Attention Spillover in Asset Pricing*

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First Draft: February 2020
This Draft: September 2020

* We thank Zhi Da and seminar participants at Tsinghua University PBCSF, Central University of Finance and Economics, University of International Business and Economics, Southwestern University of Finance and Economics, and China Financial Research Conference for helpful comments. All errors are our own.

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Abstract

Exploiting a screen display feature whereby the order of stock display is determined by the stock listing codes, we lever a novel identification strategy and study the impact of attention spillover on stock prices and turnover. We find that stocks with neighbors on the display that experience higher returns in the past two weeks are associated with higher returns and turnover in the future week, after adjusting for a battery of risk and characteristic benchmarks. This finding is consistent with our conjectures that investors (a) tend to trade more after positive investment experience, and (b) are more likely to pay attention to neighboring stocks. Both conjectures are confirmed using trading data. We further sharpen the identification using a quasi-natural experiment in which the screen display for affected stocks is exogenously changed.

JEL Classification: G11, G12, G41

Keywords: limited attention, overconfidence, attention spillover, price impact, return predictability

1. Introduction

Overconfidence and limited attention are two widely documented behavioral biases in the psychological literature, and asset pricing theories have extensively used both 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). However, it is empirically challenging to directly establish the *causal* effect of overconfidence and limited attention on prices and volume. Variables that boost investor overconfidence (e.g., past experienced returns) or attract or reflect investor attention (e.g., extreme past returns, trading volume, google search volume, news headlines) are typically also associated with fundamental information. With a few exceptions, ideal settings allowing researchers to identify pure variation in overconfidence and attention are hard to come by. In this paper, we exploit a novel setting to study the causal impact of these two behavior biases on equilibrium prices and volume.

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)). This insight has been confirmed empirically that investors tend to trade more intensively after positive investment experience, even if the positive experience comes from winning IPO lotteries purely by chance (Ben-David, Birru, and Prokopenya, 2018; Anagol, Balasubramaniam, and Ramadorai, 2020; Gao, Shi, and Zhao, 2019). Since individual investors rarely short stocks, the overtrading induced by positive past investment experience is likely to have a stronger effect on buying rather than selling decisions. That is, there is a *positive feedback channel* whereby investors tend to increase their positions after positive investment experience (Pearson, Yang, and Zhang, 2020).

In addition, trading requires investor attention, which is a scarce resource, especially when deciding which stock to buy from among thousands of choices (Barber and Odean, 2008). On the other hand, since individual investors typically hold only a few stocks, attention is not as constrained when deciding to sell, leading to *an asymmetric attention effect*. Overall, combining the attention effect and the positive feedback effect, after a positive trading experience, stocks that can attract investor attention tend to experience more buying pressure; given short-sale impediments, buying pressure would lead to higher subsequent short-term returns for these stocks.

To empirically test the above effect on asset prices, a main challenge is to identify the stocks that attract the attention of the investors who just had a positive investment experience. In this study, we exploit a screen display feature whereby the order of stock display is determined by the 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*. Thus, stocks with neighbors that experience higher returns in the past two weeks face more buying pressure from the owners of the neighboring stocks and should experience higher returns and turnover in the subsequent week. Consequently, we arrive at the following key hypothesis: A stock's short-term future return and turnover is positively associated with the past performance of stocks with listing codes close to the focal stock.

To test this hypothesis, we construct a LOCAL variable for each stock, computed as the value-weighted average return over the past two weeks of the 10 stocks with listing codes closest to the focal stock. We also compute an RLOCAL variable for each stock as the residual of the cross-sectional regression of LOCAL on the focal stock's own return in the past two weeks. This construction partly addresses the reflection problem (i.e., the focal stock's extreme return attracting attention to its neighboring stocks and then being reflected in the LOCAL variable) and alleviates the concern of short-term auto-correlation in returns when we examine return predictability of the focal stock.

We then form quintile portfolios based on the lagged RLOCAL variable, 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 8.048% (t-stat = 5.44) and 8.742% (t-stat = 2.75), respectively. These results remain significant after controlling for firm age effect; industry effect; DGTW characteristic-based adjustment (Daniel, Grinblatt, Titman, and Wermers, 1997); 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-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 inspect the underlying mechanism for our findings, we evaluate the importance of the attention spillover channel and the positive feedback channel separately. We conduct several placebo tests that turn off each of the two channels in turn. More specifically, to assess the role of attention spillover, we construct a placebo variable for the LOCAL variable by replacing the past return of the immediate adjacent stocks with returns of distant stocks and find the predictive ability of this placebo variable is no longer significant. This suggests that positive feedback investors cannot exert an asset pricing effect on 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 turnover and volatility of these stocks, respectively. These two proxies are likely to capture arrival of news and large price movements, and thus investor attention, but they do not necessarily relate to positive investment experience. We find that these placebo variables cannot forecast stock returns. These results suggest that the joint effect of positive feedback channel and the attention spillover channel drive our key findings on the return spread based on RLOCAL.

In addition, 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 would be higher. We find that the pairwise correlation between stocks decreases as the "distance" between their listing codes increases. In addition, as a placebo test, we find that the fundamental correlation does not present this pattern. To further sharpen our identification on investor attention, we exploit a quasi-natural experiment in which the screen display order for stocks is exogenously changed. We find that the correlation between stocks is indeed decreased after the distance of these stocks is exogenously increased by the introduction of the Small and Medium Enterprise (SME) Board in May 2004.

Our evidence so far suggests that the predictive ability of the LOCAL variable is more likely to stem from the attention spillover effect and positive feedback trading. Since these effects should be transitory, we also investigate the long-term holding period return for portfolios sorted on RLOCAL. Indeed, the cumulative return of RLOCAL hedged portfolio is positive in the short period, but it diminishes as time passes and vanishes in about 18 weeks, consistent with the temporary price pressure effect due to attention and positive feedback trading. In addition, as with other anomalies induced by behavioral bias, the return of the RLOCAL hedged portfolio is higher among stocks with higher arbitrage costs, measured by market capitalization, Amihud illiquidity, and the number of covering analysts. Third, as Stambaugh, Yu, and Yuan (2012) argue, the performance of a mispricing-driven anomaly should be more pronounced following high-sentiment periods relative to low-sentiment periods. Consistent with this argument, we find that the return of RLOCAL hedged portfolio is higher in high-sentiment periods, measured by close-end fund discount, turnover of stock market, IPO number, IPO return, number of newly participating investors, consumer confidence index, and the composite index.

Lastly, we use account-level trading data to study whether investor attention and overconfidence affect investor trading behavior in a way that is consistent with our hypothesis. We find that investors are more likely to purchase stocks after a positive investment experience than after a negative investment experience, consistent with overconfidence. Investors are also more likely to purchase stocks with listing codes adjacent to stocks that they already own, consistent with limited investor attention. In addition, the difference in purchase probability after positive and negative investment experiences also decreases according to the distance between the listing code of the newly purchased stocks and the currently owned stocks. Lastly, the above effects are more pronounced when the purchase of the currently owned stock is more recent, consistent with the notion that a recent positive experience leads to more overconfidence than a positive experience further in the past.

Our research is closely related to the literature of limited attention and overconfidence bias. In the limited attention literature, researchers have developed many proxies to measure attention, such as abnormal trading volume and extreme return (e.g., Barber and Odean, 2008; Hou, Peng, and Xiong, 2009; Corwin and Coughenour, 2008), Google search volume index (e.g., Da, Engelberg and Gao, 2011), Bloomberg search volume and readership (e.g., Ben-Rephael, Da, and Israelsen, 2017), media coverage (e.g., Huberman and Regev, 2001; Fang and Peress, 2009; Kaniel and Parham, 2017), account logins (e.g., Sicherman, Loewenstein, Seppi, and Utkus, 2016; Gargano and Rossi, 2018), advertising expenditure (e.g., Lou, 2014), price limits (e.g., Chen, Gao, He, Jiang, and Xiong, 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 the 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 overconfidence leads to more trading and more 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 in two key dimensions. First, we study the implications of the interaction between limited attention and overconfidence on asset pricing, while most previous studies study the implications of overconfidence and limited attention separately. Second, and more importantly, separating the asset pricing effect of attention from that of fundamental news is typically very difficult, since investors tend to pay more attention to the stock market 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 risks. Our unique setting provides a cleaner identification because the order of listing code is largely exogenous, as we show in detail in Sections 2.2 and 4.6.

The rest of the paper is organized as follows. Section 2 introduces the institutional details on the display feature of trading platforms in China. Section 3 introduces the data sample and the constructive methods of the key variable. Section 4 presents the supportive evidence for the impact that the attention spillover effect has on asset prices. Section 5 provides corroborating evidence from the investor trading behavior. Finally, section 6 concludes.

2. Institutional Background and Empirical Design

2.1 The Display Feature of Trading Platforms

In this paper, we study attention spillover, using a particular display feature of common trading platforms in China[1]: 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 therefore argue that these neighboring stocks are likely to receive investors' attention spilled over from the focal stock.

[1] Although each brokerage house provides its own version of trading software for its investors, these versions of software are mostly developed by two leading platform and data providers. Therefore, the design and display features are similar across software from different brokers.

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 stock, for example, GuiZhou MaoTai. The investor can search either by the acronym GZMT or by the listing code 600519. Typing in GZMT and pressing "enter" links to the main page of Guizhou Maotai (Figure 1(b)). Pressing "Page-Up" or "Page-Down" brings the investor to the main page of the stock with the previous listing code (i.e., 600518) or the next one (i.e., 600520) (Figure 1(c) and 1(d)). 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(e)). Alternatively, if the investor initially searches for the stock using its listing code, a drop-down menu shows a list of stocks around the focal listing code (Figure 1(f)). Overall, these display features, designed to present stocks in the order of listing codes, lead to adjacent stocks being more likely than distant stocks to catch investors' attention.

2.2 Determinants of Listing Codes

At the heart of our identification strategy, we rely 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 initial public offering (IPO), and it 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: Shanghai and Shenzhen main boards have no clear statement on how they assign the listing codes, while the SME Board and the ChiNext Board assign the codes based on listing dates.

Empirically, we examine the relation between listing codes and a battery list of stock characteristics, including listing date, firm size, industry, and headquarter location. As shown in Figure 2(a), listing codes for firms in the SME board and the

ChiNext board are almost entirely 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 shown in Figure 2(b)-2(d).

A potential concern is that firms may time the dates of their listing such that stocks with adjacent listing codes could share certain similarities in unobserved characteristics, thus creating an omitted variable problem. This is unlikely to be the case, 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, which usually takes several years to complete.[2] Therefore, firms typically apply as soon as they meet the requirements. Moreover, for our purpose, the *immediate* neighboring firms are likely to be randomly determined in this process.

3. Data and Variables

Our sample covers all Chinese A shares listed in Shanghai and Shenzhen stock exchanges from January 2002 through December 2018.[3] To avoid the impact of the smallest and most illiquid stocks, we exclude stocks with a price lower than 2 RMB, those that are traded less than 10 days (120 days) in the past 4 weeks (52 weeks), stocks that are listed less than two years, as well as the "special treatment" (ST) stocks.

3.1. Definition of the Key Variables

For each stock at the end of each week, we construct the variable 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 codes closest to the focal stock (5 above and 5 below). The neighboring

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

[3] Our sample starts from the year of 2002 because the two leading trading software providers, Da-Zhi-Hui and Tong-Hua-Shun, are established in the year of 2000 and 2001, respectively.

stocks are drawn from the full sample of A shares, without applying filters on price level and stock liquidity.

Additionally, we construct the RLOCAL variable as the residual of the cross-sectional regression of LOCAL on the focal stock's own return in 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 the LOCAL variable) and rules out short-term auto-correlation in returns when we examine return predictability of the focal stock.

3.2. Control Variables

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

In most of the tests on return predictability, we consider the following control variables. Market beta (*Beta*) is estimated using monthly returns in the past 36 months. Ret_{-2w} is the stock's own return in the past two weeks, $Ret_{-12m,-2m}$ is the past 12- to 2-month cumulative return, and $Ret_{-36m,-13m}$ measures the past three- to one-year cumulative return. These variables are designed to control for the short-term reversal (Jegadeesh, 1990), the momentum effect (Jegadeesh and Titman, 1993), and the long-term reversal (De Bondt and Thaler, 1985), respectively. A firm's age (*LogAge*) is the logarithm of the number of months since its IPO. A firm's size (*LogME*) is calculated as the logarithm of a firm's total market capitalization at the end of the week. Book-to-market ratio (*LogBM*) is the logarithm of the ratio of book value over market capitalization, following Fama and French (1992). The Amihud illiquidity measure (*ILLIQ*) is the average daily ratio of the absolute return over hundred-yuan trading volume in the past four weeks (Amihud, 2002). The idiosyncratic volatility (*IVOL*) is the volatility of daily return residuals with respect to the Fama-French three-factor model in the past four weeks (Ang, Hodrick, Xing, and Zhang, 2006). Following Bali, Cakici, and Whitelaw (2011), we define a stock's max return (*Max*) as the average of the three largest daily returns in the previous four weeks. *Skew* is the skewness of daily returns in the previous 52 weeks. And finally, a stock's turnover (*Turnover*) is calculated as the average number of daily turnovers over the past four weeks.

In our tests on turnover, we follow Chordia, Huh, and Subrahmanyam (2007) and consider the following set of 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 over total asset. 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 in 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 (EPS) forecasts issued by different security companies.

3.3. Summary Statistics

Table 1 reports the summary statistics. Panel A shows the equal-weighted average of stock characteristics for portfolios sorted by RLOCAL. In addition to the two LOCAL variables, other characteristics are mostly equally distributed across different quintiles.[4] Panel B reports the correlation matrix across LOCAL variables 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 facts suggest that our LOCAL variables, designed to take advantage of the quasi-random assignment of listing codes, indeed have little association with other stock characteristics.

[4] The only exception is turnover—stocks in the RLOCAL5 portfolio have a slightly higher turnover ratio over the past 4 weeks, which may reflect the concurrent impact of attention spillover.

4. Empirical 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-MacBeth (1973) regressions for better control of potential confounding factors. We then provide evidence on several placebo tests, designed to examine the role of two key ingredients—attention spillover and overconfidence—in generating price impacts. Additionally, we exploit a quasi-natural experiment that allows for sharper identification.

4.1. One-Way Sorts

In Table 2, we report the 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 in 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,[5] DGTW characteristics-adjusted returns, alphas of the four-factor model for the Chinese market (Li, Stambaugh, and Yuan, 2019), and alphas of the Fama-French five-factor model (Fama and French, 2015). We report equal-weighted and value-weighted returns, as well as portfolio returns, using a value-weighting scheme that excludes the largest 30 stocks from the sample. The last weighting scheme is to address the concern that a few giant firms may dominate the value-weighting results. All returns are annualized and reported as percentage points, and the t-statistics are computed based on standard errors with Newey-West (1987) adjustments of 12 lags.

[5] 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 make sure 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.

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, and the t-stats range from 2.75 to 5.44. After adjusting for various risk benchmarks, the return spread remains economically large and statistically significant. The adjusted return spread is around 4%–6% per year after adjusting for industry and DGTW characteristics, and it remains higher than 7% using the Chinese four-factor model, the Fama-French five-factor model, and the age benchmark. Compared across weighting schemes, the return spreads are similar in magnitude, while the t-stats are generally smaller when returns are value weighted (around 2 to 3) rather than equal weighted (around 4 to 5). After the 30 largest stocks are excluded from the sample and the value-weighted portfolio is constructed based on the remaining stocks, the t-stats for return differences are comparable to those under the equal weighting scheme.

From the alphas of the four-factor model for the Chinese market (Liu, Stambaugh, and Yuan, 2019), we find the strategy's excess return comes from the superior performance of the long leg portfolio (P5). For all the weighting schemes, the long leg has positive and significant CH4 alphas, with t-stats ranging from 4.91 to 8.11, while the short leg has insignificant CH4 alphas, with t-stats less than 1.34. This outcome suggests that the buying pressure pushes up the price of the high RLOCAL stocks.

4.2. 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 finally, the stock-exchange board on which the stocks are listed. Specifically, with size for instance, we first sort all stocks into five quintiles based on the firm's market capitalization; within each quintile, we then divide stocks into five groups based on RLOCAL; and finally, we collapse across the size groups. This way, we obtain five size-adjusted RLOCAL portfolios, and each portfolio contains stocks with a similar level of market capitalization.

Table 3 reports equal-weighted and value-weighted returns for each of the characteristic-adjusted portfolio returns, the hedge portfolio (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.

4.3 Fama-MacBeth Regressions

In order to simultaneously control for various confounding factors, we conduct Fama-MacBeth (1973) regressions of return in the next week on the LOCAL variable and the same set of stock characteristics as in Section 4.2. We additionally include a set of firm age dummy variables in all specifications to carefully control for a potential non-linear age effect. The results are reported in Table 4.

We see that in the univariate regression, LOCAL positively and significantly predicts the future one-week return. The coefficient of 0.008 suggests that a one-percentage-point increase in neighboring stocks' return in the past two weeks would lead to a 0.008% increase in the focal stock's future one-week return, or 0.42% annualized. After controlling for the whole set of control variables, the coefficient on LOCAL is reduced to 0.004, with a t-stat equal to 2.26.

The coefficient estimations for 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. This outcome may be due to a short forecasting horizon in our specification. Overall, the Fama-MacBeth regression results further confirm the return predictability of LOCAL variables.

4.4. Tests on Key Mechanisms

We conjecture that the return predictability of LOCAL variables originates from the interaction of two channels: a positive feedback channel in which investors tend to increase their positions after positive investment experience, and an attention spillover channel in which investors are more likely to pay 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 by one. These exercises help shed light on the mechanisms of the return predictability we document.

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

The left panel of Table 5 shows the 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 for LOCAL remains positive and significant—its magnitude and significance are similar to the results in Table 4. This evidence suggests that the past performance of distant stocks does not affect investors' trading and thus the future return of the focal stock, possibly because it is too distant to be noticed.

Secondly, we investigate the positive feedback channel. Imagine a case of a negative investment experience—an investor may have noticed the stocks displayed next to the stock that he or she already owns, but if the investor hesitates to expand his or her positions due to a negative experience on the owned stock, the attention per se is not likely to generate an impact on trading and price for the neighboring stocks. To shut down the positive feedback channel, we construct two placebo variables for LOCAL by replacing the *return* of neighboring stocks with *turnover* and *volatility* of these stocks, respectively. These two proxies are likely to capture arrival of news and large price movements, but they do not necessarily relate to positive investment experience.

The middle and right panels of Table 5 report the Fama-MacBeth regression results for these two placebo tests. Similar to the specifications in the left panel, we include the true LOCAL variable in columns (2) and (4) and add control variables in columns (3) and (4). Again, we see the placebo variables are not associated with the future return, and the coefficient for LOCAL remains largely unchanged.

These placebo tests also help to 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. By a similar logic, one might be concerned that confused investors may have one stock in mind but trade a neighboring stock instead by mistake, therefore generating the return pattern we find. If this is true, neighboring stocks' turnover, rather than their returns, should be a stronger predictor for the price impact because it would better capture investors' trading propensity. However, our placebo tests show that the neighboring stocks' turnover has little return predictability for the focal stock, contradicting this prediction.

4.5. Forecasting Turnover

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

Table 6 reports turnover, abnormal turnover, and order imbalance 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 the average turnover in the previous 52 weeks. Using TAQ data from RESSET, we calculate order imbalance as the difference between buyer-initiated trades and seller-initiated trades (measured either in the number of trades or in yuan volume), normalized by the sum of the two in each week.

We see that higher RLOCAL is indeed associated with both higher turnover and abnormal turnover in the next week. The difference between P5 and P1 is 0.371% (t-stat = 2.95) and 0.495% (t-stat = 2.70) for equal-weighted and value-weighted turnover, respectively, and the difference is 0.221% (t-stat = 3.89) and 0.294% (t-stat = 4.36) when measured in equal-weighted and value-weighted abnormal turnover, respectively.[6] Moreover, RLOCAL is positively associated with order imbalance in the next week. With the value-weighted order imbalance as an example, the differences between P5 and P1 are 0.385% (t-stat = 2.19) and 0.392% (t-stat = 2.25) for measures based on the number of trades and yuan volume, respectively. This outcome suggests that the increased turnover is mostly driven by buying pressure, consistent with our conjecture. We also conduct Fama-MacBeth regressions and find that LOCAL positively and significantly predicts future turnover, after controlling for a battery of variables known to be related to turnover (following Chordia, Huh, and Subrahmanyam, 2007). These results are reported in the Appendix. Overall, the evidence on turnover predictability provides further support to our conjecture.

4.6. Comovement for Adjacent vs. Distant Stocks

The attention spillover effect has a natural implication for stock 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. We now examine pairwise correlation between stocks as a function of their listing code "distance."

[6] The value for abnormal turnover is all negative because there is a negative time trend in this period due to conversion of non-tradable shares into tradable shares. Our results are robust to alternative construction of the turnover variable using total shares outstanding (instead of total tradable shares) as the denominator.

Figure 3(a) and 3(b) plot 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 the closest 10 stocks measured in listing codes, S2 indicates the second closest 10 stocks, and so on. We see a clear pattern that both return comovement and turnover comovement decrease as the stocks become more distant. The correlation in returns (turnover) between a stock and its closest 10 neighbors (S1) is 0.297 (0.282), and the correlation with the 41st to 50th closest stocks (S5) decreases to 0.286 (0.247); the difference (S5-S1) of 0.011 (0.035) is statistically significant with a t-stat equal to 3.43 (4.63).

Figure 3(c) to 3(h) plot the correlation of accounting variables between stocks with difference distances, including debt-to-asset ratio, current ratio, cost-to-income ratio, return on equity ratio, asset turnover ratio, and inventory turnover ratio. In contrast, no clear pattern emerges in the correlation of these fundamental variables as the distance becomes larger, and none of these differences in correlation calculated using S1 versus S5 (S1-S5) are significant. This suggests that the comovement in returns and turnover is likely to be driven by trading induced by attention spillover, rather than commonality in fundamentals.

4.7 A Quasi-Natural Experiment

So far, 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 benchmarks. However, concerns may remain about unobservable characteristics or unknown functional forms in which these characteristics might potentially relate to listing codes and stock returns. To further sharpen our identification, we exploit a quasi-natural experiment that exogenously changes the screen display for a group of affected stocks.

Particularly, 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 they are thus ranked between stocks that have listing codes starting with 000 and 600. For our purpose, the block of newly listed SME stocks exogenously separates 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 blocks of stocks would decrease.

Taking advantage of this event, we employ a difference-in-difference approach to examine the change in correlation. Specifically, we label the last 20 stocks in the Shenzhen Main Board as the 000Z group, and the first 20 stocks in Shanghai Main Board the 600A group. For control purposes, we also look at the second last 20 stocks in Shenzhen (labeled as 000Y) and the 21st to 40th stocks in Shanghai (labeled as 600B), for which the relative location was not affected by the introduction of the SME Board. We calculate the average pairwise correlation between stocks in the 000Z and 600A groups in March to May (before) and in October to December (after), and we compare their difference to the change in correlation between 000Y and 000Z and that between 600A and 600B.

Table 7 shows this difference-in-difference results. Relative to the change in correlation between the unaffected Shenzhen groups 000Z and 000Y, the correlation between the two affected groups 000Z and 600A drops more, by 0.08 ($t = 6.09$) in returns and 0.10 ($t = 4.77$) in turnover. The corresponding numbers benchmarked to the unaffected Shanghai groups 600A and 600B are 0.03 ($t = 2.55$) in returns and 0.05 ($t = 2.03$) in turnover. This evidence suggests that the exogenous increase in distance indeed leads to lower comovement in returns and turnover.

4.8 Additional Results and Robustness Checks

4.8.1 The long-run return of the RLOCAL hedge portfolio

If the higher return in the next week predicted by higher RLOCAL variable is indeed coming from attention spillover, the price impact should be temporary and revert in the long run.

Figure 4 plots the equal-weighted (in the upper panel) and value-weighted (in the lower panel) 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, and is completely reversed by the 10th (10th) week. This outcome suggests that the price impact is indeed temporary and unlikely to be explained by firms' fundamentals.

4.8.2 The moderating effects of cost of arbitrage and investor sentiment

We then examine how the return pattern we document varies with the cost of arbitrage and investor sentiment. When costs of arbitrage or investor sentiment are higher, we expect the return pattern to be stronger as correction of such mispricing becomes more difficult. Table 8 Panel A 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. Indeed, the RLOCAL return spreads (P5-P1) are higher, at 9.207%, 8.488%, and 12.817% among firms with smaller size, lower liquidity, and fewer analysts' coverage, respectively. In contrast, the return spreads are 5.976%, 6.089%, and 6.022% among the corresponding other half of the sample.

Panel B reports the return of RLOCAL strategy in high versus low sentiment periods. Following Yi and Mao (2009), we employ seven proxies in the Chinese market to measure investor sentiment, including the consumer confidence index (CCI), the discount rate of close-end fund (DCEF), the number of initial public offerings (IPON), the return of initial public offerings (IPOR), the number of new investors (NIA), the turnover of stock market (MTURN), and finally, a composite indicator for all the six variables (CICSI). Consistent with our conjecture, the return pattern is indeed stronger in high-sentiment periods across all sentiment proxies.

5. The Micro-Foundation: Investor Trading Behavior

The previous sections document return predictability and turnover patterns that we hypothesized to be driven by positive feedback trading and attention spillover. In this section, we provide further evidence on the micro-foundation. Using brokerage account data, we investigate whether investors' trading behaviors are consistent with the stock-level evidence.

Our data come from a retail brokerage firm in China and contain daily trading and holding records of roughly 430,000 investors from January 2009 to September 2012. This dataset has a similar structure as the Odean dataset in the United States (Odean, 1998), as well as several Chinese brokerage account datasets used in previous studies (e.g., Feng and Seasholes, 2004, 2005; Frydman and Wang, 2020; An, Engelberg, Henriksson, Wang, and Williams, 2020).

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) stock on that day.[7][8] Similar to the metrics constructed in Odean (1998), we define

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

and

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

[7] A winning (losing) stock is a stock whose price has increased (decreased) from purchase till the day in question.

[8] If an investor holds more than one stock, we treat each of the stocks independently. 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 stock. This assumption simplifies the empirical strategy in examining investor behavior, and more importantly, it better maps to our empirical design for stock-level tests.

Both the numerators and the denominators are counted at the level of investor×day×currently held stock. We calculate these metrics in each week and report the time-series average.

Figure 5(a) shows the expected number of purchases conditional on having a winning position versus a losing one. An investor on average purchases 0.108 stocks per day during days with a winning position and only purchases 0.077 stocks during days with a losing position. The difference of 0.031 is highly statistically significant (t-stat = 21.08). This pattern is consistent with previous evidence that investors tend to increase their positions after a positive investment experience (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).

Second, we examine the attention spillover effect, which is unique to our setting and is a key premise to our identification strategy. Here we calculate the probability of buying a new stock whose distance to a currently held stock is equal to x, conditioning on the investor buying any stocks on that day. Specifically,

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

where both the numerators and the denominators are counted at the level of investor×day×currently held stock×newly purchased stock. Distance x, with a multiplier of 5, 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 stock on each side, and so on.

Figure 5(b) shows the probability of purchasing a new stock as a function of the new stock's distance to a currently held stock. We see a clear monotonically decreasing relation. Conditional on making a purchase, an investor has a 0.875% chance of buying a stock among the closet 10 stocks around the one he or she currently holds (x=1), but this probability decreases to 0.622%, for a stock that is

50 ranks away (x = 10). The difference between the two, 0.253%, is highly statistically significant (t-stat = 32.24). This result shows that investors are indeed more likely to buy stocks ranked and displayed closer to stocks that they currently hold, potentially driven by attention spillover.

Finally, Figure 5(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*,

$$Exp(\#buy, dist = x|win) = Exp(\#buy|win) \times Prob(dist = x|buy) \tag{4}$$

and

$$Exp(\#buy, dist = x|lose) = Exp(\#buy|lose) \times Prob(dist = x|buy) \tag{5}$$

capture the expected number of stocks bought at that particular distance, given that the currently held stock is winning or losing. Figure 5(d) further shows the difference between the winning versus losing conditions. We find this difference is significantly greater than zero and is downward sloping in distance.

For robustness, we further separate positions by holding periods and plot the results in Figure 6. Both positive feedback trading and attention spillover are highly significant in all subsamples, and are stronger among positions with a shorter holding period. For instance, $Exp(\#buy, dist = 1|win) - Exp(\#buy, dist = 1|lose) = 0.0006$ for positions that are held less than a month, and it becomes 0.0003 for holding periods of one to three months, and less than 0.0002 for holding periods longer than three months. This further justifies using the previous two-week return in construction of our LOCAL variable.

In sum, using account-level trading data, we find that investors are more likely to buy stocks after a positive investment experience and to buy stocks adjacent to stocks that they own. This effect is stronger when the purchase of the currently owned stock is more recent. This set of evidence lays out the micro-foundation for the price and turnover effects we document.

6. Conclusion

Exploiting a unique display feature of common trading platforms in China, our paper levers a novel identification strategy and studies the impact of attention spillover on stock prices and turnover. We show that LOCAL, a variable constructed to capture recent performance of neighboring stocks, can positively predict future returns and turnover of the focal stock. Additional analyses suggest that the return predictability we document crucially relies on our two proposed mechanisms: (a) investors tend to expand their positions after winning experiences (i.e., the positive feedback effect), and (b) investors are more likely to pay attention to stocks adjacent to their winning stocks due to the display feature of the trading platform (i.e., the attention spillover effect). We also confirm the two behavioral patterns—the micro-foundation of our price impacts—by using brokerage trading data. Overall, our study clearly identifies and documents an attention-induced price impact that confounding factors cannot explain.

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Table 1. Summary Statistics

This table reports summary statistics for key variables and control variables in our asset pricing tests. Panel A reports the time-series average of the equal-weighted stock characteristics for portfolios sorted by RLOCAL. Panel B shows the time-series average of the cross-sectional correlation of these variables. 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 own return in the past two weeks. Ret_{-2w}, $\mathrm{Ret}_{-12m,-2m}$, and $\mathrm{Ret}_{-36m,-13m}$ denote cumulative return of the own stock in the past two weeks, from month t−12 to month t−2, and from month t−36 to month t−13, respectively. LogAge is the logarithm of the number of months since the firm's IPO. Beta is estimated with the CAPM using monthly return over 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 4 weeks. Turnover is the average daily ratio of trading volume over total tradable shares in the past 4 weeks (in percentage points). IVOL is the idiosyncratic volatility with respect to Fama-French three-factor model using daily return in the past four weeks. Max denotes the average of the three highest daily returns in the past four weeks. Skew is the skewness of daily returns in the past 52 weeks. All variables are winsorized each week at the 1% and 99% levels. T-statistics, shown in parentheses, are computed based on standard errors with Newey-West adjustments of 12 lags.

Panel A. Average Stock Characteristics

	RLOCAL	LOCAL	Ret_{-2w}	logAge	logME	Beta	logBM	$\mathrm{Ret}_{-12m,-2m}$	$\mathrm{Ret}_{-36m,-13m}$	ILLIQ	Turnover	IVOL	Max	Skew
RLOCAL1	−0.042	−0.036	0.006	4.518	22.196	1.101	−1.054	0.193	0.510	0.187	2.294	0.019	0.055	0.151
RLOCAL2	−0.017	−0.012	0.005	4.574	22.162	1.101	−1.050	0.187	0.513	0.186	2.275	0.019	0.055	0.146
RLOCAL3	−0.002	0.003	0.005	4.572	22.155	1.101	−1.047	0.189	0.512	0.186	2.285	0.019	0.055	0.148
RLOCAL4	0.014	0.020	0.005	4.551	22.148	1.100	−1.053	0.190	0.512	0.188	2.312	0.019	0.055	0.143
RLOCAL5	0.046	0.051	0.006	4.492	22.175	1.097	−1.053	0.196	0.510	0.185	2.353	0.019	0.055	0.144
P5-P1	0.087	0.087	0.000	−0.026	−0.022	−0.004	0.001	0.003	0.000	−0.002	0.058	0.000	0.000	−0.007
	(25.26)	(25.27)	(1.21)	(−1.23)	(−1.44)	(−1.55)	(0.16)	(0.76)	(0.04)	(−1.27)	(2.40)	(−0.97)	(−0.74)	(−1.65)

Panel B. Correlation Matrix

	RLOCAL	LOCAL	Ret_{-2w}	logAge	logME	Beta	logBM	$Ret_{-12m,-2m}$	$Ret_{-36m,-13m}$	ILLIQ	Turnover	IVOL	Max	Skew
RLOCAL	1.00													
LOCAL	1.00	1.00												
Ret_{-2w}	0.00	0.06	1.00											
logAge	−0.02	−0.02	−0.01	1.00										
logME	−0.01	0.00	0.05	0.07	1.00									
Beta	0.00	0.00	0.00	0.08	−0.11	1.00								
logBM	0.00	0.00	0.01	0.09	0.07	0.08	1.00							
$Ret_{-12m,-2m}$	0.00	0.00	0.00	−0.02	0.24	−0.14	0.01	1.00						
$Ret_{-36m,-13m}$	0.00	0.00	−0.01	0.02	0.23	−0.12	−0.39	−0.04	1.00					
ILLIQ	0.00	0.00	0.00	−0.12	−0.57	−0.01	−0.09	−0.18	−0.16	1.00				
Turnover	0.01	0.02	0.09	−0.12	−0.18	0.11	−0.11	0.09	0.02	−0.19	1.00			
IVOL	0.00	0.01	0.18	−0.02	−0.07	0.06	−0.16	0.15	0.05	−0.04	0.57	1.00		
Max	0.00	0.02	0.28	−0.01	−0.05	0.17	−0.09	0.06	0.02	−0.03	0.45	0.72	1.00	
Skew	−0.01	0.00	0.05	0.03	0.25	−0.12	−0.05	0.24	0.07	−0.12	0.01	0.11	0.14	1.00

Table 2. 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 track returns of these portfolios in the next week. For each stock, LOCAL is calculated as 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 own return in the past two weeks. We report portfolio returns using three weighting schemes: equal weighting (EW), value weighting (VW), and value weighting using stocks that exclude the 30 largest stocks in the sample (VW (-top 30)). 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) following Daniel et al. (1997), four-factor alpha (CH4 Alpha) following Liu et al. (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 ranges from January 2002 to December 2018. T-statistics, shown in parentheses, are computed 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	7.914	10.752	12.191	13.100	15.962	8.048	7.261	5.829	4.166	8.955	8.003
	(0.86)	(1.15)	(1.31)	(1.39)	(1.68)	(5.44)	(5.51)	(5.49)	(3.95)	(5.51)	(5.44)
VW	2.951	6.321	8.517	8.400	11.693	8.742	7.576	3.624	4.005	12.024	8.068
	(0.35)	(0.77)	(1.03)	(0.97)	(1.41)	(2.75)	(3.33)	(2.74)	(2.20)	(3.28)	(2.60)
VW (-top 30)	3.259	7.331	7.584	9.579	11.554	8.295	7.702	5.339	3.985	8.811	7.995
	(0.37)	(0.82)	(0.86)	(1.06)	(1.30)	(4.68)	(4.94)	(4.86)	(3.02)	(4.60)	(4.51)

Table 3. Double-Sorted Portfolio Return by RLOCAL and Confounding Factors

This table reports double-sorted portfolio results based on RLOCAL and a list of 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 in different horizons, and the stock's listing board. At the end of each week, for each control variable, we sort all stocks into five quintiles based on this variable; within each quintile, we then divide stocks into five groups based on RLOCAL; and finally, we collapse across the groups based on the control variable. We report equal-weighted and value-weighted returns in the next week for these characteristic-adjusted portfolios. 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) following Daniel et al. (1997), four-factor alpha (CH4 Alpha) following Liu et al. (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 ranges from January 2002 to December 2018. T-statistics, shown in parentheses, are computed based on standard errors with Newey-West adjustments of 12 lags.

	LogME		Beta		LogBM		$Ret_{-12m,-2m}$		$Ret_{-36m,-13m}$	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
P1	8.668	8.285	8.409	3.486	8.354	4.561	7.929	2.873	8.227	4.790
P2	11.033	10.498	10.974	5.892	11.372	6.824	11.015	5.562	10.970	7.300
P3	11.772	11.436	12.080	8.727	11.651	7.467	11.755	6.797	12.053	8.076
P4	13.574	13.102	13.425	9.125	13.371	8.168	13.462	7.249	13.465	8.861
P5	15.001	14.256	15.701	12.666	15.248	10.356	15.834	10.892	15.394	12.031
P5-P1	6.334	5.971	7.292	9.180	6.894	5.795	7.905	8.020	7.166	7.241
	(4.96)	(4.34)	(4.94)	(3.32)	(5.35)	(2.32)	(5.61)	(3.20)	(5.11)	(2.91)
Age-adj Ret	5.724	5.548	6.624	7.761	6.204	5.142	7.253	7.402	6.538	6.358
	(4.95)	(4.64)	(4.97)	(3.73)	(5.24)	(2.64)	(5.75)	(3.88)	(4.99)	(3.25)
Ind-adj Ret	4.403	3.693	5.178	4.323	5.203	3.145	5.807	4.537	5.379	3.995
	(4.54)	(3.79)	(4.88)	(3.42)	(5.33)	(2.41)	(5.65)	(3.96)	(5.25)	(3.12)
DGTW Ret	4.255	4.261	4.074	4.529	4.108	2.363	4.202	3.786	3.942	3.844
	(3.83)	(3.65)	(3.95)	(2.84)	(4.04)	(1.43)	(4.12)	(2.61)	(3.84)	(2.43)
CH4 Alpha	6.879	6.788	7.917	10.385	7.501	7.989	8.539	9.853	7.841	8.786
	(4.79)	(4.28)	(4.83)	(3.40)	(5.35)	(2.90)	(5.73)	(3.51)	(5.21)	(3.10)
FF5 Alpha	6.349	5.944	7.190	8.495	6.833	5.025	7.766	7.277	6.992	6.284
	(5.04)	(4.37)	(4.99)	(3.14)	(5.37)	(2.04)	(5.68)	(3.12)	(5.25)	(2.63)

	ILLIQ		Turnover		IVOL		Max		Skew		Board	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
P1	8.775	9.209	8.074	1.787	7.738	1.624	8.273	3.741	8.106	4.477	8.729	6.533
P2	11.060	11.271	10.721	5.151	11.083	5.712	10.768	6.621	11.064	7.063	11.516	8.477
P3	12.088	12.000	11.849	5.842	11.626	5.960	11.873	7.910	12.060	9.344	13.720	10.332
P4	13.252	13.072	13.599	7.402	13.524	8.696	13.332	8.202	12.884	9.008	13.446	9.687
P5	14.800	14.939	15.596	9.455	15.797	10.262	15.753	12.112	15.809	13.368	13.549	10.352
P5-P1	6.025	5.730	7.522	7.669	8.059	8.638	7.480	8.371	7.704	8.891	4.820	3.819
	(4.57)	(3.83)	(5.68)	(3.48)	(5.53)	(3.36)	(5.30)	(3.21)	(5.50)	(3.62)	(5.07)	(2.29)
Age-adj Ret	5.443	4.996	6.810	6.898	7.196	7.448	6.709	7.386	7.048	7.853	5.369	4.422
	(4.55)	(3.91)	(5.55)	(3.83)	(5.51)	(3.79)	(5.28)	(3.73)	(5.52)	(4.17)	(5.08)	(3.02)
Ind-adj Ret	4.072	3.597	5.691	4.538	5.945	4.566	5.319	3.751	5.670	4.218	3.908	1.623
	(4.14)	(3.58)	(5.83)	(3.79)	(5.62)	(3.39)	(5.15)	(2.73)	(5.51)	(3.63)	(4.56)	(1.28)
DGTW Ret	3.735	3.040	4.330	3.759	4.226	3.724	3.890	3.819	4.040	3.755	3.616	2.251
	(3.49)	(2.64)	(4.17)	(2.52)	(3.86)	(2.39)	(3.68)	(2.27)	(3.94)	(2.60)	(2.44)	(1.18)
CH4 Alpha	6.856	6.282	7.993	8.221	8.985	10.430	8.401	10.416	8.650	10.345	3.014	1.504
	(4.63)	(3.69)	(5.84)	(3.33)	(5.72)	(3.61)	(5.48)	(3.56)	(5.69)	(3.86)	(3.03)	(0.82)
FF5 Alpha	5.975	5.574	7.447	6.835	7.916	8.345	7.361	8.011	7.684	8.056	4.884	3.109
	(4.53)	(3.67)	(5.81)	(3.37)	(5.57)	(3.32)	(5.34)	(3.08)	(5.52)	(3.47)	(5.03)	(1.83)

Table 4. Fama-MacBeth Regressions

This table reports Fama-MacBeth regression results where the dependent variable is the future one-week stock return. 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 a battery 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 in different horizons, and a list of dummy variables indicating the listed year. All variables are winsorized in each week at the 1% and 99% levels. T-statistics, shown in parentheses, are computed based on standard errors with Newey-West adjustments of 12 lags.

	(1)	(2)	(3)	(4)	(5)
LOCAL	0.008	0.009	0.004	0.004	0.004
	(3.69)	(4.49)	(2.25)	(2.38)	(2.26)
Ret_{-2w}		−0.026	−0.036	−0.029	−0.032
		(−6.94)	(−10.98)	(−9.23)	(−10.33)
LogME			−0.001	−0.000	−0.000
			(−1.66)	(−1.19)	(−1.16)
Beta			−0.001	0.001	0.000
			(−1.05)	(1.04)	(0.74)
LogBM			0.001	0.000	0.000
			(1.99)	(0.53)	(0.48)
$Ret_{-12m,-2m}$			0.000	0.002	0.002
			(0.31)	(1.95)	(2.63)
$Ret_{-36m,-13m}$			−0.000	−0.000	−0.000
			(−1.48)	(−0.67)	(−0.52)
ILLIQ				0.036	0.035
				(5.08)	(5.11)
Turnover				−0.075	−0.084
				(−5.63)	(−6.31)
IVOL				−0.177	−0.251
				(−10.25)	(−13.35)
Max					0.058
					(6.09)
Skew					−0.000
					(−0.54)
Age FE	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.012	0.032	0.087	0.104	0.107
Observations	1341130	1341130	1341130	1341130	1341130

Table 5. Fama-MacBeth Regressions: Placebo Tests

This table reports Fama-MacBeth regression results where the dependent variable is the future one-week stock return. 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. To examine the mechanism, we change this specification and construct three placebo variables. First, we skip 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 turnover of these stocks in the past two weeks. And finally, the third construction uses return volatility of neighboring stocks in stead of returns. The regression results using these three placebo variables are reported in Panels A, B, and C, respectively. We also control for a battery 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 in different horizons, and a list of dummy variables indicating the listed year. All variables are winsorized in each week at the 1% and 99% levels. T-statistics, shown in parentheses, are computed based on standard errors with Newey-West adjustments of 12 lags.

	Panel A: Placebo – Gap100				Panel B: Placebo – Turnover				Panel C: Placebo – TVOL			
Placebo	0.003	0.002	0.001	0.000	0.001	0.000	0.001	0.000	0.033	0.018	0.027	0.021
	(1.47)	(1.27)	(0.54)	(0.37)	(1.08)	(0.37)	(0.78)	(0.46)	(1.55)	(0.87)	(1.97)	(1.55)
LOCAL		0.008		0.004		0.007		0.004		0.007		0.003
		(3.91)		(2.39)		(3.55)		(2.08)		(3.27)		(1.93)
Ret_{-2w}			−0.032	−0.032			−0.032	−0.032			−0.032	−0.032
			(−10.34)	(−10.34)			(−10.34)	(−10.35)			(−10.33)	(−10.33)
LogME			−0.000	−0.000			−0.000	−0.000			−0.000	−0.000
			(−1.18)	(−1.16)			(−1.12)	(−1.11)			(−1.12)	(−1.11)
Beta			0.000	0.000			0.000	0.000			0.000	0.000
			(0.74)	(0.74)			(0.73)	(0.73)			(0.75)	(0.75)
LogBM			0.000	0.000			0.000	0.000			0.000	0.000
			(0.48)	(0.48)			(0.51)	(0.52)			(0.51)	(0.51)
$Ret_{-12m,-2m}$			0.002	0.002			0.002	0.002			0.002	0.002
			(2.66)	(2.65)			(2.61)	(2.60)			(2.60)	(2.59)
$Ret_{-36m,-13m}$			−0.000	−0.000			−0.000	−0.000			−0.000	−0.000
			(−0.45)	(−0.52)			(−0.51)	(−0.55)			(−0.50)	(−0.55)
ILLIQ			0.035	0.035			0.035	0.035			0.036	0.036
			(5.14)	(5.13)			(5.12)	(5.10)			(5.14)	(5.12)
Turnover			−0.084	−0.084			−0.084	−0.084			−0.084	−0.084
			(−6.34)	(−6.33)			(−6.38)	(−6.36)			(−6.37)	(−6.35)
IVOL			−0.251	−0.251			−0.250	−0.250			−0.250	−0.250
			(−13.34)	(−13.37)			(−13.36)	(−13.38)			(−13.38)	(−13.40)
Max			0.058	0.058			0.057	0.057			0.057	0.057
			(6.08)	(6.05)			(6.18)	(6.16)			(6.15)	(6.13)
Skew			−0.000	−0.000			−0.000	−0.000			−0.000	−0.000
			(−0.57)	(−0.56)			(−0.52)	(−0.50)			(−0.52)	(−0.51)
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.012	0.013	0.107	0.107	0.013	0.014	0.107	0.108	0.014	0.014	0.107	0.108
Observations	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130	1,341,130

Table 6. Forecasting Turnover by RLOCAL

This table reports future one-week turnover and order imbalance for single-sorted portfolios based on RLOCAL. At the end of each week, we sort stocks into five groups based on RLOCAL, and track turnover and order imbalance of these portfolios in the next week. 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 own return in the past two weeks. We report equal-weighted and value-weighted turnover, as well as the abnormal turnover, which is the difference between weekly turnover and the average turnover in the previous 52 weeks. We also report results for order imbalance, calculated in two ways: OIBNUM is the weekly number of buyer-initiated trades minus that of seller-initiated trades, scaled by the total number of trades; OIBVOL is the weekly difference between buyer-initiated yuan volume and seller-initiated yuan volume, scaled by the total yuan volume. Turnover variables and order-imbalance variables are reported in percentage points. The sample ranges from January 2002 to December 2018 for turnover variables, and from October 2008 to December 2018 for order-imbalance variables. T-statistics, shown in parentheses, are computed based on standard errors with Newey-West adjustments of 12 lags.

	Turnover		Abnormal Turnover		OIBNUM		OIBVOL	
	EW	VW	EW	VW	EW	VW	EW	VW
P1	10.846	7.088	−0.302	−0.322	−2.247	−1.324	−2.136	−1.258
P2	10.756	7.281	−0.262	−0.213	−2.266	−1.189	−2.155	−1.119
P3	10.814	7.42	−0.231	−0.167	−2.228	−1.148	−2.116	−1.076
P4	10.946	7.58	−0.186	−0.112	−2.226	−1.068	−2.115	−0.994
P5	11.217	7.583	−0.081	−0.028	−2.143	−0.939	−2.031	−0.865
P5-P1	0.371	0.495	0.221	0.294	0.105	0.385	0.105	0.392
	(2.95)	(2.70)	(3.89)	(4.36)	(1.65)	(2.19)	(1.65)	(2.25)

Table 7. Comovement in Return and Turnover: Difference-in-Difference (DID) Approach

This table shows return and turnover correlation between the affect groups of stocks versus control groups before and after the introduction of the SME Board, on which the first wave of 38 stocks were listed from June to September 2004. Panel A reports results on return correlation, and Panel B reports results on turnover correlation. The before-period covers March until May, while the after-period ranges from October to December. 000Z and 000Y indicate the last 20 stocks and the second last 20 stocks listed on 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 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. $\rho(000Y, 000Z)$ refers to 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 reported in parentheses.

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
	(−0.04)	(−8.38)	(−6.09)		(−8.38)	(−6.42)	(2.55)
N	400	400	400		400	400	400

Panel B. DID tests on turnover correlation

	$\rho(000Y, 000Z)$	$\rho(000Z, 600A)$	diff		$\rho(000Z, 600A)$	$\rho(600A, 600B)$	Diff
Before	0.426	0.403	−0.023		0.403	0.389	−0.013
	(41.79)	(45.10)	(−1.82)		(45.10)	(31.71)	(−0.79)
After	0.377	0.255	−0.122		0.255	0.289	0.035
	(30.66)	(20.83)	(−6.68)		(20.83)	(24.96)	(1.94)
Diff	−0.049	−0.148	−0.099		−0.148	−0.100	0.048
	(−3.15)	(−10.10)	(−4.77)		(−10.10)	(−6.65)	(2.03)
N	400	400	400		400	400	400

Table 8. Heterogeneous Tests

This table reports double-sorted portfolio results based on RLOCAL and moderating factors. Panel A shows the results using a list of proxy for arbitrage costs, including firm size, illiquidity, and analyst coverage. Panel B shows the results for investor sentiment. At the end of each week, we sort stocks into two groups based on each of the moderating factors, and then sort stocks into five quintiles based on RLOCAL within each group. We report the value-weighted returns in the next week for the long short portfolio (P5-P1) in high and low moderator groups, as well as a battery of risk-adjusted return spreads using different benchmarks: age-adjusted return (Age-adj Ret), industry-adjusted return (Ind-adj Ret), DGTW characteristic-adjusted return (DGTW Ret) following Daniel et al. (1997), four-factor alpha (CH4 Alpha) following Liu et al. (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 ranges from January 2002 to December 2018. T-statistics, shown in parentheses, are computed based on standard errors with Newey-West adjustments of 12 lags.

Panel A. VW long-short (P5-P1) portfolio returns based on RLOCAL in stocks with high versus low arbitrage cost

		P5-P1		Age-adj Ret		Ind-adj Ret		DGTW Ret		CH4 Alpha		FF5 Alpha	
		para	t	para	t	para	t	para	t	para	t	para	t
LogME	Low	9.207	5.29	9.255	5.32	7.464	4.81	8.289	4.97	9.884	5.30	9.332	5.66
	High	5.976	1.90	4.854	2.20	1.364	0.98	2.768	1.31	8.536	2.28	5.064	1.65
	H-L	−3.231	−0.99	−4.400	−1.74	−6.100	−3.01	−5.521	−2.08	−1.348	−0.35	−4.268	−1.35
ILLIQ	Low	6.089	1.97	4.909	2.31	1.168	0.85	2.411	1.17	9.120	2.50	5.066	1.67
	High	8.488	5.02	7.942	4.82	6.924	5.08	5.871	3.70	8.030	4.56	8.534	5.17
	H-L	2.399	0.79	3.033	1.31	5.757	3.22	3.460	1.40	−1.090	−0.32	3.469	1.14
Analyst	Low	12.817	5.10	12.211	5.23	8.210	4.12	7.842	3.60	14.125	5.06	13.033	4.94
	High	6.022	1.30	4.417	1.38	−0.719	−0.39	2.139	0.71	9.495	1.85	5.058	1.16
	H-L	−6.795	−1.49	−7.794	−2.34	−8.929	−3.51	−5.703	−1.52	−4.630	−0.88	−7.975	−1.78

Panel B. VW long-short (P5-P1) portfolio returns based on RLOCAL in high versus low sentiment periods													
		P5-P1		Age-adj Ret		Ind-adj Ret		DGTW Ret		CH4 Alpha		FF5 Alpha	
		para	t	para	t	para	t	para	t	para	t	para	t
CICSI	Low	1.006	0.27	2.176	0.72	2.261	1.00	−1.044	−0.40	5.671	1.24	1.055	0.26
	High	16.827	3.32	13.373	3.97	5.274	3.07	9.201	4.00	19.447	3.76	15.415	3.25
	H-L	15.821	2.48	11.197	2.40	3.013	1.04	10.245	2.86	13.776	2.20	14.360	2.33
CCI	Low	0.975	0.25	1.521	0.53	1.116	0.49	−0.590	−0.20	4.505	0.98	−0.405	−0.10
	High	17.697	3.35	14.643	4.02	6.616	3.91	9.275	4.00	21.120	3.88	17.587	3.38
	H-L	16.723	2.49	13.123	2.77	5.500	1.87	9.865	2.63	16.615	2.42	17.993	2.71
DCEF	Low	7.428	1.76	5.498	1.75	4.745	1.94	1.369	0.36	10.049	1.86	5.191	1.11
	High	9.923	2.25	8.986	2.87	3.446	2.07	5.442	2.52	14.006	2.94	9.879	2.27
	H-L	2.496	0.41	3.488	0.79	−1.299	−0.44	4.073	0.93	3.957	0.58	4.688	0.71
IPON	Low	4.633	1.11	5.018	1.58	1.589	0.80	2.547	0.94	9.264	1.92	4.341	0.95
	High	15.742	2.84	12.212	3.24	7.020	4.07	6.719	2.40	17.851	3.15	14.345	2.67
	H-L	11.109	1.57	7.194	1.46	5.431	1.99	4.172	1.00	8.587	1.18	10.004	1.37
IPOR	Low	7.870	1.82	7.139	2.17	3.857	2.23	3.861	1.71	10.105	2.38	6.624	1.72
	High	11.383	2.46	9.348	2.94	3.764	1.85	4.922	1.57	17.688	3.18	11.726	2.39
	H-L	3.514	0.61	2.209	0.54	−0.093	−0.04	1.061	0.29	7.583	1.32	5.102	0.83
NIA	Low	3.091	0.88	3.330	1.28	4.158	2.22	0.833	0.30	4.944	1.30	1.273	0.34
	High	13.317	2.62	11.106	3.11	3.595	1.90	6.573	2.55	18.436	3.29	13.424	2.65
	H-L	10.225	1.69	7.776	1.81	−0.563	−0.22	5.740	1.60	13.492	2.12	12.151	1.94
MTURN	Low	8.592	2.37	6.755	2.53	4.466	2.91	5.381	2.45	9.876	2.50	6.887	1.78
	High	10.226	1.59	10.032	2.20	2.738	1.15	2.380	0.81	18.567	2.45	11.394	1.64
	H-L	1.634	0.22	3.277	0.61	−1.728	−0.63	−3.002	−0.80	8.691	1.05	4.507	0.56

Figure 1. Screen Display of the Trading Software

This figure illustrates the screen display when an investor searches for a particular stock, for instance, 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. Figures (c) and (d) show the screen after the investor presses "Page Up" or "Page Down", which brings the investor to the main page of the previous stock (whose listing code is 600518) or the next stock (whose listing code is 600520). Figure (e) shows the screen if the investor presses "Enter" again 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, Figure (f) shows the screen display when the investor types in the listing code.

(a) Input "GZMT"

(b) Press "Enter"

(c) Press "Page-Up"

(d) Press "Page-Down"

(e) Press "Enter"

(f) Input "60051"

Figure 2. Listing Code and Stock Characteristics

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

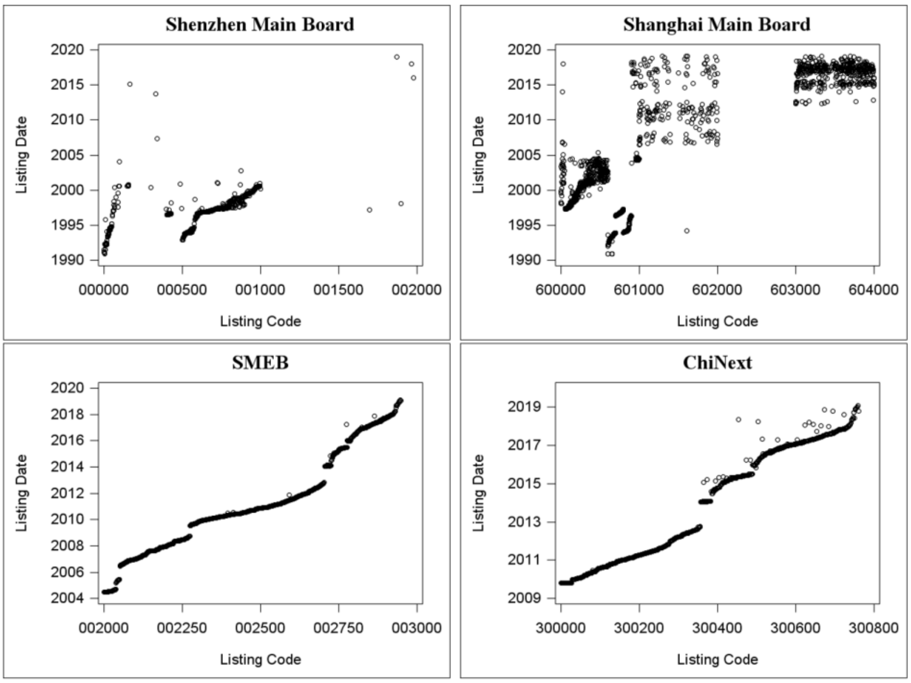


Figure 2A. Listing code and listing date

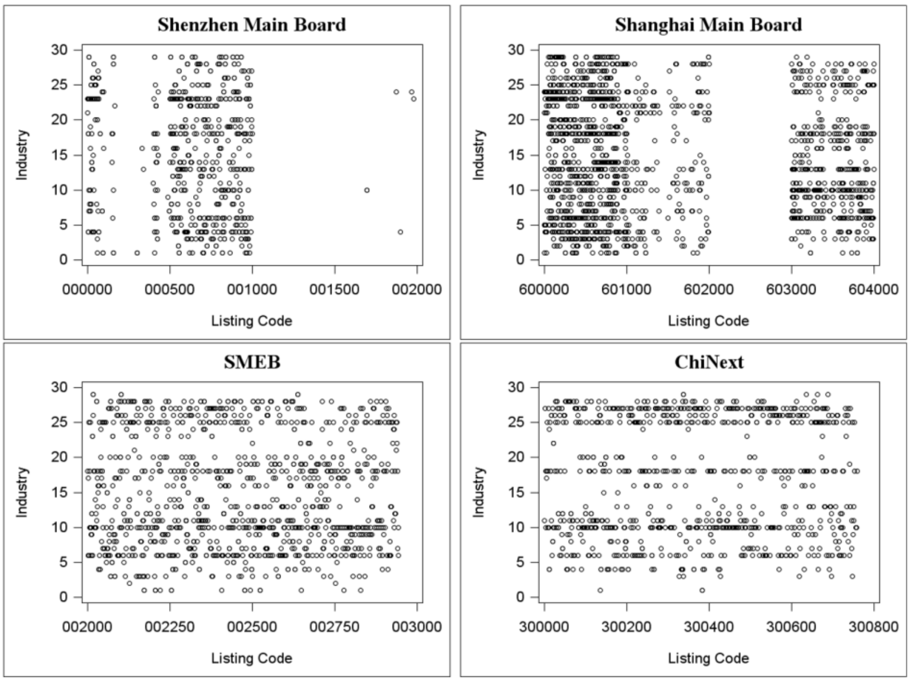


Figure 2B. Listing code and industry

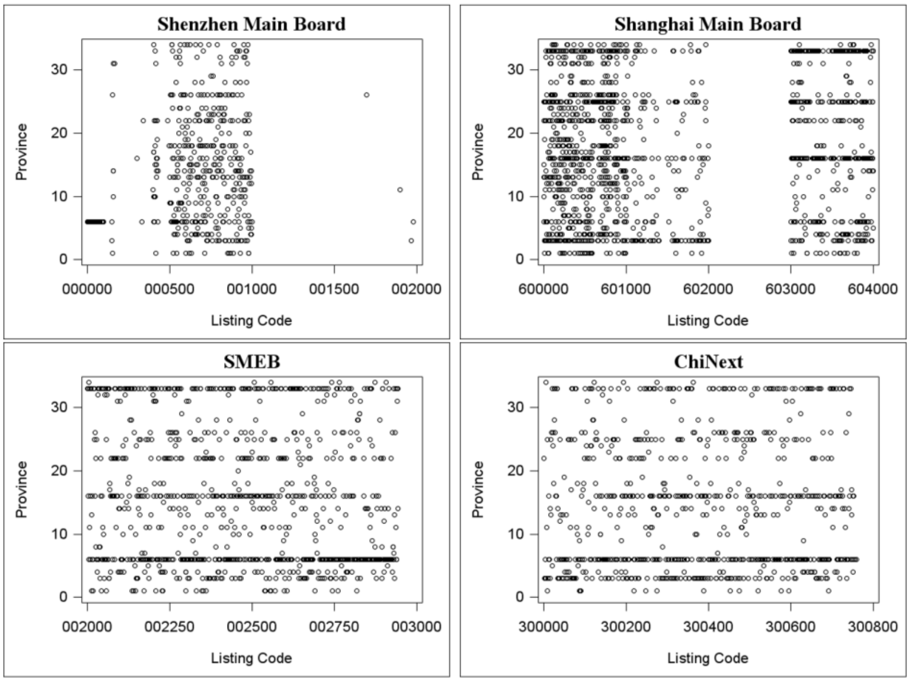


Figure 2C. Listing code and the province of registration

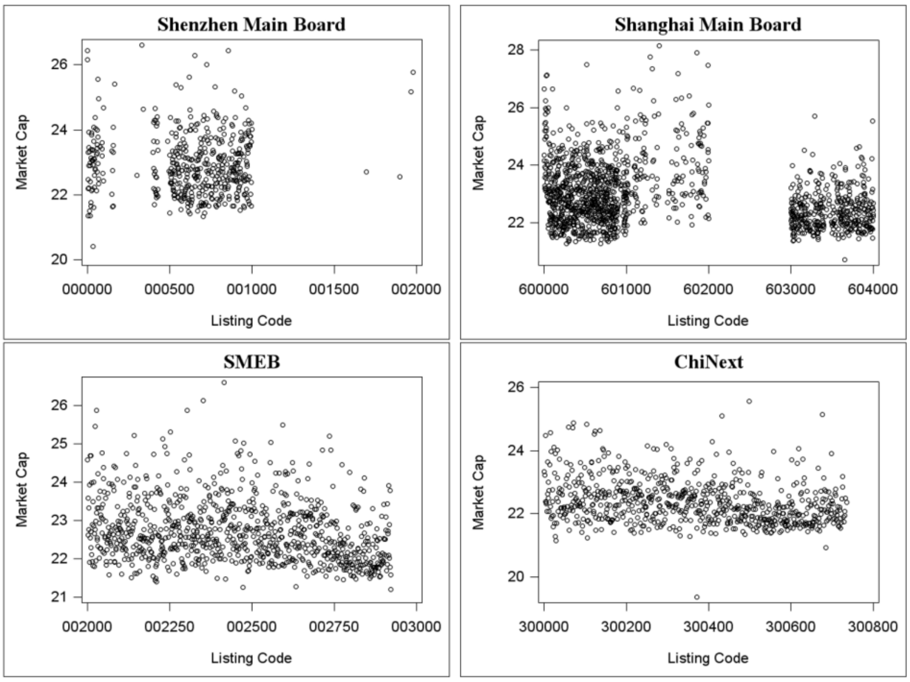
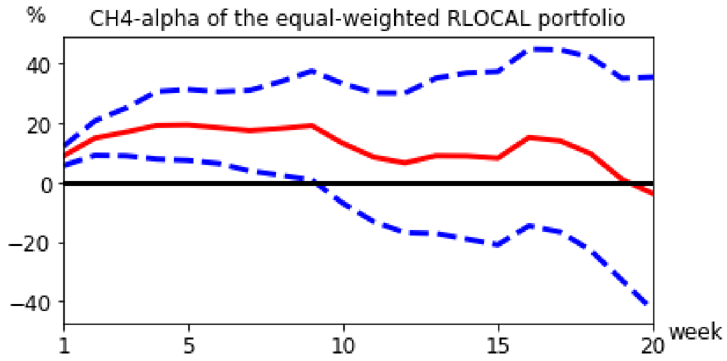


Figure 2D. Listing code and market capitalization

Figure 3. Cumulative Return of the Long-Short Portfolio Based on RLOCAL

This figure shows the annualized cumulative Ch4-alpha (in percentage points) to the equal-weighted 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 own return in the past two weeks. Portfolios are formed at the end of week *t* based on RLOCAL.



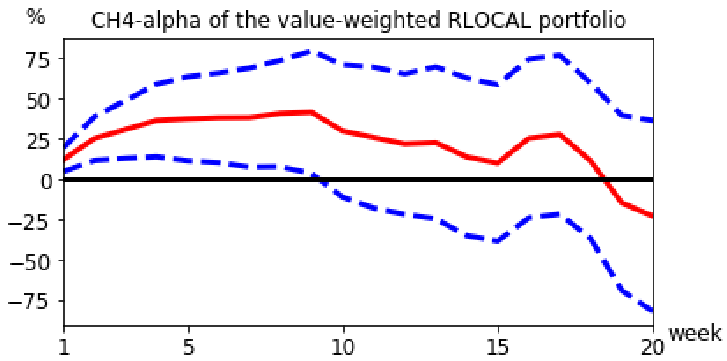


Figure 4. Comovement in Return and Turnover and Distance Between Stocks

This figure shows the average pairwise correlation in returns, turnover, and a list of 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 ratio, 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 plots 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).

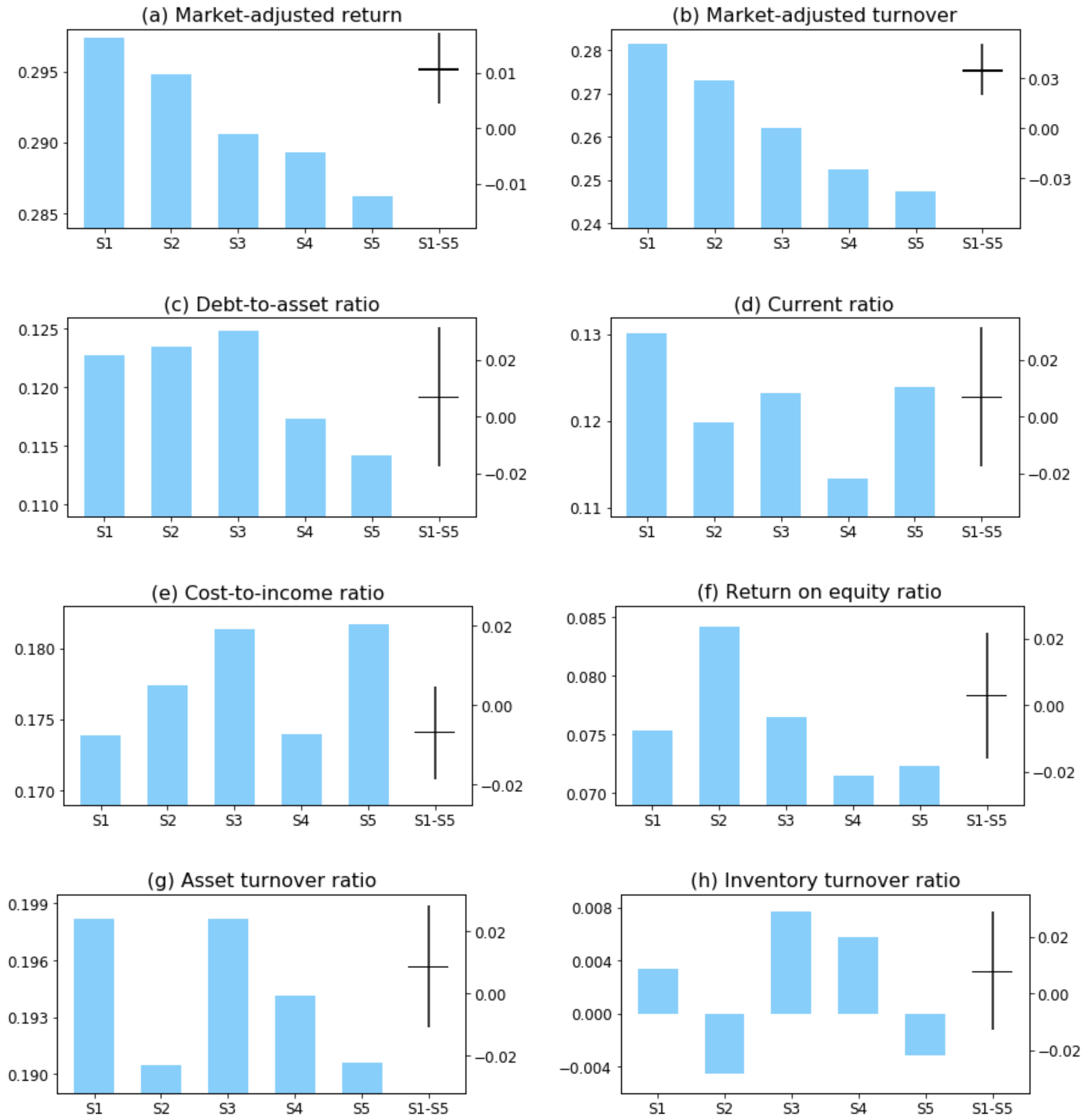


Figure 5. Investor Trading Behavior: Positive Feedback and Attention Spillover

This figure shows the results on investor trading behavior using a brokerage dataset that covers 430,000 investors from January 2009 to September 2012. Figure (a) shows the expected number of purchases per day conditional on having a winning position versus a losing one, denoted as $Exp(\#buy|win)$ and $Exp(\#buy|lose)$, respectively (Equations (1) and (2)). Figure (b) shows the probability of buying a new stock whose distance to a currently held stock is equal to x, conditioned on the investor buying any stocks on that day. We denote this probability as $Prob(dist = x|buy)$ (Equation (3)). Distance x, with a multiplier of 5, indicates that (the absolute value of) the difference in display rank between two stocks falls in $(5(x-1), 5x)$. Figure (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 as $Exp(\#buy, dist = x|win)$ and $Exp(\#buy, dist = x|lose)$ (Equations (4) and (5)). Finally, Figure 4(d) reports the difference between $Exp(\#buy, dist = x|win)$ and $Exp(\#buy, dist = x|lose)$, and the 95% confidence interval. All metrics are calculated in each week, and we report the time-series average of these metrics and corresponding confidence interval.

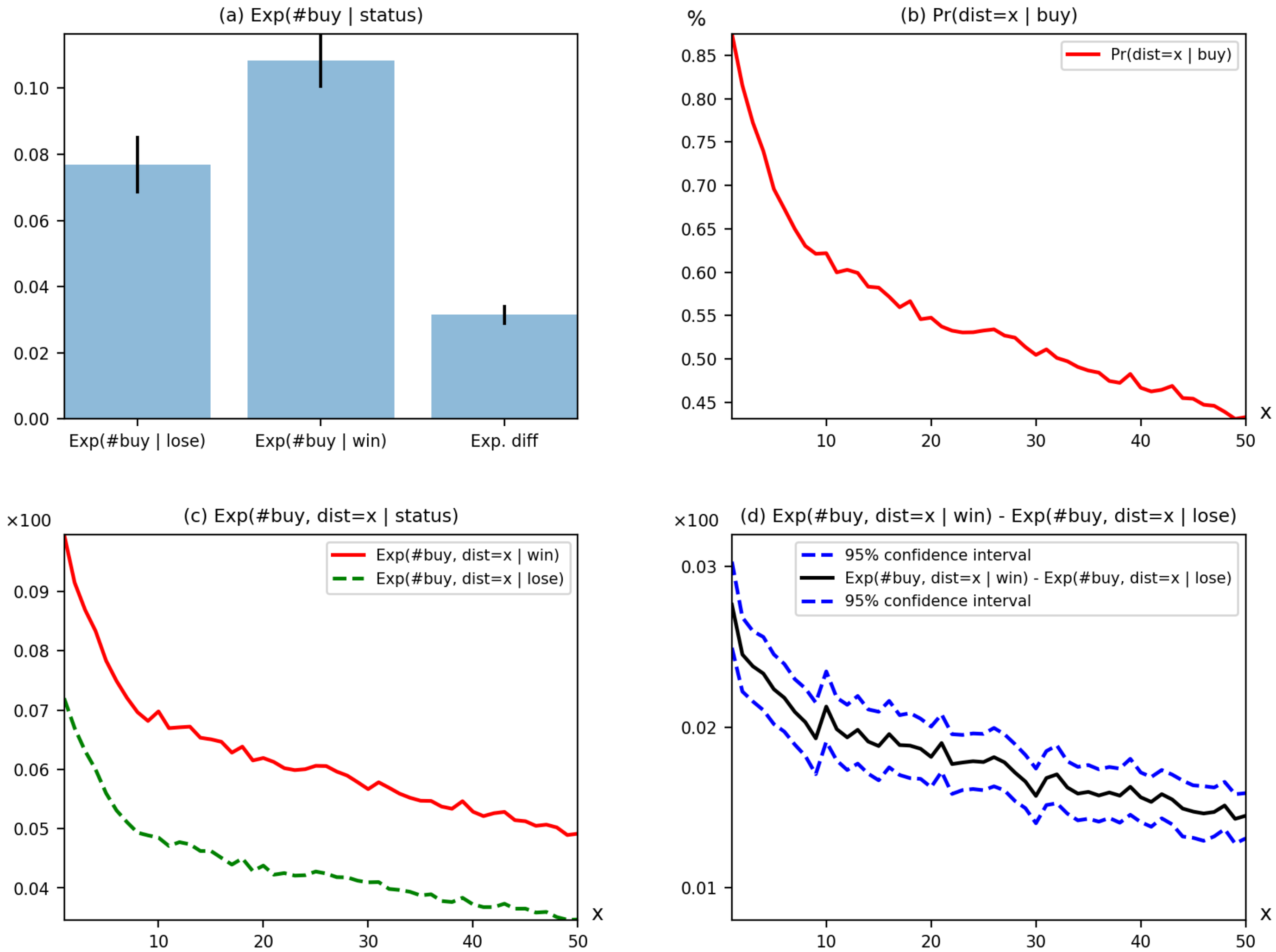


Figure 6. Investor Trading Behavior: by Holding Period

This figure shows the results on investor trading behavior using a brokerage dataset that covers 430,000 investors from January 2009 to September 2012. We calculate the expected number of stocks bought at a particular distance (dist = x) per day, conditional on the currently held stock being winning or losing. We denote these metrics as $Exp(\#buy, dist = x|win)$ and $Exp(\#buy, dist = x|lose)$ (Equations (4) and (5)). Distance x, with a multiplier of 5, indicates that (the absolute value of) the difference in display rank between two stocks falls in $(5(x-1), 5x)$. Panels (a), (b), (c), and (d) show the results for positions held shorter than 1 month, from 1 to 3 months, from 4 to 6 months, and longer than 6 months, respectively. All metrics are calculated in each week, and the time-series average is reported.