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Attention Spillover in Asset Pricing

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ABSTRACT

Exploiting a screen display feature whereby the order of stock display is determined by the stock's listing code, we lever a novel identification strategy and study how the interaction between overconfidence and limited attention affect asset pricing. We find that stocks displayed next to those with higher returns in the past two weeks are associated with higher returns in the future week, which are reverted in the long run. This is consistent with our conjectures that investors tend to trade more after positive investment experience and are more likely to pay attention to neighboring stocks, both confirmed using trading data.

OVERCONFIDENCE AND LIMITED ATTENTION ARE TWO widely documented features of investor behavior, and asset pricing theories have used both biases extensively to explain a wide range of market phenomena (see Daniel and Hirshleifer (2015), Barber, Lin, and Odean (2019), and Gabaix (2019) for reviews of the literature). Previous studies that investigate the pricing implications of these two behavioral biases typically focus on one at a time, abstracting from potential interactions among them. This is likely due to the empirical challenge in establishing a causal effect. Indeed, overconfidence and limited attention are difficult to identify even when considered alone — variables that boost investor overconfidence (e.g., past experienced returns) or that attract or reflect investor attention (e.g., news headlines, extreme past returns, trading volume) are typically also associated with fundamental information. In addition, potential interaction effects can be confounded by simple additive ef-

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fects or a correlation between the behavioral biases. In this paper we exploit a novel setting to study the causal impact of the interaction between overconfidence and limited attention on equilibrium prices and volume. We show that the two biases work through a mechanism that each bias alone would not generate.

Classic models of investor overconfidence typically posit that investors who have experienced high returns tend to attribute this outcome to their own skill and become overconfident (Daniel, Hirshleifer, and Subrahmanyam (1998), Gervais and Odean (2001)).[1] This insight has been confirmed empirically. In particular, prior evidence shows that investors tend to trade more intensively after a positive investment outcome, even if the positive outcome is due to winning initial public offering (IPO) lotteries purely by chance (Ben-David, Birru, and Prokopenya (2018), Anagol, Balasubramaniam, and Ramadorai (2021), Gao, Shi, and Zhao (2021)). Since individual investors rarely short stocks, the overtrading induced by positive past investment outcomes is likely to have a stronger effect on buying decisions than on selling decisions. Accordingly, we expect a *positive feedback effect* whereby investors tend to increase their positions after positive investment experiences (Pearson, Yang, and Zhang (2020)).[2]

Turning to investor attention, attention is a scarce resource, especially when deciding which stock to buy from among thousands of choices (Barber and Odean (2008)). However, since individual investors typically hold only a few stocks, attention is not as constrained when deciding to sell, leading to an asymmetry in buying versus selling. Combining the attention effect and the positive feedback effect, we posit that: after a positive trading outcome, stocks that attract investor attention tend to experience more buying pressure. We further posit that given short-sale constraints, buying pressure leads to higher subsequent short-term returns for high-attention stocks that reverts in the long run.

To provide empirical evidence on the pricing effect above, the main challenge is to identify stocks that attract the attention of investors who just had a positive investment outcome. In this study we exploit a screen display feature — the order of stock display is determined by stock listing codes — to study the impact of investor attention on asset pricing. Due to this display feature, investors tend to pay more attention to stocks with listing codes adjacent to their currently held stocks, that is, there is *an attention spillover effect*. Stocks with neighbors that experience higher returns in the past two weeks are therefore expected to face more buying pressure from the owners of neighboring stocks and in turn should observe higher returns and turnover in the subsequent week. This leads to the following hypothesis: stock's short-term future return

[1] Here, we use the term "overconfidence" in a broad sense. It can refer to optimism induced by overestimation, overplacement, overprecision, or even self-attribution bias.

[2] Positive feedback trading could also be due to factors other than overconfidence. Here, we mainly focus on overconfidence-induced positive-feedback trading.

and turnover should be positively associated with the past performance of its neighboring stocks.[3]

We start our analyses by investigating the microfoundation of the price impact, that is, by examining whether investors exhibit positive feedback trading and attention spillover. We find that investors are more likely to make a purchase after a positive investment experience than after a negative investment experience, suggesting that investors engage in positive feedback trading. In addition, the probability of making a new purchase decreases with the distance between the currently held stock and stocks that can potentially be bought, consistent with attention spillover. More importantly, the interaction between the two effects implies, as we confirm in the data, that the difference between buying probabilities conditional on winning versus losing positions also decreases with the distance. This is the condition we need to generate the price impacts.

Using survey tools and our clean identification setting, we next provide evidence that helps pin down the mechanisms that underlie investors' trading behaviors, and in turn helps sharpen the construction of stock-level signals. Specifically, we survey investors directly and combine survey responses with investors' observed trading data, following the empirical framework developed by Liu et al. (2022). We find that self-attribution bias has the most power in explaining positive feedback trading, in terms of both economic magnitude and statistical significance. This result suggests that, as posited by Gervais and Odean (2001), the "learning to be overconfident" mechanism is a primary determinant of positive feedback trading.

To further gauge the empirical importance of our proposed mechanism, we empirically pit the mechanism against an alternative. In theory, in the absence of positive feedback trading, other attention-grabbing events such as stock prices hitting the upper daily price limit can interact with the attention spillover effect to have similar asset pricing implications as our proposed mechanism. We find that, compared to salient events in which stock prices hit their upper price limit, the effect of holding a stock that just experienced a similarly sized extreme positive return is at least an order of magnitude stronger in explaining investor trading behavior. This finding underscores the importance of the interaction between overconfidence and limited attention in driving our conjectured price effect.

To provide evidence on the pricing implications of these trading patterns for each stock, we first construct a *LOCAL* variable, computed as the value-weighted average return over the past two weeks of the 10 stocks whose listing codes are closest to the focal stock, and an *RLOCAL* variable, computed as the residual of the cross-sectional regression of *LOCAL* on the focal stock's

[3] Due to short-sale constraints and asymmetric attention, our argument focuses on excess buying pressure, rather than selling pressure, as a result of positive feedback trading and attention spillover. However, stocks with neighbors that experience lower returns in the past two weeks face lower demand from owners of the neighboring stocks and should therefore experience lower returns in the subsequent week.

own return over the past two weeks. This construction helps address the reflection problem (i.e., the focal stock's extreme return attracting attention to its neighboring stocks and then being reflected in *LOCAL*) and alleviates the concern of short-term autocorrelation in returns when we examine return predictability of the focal stock. We then form quintile portfolios based on the lagged *RLOCAL*, and we find that the portfolio return increases as *RLOCAL* increases. In addition, the equal- and value-weighted long-short portfolios constructed by longing the quintile with the highest *RLOCAL* and shorting the quintile with the lowest *RLOCAL* earn an annualized return of 8.020% (t-statistic = 5.45) and 8.511% (t-statistic = 2.67), respectively. These results remain significant after controlling for firm age effects, industry effects, Daniel et al. (1997, DGTW) characteristic-based adjustments, the Liu, Stambaugh, and Yuan (2019) four factors for the Chinese market and the Fama and French (2015) five factors. Our results also hold in double-sorting exercises and Fama and MacBeth (1973) regressions that control for a long list of potential confounding variables, including listing age, size, beta, book-to-market ratio, momentum, long-term return, Amihud illiquidity, turnover, idiosyncratic volatility, max daily return, and skewness.

To further assess the underlying mechanism for our findings, we separately examine the importance of the attention spillover channel and the positive feedback channel using several placebo tests that turn off each of the two channels in turn. To assess the role of attention spillover, we construct a placebo for the *LOCAL* variable by replacing the past return of the immediate adjacent stocks with returns of distant stocks. We find that the predictive ability of this placebo variable is not significant, which suggests that positive feedback investors to not affect the pricing of stocks that are less visible to them. To assess the role of the positive feedback channel, we construct two placebo variables for *LOCAL* by replacing the return of neighboring stocks with the turnover and return volatility of these stocks. These two proxies likely capture the arrival of news and large price movements, and thus investor attention, but they do not necessarily relate to positive investment outcomes. We find that these placebo variables cannot forecast stock returns after controlling *LOCAL*. Taken together, these results suggest that the interaction (rather than simple addition) of positive feedback trading and attention spillover drive our key findings on return predictability.

Note that, the attention spillover effect has a natural implication for return comovement: since stocks that are closer in listing codes are more likely to be traded together, their correlation in returns and turnover should be higher. Consistent with this view, we find that the pairwise correlation between stocks decreases as the "distance" between their listing codes increases. Moreover, we find that the fundamental correlation does not present this pattern. To further sharpen our identification of investor attention, we exploit a quasi-natural experiment in which the screen display order for stocks is changed exogenously. We find that the correlation between stocks is indeed lower after the distance of these stocks is increased by the exogenous introduction of the Small and Medium Enterprise (SME) Board in May 2004.

Our evidence thus far suggests that the predictive ability of *LOCAL* stems from the interaction between attention spillover and positive feedback trading. Since such price pressure should be transitory, we also investigate the long-term returns of portfolios sorted on *RLOCAL*. We find that the cumulative return on the *RLOCAL*-hedged portfolio is positive in the short term but reverts as time passes, vanishing in about 18 weeks, consistent with temporary price pressure. In addition, as with other anomalies induced by behavioral biases, the return on the *RLOCAL*-hedged portfolio is higher among stocks with higher arbitrage costs as measured by market capitalization, Amihud illiquidity, and the number of analysts covering the stock.

Our study is closely related to the literatures on limited attention and overconfidence. In the limited attention literature, researchers have developed many proxies for attention, such as abnormal trading volume and extreme returns (e.g., Barber and Odean (2008), Hou, Peng, and Xiong (2009), Corwin and Coughenour (2008)), the Google search volume index (e.g., Da, Engelberg, and Gao (2011)), Bloomberg search volume and readership (e.g., Ben-Rephael, Da, and Israelsen (2017)), the cosearch list from Yahoo Finance (Leung et al. (2017)), media coverage (e.g., Huberman and Regev (2001), Fang and Peress (2009), Kaniel and Parham (2017)), account logins (e.g., Sicherman et al. (2016), Gargano and Rossi (2018)), advertising expenditure (e.g., Lou (2014)), price limits (e.g., Chen et al. (2019), Seasholes and Wu (2007), Wang (2017)), the Dow index historical high (e.g., Li and Yu (2012)), announcement days (e.g., Hirshleifer, Lim, and Teoh (2009), Schmidt (2019)), and days of the week (e.g., DellaVigna and Pollet (2009)).

The literature on overconfidence is too voluminous to summarize here, so we focus on indicative examples. On investor trading behavior, Barber and Odean (2000) show that investor overconfidence leads to more trading and greater underperformance. On corporate behavior, Malmendier and Tate (2005) and Ben-David, Graham, and Harvey (2013), among others, show that more overconfident CEOs tend to make more aggressive corporate decisions that lead to worse outcomes. On asset pricing, Daniel, Hirshleifer, and Subrahmanyam (1998) and Chui, Titman, and Wei (2010) illustrate the asset pricing effects of overconfidence, especially the momentum anomaly. Daniel and Hirshleifer (2015) and Malmendier and Tate (2015) provide in-depth reviews of the literature.

Our study differs from the existing literature along three key dimensions. First, we study the implications of the *interaction* between limited attention and overconfidence on asset pricing, while most prior studies examine the implications of overconfidence and limited attention separately. We show that neither attention spillover nor positive feedback trading alone is sufficient to produce our return predictability pattern, which underscores the importance of the interaction, rather than simple addition, of these two behavioral biases. Second, the interaction effect that we study highlights an economic mechanism that is distinct from price impacts that limited attention alone would typically generate. An extensive literature documents that limited attention can produce asset return predictability, such as the post earnings announcement drift (PEAD) effect and lead-lag return patterns in economically linked firms (e.g., Cohen and Frazzini (2008)), mostly through an underreaction channel.[4] In particular, limited attention can lead to an underreaction to information, such as that conveyed in the lagged returns of customer firms, firms with shared geographic location, shared technology, or shared analyst coverage. As a result, the lagged returns of economically linked firms can positively forecast the focal stock's return. A key difference between our attention spillover effect and these studies on limited attention is that the return patterns in these studies typically stem from investor underreaction to information, while the attention spillover effect in our paper implies continued overreaction, especially when coupled with positive feedback trading.

Finally, our study provides better-identified evidence of the attention effect. Distinguishing the asset pricing effect of attention from that of fundamental news is typically challenging because investors tend to pay more attention when there is more fundamental news. For example, stocks attracting more Google searches could have just released some news, leading to higher or lower fundamental risk. Our unique setting provides a cleaner identification because the order of the listing code is largely exogenous, as we show in Sections I.B and IV.F.

The rest of the paper is organized as follows. Section I provides institutional background on the display feature of trading platforms in China and discusses our empirical strategy. Section II examines investors' positive feedback trading and attention spillover using account-level data, and investigates the underlying mechanisms that drive these trading behaviors. Section III describes the data sample and the construction of the key variables in our pricing tests. Section IV presents evidence of price impacts that stem from attention spillover and positive feedback trading. Finally, Section V concludes.

I. Institutional Background and Empirical Strategy

A. *The Display Feature of Trading Platforms*

In this paper, we study attention spillover using a particular display feature of common trading platforms in China[5]: when an investor browses or searches for information on one particular stock, stocks that have adjacent listing codes are likely to be displayed as well. We argue that these neighboring stocks are likely to receive investor attention that spills over from the focal stock.

Similar to ticker symbols for stocks in the United States, each traded firm in China has a unique listing code—a six-digit number assigned by the stock exchange to represent that particular security. Figure 1 shows an example of the trading screen when an investor searches for a particular stock — in this

[4] A few other studies, such as Da, Engelberg, and Gao (2011), document price effects through investor overreaction.

[5] Although each brokerage house provides its own trading software for its investors, the software is mostly developed by two leading platform and data providers. The design and display features are therefore similar across brokers' software.

Panel A. Input "GZMT" Panel B. Press "Enter"

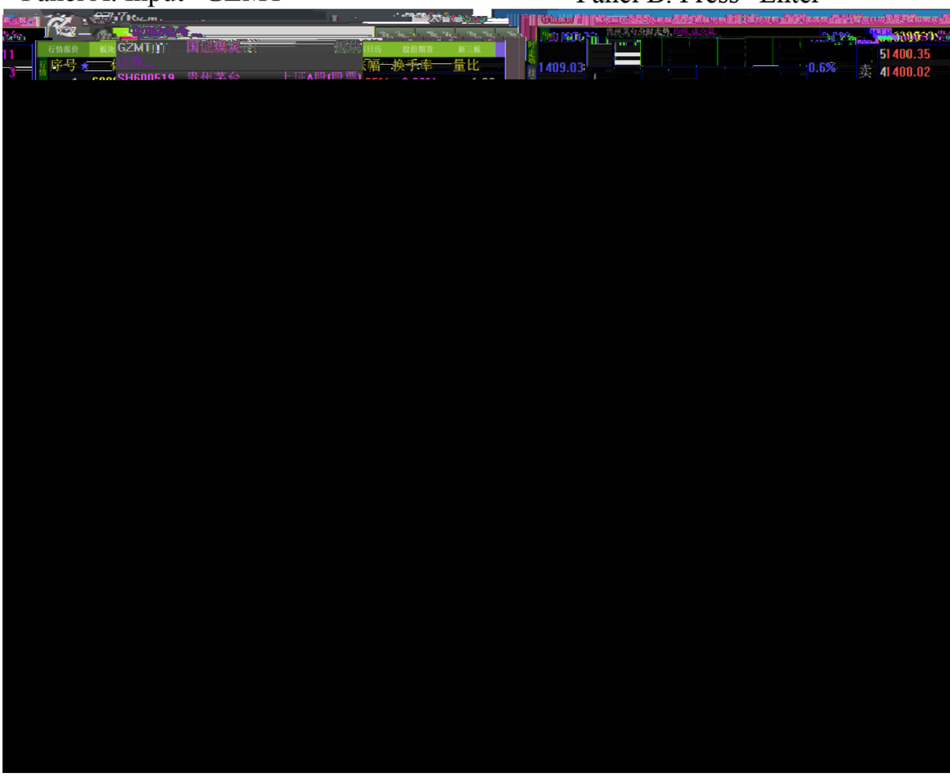

Figure 1. Screen display of the trading software. This figure illustrates the screen display when an investor searches for a particular stock. In this example, the stock corresponds to Guizhou Maotai (listing code = 600519). Panels A and B show the screen display when the investor types in the acronym "GZMT" and presses "enter" to link to the stock's main page. Panels C and D show the screen after the investor presses "Page Up" or "Page Down," which takes the investor to the main page of the previous stock (listing code 600518) or the next stock (listing code 600520). Panel E shows the screen if the investor again presses "Enter" on the main page of Guizhou Maotai, which shows a list of stocks around the focal stock, displayed in the order of listing code. Finally, Panel F shows the screen display when the investor types in the listing code. (Color figure can be viewed at wileyonlinelibrary.com)

case, for Guizhou Maotai. The investor can search for the stock by its acronym GZMT or by its listing code 600519. Typing in "GZMT" and pressing "enter" takes we to the main page of Guizhou Maotai (Figure 1, Panel B). If investors instead presses "Page-Up" or "Page-Down", they are taken to the main page of the stock with the previous listing code (i.e., 600518) or the next listing code (i.e., 600520) (Figure 1, Panels C and D), respectively. In addition, pressing "enter" on the main page of Guizhou Maotai links to the page that lists the stocks neighboring 600519, displayed in the order of their listing codes (Figure 1, Panel E). Alternatively, if the investor initially searches for the stock using its listing code, a drop-down menu lists stocks around the focal listing code

(Figure 1, Panel F). Overall, these display features, which present stocks in the order of listing codes, lead to adjacent stocks being more likely than distant stocks to catch investors' attention.

B. Determinants of Listing Codes

Our identification strategy relies on the quasi-random assignment of listing codes. Here we provide more details on how the listing codes are determined.

The listing code for each publicly traded firm is assigned at the time of the IPO and consists of six digits. The first three digits refer to the listing board—000 indicates the Shenzhen Main Board, 002 the SME Board, 300 the ChiNext Board and 600 the Shanghai Main Board. The four boards have different assignment rules for the next three digits: the Shanghai and Shenzhen main boards provide no clear statement on how they assign listing codes, while the SME Board and the ChiNext Board indicate that they assign codes based on listing dates.

Empirically, we examine the relation between listing codes and a battery of stock characteristics, including listing date, firm size, industry, and headquarters location. As Figure 2, Panel A shows, listing codes for firms in the SME board and the ChiNext board are typically determined by the time they go public. In contrast, firms in the Shanghai main board fall into three blocks of codes based on their listing dates, but there is no clear relation within each block. Aside from the relation to listing dates, no discernable patterns exist between listing code and other stock characteristics, as can be seen in Figure 2, Panels B to D.

One may be concerned that firms time their listing dates such that stocks with adjacent listing codes could share certain similarities along unobserved characteristics, leading to an omitted variable problem. This is unlikely to be the case, however, owing to the IPO system in China. A firm seeking to conduct an IPO in China must go through a lengthy administrative approval-based process that usually takes several years to complete.[6] Firms therefore tend to apply as soon as they meet the requirements. As a result, for our purposes, *immediate* neighboring firms are likely to be randomly determined in this process.

More importantly, the concern that firms may share common fundamental factors that generate a predictable return pattern has distinct asset pricing predictions from our conjectured mechanism. Specifically, return predictability due to common fundamental factors typically arises because investors underreact to available information in economically linked firms (e.g., Cohen and Frazzini (2008)). This underreaction channel implies that the predictable return pattern reflects a delayed price reaction to relevant fundamental information and should not revert in the future. In contrast, our proposed attention

[6] See Li, Sun, and Tian (2018) and Cong and Howell (2018), among others, for more details on the IPO process in China.

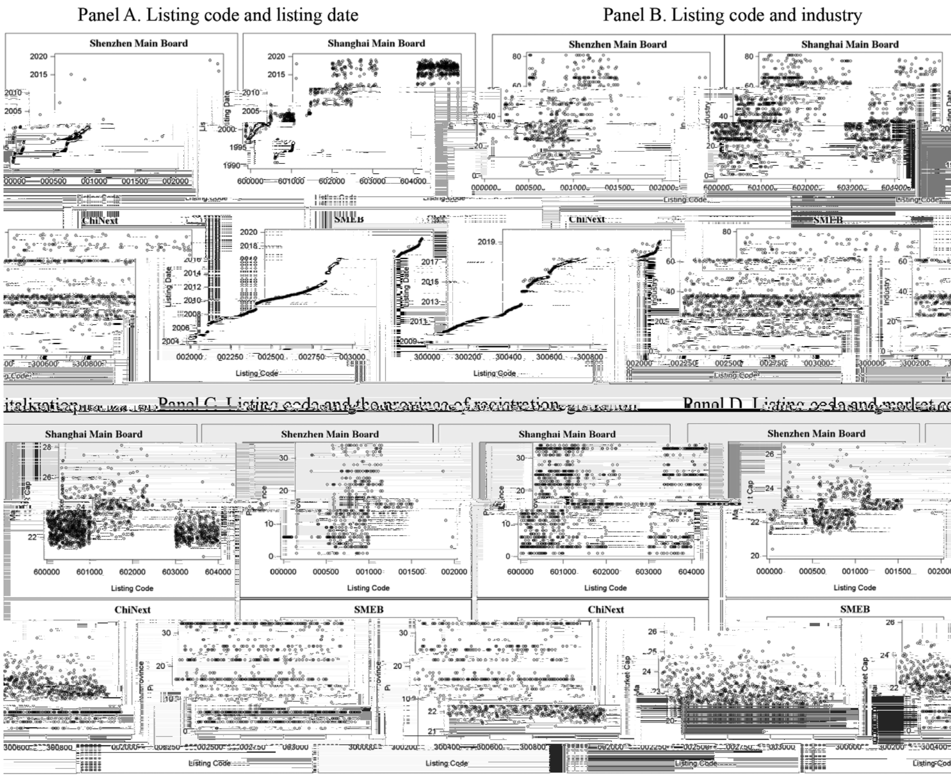

Figure 2. Listing code and stock characteristics. This figure plots the relation between listing code and listing date (Panel A), industry (Panel B), province of registration (Panel C), and market capitalization (Panel D). For clearer presentation, these relations are shown for stocks in each of the four listing boards separately.

spillover effect is based on continued overreaction, which implies that the price impact should be temporary and revert in the long run.

II. The Microfoundation: Investor Trading Behavior

In this section, we employ brokerage account data to examine investors' positive feedback trading and attention spillover. This serves to provide a microfoundation for the price patterns we study in later sections. Moreover, using survey tools and our clean identification setting, we provide evidence that helps us further understand the mechanisms behind investors' trading behaviors, and in turn helps sharpen the construction of stock-level signals.

Our main data come from a retail brokerage firm in China and contain daily trading and holdings records of 401,014 investors from January 2009 to September 2012. This data set has a similar structure to the Odean data set in the United States (Odean (1998)), as well as several Chinese brokerage account data sets used in previous studies (e.g., Feng and Seasholes (2004, 2005), An et al. (forthcoming)). Internet Appendix[7] Table IA.III reports summary statistics.

A. Baseline Results

A.1. Graphic Illustration

We first examine whether investors engage in positive feedback trading. In particular, we calculate the expected number of purchases in a day, conditioning on having a winning (losing) position on that day. If an investor holds more than one stock, we treat each of the stocks independently.[8] Similar to the metrics constructed in Odean (1998), we define

$$\text{Exp}\ \left(\#buy|win\right) = \#\ stocks\ purchased\ during\ days\ with\ a\ winning\ position \quad (1)$$

and

$$\text{Exp}\ \left(\#buy|lose\right) = \#\ stocks\ purchased\ during\ days\ with\ a\ losing\ position. \quad (2)$$

The right-hand-side measure is counted at the level of the investor×day×currently held stock. We calculate the average number for each day and report the time-series average.

Figure 3, Panel A shows the expected number of purchases conditional on having a winning position versus a losing one. An investor on average purchases 0.119 stocks per day during days with a winning position and only 0.084 stocks per day during days with a losing position. The difference of 0.036 is highly statistically significant (t-statistic = 32.57), and is 38% of that of the unconditional number of purchases (0.095). This pattern is consistent with previous evidence that investors tend to increase their positions after a positive investment outcome (e.g., Ben-David, Birru, and Prokopenya (2018)). It is also in line with the notion that positive feedback may lead to overconfidence and excessive trading (e.g., Gervais and Odean (2001)).

We next investigate the attention spillover effect, which is unique to our setting and is a key premise of our identification strategy. Here we calculate the probability of buying a new stock whose distance to a currently held winning (losing) stock is equal to x, conditioning on the investor buying any stocks on that day and holding a winning (losing) position. Specifically,

$$Prob\left(dist = x|buy, win\right) = \frac{\#\ newly-purchased\ stocks\ whose\ distance\ to\ a\ currently-held\ winning\ stock\ = x}{\#\ newly-purchased\ stocks\ with\ any\ distance\ to\ the\ currently-held\ winning\ stock} \quad (3)$$

[7] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[8] Here we implicitly assume that people engage in narrow framing. Under this assumption, one investor holding three stocks is observationally equivalent to three investors each holding one

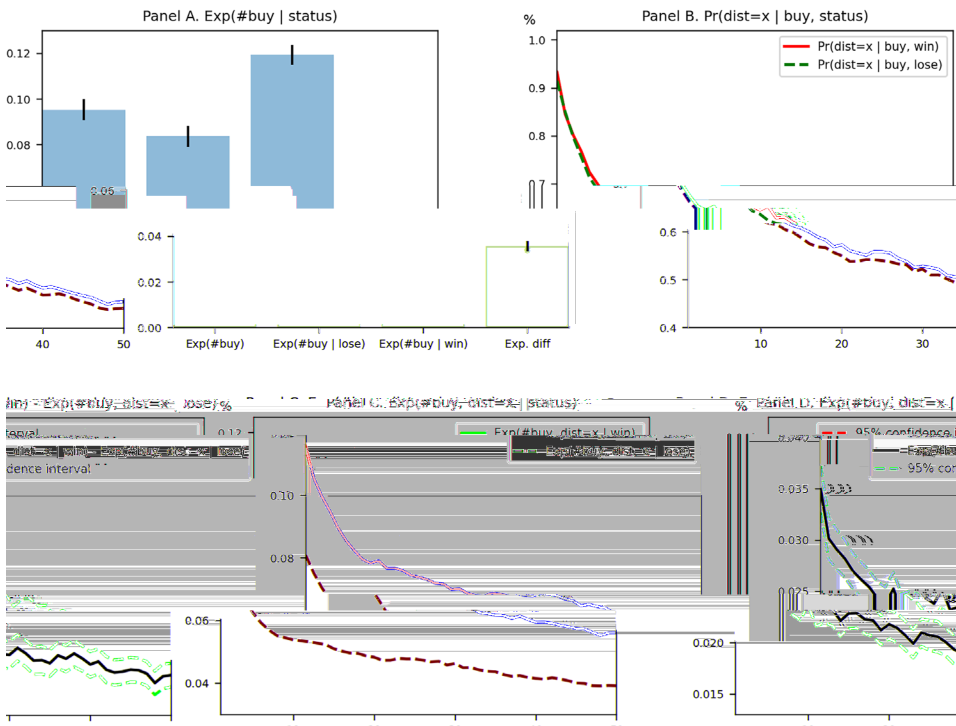

Figure 3. Positive feedback trading and attention spillover. This figure shows results of investor trading behavior using a brokerage data set that covers 401,014 investors from January 2009 to September 2012. Panel A shows the expected number of purchases in a day, as well as the expected number of purchases contingent on having a winning or losing position on that day, denoted by $\exp(\#buy)$, $\exp(\#buy|win)$, and $\exp(\#buy|lose)$, respectively (equations (1) and (2)). The difference between $\exp(\#buy|win)$ and $\exp(\#buy|lose)$ is given by $Exp.\ diff$. Panel B shows the probability of purchasing a new stock whose distance to a currently held stock is equal to x, contingent on the investor buying any stocks on that day and the currently held stock being in either a winning or losing status, which is denoted by $Prob(dist = x|buy, win)$ and $Prob(dist = x|buy, lose)$ (equations (3) and (4)). Distance x, with a multiplier of five, indicates that (the absolute value of) the difference in display rank between two stocks falls in $(5(x-1),\ 5x)$. Panel C shows the expected number of stocks bought at a particular distance ($dist = x$), given that the currently held stock is winning or losing, denoted by $\exp(\#buy,\ dist = x|win)$ and $\exp(\#buy,\ dist = x|lose)$ (equations (5) and (6)). Finally, Panel D shows the difference between $\exp(\#buy,\ dist = x|win)$ and $\exp(\#buy,\ dist = x|lose)$, as well as the 95% confidence interval. All metrics are calculated each day, and we show the time-series average of these metrics and their corresponding confidence interval. (Color figure can be viewed at wileyonlinelibrary.com)

and

$$Prob\left(dist = x|buy, lose\right) = \frac{\#\ newly-purchased\ stocks\ whose\ distance\ to\ a\ currently-held\ losing\ stock\ = x}{\#\ newly-purchased\ stocks\ with\ any\ distance\ to\ the\ currently-held\ losing\ stock}, \tag{4}$$

where both the numerators and the denominators are counted at the level of the investor×day×currently held stock. Distance x, with a multiplier of five, indicates that (the absolute value of) the difference in display rank between two stocks falls in $[5(x-1)+1,\ 5x]$. For instance, given a focal stock, $x = 1$ indicates the closest five stocks on each side, $x = 2$ indicates the 6th to 10th stocks on each side, and so on.

Figure 3, Panel B shows the probability of purchasing a new stock as a function of the new stock's distance to the currently held stock. We see a clear monotonically decreasing relation. Conditional on making a purchase and the current position winning, an investor has a 0.933% chance of buying a stock among the 10 closest stocks around the one he or she currently holds ($x = 1$), with this probability decreasing to 0.653% for a stock that is 50 ranks away ($x = 10$). The difference between the two, 0.28%, is highly statistically significant (t-statistic = 53.86). The results are almost identical when the currently held stock is in a losing position. These findings indicate that investors are indeed more likely to buy stocks ranked and displayed closer to stocks that they currently hold, potentially driven by attention spillover.

Figure 3, Panel C shows the product of the previous two metrics, which captures the overall effect of positive feedback trading and attention spillover. Given a fixed distance x,

$$\text{Exp}\ \left(\#buy,\ dist = x|win\right) = \exp\left(\#buy|win\right) \times Prob\left(dist = x|buy,\ win\right) \quad (5)$$

and

$$\text{Exp}\ \left(\#buy,\ dist\ =\ x|lose\right) = \exp\left(\#buy|lose\right) \times Prob\left(dist = x|buy, lose\right) \quad (6)$$

capture the expected number of stocks bought at that distance, given that the current position is winning or losing. Figure 3, Panel D further shows the difference between the winning and losing conditions. We find that this difference is significantly greater than zero and is decreasing in distance.

We also study the heterogeneity of these trading patterns across different groups of investors and report these findings in Internet Appendix Figure IA.1. As with most behavioral biases, we find that less sophisticated investors, as proxied by smaller account size and lower diversification, exhibit stronger positive feedback trading and stronger attention spillover.

A.2. Panel Regressions

The previous subsection provides intuitive evidence on positive feedback trading and attention spillover. We now formally test these trading patterns in a panel regression framework that allows for better identification by including highly saturated fixed effects. We examine how an investor's past performance affects his/her future purchases, as a function of the distance to the currently held position. Specifically, we run a series of regressions of the form

$$\mathbf{1}_{(x,\ x+5}$$

Table I

Positive Feedback Trading and Attention Spillover: Panel Regressions

This table shows how an investor's past performance affects their future purchases, as a function of the distance to the currently held stock. We randomly select 50,000 investors to form the sample and then perform a series of regressions of the form $1_{(\mathbf{x},\ \mathbf{x}+5]} = \alpha_{(\mathbf{x},\ \mathbf{x}+5]} + \beta_{(\mathbf{x},\ \mathbf{x}+5]} 1_{\mathbf{win}} + \mathbf{controls} + \epsilon$. The dependent variable ($1_{(\mathbf{x},\mathbf{x}+5]}$) is a dummy indicating whether the investor buys any stocks whose distance to the currently held stock is between $\mathbf{x}$ and $\mathbf{x}+5$, and the main independent variable of interest, $1_{\mathbf{win}}$, indicates whether the current position has increased or decreased in value from the purchase date to the day in question. Panel A reports univariate results, while in Panel B we control for confounding factors. $\mathbf{Age}_{(\mathbf{x},\mathbf{x}+5]}$ ($\mathbf{Ind}_{(\mathbf{x},\mathbf{x}+5]}$) indicates the fraction of stocks among the corresponding group (distance between $\mathbf{x}$ and $\mathbf{x}+5$) that have the same listing year (industry) as the currently held stock. We include both $\mathbf{Age}_{(\mathbf{x},\mathbf{x}+5]}$ and $\mathbf{Ind}_{(\mathbf{x},\mathbf{x}+5]}$, as well as their interactions with $1_{\mathbf{win}}$. All regressions in both panels include fixed effects for investor, date, and the currently held stock. Standard errors are clustered at the investor, date, and currently held stock level. All estimated parameters are reported in percentage, and t-statistics are reported in brackets.

Panel A. Univariate regressions

$Y =$	$1_{(0,5]}$	$1_{(5,10]}$	$1_{(10,15]}$	$1_{(15,20]}$	$1_{(20,25]}$	$1_{(25,30]}$	$1_{(30,35]}$	$1_{(35,40]}$	$1_{(40,45]}$	$1_{(45,50]}$
1_{win}	0.029	0.023	0.022	0.018	0.019	0.015	0.013	0.013	0.013	0.013
	[15.19]	[14.06]	[15.00]	[13.16]	[14.83]	[12.16]	[10.80]	[10.63]	[10.81]	[10.18]
Intercept	0.068	0.064	0.060	0.058	0.054	0.054	0.052	0.050	0.050	0.049
	[123.86]	[138.86]	[156.15]	[157.29]	[157.40]	[165.17]	[161.39]	[159.57]	[155.40]	[138.18]
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.004	0.004	0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003
No. of Obs.	85m	85m	85m	85m	85m	85m	85m	85m	85m	85m

(*Continued*)

Table I—*Continued*

Panel B. Regressions controlling for age and industry effects										
$Y =$	$1_{(0,5]}$	$1_{(5,10]}$	$1_{(10,15]}$	$1_{(15,20]}$	$1_{(20,25]}$	$1_{(25,30]}$	$1_{(30,35]}$	$1_{(35,40]}$	$1_{(40,45]}$	$1_{(45,50]}$
1_{win}	0.046	0.031	0.025	0.017	0.018	0.008	0.005	0.007	0.009	0.007
	[8.80]	[8.04]	[8.92]	[6.56]	[8.75]	[3.74]	[2.94]	[4.28]	[5.48]	[4.41]
$Age_{(x,x+5]}$	0.153	0.140	0.073	0.055	0.018	0.015	0.021	0.020	0.029	0.018
	[3.66]	[4.59]	[3.64]	[4.90]	[3.03]	[1.77]	[2.73]	[3.14]	[5.14]	[3.04]
$Ind_{(x,x+5]}$	0.185	0.094	−0.017	0.038	0.055	0.038	0.016	0.011	0.018	0.006
	[2.30]	[2.76]	[−0.77]	[1.46]	[2.33]	[2.54]	[1.25]	[1.04]	[1.60]	[0.59]
$1_{win} \times Age_{(x,x+5]}$	−0.035	−0.020	−0.013	−0.002	0.000	0.017	0.024	0.017	0.015	0.025
	[−5.00]	[−3.71]	[−2.82]	[−0.39]	[0.06]	[3.90]	[5.06]	[3.77]	[3.38]	[4.45]
$1_{win} \times Ind_{(x,x+5]}$	0.123	0.086	0.083	0.065	0.031	0.048	0.035	0.049	0.035	0.060
	[3.24]	[2.58]	[3.34]	[2.87]	[1.42]	[2.56]	[1.65]	[2.99]	[2.28]	[2.91]
Intercept	−0.034	−0.014	0.027	0.034	0.045	0.047	0.045	0.045	0.043	0.045
	[−1.27]	[−0.88]	[2.98]	[6.91]	[19.79]	[16.19]	[19.24]	[26.28]	[32.99]	[40.17]
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.004	0.004	0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003
No. of Obs.	85m	85m	85m	85m	85m	85m	85m	85m	85m	85m

the difference between buying probabilities conditional on winning versus losing positions ($\beta_{(x,x+5]}$) continues to decrease with distance, with the decreasing pattern even stronger than that in Panel A.

A.3. The "Necessary Condition" for Price Impacts

We now discuss how the interaction between positive feedback trading and attention spillover can generate price impacts. Because investors tend to increase their positions after positive returns, and they are more likely to notice stocks that are displayed close to their currently held stocks, we hypothesize that stocks whose neighbors experience higher past returns face more buying pressure (from the owners of their neighboring stocks) and experience higher future returns.

The trading patterns that are necessary to generate the price impacts can be summarized by

$$\mathrm{Exp}\left(\#buy,\ dist\ =\ x|win\right) - \exp\left(\#buy,\ dist\ =\ x|lose\right) \tag{8}$$

being positive and decreasing in the distance x, as we show in Figure 3, Panel D and Table I. In words, we need more buying pressure on the focal stock if the neighboring stocks experience profits as compared with losses. In addition, this difference in buying pressure should decrease with distance, so that the returns of neighboring stocks can serve as a proxy for the overall buying pressure on the focal stock. Note that our conjectured price impacts depend crucially on the interaction between positive feedback trading and attention spillover. On the one hand, if there is no attention spillover, the difference in buying pressure would be constant across all distances, and thus the buying pressure from owners of all other firms would be independent of their distance, leading to no cross-sectional difference in total buying pressure for different focal stocks. On the other hand, if investors do not engage in positive feedback trading, there would be no excess buying pressure after positive returns, and thus the past returns of neighboring stocks would not predict the future return of the focal stock.

B. Understanding the Mechanisms

B.1. What Drives Positive Feedback Trading?

While classic models typically ascribe positive feedback trading to investors' self-attribution bias and "learning to be overconfident" (Daniel, Hirshleifer, and Subrahmanyam (1998), Gervais and Odean (2001)), this trading pattern can stem from other mechanisms as well. For instance, the wealth effect can lead to positive feedback trading in the sense that past positive returns relax investors' borrowing constraints so they can buy more stocks to return to their target leverage. Another potential mechanism is belief extrapolation – investors observing past positive returns become more optimistic and therefore increase future positions. Understanding the (primary) determinant of the trading pattern would also help sharpen the design of stock-level signals.

Disentangling these competing theories using field data is difficult because they generate similar empirical predictions for investor trading behavior. To address this challenge, we conduct a survey to elicit investors' behavioral biases and combine them with investors' observed trading data, adopting the empirical approach and survey questions developed by Liu et al. (2022). Specifically, we collaborate with a brokerage firm in China and conduct the survey in October 2021. We administer the survey to all investors using the brokerage firm's trading app during that period and collect an initial sample of 1,736 respondents. We then collect trading data of these investors between January 2000 to December 2021. After eliminating investors who do not have trading records during this period, our final data set contains 1,229 investors. Note that the data set employed in this subsection is different from the main trading data that we use in this paper, but it nonetheless contains a similar data structure.

Our survey contains 12 questions designed to capture the following behavioral biases: overplacement of performance, upside and downside self-attribution, upside and downside extrapolation, overconfidence in perceived information advantage and dismissiveness of others' information, gambling preference ("blockbuster" and "lotteries"), realized utility for winners and losers, and home bias.[9] Internet Appendix Section I presents the survey questions as well as additional details on survey administration. We create a dummy variable for each of the biases, where the dummy is equal to one if an investor answers the corresponding question with "strongly agree" or "agree" and zero otherwise; for overplacement, the dummy variable is equal to one if the investor's assessment of his/her own performance rank among all investors is higher than his/her actual rank.

Using these dummies, we run investor-day-level panel regressions of the following form to examine the relation between an investor's positive feedback trading and his/her behavioral biases:

$$\mathbf{1}_{i,t+1}^{net\ buy} = \alpha + \beta \mathbf{1}_{i,t}^{win} + \theta \mathbf{1}_{i}^{bias} + \gamma \mathbf{1}_{i,t}^{win} \times \mathbf{1}_{i}^{bias} + \epsilon_{t+1}. \tag{9}$$

The dependent variable is a dummy variable indicating whether an investor makes a net purchase the next day. The independent variables include a dummy variable indicating whether the investor currently has a winning or losing portfolio, a dummy variable indicating the behavioral bias in question, and the interaction between the two. We include date fixed effects in all regressions.

Table II, Panel A presents the results for each behavioral bias examined separately. In Panel B we include all elicited biases in the same regression to compare their explanatory power in a horse race. In the baseline regression

[9] Except for the questions on upside and downside self-attribution, the remaining 10 questions come directly from Liu et al. (2022).

Table II

Table II—*Continued*

Panel B. A horse race of multiple behavioral biases

	1_{bais}	$1_{win}1_{bias}$
Overplacement	0.052	−0.015
	[0.17]	[−0.02]
Upside self-attribution	0.592	2.198
	[1.55]	[2.83]
Downside self-attribution	−1.960	4.281
	[−5.55]	[5.74]
Upside extrapolation	−1.733	1.638
	[-4.18]	[1.93]
Downside extrapolation	0.655	−1.608
	[1.48]	[−1.76]
Perceived information advantage	−2.832	1.332
	[-8.49]	[1.90]
Dismissiveness of others' information	0.613	−1.548
	[2.02]	[−0.24]
Gambling preference, blockbusters	0.996	-3.615
	[2.95]	[−5.13]
Gambling preference, lotteries	−1.205	0.408
	[−3.62]	[0.59]
Realized utility, winner	1.975	−0.189
	[6.42]	[−0.29]
Realized utility, loser	0.811	−0.278
	[2.67]	[−0.43]
Home bias	0.553	0.058
	[1.73]	[0.09]
Date FE	Yes	
R^2	0.018	
No. of Obs.	121,393	

in Panel A, where the only independent variable is $1^{win}_{i,t}$, we see that the coefficient is significantly positive, indicating the presence of positive feedback trading in this sample. Our coefficients of interest are those on the interaction terms, which indicate whether investors with stronger behavioral biases exhibit stronger positive feedback trading.

Focusing on the estimation in Panel B, we see that self-attribution, on both the upside and the downside, has the strongest explanatory power for positive feedback trading. The coefficient on upside (downside) self-attribution is 2.198% (4.281%) with a t-statistic of 2.83 (5.74), more than double the effect (1.627%) in the baseline regression in Panel A). This suggests that the "learning to be overconfident" mechanism, as posited by Gervais and Odean (2001), is indeed a primary determinant of positive feedback trading.

Upside extrapolation and perceived information advantage are also positively associated with this trading pattern, albeit with marginal statistical significance, while downside extrapolation has a negative interaction coefficient, also with marginal significance.[10] While self-attribution and extrapolation both predict a positive association between past returns and future expected returns, a key conceptual difference between the two lies in whether investors own the asset and experience the past return by themselves. Our horse-race results suggest that owning the asset may play an economically important role in driving this trading behavior.

B.2. Experienced Returns versus Observed Extreme Returns

In this subsection, we exploit the clean setting of attention spillover to study the empirical importance of our proposed mechanism, namely, the interaction between positive feedback trading and attention spillover. In theory, in the absence of positive feedback trading, other attention-grabbing events can potentially interact with the attention spillover effect, leading to similar asset pricing implications. For instance, hitting the daily price limit is a salient event that can attract investor attention to the focal stock and spill over to neighboring stocks.[11] We pit our proposed mechanism against this alternative in explaining investor behavior.

Using our main brokerage data, we construct the sample as follows. Each day, we start with the full list of stocks that hit the upper (lower) daily price limit. For comparison, we also include the same number of stocks that almost hit the price limit on the same day, that is, those with extremely high (low) returns that do not reach the limit. While both provide a good (bad) return for their current owners, a key difference between the two types of stocks lies in the fact that those who actually hit the price limit receive disproportionate attention from new investors due to increased media coverage.[12] We then construct the stock-day-investor sample as the Cartesian product of the daily stock list described above and 50,000 randomly selected investors (for ease of computation) who may or may not hold these stocks.

We construct a dummy variable, 1_{hold}, to indicate whether an investor holds the focal stock in question, and another dummy variable, 1_{hit}, to indicate whether the focal stock hits the daily price limit at the end of the current day. We then employ a similar empirical framework as in Section II.A.2 to analyze how holding or observing a stock that experiences extreme return affects investors' future purchases. Specifically, we run a series of panel regressions of

[10] Gambling preference (blockbuster) also has a negative interaction coefficient. This is consistent with the finding in An et al. (forthcoming) that investors' gambling preference tends to become stronger when their investment is under water.

[11] China's equity market imposes daily price limits of 10% on regular stocks and 5% on special treatment stocks. Seasholes and Wu (2007) and Chen et al. (2019), among others, show that stock prices hitting the upper daily price limit attract the attention of new investors, especially inexperienced ones.

[12] This design is similar to the identification strategy in Jiang et al. (2022), who use the display order among upper-price-limit-hitting stocks as a source of exogenous variation in investor attention.

the form

$$1_{(x,\ x+5]} = \alpha_{(x,\ x+5]} + \beta^{\,hold}_{(\mathrm{x},\ \mathrm{x}+5]} 1_{hold} + \beta^{\,hit}_{(\mathrm{x},\ \mathrm{x}+5]} 1_{hit} + \beta^{\,inter}_{(\mathrm{x},\ \mathrm{x}+5]} 1_{hold} \times 1_{hit} + \epsilon. \quad (10)$$

We include fixed effects at the level of the investor, day, and focal stock in question.

Table III, Panel A reports the results for stocks experiencing extreme positive returns (hitting or almost hitting the upper price limit) and Panel B reports results for stocks experiencing extreme negative returns (hitting or almost hitting the lower price limit). In Panel A, we see that the coefficients on 1_{hold} are significantly positive and decreasing on the distance between the focal stock and the stocks that can be potentially bought. For instance, when the distance is between zero to five, the investor is 0.032% (t-statistic = 5.67) more likely to make a purchase when he/she holds a stock that just experienced an extreme positive return, with this probability decreasing to 0.004% (t-statistic = 0.78) when the distance increases to between 20 and 25. In comparison, the coefficients on 1_{hit} are mostly indistinguishable from zero. When the distance is between zero to five, the increased probability due to the stock hitting the upper price limit (and potentially attracting the attention of new investors) is merely 0.003% (t-statistic = 1.68), one-tenth of the holding effect. The interaction between 1_{hold} and 1_{hit} is mostly insignificant. In Panel B where we analyze stocks that experience extreme negative returns, the coefficients on 1_{hold} and 1_{hit} are mostly indistinguishable from zero for almost all distances. This serves as a nice placebo test to show the asymmetry between past positive and negative performance.[13]

These results suggest that, while in theory both positive feedback trading and attention-grabbing events can both interact with attention spillover and

Table III

Experienced Returns versus Observed Extreme Returns

This table compares the trading impact of experienced returns and observed extreme returns by analyzing events in which stocks experience extreme positive/negative returns. The sample is constructed as follows. Each day, we start with the full list of stocks hitting the upper (lower) daily price limit. For comparison, we also include the same number of stocks that almost hit the price limit on the same day, that is, those with extremely high (low) returns that did not reach the limit. We then construct the stock-day-investor sample as the Cartesian product of this daily stock list and 50,000 randomly selected investors who may or may not hold these stocks and run regressions of the form $1_{(\mathbf{x},\ \mathbf{x}+5]} = \alpha_{(\mathbf{x},\ \mathbf{x}+5]} + \boldsymbol{\beta}^{\mathbf{hold}}_{(\mathbf{x},\ \mathbf{x}+5]} 1_{\mathbf{hold}} + \boldsymbol{\beta}^{\mathbf{hit}}_{(\mathbf{x},\ \mathbf{x}+5]} 1_{\mathbf{hit}} + \boldsymbol{\beta}^{\mathbf{inter}}_{(\mathbf{x},\ \mathbf{x}+5]} 1_{\mathbf{hold}} \times 1_{\mathbf{hit}} + \epsilon$, where $1_{\mathbf{hold}}$ indicates whether an investor holds the focal stock in question and $1_{\mathbf{hit}}$ indicates whether the focal stock hits the daily price limit at the end of the current day. Panel A reports results for stocks experiencing extreme positive returns (hitting or almost hitting the upper price limit), and Panel B reports results for stocks experiencing extreme negative returns (hitting or almost hitting the lower price limit). We include fixed effects at the level of the investor, day, and focal stock. All estimated parameters are reported in percentage, and t-statistics are reported in brackets.

Panel A. The sample of stocks experiencing extreme positive returns (hitting or almost hitting the upper price limit)

$Y =$	$1_{(0,5]}$	$1_{(5,10]}$	$1_{(10,15]}$	$1_{(15,20]}$	$1_{(20,25]}$	$1_{(25,30]}$	$1_{(30,35]}$	$1_{(35,40]}$	$1_{(40,45]}$	$1_{(45,50]}$
1_{hold}	0.032	0.018	0.013	0.013	0.004	0.003	0.007	0.006	0.003	0.014
	[5.67]	[3.55]	[2.72]	[2.73]	[0.78]	[0.73]	[1.55]	[1.44]	[0.79]	[1.91]
1_{hit}	0.003	0.002	0.001	0.003	0.001	0.002	0.003	0.002	0.002	0.001
	[1.68]	[1.26]	[0.67]	[1.86]	[0.99]	[1.58]	[1.83]	[1.21]	[1.46]	[0.77]
$1_{hold} \times 1_{hit}$	0.008	0.012	0.011	0.005	0.014	0.005	0.017	0.006	0.011	0.004
	[1.02]	[1.48]	[1.47]	[0.78]	[2.04]	[0.83]	[2.44]	[0.87]	[1.70]	[0.56]
Intercept	0.089	0.088	0.088	0.086	0.087	0.086	0.083	0.085	0.085	0.085
	[205.79]	[233.68]	[193.21]	[194.84]	[205.02]	[209.01]	[160.03]	[231.07]	[268.87]	[197.31]
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
No. of Obs.	47m	47m	47m	47m	47m	47m	47m	47m	47m	47m

(*Continued*)

Table III—*Continued*

Panel B. The sample of stocks experiencing extreme negative returns (hitting or almost hitting the lower price limit)										
$Y =$	$1_{(0,5]}$	$1_{(5,10]}$	$1_{(10,15]}$	$1_{(15,20]}$	$1_{(20,25]}$	$1_{(25,30]}$	$1_{(30,35]}$	$1_{(35,40]}$	$1_{(40,45]}$	$1_{(45,50]}$
1_{hold}	0.016	0.012	0.001	0.002	0.003	0.006	−0.002	0.004	0.007	0.008
	[1.72]	[1.60]	[0.23]	[0.21]	[0.36]	[0.88]	[−0.34]	[0.58]	[0.94]	[0.98]
1_{hit}	−0.001	0.000	−0.002	−0.001	0.000	0.001	0.002	0.000	−0.002	−0.001
	[−0.71]	[−0.07]	[−1.80]	[−0.61]	[−0.32]	[1.20]	[1.48]	[−0.02]	[−0.98]	[−

lower than 2 RMB, stocks traded less than 10 days (120 days) over the past four weeks (52 weeks), stocks that are listed less than two years,[15] and the special treatment (ST) stocks.

A. Definition of the Key Variables

For each stock at the end of each week, we construct *LOCAL* to measure the performance of its neighboring stocks. Specifically, *LOCAL* is equal to the value-weighted average return over the past two weeks of the 10 stocks with listing code closest to the focal stock (five above and five below). The horizon of two weeks is designed to match the median investor holding period in our trading data. Neighboring stocks are drawn from the full sample of A-shares, without applying filters on the price level and stock liquidity.[16]

Additionally, we construct *RLOCAL* as the residual of the cross-sectional regression of *LOCAL* on the focal stock's own return over the past two weeks. This construction partly addresses the reflection problem (i.e., when the focal stock's extreme return attracts attention to its neighboring stocks and is then captured in *LOCAL*) and rules out short-term autocorrelation in returns when we examine return predictability of the focal stock.

B. Control Variables

To tease out the effects of attention spillover, we control for two sets of variables known to affect future returns and turnover.

In most of the tests on return predictability, we control for market beta (*Beta*), estimated using monthly returns over the past 36 months, the stock's own return over the past two weeks (Ret_{-2w}), the past 12- to 2-month cumulative return ($Ret_{-12m,-2m}$), and the past three- to one-year cumulative return ($Ret_{-36m,-13m}$). The latter three variables are designed to control for short-term reversal (Jegadeesh (1990)), the momentum effect (Jegadeesh and Titman (1993)), and long-term reversal (De Bondt and Thaler (1985)), respectively. We also control for firm size (*LogME*), the logarithm of a firm's total market capitalization at the end of the week, book-to-market ratio (*LogBM*), the logarithm of the ratio of book value over market capitalization following Fama and French (1992), the Amihud illiquidity measure (*ILLIQ*), the average

[15] Due to severe IPO underpricing in China, newly listed stocks typically hit the upper price limit in several consecutive days, which attracts the attention of inexperienced investors and leads to a price overreaction in the short run and reversal in the long run. To avoid such confounding price effects, in our main analyses we exclude stocks that are listed in the past two years. However, including these stocks has little impact on our results, as shown in Internet Appendix Table IA.XII.

[16] We design *LOCAL* to measure the buying pressure from investors of neighboring stocks. What specific definition can best capture the effect we conjecture is an empirical question. Our choices of the number of neighboring stocks and the past return horizon roughly match the combination that captures the most retail order imbalance in the next week, as shown in Internet Appendix Table IA.XVII. That said, our results are robust to a battery of alternative constructions, including using different numbers of neighboring stocks, different formation periods, different weighting schemes, different ways to define neighbors, etc. The results are reported in Internet Appendix Section III.

daily ratio of the absolute return over hundred-yuan trading volume in the past four weeks (Amihud (2002)), and idiosyncratic volatility (*IVOL*), the volatility of daily return residuals with respect to the Fama-French three-factor model in the past four weeks (Ang et al. (2006)). We further control for a stock's max return (*Max*), the average of the three largest daily returns in the previous four weeks, following Bali, Cakici, and Whitelaw (2011), the skewness of daily returns in the previous 52 weeks (*Skew*), and a stock's turnover (*Turnover*), the average number of daily turnover over the past four weeks.

In our tests on turnover, we follow Chordia, Huh, and Subrahmanyam (2007) and consider the following set of control variables. Positive return (Ret^{+}_{-2w}) is a stock's past two-week return if it is positive, and zero otherwise. Negative return (Ret^{-}_{-2w}) is a stock's past two-week return if it is negative, and zero otherwise. Financial leverage (*Leverage*) is the ratio of the book value of debt to total assets. Firm age (*LogAge*) is the logarithm of the number of months since IPO. A stock's price level (*LogPrice*) is the logarithm of the closing price at the end of the week. Earning surprise (*ESURP*) is the ratio of the difference between current earnings and the earnings from four quarters ago over the market value at the end of the week. Earnings volatility (*EVOL*) is the variance of earnings over the most recent eight quarters. Analyst coverage (*ALANA*) is the logarithm of one plus the number of security companies that issue at least one financial forecast in the past 12 months. Forecast dispersion (*Dispersion*) is the variance of earnings per share forecasts issued by different security companies.

C. Summary Statistics

Table IV reports the summary statistics. We present the equal-weighted average of stock characteristics for portfolios sorted by *RLOCAL*. In addition to the two *LOCAL* variables, other characteristics are generally equally distributed across quintiles.[17] We also report the correlations between *LOCAL* (*RLOCAL*) and our control variables. We see that both *RLOCAL* and *LOCAL* are largely uncorrelated with any other stock characteristics (the highest correlation is 0.06 between *LOCAL* and Ret_{-2w}). These results suggest that our *LOCAL* variables, designed to take advantage of the quasi-random assignment of listing codes, have little association with other stock characteristics.

IV. Pricing Results

This section explores the ability of *LOCAL* variables to explain future returns and turnover. We first examine returns and turnover in sorted portfolios and employ Fama and MacBeth (1973) regressions to control for potential confounding factors. We then provide evidence on several placebo tests designed

[17] The only exception is turnover—stocks in the RLOCAL5 portfolio have a slightly higher turnover ratio over the past four weeks, which may reflect the concurrent impact of attention spillover.

Table IV

Summary Statistics

This table reports summary statistics for key variables and control variables in our asset pricing tests. We report the time-series average of the equal-weighted stock characteristics for portfolios sorted by *RLOCAL* and the time-series average of the cross-sectional correlation between characteristics and *RLOCAL* (*LOCAL*). For each stock. *LOCAL* is the value-weighted average return over the past two weeks of the 10 closest stocks on the screen display. *RLOCAL* is the residual of the cross-sectional regression of *LOCAL* on the focal stock's return over the past two weeks. $\mathbf{Ret}_{-2w}$, $\mathbf{Ret}_{-12m,\,-2m}$, and $\mathbf{Ret}_{-36m,\,-13m}$ denote the cumulative return of the own stock in the past two weeks, from month $\mathbf{t}-12$ to month $\mathbf{t}-2$, and from month $\mathbf{t}-36$ to month $\mathbf{t}-13$, respectively. *LogAge* is the logarithm of the number of months since the firm's IPO. *Beta* is estimated using the CAPM and the monthly returns in the past 36 months. *LogME* is the logarithm of a firm's market capitalization at the end of the week. *LogBM* is the logarithm of the book-to-market ratio. *ILLIQ* denotes the Amihud illiquidity measure, calculated as the average daily ratio of the absolute return over trading volume in the past four weeks. *Turnover* is the average daily ratio of trading volume over total tradable shares in the past four weeks (in percentage points). *IVOL* is idiosyncratic volatility with respect to the Fama-French three-factor model using daily returns over the past four weeks. *Max* is the average of the three highest daily returns over the past four weeks. *Skew* is skewness of daily returns over the past 52 weeks. All variables are winsorized each week at the 1% and 99% levels. *t*-Statistics are shown in brackets.

	RLOCAL	*LOCAL*	Ret_{-2w}	*logAge*	*logME*	*Beta*	*logBM*	$Ret_{-12m,-2m}$	$Ret_{-36m,-13m}$	*ILLIQ*	*Turnover*	*IVOL*	*Max*	*Skew*
RLOCAL1	−0.042	−0.036	0.006	4.517	22.197	1.101	−1.055	0.191	0.507	0.186	2.292	0.019	0.055	0.150
RLOCAL2	−0.017	−0.012	0.005	4.574	22.163	1.101	−1.050	0.185	0.510	0.186	2.272	0.019	0.055	0.145
RLOCAL3	−0.002	0.003	0.005	4.572	22.156	1.102	−1.048	0.187	0.509	0.186	2.282	0.019	0.055	0.146
RLOCAL4	0.014	0.020	0.005	4.551	22.149	1.100	−1.053	0.188	0.509	0.187	2.308	0.019	0.055	0.142
RLOCAL5	0.046	0.051	0.006	4.493	22.176	1.097	−1.053	0.194	0.507	0.184	2.349	0.019	0.055	0.143
RLOCAL5-1	0.087	0.087	0.000	−0.024	−0.021	−0.004	0.002	0.003	0.000	−0.002	0.057	0.000	0.000	−0.007
	[25.35]	[25.36]	[1.22]	[−1.15]	[−1.39]	[−1.59]	[0.22]	[0.78]	[0.03]	[−1.28]	[2.33]	[−1.03]	[−0.78]	[−1.65]
Corr. RLOCAL	1.00	1.00	0.00	−0.02	−0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	−0.01
Corr. LOCAL	1.00	1.00	0.06	−0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.02	0.00

to shed light on the role of attention spillover and overconfidence in generating price impacts. We additionally exploit a quasi-natural experiment that allows for sharper identification.

A. One-Way Sorts

In Table V, we report results of single-sorted portfolio returns based on *RLOCAL*. Specifically, we sort stocks into five portfolios based on *RLOCAL* at the end of each week, and then track returns over the next week for these five portfolios, as well as the hedge portfolio (P5-P1) that longs stocks with the highest *RLOCAL* and shorts stocks with the lowest *RLOCAL*. We also report risk-adjusted returns using several benchmarks, including age-adjusted returns, industry-adjusted returns,[18] DGTW characteristic-adjusted returns, alphas of the four-factor model for the Chinese market (Liu, Stambaugh, and Yuan (2019)), and alphas of the Fama-French five-factor model (Fama and French (2015)). We report equal- and value-weighted returns, as well as portfolio returns, using a capped value-weighting scheme that winsorizes market caps at the 80$^{\text{th}}$ percentile across all stocks following Jensen, Kelly, and Pedersen (2021). The last weighting scheme addresses the concern that a few large firms may dominate the value-weighting results. All returns are annualized and reported as percentage points, and *t*-statistics are based on standard errors with Newey and West (1987) adjustments of 12 lags.

For all weighting schemes, we see a clear monotonic relation between *RLOCAL* and future returns. The difference between P5 and P1 is around 8% per year for all weighting schemes, with *t*-statistics ranging from 2.67 to 5.45. After adjusting for various risk benchmarks, the return spread remains economically large and statistically significant. The adjusted return spread is around 3% to 6% per year after adjusting for industry and DGTW characteristics, and it remains higher than 6% using the Chinese four-factor model, the Fama-French five-factor model, and the age benchmark. Comparing across weighting schemes, the return spreads are similar in magnitude, while *t*-statistics are generally smaller when returns are value weighted (around two to three) rather than equal weighted (around four to five). After winsorizing the value weights at the 80$^{\text{th}}$ percentile, the *t*-statistics for the return differences are comparable to those under the equal-weighting scheme.

From the alphas of the four-factor model for the Chinese market (CH4; Liu, Stambaugh, and Yuan (2019)), we find that the strategy's excess return comes from the superior performance of the long portfolio (P5). For all of the weighting schemes, the long leg has positive and significant CH4 alphas, with *t*-statistics ranging from 4.89 to 8.08, while the short leg has insignificant CH4

[18] Specifically, age- and industry-adjusted returns are constructed by taking the raw return of a stock and subtracting the value-weighted average return of firms that are listed in the same year or from the same industry. Because the number of IPOs can be very small (less than 20) in certain years (e.g., 1990, 1991, 2005, and 2013), to ensure that each age portfolio has enough stocks, we include stocks that are listed in the previous year when the number of IPOs in the current year is less 30.

Table V

Single-Sorted Portfolio Return by *RLOCAL*

This table reports single-sorted portfolio results. At the end of each week, we sort stocks into five groups based on *RLOCAL* and we track the returns of these portfolios over the next week. For each stock, *LOCAL* is the value-weighted average return over the past two weeks of the 10 closest stocks on the screen display, and *RLOCAL* is the residual of the cross-sectional regression of *LOCAL* on the focal stock's return over the past two weeks. We report portfolio returns using three weighting schemes: equal weighting (EW), value weighting (VW), and capped-value weighting (CVW), which weights stocks by their market value winsorized at the 80th percentile across all stocks following Jensen, Kelly, and Pedersen (2021). We also report the long-short portfolio return (P5-P1) as well as a battery of risk-adjusted returns using different benchmarks: age-adjusted return (*Age-adj Ret*), industry-adjusted return (*Ind-adj Ret*), DGTW characteristic-adjusted return (*DGTW Ret*), four-factor alpha (*CH4 Alpha*) following Liu, Stambaugh, and Yuan (2019), and five-factor alpha (FF5 Alpha) following Fama and French (2015). All returns and alphas are annualized and reported in percentage points. The sample is from January 2002 to December 2019. t-Statistics, shown in brackets, are based on standard errors with Newey-West adjustments of 12 lags.

	P1	P2	P3	P4	P5	P5-P1	Age-adj Ret	Ind-adj Ret	DGTW Ret	CH4 Alpha	FF5 Alpha
EW	8.120	10.942	12.401	13.274	16.140	8.020	7.229	5.625	4.146	8.929	7.979
	[0.88]	[1.18]	[1.34]	[1.41]	[1.71]	[5.45]	[5.51]	[5.45]	[3.94]	[5.51]	[5.45]
VW	3.311	6.557	8.715	8.628	11.822	8.511	7.427	2.995	3.827	11.825	7.862
	[0.40]	[0.80]	[1.06]	[1.00]	[1.43]	[2.67]	[3.26]	[2.65]	[2.09]	[3.23]	[2.53]
CVW	5.471	8.293	9.265	10.050	12.367	6.896	6.304	4.278	3.173	7.697	6.933
	[0.61]	[0.92]	[1.03]	[1.10]	[1.36]	[4.59]	[4.64]	[4.39]	[2.84]	[4.54]	[4.61]

alphas, with t-statistics less than 1.32. These results suggest that the buying pressure pushes up the price of the high-*RLOCAL* stocks.

B. Double Sorts

To rule out potential confounding effects, we conduct a series of characteristic-adjusted portfolio sorts, controlling for size, beta, book-to-market ratio, past 12- to 2-month return, past 36- to 13-month return, illiquidity, turnover, idiosyncratic volatility, max return, skewness, and the stock exchange on which the stocks are listed. Specifically, taking size as an example, we first sort all stocks into five quintiles based on the firm's market capitalization. Then, within each quintile, we divide stocks into five groups based on *RLOCAL*. Finally, we collapse across the size groups. In this way we obtain five size-adjusted *RLOCAL* portfolios, with each portfolio containing stocks that have a similar level of market capitalization.

Table VI reports equal- and value-weighted returns for each of the characteristic-adjusted hedge portfolio returns (P5-P1), as well as risk-adjusted returns using various benchmarks. The magnitude and statistical significance of return spreads become slightly smaller, but they are mostly comparable to single-sorted results. This suggests that the return predictability of *RLOCAL* that we document is unlikely to be explained by known return predictors.

C. Fama-MacBeth Regressions

To simultaneously control for various confounding factors, we conduct Fama and MacBeth (1973) regressions of returns over the next week on *LOCAL* and the same set of stock characteristics as in Section IV.B. We additionally include a set of dummy variables indicating firm age and firm industry to carefully control for potential non-linear relations between these variables and future returns. The results are reported in Table VII.

We see that in the regression with both age and industry dummy variables, *LOCAL* significantly positively predicts future one-week returns. The coefficient of 0.611% suggests that a one-percentage-point increase in neighboring stocks' returns over the past two weeks would lead to a 0.006% increase in the focal stock's future one-week return, or 0.32% annualized. When controlling for the full set of control variables, the coefficient on *LOCAL* decreases to 0.38%, with a t-statistic of 2.23.

The coefficient estimates on the control variables are mostly in line with previous studies. The only exception is that the max daily return (Bali, Cakici, and Whitelaw (2011)) is positively associated with future returns, opposite to the findings in the original study. The difference may be due to a short forecasting horizon in our specification. Overall, the Fama-MacBeth regression results further confirm the return predictability of the *LOCAL* variable.

Although we have controlled for the age and industry dummies in our Fama-MacBeth regression, it remains possible that neighboring firms share a latent

Table VI
Double-Sorted Portfolio Return by *RLOCAL* and Confounding Factors

This table reports double-sorted portfolio results based on *RLOCAL* and various control variables, including beta, firm size (*logME*), book-to-market ratio (*logBM*), illiquidity (*ILLIQ*), turnover, idiosyncratic volatility (*IVOL*), max return (*Max*), return skewness (*Skew*), past returns over different horizons, and the stock's listing board. At the end of each week, for each control variable we sort stocks into five quintiles based on this variable, within each quintile, we divide stocks into five groups based on *RLOCAL* and we collapse across the groups based on the control variable. We report the long-short portfolio return (P5-P1) as well as a battery of risk-adjusted returns using different benchmarks: age-adjusted return (*Age-adj Ret*), industry-adjusted return (*Ind-adj Ret*), DGTW characteristic-adjusted return (*DGTW Ret*), four-factor alpha (*CH4 Alpha*), and five-factor alpha (*FF5 Alpha*). All returns and alphas are annualized and reported in percentage points. t-Statistics, shown in brackets, are based on standard errors with Newey-West adjustments of 12 lags.

	LogME		Beta		LogBM		$Ret_{-12m,\,-2m}$		$Ret_{-36m,\,-13m}$		ILLIQ
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW
P5-P1	6.312	5.908	7.877	6.806	6.871	5.649	7.878	7.915	7.148	7.146	6.007
	[4.96]	[4.30]	[5.54]	[2.89]	[5.35]	[2.26]	[5.61]	[3.16]	[5.11]	[2.88]	[4.58]
Age-adj Ret	5.698	5.506	7.080	6.244	6.181	5.046	7.221	7.328	6.515	6.307	5.422
	[4.95]	[4.62]	[5.51]	[3.37]	[5.24]	[2.60]	[5.74]	[3.85]	[4.99]	[3.24]	[4.55]
Ind-adj Ret	4.516	3.861	5.557	2.852	5.169	2.735	5.598	3.962	5.310	3.289	4.193
	[4.59]	[3.97]	[5.38]	[2.61]	[5.36]	[2.33]	[5.67]	[3.89]	[5.29]	[2.94]	[4.36]
DGTW Ret	4.241	4.220	4.379	3.183	4.074	2.246	4.183	3.703	3.916	3.780	3.730
	[3.83]	[3.63]	[4.14]	[2.13]	[4.02]	[1.35]	[4.11]	[2.56]	[3.83]	[2.39]	[3.50]
CH4 Alpha	6.857	6.728	8.739	8.032	7.478	7.864	8.512	9.762	7.825	8.703	6.839
	[4.78]	[4.25]	[5.52]	[3.05]	[5.35]	[2.86]	[5.72]	[3.48]	[5.21]	[3.08]	[4.63]
FF5 Alpha	6.328	5.882	7.791	6.422	6.814	4.901	7.743	7.193	6.976	6.202	5.956
	[5.05]	[4.33]	[5.42]	[2.73]	[5.37]	[1.99]	[5.68]	[3.08]	[5.26]	[2.60]	[4.53]

	ILLIQ	Turnover		IVOL		Max		Skew		Board	
	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
P5-P1	5.660	7.481	7.516	8.031	8.477	7.459	8.270	7.681	8.733	4.810	3.727
	[3.79]	[5.67]	[3.42]	[5.53]	[3.30]	[5.30]	[3.18]	[5.50]	[3.56]	[5.08]	[2.24]
Age-adj Ret	4.954	6.767	6.775	7.165	7.331	6.683	7.319	7.021	7.756	5.363	4.357
	[3.89]	[5.53]	[3.76]	[5.51]	[3.73]	[5.28]	[3.70]	[5.52]	[4.13]	[5.10]	[2.99]
Ind-adj Ret	3.438	5.400	3.570	5.739	3.594	5.110	3.076	5.525	3.628	3.704	1.288
	[3.70]	[5.58]	[3.17]	[5.51]	[3.01]	[5.10]	[2.53]	[5.49]	[3.43]	[4.41]	[1.08]
DGTW Ret	3.003	4.307	3.639	4.195	3.583	3.874	3.741	4.018	3.633	3.615	2.180
	[2.62]	[4.16]	[2.44]	[3.84]	[2.29]	[3.68]	[2.23]	[3.93]	[2.51]	[2.45]	[1.15]
CH4 Alpha	6.216	7.953	8.084	8.958	10.286	8.384	10.337	8.629	10.205	3.004	1.420
	[3.65]	[5.82]	[3.27]	[5.72]	[3.56]	[5.49]	[3.54]	[5.70]	[3.81]	[3.03]	[0.78]
FF5 Alpha	5.508	7.411	6.695	7.891	8.197	7.344	7.931	7.664	7.912	4.879	3.025
	[3.63]	[5.79]	[3.30]	[5.57]	[3.26]	[5.34]	[3.05]	[5.53]	[3.40]	[5.04]	[1.78]

Table VII
Fama-MacBeth Regressions

This table reports Fama-MacBeth regression results where the dependent variable is the future one-week stock return (in percentage). The main independent variable of interest, *LOCAL*, is calculated as the value-weighted average return over the past two weeks of the 10 stocks that are closest in listing code to the focal stock. We also control for various stock characteristics, including beta, firm size (*logME*), book-to-market ratio (*logBM*), illiquidity (*ILLIQ*), turnover, idiosyncratic volatility (*IVOL*), max return (*Max*), return skewness (*Skew*), past returns over different horizons, and a number of dummy variables indicating the industry and listed year. All of the independent variables except those related to returns are winsorized each week at the 1% and 99% levels. *t*-Statistics, shown in brackets, are based on standard errors with Newey-West adjustments of 12 lags.

	[1]	[2]	[3]	[4]	[5]	[6]
LOCAL	0.823	0.667	0.801	0.422	0.611	0.380
	[3.90]	[3.55]	[3.71]	[2.30]	[3.43]	[2.23]
Ret_{-2w}		−2.889		−2.587		−2.939
		[-10.04]		[-8.50]		[-10.05]
LogME		−0.055		−0.052		−0.058
		[−1.55]		[−1.37]		[−1.61]
Beta		0.052		0.061		0.059
		[1.22]		[1.13]		[1.39]
LogBM		0.036		0.019		0.033
		[1.51]		[0.66]		[1.40]
$Ret_{-12m,-2m}$		0.149		0.167		0.145
		[1.95]		[2.05]		[1.89]
$Ret_{-36m,-13m}$		−0.023		−0.027		−0.025
		[−0.72]		[−0.84]		[−0.86]
ILLIQ		4.194		4.015		3.991
		[5.59]		[5.21]		[5.36]
Turnover		-8.183		-7.924		-8.613
		[−5.90]		[−5.65]		[-6.34]
IVOL		-26.228		-25.993		-25.513
		[-13.35]		[-12.80]		[-12.87]
Max		5.259		5.893		5.118
		[7.18]		[6.10]		[7.03]
Skew		−0.002		0.005		−0.000
		[−0.04]		[0.12]		[−0.01]
Ind FE	Yes	Yes	No	No	Yes	Yes
Age FE	No	No	Yes	Yes	Yes	Yes
Avg. weekly obs.	1,616	1,566	1,616	1,566	1,616	1,566
Adj-R^2	0.071	0.141	0.012	0.100	0.076	0.145
#. of weeks	864	864	864	864	864	864

common fundamental factor as in Grieser, Lee, and Zekhnini (2020), leading to return predictability. Specifically, firms with neighboring codes may share similar fundamentals due to their potentially similar listing time. For a firm return for the focal firm. However, this inattention-to-fundamental channel is an underreaction effect, while our proposed attention spillover channel is based on continued overreaction. Our results in Section IV.H.2 show that the high returns of high-*LOCAL* firms are temporary and revert in the long run, indicating that the return pattern we document is likely driven by continued overreaction. In addition, the underreaction channel also typically implies that *LOCAL* should be able to predict subsequent analyst forecast errors or announcement returns. In Internet Appendix Table IA.XVI, we find that there is no such predictive ability. We discuss this potential alternative channel more in Section IV.H.1 below.

D. Tests on Key Mechanisms

We conjecture that the return predictability of *LOCAL* originates from the interaction of two channels: a positive feedback channel in which investors tend to increase their positions after a positive investment outcome, and an attention spillover channel in which investors are likely to pay more attention to stocks that are adjacent to their winning stocks. In this subsection we conduct several placebo tests that turn off each of the key channels one at a time. These tests help shed light on the mechanisms driving the return predictability that we document.

First, to examine the attention spillover channel, we reconstruct *LOCAL* by replacing the past return of *immediate adjacent* stocks with that of *distant* stocks. Specifically, for each focal stock, we skip the 100 stocks with the closest listing codes and construct the placebo variable using the returns of the next 10 stocks.

Panel A of Table VIII reports results of Fama-MacBeth regressions of the future one-week return on the placebo variable. We include the true *LOCAL* variable in columns (2) and (4) and additionally control for other stock characteristics in columns (3) and (4). In all specifications, the placebo variable has no association with the future return, while the coefficient on *LOCAL* remains positive and significant—its magnitude and significance are similar to the results in tha14JE0688BT0Tc1.2006(61g991(a)2d6672.5(seral)60431uture)612378.145686672nde

Table VIII

Fama-MacBeth Regressions: Placebo Tests

This table reports results of Fama-MacBeth regressions in which the dependent variable is the future one-week stock return (in percentage). The main independent variable of interest, *LOCAL*, is the value-weighted average return over the past two weeks of the 10 stocks that are closest in listing code to the focal stock. To examine the mechanism, we change this specification and construct three placebo variables. First, we skip the 100 stocks with the closest listing codes and construct the placebo variable using returns of the next 10 stocks. Second, we replace returns of neighboring stocks with the turnover of these stocks over the past two weeks. The third construction uses return volatility of neighboring stocks instead of returns. The regression results using these three placebo variables are reported in Panels A, B, and C, respectively. We also control for a number of stock characteristics, including beta, firm size (*logME*), book-to-market ratio (*logBM*), illiquidity (*ILLIQ*), turnover, idiosyncratic volatility (*IVOL*), max return (*Max*), return skewness (*Skew*), past returns over different horizons, and dummy variables indicating industry and listed year. All of the independent variables except those related to returns are winsorized each week at the 1% and 99% levels. t-Statistics, shown in brackets, are based on standard errors with Newey-West adjustments of 12 lags.

	Panel A: Placebo–Gap100				Panel B: Placebo–Turnover				Panel C: Placebo–TVOL			
Placebo	0.068	0.057	0.051	0.051	0.108	0.031	0.036	0.005	3.572	2.456	2.599	1.865
	[0.39]	[0.33]	[0.31]	[0.31]	[1.05]	[0.31]	[0.39]	[0.06]	[2.19]	[1.57]	[1.96]	[1.47]
LOCAL		0.585		0.353		0.584		0.376		0.570		0.397
		[3.36]		[2.10]		[3.32]		[2.18]		[3.24]		[2.28]
Controls	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. weekly obs.	1,616	1,616	1,566	1,566	1,616	1,616	1,566	1,566	1,593	1,593	1,545	1,545
Adj.R^2	0.076	0.077	0.145	0.145	0.077	0.077	0.145	0.145	0.077	0.077	0.145	0.146
# of weeks	864	864	864	864	864	864	864	864	864	864	864	864

the true *LOCAL* variable in columns (2) and (4) and add control variables in columns (3) and (4). We again find that the placebo variables are not associated with future returns, and the coefficient on *LOCAL* remains largely unchanged.

These placebo tests also help rule out the alternative explanation that investors may trade neighboring stocks by mistake. Rashes (2001) finds that the comovement is excessively high for stock pairs with similar ticker symbols, possibly due to confused investors trading in error. One might be concerned that confused investors may have one stock in mind but trade a neighboring stock instead by mistake, leading to the return pattern we find. Note that this trading-by-mistake story does not rely on the asymmetry between positive and negative previous investment experience, and therefore neighboring stocks' turnover and volatility, rather than their returns, should be stronger predictors for the price impact because they better capture investors' trading propensity and do not distinguish the sign of the return. However, our placebo tests show that neighboring stocks' turnover has little return predictability for the focal stock, contradicting this prediction.

E. Forecasting Turnover

The interaction between investors' positive feedback trading and attention spillover has predictions not only for future return patterns, but also for trading volume and order imbalance—neighboring stocks' past returns should positively predict the focal stock's turnover, with this increase driven mainly by buying pressure. In this subsection, we examine these testable predictions.

Table IX reports the average daily turnover, abnormal turnover, and order imbalance of small investors (focusing on trades with size smaller than 50,000 yuan to better capture retail trading) in the next week for the five portfolios sorted based on *RLOCAL* at the end of last week. Abnormal turnover is calculated as the difference between weekly turnover and average turnover over the previous 52 weeks. Using TAQ data from China Stock Market & Accounting Research Database (CSMAR), we calculate the order imbalance of small investors each day as the difference between buyer-initiated small trades and seller-initiated small trades, normalized by total daily trades. We then obtain the weekly number by taking the average over the week.

We see that higher *RLOCAL* is indeed associated with both higher turnover and higher abnormal turnover over the next week. The difference between P5 and P1 is 0.076% (t-statistic = 2.83) and 0.101% (t-statistic = 2.64) for equal- and value-weighted turnover, respectively, and the difference is 0.048% (t-statistic = 4.09) and 0.058% (t-statistic = 4.33) for equal- and value-weighted abnormal turnover, respectively.[19] Moreover, *RLOCAL* is positively associated with order imbalance over the next week. With the capped-value-weighting

[19] The value for abnormal turnover is consistently negative because there is a negative time trend in this period due to conversion of nontradable shares into tradable shares. Our results are robust to alternatively constructing the turnover variable using total shares outstanding (instead of total tradable shares) in the denominator.

Table IX

Forecasting Turnover by *RLOCAL*

This table reports the average daily turnover and order imbalance over the next week for single-sorted portfolios based on *RLOCAL*. At the end of order imbalance as an example, the difference between P5 and P1 is 0.038% (t-statistic = 2.56), or 0.19% in the weekly terms. This result suggests that the increased turnover is driven mostly by buying pressure from small trades, consistent with our conjecture. We also conduct Fama-MacBeth regressions and find that *LOCAL* significantly positively predicts future turnover, after controlling for a number of variables known to be related to turnover (following Chordia, Huh, and Subrahmanyam (2007)). The results are reported in Internet Appendix Table IA.XV. Overall, the evidence on turnover predictability provides further support for our conjecture.

F. Comovement for Adjacent versus Distant Stocks

The attention spillover effect has a natural implication for stock comovement: since stocks that are closer in listing code terms are more likely to be traded together, their correlation in returns and turnover should be higher. We now examine pairwise correlation between stocks as a function of their listing code "distance."

Figure 4, Panels A and B show the average pairwise correlation in market-adjusted returns and turnover between the focal stock and stocks at various distances. S1 indicates an equal-weighted portfolio consisting of the closest 10 stocks in terms of listing codes, S2 indicates the second closest 10 stocks, and so on. We see a clear pattern whereby both return comovement and turnover comovement decrease as stocks become more distant. The correlation in returns (turnover) between a stock and its closest 10 neighbors (S1) is 0.297 (0.282), while the correlation with the 41st to 50th closest stocks (S5) is 0.286 (0.247); the difference (S5-S1) of 0.011 (0.035) is statistically significant with a t-statistic of 3.43 (4.63).

Figure 4, Panels C to H show the correlation of accounting variables between stocks with different distances, including debt-to-asset ratio, current ratio, cost-to-income ratio, return on equity, asset turnover ratio, and inventory turnover ratio. No clear pattern emerges in the correlation of these fundamental variables as distance becomes larger, and none of these differences in correlation calculated using S1 versus S5 (S1-S5) is significant. These results suggest that the comovement in returns and turnover is likely driven by trading induced by attention spillover, rather than by commonality in fundamentals.

G. A Quasi-Natural Experiment

Thus, our identification strategy has relied on the assumption that the order of listing codes has no relation to stock characteristics except for the IPO date (which we confirm in the data), and we explicitly adjust returns and turnover for firm age and industry benchmarks. However, concerns may remain about potential unobservable characteristics or unknown functional forms through which these characteristics may relate to listing codes and stock returns. To

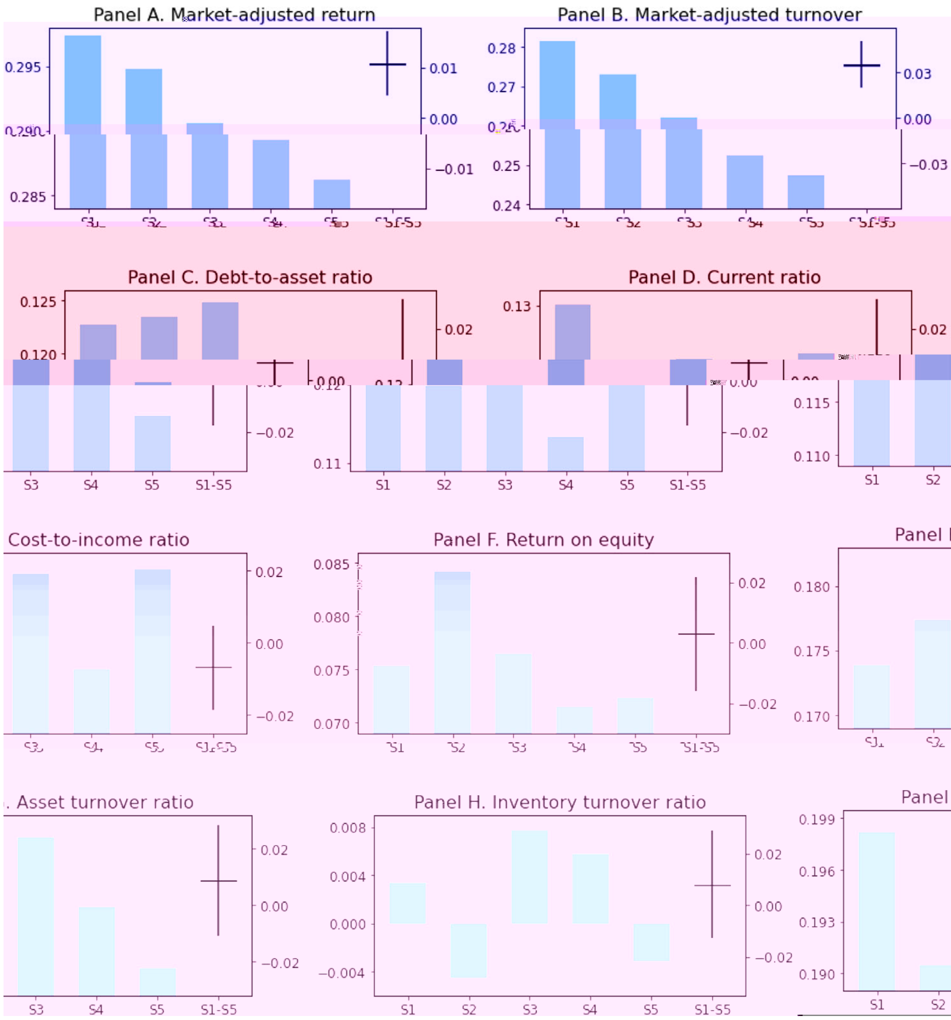

Figure 4. Comovement in return and turnover and distance between stocks. This figure shows the average pairwise correlation in returns, turnover, and various accounting variables between the focal stock and stock portfolios constructed by distance from the focal stock. The variables of interest include market-adjusted return (stock return minus market return), market-adjusted turnover (stock turnover minus market turnover), debt-to-asset ratio, current ratio, cost-to-income ratio, return on equity, asset turnover ratio, and inventory turnover ratio. For each stock, we calculate the Spearman-rank correlation between the focal stock and equal-weighted portfolios that consist of 10 stocks in different locations: S1 refers to the closest 10 stocks around the focal stock, S2 refers to the next closest 10 stocks, and so on. The figure shows the cross-sectional average for corresponding correlations, as well as the difference between S1 and S5 and its 95% confidence interval (based on Newey-West adjustments of 60 lags). (Color figure can be viewed at wileyonlinelibrary.com)

further sharpen our identification, we exploit a quasi-natural experiment that exogenously changes the screen display for a group of affected stocks.

In particular, we exploit the introduction of the SME Board in May 2004. Before this introduction, only two listing boards exist for Chinese A shares: the Shenzhen Main Board (in which stocks' listing codes start with 000) and the Shanghai Main Board (in which stocks' listing codes start with 600). When ranked in the order of listing code, the last stocks in Shenzhen (000s) are displayed immediately before the first stocks in Shanghai (600s). Soon after the introduction of the SME Board, a first wave of 38 stocks were listed on this new board from June to September 2004. SME stocks have listing codes that start with 002, and thus they are ranked between stocks that have listing codes starting with 000 and 600. For our purposes, the newly listed SME stocks exogenously separate the screen display of the last "000" stocks and the first "600" stocks. We therefore expect the correlation in return and turnover between these two subsets of stocks to decrease.

Taking advantage of this event, we examine the change in correlation using a difference-in-difference approach. Specifically, we label the last 20 stocks in the Main Board as group, and the 20ks inthe
Shanghai Main Board 600A group. For control purposes, we also look at the second-last 20 stocks in the Shenzhen Board (labeled 000Y) and the 21st to 40th stocks in the Shanghai Board (labeled 600B), for which relative

the average pairwise correlation betweenks inthe 000Z groups
in March to May (before) in October to December (after), and we compare their difference to change in correlation between 000Y 000Z and that between and 600B

Table X reports the difference-in-difference results. Relative to the change in correlation between the unaffected Shenzhen groups (000Z the

0.08(t-statistic = 6.09) in returns 0.10 (t-statistic 4.77) in turnover The corresponding numbers benchmarked to the unaffected Shanghai groups (600A 600B) are 0.03 (-statistic = 2.55) in returns and 0.05 (t-statistic = 2.03) in turnover This evidence suggests that the exogenous increase in distance does indeed lead to lower comovement in returns and turnover

H. Additional Results and Robustness Checks

H.1. The Pre-2002 Sample Period as a Placebo Test

nism. In the pre-2002 period, the two most popular stock trading platforms in China are still unavailable. Thus, if our mechanism is responsible for the predictive power of *RLOCAL*, there should be no such *RLOCAL*
spread. This is indeed case as reported in Table XI
ability of *RLOCAL* were due to other forces such as fundamental correlations between neighboring firms, then the portfolio return spreads should be

Table X

Comovement in Return and Turnover: Difference-in-Difference (DID) Approach

This table reports the return and turnover correlations between treatment stocks and control stocks before and after the introduction of the SME Board in May 2004. Panel A reports results on return correlations, and Panel B reports results on turnover correlations. The before period is March to May, while the after period is October to December. 000Z and 000Y indicate the last 20 stocks and the second-last 20 stocks listed on the Shenzhen Main Board (where listing codes start with 000), respectively, while 600A and 600B refer to the first 20 stocks and the 20th to 40th stocks listed on the Shanghai Main Board (where listing codes start with 600). Our sample includes stocks that have at least 15 observations in both before and after periods. $\rho(000\mathbf{Y}, 000\mathbf{Z})$ is the average pairwise Spearman-rank correlation of daily returns or turnover between stocks in the 000Y group and stocks in the 000Z group; likewise for other groups. "Diff" denotes the difference between stock groups or time periods. t-Statistics are shown in brackets.

Panel A. DID tests on return correlation

	$\rho(000Y, 000Z)$	$\rho(000Z, 600A)$	Diff	$\rho(000Z, 600A)$	$\rho(600A, 600B)$	Diff
Before	0.415	0.382	−0.033	0.382	0.384	0.002
	[55.62]	[60.85]	[−3.35]	[60.85]	[62.26]	[0.24]
After	0.415	0.302	−0.113	0.302	0.333	0.032
	[53.87]	[36.64]	[−9.59]	[36.64]	[43.90]	[2.85]
Diff	0.000	−0.080	−0.080	−0.080	−0.051	0.030
	[−−					

Table XI

Performance of *RLOCAL* Portfolio in Pre-2002 Period

This table reports results of a single sort on *RLOCAL* from 1996 to 2001. We start the sample in 1996 to ensure that each portfolio has at least 30 stocks. For each stock, *LOCAL* is the value-weighted average return over the past two weeks of the 10 closest stocks on the screen display, and *RLOCAL* is the residual of the cross-sectional regression of *LOCAL* on the focal stock's return over the past two weeks. Raw and adjusted returns of hedge portfolios are reported. All returns and alphas are annualized and reported in percentage points. *t*-Statistics, shown in brackets, are based on standard errors with Newey-West adjustments of 12 lags.

	P1	P2	P3	P4	P5	P5-P1	Age-adj Ret	Ind-adj Ret	DGTW Ret	CH4 Alpha	FF5 Alpha
EW	28.659	29.977	28.186	30.088	30.799	2.140	2.159	0.938	−0.085	1.249	−0.075
	[2.19]	[2.15]	[2.01]	[2.21]	[2.12]	[0.42]	[0.44]	[0.20]	[−0.02]	[0.24]	[−0.02]
VW	24.560	25.347	24.704	27.708	24.837	0.276	−0.117	−0.023	0.032	0.115	-3.037
	[1.72]	[1.75]	[1.67]	[1.76]	[1.62]	[0.05]	[−0.03]	[−0.00]	[0.01]	[0.02]	[−0.63]
CVW	25.285	26.939	24.689	27.387	27.054	1.769	1.654	0.917	0.922	0.116	−0.664
	[1.86]	[1.90]	[1.73]	[1.94]	[1.77]	[0.32]	[0.32]	[0.18]	[0.24]	[0.02]	[−0.13]

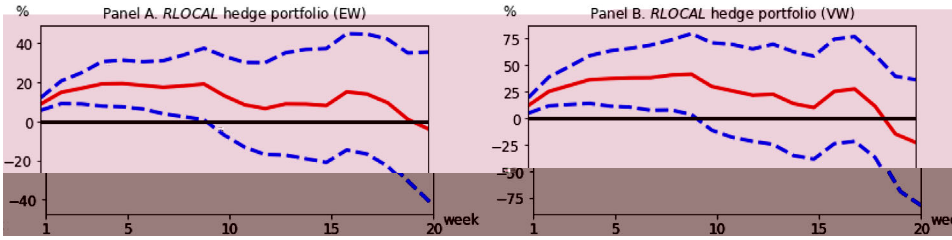

Figure 5. Cumulative return of the long-short portfolio based on *RLOCAL*. This figure shows the annualized cumulative CH4-alpha (in percentage points) to the equal- and value-weighted long-short portfolios (P5-P1) based on *RLOCAL* from week $t + 1$ to week $t + 20$, as well as the 95% confidence interval. For each stock, *LOCAL* is calculated as the value-weighted average return over the past two weeks of the 10 closest stocks on screen display, and *RLOCAL* is the residual of the cross-sectional regression of *LOCAL* on the focal stock's return over the past two weeks. Portfolios are formed at the end of week t based on *RLOCAL*. (Color figure can be viewed at wileyonlinelibrary.com)

Figure 5 plots the equal-weighted (Panel A) and value-weighted (Panel B) annualized cumulative CH4-alpha of the long-short portfolio (P5-P1) based on *RLOCAL* from week t to week t+20. We see that the CH4-alpha of the equal-weighted (value-weighted) hedge portfolio peaks at 19.4% (41.5%) in the 5th (9th) week but is completely reversed by the 10th (10th) week. This result suggests that the price impact is indeed temporary and unlikely to be explained by firm fundamentals.

H.3. The Moderating Effects of Cost of Arbitrage

We next examine how the return pattern we document varies with the cost of arbitrage. When costs of arbitrage are higher, we expect the return pattern to be stronger as the countervailing correction forces become weaker. Table XII reports returns of portfolios sorted by *RLOCAL* and three proxies for costs of arbitrage: market value (*LME*), Amihud illiquidity (*ILLIQ*), and analysts' coverage (*ALANA*). Specifically, at the end of each week, we first sort stocks into two groups based on the proxy for costs of arbitrage and then sort stocks into *RLOCAL* quintiles within each group. We find that the *RLOCAL* return spreads (P5-P1) are indeed higher, at 9.177%, 8.465%, and 12.795% among firms with smaller size, lower liquidity, and lower analyst coverage, respectively. In contrast, the return spreads are 5.737%, 5.824 %, and 5.654 % among the corresponding other halves of the sample.

V. Conclusion

Exploiting a unique display feature of common trading platforms in China, our paper levers a novel identification strategy and studies the asset pricing implications of the interaction between overconfidence and limited attention. We first investigate the microfoundation and show that investors do indeed

Table XII

engage in positive feedback trading and exhibit attention spillover. We then show that *LOCAL*, a variable constructed to capture the recent performance of neighboring stocks, can positively predict future returns and turnover for the focal stock. Additional analyses suggest that the return predictability we document relies crucially on the interaction between the two behavioral biases.

While identified by a unique setting in China, our findings have broader implications for understanding investor behaviors and how they affect asset pricing. For instance, the attention spillover effect that we document is broadly consistent with Charles (2021) who uses trading data from retail investors and mutual fund managers in the United States and shows that adjacent stocks listed in investors' monthly statements are more likely to be traded together in the future. This finding suggests that the economic insights we uncover using Chinese data can shed light on phenomea in other markets and broader settings.

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Appendix S1: Internet Appendix.
Replication Code.