panel B. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Brokerage Trade Data

	$SELL$	$SELL$	$SELL$
RET	0.031***	0.037***	0.035***
	(3.65)	(5.30)	(6.17)
$GAIN$	0.003*	0.011***	0.013***
	(1.94)	(7.61)	(10.12)
$RET \times GAIN$	0.037***	0.040***	0.040***
	(3.67)	(5.16)	(5.48)
Controls		x	x
Investor FE			x
Month FE			x
Observations	5,455,872	5,455,872	5,455,872
R^2	0.001	0.020	0.092

Panel B: RobinTrack Data

	CHG	CHG	CHG	$RATIO$	$RATIO$	$RATIO$
RET	0.164***	0.035	0.089	-0.042**	-0.054***	-0.013
	(2.83)	(0.66)	(1.63)	(-2.38)	(-3.10)	(-0.65)
CGO	-0.107***	-0.148***	0.108**	-0.135***	-0.151***	-0.063***
	(-5.49)	(-4.92)	(2.44)	(-21.08)	(-16.40)	(-4.84)
$RET \times CGO$	-0.303**	-0.229*	-0.275**	-0.126***	-0.097**	-0.073*
	(-1.97)	(-1.66)	(-2.13)	(-2.65)	(-2.07)	(-1.69)
Controls		x	x		x	x
Stock FE			x			x
Month FE			x			x
Observations	37,508	37,508	37,508	37,508	37,508	37,508
R^2	0.004	0.119	0.422	0.024	0.037	0.214

TABLE 4

Stock Market Summary Statistics

This table reports time-series averages of cross-sectional summary statistics (mean, standard deviation, minimum, 0.1-quantile, median, 0.9-quantile, maximum) and correlation coefficients for the stock market variables of interest. CGO is the capital gains overhang measure, reflecting the average investor's log return since stock purchase at the end of month *t-1* and RET is the stock's log return in month *t*. $BETA$ is the market beta, $SIZE$ the log market value of equity, and BM the book-to-market ratio. MOM and $ltREV$ are the log returns of months *t-11* to *t-1* and *t-59* to *t-12*, respectively. OP, AG, and LEV denote operating profitability, asset growth, and leverage, respectively. $IVOL$ is the idiosyncratic return volatility with respect to the three Fama and French (1993) factors and PRC the log stock price. $ILLIQ$ denotes the Amihud (2002) illiquidity measure and TO the stock's turnover. The sample period is from January 1962 to December 2024.

Summary Statistics

	CGO	RET	$BETA$	$SIZE$	BM	MOM	$ltREV$	OP	AG	LEV	$IVOL$	PRC	$ILLIQ$	TO
mean	-0.05	0.00	1.04	19.26	0.89	0.03	0.23	0.19	0.12	0.77	0.35	2.78	4.07	0.09
SD	0.33	0.11	0.30	1.97	0.69	0.37	0.76	0.34	0.27	1.28	0.25	1.07	13.47	0.11
min	-1.22	-0.32	0.48	15.16	0.08	-1.13	-2.13	-1.53	-0.35	0.00	0.08	-0.25	0.00	0.00
$q_{0.1}$	-0.48	-0.12	0.68	16.67	0.26	-0.41	-0.73	-0.08	-0.09	0.02	0.14	1.24	0.01	0.01
med	0.00	0.00	1.01	19.22	0.73	0.06	0.30	0.22	0.07	0.34	0.28	2.96	0.18	0.06
$q_{0.9}$	0.30	0.13	1.45	21.86	1.65	0.45	1.09	0.43	0.35	1.81	0.66	4.01	8.41	0.19
max	0.56	0.33	1.94	24.01	4.13	0.98	1.98	1.24	1.60	8.36	1.43	4.80	97.84	0.69

Correlation Coefficients

	CGO	RET	$BETA$	$SIZE$	BM	MOM	$ltREV$	OP	AG	LEV	$IVOL$	PRC	$ILLIQ$	TO
CGO	1.00													
RET	0.04	1.00												
$BETA$	-0.19	-0.03	1.00											
$SIZE$	0.41	0.08	0.08	1.00										
BM	-0.19	0.01	-0.07	-0.34	1.00									
MOM	0.69	0.03	-0.13	0.21	0.00	1.00								
$ltREV$	0.41	0.02	-0.08	0.33	-0.38	0.04	1.00							
OP	0.30	0.04	-0.09	0.32	-0.21	0.13	0.37	1.00						
AG	0.08	-0.01	0.05	0.10	-0.19	-0.04	0.29	0.15	1.00					
LEV	-0.13	-0.00	0.04	-0.13	0.46	-0.02	-0.22	-0.06	-0.05	1.00				
$IVOL$	-0.43	0.03	0.30	-0.53	0.15	-0.24	-0.29	-0.30	-0.03	0.10	1.00			
PRC	0.60	0.14	-0.11	0.78	-0.29	0.36	0.47	0.39	0.11	-0.17	-0.61	1.00		
$ILLIQ$	-0.31	-0.02	-0.09	-0.46	0.25	-0.14	-0.22	-0.17	-0.10	0.12	0.41	-0.46	1.00	
TO	0.03	0.08	0.42	0.10	-0.07	0.06	0.03	-0.03	0.10	0.01	0.27	0.06	-0.13	1.00

TABLE 5

CGO-Dependent Short-Term Reversals: Portfolio Double Sorts

This table reports monthly value-weighted returns from portfolio double sorts. At the end of each month t, each stock is independently allocated to one quintile portfolio based on CGO and one quintile portfolio based on RET. CGO is the capital gains overhang measure, reflecting the average investor's log return since stock purchase and RET is the stock's log return in month t. The average portfolio returns of month *t+1* are presented either on a raw basis (left panel) or adjusted for their exposure with respect to the three Fama and French (1993) factors (right panel). The portfolio returns are based on a sample period from January 1962 to December 2024. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Raw Returns							Fama-French-Adjusted Returns						
	CGO							CGO						
	low	2	3	4	high	5-1	t(5-1)	low	2	3	4	high	5-1	t(5-1)
low RET	1.60	1.12	1.15	1.15	1.29	-0.31	(-0.93)	0.11	-0.22	-0.06	0.07	0.31	0.20	(0.68)
2	1.23	1.38	1.14	1.08	1.26	0.03	(0.12)	-0.10	0.22	0.08	0.09	0.38	0.48	(1.94)
3	0.83	1.05	0.91	0.99	1.07	0.24	(0.85)	-0.49	-0.09	-0.09	0.04	0.21	0.70	(2.86)
4	0.60	0.82	0.93	0.87	1.07	0.47	(1.75)	-0.67	-0.26	-0.04	-0.05	0.26	0.93	(3.88)
high RET	0.07	0.38	0.73	0.71	1.01	0.94	(3.74)	-1.13	-0.71	-0.27	-0.20	0.13	1.26	(5.28)
5-1	-1.54	-0.74	-0.42	-0.44	-0.29	1.25	(4.37)	-1.23	-0.49	-0.21	-0.27	-0.18	1.05	(3.79)
t(5-1)	(-6.06)	(-3.80)	(-2.26)	(-2.52)	(-1.65)	(4.37)		(-5.08)	(-2.50)	(-1.11)	(-1.48)	(-0.96)	(3.79)	

TABLE 6

CGO-Dependent Short-Term Reversals: Fama-MacBeth Regressions

This table presents time-series averages from the following monthly cross-sectional regressions:

$$SRET_j = \alpha + \beta_1 CGO_j + \beta_2 RET_j + \beta_3 CGO_j \times RET_j + \epsilon_j.$$

The dependent variable is the stock return of month *t+1*. The explanatory variables are given in the first column. CGO is the capital gains overhang measure, reflecting the average investor's log return since stock purchase at the end of month *t-1* and RET is the stock's log return in month *t*. $BETA$ is the market beta, $SIZE$ the log market value of equity, and BM the book-to-market ratio. MOM and $ltREV$ are the log returns of months *t-11* to *t-1* and *t-59* to *t-12*, respectively. OP, AG, and LEV denote operating profitability, asset growth, and leverage, respectively. $IVOL$ is the idiosyncratic return volatility with respect to the three Fama and French (1993) factors and PRC the log stock price. $ILLIQ$ denotes the Amihud (2002) illiquidity measure and TO the stock's turnover. The subsequent returns are based on a sample period from January 1962 to December 2024. In the last column, the analysis excludes all stock-month observations that fall below the 20%-NYSE size threshold. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using three lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SRET$	$SRET$	$SRET$	$SRET$	$SRET$	$SRET$
CGO	0.573**	0.667***	0.131	0.020	0.126	0.278
	(2.44)	(3.74)	(0.68)	(0.11)	(0.72)	(1.28)
RET	-2.912***	-3.806***	-4.025***	-4.200***	-3.527***	-3.654***
	(-7.18)	(-10.28)	(-11.13)	(-11.74)	(-9.71)	(-8.71)
$RET \times CGO$	7.923***	7.870***	7.799***	7.837***	6.372***	2.416**
	(10.66)	(11.03)	(10.91)	(11.03)	(8.55)	(2.21)
$BETA$		-0.062	-0.095	0.006	0.158	0.031
		(-0.21)	(-0.35)	(0.02)	(0.65)	(0.12)
$SIZE$		-0.067*	-0.068**	-0.085***	-0.050*	-0.088***
		(-1.83)	(-2.07)	(-2.68)	(-1.85)	(-2.79)
BM		0.241***	0.129**	0.197***	0.158***	0.143**
		(4.38)	(2.41)	(4.10)	(3.33)	(2.07)
MOM			0.761***	0.746***	0.692***	0.634***
			(4.61)	(4.65)	(4.55)	(3.60)
$ltREV$			-0.144**	-0.159***	-0.131***	-0.117**
			(-2.52)	(-2.89)	(-2.60)	(-2.10)
OP				0.828***	0.772***	0.635***
				(7.61)	(7.38)	(5.11)
AG				-0.576***	-0.549***	-0.284***
				(-6.86)	(-6.58)	(-3.29)
LEV				-0.080***	-0.090***	-0.059*
				(-2.97)	(-3.33)	(-1.95)
$IVOL$					-1.500***	-1.326***
					(-9.78)	(-6.88)
PRC					-0.229***	-0.149***
					(-4.16)	(-3.09)
TO					4.039***	3.304***
					(4.60)	(3.87)
$ILLIQ$					0.064***	0.756
					(3.53)	(0.75)
$ILLIQ \times RET$					-0.505***	-24.324
					(-3.24)	(-1.31)
Observations	1,772,736	1,772,736	1,772,736	1,772,736	1,772,736	951,273
Avg. R^2	0.034	0.067	0.075	0.081	0.095	0.125

TABLE 7

CGO-Dependent Short-Term Reversals: Stock Illiquidity

This table reports monthly value-weighted returns from conditional portfolio double sorts for two subsamples. At the end of each month *t*, each stock is allocated to a below-median $ILLIQ$ or above-median $ILLIQ$ subsample based on its level of Amihud (2002) illiquidity. Within these subsamples, each stock is allocated to a quintile portfolio based on CGO, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on RET, the stock's log return in month *t*. The table shows the average portfolio returns of month *t+1*. The portfolio returns are based on a sample period from January 1962 to December 2024. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Low Amihud (2002) Illiquidity							High Amihud (2002) Illiquidity						
	CGO							CGO						
	low	2	3	4	high	5-1	t(5-1)	low	2	3	4	high	5-1	t(5-1)
low RET	1.17	1.09	1.10	1.03	1.53	0.36	(1.42)	2.49	2.02	1.59	1.74	2.05	-0.44	(-1.19)
2	1.11	1.06	0.96	1.01	1.23	0.12	(0.54)	1.30	1.47	1.36	1.53	1.43	0.13	(0.44)
3	1.15	0.88	1.04	0.92	1.17	0.01	(0.06)	0.97	1.10	1.14	1.31	1.36	0.39	(1.43)
4	0.67	0.79	0.70	0.79	1.08	0.41	(2.04)	0.47	0.69	0.83	1.08	1.05	0.57	(2.07)
high RET	0.25	0.80	0.80	0.66	0.92	0.67	(3.08)	-0.87	0.19	0.44	0.79	1.07	1.94	(8.13)
5-1	-0.92	-0.28	-0.30	-0.37	-0.61	0.31	(1.31)	-3.36	-1.82	-1.15	-0.94	-0.99	2.38	(6.44)
t(5-1)	(-4.24)	(-1.62)	(-1.91)	(-2.26)	(-3.62)	(1.31)		(-9.47)	(-8.08)	(-6.73)	(-5.91)	(-6.01)	(6.44)	

TABLE 8

CGO-Dependent Short-Term Reversals: Bid-Ask Bounce

This table reports monthly value-weighted returns from conditional portfolio double sorts for the subsample of stock-month observations with above-median Amihud (2002) illiquidity. Each stock is allocated to a quintile portfolio based on CGO, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on RET, the stock's log return in month *t*. The table shows the average portfolio returns of month *t+1*. On the left side, RET and subsequent returns are based on standard closing prices. On the right side, RET is based on the bid-ask midpoint at the end of month *t* and the subsequent return measurement starts from this bid-ask midpoint. The portfolio returns are based on a sample period from January 1993 to December 2024. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Closing Prices							Bid-Ask Midpoints						
	CGO							CGO						
	low	2	3	4	high	5-1	t(5-1)	low	2	3	4	high	5-1	t(5-1)
low RET	1.95	1.61	1.18	1.63	1.80	-0.14	(-0.24)	1.64	1.42	1.10	1.46	1.76	0.13	(0.22)
2	1.07	1.19	1.28	1.31	1.28	0.20	(0.44)	0.66	1.10	1.25	1.25	1.23	0.57	(1.31)
3	0.89	1.08	1.14	1.26	1.18	0.29	(0.69)	1.12	1.00	1.09	1.26	1.15	0.03	(0.07)
4	0.86	0.86	1.03	1.09	1.12	0.25	(0.58)	0.74	0.92	1.07	1.16	1.22	0.48	(1.20)
high RET	-0.34	0.60	0.62	1.00	1.20	1.54	(4.38)	-0.20	0.80	0.81	1.11	1.37	1.57	(4.42)
5-1	-2.28	-1.00	-0.57	-0.63	-0.60	1.68	(2.92)	-1.83	-0.62	-0.29	-0.35	-0.39	1.44	(2.56)
t(5-1)	(-4.23)	(-3.04)	(-2.23)	(-2.82)	(-2.38)	(2.92)		(-3.43)	(-1.94)	(-1.18)	(-1.45)	(-1.50)	(2.56)	

TABLE 9

Domain-Based Contrarian Selling: Stock Splits

This table examines the impact of stock splits on domain-based contrarian selling. The sample is split into two groups based on whether the position has experienced a stock split during the investor's holding period. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day *t*. RET is the stock return on day *t-1*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$NON\text{-}SPLIT$	$SPLIT$	$DIFF$
RET	-0.113***	-0.190***	-0.076*
	(-5.13)	(-4.68)	(-1.82)
$RET \times GAIN$	0.562***	-0.047	-0.609***
	(18.42)	(-0.78)	(-9.49)
$GAIN$	0.033***	0.008***	-0.025***
	(19.35)	(3.73)	(-11.28)
Controls	x	x	
Investor FE	x	x	
Date FE	x	x	
Observations	2,083,945	350,127	
R^2	0.072	0.119	

TABLE 10

CGO-Dependent Short-Term Reversals: Stock Splits

This table reports monthly value-weighted returns from conditional portfolio double sorts for two subsamples. At the end of each month *t*, each stock is allocated to a subsample depending on whether the stock experienced a stock split in the previous twelve months or not. Within these subsamples, each stock is allocated to a quintile portfolio based on CGO, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on RET, the stock's log return in month *t*. The table shows the average portfolio returns of month $t+1$. The portfolio returns are based on a sample period from January 1962 to December 2024. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Stocks without Splits							Stocks with Splits						
	CGO							CGO						
	low	2	3	4	high	5-1	t(5-1)	low	2	3	4	high	5-1	t(5-1)
low RET	1.89	1.30	1.27	1.15	1.22	-0.67	(-1.73)	1.20	0.37	1.54	1.18	1.91	0.71	(1.18)
2	1.30	1.32	1.25	1.14	1.14	-0.16	(-0.56)	0.51	1.24	1.15	1.29	1.45	0.94	(1.71)
3	1.09	1.10	0.92	0.96	1.15	0.06	(0.21)	0.73	1.21	1.27	0.87	1.51	0.79	(2.06)
4	0.51	0.79	0.88	0.90	0.92	0.41	(1.49)	0.54	0.67	0.64	1.02	1.04	0.50	(1.36)
high RET	-0.22	0.35	0.68	0.75	0.89	1.11	(4.21)	-0.48	0.37	0.56	0.70	1.15	1.63	(3.79)
5-1	-2.11	-0.95	-0.59	-0.40	-0.33	1.78	(5.21)	-1.68	0.00	-0.98	-0.48	-0.76	0.92	(1.31)
t(5-1)	(-6.56)	(-4.33)	(-3.33)	(-2.65)	(-1.94)	(5.21)		(-2.83)	(0.01)	(-2.14)	(-1.27)	(-2.20)	(1.31)	

Appendix: Variable Definitions

Retail Investor Analysis (Daily)

$BEST$: An indicator variable equal to one if stock *j* has the highest capital gain, relative to its purchase price, in investor *i*'s portfolio on day *t-1*. We require at least 5 securities in investor *i*'s portfolio for this indicator to be non-missing.

$GAIN$: An indicator variable equal to one if stock *j* is trading at a gain relative to its purchase price for investor *i* on a given day, generally day *t-1*.

HP: The square root of the number of days investor *i* has held stock *j* on day *t-1*.

$LOSS$: An indicator variable equal to one if *GAIN* is zero.

NEG: An indicator variable equal to one if *POS* is zero.

POS: An indicator variable equal to one if RET is greater than zero.

RET: The return of stock *j* on a given day, generally day *t-1*.

$SELL$: An indicator variable equal to one if investor *i* sells stock *j* on day *t*.

VOL: The standard deviation of daily stock returns for stock *j* over the previous year from day *t-1*, requiring at least 50 observations.

$WORST$: An indicator variable equal to one if stock *j* has the lowest capital gain, relative to its purchase price, in investor *i*'s portfolio on day *t-1*. We require at least 5 securities in investor *i*'s portfolio for this indicator to be non-missing.

Retail Investor Analysis (Monthly)

CGO *(RobinTrack Data)*: A proxy for the average unrealized capital gain of investors in stock *j* at the end of month *t-1*. This value is generated using weekly split-adjusted price and trading volume data over five years to infer the average purchase price of investors, requiring observations from at least the previous 100 weeks. See equation (2). The underlying trading volume of NASDAQ stocks is adjusted following Gao and Ritter (2010).

CHG *(RobinTrack Data)*: The monthly change in the number of Robinhood investors holding stock *j* based on the last day of month *t-1* and the last day of month *t*.

Control Variables (Brokerage Data): In the brokerage data tests, we control for *HP*, *VOL*, *BEST*, and *WORST*. These variables are described above and defined here based on the last day of month *t-1*.

Control Variables (RobinTrack Data): In the RobinTrack data tests, we control for ***BETA***, ***SIZE***, ***MOM***, *ltREV*, ***OP***, ***AG***, ***LEV***, ***IVOL***, ***PRC***, ***TO***, and ***ILLIQ***. These variables are described below and defined here based on month *t-1*.

$GAIN$ *(Brokerage Data)*: An indicator variable equal to one if stock *j* is trading at a gain relative to its purchase price for investor *i* on the last day of month *t-1*.

$RATIO$ *(RobinTrack Data)*: The monthly percent change in the number of Robinhood investors holding stock *j* based on the last day of month *t-1* and the last day of month *t*.
RET: The return of stock *j* during month *t*.

$SELL$ *(Brokerage Data)*: An indicator variable equal to one if investor *i* sells stock *j* during month *t*.

Asset Pricing Analysis

All predictive variables are publicly available at the end of month *t* and used to predict subsequent returns in month *t+1*. Annual accounting data for a fiscal year ending in calendar year *y* is not used before the end of June in calendar year *y+1*.

AG: Asset growth is the relative annual change in balance sheet total assets from the fiscal year ending in *y-1* to the fiscal year ending in y (Fama and French (2015)).

$BETA$: The Frazzini and Pedersen (2014) beta is based on daily returns over months *t-59* through *t*.

BM: The book-to-market ratio is the ratio of book equity in year *y* to market value of equity at the end of year *y*. Book equity is estimated as book value of stockholders' equity plus deferred taxes and investment tax credit minus book value of preferred stock (Fama and French (1993)). If unavailable, book equity is calculated as the sum of common equity and deferred taxes and investment tax credit. If also unavailable, we use the difference between the book value of assets and the book value of liabilities.

CGO: Capital gains overhang is a proxy for the average unrealized capital gain for investors in a given stock at the end of month *t-1*. This value is generated using weekly split-adjusted price and trading volume data over five years to infer the average purchase price of investors, requiring observations from at least the previous 100 weeks. See equation (2). The underlying trading volume of NASDAQ stocks is adjusted following Gao and Ritter (2010).

$ILLIQ$: The Amihud (2002) illiquidity measure is calculated as the average ratio of absolute daily return over daily dollar trading volume in months *t-5* to *t*, in millions. The trading volume of NASDAQ stocks is adjusted following Gao and Ritter (2010).

$IVOL$: The annualized idiosyncratic return volatility of a stock in month *t* is calculated with respect to the three Fama and French (1993) factors (Ang, Hodrick, Xing, and Zhang (2006)).

LEV: Financial leverage is the ratio of the firm's outstanding current and long-term debt in year *y* to its market value of equity at the end of year *y*.

$ltREV$: A stock's log return over months *t-59* to *t-12* is used to capture potential long-term reversal effects.

MOM: A stock's log return over months *t-11* to *t-1* is used to capture potential momentum effects.

OP: Operating profitability is the ratio of annual revenues minus cost of goods sold, minus selling/general/administrative expenses, minus interest expense to book equity in year *y* (Fama and French (2015)). *OP* is estimated only if book equity is positive.

PRC: The log nominal stock price at the end of month *t*.

RET: The log return of a stock in month *t*.

$SIZE$: The natural logarithm of a stock's market capitalization at the end of month *t*.

$SRET$: The subsequent return of a stock in month *t+1*.

TO: A stock's turnover in month *t*. The trading volume of NASDAQ stocks is adjusted following Gao and Ritter (2010).

References

Amihud, Y. "Illiquidity and stock returns: Cross–section and time–series effects." *Journal of Financial Markets*, 5 (2002), 31–56.

An, L. "Asset pricing when traders sell extreme winners and losers." *Review of Financial Studies*, 29 (2016), 823–861.

Ang, A.; R. J. Hodrick; Y. Xing; and X. Zhang. "The cross–section of volatility and expected returns." *Journal of Finance*, 61 (2006), 259–299.

Baker, M., and J. Wurgler. "Investor sentiment and the cross–section of stock returns." *Journal of Finance*, 61 (2006), 1645–1680.

Barber, B. M.; X. Huang; T. Odean; and C. Schwarz. "Attention–induced trading and returns: Evidence from Robinhood users." *Journal of Finance*, 77 (2022), 3141–3190.

Barber, B. M., and T. Odean. "Trading is hazardous to your wealth: The common stock investment performance of individual investors." *Journal of Finance*, 55 (2000), 773–806.

Barber, B. M., and T. Odean. "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors." *Review of Financial Studies*, 21 (2008), 785–818.

Barber, B. M., and T. Odean. "The behavior of individual investors." *Handbook of the Economics of Finance*, 2 (2013), 1533–1570.

Barber, B. M.; T. Odean; and N. Zhu. "Do retail trades move markets?" *Review of Financial Studies*, 22 (2009), 151–186.

Barrot, J.-N.; R. Kaniel; and D. Sraer. “Are retail traders compensated for providing liquidity?” *Journal of Financial Economics*, 120 (2016), 146–168.

Ben-David, I., and D. Hirshleifer. “Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect.” *Review of Financial Studies*, 25 (2012), 2485–2532.

Benston, G. J., and R. L. Hagerman. “Determinants of bid–asked spreads in the over–the–counter market.” *Journal of Financial Economics*, 1 (1974), 353–364.

Birru, J. “Confusion of confusions: A test of the disposition effect and momentum.” *Review of Financial Studies*, 28 (2015), 1849–1873.

Boehmer, E.; C. M. Jones; X. Zhang; and X. Zhang. “Tracking retail investor activity.” *Journal of Finance*, 76 (2021), 2249–2305.

Cheng, S.; A. Hameed; A. Subrahmanyam; and S. Titman. “Short–term reversals: The effects of past returns and institutional exits.” *Journal of Financial and Quantitative Analysis*, 52 (2017), 143–173.

Choe, H.; B.-C. Kho; and R. M. Stulz. “Do foreign investors destabilize stock markets? The Korean experience in 1997.” *Journal of Financial Economics*, 54 (1999), 227–264.

Copeland, T. E., and D. Galai. “Information effects on the bid–ask spread.” *Journal of Finance*, 38 (1983), 1457–1469.

Corwin, S. A., and P. Schultz. “A simple way to estimate bid–ask spreads from daily high and low prices.” *Journal of Finance*, 67 (2012), 719–760.

Da, Z.; J. Engelberg; and P. Gao. "In search of attention." *Journal of Finance*, 66 (2011), 1461–1499.

Da, Z., and P. Gao. "Clientele change, liquidity shock, and the return on financially distressed stocks." *Journal of Financial and Quantitative Analysis*, 45 (2010), 27–48.

Da, Z.; Q. Liu; and E. Schaumburg. "A closer look at the short–term return reversal." *Management Science*, 60 (2014), 658–674.

De Long, J. B.; A. Shleifer; L. H. Summers; and R. J. Waldmann. "Noise trader risk in financial markets." *Journal of Political Economy*, 98 (1990), 703–738.

Fama, E. F., and K. R. French. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E. F., and K. R. French. "A five–factor asset pricing model." *Journal of Financial Economics*, 116 (2015), 1–22.

Fama, E. F., and K. R. French. "Choosing factors." *Journal of Financial Economics*, 128 (2018), 234–252.

Frazzini, A., and L. H. Pedersen. "Betting against beta." *Journal of Financial Economics*, 111 (2014), 1–25.

Gao, X., and J. R. Ritter. "The marketing of seasoned equity offerings." *Journal of Financial Economics*, 97 (2010), 33–52.

Green, J.; J. R. M. Hand; and X. F. Zhang. "The characteristics that provide independent information about average US monthly stock returns." *Review of Financial Studies*, 30 (2017), 4389–4436.

Grinblatt, M., and B. Han. "Prospect theory, mental accounting, and momentum." *Journal of Financial Economics*, 78 (2005), 311–339.

Grinblatt, M., and M. Keloharju. "What makes investors trade?" *Journal of Finance*, 56 (2001), 589–616.

Grinblatt, M.; M. Keloharju; and J. T. Linnainmaa. "IQ, trading behavior, and performance." *Journal of Financial Economics*, 104 (2012), 339–362.

Hartzmark, S. M. "The worst, the best, ignoring all the rest: The rank effect and trading behavior." *Review of Financial Studies*, 28 (2015), 1024–1059.

Hendershott, T., and A. J. Menkveld. "Price pressures." *Journal of Financial Economics*, 114 (2014), 405–423.

Ho, T., and H. R. Stoll. "Optimal dealer pricing under transactions and return uncertainty." *Journal of Financial Economics*, 9 (1981), 47–73.

Hou, K.; H. Mo; C. Xue; and L. Zhang. "An augmented q–factor model with expected growth." *Review of Finance*, 25 (2021), 1–41.

Hou, K.; C. Xue; and L. Zhang. "Digesting anomalies: An investment approach." *Review of Financial Studies*, 28 (2015), 650–705.

Jegadeesh, N. "Evidence of predictable behavior of security returns." *Journal of Finance*, 45 (1990), 881–898.

Jegadeesh, N., and S. Titman. “Short–horizon return reversals and the bid–ask spread.” *Journal of Financial Intermediation*, 4 (1995), 116–132.

Kaniel, R.; S. Liu; G. Saar; and S. Titman. “Individual investor trading and return patterns around earnings announcements.” *Journal of Finance*, 67 (2012), 639–680.

Kaniel, R.; G. Saar; and S. Titman. “Individual investor trading and stock returns.” *Journal of Finance*, 63 (2008), 273–310.

Kelley, E. K., and P. C. Tetlock. “How wise are crowds? Insights from retail orders and stock returns.” *Journal of Finance*, 68 (2013), 1229–1265.

Medhat, M., and M. Schmeling. “Short–term momentum.” *Review of Financial Studies*, 35 (2022), 1480–1526.

Nagel, S. “Short sales, institutional investors and the cross–section of stock returns.” *Journal of Financial Economics*, 78 (2005), 277–309.

Newey, W. K., and K. D. West. “A simple, positive semi–definite, heteroskedasticity and autocorrelation consistent covariance matrix.” *Econometrica*, 55 (1987), 703–708.

Odean, T. “Are investors reluctant to realize their losses?” *Journal of Finance*, 53 (1998), 1775–1798.

Richards, A. “Big fish in small ponds: The trading behavior and price impact of foreign investors in Asian emerging equity markets.” *Journal of Financial and Quantitative Analysis*, 40 (2005), 1–27.

Roll, R. "A simple implicit measure of the effective bid–ask spread in an efficient market." *Journal of Finance*, 39 (1984), 1127–1139.

Shumway, T. "The delisting bias in CRSP data." *Journal of Finance*, 52 (1997), 327–340.

Zhu, Z., and K. Yung. "The interaction of short–term reversal and momentum strategies." *Journal of Portfolio Management*, 42 (2016), 96–107.

Online Appendix for

"Swimming Against the Current: Contrarian Retail Trading"

1. Individual Investor Behavior Mechanism Tests

In this section of the Online Appendix, we provide tests of the mechanism behind domain-dependent contrarian selling. We interpret our retail investor findings from Section II as consistent with the belief-updating mechanism of Ben-David and Hirshleifer (2012). However, the disposition effect or rational selling could help explain some of the results. Here, we further investigate the belief-driven interpretation and evaluate these alternative explanations.

Belief Updating: Building on the belief-updating theory described in Ben-David and Hirshleifer (2012), we further conjecture that investors are more likely to revise their beliefs for stock positions that are more salient. Following the logic in Hartzmark (2015), we classify the stock with the largest capital gain in an investor's portfolio as the most salient position trading at a gain ($BEST$). Similarly, we classify the stock with the smallest capital gain as the most salient position at a loss ($WORST$). In Table OA1, we show that our results are especially strong for these salient positions. In Tables OA2 and OA3, we extend this analysis by using the recency of an investor's stock purchase as a proxy for the position's salience. Again, consistent with the belief-updating mechanism, domain-dependent contrarian selling is stronger when investors have held a stock for a shorter period of time.

Disposition Effect: Because of our focus on the trading domain, our results are closely related to the disposition effect—investors' tendency to sell gains more readily than losses (Shefrin and Statman, 1985). In this context, Grinblatt and Keloharju (2001) argue that investors' reluctance to realize losses could also imply that they are less responsive to short-term price run-ups when at a loss. In a large study of investor behavior, Grinblatt and Keloharju (2001) provide empirical evidence in support of this prediction. Though their arguments can explain a *weaker* return sensitivity in the loss domain, they cannot accommodate the switch to a *negative* return sensitivity that we document for positions at a loss.

Another way that the disposition effect potentially relates to our findings is through an attention-driven disposition effect. Our evidence of a significant interaction between RET and $GAIN$ could arise if attention moderates the disposition effect through RET. Since prior work shows that extreme recent returns increase investor attention (Barber and Odean, 2008), this could amplify the tendency to sell at a gain. In Table OA4, we find that selling propensity is higher in the gain domain and even more so after extreme daily returns (both positive and negative returns). Hence, the attention-based disposition effect could help explain the positive $RET \times GAIN$ interaction after positive returns. However, it cannot explain why we observe trend-following selling in the loss domain.[1]

Taken together, these findings suggest that the disposition effect may contribute to the asymmetric return responses we observe in the last column of Table 2: the effect of recent returns on selling is comparably strong for positive recent returns in the gain domain because belief updating and attention-driven disposition effect work in the same direction. For negative returns in the loss domain, there is no reinforcing effect from the disposition effect such that the return sensitivity is weaker.

Rational Selling: Though we provide tests of behavioral mechanisms that relate to domain-dependent contrarian selling, there are rational reasons why investor selling can

[1]Dierick et al. (2019) use log-ins to brokerage accounts as a general measure of investor attention towards their portfolios. They find that attention reduces the disposition effect. In our setting (Table OA4), individual stock returns proxy for stock-level attention, and this kind of attention increases the disposition effect. We attribute the difference in our findings to where attention is directed. The tests of Dierick et al. (2019) are related to portfolio attention, while our tests explore attention to individual stocks within a portfolio.

be related to unrealized gains. Similar to Ben-David and Hirshleifer (2012), we examine portfolio rebalancing, tax-loss selling, and margin selling. In Table OA5, we do not find evidence in support of any of these mechanisms. We show that our findings persist if we only consider selling decisions where the entire position is sold (excluding sells with rebalancing motives), if we exclude December from our sample (excluding sells with tax-loss selling motives), and if we split our sample into stocks with either high or low portfolio weights (margin selling).

As a more broad test of selling rationality, we analyze the profitability of contrarian sells for retail investors. If retail investors behave like rational market makers, we should expect them to be contrarian traders when it is more profitable. We test this prediction in Table OA6. Consistent with prior work (e.g., Kelley and Tetlock, 2013), we find that retail investors' contrarian sells are generally more profitable than trend-following sells (i.e., subsequent stock returns are lower after a contrarian sell compared to a trend-following sell). However, in contrast to the prediction that investors act as rational liquidity providers, we find that contrarian selling, relative to trend-following selling, is actually more profitable in the loss domain than the gain domain. This pattern suggests that retail investors tend to provide liquidity when it is least rewarded.

Table OA1. Domain-Based Contrarian Selling: Salient Gains and Losses
This table tests whether more salient gains and losses strengthen domain-based contrarian behavior. *BEST* is an indicator variable equal to one if the stock has the highest return, relative to its purchase price, in the investor's portfolio as of day *t-1*. *WORST* is an indicator variable equal to one if the stock has the lowest return, relative to its purchase price, in the investor's portfolio as of day *t-1*. The dependent variable in these regressions is *SELL*, an indicator variable equal to one if an investor sells the stock on day *t*. *RET* is the stock return on day *t-1*. *GAIN* is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. Control variables include *HP* and *VOL*. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	SELL	*SELL*	*SELL*
RET	-0.130***	-0.047*	
	(-4.68)	(-1.94)	
$RET \times GAIN$	0.359***	0.235***	0.109***
	(11.83)	(8.17)	(2.88)
$RET \times GAIN \times BEST$	0.727***	0.739***	0.536***
	(13.66)	(13.79)	(9.01)
$RET \times WORST$	-0.248***	-0.272***	-0.359***
	(-8.36)	(-9.58)	(-8.27)
GAIN	0.022***	0.032***	0.035***
	(9.13)	(19.79)	(25.62)
BEST	0.117***	0.086***	0.066***
	(33.62)	(41.87)	(31.59)
WORST	0.059***	0.033***	0.042***
	(22.30)	(17.79)	(20.67)
Controls		x	x
Investor FE		x	x
Date FE		x	
Stock-Date FE			x
Observations	2,434,072	2,434,072	2,434,072
R^2	0.017	0.067	0.418

Table OA2. Domain-Based Contrarian Selling: Holding Period ≤ 25 Days
This table tests whether investors' contrarian selling is influenced by trading in the gain domain. We consider only investor-stock-day observations with a holding period less than or equal to 25 days, irrespective of whether the investor sells at least one stock from the portfolio or not. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day *t*. RET is the stock return on day *t-1*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. POS is an indicator variable equal to one if the stock return on day *t-1* is positive. NEG is an indicator variable equal to one if POS is zero. $LOSS$ is an indicator variable equal to one if $GAIN$ is zero. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SELL$	$SELL$	$SELL$	$SELL$
RET	-0.024***	-0.019***		0.014*
	(-3.35)	(-3.40)		(1.89)
$RET \times GAIN$	0.102***	0.075***	0.036***	
	(15.26)	(14.15)	(4.19)	
$RET \times POS \times GAIN$				0.086***
				(10.51)
$RET \times NEG \times LOSS$				-0.082***
				(-9.45)
$GAIN$	0.002***	0.003***	0.003***	0.002***
	(8.12)	(12.70)	(15.15)	(10.23)
Controls		x	x	x
Investor FE		x	x	x
Date FE		x		x
Stock-Date FE			x	
Observations	5,440,389	5,440,389	5,440,389	5,440,389
R^2	0.001	0.038	0.242	0.041

Table OA3. Domain-Based Contrarian Selling: 26 Days ≤ Holding Period ≤ 100 Days
This table tests whether investors' contrarian selling is influenced by trading in the gain domain. We consider only investor-stock-day observations with a holding period between 26 and 100 days, irrespective of whether the investor sells at least one stock from the portfolio or not. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day t. RET is the stock return on day t-1. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day t-1. POS is an indicator variable equal to one if the stock return on day t-1 is positive. NEG is an indicator variable equal to one if POS is zero. $LOSS$ is an indicator variable equal to one if $GAIN$ is zero. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SELL$	$SELL$	$SELL$	$SELL$
RET	-0.026***	-0.021***		-0.021***
	(-12.08)	(-12.10)		(-9.22)
$RET \times GAIN$	0.050***	0.039***	0.027***	
	(17.12)	(15.43)	(7.76)	
$RET \times POS \times GAIN$				0.082***
				(22.36)
$RET \times NEG \times LOSS$				-0.019***
				(-4.70)
$GAIN$	0.002***	0.002***	0.001***	0.001***
	(17.80)	(15.51)	(16.74)	(11.43)
Controls		x	x	x
Investor FE		x	x	x
Date FE		x		x
Stock-Date FE			x	
Observations	14,021,129	14,021,129	14,021,129	14,021,129
R^2	0.000	0.013	0.187	0.015

Table OA4. Attention-Based Disposition Effect
This table examines how the disposition effect combines with attention-driven selling. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day t. RET is the stock return on day t-1. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day t-1. The first two columns are estimated for the sample where $RET > 0$. The remaining columns are estimated for the sample where $RET < 0$. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$RET > 0$		$RET < 0$	
	$SELL$	$SELL$	$SELL$	$SELL$
$GAIN$	0.048***	0.021***	0.021***	0.009***
	(22.49)	(10.97)	(12.65)	(5.30)
RET		0.253***		-0.597***
		(6.16)		(-14.52)
$RET \times GAIN$		1.041***		-0.670***
		(20.67)		(-10.84)
Controls	x	x	x	x
Investor FE	x	x	x	x
Date FE	x	x	x	x
Observations	1,030,912	1,030,912	1,040,097	1,040,097
R^2	0.093	0.097	0.092	0.094

Table OA5. Domain-Based Contrarian Selling: Alternative Explanations
This table tests whether alternative selling motives can explain conditional contrarian behavior. The dependent variable in these regressions is $SELL_{i,j,t}$, an indicator variable equal to one if investor *i* sells stock *j* on day *t*. In column 1, we examine the importance of portfolio rebalancing and use *FULL SELL* as the dependent variable, which is an indicator variable equal to one if investor *i* closes the position of stock *j* on day *t*. In column 2, we examine the importance of tax loss selling by excluding December observations from the sample. In the remaining columns, we study the role of margin calls. Column 3 consists of observations where a position is not above the median position value in an investor's portfolio on the given date. Column 4 consists of observations where a position is above the median position value in an investor's portfolio on the given date. *RET* is the stock return on day *t-1*. *GAIN* is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. Control variables include *HP* and *VOL*. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	FULL SELL	*NO DEC*	*LOW VALUE*	*HIGH VALUE*
	SELL	*SELL*	*SELL*	*SELL*
RET	-0.163***	-0.116***	-0.177***	0.023
	(-8.51)	(-5.33)	(-10.22)	(0.59)
$RET \times GAIN$	0.414***	0.461***	0.425***	0.362***
	(16.37)	(15.38)	(14.31)	(8.63)
GAIN	0.027***	0.036***	0.011***	0.055***
	(17.92)	(21.78)	(7.38)	(25.10)
Controls	x	x	x	x
Investor FE	x	x	x	x
Date FE	x	x	x	x
Observations	2,434,072	2,243,000	1,274,002	1,160,070
R^2	0.069	0.069	0.086	0.098

Table OA6. Portfolio-Adjusted Average Stock Returns Following Retail Investor Sells
This table shows the average difference in returns (in percentage points) between stocks that are sold by retail investors on day *t* and other stocks in the investor's portfolio. The first three columns report average differences for day *t+1* and the last three columns report report average cumulative differences from day *t+1* to day *t+5*. Each sell observation is classified as a contrarian (*CONTR*) or trend-following (*TREND*) sell based on the sign of the stock's return on day *t-1*. In addition, the sample is split based on whether the stock is sold for more than its purchase price (*GAIN*) or not (*LOSS*). The *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	RET_{t+1}			$RET_{t+1,t+5}$		
	TREND	*CONTR*	*DIFF*	*TREND*	*CONTR*	*DIFF*
LOSS	0.301***	-0.138***	-0.439***	0.650***	-0.436***	-1.085***
	(14.71)	(-5.80)	(-13.89)	(16.64)	(-9.63)	(-18.02)
GAIN	0.181***	-0.132***	-0.313***	0.434***	-0.466***	-0.901***
	(12.63)	(-9.87)	(-15.85)	(15.04)	(-18.06)	(-23.22)
DIFF	-0.120***	0.006	0.126***	-0.215***	-0.031	0.185***
	(-4.90)	(0.22)	(3.55)	(-4.50)	(-0.63)	(2.70)

2. Robustness Tests on Individual Investor Behavior

In this section of the Online Appendix, we provide robustness tests for our evidence of domain-based contrarian trading among retail investors. For the main specification in our paper, we only consider positions that are part of a portfolio with at least 5 stocks (to compute $BEST$ and $WORST$) and restrict our sample to days where investors sold at least one stock. In Table OA7, we remove the restriction on the number of stocks required in a portfolio and in Table OA8, we consider all investor-stock-date observations. In these tests, we continue to find strong evidence of domain-based contrarian trading. We note that the coefficient of interest is lower in the sample with all potential trading days. This is because the mean selling propensity reduces dramatically in this sample (from 11% to 0.23%)—the relative increase in selling propensity from domain-based contrarian trading remains comparable.

For our main analysis, we use RET to identify contrarian behavior. While this variable captures both return direction and magnitude, it is also associated with attention (Barber and Odean, 2008), which could potentially confound our inference. In Table OA9, we use POS, an indicator variable equal to one for positive returns RET, as our variable to assess contrarian trading activity. With this alternative definition of contrarian behavior, we continue to observe contrarian selling in the gain domain and trend-following selling in the loss domain.

In Table OA10, to determine whether a stock is trading at a gain or a loss, we apply share-weighted purchase prices if an investor buys the same stock at different points in time. Depending on how investors track gains, this could potentially reduce noise in our measure of $GAIN$. We find similar coefficient estimates of domain-based contrarian selling when using share-weighted prices to determine gains and losses.

As discussed in detail in Subsection II.D, the timing of domain-based contrarian trading is crucial for our asset pricing predictions. In Table OA11, we report the $RET \times GAIN$ coefficient estimates at lags of 0 through 20, relative to the trading date. These coefficient estimates are used to create the corresponding figure in the main paper. The estimates show that the $RET \times GAIN$ coefficient is strongest on day t and that it declines over the course of a month.

In Table OA12, we replicate our main evidence from Table 2 based on monthly brokerage data. On a monthly basis, retail investors sell stocks in a contrarian way in both gain and loss domains. However, the contrarian behavior is twice as strong in the gain domain compared to the loss domain. As such, we expect weaker return reversals for these stocks in the following month.

For our main tests, we use CGO (Grinblatt and Han, 2005) to proxy for the fraction of retail investors trading at a gain. This variable is constructed from stock-level prices and trading volume and, therefore, does not directly reflect retail investor trades. In Figures OA1 and OA2, we assess how well CGO proxies for the unrealized capital gains of retail investors by comparing CGO to the fraction of retail investor holdings trading at a gain in our brokerage data. We find that CGO is strongly correlated with the fraction of retail investor holdings trading at a gain—both in the time-series and in the cross-section.

Table OA7. Domain-Based Contrarian Selling: No Portfolio Holding Restrictions
This table tests whether investors' contrarian selling is influenced by the domain in which a position is trading. The sample consists of all days where an investor sells at least one stock, without conditioning on the number of stocks in the portfolio. The dependent variable in these regressions is *SELL*, an indicator variable equal to one if an investor sells the stock on day *t*. *RET* is the stock return on day *t-1*. *GAIN* is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. *POS* is an indicator variable equal to one if the stock return on day *t-1* is positive. *NEG* is an indicator variable equal to one if *POS* is zero. *LOSS* is an indicator variable equal to one if *GAIN* is zero. Control variables include *HP* and *VOL*. *BEST* and *WORST* are excluded due to the presence of small portfolios. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	SELL	*SELL*	*SELL*	*SELL*
RET	-0.235***	-0.123***		-0.122***
	(-9.58)	(-5.97)		(-4.14)
$RET \times GAIN$	1.110***	0.670***	0.351***	
	(28.98)	(21.66)	(9.98)	
$RET \times POS \times GAIN$				1.390***
				(31.35)
$RET \times NEG \times LOSS$				-0.392***
				(-9.59)
GAIN	0.050***	0.061***	0.052***	0.051***
	(14.44)	(28.60)	(33.19)	(25.52)
Controls		x	x	x
Investor FE		x	x	x
Date FE		x		x
Stock-Date FE			x	
Observations	2,961,314	2,961,314	2,961,314	2,961,314
R^2	0.008	0.186	0.488	0.204

Table OA8. Domain-Based Contrarian Selling: Extended Sample
This table tests whether investors' contrarian selling is influenced by the domain in which a position is trading. The sample consists of all investor-stock-day observations during every investor-stock holding period in our sample, irrespective of whether the investor sells at least one stock from the portfolio or not. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day *t*. RET is the stock return on day *t-1*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. POS is an indicator variable equal to one if the stock return on day *t-1* is positive. NEG is an indicator variable equal to one if POS is zero. $LOSS$ is an indicator variable equal to one if $GAIN$ is zero. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SELL$	$SELL$	$SELL$	$SELL$
RET	-0.008***	-0.004***		-0.008***
	(-9.45)	(-6.94)		(-9.15)
$RET \times GAIN$	0.027***	0.018***	0.019***	
	(23.04)	(18.41)	(15.42)	
$RET \times POS \times GAIN$				0.049***
				(31.13)
$RET \times NEG \times LOSS$				-0.003**
				(-2.41)
$GAIN$	0.000***	0.001***	0.001***	
	(10.79)	(23.53)	(23.15)	
Controls		x	x	x
Investor FE		x	x	x
Date FE		x		x
Stock-Date FE			x	
Observations	116,880,869	116,880,869	116,880,869	116,880,869
R^2	0.000	0.008	0.076	0.009

Table OA9. Domain-Based Contrarian Selling: Positive Return Indicator
This table tests whether investors' contrarian selling is influenced by the domain in which a position is trading. For this table, we infer contrarian trading based on *POS*, an indicator variable equal to one if the stock return on day *t-1* is positive. The dependent variable in these regressions is *SELL*, an indicator variable equal to one if an investor sells the stock on day *t*. *GAIN* is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day *t-1*. Control variables include *HP*, *VOL*, *BEST*, and *WORST*. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	SELL	*SELL*	*SELL*	*SELL*
POS	0.007***	-0.007***	-0.002*	
	(5.49)	(-5.70)	(-2.20)	
$POS \times GAIN$		0.020***	0.013***	0.012***
		(14.44)	(10.10)	(6.29)
GAIN		0.022***	0.027***	0.030***
		(8.18)	(16.78)	(18.97)
Controls			x	x
Investor FE			x	x
Date FE			x	
Stock-Date FE				x
Observations	2,434,072	2,434,072	2,434,072	2,434,072
R^2	0.000	0.003	0.066	0.417

Table OA10. Domain-Based Contrarian Selling: Share-Weighted Purchase Price
This table tests whether investors' contrarian selling is influenced by the domain in which a position is trading. For this table, we define the purchase price as the average of all purchase prices during the holding period, weighted by shares, instead of the first purchase price during the holding period. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if an investor sells the stock on day t. RET is the stock return on day t-1. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price on day t-1. POS is an indicator variable equal to one if the stock return on day t-1 is positive. NEG is an indicator variable equal to one if POS is zero. $LOSS$ is an indicator variable equal to one if $GAIN$ is zero. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SELL$	$SELL$	$SELL$	$SELL$
RET	-0.259***	-0.166***		-0.169***
	(-10.55)	(-7.80)		(-5.69)
$RET \times GAIN$	0.732***	0.552***	0.426***	
	(22.33)	(18.01)	(10.58)	
$RET \times POS \times GAIN$				1.157***
				(26.07)
$RET \times NEG \times LOSS$				-0.295***
				(-7.43)
$GAIN$	0.031***	0.035***	0.039***	0.029***
	(11.83)	(19.79)	(27.11)	(16.68)
Controls		x	x	x
Investor FE		x	x	x
Date FE		x		x
Stock-Date FE			x	
Observations	2,434,072	2,434,072	2,434,072	2,434,072
R^2	0.004	0.067	0.418	0.085

Table OA11. Domain-Based Contrarian Selling Dynamics
This table tests how domain-based contrarian selling evolves over the course of one month. We estimate the following regression:

$$SELL_{i,j,t} = \alpha + \beta_1 RET_{j,t-T} + \beta_2 GAIN_{i,j,t-T} + \beta_3 RET_{j,t-T} \times GAIN_{i,j,t-T} + \epsilon_{i,j,t}$$

where $SELL_{i,j,t}$ is an investor-stock-date indicator variable equal to one if investor i sells stock j on day t. $RET_{j,t-T}$ is the return for stock j on day t-T. $GAIN_{i,j,t-T}$ is an indicator variable equal to one if investor i's position in stock j on day t-T is trading in the gain domain. For all specifications, we include HP, VOL, $BEST$, and $WORST$ as well as investor and date fixed effects. The sample period is from January 1991 to November 1996. The t-statistics in parentheses are based on standard errors that are double-clustered by investor and date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$
$RET \times GAIN$	0.694***	0.455***	0.275***	0.185***	0.142***	0.140***	0.134***
	(18.17)	(15.26)	(11.63)	(8.59)	(7.05)	(7.14)	(7.04)
	$t-7$	$t-8$	$t-9$	$t-10$	$t-11$	$t-12$	$t-13$
$RET \times GAIN$	0.061***	0.100***	0.052***	0.063***	0.054***	0.035*	0.058***
	(2.90)	(4.80)	(2.79)	(3.23)	(3.00)	(1.94)	(3.31)
	$t-14$	$t-15$	$t-16$	$t-17$	$t-18$	$t-19$	$t-20$
$RET \times GAIN$	0.056***	0.032	0.019	0.023	-0.011	0.009	0.039**
	(3.05)	(1.64)	(1.05)	(1.25)	(-0.59)	(0.47)	(2.16)

Table OA12. Domain-Based Contrarian Selling: Monthly Sample
This table examines whether contrarian trading over the course of a month depends on retail investor capital gains. The sample consists of all investor-stock-month observations where investor *i* is holding stock *j* at the end of month *t-1*. The dependent variable in these regressions is $SELL$, an indicator variable equal to one if investor *i* sells their position in stock *j* during month *t*. RET is the return of the stock during month *t*. $GAIN$ is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price at the end of month *t-1*. POS is an indicator variable equal to one if the stock return during month *t* is positive. POS is an indicator variable equal to one if the stock return on day *t-1* is positive. NEG is an indicator variable equal to one if POS is zero. $LOSS$ is an indicator variable equal to one if $GAIN$ is zero. Control variables include HP, VOL, $BEST$, and $WORST$. The sample period is from January 1991 to November 1996. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and month. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$SELL$	$SELL$	$SELL$	$SELL$
RET	0.031***	0.035***		0.030***
	(3.65)	(6.17)		(5.65)
$RET \times GAIN$	0.037***	0.040***	0.041***	
	(3.67)	(5.48)	(6.90)	
$RET \times POS \times GAIN$				0.109***
				(9.63)
$RET \times NEG \times LOSS$				-0.043***
				(-3.72)
$GAIN$	0.003*	0.013***	0.009***	0.011***
	(1.94)	(10.12)	(8.94)	(10.35)
Controls		x	x	x
Investor FE		x	x	x
Month FE		x		x
Stock-Month FE			x	
Observations	5,455,872	5,455,872	5,455,872	5,455,872
R^2	0.001	0.092	0.170	0.101

Figure OA1. Time-Series of Cross-Sectional Averages of *CGO* and *AVG GAIN*

In this figure, we plot the cross-sectional averages of *CGO* and *AVG GAIN*. *CGO* is a stock's capital gains overhang measure reflecting the average investor's log return since stock purchase. *AVG GAIN* is a stock-level measure of the fraction of retail investors trading at a gain relative to their purchase price, based on brokerage trade data. We plot each value averaged across the same set of stocks in the cross-section. The sample period is from January 1991 to November 1996.

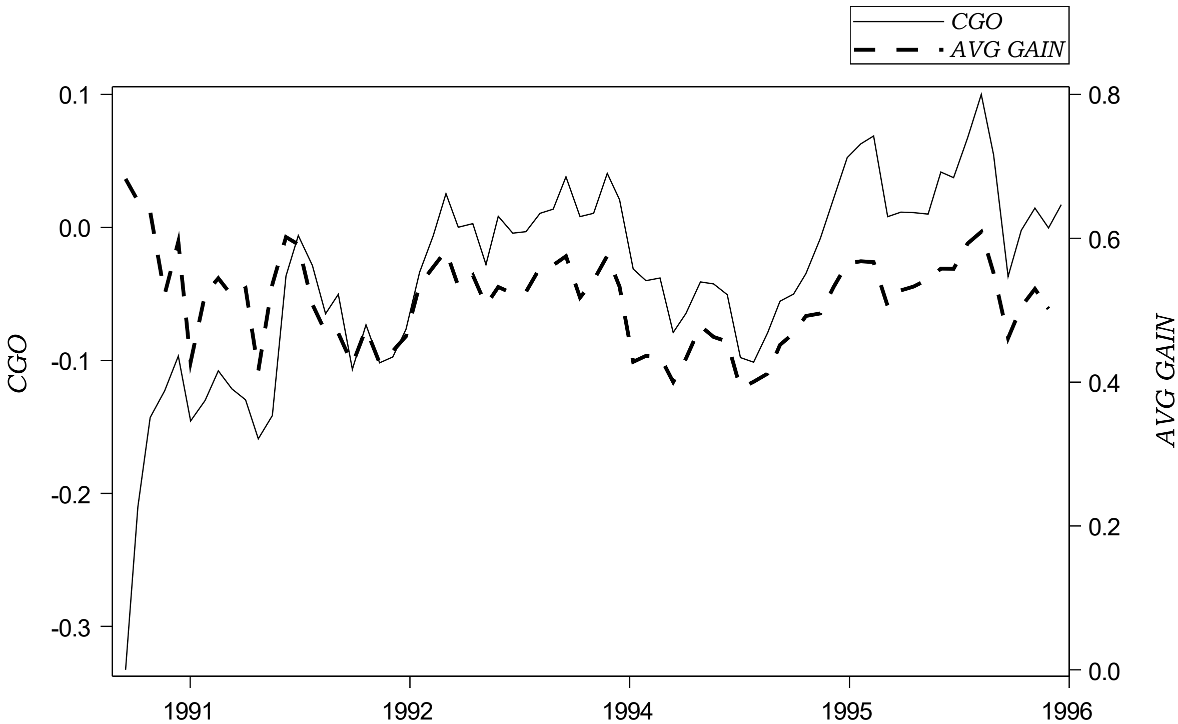
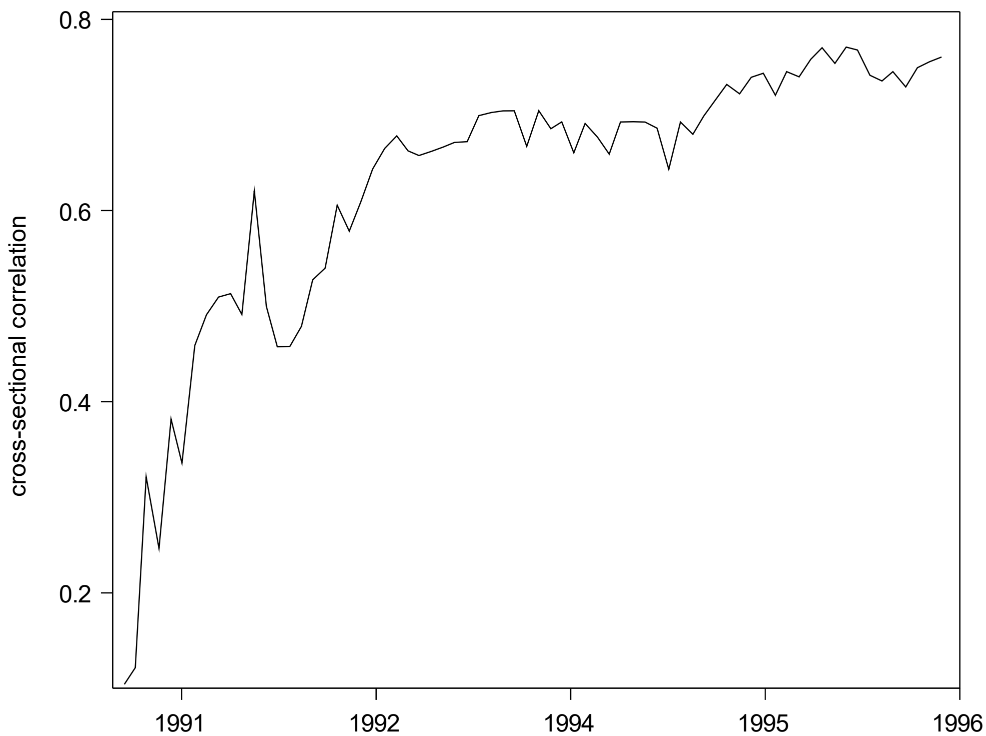


Figure OA2. Cross-Sectional Correlation between *CGO* and *AVG GAIN*

In this figure, we plot the cross-sectional correlation between *CGO* and the *AVG GAIN* for each month from January 1991 to November 1996. *CGO* is a stock's capital gains overhang measure reflecting the average investor's log return since stock purchase. *AVG GAIN* is a stock-level measure of the fraction of retail investors trading at a gain relative to their purchase price, based on brokerage trade data.



3. Alternative Specification of Baseline Portfolio Double Sort

This section of the Online Appendix provides robustness tests for portfolio double sorts. While the analyses in the main paper examine the *CGO*-dependence of short-term reversals based on raw returns and the Fama and French (1993) factor model, Table OA13 shows that these findings remain robust after accounting for exposure to alternative factor models. More specifically, Table OA13 considers the the Fama and French (2015) five-factor model, the Fama and French (2018) six-factor model, the Hou et al. (2015) q-factors, and the Hou et al. (2021) q^5-factors.

Table OA14 applies equal-weighted instead of value-weighted portfolio returns. Since equal-weighting gives more weight to small stocks than value-weighting, we expect a larger impact of illiquid stocks and a more pronounced *CGO*-dependence of short-term return reversals. Table OA14 supports this conjecture.

In the main paper, *CGO* is based on split-adjusted prices to calculate investors' unrealized capital gains. Table OA15 considers alternative versions of *CGO*. In Panel A, we estimate *CGO* based on raw prices, i.e., the prices are not adjusted for stock splits. In Panel B, we estimate *CGO* based on split- and dividend-adjusted prices. In Panel C, we use standard split-adjusted prices but assume a fixed weekly turnover rate of 10%.[2] While such a fixed turnover level completely ignores trading volume heterogeneity in both time-series and cross-section, it addresses potential concerns that turnover might be a weak proxy for retail investor trading such that *CGO* might be a weak proxy for retail

[2]In a sample of retail trades from 2002 to 2010, Barrot et al. (2016) show that retail investors' median holding period is 40 days, implying an approximately 10% weekly turnover rate. Following our *CGO* estimation, a 10% turnover implies a 90% probability to remain invested. Under iid-assumptions, an investor still holds a stock after 6 weeks (approximately 40 days) with a probability of 0.9^6 (approximately 50%). Hence, a 10% turnover rate implies that approximately 50% of the holdings are sold within 40 days, and 50% are sold later.

investors' unrealized capital gains. The *CGO*-dependence of short-term reversals remains highly significant across all three panels.

Table OA16 examines daily short-term reversals. Equivalent to our monthly findings, daily returns show stronger reversals on the next day if the level of *CGO* is comparably low. Finally, Table OA17 examines whether positive monthly returns *RET* or negative monthly returns *RET* are more prone to *CGO*-dependent short-term return reversals. In line with a stronger impact of unrealized capital gains on contrarian retail selling as a response to positive returns, the return reversals are stronger if *RET* is positive.

Table OA13. *CGO*-Dependent Short-Term Reversals: Other Factor Models
This table reports monthly value-weighted returns from portfolio double sorts. At the end of each month *t*, each stock is independently allocated to one quintile portfolio based on *CGO* and one quintile portfolio based on *RET*. *CGO* is the capital gains overhang measure reflecting the average investor's log return since stock purchase and *RET* is the stock's log return in month *t*. The average portfolio returns of month *t+1* are adjusted for their exposure with respect to the Fama and French (2015) five factors (sample period July 1963 to December 2024), the Fama and French (2018) six factors (sample period from July 1963 to December 2024), the Hou et al. (2015) q-factors (sample period from January 1967 to December 2023), or the Hou et al. (2021) q^5-factors (sample period from January 1967 to December 2023). The factors are obtained from `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` and `http://global-q.org/factors.html`. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Fama and French (2015) Five Factors							Fama and French (2018) Six Factors						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	0.36	-0.10	0.02	0.04	0.30	-0.06	(-0.18)	1.09	0.39	0.33	0.10	0.18	-0.91	(-3.37)
2	0.02	0.34	0.07	0.06	0.31	0.29	(1.13)	0.55	0.78	0.26	0.07	0.15	-0.40	(-1.96)
3	-0.37	-0.06	-0.13	-0.02	0.11	0.48	(1.76)	0.15	0.28	0.01	-0.03	-0.10	-0.24	(-1.24)
4	-0.51	-0.26	-0.08	-0.18	0.15	0.66	(2.40)	-0.02	0.06	0.04	-0.21	-0.06	-0.04	(-0.18)
high *RET*	-0.98	-0.65	-0.27	-0.30	0.09	1.07	(3.90)	-0.58	-0.46	-0.19	-0.38	-0.19	0.39	(2.01)
5-1	-1.34	-0.56	-0.28	-0.34	-0.21	1.13	(3.82)	-1.68	-0.84	-0.52	-0.48	-0.37	1.31	(4.19)
t(5-1)	(-4.87)	(-2.58)	(-1.36)	(-1.77)	(-1.04)	(3.82)		(-6.26)	(-3.82)	(-2.50)	(-2.46)	(-1.84)	(4.19)	

	Hou et al. (2015) q-factors							Hou et al. (2021) q^5-factors						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.14	0.35	0.32	0.08	0.17	-0.97	(-2.53)	1.32	0.42	0.51	0.22	0.31	-1.01	(-2.74)
2	0.53	0.72	0.30	0.05	0.08	-0.44	(-1.48)	0.61	0.74	0.33	0.05	0.12	-0.49	(-1.61)
3	0.13	0.26	-0.02	-0.04	-0.10	-0.24	(-0.80)	0.22	0.41	-0.01	-0.00	-0.10	-0.32	(-1.01)
4	0.05	0.02	-0.01	-0.23	-0.08	-0.13	(-0.44)	0.20	0.03	-0.11	-0.28	-0.20	-0.41	(-1.30)
high *RET*	-0.60	-0.48	-0.19	-0.34	-0.13	0.47	(1.63)	-0.62	-0.51	-0.26	-0.42	-0.25	0.37	(1.18)
5-1	-1.75	-0.83	-0.51	-0.42	-0.30	1.45	(4.24)	-1.94	-0.93	-0.77	-0.64	-0.56	1.38	(3.96)
t(5-1)	(-5.39)	(-3.06)	(-2.11)	(-1.83)	(-1.30)	(4.24)		(-5.50)	(-3.11)	(-2.97)	(-2.47)	(-2.42)	(3.96)	

Table OA14. *CGO*-Dependent Short-Term Reversals: Equal-Weighted Portfolio Double Sorts This table reports monthly equal-weighted returns from portfolio double sorts. At the end of each month *t*, each stock is independently allocated to one quintile portfolio based on *CGO* and one quintile portfolio based on *RET*. *CGO* is the capital gains overhang measure, reflecting the average investor's log return since stock purchase and *RET* is the stock's log return in month *t*. The average portfolio returns of month *t+1* are presented either on a raw basis (left panel) or adjusted for their exposure with respect to the three Fama and French (1993) factors (right panel). The portfolio returns are based on a sample period from January 1962 to December 2024. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Raw Returns							Fama-French-Adjusted Returns						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	2.41	1.61	1.50	1.54	1.84	-0.57	(-2.14)	0.98	0.28	0.24	0.35	0.74	-0.25	(-1.06)
2	1.34	1.35	1.30	1.32	1.59	0.25	(1.07)	0.04	0.14	0.16	0.23	0.56	0.52	(2.73)
3	1.00	1.15	1.14	1.22	1.39	0.39	(1.74)	-0.26	-0.02	0.06	0.17	0.41	0.67	(3.69)
4	0.68	0.84	0.95	1.01	1.27	0.59	(2.84)	-0.53	-0.30	-0.11	-0.01	0.31	0.85	(4.75)
high *RET*	-0.46	0.36	0.84	1.04	1.25	1.71	(8.60)	-1.67	-0.77	-0.25	0.03	0.27	1.93	(10.34)
5-1	-2.87	-1.25	-0.67	-0.51	-0.59	2.28	(9.54)	-2.65	-1.05	-0.49	-0.32	-0.47	2.18	(8.70)
t(5-1)	(-12.90)	(-8.51)	(-4.56)	(-3.51)	(-4.40)	(9.54)		(-11.76)	(-6.96)	(-3.27)	(-2.05)	(-3.22)	(8.70)	

Table OA15. *CGO*-Dependent Short-Term Reversals: Other *CGO*-Specifications
This table reports monthly value-weighted returns from portfolio double sorts. At the end of each month *t*, each stock is independently allocated to one quintile portfolio based on *CGO* and one quintile portfolio based on *RET*. *CGO* is the capital gains overhang measure and is computed differently in each panel. *RET* is the stock's log return in month *t*. In Panel A, *CGO* is based on raw prices instead of split-adjusted prices. In Panel B, *CGO* is based on split- and dividend-adjusted prices. In Panel C, *CGO* is based on split-adjusted prices, but we assume a constant weekly turnover rate of 10%. The average portfolio returns of month *t+1* are presented either on a raw basis (left panel) or adjusted for their exposure with respect to the three Fama-French-factors (right panel). The portfolio returns are based on a sample period from January 1962 to December 2024. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

Panel A: *CGO* Based on Raw Prices

	Raw Returns							Fama-French-Adjusted Returns						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.90	1.23	1.10	0.97	1.19	-0.71	(-2.44)	0.51	-0.05	-0.08	-0.12	0.17	-0.34	(-1.27)
2	1.53	1.26	1.21	0.96	1.26	-0.27	(-1.18)	0.38	0.18	0.16	-0.02	0.33	-0.05	(-0.22)
3	1.16	1.01	0.84	0.97	1.11	-0.05	(-0.25)	0.06	-0.09	-0.13	0.03	0.23	0.17	(0.96)
4	0.95	0.74	0.92	0.87	1.07	0.12	(0.60)	-0.13	-0.28	-0.02	-0.06	0.23	0.36	(1.98)
high *RET*	0.30	0.39	0.81	0.83	1.08	0.78	(3.74)	-0.76	-0.65	-0.18	-0.06	0.18	0.95	(4.45)
5-1	-1.60	-0.84	-0.30	-0.14	-0.11	1.49	(5.01)	-1.28	-0.59	-0.10	0.05	0.01	1.28	(4.34)
t(5-1)	(-6.10)	(-4.08)	(-1.55)	(-0.83)	(-0.54)	(5.01)		(-5.11)	(-2.85)	(-0.53)	(0.30)	(0.04)	(4.34)	

Panel B: *CGO* Based on Split- and Dividend-Adjusted Prices

	Raw Returns							Fama-French-Adjusted Returns						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.60	1.15	1.10	1.09	1.39	-0.21	(-0.62)	0.07	-0.16	-0.12	0.01	0.40	0.33	(1.12)
2	1.30	1.35	1.09	1.12	1.26	-0.04	(-0.14)	-0.01	0.16	0.04	0.14	0.38	0.39	(1.56)
3	0.84	0.96	0.94	0.97	1.05	0.20	(0.69)	-0.51	-0.20	-0.07	0.03	0.19	0.70	(2.87)
4	0.55	0.69	0.92	0.93	1.06	0.50	(1.90)	-0.74	-0.40	-0.05	0.01	0.25	0.99	(4.27)
high *RET*	-0.07	0.49	0.76	0.77	0.94	1.01	(3.98)	-1.28	-0.61	-0.24	-0.13	0.07	1.35	(5.60)
5-1	-1.67	-0.66	-0.34	-0.31	-0.45	1.22	(4.22)	-1.35	-0.46	-0.12	-0.15	-0.33	1.02	(3.59)
t(5-1)	(-6.46)	(-3.34)	(-1.88)	(-1.85)	(-2.47)	(4.22)		(-5.38)	(-2.30)	(-0.68)	(-0.80)	(-1.68)	(3.59)	

Panel C: *CGO* Based on a Fixed 10% Weekly Turnover

	Raw Returns							Fama-French-Adjusted Returns						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.62	1.19	1.15	1.06	1.13	-0.49	(-1.82)	0.21	-0.05	0.02	0.02	0.05	-0.16	(-0.64)
2	1.31	1.26	1.29	0.93	1.28	-0.03	(-0.14)	0.09	0.19	0.29	-0.05	0.33	0.24	(1.09)
3	0.86	0.95	1.01	0.87	1.14	0.27	(1.15)	-0.30	-0.09	0.04	-0.05	0.24	0.55	(2.48)
4	0.52	1.02	0.95	0.91	0.98	0.46	(2.16)	-0.63	0.03	-0.00	0.03	0.13	0.76	(3.74)
high *RET*	-0.11	0.70	0.81	0.81	0.99	1.10	(4.88)	-1.25	-0.35	-0.13	-0.10	0.10	1.35	(5.96)
5-1	-1.73	-0.49	-0.34	-0.25	-0.14	1.59	(5.77)	-1.46	-0.30	-0.15	-0.11	0.04	1.51	(5.29)
t(5-1)	(-7.77)	(-2.48)	(-1.92)	(-1.37)	(-0.72)	(5.77)		(-6.73)	(-1.52)	(-0.83)	(-0.59)	(0.21)	(5.29)	

Table OA16. *CGO*-Dependent Daily Short-Term Reversals

This table reports daily value-weighted returns from independent portfolio double sorts. At the end of each day *t*, each stock is allocated to one quintile portfolio based on *CGO* and one quintile portfolio based on the stock return on day *t*, *RET*. *CGO* is the capital gains overhang measure, reflecting the average investor's log return since stock purchase at the end of the previous month. The average portfolio returns of the next day *t+1* are presented either on a raw basis (left panel) or adjusted for their exposure with respect to the three Fama-French-factors (right panel). The portfolio returns are based on a sample period from January 1962 to December 2024. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using 20 lags.

	Daily Raw Returns							Daily Fama-French-Adjusted Returns						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	0.27	0.12	0.09	0.08	0.07	-0.20	(-11.81)	0.21	0.06	0.04	0.02	0.02	-0.19	(-11.20)
2	0.00	0.03	0.03	0.03	0.03	0.02	(1.72)	-0.05	-0.02	-0.02	-0.02	-0.02	0.03	(2.94)
3	-0.00	0.03	0.03	0.03	0.03	0.04	(2.93)	-0.06	-0.02	-0.02	-0.02	-0.01	0.05	(4.26)
4	0.01	0.04	0.05	0.05	0.06	0.04	(3.31)	-0.04	-0.02	0.00	0.01	0.02	0.06	(4.71)
high *RET*	-0.09	0.03	0.07	0.06	0.07	0.16	(9.16)	-0.15	-0.03	0.02	0.01	0.02	0.17	(10.44)
5-1	-0.37	-0.10	-0.02	-0.01	-0.01	0.36	(15.88)	-0.36	-0.09	-0.02	-0.01	-0.00	0.36	(15.45)
t(5-1)	(-17.15)	(-8.08)	(-2.45)	(-1.36)	(-0.43)	(15.88)		(-16.53)	(-7.52)	(-1.99)	(-0.96)	(-0.11)	(15.45)	

Table OA17. ***CGO*****-Dependent Short-Term Reversals: The Sign of** ***RET***

This table reports monthly value-weighted returns from conditional portfolio double sorts for two subsamples. At the end of each month *t*, each stock is allocated to a subsample based on the sign of *RET* (positive return *RET* and negative return *RET*), the stock's log return in month *t*. Within these subsamples, each stock is allocated to a quintile portfolio based on *CGO*, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on *RET*. Subsample months with an insufficient number of stock-month observations for the portfolio double sort are excluded (in total four months across the two subsamples). The table shows the average subsequent portfolio returns of month *t+1*. The portfolio returns are based on a sample period from January 1962 to December 2024. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Positive Return *RET*							Negative Return *RET*						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	0.94	0.97	1.10	0.98	1.11	0.17	(0.57)	2.15	1.21	1.25	1.18	1.50	-0.65	(-1.32)
2	0.71	0.89	1.04	0.85	1.02	0.31	(1.04)	1.81	1.23	1.18	1.28	1.52	-0.29	(-0.80)
3	0.27	0.44	0.84	0.90	0.86	0.59	(2.07)	1.62	1.67	1.29	1.33	1.46	-0.16	(-0.44)
4	-0.06	0.46	0.74	0.66	1.04	1.09	(4.04)	1.16	1.37	1.31	1.20	1.27	0.11	(0.37)
high *RET*	-0.56	0.38	0.66	0.69	0.89	1.45	(4.93)	1.15	1.62	1.11	1.04	1.06	-0.09	(-0.27)
5-1	-1.50	-0.59	-0.44	-0.29	-0.22	1.28	(3.95)	-1.00	0.40	-0.14	-0.14	-0.44	0.56	(1.26)
t(5-1)	(-5.38)	(-2.94)	(-2.52)	(-1.61)	(-1.12)	(3.95)		(-2.38)	(1.41)	(-0.62)	(-0.68)	(-2.24)	(1.26)	

4. Additional Analyses on the Transmission Mechanism

This section of the Online Appendix provides additional analyses on the transmission mechanism underlying our cross-sectional asset pricing findings and the impact of stock illiquidity.

Table OA18 shows that the interaction term $CGO \times RET$ remains a significant return predictor after controlling for other moderators of short-term return reversals. In particular, we show that interactions of RET with firm size $SIZE$, financial leverage LEV, nominal share price PRC, and stock turnover TO, do not substantially reduce the CGO-dependence of return reversals.

Table OA19 shows that the CGO-dependence of return reversals is stronger among small firms, stocks with high idiosyncratic return volatility, high high-low spreads, and high bid-ask spreads. This evidence supports our conjecture that contrarian retail selling has a more substantial impact among illiquid stocks that are more difficult to arbitrage.

Table OA20 presents conditional portfolio double sorts that examine the relationship between residual institutional ownership and our empirical findings. In line with our argument that retail investors' contrarian sells can reduce *institutional* price impact, the CGO-dependence of short-term reversals is particularly strong in the subsample of stocks with high residual (i.e., size-adjusted) institutional ownership (Nagel, 2005).

Table OA21 supports the evidence from the main paper that the CGO-dependence of return reversals is not completely driven by bid-ask bounce effects. Since the analyses in the main paper are based on bid-ask midpoints, they require data on bid and ask prices such that these analyses are only based on a subsample starting in 1993. In contrast, Table OA21 uses the entire sample period and skips the last day of month from the calculation of *RET* such that bid-ask bounce effects should be substantially reduced. Within the subsample of high-*ILLIQ* stocks, reversals are indeed weaker for this amended *RET* specification. Despite this, short-term reversals are still 1.54% (*t*-stat=4.46) stronger among low-*CGO* stocks compared to high-*CGO* stocks.

As an additional test of the transmission mechanism, we examine how *CGO* is related to measures of spreads and liquidity. If retail investors provide liquidity for high-*CGO* stocks, the attenuated price pressure implies less return volatility. Moreover, retail investors' contrarian trades can (partially) offset market makers' inventory imbalances, such that the latter face less inventory risk. Consequently, they can offer lower spreads and the stocks' high-frequency order imbalance volatility, a proxy for their inventory risk following Bogousslavsky and Collin-Dufresne (2023), should be lower. Table OA22 provides evidence in support of these hypotheses by showing that *CGO* is strongly correlated with volatility, spreads, and high-frequency order imbalance volatility. While this empirical evidence is consistent with our main arguments, we caution against interpreting these findings as coming solely from contrarian retail trading. For example, various economic mechanisms can generate a negative relationship between past returns and return volatility (see, for example, Schwert, 1989). Hence, we rather view our findings as evidence consistent with domain-dependent contrarian trading though other effects are likely at play.

Table OA18. *CGO*-Dependent Short-Term Reversals: Controlling for Other Moderators of Short-Term Reversals in Fama-MacBeth-Regressions

This table presents time-series averages from the following monthly cross-sectional regressions:

$$SRET_j = \alpha + \beta_1 CGO_j + \beta_2 RET_j + \beta_3 CGO_j RET_j + \epsilon_j.$$

The dependent variable is the stock return of month *t+1*. The explanatory variables are given in the first column. *CGO* is the capital gains overhang measure, reflecting the average investor's log return since stock purchase at the end of month *t-1* and *RET* is the stock's log return in month *t*. *BETA* is the market beta, *SIZE* the log market value of equity, and *BM* the book-to-market ratio. *MOM* and *ltREV* are the log returns of months *t-11* to *t-1* and *t-59* to *t-12*, respectively. *OP*, *AG*, and *LEV* denote operating profitability, asset growth, and leverage, respectively. *IVOL* is the idiosyncratic return volatility with respect to the three Fama and French (1993) factors and *PRC* the log stock price. *ILLIQ* denotes the Amihud (2002) illiquidity measure and *TO* the stock's turnover. The subsequent returns are based on a sample period from January 1962 to December 2024. In the last column, the analysis excludes all stock-month observations that fall below the 20%-NYSE size threshold. The *t*-statistics in parentheses are based on standard errors following Newey and West (1987) using three lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(continued)

Table OA18. Continued

	$SRET$	$SRET$	$SRET$	$SRET$	$SRET$	$SRET$	$SRET$
CGO	0.126	0.072	0.106	0.037	0.078	0.016	0.120
	(0.72)	(0.41)	(0.60)	(0.22)	(0.44)	(0.10)	(0.55)
RET	-3.527***	-9.128***	-4.536***	-5.698***	-6.053***	-5.814**	-5.093
	(-9.71)	(-3.92)	(-11.69)	(-6.73)	(-13.62)	(-2.12)	(-1.55)
$RET \times CGO$	6.372***	7.294***	8.231***	7.078***	7.669***	7.029***	3.594***
	(8.55)	(10.28)	(11.50)	(9.83)	(11.07)	(9.71)	(3.03)
$BETA$	0.158	0.188	0.165	0.180	0.190	0.206	0.036
	(0.65)	(0.78)	(0.68)	(0.74)	(0.78)	(0.85)	(0.14)
$SIZE$	-0.050*	-0.036	-0.051*	-0.052*	-0.054*	-0.040	-0.080**
	(-1.85)	(-1.25)	(-1.87)	(-1.92)	(-1.95)	(-1.36)	(-2.39)
BM	0.158***	0.154***	0.154***	0.158***	0.155***	0.156***	0.145**
	(3.33)	(3.26)	(3.24)	(3.32)	(3.28)	(3.29)	(2.11)
MOM	0.692***	0.707***	0.709***	0.707***	0.721***	0.699***	0.643***
	(4.55)	(4.66)	(4.65)	(4.65)	(4.72)	(4.62)	(3.71)
$ltREV$	-0.131***	-0.127**	-0.132***	-0.129**	-0.115**	-0.118**	-0.100*
	(-2.60)	(-2.51)	(-2.62)	(-2.56)	(-2.29)	(-2.39)	(-1.84)
OP	0.772***	0.770***	0.755***	0.781***	0.771***	0.767***	0.624***
	(7.38)	(7.36)	(7.24)	(7.49)	(7.36)	(7.41)	(5.06)
AG	-0.549***	-0.550***	-0.547***	-0.550***	-0.540***	-0.535***	-0.271***
	(-6.58)	(-6.58)	(-6.56)	(-6.58)	(-6.49)	(-6.44)	(-3.16)
LEV	-0.090***	-0.087***	-0.102***	-0.088***	-0.090***	-0.097***	-0.069**
	(-3.33)	(-3.24)	(-3.67)	(-3.28)	(-3.34)	(-3.57)	(-2.16)
$IVOL$	-1.500***	-1.531***	-1.497***	-1.525***	-1.478***	-1.457***	-1.307***
	(-9.78)	(-10.05)	(-9.90)	(-10.04)	(-9.75)	(-9.73)	(-6.91)
PRC	-0.229***	-0.226***	-0.223***	-0.192***	-0.209***	-0.186***	-0.099**
	(-4.16)	(-4.11)	(-4.07)	(-3.44)	(-3.80)	(-3.36)	(-2.02)
TO	4.039***	4.122***	3.839***	4.120***	2.782***	2.729***	2.167**
	(4.60)	(4.70)	(4.42)	(4.68)	(2.81)	(2.80)	(2.19)
$ILLIQ$	0.064***	0.064***	0.064***	0.064***	0.060***	0.065***	2.454**
	(3.53)	(3.74)	(3.75)	(3.74)	(3.54)	(3.75)	(2.21)
$ILLIQ \times RET$	-0.505***					-0.365*	-25.305
	(-3.24)					(-1.94)	(-1.49)
$SIZE \times RET$		0.280**				-0.065	-0.150
		(2.29)				(-0.41)	(-0.86)
$LEV \times RET$			0.893***			0.952***	0.549**
			(3.49)			(3.70)	(2.04)
$PRC \times RET$				0.653**		0.167	0.299
				(2.57)		(0.54)	(0.72)
$TO \times RET$					44.119***	41.647***	55.134***
					(6.55)	(5.78)	(6.62)
Observations	1,772,736	1,772,736	1,772,736	1,772,736	1,772,736	1,772,736	951,273
Avg. R^2	0.095	0.094	0.094	0.094	0.095	0.102	0.134

Table OA19. ***CGO*-Dependent Short-Term Reversals: Subsamples**
This table reports monthly value-weighted returns from conditional portfolio double sorts for various subsamples. At the end of each month *t*, each stock is allocated to one of two subsamples based on the stock's market capitalization in Panel A, the stock's idiosyncratic return volatility in Panel B, the high-low spread obtained from `https://sites.nd.edu/scorwin/research/` (Corwin and Schultz, 2012) in Panel C, and the stock's average relative closing bid-ask spread during month *t* in Panel D. Within these subsamples, each stock is allocated to a quintile portfolio based on *CGO*, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on *RET*, the stock's log return in month *t*. The table shows the average portfolio returns of month *t+1*. For Panels A and B, the portfolio returns are based on a sample period from January 1962 to December 2024. For the analyses on the high-low spread, the sample period ends in December 2018. For the analyses on bid-ask spreads, the sample period is from January 1987 to December 2024. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

Panel A: Size

	Large Firms							Small Firms						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.15	1.14	1.10	1.01	1.53	0.39	(1.70)	2.48	1.96	1.51	1.58	2.11	-0.37	(-0.94)
2	1.16	1.08	1.03	0.99	1.26	0.10	(0.46)	1.23	1.34	1.40	1.42	1.58	0.35	(1.21)
3	1.04	0.93	0.96	0.90	1.13	0.09	(0.44)	0.94	1.17	1.13	1.19	1.58	0.65	(2.38)
4	0.71	0.74	0.74	0.83	1.01	0.30	(1.55)	0.35	0.72	0.81	1.13	1.37	1.01	(3.84)
high *RET*	0.29	0.75	0.71	0.69	0.80	0.51	(2.42)	-1.04	0.03	0.57	0.98	1.37	2.41	(9.85)
5-1	-0.86	-0.39	-0.38	-0.31	-0.73	0.12	(0.55)	-3.51	-1.93	-0.94	-0.60	-0.74	2.78	(6.79)
t(5-1)	(-4.53)	(-2.26)	(-2.50)	(-1.96)	(-4.54)	(0.55)		(-9.05)	(-7.88)	(-5.13)	(-3.43)	(-4.55)	(6.79)	

Panel B: Idiosyncratic Volatility

	Low Idiosyncratic Return Volatility							High Idiosyncratic Return Volatility						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.56	1.25	1.29	1.13	1.55	-0.01	(-0.04)	2.11	1.61	0.87	0.75	1.48	-0.63	(-1.54)
2	1.39	1.22	1.12	1.07	1.25	-0.14	(-0.66)	1.38	1.07	1.16	0.95	1.48	0.10	(0.30)
3	1.25	1.09	0.98	0.90	1.19	-0.06	(-0.30)	0.79	0.88	0.79	0.74	1.27	0.48	(1.39)
4	0.92	0.74	0.71	0.89	1.06	0.14	(0.69)	0.56	0.52	0.79	1.08	0.95	0.39	(1.26)
high *RET*	0.32	0.62	0.73	0.67	0.73	0.41	(2.04)	-0.71	-0.05	0.51	0.98	1.33	2.04	(6.19)
5-1	-1.23	-0.63	-0.56	-0.46	-0.81	0.42	(1.90)	-2.82	-1.66	-0.35	0.23	-0.16	2.67	(5.87)
t(5-1)	(-6.42)	(-3.76)	(-3.54)	(-2.88)	(-5.29)	(1.90)		(-6.89)	(-5.08)	(-1.20)	(1.03)	(-0.66)	(5.87)	

(continued)

Table OA19. Continued

Panel C: High-Low Spread

	Low High-Low Spread							High High-Low Spread						
	CGO							*CGO*						
	low	2	3	4	high	5-1	t(5-1)	low	2	3	4	high	5-1	t(5-1)
low *RET*	1.33	1.23	1.09	1.07	1.56	0.22	(0.94)	2.39	1.65	0.99	0.98	1.45	-0.94	(-2.28)
2	1.31	1.05	1.04	1.10	1.23	-0.08	(-0.37)	1.31	1.25	1.40	1.03	1.61	0.30	(0.87)
3	1.13	0.79	0.92	0.91	1.17	0.04	(0.17)	0.98	0.93	1.02	1.29	1.19	0.21	(0.59)
4	0.66	0.78	0.71	0.89	0.93	0.27	(1.33)	0.55	0.74	0.97	0.79	1.01	0.46	(1.37)
high *RET*	0.27	0.69	0.65	0.48	0.76	0.49	(2.39)	-1.09	0.04	0.18	0.66	0.97	2.05	(6.30)
5-1	-1.07	-0.55	-0.44	-0.59	-0.80	0.27	(1.14)	-3.47	-1.61	-0.80	-0.33	-0.48	3.00	(6.57)
t(5-1)	(-5.05)	(-3.09)	(-2.72)	(-3.68)	(-4.65)	(1.14)		(-8.30)	(-5.05)	(-2.82)	(-1.32)	(-1.91)	(6.57)	

Panel D: Bid-Ask Spread

	Low Bid-Ask Spread							High Bid-Ask Spread						
	CGO							*CGO*						
	low	2	3	4	high	5-1	t(5-1)	low	2	3	4	high	5-1	t(5-1)
low *RET*	1.12	0.92	1.03	1.04	1.66	0.54	(1.62)	2.10	1.73	1.25	1.48	1.63	-0.47	(-0.79)
2	1.21	1.45	1.08	1.20	1.39	0.18	(0.63)	1.05	1.15	1.40	1.13	1.27	0.22	(0.48)
3	1.08	0.89	1.04	1.02	1.27	0.20	(0.71)	1.23	0.65	0.97	1.08	1.24	0.01	(0.02)
4	0.72	0.93	0.82	0.93	1.13	0.40	(1.58)	0.51	0.56	0.87	0.78	0.82	0.31	(0.68)
high *RET*	0.39	0.91	0.63	0.72	1.04	0.65	(2.21)	-0.78	-0.02	0.28	0.75	0.92	1.71	(4.42)
5-1	-0.74	-0.02	-0.40	-0.32	-0.62	0.11	(0.31)	-2.88	-1.74	-0.97	-0.73	-0.70	2.18	(3.28)
t(5-1)	(-2.34)	(-0.06)	(-1.69)	(-1.36)	(-2.42)	(0.31)		(-4.58)	(-3.84)	(-2.92)	(-2.16)	(-2.98)	(3.28)	

Table OA20. ***CGO*-Dependent Short-Term Reversals: Institutional Ownership**
This table reports monthly value-weighted returns from conditional portfolio double sorts for two subsamples. At the end of each month *t*, each stock is allocated to one of two subsamples based on the stock's level of residual institutional ownership (Nagel, 2005). Within these subsamples, each stock is allocated to a quintile portfolio based on *CGO*, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on *RET*, the stock's log return in month *t*. The table shows the average portfolio returns of month *t+1*. The portfolio returns are based on a sample period from April 1980 to March 2022. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Low Residual Institutional Ownership							High Residual Institutional Ownership						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	1.03	1.17	1.20	1.16	1.49	0.46	(0.93)	2.65	1.94	1.36	1.44	1.37	-1.29	(-2.42)
2	1.60	1.56	1.37	1.17	1.13	-0.47	(-1.23)	1.45	1.72	1.41	1.53	1.89	0.44	(1.11)
3	1.20	1.21	1.20	1.12	1.10	-0.10	(-0.27)	0.98	1.68	1.27	1.23	1.54	0.56	(1.34)
4	0.88	1.02	1.12	1.03	1.07	0.19	(0.64)	0.74	0.93	0.98	0.92	1.29	0.55	(1.42)
high *RET*	0.18	0.95	0.89	0.82	0.93	0.75	(2.30)	-0.25	0.26	1.02	0.81	1.02	1.28	(3.51)
5-1	-0.85	-0.23	-0.31	-0.34	-0.57	0.29	(0.55)	-2.91	-1.69	-0.33	-0.63	-0.34	2.56	(5.32)
t(5-1)	(-1.81)	(-0.92)	(-1.61)	(-1.47)	(-2.33)	(0.55)		(-6.39)	(-5.58)	(-1.22)	(-2.62)	(-1.49)	(5.32)	

Table OA21. *CGO*-Dependent Short-Term Reversals: Excluding the Last Day from *RET*
This table reports monthly value-weighted returns from conditional portfolio sorts for the subsample of firm-month observations with above-median Amihud (2002) illiquidity. Each stock is allocated to a quintile portfolio based on *CGO*, the capital gains overhang measure reflecting the average investor's log return since stock purchase. Then, each stock is allocated to a quintile portfolio based on *RET*, the stock's log return in month *t*. The table shows the average portfolio returns of month *t+1*. On the left side, *RET* covers the entire month *t* while *RET* excludes the last day of month *t* on the right side. The portfolio returns are based on a sample period from January 1962 to December 2024. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	Standard *RET*							*RET* Excluding the Last Day of Month						
	CGO							*CGO*						
	low	2	3	4	high	5-1	*t*(5-1)	low	2	3	4	high	5-1	*t*(5-1)
low *RET*	2.49	2.02	1.59	1.74	2.05	-0.44	(-1.19)	1.54	1.42	1.21	1.46	1.68	0.14	(0.42)
2	1.30	1.47	1.36	1.53	1.43	0.13	(0.44)	1.11	1.41	1.23	1.35	1.41	0.30	(1.02)
3	0.97	1.10	1.14	1.31	1.36	0.39	(1.43)	1.16	1.09	1.18	1.30	1.33	0.17	(0.58)
4	0.47	0.69	0.83	1.08	1.05	0.57	(2.07)	0.66	0.82	0.93	1.26	1.20	0.54	(2.07)
high *RET*	-0.87	0.19	0.44	0.79	1.07	1.94	(8.13)	-0.49	0.46	0.64	0.94	1.20	1.69	(7.02)
5-1	-3.36	-1.82	-1.15	-0.94	-0.99	2.38	(6.44)	-2.03	-0.96	-0.56	-0.52	-0.49	1.54	(4.46)
t(5-1)	(-9.47)	(-8.08)	(-6.73)	(-5.91)	(-6.01)	(6.44)		(-6.22)	(-4.58)	(-3.27)	(-3.18)	(-2.82)	(4.46)	

Table OA22. *CGO* and Illiquidity

This table reports value-weighted portfolio characteristics related to liquidity. Stocks are allocated to quintile portfolios based on *CGO*. For each portfolio, this table presents the time-series average of *CGO*, *HLS*, *rBAS*, *HFOIV*, and *IVOL*. *CGO* is the capital gains overhang measure reflecting the average investor's log return since stock purchase at the end of month *t-1* (standard sample period January 1962 to December 2024). *HLS* is the high-low spread (Corwin and Schultz, 2012) in month *t* obtained from `https://sites.nd.edu/scorwin/research/` (sample period January 1962 to December 2018). *rBAS* is the average relative closing bid-ask spread during month *t* (sample period January 1987 to December 2024). *HFOIV* is the high-frequency order imbalance volatility (Bogousslavsky and Collin-Dufresne, 2023) in month *t* obtained from `https://bogousslavsky.github.io/` (sample period February 2002 to January 2018). *IVOL* is the idiosyncratic return volatility (sample period January 1962 to December 2024). The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using three lags.

	CGO	*HLS*	*rBAS*	*HFOIV*	*IVOL*
low *CGO*	-0.4013	0.0127	0.0175	0.0069	0.3660
2	-0.1367	0.0070	0.0082	0.0051	0.2364
3	0.0057	0.0056	0.0058	0.0043	0.1960
4	0.1284	0.0052	0.0049	0.0042	0.1831
high *CGO*	0.3036	0.0054	0.0050	0.0048	0.1938
5-1	0.7049	-0.0074	-0.0124	-0.0022	-0.1722
t(5-1)	(47.00)	(-15.60)	(-9.42)	(-6.59)	(-17.59)

5. The Time-Series of the Short-Term Reversal Strategy

In this section, we turn to the time series of short-term return reversals. We hypothesize that *CGO* does not only allow us to identify *which* stocks should be most prone to reversals, but also *when* reversals are strongest. In particular, if many stocks in the market have a low level of *CGO*, we should expect higher returns from short-term reversal strategies as retail investors are less likely to be contrarian traders.

To examine this conjecture, we estimate a market-wide level of *CGO* each month, defined as the value-weighted cross-sectional average of all individual stock *CGO*-estimates from our sample. We compute returns to a short-term reversal strategy by assigning all sample stocks to monthly decile portfolios based on *RET* (the stock return in month *t*). We then test whether the return spread between the value-weighted portfolios of low-*RET* and high-*RET* stocks in month *t+1* depends on the market-wide level of *CGO*.

In Table OA23, we find that the market-wide level of *CGO* shows a negative relation with subsequent short-term reversals. This negative relation also exists after accounting for variables previously shown to predict reversals including lagged market returns, option-implied volatility, and sentiment (Nagel, 2005; Da et al., 2012).

Table OA23. Short-Term Reversal Strategy Returns and the Market-Wide Level of *CGO*
This table reports linear regression coefficients from the time-series regressions

$$LSRET_{t+1} = \alpha + \beta mCGO_{t-1} + \gamma CTRL + \epsilon_t$$

with monthly short-term reversal strategy returns as the dependent variable. The lagged market-wide level of *CGO* is the main independent variable. At the end of each month *t*, each stock is sorted into decile portfolios based on *RET*, the stock's log return in month *t*. The returns of the short-term reversal strategy in month *t+1* are given by the returns of a value-weighted portfolio that is long in the stocks of the low-*RET* decile and short in the stocks of the high-*RET* decile. These long-short portfolio returns of month *t+1* serve as dependent variable. The main independent variable, *mCGO*, is the market-wide level of *CGO* in month *t-1* which is calculated as the value-weighted average of all stock-level *CGO*-estimates. *MKT*, *SMB*, and *HML* refer to the three Fama-French-factors. *preDEC* is a dummy variable for the sample months prior to decimalization (April 2001). *VIX* is the option-implied volatility index from the Chicago Board Options Exchange. Since VIX data is not available before 1990, *VXO* is used for these earlier months instead. *mILLIQ* refers to the market-wide value-weighted average of Amihud (2002) illiquidity. *SENT* is the Michigan Consumer Sentiment Index. The sample period of long-short returns is January 1962 to December 2024 in columns 1 to 3 and February 1986 to December 2024 in columns 4 and 5. The *t*-statistics in parentheses are based on standard errors following Newey and West (1987) using three lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$LSRET_{t+1}$	$LSRET_{t+1}$	$LSRET_{t+1}$	$LSRET_{t+1}$	$LSRET_{t+1}$
$mCGO_{t-1}$	-5.962***	-4.558*	-6.267***	-11.327**	-12.109**
	(-2.60)	(-1.91)	(-2.74)	(-2.37)	(-2.44)
MKT_{t+1}		32.420***	32.428***	37.478***	
		(4.13)	(4.16)	(3.65)	
SMB_{t+1}		13.557	13.824	13.303	
		(0.80)	(0.78)	(0.53)	
HML_{t+1}		19.581	18.645	25.771	
		(1.39)	(1.33)	(1.44)	
MKT_t			-4.333	-7.165	-3.374
			(-0.69)	(-0.72)	(-0.36)
$preDec_t$			1.078***	1.765	1.775
			(2.67)	(0.93)	(0.93)
VIX_t				-0.002	0.008
				(-0.04)	(0.16)
$mILLIQ_t$				-9.011	-6.967
				(-0.60)	(-0.47)
$SENT_t$				0.034	0.031
				(1.09)	(0.92)
Observations	756	756	756	467	467
R^2	0.009	0.073	0.080	0.082	0.015

6. Additional Analyses on Stock Splits

This section provides additional evidence that both our retail investor findings and our asset pricing evidence depends on stock splits. Table OA24 investigates monthly retail trading in split versus non-split sample. In both brokerage and Robintrack data, we find that more unrealized capital gains imply significantly stronger contrarian retail behavior only in the non-split sample. By means of Fama-MacBeth regressions, Table OA25 shows that the *CGO*-dependence of short-term return reversals is also stronger in the non-split compared to the split sample.

Table OA24. Monthly Domain-Based Contrarian Trading: Stock Splits
This table examines the impact of stock splits on monthly domain-based contrarian trading. Panel A uses brokerage trade data and reports results for two samples based on whether the position has experienced a stock split during the investor's holding period. Panel B uses RobinTrack data and reports results for two samples based on whether the stock has experienced a stock split during the previous year. In Panel A, we estimate investor-position regressions where our dependent variable *SELL* is an indicator variable equal to one if an investor sells the stock during month *t*. *GAIN* is an indicator variable equal to one if the stock is trading at a gain relative to its purchase price at the end of month *t-1*. *RET* is the stock return during month *t* for both Panels A and B. In Panel B, we estimate stock-level regressions. In columns 1-3, the dependent variable is *CHG*, the change in the number of Robinhood investors holding the stock between the end of month *t-1* and the end of month *t*. In columns 4-6, the dependent variable is *RATIO*, the percent change in the number of Robinhood investors holding the stock between the end of month *t-1* and the end of month *t*. *CGO* is the stock-level capital gains overhang measure from month *t-1*. The *t*-statistics in parentheses are based on standard errors that are double-clustered by investor and month in Panel A and robust standard errors in Panel B. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Brokerage Trade Data

	Dependent Variable: *SELL*		
	NON-SPLIT	*SPLIT*	*DIFF*
RET	0.033***	0.011*	-0.022***
	(3.74)	(1.74)	(-3.24)
GAIN	0.007***	0.001	-0.006***
	(3.58)	(0.62)	(-4.73)
$RET \times GAIN$	0.058***	-0.020*	-0.078***
	(5.69)	(-1.69)	(-8.42)
Observations	4,538,166	917,706	
R^2	0.001	0.000	

Panel B: Robintrack Data

	Dependent Variable: *CHG*			Dependent Variable: *RATIO*		
	NON-SPLIT	*SPLIT*	*DIFF*	*NON-SPLIT*	*SPLIT*	*DIFF*
RET	0.081	1.146***	1.065***	-0.072***	0.314***	0.386***
	(1.39)	(4.31)	(3.92)	(-3.98)	(4.58)	(5.46)
CGO	-0.116***	0.047	0.163**	-0.137***	-0.102***	0.035
	(-5.73)	(0.69)	(2.28)	(-20.69)	(-3.87)	(1.30)
$RET \times CGO$	-0.407**	0.972*	1.379***	-0.152***	0.195	0.347**
	(-2.52)	(1.92)	(2.59)	(-3.07)	(1.18)	(2.01)
Observations	35,844	1,664		35,844	1,664	
R^2	0.003	0.042		0.026	0.049	

Table OA25. *CGO*-Dependent Short-Term Reversals: Stock Splits in Fama-MacBeth-Regressions

This table presents time-series averages from the following monthly cross-sectional regressions:

$$SRET_j = \alpha + \beta_1 CGO_j + \beta_2 RET_j + \beta_3 CGO_j RET_j + \epsilon_j.$$

The dependent variable is the stock return of month *t+1*. The explanatory variables are given in the first column. *CGO* is the capital gains overhang measure, reflecting the average investor's log return since stock purchase at the end of month *t-1* and *RET* is the stock's log return in month *t*. *BETA* is the market beta, *SIZE* the log market value of equity, and *BM* the book-to-market ratio. *MOM* and *ltREV* are the log returns of months *t-11* to *t-1* and *t-59* to *t-12*, respectively. *OP*, *AG*, and *LEV* denote operating profitability, asset growth, and leverage, respectively. *IVOL* is the idiosyncratic return volatility with respect to the three Fama and French (1993) factors and *PRC* the log stock price. *ILLIQ* denotes the Amihud (2002) illiquidity measure and *TO* the stock's turnover. The subsequent returns are based on a sample period from January 1962 to December 2024. The first two columns are based on a subsample of stocks that experienced a stock split in the previous twelve months while the last two columns are based on a subsample of stocks that did not experience a stock split in the previous twelve months. The *t*-statistics in parentheses are based on standard errors following Newey and West (1987) using three lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(continued)

Table OA25. Continued

	Stocks with Splits		Stocks without Splits	
	SRET	*SRET*	*SRET*	*SRET*
CGO	0.464	-0.260	0.693***	0.156
	(1.43)	(-0.65)	(3.80)	(0.89)
RET	-4.298***	-3.423***	-3.696***	-3.500***
	(-5.86)	(-4.19)	(-9.64)	(-9.17)
$RET \times CGO$	7.726***	3.393	8.040***	6.814***
	(3.17)	(1.41)	(10.20)	(8.37)
BETA	-0.569	0.161	-0.016	0.135
	(-1.51)	(0.39)	(-0.05)	(0.55)
SIZE	0.049	-0.057	-0.083**	-0.062**
	(1.13)	(-1.19)	(-2.24)	(-2.27)
BM	0.160	-0.018	0.251***	0.170***
	(1.52)	(-0.14)	(4.52)	(3.48)
MOM		0.954***		0.634***
		(3.51)		(4.17)
ltREV		0.040		-0.171***
		(0.40)		(-3.28)
OP		0.292		0.799***
		(1.16)		(7.34)
AG		-0.359		-0.614***
		(-1.61)		(-7.06)
LEV		-0.089		-0.086***
		(-1.07)		(-3.20)
IVOL		-2.493***		-1.440***
		(-6.22)		(-9.03)
PRC		-0.321***		-0.202***
		(-2.59)		(-3.45)
TO		3.310**		4.465***
		(2.33)		(4.82)
ILLIQ		-0.002		0.076***
		(-0.01)		(4.00)
$ILLIQ \times RET$		-4.174		-0.411**
		(-1.56)		(-2.44)
Observations	190,781	190,781	1,581,955	1,581,955
Avg. R^2	0.115	0.218	0.068	0.098

References

Amihud, Y. (2002), Illiquidity and stock returns: Cross–section and time–series effects, *Journal of Financial Markets* **5**(1), 31–56.

Barber, B. M. and Odean, T. (2008), All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* **21**(2), 785–818.

Barrot, J.-N., Kaniel, R. and Sraer, D. (2016), Are retail traders compensated for providing liquidity?, *Journal of Financial Economics* **120**(1), 146–168.

Ben-David, I. and Hirshleifer, D. (2012), Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect, *Review of Financial Studies* **25**(8), 2485–2532.

Bogousslavsky, V. and Collin-Dufresne, P. (2023), Liquidity, volume, and order imbalance volatility, *Journal of Finance* **78**(4), 2189–2232.

Corwin, S. A. and Schultz, P. (2012), A simple way to estimate bid–ask spreads from daily high and low prices, *Journal of Finance* **67**(2), 719–760.

Da, Z., Guo, R.-J. and Jagannathan, R. (2012), CAPM for estimating the cost of equity capital: Interpreting the empirical evidence, *Journal of Financial Economics* **103**(1), 204–220.

Dierick, N., Heyman, D., Inghelbrecht, K. and Stieperaere, H. (2019), Financial attention and the disposition effect, *Journal of Economic Behavior & Organization* **163**, 190–217.

Fama, E. F. and French, K. R. (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* **33**(1), 3–56.

Fama, E. F. and French, K. R. (2015), A five–factor asset pricing model, *Journal of Financial*

Economics **116**(1), 1–22.

Fama, E. F. and French, K. R. (2018), Choosing factors, *Journal of Financial Economics* **128**(2), 234–252.

Grinblatt, M. and Han, B. (2005), Prospect theory, mental accounting, and momentum, *Journal of Financial Economics* **78**(2), 311–339.

Grinblatt, M. and Keloharju, M. (2001), What makes investors trade?, *Journal of Finance* **56**(2), 589–616.

Hartzmark, S. M. (2015), The worst, the best, ignoring all the rest: The rank effect and trading behavior, *Review of Financial Studies* **28**(4), 1024–1059.

Hou, K., Mo, H., Xue, C. and Zhang, L. (2021), An augmented q–factor model with expected growth, *Review of Finance* **25**(1), 1–41.

Hou, K., Xue, C. and Zhang, L. (2015), Digesting anomalies: An investment approach, *Review of Financial Studies* **28**(3), 650–705.

Kelley, E. K. and Tetlock, P. C. (2013), How wise are crowds? Insights from retail orders and stock returns, *Journal of Finance* **68**(3), 1229–1265.

Nagel, S. (2005), Short sales, institutional investors and the cross–section of stock returns, *Journal of Financial Economics* **78**(2), 277–309.

Newey, W. K. and West, K. D. (1987), A simple, positive semi–definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* **55**(3), 703–708.

Schwert, G. W. (1989), Why does stock market volatility change over time?, *Journal of Finance* **44**(5), 1115–1153.

Shefrin, H. and Statman, M. (1985), The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* **40**(3), 777–790.