Retail Short Selling and Stock Prices

ERIC K. KELLEY and PAUL C. TETLOCK*

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ABSTRACT

This study tests asset pricing theories that feature short selling using a large database of retail trading. We find that retail short selling negatively predicts firms' monthly stock returns and news tone, even controlling for overall short selling. Predictability from retail shorting is strongest in stocks with low analyst and media coverage, high idiosyncratic volatility, and high turnover; it does not depend on short sales constraints. Retail buying positively predicts returns in similar types of stocks. These results are consistent with the theory that retail short selling informs market prices, but are inconsistent with alternative theories in which retail short selling is a proxy for sentiment or attention.

* University of Arizona and Columbia University. The authors thank the following people for their helpful comments: Kent Daniel, Robin Greenwood, Cam Harvey, Charles Jones, Andy Puckett, Jay Ritter, Sorin Sorescu, Ingrid Werner, and Wei Xiong, and seminar participants at Arizona State, Temple, Tennessee, Texas Tech, UC San Diego, UT Austin,, Wharton, and the Miami Behavioral Finance Conference. The authors also thank Arizona and Columbia for research support and Dow Jones and RavenPack for news data and analysis, respectively. All results and interpretations are the authors' and are not endorsed by the news or retail order data providers. Please send correspondence to paul.tetlock@columbia.edu.

Short selling now accounts for roughly one quarter of all trading in the US stock market (Diether, Lee, and Werner (2009)), suggesting shorting is a key determinant of stock prices. While numerous studies find that short interest and short selling negatively predict stock returns, far fewer systematically test competing theories of why this is the case.[1] Understanding the economic forces driving the relation between short selling and prices is important because recent models highlight vastly different mechanisms, ranging from informed trading to attention-based mispricing. Such mechanisms determine how markets incorporate information, the role of traders' potentially incorrect beliefs, and the implications of short sale constraints.

We test competing asset pricing theories by exploiting unique data on retail investor behavior, including short selling. Because retail investors differ widely in their trading skill and access to information, our data likely includes trades motivated by perceived information and those motivated by genuine information.[2] Our data can help us distinguish these motives if short sellers are more likely than other retail traders to be informed, as argued in Boehmer, Jones, and Zhang (2008). In addition, retail short selling may be easier to interpret than institutional short selling, which depends on portfolio managers' beliefs and conflicts of interest as well as their clients' beliefs and liquidity needs (Lamont and Stein (2004)).

We propose a parsimonious model of stock prices that features three primitive investor types: rational arbitrageurs without short sale constraints; and two types of agents with belief biases, one of which is subject to short sale constraints. Retail investors consist of an unknown mixture of the unconstrained arbitrageurs and the biased and constrained agents. The model nests

[1] Studies documenting return predictability from shorting activity include Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), and Diether, Lee, and Werner (2009). Studies such as Chen, Hong, and Stein (2002) and Boehme, Danielsen, and Sorescu (2006) analyze models inspired by Miller's (1977) reasoning, while other studies consider Diamond and Verrecchia's (1987) model.

[2] Previous research finds that both motives are important. Barber and Odean (2000) and Barber, Lee, Liu, and Odean (2009) find that retail traders are overconfident and trade excessively, whereas Kaniel, Saar, and Titman (2008) and Kelley and Tetlock (2013) show that some retail traders act on information not yet incorporated in stock prices.

three leading joint hypotheses about retail investor behavior and stock pricing. First, retail short sellers could be uniquely *informed* and predict decreases in firm value. Second, retail short sellers could act on pessimistic *investor sentiment*, which could cause stock underpricing and positively predict stock returns. Third, retail short selling could simply reflect *attention* from traders whose opinions differ. Because differences in investors' opinions and attention can combine with short sales constraints to cause overpricing (e.g., as in Miller (1977)), retail short selling could negatively predict returns even if these traders are not well-informed.

We analyze the comparative statics of the above information, sentiment, and attention hypotheses and distinguish among models using empirical return predictability. Our main empirical result is that retail short selling robustly negatively predicts returns in a wide range of stocks—all except the top NYSE size quintile—with annualized magnitudes of 5% to 10%. Controlling for retail trading activity, overall short selling, and changes in mutual fund ownership breadth does not materially reduce predictability from retail shorting. Predictability decreases with firm size, analyst coverage, and media coverage; it increases with idiosyncratic volatility and turnover; and it does not depend on proxies for short sales constraints. Furthermore, retail buying is a positive predictor of stock returns, especially in small stocks.

The evidence that return predictability from retail shorting is negative in nearly all subsamples and horizons contradicts the sentiment hypothesis. Reconciliation with the attention hypothesis is also difficult. The strongest evidence against the attention hypothesis is the positive return predictability from retail buying, particularly in small stocks in which retail short selling negatively predicts returns. Moreover, short sales constraints do not interact with predictability as required by the attention hypothesis.

In contrast, the evidence is consistent with the hypothesis that retail short sellers are well-informed. In this theory, predictability depends negatively on the extent to which prices already reflect information and positively on the extent to which prices reflect sentiment. Prices more accurately reflect information in large stocks and those with high analyst and media coverage, consistent with weaker predictability from retail shorting in these stocks. Sentiment-induced mispricing is greater in stocks with high idiosyncratic volatility and turnover, consistent with stronger predictability in such stocks. Lastly, if short sellers are better informed than other retail traders, short selling should be a stronger negative predictor of returns in stocks in which others are buying and inflating prices. Indeed, we find that predictability from retail short selling is stronger in stocks with high concurrent retail buying. We complement our return predictability evidence by showing that retail shorting predicts negative firm-specific information in news stories, particularly those about firm earnings.

Our primary finding of negative return predictability from retail short selling contributes to the literatures on short selling and retail trading. Two previous studies examine retail short selling. First, Boehmer, Jones, and Zhang (2008) use NYSE system order data from 2000 to 2004 containing short sale indicators and account type designations (e.g., retail or program). Retail shorting is a scant portion—about 1.5%—of all short sales in their sample. Because brokers route most of their retail orders away from the exchange, retail shorting at the NYSE is at best a noisy reflection of all retail shorting. Thus, these authors offer no strong interpretation of their lack of evidence that retail shorting predicts future returns. Our sample draws from a broad range of retail brokers and includes a large fraction of many brokers' orders, thereby mitigating these concerns. Second, Gamble and Xu (2013) identify 35 thousand retail short sales in the Barber and Odean (2000) database and find no predictability from overall retail shorting.

Their sample, which consists of data from a single broker from 1991 to 1996, is 200 times smaller than ours. Our large sample enables us to identify novel patterns in predictability from retail shorting, which we use to discriminate among theoretical explanations.

Our empirical results build on those in Kelley and Tetlock (2013), the only other study to analyze our retail trading data. Kelley and Tetlock (2013) find that daily retail buy-minus-sell imbalance positively predicts returns, a result driven primarily by variation in buy orders. We show that weaker overall predictability from retail sell orders masks robust negative predictability from retail short sales. Furthermore, short sales are stronger negative predictors of returns in stocks with numerous buy orders. This finding illustrates the importance of recognizing retail investor heterogeneity in theoretical models as well as jointly studying these order types in empirical work. Our emphasis on heterogeneity also sheds light on the mixed results in prior studies. Whereas Kaniel, Saar, and Titman (2008), Dorn, Huberman, and Sengmueller (2008), Kelley and Tetlock (2013) show that net retail buying positively predicts returns, Barber and Odean (2000), Hvidkjaer (2008) and Barber, Odean, and Zhu (2009) document opposing results.

The structure of the paper is as follows. Section I introduces the model of stock pricing and develops testable hypotheses. Section II describes the data on retail orders. Section III presents the main tests of whether retail short selling predicts returns in various subsamples. We also analyze whether retail buying and total retail trading predict returns and discuss these empirical results in relation to the model. Section IV examines robustness issues, including relations with known predictors of returns. Section V concludes.

I. Model of Stock Pricing

A. Framework

Our stylized model of stock prices features investors with limited attention, different opinions, and short sale constraints in the spirit of Chen, Hong, and Stein (2002) and Hong and Jiang (2011). We analyze the price of a single equity-financed firm in two periods. At date 1, the share price of the stock (p) endogenously adjusts to clear the market. At date 2, the firm liquidates all assets and pays all cash flows. We normalize the return on the risk-free asset to zero and the supply of the stock to zero.[3]

All investors have CARA utility defined over next period's wealth. There is a continuum of investors of type $X \in \{A, B, C\}$, and we normalize the total mass of investors in each type to one. Because investors are small, each has no price impact. The aggregate risk tolerance of each type is γ_X.

The three types of investors differ in their short-sale constraints, attention, and beliefs. Type A represents unconstrained rational arbitrageurs, such as hedge funds and other sophisticated investors. Type B investors also face no shorting constraints but may trade for reasons other than information, much like institutional traders with biased beliefs or liquidity needs. Type C represents investors that face restrictions on short selling and may also trade for reasons other than information, such as many mutual funds and pension funds and many retail investors. A fraction $\theta < 1$ of type C investors can short sell, while the remaining $(1 - \theta)$ fraction of type C investors cannot. Type A and B investors always pay attention to the stock, whereas only a fraction $\alpha < 1$ of type C investors do so. Following Miller (1977) and Merton (1987), we suppose that only investors who pay attention have non-zero demand for the stock.

[3] The zero supply assumption eliminates any risk discount in the stock price. We apply the model to the cross-section of individual stocks and control for factor exposures. The discount for idiosyncratic risk should be small.

Investors receive the same information about firm value, but they may disagree about how to interpret it. At date 0, investors have a common prior that the firm's date 2 value is normally distributed with a mean of F and a variance of σ^2—i.e., $V \sim \mathrm{N}(F, \sigma^2)$. At date 1, investors observe an intangible signal, s_I, and a tangible signal, s_T, about firm value. Investors agree that the tangible signal is distributed as $s_T \sim \mathrm{N}(V, \sigma^2/k)$, where $k > 0$ measures the precision of the signal. We interpret k as a measure of the richness of a stock's public information environment. Investor disagreement is solely based on the intangible signal. All type A investors recognize this signal has a distribution of $s_I \sim \mathrm{N}(V, \sigma^2)$, whereas each investor i of type $X \in \{B, C\}$ perceives the distribution to be $s_I \sim \mathrm{N}(V - m_i, \sigma^2)$. We interpret m_i as a measure of trader i's optimism and assume it to be uniformly distributed in the interval $[m - \eta, m + \eta]$. The parameter $\sigma \geq 0$ measures uncertainty about the firm's value. The parameters m and η reflect the extent of average optimism and dispersion, respectively, in traders' beliefs.

In summary, type A investors are rational, whereas type B and C investors hold uniformly distributed beliefs according to their interpretation of the intangible signal. Opinion differences often arise in practice when investors are overconfident in the precision of their preferred signal and pay insufficient attention to alternative signals. Investors could perceive different intangible signals because they focus on certain aspects of the information environment and ignore others. Importantly, the above specification allows for biases in average beliefs and differences in beliefs from the average. If $m = \eta = 0$, all traders exhibit rational beliefs.

B. Equilibrium

We solve the model by backward induction. At date 1, after observing the intangible and tangible signals, rational traders expect firm value to be $(F + s_I + k\, s_T) / (2 + k)$, which is a

precision-weighted average of the prior mean and the two signals. In contrast, the expectation of investors i of types $X \in \{B, C\}$ of the firm's date 2 value (E_i) is

$$E_i = \left(F + m_i + s_I + ks_T\right)/\left(2+k\right). \tag{1}$$

The range of these investors' beliefs is thus

$$E_i \in \left[\left(F + m - \eta + s_I + ks_T\right)/\left(2 + k\right),\ \left(F + m + \eta + s_I + ks_T\right)/\left(2+k\right)\right] \tag{2}$$

The CARA-normal structure simplifies traders' demand functions above, which implies date 1 demand functions (q_{Xi}) are given by

$$q_{Xi} = \frac{\gamma_X (E_i - p_1)}{\sigma^2/(2+k)} \tag{3}$$

for unconstrained traders and by max(0, q_{Xi}) for traders with short sale constraints. Integrating across traders with different beliefs, the aggregate demand for type X (Q_X) with attention α_X is

$$\begin{aligned} Q_X &= \frac{\alpha_X \gamma_X}{\sigma^2/\left(2+k\right)} \int_{p_1}^{\frac{F + s_I + ks_T + m + \eta}{2+k}} \left(E_i - p_1\right)\left[\frac{2+k}{2\eta}\right] \mathrm{d}E_i \\ &= \frac{\alpha_X \gamma_X (2+k)^2}{\sigma^2 (4\eta)} \left[\left(F + s_I + ks_T + m + \eta\right)/\left(2+k\right) - p_1\right]^2, \end{aligned} \tag{4}$$

when the short sale constraint is binding. If the constraint does not bind, aggregate demand is

$$\begin{aligned} Q_X &= \frac{\alpha_X \gamma_X}{\sigma^2/\left(2+k\right)} \int_{\frac{F + s_I + ks_T + m - \eta}{2+k}}^{\frac{F + s_I + ks_T + m + \eta}{2+k}} \left(E_i - p_1\right)\left[\frac{1}{2\eta}\right] \mathrm{d}E_i \\ &= \frac{\alpha_X \gamma_X}{\sigma^2/(2+k)} \left[(F + s_I + ks_T + m)/(2+k) - p_1\right]. \end{aligned} \tag{5}$$

Demand from type A traders, who all pay attention ($\alpha_A = 1$) and have rational beliefs ($m = \eta = 0$), is

$$Q_A = \frac{\gamma_A}{\sigma^2/(2+k)} \left[(F + s_I + ks_T)/(2+k) - p_1\right]. \tag{6}$$

Equations (5) and (6) show that aggregate demand from type $X \in \{B, C\}$ has the same form as arbitrageur demand if there is no short sale constraint, no inattention, and no average belief bias.

The market clearing price is such that aggregate demand from all types equals the zero supply of stock. If there is no constraint ($\theta = 1$), the price p_U satisfies

$$p_U = \frac{F + s_I + ks_T}{(2+k)} + \frac{(\gamma_B + \alpha\gamma_C)m}{(\gamma_A + \gamma_B + \alpha\gamma_C)(2+k)}. \tag{7}$$

This unconstrained price equals the rational expected firm value plus a mispricing term. Average belief bias (m) influences the price only if the risk-bearing capacity of arbitrageurs is limited and the stock's future value is uncertain—i.e., γ_A and k, respectively, are finite. We now analyze pricing with short sales constraints by separately considering cases in which there is no difference in opinion ($\eta = 0$) and no average bias ($m = 0$).

<u>Case 1: No difference in opinion</u>

In general, the short sales constraint for type $X \in \{B, C\}$ binds when the most pessimistic trader of type X wants to short the stock. With no difference in opinion ($\eta = 0$), the short sales constraint for type X binds only when these traders are irrationally pessimistic ($m < 0$). Therefore the unconstrained irrational type X traders short the stock when $m < 0$, and all traders buy the stock when $m > 0$. Imposing the market clearing condition, the equilibrium price is

$$p_1 = \frac{F + s_I + ks_T}{2+k} + \frac{[\gamma_B + [\theta + I(m>0)(1-\theta)]\alpha\gamma_C]m}{[\gamma_A + \gamma_B + [\theta + I(m>0)(1-\theta)]\alpha\gamma_C](2+k)}, \tag{8}$$

where we define the indicator $I(m > 0)$ to be equal to one when $m > 0$ and zero otherwise.

The second term in equation (8) represents overpricing relative to the price when all traders are rational. Mispricing is driven by the average sentiment bias m. The absolute value of

mispricing decreases with k and γ_A, whereas it increases with α, γ_B, and γ_C. When $m < 0$, the stock is underpriced; underpricing increases with θ. If $\theta = 1$, equation (8) simplifies to equation (7).

Case 2: No average bias

We next consider the pricing function when there is no average bias, but there is difference in opinion ($\eta > 0$). In this case, the short sale constraints bind for $(1 - \theta)$ of the type C traders whose unconstrained demand is negative. After imposing market clearing, we obtain a quadratic pricing equation with the solution:

$$p_1 = \frac{F + s_I + ks_T}{2+k} + \frac{\eta}{2+k}\left[(2\gamma_U + 1) - \sqrt{(2\gamma_U + 1)^2 - 1}\right], \tag{9}$$

where we define the relative risk tolerance of unconstrained investors, γ_U, as

$$\gamma_U = \frac{\gamma_A + \gamma_B + \theta\alpha\gamma_C}{(1-\theta)\alpha\gamma_C}. \tag{10}$$

Only the negative root of the pricing equation is relevant because the positive root of price exceeds the valuation of the most optimistic trader and thus is not an equilibrium.

The second term in equation (9) represents overpricing relative to the price when $\eta = 0$ and all traders are rational. Overpricing in this case is driven by the combination of difference in opinion, attention, and short sales constraints. Overpricing increases with difference in opinion (η), decreases with the precision of tangible public information (k), and decreases with the relative risk tolerance of unconstrained investors with no average bias (γ_U).

C. Joint Hypothesis about Investors' Beliefs and Retail Investor Behavior

Suppose retail traders consist of a fraction g of rational unconstrained type A traders and $(1 - g)$ of irrational constrained type C traders. The fraction g determines the effective rationality

of retail traders and their possibly self-imposed constraints. The aggregate risk tolerance of retail investors is γ_R, which satisfies $\gamma_R < \min(\gamma_A, \gamma_C)$ for convenience. We now formally define three joint hypotheses about the model parameters and retail investor behavior. The above model nests these hypotheses, which differ only in their assumptions about g, m, η, and α:

- H1: Information: m varies across stocks; $\eta = 0$; and $\Pr(g > g_S) > 0.5$.
- H2: Sentiment: m varies across stocks; $\eta = 0$; and $\Pr(g < g_S) < 0.5$.
- H3: Attention: α varies across stocks; $m = 0$; and $g = 0$.

The pricing equation (8) without difference in opinion encompasses the information and sentiment hypotheses, denoted by H1 and H2, respectively. H1 and H2 differ only in whether the rationality of retail traders exceeds the threshold g_S, which we define as

$$g_S \equiv \frac{\theta\alpha\gamma_A}{\theta\alpha\gamma_A + \gamma_B + \theta\alpha\gamma_C}. \tag{11}$$

For future reference, we also define a higher threshold g_B as follows

$$g_B \equiv \frac{\alpha\gamma_A}{\alpha\gamma_A + \gamma_B + \alpha\gamma_C} > g_S. \tag{12}$$

The g_S and g_B thresholds determine the sign of return predictability from retail shorting and retail buying, respectively, based on equations (A8) and (A11) in the Appendix. In H1 and H2, mispricing is driven solely by average bias m. In the information hypothesis, g is relatively high and retail traders act as informed traders by opposing sentiment. However, in the sentiment hypothesis, g is lower and retail traders contribute to sentiment-based mispricing. The threshold fractions, g_S and g_B, are the lowest values of g at which retail investors trade against sentiment and appear rational. Short sale constraints suppress type C (irrational) retail investors who would otherwise have negative demand, so the threshold for retail short sellers is lower than that for buyers ($g_S < g_B$). As a consequence, at intermediate levels of g, retail short sellers as a group

trade opposite retail buyers. Because type *B* investors are effectively noise traders, their inclusion in the model lowers the threshold fractions (g_S and g_B) at which retail investors trade against sentiment and appear rational—i.e., the nonretail population acts less rationally when $\gamma_B > 0$.

The pricing equation (9) without average bias characterizes the attention hypothesis, denoted by H3. Type *C* traders' opinions differ ($\eta > 0$), and they face short sale constraints. Overpricing arises because some pessimistic investors cannot short the stock and exists even in the absence of average belief bias. Type *C* traders' attention differs across stocks, generating variation in overpricing.

We make additional assumptions about the cross-sectional distributions of g, m, η, and α solely for tractability. In each hypothesis, we assume the parameters vary independently in the cross section. In H1 and H2, we assume m is symmetrically distributed around a zero mean. In H3, we assume $g = 0$ in all stocks, but the results generalize as long as g is low for most stocks.

D. Intuition and Predictions from the Model

In this subsection, we discuss insights from our analysis of the model in the Appendix. There we derive closed-form expressions for observable equilibrium variables, including stock returns, expected returns, return volatility, trading volume, total short interest, retail short selling, and retail buying. We solve for cross-sectional return predictability from retail shorting and show how it depends on key model parameters: amount of tangible information (k), expected magnitude of sentiment ($\mathrm{E}[|m|]$), attention (α), difference in opinion (η), and short sale constraints ($1 - \theta$). We also solve for predictability from retail buying. We prove several propositions relating return predictability to observables, such as trading volume.

Proposition 1 establishes the sign of return predictability from retail shorting scaled by volume. In the information and sentiment hypotheses (H1 and H2), the sign of predictability depends on whether the fraction of rational retail traders (g) exceeds the threshold g_S in equation (8). In the information hypothesis, retail shorting arises mainly because traders act on negative information not yet incorporated in prices, and thus it negatively predicts returns. In the sentiment hypothesis, retail shorting is primarily based on unduly pessimistic sentiment, and thus it positively predicts returns.

In the attention hypothesis (H3), retail shorting scaled by volume is a negative predictor of returns. Short sales constraints and difference in opinion jointly cause overpricing as in Miller (1977). Greater attention from traders with differences in opinion magnifies overpricing and increases short sales from these traders. This positive relation between short selling and overpricing implies retail short selling negatively predicts returns despite these traders' lack of superior information.

We also show in the Appendix that variation in difference in opinion alone, holding attention constant, cannot explain predictability from retail shorting scaled by volume. The reason is that retail shorting and volume are equally effective proxies for difference in opinion—e.g., see volume equation (A19). Therefore dividing retail shorting by volume eliminates its relation with difference in opinion, as shown in equation (A20), along with any return predictability.

Proposition 2 states that the magnitude of return predictability from retail shorting decreases with the amount of tangible information (k) in all three theories. Tangible information resolves uncertainty, thereby mitigating mispricing and predictability.

Proposition 3 shows the magnitude of predictability in the information and sentiment theories increases with expected absolute sentiment. Sentiment simultaneously causes mispricing, price movements, and trading between rational and irrational investors. Therefore cross-sectional variation in expected absolute sentiment generates associations between strong predictability from retail shorting, high volatility, high volume, and high short interest.

Propositions 4 and 5 demonstrate that Miller's (1977) reasoning about difference in opinion and short sales constraints applies to the attention hypothesis. The key intuition is that the joint interaction of attention, difference in opinion, and short sales constraints generates return predictability from retail shorting. Proposition 4 shows greater difference in opinion amplifies predictability from retail shorting because optimists become even more optimistic while constrained pessimists remain sidelined, exacerbating overpricing. Proposition 5 shows that short sales constraints magnify predictability from retail shorting because they decrease pessimists' influence on stock prices and thus increase overpricing.

Proposition 6 examines return predictability from retail buying scaled by volume in each hypothesis. In the attention hypothesis, retail buying increases with attention and thus negatively predicts returns. In contrast, return predictability from retail buying is positive in the information and sentiment hypotheses if the fraction of retail traders that are rational (g) exceeds the relatively high threshold $g_B > g_S$. The rationality threshold for retail shorting is lower than the threshold for retail buying because constraints on short sales screen unsophisticated investors, suppressing their trading on negative sentiment. In the extreme, if no unsophisticated traders can short ($\theta = 0$), all retail short sellers must be sophisticated.

Proposition 7 analyzes the fraction of trading volume attributable to retail traders or simply "retail trading." In the attention hypothesis, higher retail trading serves as a proxy for

attention and therefore predicts lower stock returns. In fact, after controlling for retail trading, retail shorting should no longer negatively predict returns in H3. The reason is that attention positively influences retail buying and selling, the two components in retail trading, making retail trading just as effective a proxy for attention as retail shorting alone.

Proposition 8 builds on the idea that shorting constraints suppress short selling by irrationally pessimistic retail traders in H1. It establishes that retail short sellers' beliefs are more likely to be correct if they conflict with retail buyers' beliefs—that is, in stocks where retail buying and shorting are simultaneously high. In the model, this situation only arises when g falls within the intermediate range in which $g_S < g < g_B$. In such stocks, return predictability from retail shorting (buying) must be negative (negative). Intuitively, retail buying is a less reliable signal than retail shorting in H1 insofar as shorting constraints weed out irrational shorting.[4]

II. Data

In our empirical analysis, we initially analyze all common stocks listed on the NYSE, AMEX, or NASDAQ exchanges from February 26, 2003 to December 31, 2007. To minimize market microstructure biases associated with highly illiquid stocks, we exclude stocks with prior quarter closing prices less than one dollar. We require nonzero retail shorting in the prior quarter to eliminate stocks that retail investors are not able to short. Because of this retail shorting filter, the final sample spans June 4, 2003 through December 31, 2007. The sample contains an average of 3,376 stocks per day.

[4] In a generalized version of the attention hypothesis that allows g to vary, it is possible to obtain similar predictions to those in Proposition 8. Intuitively, stocks with concurrent high retail shorting and high retail buying tend to be those with the most irrational traders with differences in opinions. As a result, return predictability from attention-driven retail shorting is more likely to be negative in such stocks.

Our retail short selling data is based on the proprietary sample of Kelley and Tetlock (2013), which covers an estimated one-third of self-directed retail order flow from February 26, 2003 through December 31, 2007. This dataset includes over 225 million orders, amounting to $2.60 trillion, in U.S. stocks executed by two related over-the-counter market centers. One market center primarily deals in NYSE and Amex securities, while the other primarily deals in NASDAQ securities. Orders originate from retail clients of hundreds of different brokers. SEC Rule 11Ac1-6 (now Rule 606 under Regulation National Market Systems) reports reveal that most large retail brokers route significant order flow to these market centers during our sample period, including four of the top five online brokerages in 2005.

The order data include codes identifying retail orders and differentiating short sales from long sales. The sample includes nearly seven million executed retail short sale orders, representing $144 billion in dollar volume.[5] Short sales account for 9.66% (5.54%) of the dollar volume of executed sell orders (all executed orders). The average trade size for short sales is $20,870, which is larger than the average size of all trades in the sample ($11,566) as well as average trade sizes in the retail trading samples of Barber and Odean (2000), Barber and Odean (2008), and Kaniel, Saar, and Titman (2008).

Throughout the paper, we aggregate retail short selling activity across five-day windows and use weekly variables as the basis for our analysis. Our main variable is *Short_Volm*, defined as shares shorted by retail investors scaled by total CRSP share volume. We primarily analyze shorting scaled by total share volume to match our theoretical analysis, but we also consider scaling by retail share volume (*Short_RtlVolm*) or shares outstanding (*Short_ShrOut*). We

[5] Of these executed orders, $103 billion are marketable orders and $41 billion are nonmarketable limit orders at the time of order placement. The data also contain over four million orders that do not execute. In our analysis, we aggregate all executed short sale orders across order types. Separate analyses of executed marketable orders, executed nonmarketable orders, and all nonmarketable orders yield quantitatively similar results.

measure other aspects of retail trading using the variables *Retail_Volm*, which is retail volume scaled by total volume, and *LongImb_Volm*, which is shares bought minus long positions sold scaled by volume. Table I provides definitions for all variables used in this study.

[Insert Table I here.]

Table II, Panel A provides statistics for the cross-sectional distribution averaged across all days in the sample. The row for *Short_Volm* shows that retail shorting is a small percentage (0.12%, on average) of overall trading. This result arises for three reasons: 1) shorts are a small fraction of retail trades; 2) our sample does not include all retail trading; and 3) retail trading is a fairly small, though nontrivial portion, of all trading. In a typical week, roughly half of the stocks in the final sample have retail shorting activity, while the other half do not.

[Insert Table II about here.]

Table II, Panel B reports average daily cross-sectional correlations among our main variables. In these correlations as well as the cross-sectional regressions at the end of our paper, we use log transformations for variables with high skewness to minimize the influence of outliers.[6] Notably, the three retail shorting variables have average pairwise correlations exceeding 0.80. Interestingly, retail shorting is positively related to *Turnover* and *ShortInt*. Finally, retail short sellers tend to act as contrarians; the correlations with contemporaneous, prior month, and prior eleven-month returns (*Ret*[-4,0], *Ret*[-25,5], and *Ret*[-251,-26], respectively) are positive, and the correlation with book-to-market (*BM*) is negative.

[6] To transform a variable that sometimes equals zero, we add a constant *c* to the variable before taking the natural log. Each day we set *c* to be the 10th percentile of the raw variable conditional on the raw variable exceeding zero.

III. Empirical Tests of the Model

Here we analyze whether retail short selling predicts stock returns and the mechanisms underlying predictability. Our main tests feature calendar-time portfolios whose returns represent the performance of stocks with various degrees of retail shorting. We supplement these tests with cross-sectional return regressions in the spirit of Fama and MacBeth (1973). Although regressions impose the assumption of linear predictive relationships, they allow us to control for numerous likely predictors of stock returns.

A. Portfolio Methodology

We construct portfolios based on retail short selling as follows. Within a given subsample, we sort stocks into five "quintiles" at the end of each day based on weekly *Short_Volm*. Quintile 1 comprises stocks with zero retail shorting, which often represents half of the stocks in the sample. Stocks with positive retail shorting are evenly distributed across quintiles 2 through 5, with quintile 2 containing stocks with the lowest positive shorting and quintile 5 containing stocks with the most shorting. We evaluate the returns to these portfolios in calendar time over various future event windows.

The daily calendar time return of each quintile portfolio is a weighted average of individual stocks' returns, where day t weights are based on stocks' day $t - 1$ gross returns. Asparouhova, Bessembinder, and Kalcheva (2010) show that the expected return of this gross-return weighted (GRW) portfolio is the same as that of an equal-weighted portfolio, except that it corrects for the bid-ask bounce bias noted by Blume and Stambaugh (1983).

To measure the returns of quintile portfolios over horizons beyond daily, we use the Jegadeesh and Titman (1993) procedure that combines portfolios formed on adjacent days.

Specifically, the calendar day t return of quintile portfolio $q \in \{1, 2, 3, 4, 5\}$ during horizon $[x,y]$ days after portfolio formation is the equal-weighted average of the day t returns of the quintile q portfolios formed on days $t - x$ through $t - y$. We compute the excess return on a long-short *spread* portfolio as the return of the top minus the return of the bottom quintile portfolio. Each quintile portfolio's excess return is its daily return minus the risk-free rate that prevails at the end of the prior day. Each portfolio's alpha is the intercept from a time-series regression of its daily excess returns on the three Fama-French (1993) daily return factors, which are based on the market, size, and book-to-market.

B. Return Predictability from Retail Shorting

Panel A of Table III reports the average daily GRW returns of five portfolios sorted by retail shorting scaled by volume (*Short_Volm*) at horizons up to one quarter after portfolio formation. The spread portfolio return in the bottom row represents the return of heavily shorted stocks minus the return of stocks with no shorting. The left side of Panel A shows portfolios' three-factor alphas, while the right side shows portfolios' excess returns. Panel B displays the three-factor loadings of the five retail shorting portfolios and the spread portfolio, along with the average number of firms in these portfolios at the time of portfolio formation.

[Insert Table III here.]

The main result in Table III is that retail shorting negatively predicts returns at daily to quarterly horizons. The three-factor alpha on the spread portfolio indicates that risk-adjusted predictability is significantly negative in the each of the first three months (days [2,20], [21,60], and [41,60]) after portfolio formation. Daily (annualized) alphas of the spread portfolio are -0.067%, -0.031%, -0.019% (-9.1%, -7.9%, -4.7%) in the first, second, and third months,

respectively. Negative predictability from retail shorting persists beyond three months to days [61,252] (not tabulated) in which the annualized spread alpha is -5.8%. We exclude the first day from the initial month (days [2,20]) after portfolio formation to be conservative; the annualized spread alpha on this day is 252*(-0.069%) = -16.9%. The annualized alphas in days [2,20] decline monotonically from 2.9% to -6.2% from the bottom to the top retail shorting quintile.

Properly adjusting for risk is important when analyzing the performance of the retail shorting portfolios. Panel B shows that market risk increases significantly across the retail shorting portfolios; highly shorted stocks have market betas of 1.068 as compared to betas of 0.794 for stocks with no shorting—a substantial difference of 0.274. Size factor loadings also increase significantly with retail shorting, with highly shorted stocks having 0.335 higher exposures to the small stock factor than stocks without shorting. Because retail short sellers tend to short high beta stocks, the positive realized return of the market factor during our sample period decreases the raw spread in performance between extreme shorting portfolios. The right side of Panel A shows the excess returns of retail shorting portfolios are less striking than the alphas, though they are still economically meaningful. The annualized day-[2,20] predictability in excess returns is 252*-0.023% = -5.9% as compared to the corresponding alpha of -9.1%.

The results in Table III are inconsistent with the sentiment hypothesis: if retail short selling is a proxy for investor sentiment, it should be associated with underpricing and positively predict risk-adjusted returns. However, the information and attention hypotheses both offer explanations, though these hypotheses emphasize quite different economic mechanisms. Retail short selling could be a proxy for information about firm values that is not yet incorporated in stock prices; so retail short selling negatively predicts returns. Alternatively, retail short selling could be a proxy for unsophisticated investors' attention, which negatively predicts returns when

investors' opinions differ and they face short sale constraints. In the remainder of the paper, we subject these two theories to further scrutiny.

C. Predictability from Retail Shorting in Subsamples

Guided by Propositions 2 to 5 in the Appendix, we now investigate subsamples of stocks in which return predictability should be strongest according to the information hypothesis, the attention hypothesis, or both. We use the following stock characteristics, as defined in Table I, to represent aspects of the model:

- *Size*, *Analysts*, and *NewsStories* to represent the amount of tangible information (k);
- *IdioVol*, *Turnover*, *ShortInt*, and *Dispersion* to represent the expected sentiment shock ($E|m|$) in H1 and difference in opinion (η) in H3;
- option listing (*OptionDum*) and failures to deliver shares (*HighFails*) as proxies for short sale constraints ($1 - \theta$).

To measure interaction effects with these characteristics, we conduct the calendar-time procedure in Section III.A separately within groups of stocks sorted by each characteristic—e.g., within five groups based on the *Size* proxy for the information environment parameter, k. These 5x5 dependent sorts produce twenty-five portfolios.

Our first proxy for k is *Size*. Intuitively, abundant tangible information about large firms is publicly available (k is high), which reduces investors' reliance on intangible information–the source of mispricing and return predictability in the model. Our other proxies for k are *Analysts* and *NewsStories*. Both are positively related to the availability of tangible information and, as expected, both are positively correlated with *Size*, as shown in Table II, Panel B. In sorts by *Size*,

we define groups based on quintiles of NYSE firms; in sorts by *Analysts* and *NewsStories*, we use quintiles based on all firms.

Table IV reports the average GRW daily alphas during days [2,20] of portfolios resulting from the two-way sorting procedure. In Panels A, B, and C, the initial sorting variables are *Size*, *Analysts*, and *NewsStories*, respectively, while the second sorting variable in all panels is retail shorting (*Short_Volm*). The bottom rows in each panel show alphas of spread portfolios that measure one-month predictability from retail shorting in each subsample. The rightmost column in each panel shows the difference between alphas of stocks with high and low values of the three proxies for *k*, holding the retail shorting quintile constant.

[Insert Table IV here.]

One-month return predictability from retail shorting is negative in all 15 subsamples in Table IV. However, the magnitude of predictability decreases significantly with *Size*, *Analysts*, and *NewsStories*, with declines of 93%, 61%, and 72%, respectively.[7] Panel A shows the annualized alphas of the retail shorting spread portfolio are -10.9%, -8.1%, -8.4%, -5.9%, and -0.7% in NYSE *Size* quintiles 1, 2, 3, 4, and 5, respectively. The dramatic difference in return predictability in quintile 4 versus 5 could arise because most firms in quintile 5 are members of the S&P 500 Index that receive immense public scrutiny. Negative return predictability from retail shorting is economically and statistically significant in all but the top quintile. The difference between predictability in the top and bottom size quintiles is highly significant at 10.1% annualized. The results are qualitatively similar, though not as strong, for the two-way sorts by *Analysts* and *NewsStories* shown in Panels B and C, respectively.

[Insert Figure 1]

[7] Engelberg, Reed, and Ringgenberg (2012) show that total short selling is a stronger negative predictor of returns within stocks in which news occurs. Our results could differ because they analyze total, not retail, shorting.

Figure 1 shows how return predictability from retail shorting in each *Size* quintile varies with the horizon. Negative predictability persists up to one quarter in all but the top *Size* quintile. Although there is some decay of predictability over time, the negative alphas after portfolio formation do not become positive. The positive alphas before formation illustrate the contrarian nature of retail shorting: heavily shorted stocks have relatively high recent returns.

The results in Table IV and Figure 1 are consistent with models in which negative predictability from retail shorting attenuates with the availability of tangible information. Both the information and attention hypothesis proposed in Section I make this prediction because the availability of tangible information reduces mispricing and thus return predictability.

Henceforth, we control for firm size in double-sorted portfolios by adding a layer to the procedure used in Table III. Prior to double-sorting, we stratify the sample into *Size* quintiles based on NYSE breakpoints. We then conduct two-way dependent portfolio sorts as described above within each strata, producing calendar-time returns for 5x5x5 = 125 triple-sorted portfolios. Finally, we recombine portfolios by averaging portfolio returns across the five *Size* strata within each double-sorted portfolio. Consequently, each NYSE *Size* quintile is equally represented in the returns of the resulting 5x5 = 25 calendar-time portfolios that we analyze.

We apply this procedure to test whether return predictability from retail shorting varies with empirical proxies for the expected magnitude of investor sentiment $E[|m|]$ and irrational difference in opinion (η). Propositions 3 and 4 in the Appendix summarize the predictions from the model. In the information hypothesis, sentiment causes mispricing; higher expected sentiment is associated with higher return predictability and return volatility, as well as higher trading volume and short interest as rational and irrational traders' beliefs diverge. In the attention hypothesis, overpricing arises from difference in opinion η and short sale constraints;

higher η is associated with higher return predictability and volatility, as well as higher volume and short interest as irrational traders' beliefs diverge from each other.

Panel A of Table V reports the average GRW daily alphas during days [2,20] of size-stratified portfolios based on initial sorts by return volatility (*IdioVol*) and then by retail shorting (*Short_Volm*). Panels B, C, and D of Table V display analogous results for initial sorts by trading volume (*Turnover*), short interest (*ShortInt*), and analyst forecast dispersion (*Dispersion*), respectively. The volatility, turnover, and short interest proxies are indirect measures of differences in agents' beliefs, whereas *Dispersion* more directly measures differences in beliefs. In the information hypothesis, the relevant difference in beliefs is that between rational and irrational traders, whereas the relevant difference is that among irrational traders in the attention hypothesis. In practice, this distinction is difficult to measure. Although the tests in Table V do not distinguish between the information and attention hypotheses, they do provide evidence on whether both hypotheses have merit.

[Insert Table V here.]

The main result in Table V is that return predictability from retail shorting is stronger in stocks in which differences in investors' beliefs are likely to be larger by all four metrics above. The differences in predictability from retail shorting are economically material, ranging from -0.016% * 252 = -4.1% annualized for the initial sort by *Dispersion* to -6.3% for the sort by *ShortInt*. The percentage increases in predictability from the bottom to top deciles range are 85%, 100%, 163%, and 191% for the sorts by *Dispersion*, *Turnover*, *ShortInt*, and *IdioVol*, respectively. The statistical differences in predictability, however, are only marginally significant, with *t*-statistics ranging from -1.32 for *Dispersion* to -1.94 for *ShortInt* corresponding to *p*-values of 0.187 and 0.053, respectively. Considering this evidence together with our

previous findings, we infer that both the information and attention hypotheses are promising explanations for return predictability from retail shorting.

Analyzing whether predictability depends on short sales constraints can help distinguish the two hypotheses. Proposition 5 shows that return predictability from retail shorting in the attention hypothesis *requires* short sale constraints and intensifies with their severity. In contrast, shorting constraints have two opposing effects on predictability in the information hypothesis. On one hand, relaxing constraints allows more shorting by irrational traders, which amplifies mispricing and enhances predictability, as shown in equation (A13). On the other hand, relaxing constraints allows more shorting by irrational *retail* traders, which increases the rationality threshold g_S above which retail shorting negatively predicts returns—see equation (11).

Table VI presents the average GRW daily alphas during days [2,20] of size-stratified portfolios based on initial sorts by shorting constraints and then by retail shorting (*Short_Volm*). Panel A shows initial sorts based on whether stocks have nonzero option trading volume in the prior quarter, as measured by *OptionDum*. Panel B shows initial sorts based on whether exchange reported fails-to-deliver exceed 0.10 percent of shares outstanding on any day of the prior week, as measured by *HighFails*. The bottom rows in the panels reveal that 48% of stocks are constrained by the *OptionDum* criterion, while 15% are constrained by the *HighFails* criterion, indicating the latter criterion is far more restrictive. Evans et al. (2009) show that options market makers usually choose to fail to deliver stocks to buyers when shares are costly for short sellers to borrow, as measured by reductions in the rebate rates received by short sellers.

[Insert Table VI here.]

The evidence in Table VI suggests shorting constraints are unrelated to return predictability from retail shorting. The annualized increase in predictability attributable to

constraints is -0.006% *252 = -1.4% in Panel A and positive 1.4% in Panel B, with *t*-statistics of -0.69 and 0.39, respectively. Stocks with *HighFails* = 1 exhibit slightly weaker negative predictability from retail shorting, which is ostensibly inconsistent with the attention hypothesis. According to the information hypothesis, the mixed evidence here is not surprising given the opposing effects noted above.

D. Predictability from Retail Buying and Retail Trading

We further investigate the unique predictions of the information and attention hypotheses in tests that feature retail buying and total retail trading, as well as their interactions with retail shorting. Propositions 6 and 7 highlight key implications of the two hypotheses for retail buying and retail trading, with both defined as a fraction of total volume. The attention hypothesis posits that retail shorting predicts returns primarily because high attention from irrational traders causes both overpricing and high retail shorting. A distinctive aspect of this theory is that attention also causes high retail buying and high overall retail trading, implying both measures should be associated with overpricing as well. In contrast, in the information hypothesis, if a sufficient fraction of retail traders is rational ($g > g_B$ in equation (12)), retail buying activity should positively predict returns, as shown in Proposition 6. Proposition 7 highlights two cases in which the negative predictability from retail shorting and the positive predictability from buying exactly offset, implying that overall retail trading is unrelated to returns.

We first evaluate the empirical predictability from retail buying, which is unambiguously negative in the attention hypothesis and is positive in the information hypothesis if g is sufficiently high. Although the stylized model in Section I is silent about the treatment of long sales, such sales are conceptually similar to long buying in that they do not require the investor to

open a margin account. Investors who open margin accounts must self-certify that they understand basic investment principles, such as short selling, suggesting they could be more sophisticated. Therefore we subtract long sales from retail buys and use retail net buying (*LongImb_Volm*) as the basis for our empirical tests. The long imbalance variable is scaled by volume to mimic the treatment of retail buying in the model. Table VII presents the average GRW daily alphas during days [2,20] of portfolios double-sorted by *Size* and *LongImb_Volm*. Figure 2 plots cumulative 60-day alphas for the spread portfolios within each size group as well as a full sample spread portfolio (not tabulated).

[Insert Table VII here.]

The key finding is that net retail buying is not a meaningful negative predictor of returns in any NYSE size quintile. In fact, there is economically material positive predictability from net retail buying in the smallest size quintile (0.014%*252 = 3.5% annualized) and even in the largest quintile (0.010%*252 = 2.5%), though only the predictability in small stocks is statistically significant. Predictability in the middle three size quintiles is less than 1% in absolute value. These results contradict a key prediction of the attention hypothesis, but they are entirely consistent with the information hypothesis. The positive predictability from retail buying shown in Table VII is also qualitatively consistent with the findings of Kelley and Tetlock (2013), who show that *daily* net retail buying positively predicts future returns and the strongest predictability is in small stocks.[8]

[Insert Figure 2 here.]

Next we test whether retail trading scaled by total volume, *Rtl_Volm*, negatively predicts returns, as implied by the attention hypothesis. Panel A of Table VIII shows the average GRW

[8] Scaling retail net buying by retail trading, as in Kelley and Tetlock (2013), rather than by total volume would increase the magnitude of return predictability. We examine how alternative scaling affects predictability from retail shorting in Table X below.

daily alphas during days [2,20] of size-stratified portfolios sorted by *Rtl_Volm*. The annualized alpha of the spread between the high and low *Rtl_Volm* quintile portfolios is -0.50% and statistically indistinguishable from zero. The lack of evidence that retail trading predicts returns is inconsistent with the attention hypothesis.

[Insert Table VIII here.]

We also test a related prediction from the attention hypothesis in which controlling for retail trading should eliminate predictability from retail shorting. Panel B shows the average GRW daily alphas during days [2,20] of size-stratified portfolios double-sorted by *Rtl_Volm* and then *Short_Volm*. If the attention hypothesis is correct, the initial sort by retail trading (*Rtl_Volm*) controls for variation in investor attention and leaves no reason for a relation between retail shorting (*Short_Volm*) and returns. The evidence in Panel B does not support this claim. Within all quintiles of retail trading, there is economically and statistically significant negative predictability from retail shorting. The annualized magnitudes range from -0.026%*252 = -6.5% to -9.1% and are quite close to the unconditional predictability from retail shorting shown in Panel A of Table 3.

We now subject the information hypothesis to further scrutiny. The results thus far suggest significant differences between return predictability from retail short selling and that from retail buying. In the information hypothesis, these differences arise because shorting constraints suppress short selling by irrationally pessimistic retail traders, whereas retail buyers face no such constraints. As a result, stocks in which retail short sellers' beliefs conflict with those of retail buyers must be stocks in which retail short sellers are correct. Empirically, we can identify such stocks as those in which retail buying and retail shorting are simultaneously high in double-sorted portfolios.

[Insert Table IX here.]

Table IX displays the average GRW daily alphas during days [2,20] of size-stratified portfolios double-sorted by *LongImb_Volm* and then *Short_Volm*. The spread portfolios in the bottom row reveal the striking result that retail shorting is a much stronger predictor of returns in stocks in which retail net buying is highest. Annualized predictability from retail shorting ranges from -0.007%*252 = -1.8% in the bottom quintile of retail net buying to -12.3% in the top quintile. The difference in predictability is 10.5% and is highly statistically significant. A natural interpretation of this finding is that retail short sellers are better informed than retail buyers.

However, under certain parameterizations, the attention hypothesis predicts a similar pattern in the double-sorted portfolio returns in Table IX. Stocks with high retail buying could be those with fewer rational retail traders. In such stocks, retail shorting is a better proxy for attention and thus overpricing. Thus, we cannot rule out the possibility that the empirical strength of the result in Table IX is partially attributable to the reinforcing impact of the attention and information hypotheses.

IV. Interpretations and Robustness

Here we examine three additional issues to help us interpret the results. First, we analyze how alternative scaling of retail shorting affects return predictability. Second, we consider whether predictability from retail shorting is related to known sources of return predictability. Third, to scrutinize the information hypothesis, we test whether retail shorting predicts the linguistic tone of firm-specific news.

A. Alternative Scaling of Retail Shorting

The scaling of retail shorting could have a big impact on return predictability under the attention hypothesis. This theory is based on overpricing arising from the joint interaction between attention, difference in opinion, and short sales constraints; proxies for either attention (α) or difference in opinion (η) negatively predict returns. If retail traders are unsophisticated, retail shorting serves as a proxy for both α and η and thus negatively predicts returns. Total trading volume and retail trading are also valid proxies for both α and η—e.g., see equation (A19) for volume. Intuitively, scaling retail shorting by these alternative proxies for α and η should generate lower return predictability from retail shorting than scaling by shares outstanding.

In contrast, if retail shorting represents information not yet incorporated in prices, the scaling of retail shorting could have little impact on return predictability. For example, if there are no short sale constraints, total trading volume and retail trading are unrelated to the direction of investor sentiment—i.e., set $\theta = 1$ in equations (A5) and (A10). In this case, predictability from retail shorting is the same whether one scales by volume, total trading, or shares outstanding.

Table X reports the average daily GRW alphas of five portfolios sorted by retail shorting scaled by alternative measures at horizons up to one quarter after portfolio formation. In Panel A (Panel B), the sorting variable is retail shorting scaled by shares outstanding (retail trading), which we denote *Short_ShrOut* (*Short_RtlVolm*). These panels are analogous to Panel A of Table III in which the sorting variable is retail shorting scaled by volume (*Short_Volm*).

[Insert Table X here.]

The evidence in Table X reveals that the scaling of retail shorting has a small effect on the magnitude and duration of negative return predictability. Comparing Panel A (Panel B) of Table X to Panel A in Table III, the annualized alpha of the spread portfolio in days [2,20] is -10.5% (-8.0%) in sorts by *Short_ShrOut* (*Short_RtlVolm*) versus -9.1% in sorts by *Short_RtlVolm*. In Panels A and B of Table X, the alpha of the spread portfolio remains significantly negative even in the third month (days [41,60]) after portfolio formation, as it does in Panel A of Table III. Scaling by shares outstanding produces slightly larger negative return predictability than the other two measures, but there is little difference among them. The robustness of predictability to scaling is consistent with the information hypothesis.

B. Controlling for Existing Predictors of Returns

We further explore the nature of predictability from retail shorting by estimating linear regressions that include controls for well-known cross-sectional predictors of returns. Key control variables that could be related to future stock returns and retail short selling include: *Size*, *Book-to-Market*, and CAPM *Beta* as in Fama and French (1992); prior one week (*Ret*[-4,0], one month (*Ret*[-25,-5]), and eleven month stock returns (*Ret*[-251,-26]) as in Gutierrez and Kelley (2008) and Jegadeesh and Titman (1993); short interest decomposed into *Lag_ShortInt* and *Chg_ShortInt* following Figlewski (1981) and Senchack and Starks (1993); prior week *Turnover* and prior month idiosyncratic volatility (*IdioVol*) similar to Gervais, Kaniel, and Mingelgrin (2001) and Ang et al. (2006); analyst forecast dispersion (*Dispersion*) as in Diether, Malloy and Scherbina (2002); a dummy indicating no recent options trading volume (*NoOptionDum*) as a proxy for short sales constraints as in Danielsen and Sorescu (2001); and change in mutual fund ownership breadth (*Chg_Breadth*) as in Chen, Hong, and Stein (2002).

We estimate daily cross-sectional regressions in the spirit of Fama and MacBeth (1973) in which we regress day-[*t*+2,*t*+20] stock returns on retail shorting and control variables measured as of day *t*. To be consistent with our calendar-time portfolio analysis, we weight observations by gross stock returns, though equal-weighting produces similar results. We draw inferences based on the time series of daily regression coefficients and Newey-West (1987) standard errors with 19 leads and lags (i.e., the return horizon) to account for overlapping return observations. Table XI reports several regression specifications. The dependent variable in Panel A is Fama and French (1993) cumulative abnormal returns (*CAR*[2,20]) with factor loadings based on daily data from the prior year. The dependent variable in Panel B is raw compound returns (*Ret*[2,20]).

[Insert Table XI here.]

The central result from Table XI is that negative return predictability from retail shorting remains economically and statistically strong in all specifications. In the first column with no control variables, annualized return predictability from a 5th to 95th percentile change in log retail shorting (4.09) is 4.09 * (252/19) * -0.00190 = -10.3%; with all controls in column four, predictability is -7.5%. As in Table III, predictability is largest in specifications with risk-adjusted returns as the dependent variable, though predictability of raw returns is also highly significant. The absolute value of the *t*-statistic on the retail shorting coefficient exceeds 2.95 in all specifications. Other coefficients are generally consistent with prior literature.

The inclusion of control variables representing total short interest reduces retail shorting predictability by 27% = |-0.139/-0.190| – 1 in specifications with monthly risk-adjusted returns (*CAR*[2,20]) as the dependent variable. The inclusion of additional control variables has a negligible impact on retail shorting predictability. One interpretation is that, while retail and non-

retail short sellers possess some common information even after controlling for other predictors of returns, most of the information conveyed by retail short selling is unique to retail investors. We also note that controlling for price momentum in days [-251,-26], which positively predicts returns, actually increases predictability from retail shorting. The reason is that retail shorting tends to be contrary to past returns, as shown in Table II, Panel B and Figure 1.

The regression coefficients on the control variables provide mixed support for the Miller (1977) overpricing mechanism underlying the attention hypothesis. Consistent with Miller (1977), the proxies for short sale constraints and difference in opinion negatively predict returns; the interaction between constraints and difference in opinion also negatively predicts returns. However, the inclusion of these three control variables reduces predictability from retail shorting by only 3% = |-0.127/-0.131| – 1. One interpretation is that the Miller (1977) hypothesis partially explains overall return predictability, but it does not explain predictability from retail shorting.

Finally, Diether, Lee, and Werner (2009) analyze short sales reported to exchanges under Regulation SHO from 2005 to 2007 and show that daily total short-selling is a strong negative predictor of weekly returns. Using the same dataset, we compute weekly total short-selling scaled by volume—analogous to our weekly retail shorting variable. The average cross-sectional correlation between total shorting and our main retail shorting variable, *Short_Volm*, is 0.13. When we include total short-selling in the return predictability regressions (not reported), coefficients on *Short_Volm* change immaterially and remain strongly statistically significant.

C. Retail Shorting and Firm-Specific News

Given the ability of the information hypothesis to explain our evidence, we now analyze what retail short-sellers might know about the firms whose stocks they trade. Our empirical strategy is to test whether retail shorting predicts the tone of firm-specific news.

Our primary measure of news tone is the Event Sentiment Score (*ESS*) from RavenPack News Analytics. These scores reflect the linguistic tone or "sentiment" of individual stories from Dow Jones Newswires. We rescale raw scores, which range from 0 to 100, by subtracting 50 and then dividing by 50 to create an *ESS* variable spanning the interval [–1,1], where –1 is the most negative, 0 is neutral, and +1 is the most positive tone. In our analysis, we retain only stories deemed relevant by RavenPack for two or fewer U.S. stocks and eliminate stories about stock price movements or order imbalances. We compute a stock's *ESS* from day $t + x$ through $t + y$ as the average of story-level *ESS* during this interval. For intervals with no stories, we set *ESS* equal to its cross-sectional mean, thereby allowing for time variation in average news tone.

We estimate panel regressions of day-[2, 20] *ESS* on retail shorting and control variables measured as of day *t*. We include the key control variables from the return predictability regressions in Table XI. We also control for lagged *ESS* variables because news tone is persistent and retail traders may short in response to prior news. We also control for news coverage with the natural log of the number news stories per day from the prior year (*Coverage*[-251 ,-26]) as well as abnormal news coverage from the prior month (*Abn_Coverage*[-25,-5]) and week *(Abn_Coverage*[-4,0]). To account for time variation in *ESS* and control variables, we include time fixed effects. Following Petersen (2009), we cluster standard errors by firm to account for the persistence of residual *ESS*.

The results appear in Table XII. Panel A contains regressions predicting *ESS* over days-[2,20]. Most importantly, the coefficient on *Short_Volm* is significantly negative in the first model. Thus, controlling for other predictors of news tone, high retail shorting predicts negative news in the following month.[9] The coefficients on many control variables are intuitive and interesting. For example, prior short interest levels and changes predict negative news, consistent with Akbus, Boehmer, Erturk, and Sorescu (2013) who study the relation between aggregate short interest and future firm news as measured by RavenPack *ESS*.

In the other four models in Panel A, we separately construct the dependent *ESS* variable based on four broad categories of news stories to distinguish whether retail short sellers predict news relating to earnings, analysts, revenue, or mergers and acquisitions (M&A).[10] These tests reveal that retail short-selling predicts the tone of earnings and analyst news (models two and three). However, retail short-selling does not predict revenue or M&A news (models four and five). Panel B shows regressions predicting news tone of all stories and earnings stories in the second and third months after retail short selling. Similar to the decay in return predictability, there is some decay in the ability of retail shorting to predict future news. The coefficient on *Short_Volm* is insignificant (declining but still statistically significant) when predicting *ESS* for all stories (earnings stories) occurring during days [21,40] and [41,60].

For robustness, we replace the *ESS* variables with the fraction of negative words in Dow Jones Newswires stories as in the regressions in Kelley and Tetlock (2013). To maximize the power of these tests, we include only earnings-related stories when measuring negativity. Table XII Panel C shows results for regressions predicting negativity in each of the next three months. The positive coefficients on *Short_Volm* are consistent with those in the *ESS* regressions. Retail

[9] For the limited sample in which Regulation SHO short-selling data are available, all results based on the variable *Short_Volm* hold even in unreported specifications that control for total short selling.
[10] Ravenpack identifies highly specific news categories. We group several of their categories into four broad groups.

shorting predicts more negative news tone in each of the next three months, and the magnitude of predictability decays over time.

V. Concluding Discussion

We document that retail short selling strongly negatively predicts stock returns in the cross-section even after controlling for known predictors of returns. This negative predictability does not contradict the weak form of the efficient market hypothesis because retail shorting is nonpublic information. Our evidence is most consistent with the hypothesis that retail short sellers possess and act on unique information about stocks' fundamental values. Prices gradually incorporate this information in the next three months. Reinforcing this interpretation, retail short selling also predicts negative firm-specific news over similar horizons.

Large variation in return predictability hints at the sources of retail short sellers' information. Predictability is strongest in small stocks and those with low analyst coverage. Since most institutions do not devote substantial resources to valuing such stocks, retail investors, perhaps through geographical proximity, social networks, or employment, may be well-positioned to identify overpriced stocks. Still, institutional neglect cannot explain why retail shorting negatively predicts returns even in stocks as large as the fourth NYSE size quartile.

A complementary explanation is that retail short sellers are not subject to the same limitations as institutional short sellers. To attract funds from clients, asset managers can engage in window dressing in which they increase their holdings of stocks favored by clients (e.g., Lakonishok, Shleifer, Vishny, and Thaler (1991) and Sias and Starks (1997)), even though such stocks could be overpriced (Frazzini and Lamont (2008)). This incentive from fund flows could deter well-informed institutions from short selling overpriced stocks, as argued in Lamont and

Stein (2004). In contrast, retail short sellers who manage their own money are immune to such concerns and could benefit from the absence of competition from institutions.

Retail short sellers also could benefit from a lack of competition from other retail traders with poor access to short selling. Retail brokerage customers must open margin accounts to be able to short stocks, and many brokerages do not permit retail customers with margin accounts to short large subsets of stocks. These entry restrictions could contribute to the persistence of return predictability from retail shorting. Our model suggests that short sale constraints have mixed welfare consequences for retail investors. Constraints may prevent sentiment-driven shorting and information-driven shorting. On balance, our evidence indicates retail shorting contributes to the informational efficiency of stock prices, suggesting policymakers should consider acts to improve retail investor access to short selling.

Appendix: Analysis of the Model

Here we analyze the properties and predictions of the different versions of the model defined in Section I.C. In each hypothesis, retail traders consist of a fraction g of rational unconstrained type A investors and a fraction $(1 - g)$ of irrational and partially constrained type C investors. In H1 (information) and H2 (sentiment), type B and C trader sentiment (m) is symmetrically distributed around a zero mean, but traders' opinions do not differ ($\eta = 0$). In H3 (attention), type B and C traders' attention varies across stocks. Their opinions differ ($\eta > 0$), but average sentiment ($m = 0$) is zero for all stocks. We compute closed-form expressions for key equilibrium quantities in each version of the model. We use these results to prove eight propositions that constitute the testable predictions from the model.

A. Closed-form Expressions for Observable Equilibrium Variables in H1 and H2

We define the expected stock return as the negative of overpricing, which is the second term in the pricing equation (8):

$$E(Ret) = -\frac{\left[\gamma_B + \left[\theta + I\left(m > 0\right)\left(1-\theta\right)\right]\alpha\gamma_C\right]m}{\left[\gamma_A + \gamma_B + \left[\theta + I\left(m > 0\right)\left(1-\theta\right)\right]\alpha\gamma_C\right](2+k)}. \tag{A1}$$

Return volatility is the standard deviation in the period 1 price, where we treat the prior mean (F), signals, and sentiment as random variables. The volatility in price becomes

$$\sqrt{Var\left(p_1\right)} = \sqrt{\sigma^2 + \left[\frac{E[|m|]}{(2+k)}\right]^2 \left(\frac{c_1 + c_2}{2}\right)^2}, \tag{A2}$$

where we define the constants c_1 and c_2 as

$$c_1 = \frac{\gamma_B + \alpha\gamma_C}{\gamma_A + \gamma_B + \alpha\gamma_C} \tag{A3}$$

$$c_2 = \frac{\gamma_B + \alpha\theta\gamma_C}{\gamma_A + \gamma_B + \alpha\theta\gamma_C}. \tag{A4}$$

We now analyze trading volume and short interest in H1 and H2 using the simplifying convention that traders have zero initial endowments of stock. Because the model is static and the stock is in zero supply, short interest, short selling, and trading volume are the same. We compute total short interest (S) and volume (V) by summing short interest across all investors, which includes type A (arbitrageur) shorting and types B and C (irrational) shorting.

$$S = V = S_A + S_B + S_C = \left(\frac{\gamma_A}{\sigma^2}\right)\frac{\left[\gamma_B + \left[\theta + I\left(m>0\right)\left(1-\theta\right)\right]\alpha\gamma_C\right]|m|}{\gamma_A + \gamma_B + \left[\theta + I\left(m>0\right)\left(1-\theta\right)\right]\alpha\gamma_C}. \tag{A5}$$

Because m is symmetrically distributed around a zero mean, expected trading volume is

$$E\left(V\right) = \frac{E\left[|m|\right]\gamma_A}{2\sigma^2}\left[\frac{\gamma_B + \alpha\gamma_C}{\gamma_A + \gamma_B + \alpha\gamma_C} + \frac{\gamma_B + \theta\alpha\gamma_C}{\gamma_A + \gamma_B + \theta\alpha\gamma_C}\right]. \tag{A6}$$

We now analyze the behavior of retail investors, who are composed of $g\gamma_R$ type A investors and $(1 - g)\gamma_R$ type C investors. The parameter g determines whether overall retail trading activity reflects type A or type C investors' beliefs. By aggregating demand across retail traders with negative demand, we find that retail shorting (S_R) is:

$$S_R = \left(\frac{\gamma_R}{\sigma^2}\right)\left[\frac{g(\gamma_B + \alpha\gamma_C)I(m>0)}{\gamma_A + \gamma_B + \alpha\gamma_C} + \frac{(1-g)\theta\alpha\gamma_A I(m<0)}{\gamma_A + \gamma_B + \theta\alpha\gamma_C}\right]|m|. \tag{A7}$$

In empirical work, we use ratios of shorting to total volume, which for retail traders is

$$\frac{S_R}{V} = \gamma_R\left[\frac{g}{\gamma_A}I\left(m>0\right) + \frac{(1-g)\theta\alpha}{\gamma_B + \theta\alpha\gamma_C}I\left(m<0\right)\right]. \tag{A8}$$

Scaled retail shorting decreases with sentiment (i.e., $S_R/V(m > 0) > S_R/V(m < 0)$) only if a sufficient fraction of retail investors is rational, that is, if $g > g_S$, where g_S is given by equation (11).

Following similar logic, retail buying (B_R) is

$$B_R = \left(\frac{\gamma_R}{\sigma^2}\right)\left[\frac{g(\gamma_B + \theta\alpha\gamma_C)I(m<0)}{\gamma_A + \gamma_B + \theta\alpha\gamma_C} + \frac{(1-g)\alpha\gamma_A I(m>0)}{\gamma_A + \gamma_B + \alpha\gamma_C}\right]|m|. \tag{A9}$$

Total retail trading is

$$B_R + S_R = \left(\frac{\gamma_R}{\sigma^2}\right)\frac{g\gamma_B + \left[\theta + I\left(m>0\right)\left(1-\theta\right)\right]\left[\left(1-g\right)\alpha\gamma_A + g\alpha\gamma_C\right]}{\gamma_A + \gamma_B + [\theta + I\left(m>0\right)\left(1-\theta\right)]\alpha\gamma_C}|m|, \tag{A10}$$

Retail buying scaled by total trading volume is

$$\frac{B_R}{V} = \gamma_R\left[\frac{g}{\gamma_A}I\left(m<0\right) + \frac{\left(1-g\right)\alpha}{\gamma_B + \alpha\gamma_C}I\left(m>0\right)\right]. \tag{A11}$$

Buying decreases with sentiment if $g > g_B$, where g_B is given by equation (12). The rationality threshold for retail shorting to predict returns is lower than the threshold at which retail buying predicts returns because short sales constraints selectively screen unsophisticated traders.

We now consider the return predictability from retail shorting scaled by volume (S_R/V). We define return predictability from x (Px_H) in hypothesis H as the standardized regression coefficient of expected returns on x holding fixed the values of parameters other than the primary source of variation in hypothesis H. With this convention, predictability in H1 and H2 is

$$Px_{H1,H2} = \frac{Cov_m\left(E\left(Ret\right), x \mid g,\alpha,\eta,\theta,k\right)}{\sqrt{Var_m(x \mid g,\alpha,\eta,\theta,k)}}. \tag{A12}$$

Because the parameters vary independently, reasonable changes to the definition of predictability are unlikely to affect the propositions that follow. To analyze predictability from retail shorting scaled by volume, denoted by *PSRV*, we set $x = S_R/V$ to obtain

$$PSRV_{H1,H2} = -\frac{E\left[|m|\right]}{2\left(2+k\right)}\left[\frac{\gamma_B + \alpha\gamma_C}{\gamma_A + \gamma_B + \alpha\gamma_C} + \frac{\gamma_B + \theta\alpha\gamma_C}{\gamma_A + \gamma_B + \theta\alpha\gamma_C}\right]Sign\left(g - g_S\right). \tag{A13}$$

We interpret the E[$|m|$] term as the expected magnitude of sentiment.

We similarly compute return predictability (*PBRV*) from retail buying in H1 and H2 as

$$PBRV_{H1,H2} = \frac{E\left[|m|\right]}{2\left(2+k\right)}\left[\frac{\gamma_B + \alpha\gamma_C}{\gamma_A + \gamma_B + \alpha\gamma_C} + \frac{\gamma_B + \theta\alpha\gamma_C}{\gamma_A + \gamma_B + \theta\alpha\gamma_C}\right] Sign\left(g - g_B\right), \tag{A14}$$

where the threshold g_B is given in equation (12).

B. Closed-form Expressions for Observable Equilibrium Variables in H3

We use the same definitions for stock returns, volatility, volume, and other observable variables in the analysis of H3 (attention) in which α varies across stocks. Based on the pricing equation (9), expected returns in H3 are

$$E(Ret) = -\frac{\eta}{2+k}\left[\left(2\gamma_U + 1\right) - \sqrt{\left(2\gamma_U + 1\right)^2 - 1}\right], \tag{A15}$$

where we define c_3 as the term in brackets in equation (A15):

$$0 < c_3 \equiv \left(2\gamma_U + 1\right) - \sqrt{\left(2\gamma_U + 1\right)^2 - 1} < 1. \tag{A16}$$

To compute return volatility in H3, we adopt the delta method approximation that price is a linear function of attention, α. Under this assumption, return volatility is

$$\sqrt{Var\left(p_1\right)} = \sqrt{\sigma^2 + Var(\alpha)\left[\frac{dp}{d\alpha}\right]^2}. \tag{A17}$$

where the dependence of price on attention is

$$\frac{dp}{d\alpha} = \frac{2\eta}{2+k}\left[\frac{(2\gamma_U + 1)}{\sqrt{(2\gamma_U + 1)^2 - 1}} - 1\right]\frac{(\gamma_A + \gamma_B)\alpha^{-2}}{(1-\theta)\gamma_C} > 0. \tag{A18}$$

In H3, trading volume and short interest are both given by

$$V = S = S_A + S_B + S_C = \frac{\eta}{\sigma^2}\left[(\gamma_B + \theta\alpha\gamma_C)(1 + c_3)^2 / 4 + \gamma_A c_3\right]. \tag{A19}$$

Using this expression and the fact that $g = 0$ in H3, retail shorting scaled by volume is

$$\frac{S_R}{V} = \frac{\gamma_R \theta \alpha \left(1 + c_3\right)^2}{4\gamma_A c_3 + \left(\gamma_B + \theta \alpha \gamma_C\right)\left(1 + c_3\right)^2}. \tag{A20}$$

Scaled retail buying is

$$\frac{B_R}{V} = \frac{\alpha \gamma_R (c_3 - 1)^2}{4\gamma_A c_3 + (\gamma_B + \theta \alpha \gamma_C)\left(1 + c_3\right)^2}. \tag{A21}$$

Importantly, when scaled by volume, retail shorting and buying are independent of difference in opinion (η). As a result, variation in difference in opinion does not generate return predictability from retail shorting or buying.

However, retail shorting and buying still depend on attention. The impact of attention, α, on retail shorting operates directly in equation (A20) and indirectly through the overpricing term, c_3. Overpricing is related to unconstrained relative risk tolerance (γ_U), which depends on attention as shown in equation (10). We summarize the overall effect of α on retail shorting as

$$\frac{d\left(\frac{S_R}{V}\right)}{d\alpha} = \frac{\partial\left(\frac{S_R}{V}\right)}{\partial\alpha} + \frac{\partial\left(\frac{S_R}{V}\right)}{\partial c_3}\frac{\partial c_3}{\partial \gamma_U}\frac{\partial \gamma_U}{\partial \alpha}. \tag{A22}$$

We differentiate equations (10), (A16), and (A20) to compute the terms in (A22). The direct impact of attention on scaled shorting is

$$\frac{\partial\left(\frac{S_R}{V}\right)}{\partial\alpha} = \frac{\gamma_R \theta \left(1 + c_3\right)^2 \left[4\gamma_A c_3 + \gamma_B \left(1 + c_3\right)^2\right]}{\left[4\gamma_A c_3 + (\gamma_B + \theta \alpha \gamma_C)\left(1 + c_3\right)^2\right]^2}. \tag{A23}$$

The impact of overpricing on scaled shorting is

$$\frac{\partial\left(\frac{S_R}{V}\right)}{\partial c_3}=\frac{-4\gamma_R(1+c_3)(1-c_3)\theta\alpha\gamma_A}{\left[4\gamma_A c_3+(\gamma_B+\theta\alpha\gamma_C)\left(1+c_3\right)^2\right]^2}<0. \tag{A24}$$

The effect of the relative risk tolerance of unconstrained investors on overpricing is

$$\frac{\partial c_3}{\partial\gamma_U}=-2\left[\frac{\left(2\gamma_U+1\right)}{\sqrt{\left(2\gamma_U+1\right)^2-1}}-1\right]<0. \tag{A25}$$

The effect of α on γ_U is negative and given by

$$\frac{\partial\gamma_U}{\partial\alpha}=-\frac{(\gamma_A+\gamma_B)\alpha^{-2}}{(1-\theta)\gamma_C}<0. \tag{A26}$$

We now substitute these four partial derivatives into the overall effect of attention on shorting.

$$\frac{d\left(\frac{S_R}{V}\right)}{d\alpha}=\frac{\gamma_R\left(1+c_3\right)}{\sqrt{\left(2\gamma_U+1\right)^2-1}\left[4\gamma_A c_3+\left(\gamma_B+\theta\alpha\gamma_C\right)\left(1+c_3\right)^2\right]^2} \tag{A27}$$
$$*\left\{\left[4\gamma_A c_3+\gamma_B\left(1+c_3\right)^2\right]\sqrt{\left(2\gamma_U+1\right)^2-1}-8\left(1-c_3\right)c_3\theta\gamma_A\left(\gamma_U-\frac{\theta}{1-\theta}\right))\right\}>0.$$

Thus, scaled retail shorting increases with attention in H3.

We now consider the impact of attention on retail buying scaled by volume.

$$\frac{B_R}{V}=\frac{\alpha\gamma_R(c_3-1)^2}{4\gamma_A c_3+(\gamma_B+\theta\alpha\gamma_C)\left(1+c_3\right)^2}. \tag{A28}$$

The effect of α operates directly and indirectly through the overpricing term, c_3. Overpricing depends on unconstrained relative risk tolerance (γ_U), which depends on attention. We summarize the overall effect of α on retail buying as follows

$$\frac{d\left(\frac{B_R}{V}\right)}{d\alpha}=\frac{\partial\left(\frac{B_R}{V}\right)}{\partial\alpha}+\frac{\partial\left(\frac{B_R}{V}\right)}{\partial c_3}\frac{\partial c_3}{\partial\gamma_U}\frac{\partial\gamma_U}{\partial\alpha}. \tag{A29}$$

The direct impact of attention on scaled buying is

$$\frac{\partial\left(\frac{B_R}{V}\right)}{\partial\alpha}=\frac{\gamma_R(c_3-1)^2\left[4\gamma_A c_3+\gamma_B\left(1+c_3\right)^2\right]}{\left[4\gamma_A c_3+(\gamma_B+\theta\alpha\gamma_C)\left(1+c_3\right)^2\right]^2}>0. \tag{A30}$$

The overpricing parameter, c_3, has a negative impact on scaled buying, which is

$$\frac{\partial\left(\frac{B_R}{V}\right)}{\partial c_3}=\frac{4\alpha\gamma_R(c_3-1)\left(1+c_3\right)(\gamma_A+\gamma_B+\theta\alpha\gamma_C)}{\left[4\gamma_A c_3+(\gamma_B+\theta\alpha\gamma_C)\left(1+c_3\right)^2\right]^2}<0. \tag{A31}$$

Substituting the partial derivatives in (A30), (A31), (A25), and (A26) into (A29) and simplifying the resulting equation, we see that retail buying must increase with attention in H3 because

$$\frac{d\left(\frac{B_R}{V}\right)}{d\alpha}=\frac{2\gamma_R c_3(1-c_3)\left(1+c_3\right)\gamma_B\left(2\gamma_U\right)^2}{\sqrt{\left(2\gamma_U+1\right)^2-1}\left[4\gamma_A c_3+(\gamma_B+\theta\alpha\gamma_C)\left(1+c_3\right)^2\right]^2}>0. \tag{A32}$$

We now consider the return predictability from retail shorting and buying scaled by volume. We evaluate portfolio return predictability (Px) from $x = S_R/V$ and B_R/V using a linear approximation, which yields:

$$Px\approx\frac{dE\left(Ret\right)}{d\alpha}Sign\left(\frac{dx}{d\alpha}\right)\sqrt{Var(\alpha)}. \tag{A33}$$

Using previous results, we can easily show that expected returns decrease with attention:

$$\frac{dE\left(Ret\right)}{d\alpha}=-\frac{\eta}{2+k}\frac{\partial c_3}{\partial\gamma_U}\frac{\partial\gamma_U}{\partial\alpha}<0. \tag{A34}$$

After substituting (A25), (A26), (A27), and (A32) into (A33) and simplifying, the equations for predictability from scaled retail shorting (*PSRV*) and buying (*PBRV*) in H3 become:

$$PSRV_{H3} = PBRV_{H3} \approx -\frac{2\eta c_3\left(\gamma_A + \gamma_B\right)\alpha^{-2}\sqrt{Var\left(\alpha\right)}}{(2+k)\left(1-\theta\right)\gamma_C\sqrt{\left(2\gamma_U + 1\right)^2 - 1}} < 0. \tag{A35}$$

where we evaluate expressions with α at α = E[α]. Thus, under H3, return predictability from retail shorting is negative and equal to the negative return predictability from retail buying.

C. Testable Variation in Return Predictability

Combining the return predictability equations with the expressions for observable variables, we obtain several propositions relating return predictability to observables, such as turnover and volatility.

Proposition 1: Return predictability from retail shorting scaled by trading volume is negative in H1 and H3, whereas it is positive in H2.

Proof: Expected return predictability in equation (A13) has the same sign as –E[Sign($g - g_S$)] = 2*[0.5 – Pr($g > g_S$)], which is negative (positive) in H1 (H2) because Pr($g > g_S$) is greater (less) than 0.5. Equation (A35) shows that the sign of return predictability in H3 is negative.

Proposition 2: The absolute value of return predictability from retail shorting scaled by trading volume decreases with k in H1, H2, and H3.

Proof: Taking the absolute value of equations (A13) and (A35), we see that the dependence of the magnitude of return predictability on k is proportional to 1/(2+k), which decreases with k.

Proposition 3: In H1 and H2, the absolute value of return predictability from retail shorting scaled by trading volume, return volatility, trading volume, and short interest all increase with expected sentiment.

Proof: The absolute value of return predictability in equation (A13) is proportional to E[|*m*|]. Return volatility in equation (A2) increases with E[|*m*|] and trading volume (and hence short interest) in (A5) increases with |*m*|, which is associated with increases in E[|*m*|].

Proposition 4: In H3, the absolute value of predictability from retail shorting, return volatility, trading volume, and short interest all increase with difference in opinion (η).

Proof: Differentiating the absolute value of equation (A35) with respect to difference in opinion (η), we obtain

$$\frac{\partial \left| PSRV_{H3} \right|}{\partial \eta} \approx \frac{2c_3\left(\gamma_A + \gamma_B\right)\alpha^{-2}\sqrt{Var\left(\alpha\right)}}{\left(2+k\right)\sqrt{\left(2\gamma_U + 1\right)^2 - 1}\left(1-\theta\right)\gamma_C} > 0. \tag{A36}$$

Volume, which is equivalent to short interest in the model, increases with difference in opinion because the volume equation (A19) is (linearly) increasing in η. Return volatility increases in η because volatility in equation (A17) is monotonic in the sensitivity of price to attention, which increases (linearly) in η, as shown in equation (A18).

Proposition 5: In H3, if there are no short sale constraints ($1 - \theta = 0$), expected stock returns are constant and there is no return predictability from retail shorting. As ($1 - \theta$) approaches 0, the absolute value of return predictability from retail shorting increases with short sale constraints, ($1 - \theta$).

Proof: When $1 - \theta = 0$, the unconstrained stock price is given by equation (7), which simplifies when $m = 0$, as in H3, to

$$p_U = \frac{F + s_I + ks_T}{(2+k)}. \tag{A37}$$

The pricing equation (A37) is equal to the expected firm value, implying the stock's expected return is zero and thus does not depend on retail shorting.

When $1 - \theta > 0$, the absolute value of return predictability from retail shorting in H3 as given in equation (A35)

$$|PSRV_{H3}| \approx \frac{2\eta c_3 (\gamma_A + \gamma_B)\alpha^{-2}\sqrt{Var(\alpha)}}{(2+k)\sqrt{(2\gamma_U+1)^2 - 1}(1-\theta)\gamma_C}. \tag{A38}$$

Differentiating (A38) with respect to theta, we obtain

$$\frac{d|PSRV_{H3}|}{d\theta} = \frac{\partial |PSRV_{H3}|}{\partial \gamma_U}\frac{\partial \gamma_U}{\partial \theta} + \frac{\partial |PSRV_{H3}|}{\partial \theta} \propto \frac{\left[-\frac{2\left[\gamma_C + (\gamma_A + \gamma_B)\alpha^{-1}\right]}{\left[(2\gamma_U+1)^2 - 1\right]} + c_3\right]}{\sqrt{(2\gamma_U+1)^2 - 1}(1-\theta)^2 \gamma_C}. \tag{A39}$$

As $(1 - \theta)$ approaches 0, the numerator must be negative because the overpricing term (c_3) approaches zero, whereas the first term remains negative. Thus, the absolute value of predictability decreases with θ, meaning that it increases with short sale constraints $(1 - \theta)$.

Proposition 6: In H3, predictability from retail buying is negative. In H1 and H2, return predictability from retail buying is positive if the fraction of retail traders that are rational (g) exceeds the threshold g_B and negative otherwise.

Proof: Equation (A35) shows that return predictability from retail buying is negative in H3. Return predictability from retail buying in H1 and H2, shown in equation (A14), is positive if $g > g_B$ and negative if $g < g_B$.

Proposition 7: In H3, total retail trading (i.e., the sum of buying and selling) increases with attention and negatively predicts returns; negative return predictability from total retail trading is equal to predictability from retail shorting. In H1, retail trading does not predict returns if either $g = 1$ or $\theta = 1$.

Proof: In H3, retail shorting increases with attention, as shown in Proposition 1. Equation (A32) shows that retail buying also increases with attention, implying that the sum of buying and selling—i.e., total retail trading—must increase with attention. Because retail trading increases with attention in H3, return predictability from retail trading scaled by volume (*PTRV*) is negative and equal to

$$PTRV_{H3} \approx -\frac{2\eta c_3\left(\gamma_A+\gamma_B\right)\alpha^{-2}}{(2+k)\sqrt{\left(2\gamma_U+1\right)^2-1}\left(1-\theta\right)\gamma_C} Sign\left[\frac{d\left(\frac{B_R+S_R}{V}\right)}{d\alpha}\right]\sqrt{Var\left(\alpha\right)}<0. \qquad \text{(A40)}$$

Comparing equations (A35) and (A40) reveals that negative predictability from total retail trading is the same as predictability from retail shorting when the latter is negative, as it is in H3.

In H1, we combine equations (A8) and (A11) to obtain the following expression for total retail trading scaled by volume

$$\frac{B_R+S_R}{V}=\gamma_R\left[\left[\frac{g}{\gamma_A}+\frac{\left(1-g\right)\alpha}{\gamma_B+\alpha\gamma_C}\right]I\left(m>0\right)+\left[\frac{\left(1-g\right)\theta\alpha}{\gamma_B+\theta\alpha\gamma_C}+\frac{g}{\gamma_A}\right]I\left(m<0\right)\right] \qquad \text{(A41)}$$

Retail trading only predicts returns insofar as it is related to sentiment. Retail trading is invariant to sentiment if the coefficients on the indicator variables in equation (A41) are equal, which occurs when $g = 1$ or $\theta = 1$.

Proposition 8: Suppose that $\eta = 0$ and that g and m vary across stocks as in H1 and H2. Retail buying scaled by volume decreases with sentiment if and only if $g > g_B$, where $g_B > g_S$. Stocks in which retail buying and retail selling are simultaneously above average must satisfy $g_S < g < g_B$ and thus return predictability from retail shorting is negative.

Proof: Consider the case in which $\eta = 0$ and g and m vary across stocks. Equations (A8) and (A11) show that retail shorting and retail buying only assume two values, depending on whether sentiment is positive or negative. From equation (A8), retail shorting is higher with positive sentiment if and only if $g > g_S$; from equation (A11), retail buying is higher with positive sentiment if only if $g < g_B$, where $g_B > g_S$. Thus, if one observes high retail shorting and high retail buying both conditions above must be satisfied, meaning that $g_S < g < g_B$. In this range, the fraction of rational retail investors (g) exceeds the g_S threshold for negative return predictability from retail shorting.

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Table I
Variable Definitions

This table defines variables used in this study. Panel A provides definitions for the main retail shorting and trading variables. Panels B and C defines control variables and news tone variables.

Panel A: Retail trading variables

Variable	Definition
Short_Volm	Retail shares shorted / total CRSP share volume
Short_ShrOut	Retail shares shorted / shares outstanding
Short_RtlVolm	Retail shares shorted / (retail shares bought + retail shares sold)
Rtl_Volm	(Retail shares bought + retail shares sold) / total volume
LongImb_Volm	(Shares bought – long positions sold) / total CRSP share volume

Panel B: Control variables

Variable	Definition
Size	Market value of equity from CRSP as of prior quarter end
BM	(Compustat book equity) / CRSP market equity as of prior December
Beta	Market beta based on daily regression of excess returns on excess market returns estimated over the prior year
Ret[x,y]	Stock return over days $t + x$ through $t + y$
Analysts	Number of analysts with I/B/E/S annual earnings forecasts in prior month
NewsStories	Number of firm-specific articles from Dow Jones Newswires in prior quarter
IdioVol	Standard deviation of residuals from a daily Fama and French (1993) 3-factor model estimated in the prior calendar month
Turnover	(Weekly CRSP share volume) / shares outstanding
ShortInt	(Most recently reported short interest from Compstat) / shares outstanding
Dispersion	Standard deviation of I/B/E/S analysts' annual earnings forecasts divided by the absolute value of the mean forecast in the prior month
No_Option	Dummy set to one if the stock had zero reported or unreported options trading in OptionMetrics during the prior quarter
HighFails	Dummy set to one if exchanges reported fails-to-deliver exceeding 0.10% of shares outstanding on any day during the prior week
Breadth	Fraction of equity mutual funds that held the stock at the end of the prior calendar quarter

Panel C: News variables

Variable	Definition
ESS[*x*,*y*]	Average RavenPack News Analytics Event Sentiment Score for Dow Jones news stories about the firm from day $t + x$ through $t + y$
Neg[*x*,*y*]	Percentage of words in Dow Jones news stories from day $t + x$ through day $t + y$ that appear in the list of Harvard-IV negative words and the percentage that appear in the list of financial negative words of Loughran and McDonald (2011), using weights of 1/3 and 2/3, respectively
Coverage[*x*,*y*]	Natural log of number of news stories about the firm from day $t + x$ through day $t + y$ scaled by the number of days in the interval [*x*,*y*]
Abn_Coverage[*x*,*y*]	*Coverage*[*x*,*y*] – *Coverage*[-251,-26]

Table II
Cross-Sectional Summary Statistics

This table presents time-series averages of daily cross-sectional summary statistics. All variables are as defined in Table I. Panel A contains daily means, standard deviations and percentiles. Panel B contains average daily cross-sectional correlation coefficients. The abbreviation *Ln* indicates the natural logarithm.

Panel A: Average Statistics Across Days

Variable	Mean	N	Std Dev	Pctl 5	Pctl 25	Pctl 50	Pctl 75	Pctl 95
Short_Volm (%)	0.127	3376	0.321	0.000	0.000	0.007	0.099	0.638
Short_Shrout (bp)	0.767	3376	2.245	0.000	0.000	0.023	0.424	3.947
Short_RtlVolm (%)	3.169	3360	7.079	0.000	0.000	0.243	3.274	15.120
Rtl_Volm (%)	9.604	3376	15.037	0.520	1.618	4.006	10.889	38.242
LongImb_Volm (%)	-0.260	3376	7.379	-7.831	-0.930	-0.020	0.763	6.426
Beta	1.119	3376	0.600	0.175	0.721	1.093	1.489	2.156
Size ($Billion)	4.068	3376	17.049	0.044	0.207	0.603	1.989	15.782
BM	0.503	3185	0.736	0.073	0.263	0.439	0.662	1.250
Analysts	6.163	3376	6.494	0.000	1.000	4.172	8.993	19.691
NewsStories	53.230	3376	86.293	9.233	20.495	32.854	53.712	152.198
IdioVol (%)	2.279	3376	1.841	0.718	1.228	1.831	2.772	5.191
Turnover (%)	4.451	3376	4.790	0.453	1.591	2.983	5.450	13.571
ShortInt (%)	4.833	3328	5.537	0.115	1.340	3.274	6.238	15.042
Dispersion (%)	11.594	2411	28.202	0.545	1.546	3.393	8.915	45.897
ΔBreadth (%)	0.016	3375	0.215	-0.219	-0.031	0.013	0.073	0.263

Table II: continued

Panel B: Average Correlations Across Days

	Ln(Short_Volm)	*Ln(Short_Shrout)*	*Ln(Short_RtlVolm)*	*Ln(Rtl_Volm)*	*LongImb_Volm*
Ln(Short_Volm)	1.000	0.946	0.870	0.072	0.052
Ln(Short_Shrout)	0.946	1.000	0.830	0.053	0.059
Ln(Short_RtlVolm)	0.870	0.830	1.000	-0.253	0.043
Ln(Rtl_Volm)	0.072	0.053	-0.253	1.000	-0.039
LongImb_Volm	0.052	0.059	0.043	-0.039	1.000
Beta	0.192	0.248	0.194	-0.168	0.035
Ln(Size)	0.121	0.120	0.365	-0.696	0.042
Ln(BM)	-0.091	-0.114	-0.117	0.073	-0.030
Ret[-4,0]	0.082	0.092	0.049	0.018	0.034
Ret[-25,-5]	0.076	0.086	0.033	0.039	-0.024
Ret[-251,-26]	0.132	0.169	0.062	0.097	0.000
Ln(Analysts)	0.121	0.158	0.323	-0.533	0.035
Ln(NewsStories)	0.142	0.163	0.318	-0.430	0.030
Ln(IdioVol)	0.098	0.150	-0.081	0.510	-0.002
Ln(Turnover)	0.372	0.570	0.364	-0.178	0.081
Ln(ShortInt)	0.241	0.334	0.258	-0.271	0.056
ΔLn(ShortInt)	0.032	0.040	0.008	0.035	0.006
Ln(Dispersion)	0.076	0.099	-0.011	0.245	0.005
No_Option	-0.154	-0.196	-0.288	0.433	-0.033
Ln(HighFails)	0.086	0.135	-0.007	0.206	0.021
ΔBreadth	0.033	0.052	0.013	0.014	0.004

Table II: continued

Panel B: Average Correlations Across Days (continued)

	Beta	*Ln(Size)*	*Ln(BM)*	*Ret*[-4,0]	*Ret*[-25,-5]	*Ret*[-251,26]	*Ln(Analysts)*	*Ln(NewsStories)*
Ln(Short_Volm)	0.192	0.121	-0.091	0.082	0.076	0.132	0.121	0.142
Ln(Short_Shrout)	0.248	0.120	-0.114	0.092	0.086	0.169	0.158	0.163
Ln(Short_RtlVolm)	0.194	0.365	-0.117	0.049	0.033	0.062	0.323	0.318
Ln(Rtl_Volm)	-0.168	-0.696	0.073	0.018	0.039	0.097	-0.533	-0.430
LongImb_Volm	0.035	0.042	-0.030	0.034	-0.024	0.000	0.035	0.030
Beta	1.000	0.201	-0.116	-0.014	-0.039	-0.012	0.123	0.120
Ln(Size)	0.201	1.000	-0.190	-0.015	-0.034	0.000	0.736	0.712
Ln(BM)	-0.116	-0.190	1.000	0.014	0.031	0.055	-0.194	-0.144
Ret[-4,0]	-0.014	-0.015	0.014	1.000	-0.008	0.008	-0.008	-0.010
Ret[-25,-5]	-0.039	-0.034	0.031	-0.008	1.000	0.011	-0.022	-0.013
Ret[-251,26]	-0.012	0.000	0.055	0.008	0.011	1.000	-0.079	0.006
Ln(Analysts)	0.123	0.736	-0.194	-0.008	-0.022	-0.079	1.000	0.573
Ln(NewsStories)	0.120	0.712	-0.144	-0.010	-0.013	0.006	0.573	1.000
Ln(IdioVol)	0.052	-0.546	-0.024	0.010	0.101	0.112	-0.314	-0.241
Ln(Turnover)	0.365	0.196	-0.154	0.071	0.068	0.167	0.284	0.257
Ln(ShortInt)	0.462	0.226	-0.185	-0.027	-0.044	-0.004	0.179	0.172
ΔLn(ShortInt)	-0.035	-0.037	0.018	-0.008	0.088	0.053	-0.042	-0.024
Ln(Dispersion)	0.155	-0.294	0.088	-0.003	-0.010	-0.056	-0.140	-0.067
No_Option	-0.259	-0.546	0.174	0.008	0.023	0.045	-0.481	-0.411
Ln(HighFails)	0.047	-0.193	-0.123	-0.003	0.025	0.008	-0.125	-0.059
ΔBreadth	0.033	-0.039	0.017	0.003	0.007	0.188	-0.064	-0.093

Table II: continued

Panel B: Average Correlations Across Days (continued)

	Ln(IdioVol)	*Ln(Turnover)*	*Ln(ShortInt)*	*ΔLn(ShortInt)*	*Ln(Dispersion)*	*No_Option*	*Ln(HighFails)*	*ΔBreadth*
Ln(Short_Volm)	0.098	0.372	0.241	0.032	0.076	-0.154	0.086	0.033
Ln(Short_Shrout)	0.150	0.570	0.334	0.040	0.099	-0.196	0.135	0.052
Ln(Short_RtlVolm)	-0.081	0.364	0.258	0.008	-0.011	-0.288	-0.007	0.013
Ln(Rtl_Volm)	0.510	-0.178	-0.271	0.035	0.245	0.433	0.206	0.014
LongImb_Volm	-0.002	0.081	0.056	0.006	0.005	-0.033	0.021	0.004
Beta	0.052	0.365	0.462	-0.035	0.155	-0.259	0.047	0.033
Ln(Size)	-0.546	0.196	0.226	-0.037	-0.294	-0.546	-0.193	-0.039
Ln(BM)	-0.024	-0.154	-0.185	0.018	0.088	0.174	-0.123	0.017
Ret[-4,0]	0.010	0.071	-0.027	-0.008	-0.003	0.008	-0.003	0.003
Ret[-25,-5]	0.101	0.068	-0.044	0.088	-0.010	0.023	0.025	0.007
Ret[-251,26]	0.112	0.167	-0.004	0.053	-0.056	0.045	0.008	0.188
Ln(Analysts)	-0.314	0.284	0.179	-0.042	-0.140	-0.481	-0.125	-0.064
Ln(NewsStories)	-0.241	0.257	0.172	-0.024	-0.067	-0.411	-0.059	-0.093
Ln(IdioVol)	1.000	0.172	-0.023	0.059	0.331	0.243	0.273	0.036
Ln(Turnover)	0.172	1.000	0.574	0.039	0.119	-0.353	0.207	0.063
Ln(ShortInt)	-0.023	0.574	1.000	0.072	0.131	-0.388	0.268	0.052
ΔLn(ShortInt)	0.059	0.039	0.072	1.000	-0.002	0.048	0.046	-0.003
Ln(Dispersion)	0.331	0.119	0.131	-0.002	1.000	0.037	0.163	-0.023
No_Option	0.243	-0.353	-0.388	0.048	0.037	1.000	0.026	0.009
Ln(HighFails)	0.273	0.207	0.268	0.046	0.163	0.026	1.000	-0.002
ΔBreadth	0.036	0.063	0.052	-0.003	-0.023	0.009	-0.002	1.000

Table III
Calendar-Time Returns of Retail Shorting Portfolios

This table presents calendar-time returns for portfolios based on weekly retail short-selling (*Short_Volm*). Each day, we sort firms into five portfolios based on retail short selling over the prior week. Portfolio 1 contains stocks with zero shorting, and Portfolios 2 through 5 represent a quartile sort of the remaining stocks. We evaluate the returns to these portfolios in calendar time over several future event windows [*x*,*y*]. To mitigate the Blume and Stambaugh (1983) bias, we weight firms within each cohort portfolio on calendar day *t* by their gross returns on day *t* – 1. When evaluating portfolios over return windows exceeding one day, we use an overlapping procedure as in Jegadeesh and Titman (1993). Specifically, the calendar day *t* return of quintile portfolio $q \in \{1, 2, 3, 4, 5\}$ during horizon [*x*,*y*] days after portfolio formation averages day *t* returns of the quintile *q* portfolios formed on days $t - x$ through $t - y$. Panel A presents daily Fama and French 3-factor alphas and average raw returns over various future event windows. Panel B presents three-factor loadings for the [2,20] event window. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Panel A: 3-Factor Alphas and Returns on Days [x,y]

	3-Factor Alpha				Excess Return			
Shorting Quintile	[1,1]	[2,20]	[21,40]	[41,60]	[1,1]	[2,20]	[21,40]	[41,60]
1	0.018	0.011	0.009	0.004	0.056	0.049	0.043	0.042
2	0.005	0.003	0.003	0.002	0.050	0.046	0.044	0.047
3	-0.002	-0.003	-0.006	-0.002	0.046	0.044	0.037	0.045
4	-0.020	-0.012	-0.012	-0.012	0.030	0.037	0.033	0.037
5	-0.049	-0.025	-0.023	-0.015	0.003	0.026	0.022	0.033
5 - 1 spread	-0.067	-0.036	-0.031	-0.019	-0.053	-0.023	-0.021	-0.009
t-stat	(-8.01)	(-4.92)	(-4.04)	(-2.38)	(-3.94)	(-1.78)	(-1.60)	(-0.72)

Table III: continued

Panel B: Factor Loadings

Shorting Quintile	*b*(*rmrf*)	*b*(*smb*)	*b*(*hml*)	Firms per day
1	0.794	0.653	0.118	1612
2	1.015	0.489	0.033	441
3	1.078	0.671	0.009	441
4	1.125	0.853	0.004	441
5	1.068	0.988	0.112	441
5 - 1 spread	0.274	0.335	-0.006	
t-stat	(16.73)	(12.27)	(-0.18)	

Table IV
Retail Shorting Portfolios within Initial Sorts by Size, Analyst Coverage, and Media Coverage

This table presents calendar-time profits for portfolios based on two-way dependent sorts. The first sort is based on an information environment variable: size, analyst coverage, or media coverage. Within each information environment group, we conduct the sorting procedure on weekly retail short-selling (*Short_Volm*) and calendar-time evaluation in Table II. Panel A presents results from portfolios first sorted into *Size* quintile using NYSE breakpoints. Panels B and C present results from portfolio first sorted into quintiles based on number of analysts and media coverage, respectively. All portfolios are evaluated over the [2,20] window, and the numbers in the table are daily Fama and French (1993) 3-factor alphas expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Panel A: Portfolios Sorted First on Size and then Retail Shorting

	NYSE Size Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.016	0.005	0.012	0.013	0.004	-0.012
2	-0.005	0.001	0.017	0.007	0.008	0.013
3	-0.011	-0.012	-0.004	0.002	0.006	0.017
4	-0.018	-0.016	-0.011	-0.002	0.000	0.018
5	-0.027	-0.027	-0.021	-0.011	0.001	0.028
5 - 1 spread	-0.043	-0.032	-0.033	-0.024	-0.003	0.040
t-stat	(-4.53)	(-3.13)	(-2.92)	(-2.08)	(-0.25)	(2.97)

Panel B: Portfolios First Sorted on Analyst Coverage and then Retail Shorting

	Analyst Coverage Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.017	0.002	-0.005	0.008	0.005	-0.011
2	-0.003	0.002	0.001	-0.001	0.009	0.013
3	0.006	-0.013	-0.012	-0.007	0.002	-0.003
4	-0.016	-0.022	-0.014	-0.015	-0.003	0.013
5	-0.034	-0.048	-0.017	-0.018	-0.014	0.020
5 - 1 spread	-0.050	-0.050	-0.012	-0.026	-0.020	0.031
t-stat	(-3.87)	(-4.49)	(-1.23)	(-2.32)	(-1.67)	(1.93)

Table IV: continued

Panel C: Portfolios First Sorted on Media Coverage and then Retail Shorting

	Media Coverage Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.025	0.007	0.010	0.004	-0.002	-0.027
2	-0.004	-0.011	-0.001	0.005	0.010	0.014
3	-0.002	-0.012	-0.008	-0.005	0.002	0.005
4	-0.014	-0.014	-0.017	-0.014	-0.005	0.010
5	-0.016	-0.036	-0.028	-0.025	-0.014	0.002
5 - 1 spread	-0.040	-0.043	-0.037	-0.028	-0.012	0.029
t-stat	(-3.13)	(-4.31)	(-4.03)	(-2.87)	(-1.15)	(2.04)

Table V
Retail Shorting Portfolios within Initial Sorts by Differences in Investor Beliefs

This table presents calendar-time profits for portfolios based on two-way dependent sorts as in Table IV. Prior to conducting the two-way sorts, we stratify the sample into NYSE market equity quintiles. We average two-way portfolio returns across the five size strata. The first sort is a quintile sort based on one of four proxies for expected sentiment shocks (E|*m*|) and differences in opinion (η). Panels A, B, C, and D first sort stocks on idiosyncratic volatility, turnover, short interest, and analyst forecast dispersion, respectively. The second sort in each is based on retail short-selling (*Short_Volm*). We evaluate all portfolios during the day-[2,20] window after formation. The table reports daily Fama and French (1993) 3-factor alphas expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Panel A: Portfolios Sorted First on Idiosyncratic Volatility and then Retail Shorting

	Idiosyncratic Volatility Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.011	0.011	0.014	0.008	0.002	-0.009
2	0.009	0.005	0.011	-0.001	-0.002	-0.011
3	0.010	0.000	0.004	-0.007	-0.017	-0.027
4	0.002	-0.002	0.000	-0.013	-0.026	-0.027
5	0.000	-0.004	-0.011	-0.020	-0.029	-0.030
5 - 1 spread	-0.011	-0.015	-0.026	-0.028	-0.031	-0.021
t-stat	(-2.42)	(-2.88)	(-3.43)	(-3.02)	(-2.46)	(-1.59)

Panel B: Portfolios Sorted First on Turnover and then Retail Shorting

	Turnover Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.003	0.012	0.017	0.012	0.011	0.009
2	-0.005	0.006	0.008	0.008	-0.001	0.003
3	-0.009	0.002	0.004	0.005	-0.017	-0.008
4	-0.011	0.001	-0.002	-0.001	-0.022	-0.011
5	-0.016	-0.001	-0.005	-0.014	-0.027	-0.011
5 - 1 spread	-0.019	-0.013	-0.022	-0.026	-0.039	-0.019
t-stat	(-3.30)	(-2.54)	(-3.73)	(-3.75)	(-2.80)	(-1.33)

Table V: continued

Panel C: Portfolios Sorted First on Short Interest and then Retail Shorting

	Short Interest Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.025	0.009	0.003	0.000	-0.003	-0.027
2	0.047	0.007	0.009	-0.005	-0.007	-0.054
3	0.026	0.007	-0.005	-0.009	-0.024	-0.049
4	0.010	-0.001	0.002	-0.011	-0.036	-0.046
5	0.009	-0.010	-0.004	-0.017	-0.043	-0.052
5 - 1 spread	-0.015	-0.019	-0.008	-0.018	-0.040	-0.025
t-stat	(-2.19)	(-2.18)	(-0.81)	(-1.81)	(-3.38)	(-1.94)

Panel D: Portfolios Sorted First on Analyst Forecast Dispersion and then Retail Shorting

	Forecast Dispersion Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.009	0.010	0.008	0.002	0.010	0.001
2	0.011	0.005	0.001	0.003	-0.002	-0.013
3	0.008	-0.001	-0.001	-0.008	-0.015	-0.023
4	0.003	-0.004	-0.005	-0.018	-0.024	-0.027
5	-0.010	-0.009	-0.022	-0.013	-0.025	-0.015
5 - 1 spread	-0.019	-0.019	-0.029	-0.015	-0.035	-0.016
t-stat	(-2.33)	(-2.22)	(-3.23)	(-1.34)	(-2.87)	(-1.32)

Table VI
Retail Shorting Portfolios within Initial Sorts by Short-Sale Constraints

This table presents calendar-time profits for portfolios based on two-way dependent sorts. We stratify the sample by size as in Table V. The first sort is based on short-selling constraints. The second sort is based on retail short-selling (*Short_Volm*). Panel A first sorts stocks into groups with and without traded options in the prior quarter. Panel B first sorts stocks into groups without and with exchange reported fails-to-deliver exceeding 0.10 percent of shares outstanding in the prior week. We evaluate all portfolios during the day-[2,20] window after formation. The table reports daily Fama and French (1993) 3-factor alphas expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Panel A: No Options Trading as Measure of Shorting Constraints

Shorting Quintile	Options	No Options	Spread
1	0.012	0.001	-0.011
2	0.004	-0.001	-0.005
3	-0.004	-0.015	-0.011
4	-0.007	-0.022	-0.015
5	-0.014	-0.031	-0.017
5 - 1 spread	-0.026	-0.032	-0.006
t-stat	(-3.14)	(-3.18)	(-0.69)
Number of Stocks	1743	1633	

Panel B: High Fails-to-Deliver as Measure of Shorting Constraints

Shorting Quintile	Low Fails	High Fails	Spread
1	0.007	-0.010	-0.017
2	0.005	-0.020	-0.025
3	0.001	-0.029	-0.030
4	-0.005	-0.018	-0.012
5	-0.016	-0.027	-0.012
5 - 1 spread	-0.023	-0.017	0.006
t-stat	(-3.00)	(-1.10)	(0.39)
Number of Stocks	2902	524	

Table VII
Retail Net Buying Portfolios within Initial Sorts by Size

This table presents calendar-time profits for portfolios based on two-way dependent sorts. The first sort is based on *Size* quintiles using NYSE breakpoints. The second is based on *LongImb_Volm*, which is weekly shares bought less long positions sold by retail investors, scaled by total trading volume. We evaluate all portfolios during the day-[2,20] window after formation. The table reports daily Fama and French (1993) 3-factor alphas expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Long Imbalance	NYSE Size Quintile					
Quintile	1	2	3	4	5	5 - 1 spread
1	0.014	-0.008	0.001	0.005	0.000	-0.013
2	-0.006	-0.008	0.000	0.007	0.003	0.009
3	-0.008	-0.005	0.003	0.003	0.001	0.010
4	0.000	0.002	0.006	-0.003	0.005	0.005
5	0.027	-0.007	0.001	0.003	0.010	-0.017
5 - 1 spread	0.014	0.001	0.000	-0.003	0.010	-0.004
t-stat	(2.15)	(0.19)	(-0.02)	(-0.34)	(1.18)	(-0.39)

Table VIII
Portfolios based on Retail Trading and Retail Shorting

This table presents calendar-time profits for portfolios based on two-way dependent sorts. We stratify the sample by size as in Table V. The first sort is based on retail trading as a fraction of total trading (*Rtl_Volm*). The second sort is based on retail short-selling (*Short_Volm*). Panel A contains results from the retail volume sort only. Panel B contains the results of the double-sorted portfolios. We evaluate all portfolios during the day-[2,20] window after formation. The table reports daily Fama and French (1993) 3-factor alphas expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Panel A: Portfolios Sorted only on Retail Trading

	Retail Trading Quintile					
	1	2	3	4	5	5-1 spread
All firms	0.001	0.003	0.003	0.002	0.000	-0.002
						(-0.16)

Panel B: Portfolios Sorted First on Retail Trading and then on Retail Shorting

	Retail Trading Quintile					
Shorting Quintile	1	2	3	4	5	5 - 1 spread
1	0.006	0.010	0.013	0.009	0.014	0.008
2	0.002	0.008	0.009	0.000	0.001	-0.001
3	0.002	-0.002	-0.003	0.001	-0.009	-0.012
4	-0.007	-0.004	-0.009	-0.011	-0.016	-0.009
5	-0.020	-0.016	-0.016	-0.017	-0.022	-0.002
5 - 1 spread	-0.026	-0.027	-0.029	-0.026	-0.036	-0.010
t-stat	(-4.79)	(-4.30)	(-4.00)	(-3.08)	(-3.08)	(-0.84)

Table IX
Retail Shorting Portfolios within Initial Sorts by Retail Buying

This table presents calendar-time profits for portfolios based on two-way dependent sorts. We stratify the sample by size as in Table V. The first sort is based on weekly shares bought less long positions sold by retail investors, scaled by total trading volume (*LongImb_Volm*). The second sort is based on retail short-selling scaled by total trading volume (*Short_Volm*). We evaluate all portfolios during the day-[2,20] window after formation. The table reports daily Fama and French (1993) 3-factor alphas expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

	Long Imbalance Quintile					
	1	2	3	4	5	5 - 1 spread
Shorting Quintile						
1	0.002	0.005	0.008	0.017	0.024	0.022
2	0.009	0.002	0.003	0.006	0.009	0.000
3	0.001	-0.002	-0.007	-0.007	-0.005	-0.006
4	-0.001	-0.006	-0.009	-0.014	-0.010	-0.010
5	-0.005	-0.019	-0.017	-0.017	-0.025	-0.020
5 - 1 spread	-0.007	-0.024	-0.025	-0.034	-0.049	-0.042
t-stat	(-1.01)	(-3.64)	(-3.43)	(-3.53)	(-4.23)	(-4.32)

Table X
Portfolios Sorted by Retail Shorting with Alternative Scaling

This table presents calendar-time returns for portfolios based on alternative measures of weekly retail short-selling using the calendar-time method described in Table III. Panel A contains results using portfolios based on retail shorting scaled by shares outstanding (*Short_shrout*). Panel B contains results using portfolios based on retail shorting scaled by total retail trading (*Short_RtlVolm*). We evaluate all portfolios during four horizons after formation: days [1,1], [2,20], [21,40], and [41,60]. The table reports daily Fama and French (1993) 3-factor alphas and raw returns in excess of the risk-free rate, both expressed in percent. Newey and West (1987) *t*-statistics based on five leads and lags appear in parentheses.

Panel A: Shorting Portfolios Based on Retail Shorting Scaled by Shares Outstanding

	3-Factor Alpha				Excess Return			
Shorting Quintile	[1,1]	[2,20]	[21,40]	[41,60]	[1,1]	[2,20]	[21,40]	[41,60]
1	0.018	0.011	0.009	0.004	0.056	0.049	0.043	0.042
2	0.000	0.003	0.005	0.004	0.043	0.044	0.045	0.048
3	-0.005	-0.001	-0.002	0.000	0.042	0.045	0.041	0.047
4	-0.014	-0.008	-0.010	-0.008	0.036	0.041	0.035	0.041
5	-0.048	-0.030	-0.032	-0.024	0.007	0.023	0.016	0.027
5 - 1 spread	-0.066	-0.042	-0.040	-0.028	-0.049	-0.026	-0.028	-0.016
t-stat	(-6.14)	(-4.37)	(-4.00)	(-2.76)	(-2.85)	(-1.51)	(-1.58)	(-0.94)

Panel B: Shorting Portfolios Based on Retail Shorting Scaled by Total Retail Trading

	3-Factor Alpha				Excess Return			
Shorting Quintile	[1,1]	[2,20]	[21,40]	[41,60]	[1,1]	[2,20]	[21,40]	[41,60]
1	0.018	0.012	0.009	0.004	0.057	0.050	0.044	0.043
2	-0.003	-0.001	-0.006	-0.003	0.047	0.048	0.039	0.045
3	-0.006	-0.006	-0.008	-0.007	0.043	0.042	0.036	0.040
4	-0.018	-0.010	-0.011	-0.007	0.031	0.037	0.032	0.040
5	-0.040	-0.020	-0.013	-0.009	0.007	0.026	0.029	0.036
5 - 1 spread	-0.058	-0.032	-0.022	-0.013	-0.050	-0.024	-0.015	-0.007
t-stat	(-7.38)	(-4.42)	(-3.25)	(-1.94)	(-5.35)	(-2.75)	(-1.77)	(-0.77)

Table XI
Cross-sectional Regressions of Returns on Retail Shorting and Control Variables

This table presents results from daily Fama-MacBeth (1973) regressions of future returns over days *t* + 2 through *t* + 20 on retail shorting (*Short_Volm*) and control variables measured as of day *t*. The independent variables are as defined in Table I. The dependent variable in Panel A is the Fama and French (1993) 3-factor cumulative abnormal return with factor loadings based on daily data from the prior year. The dependent variable in Panel B is raw return. Regressions weight observations by gross return. The table reports average regression coefficients multiplied by 100. Newey-West (1987) *t*-statistics with 19 leads and lags appear in parentheses. The abbreviation *Ln* denotes the natural logarithm.

Panel A: Regressions Predicting 3-Factor CARs on days t + 2 through t + 20

	Model 1	Model 2	Model 3	Model 4
Ln(Short_Volm)	-0.190	-0.131	-0.127	-0.139
	(-7.32)	(-7.52)	(-6.38)	(-7.58)
LongImb_Volm				1.001
				(3.33)
Ln(Rtl_Volm)				0.042
				(0.55)
Ret[-4,0]		-1.785	-1.698	-1.808
		(-2.54)	(-2.02)	(-2.54)
Ret[-25,-5]		0.046	-0.004	0.134
		(0.09)	(-0.01)	(0.26)
Ret[-251,26]		0.459	0.272	0.458
		(2.19)	(1.09)	(2.21)
Ln(IdioVol)		-0.590	-0.571	-0.649
		(-2.06)	(-2.58)	(-3.05)
Ln(Turnover)		0.280	0.185	0.288
		(2.82)	(1.86)	(2.63)
Ln(Lag_ShortInt)		-0.490	-0.319	-0.483
		(-5.79)	(-3.96)	(-6.11)
ΔLn(Lag_ShortInt)		-0.519	-0.479	-0.498
		(-2.49)	(-2.11)	(-2.42)
ΔBreadth				-2.211
				(-0.18)
Ln(Dispersion)			-0.038	
			(-0.60)	
No_Option			-0.616	
			(-2.74)	
Dispersion x No_Option			-0.176	
			(-2.79)	
Intercept	-1.554	-5.966	-4.986	-6.082
	(-6.67)	(-6.19)	(-5.66)	(-7.39)
Avg. R^2	0.002	0.027	0.032	0.031
Avg. *n*	3359	3277	2349	3277

Table XI: continued

Panel B: Regressions Predicting Raw Returns on days t + 2 through t + 20

	Model 1	Model 2	Model 3	Model 4
Ln(Short_Volm)	-0.096	-0.096	-0.089	-0.108
	(-2.95)	(-5.31)	(-4.29)	(-6.09)
LongImb_Volm				0.543
				(1.60)
Ln(Rtl_Volm)				0.048
				(0.68)
Beta	-0.088	0.142	0.141	0.143
	(-0.36)	(0.71)	(0.64)	(0.71)
Ln(Size)	0.016	-0.083	-0.081	-0.065
	(0.19)	(-1.64)	(-1.80)	(-1.48)
Ln(BM)	0.234	0.171	0.049	0.175
	(2.63)	(2.03)	(0.56)	(2.11)
Ret[-4,0]		-1.977	-1.529	-1.980
		(-2.79)	(-1.90)	(-2.78)
Ret[-25,-5]		-0.106	0.208	-0.030
		(-0.21)	(0.36)	(-0.06)
Ret[-251,26]		0.496	0.454	0.507
		(2.45)	(1.95)	(2.58)
Ln(IdioVol)		-0.682	-0.586	-0.713
		(-2.87)	(-2.78)	(-3.32)
Ln(Turnover)		0.402	0.287	0.406
		(3.70)	(2.86)	(3.59)
Ln(Lag_ShortInt)		-0.402	-0.350	-0.395
		(-6.13)	(-4.85)	(-6.13)
ΔLn(Lag_ShortInt)		-0.505	-0.452	-0.490
		(-2.59)	(-2.05)	(-2.51)
ΔBreadth				-5.901
				(-0.45)
Ln(Dispersion)			0.071	
			(1.07)	
No_Option			-0.799	
			(-3.95)	
Dispersion x No_Option			-0.169	
			(-2.90)	
Intercept	0.079	-3.505	-2.299	-3.879
	(0.04)	(-1.96)	(-1.41)	(-2.50)
Avg. R^2	0.027	0.049	0.062	0.052
Avg. *n*	3086	3012	2169	3012

Table XII
Panel Regressions of News Tone on Retail Shorting and Control Variables

This table presents results from panel regressions of future news tone on retail shorting (*Short_Volm*) and control variables measured as of day *t*. The news tone variable in Panels A and B is the average Event Sentiment Score (*ESS*[*x*,*y*]) provided by Ravenpack for Dow Jones news stories from day *t* + *x* through day *t* + *y*. Dependent variables are constructed using all news stories, earnings news stories, analyst news stories, revenue news stories, and merger and acquisition (M&A) news stories separately. The news tone variable in Panel C (*Neg*[*x*,*y*]) is the percentage of words in Dow Jones news stories from day *t* + *x* through day *t* + *y* that appear in the list of Harvard-IV negative words and the percentage that appear in the list of financial negative words of Loughran and McDonald (2011), using weights of 1/3 and 2/3, respectively, as in Kelley and Tetlock (2013). In constructing this variable, only news stories contain the word-stem "Earn" are included. When no news stories occur over the interval [*x*,*y*], news tone variables are set to their day-*t* cross-sectional means. The variable *Coverage*[*x*,*y*] is the natural log of the number of news stories from days *t* + *x* through *t* + *y* scaled by the number of days in the interval. The variable *Abn_Coverage*[*x*,*y*] is *Coverage*[*x*,*y*] less *Coverage*[*-251*,*-26*]. A small constant of one divided by the number of days in a year is added prior to each natural log transformation for the *Coverage* variables. Other variables are as defined in Table I. Each regression uses time fixed effects and standard errors clustered by firm. Numbers in the table are regression coefficients multiplied by 100, and *t*-statistics appear in parentheses.

Table XII: continued

Panel A: Regressions Predicting ESS on days t + 2 through t + 20

Dependent Variable	*ESS*[2,20]	*ESS*[2,20]	*ESS*[2,20]	*ESS*[2,20]	*ESS*[2,20]
News Type	All	Earnings	Analysts	Revenue	M&A
ESS[-4,0]	0.059	-0.007	0.013	-0.002	0.004
	(29.23)	(4.23)	(8.08)	(1.65)	(5.54)
ESS[-25,-5]	0.026	-0.013	0.006	-0.006	0.003
	(11.60)	(5.40)	(3.32)	(4.42)	(4.40)
ESS[-251,-26]	0.217	0.187	-0.003	0.073	-0.007
	(40.09)	(30.02)	(0.77)	(19.57)	(4.58)
Ln(Short_Volm)	-0.063	-0.110	-0.078	0.017	-0.004
	(3.07)	(4.09)	(4.30)	(1.09)	(0.44)
Ln(IdioVol)	-0.007	-1.000	0.371	-0.116	0.147
	(0.07)	(7.12)	(4.11)	(1.47)	(2.75)
Ln(Turnover)	0.159	0.334	-0.024	0.173	0.052
	(2.34)	(3.73)	(0.42)	(3.16)	(1.78)
Ret[-4,0]	-4.422	6.090	-2.741	1.898	0.054
	(12.14)	(15.26)	(9.52)	(9.01)	(0.70)
Ret[-25,-5]	-1.474	6.133	-1.769	2.286	0.017
	(5.40)	(18.90)	(7.63)	(12.71)	(0.24)
Ret[-251,-26]	1.846	5.202	1.392	2.305	-0.289
	(15.78)	(28.66)	(15.37)	(24.92)	(8.19)
Ln(Lag_ShortInt)	-0.584	-0.531	-0.428	-0.046	-0.040
	(10.62)	(7.24)	(9.18)	(1.03)	(1.58)
ΔLn(Lag_ShortInt)	-0.620	-0.573	-0.659	-0.009	-0.064
	(4.61)	(3.47)	(6.17)	(0.10)	(1.54)
Beta	0.158	0.122	0.493	0.197	-0.178
	(1.90)	(1.07)	(7.15)	(2.87)	(5.28)
Ln(Size)	0.311	0.472	-0.017	0.087	0.185
	(8.42)	(10.48)	(0.50)	(2.96)	(6.52)
Ln(BM)	-0.332	-0.455	-0.324	-0.527	0.133
	(5.37)	(5.44)	(6.20)	(9.49)	(4.89)
Abn_Coverage[-4,0]	-0.362	-0.051	0.070	-0.070	0.005
	(24.74)	(3.47)	(6.74)	(8.02)	(1.05)
Abn_Coverage[-25,-5]	-0.229	0.011	0.079	-0.101	-0.007
	(9.17)	(0.34)	(4.25)	(5.68)	(1.09)
Coverage[-251,-26]	-0.255	0.031	0.045	-0.159	-0.026
	(7.60)	(0.79)	(1.98)	(6.47)	(1.82)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	By Firm	By Firm	By Firm	By Firm	By Firm
R^2	0.032	0.030	0.003	0.019	0.003
Avg Firms	3,026	3,026	3,026	3,026	3,026
Days	1,148	1,148	1,148	1,148	1,148

Table XII: continued

Panel B: Regressions Predicting ESS over longer horizons

Dependent Variable	*ESS*[21,40]	*ESS*[41,60]	*ESS*[21,40]	*ESS*[41,60]
News Type	All	All	Earnings	Earnings
ESS[-4,0]	0.034	0.053	-0.010	0.007
	(16.62)	(27.87)	(5.11)	(3.70)
ESS[-25,-5]	0.047	0.127	0.009	0.132
	(21.60)	(50.19)	(3.83)	(40.39)
ESS[-251,-26]	0.203	0.132	0.180	0.085
	(35.86)	(23.98)	(27.59)	(13.03)
Ln(Short_Volm)	-0.029	0.026	-0.088	-0.057
	(1.36)	(1.26)	(3.07)	(1.96)
Ln(IdioVol)	0.214	0.195	-1.052	-0.777
	(1.91)	(1.75)	(6.95)	(5.08)
Ln(Turnover)	0.063	0.043	0.332	0.313
	(0.87)	(0.62)	(3.47)	(3.28)
Ret[-4,0]	-1.669	0.327	5.525	6.035
	(5.09)	(1.02)	(13.90)	(13.80)
Ret[-25,-5]	0.106	2.600	5.527	9.160
	(0.38)	(9.40)	(15.54)	(21.80)
Ret[-251,-26]	2.096	1.908	5.380	4.697
	(16.70)	(15.54)	(28.04)	(25.11)
Ln(Lag_ShortInt)	-0.545	-0.505	-0.561	-0.557
	(9.44)	(8.82)	(7.11)	(6.99)
ΔLn(Lag_ShortInt)	-0.749	-0.770	-0.716	-0.709
	(5.51)	(5.40)	(4.34)	(4.15)
Beta	0.106	0.068	0.094	0.063
	(1.20)	(0.78)	(0.77)	(0.51)
Ln(Size)	0.257	0.258	0.431	0.477
	(6.88)	(7.06)	(8.84)	(9.55)
Ln(BM)	-0.317	-0.295	-0.407	-0.355
	(4.82)	(4.59)	(4.62)	(4.01)
Abn_Coverage[-4,0]	-0.089	-0.044	0.056	0.123
	(6.83)	(3.59)	(3.99)	(8.76)
Abn_Coverage[-25,-5]	-0.047	-0.098	0.078	0.085
	(1.99)	(4.21)	(2.74)	(3.11)
Coverage[-251,-26]	-0.073	-0.052	0.135	0.155
	(2.13)	(1.58)	(3.19)	(3.67)
Time fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	By Firm	By Firm	By Firm	By Firm
R^2	0.028	0.037	0.029	0.036
Avg Firms	3,026	3,026	3,026	3,026
Days	1,148	1,148	1,148	1,148

Table XII: continued

Panel C: Regressions Predicting Future News Negativity

Dependent Variable	*Neg*[2,20]	*Neg*[21,40]	*Neg*[41,60]
Neg[-4,0]	0.0561	0.0513	0.1190
	(15.23)	(14.56)	(39.71)
Neg[-25,-5]	0.0438	0.0848	0.2111
	(11.69)	(24.65)	(57.50)
Neg[-251,-26]	0.2603	0.2544	0.1950
	(39.11)	(39.10)	(36.37)
Ln(Short_Volm)	0.0070	0.0063	0.0045
	(7.95)	(6.96)	(5.47)
Ln(IdioVol)	0.0465	0.0480	0.0486
	(9.17)	(9.27)	(10.33)
Ln(Turnover)	0.0024	0.0030	0.0038
	(0.74)	(0.87)	(1.23)
Ret[-4,0]	-0.1252	-0.1079	-0.0700
	(10.33)	(9.00)	(5.74)
Ret[-25,-5]	-0.1149	-0.0873	-0.0645
	(11.38)	(8.25)	(6.26)
Ret[-251,-26]	-0.0510	-0.0520	-0.0452
	(10.58)	(10.59)	(10.08)
Ln(Lag_ShortInt)	-0.0045	-0.0052	-0.0048
	(1.55)	(1.76)	(1.84)
ΔLn(Lag_ShortInt)	0.0061	0.0112	0.0050
	(1.18)	(2.10)	(1.00)
Beta	-0.0222	-0.0235	-0.0219
	(5.97)	(6.22)	(6.52)
Ln(Size)	0.0166	0.0205	0.0205
	(6.75)	(8.34)	(9.38)
Ln(BM)	0.0075	0.0078	0.0081
	(2.20)	(2.27)	(2.70)
Coverage[-251,-26]	0.0283	0.0175	0.0067
	(7.36)	(4.53)	(2.02)
Abn_Coverage[-25,-5]	0.0199	-0.0096	-0.0080
	(16.72)	(8.87)	(8.24)
Abn_Coverage[-4,0]	0.0170	0.0113	-0.0028
	(18.69)	(13.32)	(3.91)
Time fixed effects	Yes	Yes	Yes
Clustered standard errors	By Firm	By Firm	By Firm
R^2	0.090	0.093	0.127
Avg Firms	3,026	3,026	3,026
Days	1,148	1,148	1,148

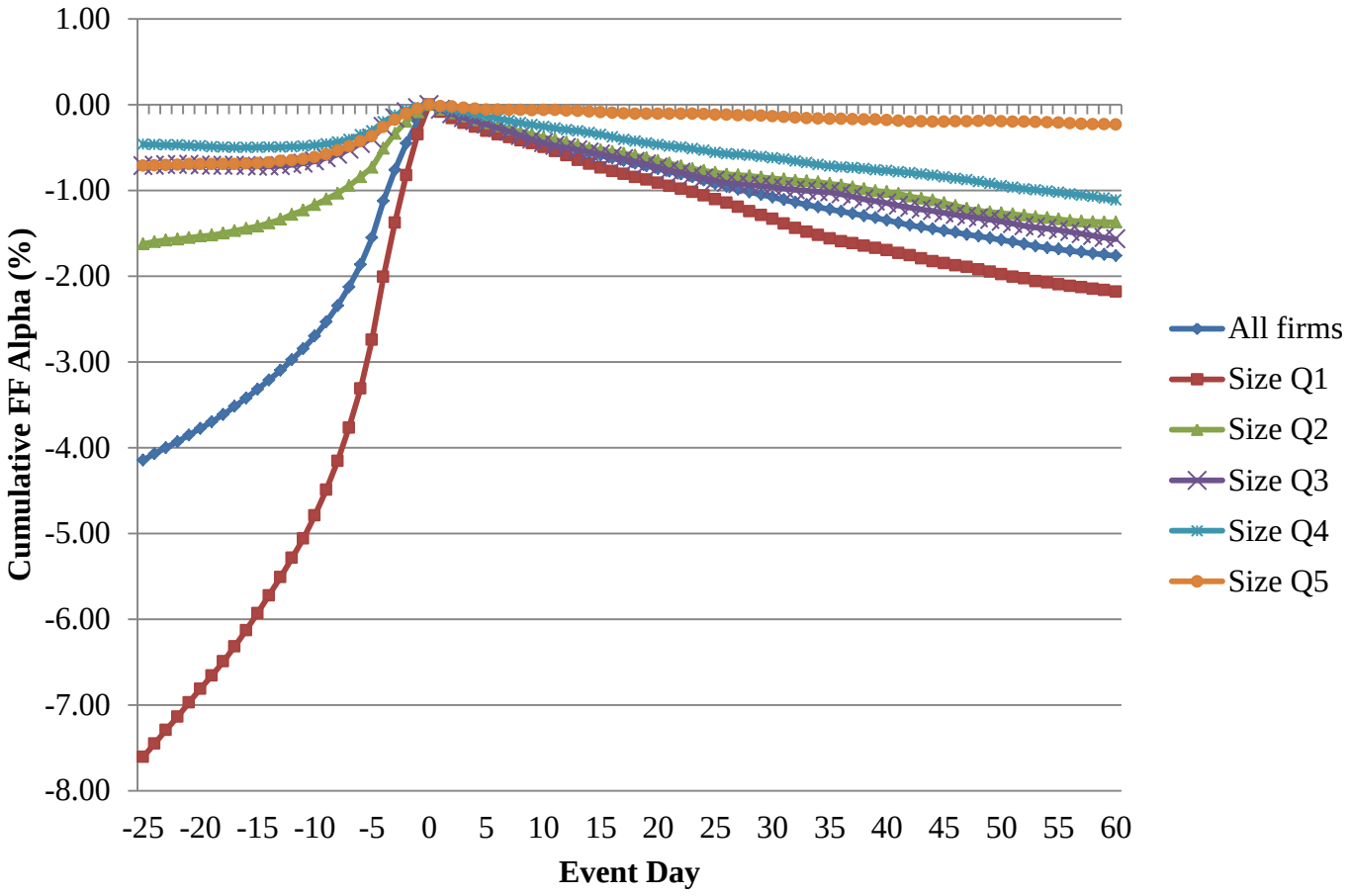

Figure 1. Alphas for long-short portfolios based on retail shorting.
Each day *t*, we sort firms into quintiles based on weekly retail short selling scaled by total volume (*Short_Volm*). Quintile 1 comprises stocks with zero retail shorting. Stocks with positive retail shorting are evenly distributed across quintiles 2 through 5, with quintile 2 containing stocks with the lowest positive shorting and quintile 5 containing stocks with the most shorting. All portfolio weights are based on prior calendar day stock returns to mitigate the Blume and Stambaugh (1983) bias. For each event day from *t* - 25 to *t* + 60, we compute Fama-French (1993) three-factor (FF) alphas for a spread portfolio that is short stocks in shorting quintile 5 and long stocks in shorting quintile 1. We plot cumulative alphas across event days and denote the series "All firms". We repeat this procedure within each NYSE market value quintile, with "Size Q1" representing the smallest stocks and "Size Q5" representing the largest stocks, and we plot cumulative alphas accordingly.

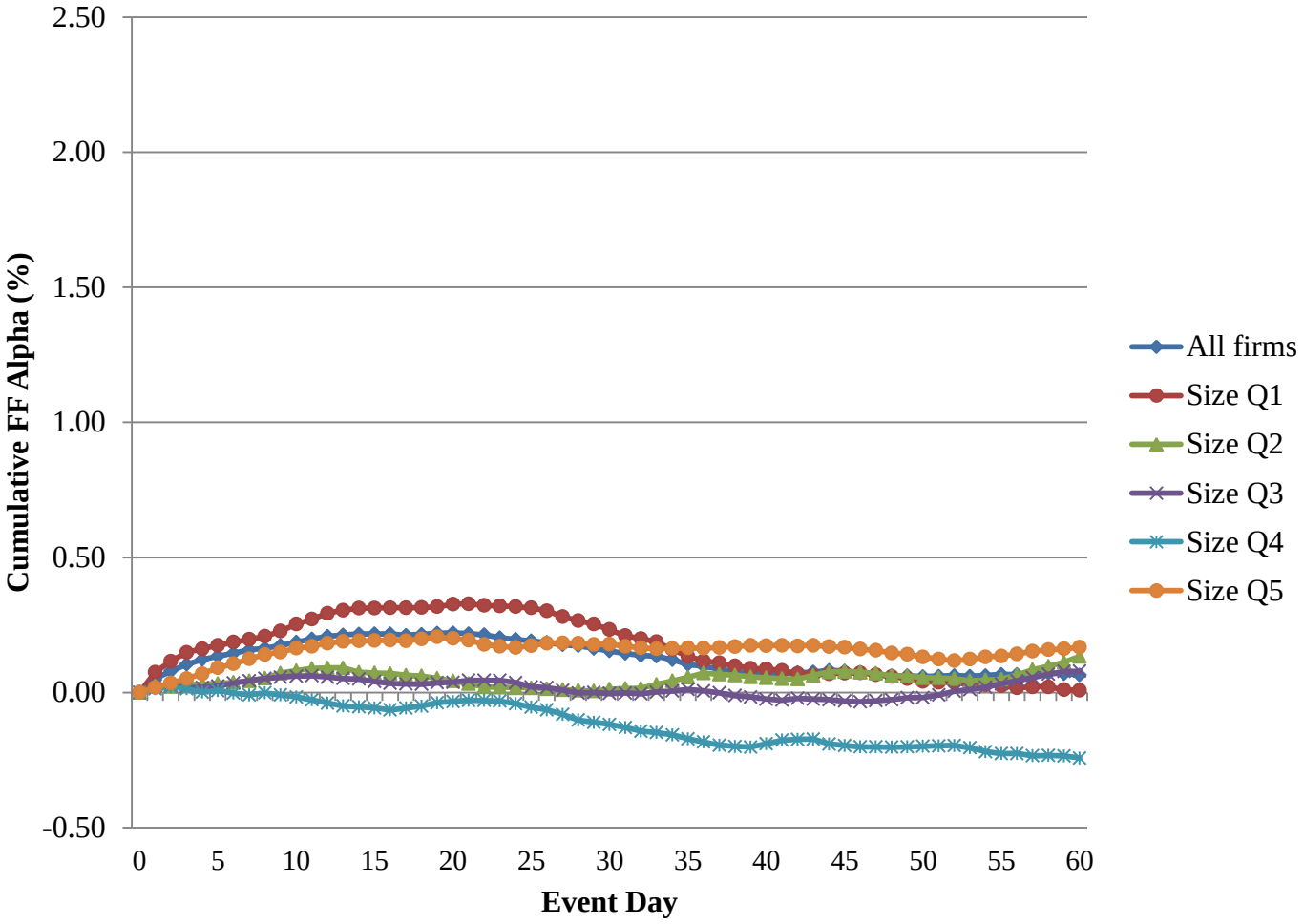

Figure 2. Alphas for long-short portfolios based on retail net buying.
Each day *t*, we sort firms into quintiles based on weekly retail purchases less long positions sold scaled by total volume (*LongImb_Volm*). All portfolio weights are based on prior calendar day stock returns to mitigate the Blume and Stambaugh (1983) bias. For each event day from $t + 1$ to $t + 60$, we compute Fama-French (1993) three-factor (FF) alphas for a spread portfolio that is long stocks in imbalance quintile 5 (those with the most buying) and short stocks in imbalance quintile 1 (those with the most selling). We plot cumulative alphas across event days and denote the series "All firms". We repeat this procedure within each NYSE market value quintile, with "Size Q1" representing the smallest stocks and "Size Q5" representing the largest stocks, and we plot cumulative alphas accordingly.