12-2022

LOCAL IPOS AND RETAIL INVESTOR TRADING

Guanhuan Wang
University of Tennessee, Knoxville, gwang19@vols.utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Guanhuan Wang entitled "LOCAL IPOS AND RETAIL INVESTOR TRADING." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

Matthew Serfling, Major Professor

We have read this dissertation and recommend its acceptance:

Matthew Serfling, Larry Fauver, Eric Kelley,Celeste Carruthers

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

LOCAL IPOS AND RETAIL INVESTOR TRADING

A Dissertation Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Guanhuan Wang

December 2022

ACKNOWLEDGEMENTS

First, I want to express my great gratitude to my adviser Matthew Serfling. I had so many failed projects throughout the five years, but he encouraged me to keep working and never give up. I cannot remember how much time he spent with me talking about ideas, solving code problems, and cleaning up the writing. I literally cannot finish this program without his help.

I also want to give special thanks to the rest of my dissertation committee, Larry Fauver, Eric Kelley, and Celeste Carruthers, for their general guidance.

Finally, I am extremely grateful to Tracie Woidtke and Andy Puckett for their generous support.

ABSTRACT

This paper examines how salient events affect retail investors' trading behavior. Using data on households' trading records from a large discount broker between 1991 and 1996, I find that Initial Public Offerings (IPOs) significantly increase the trading activities of local retail investors of stocks in the same industry over the subsequent year. The effect is stronger for less sophisticated investors and investors who live closer to the IPO firm's headquarters, consistent with salience as the channel. I also find that retail investors are net buyers of stocks right after the local IPOs and become net sellers after a year and that such trading behavior is not wealth enhancing. These results suggest that investors learn through trading and undo their actions after realizing poor choices. Finally, I find that stock purchases in the same industry tend to be of local firms, suggesting these investors also display a local bias.

TABLE OF CONTENTS

CHAPTER 1

LOCAL IPOS AND RETAIL INVESTOR TRADING

ABSTRACT

This paper examines how salient events affect retail investors' trading behavior. Using data on households' trading records from a large discount broker between 1991 and 1996, I find that Initial Public Offerings (IPOs) significantly increase the trading activities of local retail investors of stocks in the same industry over the subsequent year. The effect is stronger for less sophisticated investors and investors who live closer to the IPO firm's headquarters, consistent with salience as the channel. I also find that retail investors are net buyers of stocks right after the local IPOs and become net sellers after a year and that such trading behavior is not wealth enhancing. These results suggest that investors learn through trading and undo their actions after realizing poor choices. Finally, I find that stock purchases in the same industry tend to be of local firms, suggesting these investors also display a local bias.

1. Introduction

How do retail investors choose which stocks to hold? This problem is especially challenging given that retail investors have limited attention and there are thousands of available stocks in the market. On the one hand, the literature on attention shows that retail investors are often attracted to stocks with salient features in the short term. For example, Barber and Odean (2008) show that retail investors are more likely to purchase stocks with high trading volumes, extreme returns, and high news exposures. On the other hand, rational inattention theory implies that because investors are endowed with limited attention and information is costly to acquire, investors rationally allocate attention based on their personal experiences, information environment, and preferences in the long run (Maćkowiak, 2021). However, most retail investors lack basic financial knowledge and knowledge of what stocks are available in the market. Consequently, it is hard for retail investors to rationally allocate their attention to a specific area in the long run. To bridge the short- and long-term choice, I argue that inexperienced investors, due to a lack of focused area or specific investment ideas, will use the stocks that are salient to them as a starting point and invest in related stocks subsequently. I call this the *learning through noticing hypothesis*. I expect such an effect exists for several reasons. First, Enke (2020) shows that a substantial fraction of experimental participants follows a simple "what you see is all there is" heuristic and only use the information right in front of them to make decisions. Hanna et al. (2014) also show that people will only learn about dimensions they pay attention to. Second, Barberis and Shleifer (2003), Peng and Xiong (2006), and Huang (2019) show that people tend to have category thinking/learning process. Thus, if an investor uses a certain stock as a reference point, he is more likely to investigate and invest in other stocks in the same category as the referenced stock.

In this paper, I test the learning through noticing hypothesis by investigating how local Initial Public Offerings (IPOs) affect the trading behavior of investors in the same industry. There are two reasons I use local IPOs to investigate this hypothesis. First, IPOs are one of the most critical events in the financial industry. It attracts attention from both institutional investors and retail investors. Thus, it is a salient event to local investors. Consistent with this notion, Da, Engelberg, and Gao (2011) point out that the Google search volume of IPO firms increases dramatically around issuance, indicating that retail investors actively search for information about the IPOs. Second, the average first-day returns of IPOs in the 1990s, which is when I have detailed retail investor trade data, is around 21%. Such a large return can induce investors to investigate IPO stocks and related investment opportunities. Greenwood and Nagel (2009) show that even young fund managers will excessively extrapolate recent price movements during the Internet bubble and increase their technology holdings. However, IPO stocks are risky and opaque and may not fit the risk profile of retail investors. Thus, retail investors may trade other stocks with similar features as the IPO stock to profit without bearing the risks associated with the IPO stocks. Finally, local IPOs can increase local economic growth and activities (Butler, Fauver, and Spyridopoulos, 2019). Investors may form positive expectations based on the local economic growth after IPOs.

I study the effect of local IPOs on investors' trading behavior using two data sets. First, I use data from households' detailed trading records at a large discount broker between 1991 and 1996 (Barber and Odean, 2000). The dataset contains detailed information on households' trading activities, equity holdings, and basic demographic information. Second, I use the IPO data from the Securities Data Corporation (SDC) Platinum, which covers all US IPOs from 1990 to 1995. By observing information on the issuance date, firm headquarters' zip codes, and the zip codes of households' residences, I can identify the effect of local IPOs on investors apart from the general economic conditions. Because the trading data tracks each household for several years, I can also identify the effect of IPOs by observing the trading behavior of the same household before and after the local IPOs.

I find that local IPOs significantly increase the trading activities in the same industry of nearby households. More specifically, a standard deviation increase in the number of local IPOs in an industry within a 25-mile radius around the investors' residence is associated with 0.107 more trades in the following year in the same industry. This magnitude corresponds to 16.7% of the average trade number in an industry by a household (0.643).

If learning though noticing drives the relationship between local IPOs and the trading behavior of households, then the magnitude and significance of these results should decrease with investor sophistication and the distance between the location of households and the IPO firm. Sophisticated investors should be less affected as they are more likely to have investment focus and experience. I divide households into four groups according to self-reported investment sophistication. The results show that the local IPO effect on trading is more pronounced among investors with none or limited knowledge and marginally significant among investors with good or extensive knowledge of investments. Speaking to the magnitude, the IPO-induced trading effect for the least knowledgeable investors is around twice as large as that for the most sophisticated investors.

In addition, investors far away from the IPO firms' headquarters should pay less attention to the IPO news. Thus, the effects of local IPOs on investor trading activities should decrease as the distance between the IPO firm and the investor increases. I find that the effect of IPOs decreases monotonically as the distance increases. For IPOs within 15 miles, one IPO induces investors to make 0.0936 more trades in the same industry. In contrast, for IPOs within 100 miles, one IPO only induces investors to make 0.0424 more trades. Given that the effects decay quickly over a short distance, the effect is unlikely driven by local economic conditions.

As Barber and Odean (2008) point out, retail investors face search problems when deciding which stock to buy. If the learning through noticing hypothesis is true, I should observe that local IPOs predominately affect purchasing decisions. Thus, I split the total trade number into buys and sells. Over the entire year following local IPOs, investors carry out more sell orders, and there is no significant change in buy orders in the corresponding industry. The groups of investors with none or limited knowledge make more buy and sell trades in the year following local IPOs. However, investors with good or extensive knowledge only make more sell orders in the following year. These results at first appear to contradict the prediction made by the learning through noticing hypothesis.

To resolve the contradictions, I examine investors' equity holdings (in dollars) in the corresponding industry around the local IPOs. I find that households increase their holdings in the corresponding industry right after the issuance of the local IPOs, and they decrease their holdings over the subsequent year. Thus, the local IPO effect is short-lived. In the three months after a standard deviation increase in the number of local IPOs, retail investors increase their holdings by $3180 (76.6% of the average holdings in an industry). After one year, this amount increases to around $1088, only a third of that in the first three months. These results suggest households initially increase their holdings and subsequently undo their actions by selling the stocks they purchased in the same industry following local IPOs. This unwinding of trades helps explain the significant increase in selling one year following the local IPOs.

Next, I compare the returns earned on the purchased stocks in the same industry following the local IPOs against several counterfactual portfolios. I consistently find negative alphas across all comparisons, suggesting that investors systematically pick the wrong stocks instead of the wrong industry. Combining the previous results that individual investors initially increase their holdings and then subsequently decrease their positions, the findings suggest that investors gain experience over time and attempt to correct their mistakes. This finding is consistent with the "learning through trading" hypothesis proposed by Seru, Shumway, and Stoffman (2009).

Finally, I investigate other "induced purchases" features following the local IPOs. I find that households, apart from increasing holdings in existing positions, also purchase new stocks in the corresponding industry. The results imply that local IPOs may induce investors to learn more about the industry and explore broader investment opportunities. The results are consistent with the learning through noticing hypothesis. I also find investors prefer "local" stocks. The purchased stocks following local IPOs are, on average, 487 miles closer than the universe of stocks in the same industry. Even comparing the holdings of households in stocks in the same industries as the local IPOs with those in other industries, the holdings in the local IPOs industries are still 319 miles closer to the residence of households. The findings are consistent with the local bias literature (Ivkovic and Weisbenner, 2005; Seasholes and Zhu, 2010). I also provide evidence that retail investors seem to think about potential investment opportunities in more narrow industries. I find that using a finer industry classification, the Fama-French 48 industry classification, still yields significant results. However, the magnitude is only half of those in the Fama-French 10 industry classification. My results show that retail investors make associations within narrow industry categories (Huang, 2019).

My paper is related to several strands of literature. First, it contributes to the literature on salience. Specifically, I address how salience can induce investors to investigate related areas. Related papers include those that address how attention affects the trading behaviors of retail investors (Seasholes and Wu, 2007; Barber and Odean, 2008; Engelberg and Parsons, 2011; Engelberg, Sasseville, and Williams, 2011; Da, Engelberg, and Gao, 201; Barber, Huang, Odean, and Schwarz, 2021; Laudenbach, Loos, Pirschel, and Wohlfart, 2021) and how salience affects general decisions of fund managers (Alok et al., 2020), corporate managers (Dessaint and Matray, 2017), retail investors (Célérier and Vallée, 2017; Chaudary, 2019), and general subjects (Bordalo et al., 2013, 2022; Hanna et al., 2014; Enke, 2020).

My paper also contributes to the rational inattention literature. My paper confirms the predictions of Peng and Xiong (2006) that retail investors are more likely to engage in category thinking and learn about sector-wide information. This literature stresses that under limited attention, how investors allocate their attention rationally given their personal experience, information environment, and endowed ability (Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2009; Van Nieuwerburgh and Veldkamp, 2010; Schwartzstein, 2014; Bordalo, Gennaioli, and Shleifer, 2020; Reme, Røhr, and Sæthre, 2021).

Finally, my study contributes to the spillover effects of IPOs literature and literature related to retail investors and IPOs. Butler, Fauver, and Spyridopoulos (2019) show that local IPOs significantly increase local economic activities. Jiang, Lowry, and Qian (2022) show that local IPOs could induce retail investors to participate in the stock market. Colaco et al. (2017) and Kao et al. (2022) find that IPO valuation increases with the retail investors' attention. Bushee et al. (2020) find that media coverage affects the willingness of retail investors to trade IPO stocks. Kaustia and Knüpfer (2008) show that retail investors are more likely to subscribe to the new IPO stocks if they experience good returns from past subscriptions. My paper helps to understand the role of local IPOs in retail investors' investment decisions.

The rest of this paper is structured as follows: In Section 2, I describe the data and provide summary statistics. Section 3 presents my main results on the effects of local IPOs on the trading behaviors of retail investors. Section 4 examines cross-sectional variation in local IPO effects to test the attention hypothesis, and Section 5 provides more evidence on trading types and equity holdings. I provide more features of IPO-induced purchases in Section 6. Finally, I conclude in Section 7.

2. Datasets and descriptive statistics

2.1 Data description

The main dataset used in this paper is trading records of 78,000 households at a large discount brokerage house from 1991 to 1996. The dataset was first used by Barber and Odean (2000) and has been widely studied since. Each household in data needs to open at least one account. I aggregate all trades of accounts within the same household and have observations at the household level. In this research, I focus on common stock investments by households. I exclude investments in mutual funds (both open- and closed-end), American depository receipts (ADRs), warrants, and options. Following Huang (2019), I remove trading records with errors and short-selling trades. My final sample includes 44,150 households. The stock price and return data are from the Center for Research in Security Prices (CRSP) database.

Because my paper explores whether investors will learn through noticing, a natural starting place will be industry. I get the Standard Industrial Classifications (SIC) codes of firms in the trading data from Compstat. I use the Fama-French 10 industry classification for most of the tests. The 10 industry groupings are (1) consumer nondurables; (2) consumer durables; (3) manufacturing; (4) oil, gas, and coal extraction and products; (5) high technology; (6) telephone and television transmission; (7) wholesale, retail, and some services; (8) healthcare, medical equipment, and drugs; (9) utilities; and (10) others. In Section 6, I show my main results are robust when I use a finer industry classification, the Fama-French 48 industry classification.

I collect IPO data from the Securities Data Corporation (SDC) from 1991 to 1996 and use the address of each firm's headquarters to determine its associated ZIP code. I classify the IPOs according to the Fama-French 10 industry classification. I further aggregate the IPO information to the year-industry-location level. Then I match trading records with the past year's IPO information.

Finally, the distance data between different zip code areas are from ZIP Code Distance Database. I also supplement the distance information with the R package zipcodeR.

2.2 Descriptive statistics

Table 1 reports summary statistics. Panel A presents information on IPO frequency in different industries each year. IPOs are not evenly distributed across years and industries. In 1990, there were only 215 IPOs, while there were 780 IPOs in 1993. Also, the utility industry had only 15 IPOs from 1990 to 1995, while the high technology has 638.

Panels B, C, and D report the frequency of retail investors trading each year in different industries. At first look, there are more trading activities among three industries: (5) high tech, (7) wholesale, and (8) health care. Although IPOs also concentrate in the same three industry categories, the number of trading is not proportionate to the number of IPOs in one industry. Also, while IPOs in an industry can vary from year to year, the number of trades in an industry remains stable. Such stable trading activities can help me rule out the possibility that overall IPO market conditions drive the results.

Panel E provides summary statistics of variables used in the main regressions. The first four variables are control variables in main regressions. The first three variables are calculated by averaging the monthly number of stocks, portfolio size, and turnover rate of households in the past year. On average, a household holds 4.83 stocks in its portfolio, worth around $47,844. However, the data is right-skewed. Most households hold a few stocks, trade a few times each month, and have low stakes in equity. A few households have a lot of stocks, trade many times, and have high stakes in stocks. The *IPO number* and *number of trades* are at the household-year-industry level. Finally, Panel F shows the number of households with different self-reported knowledge levels. Most households are in two categories: limited and good stock knowledge, while a few people are in none and extensive categories.

3. Empirical Design

3.1 Local IPOs and the number of trades

I start by associating local IPOs with household trading activities in the same industry. I estimate the following regression equation:

$$trading\ number_{hi,t} = \alpha + \beta * local\ IPOnumber_{hi,t-1} + \gamma * controls_{t-1} + \varepsilon_{hi,t} \qquad (1)$$

The dependent variable ($trading\ number_{hi,t}$) is the total number of trades (sum of buy and sell number) made by household h in the industry i in t (current year). In the model, each observation corresponds to a household-industry-year set. Since I use the Fama-French 10 industry classification, each household-year pair corresponds to 9 observations, regardless of whether the household trades in a particular industry in that year. Here I exclude observations in the “others” group under the Fama-Frech 10 industry classification since the firms under this category are unrelated. I also exclude the trades of local IPOs. So, my main dependent variable captures the trading activities of other stocks in the same industry as local IPO stocks. The independent variable ($local\ IPOnumber_{hi,t-1}$) is the number of IPOs within 25 miles from household *h* in the industry *i* in *t-1* (prior year). The distance (25 miles) is the spherical distance between two zip codes where the IPO firms’ headquarters and the household are located.

I use the number of trades as the dependent variable in my main test for two reasons. First, as Seru, Shumway, and Stoffman (2009) point out, retail investors learn their ability and improve their ability through trading. So, the number of trades investors make can be a proxy for the learning process, and such a dependent variable fits my research purpose. Second, Suppose I only look at the change of holdings for the related industry. In that case, I may not discover the relationship, as the retail investors may increase their trading activities while not significantly increasing their holdings.

3.2 Assumptions and control variables

I include industry, year, zip-code, and household fixed effects in the main test. These four fixed effects control for overall industry conditions, economic conditions in a particular year, zip-code level conditions, and time-invariant household features separately. I also include control variables that might affect households' trading behaviors. The control variables include (1) industry return and (2) investors' heterogeneity. The two key assumptions that make my findings valid are: (1) investors will pay attention to local IPOs (salience), and (2) no variables affect investors' trading behavior and the presence of IPOs after controls. If such omitted variables exist, they must (1) have a long-lasting effect on the trading behaviors of investors (at least a year). (2) vary over industries, years, and different locations. In Section 4, I provide more evidence for the first assumption through cross-sectional tests.

Industry Return. Grinblatt and Keloharju (2001) find that past stock returns affect investors' trading decisions. Barber and Odean (2008) also find that investors are likely to hold stocks with extreme returns. Industry returns affect how investors trade and whether a company has an IPO. Busaba, Benveniste, and Guo (2001) find that market returns strongly predict IPO completion. Thus, I include the equal-weighted average industry returns in the prior year to rule out such confounding effects.

Investors' Heterogeneity. Investors are inherently different in their trading behavior. Some investors might be more active traders, while others prefer to hold stocks for quite a while. Investors who live in places where IPOs happen often may be open-minded and thus more likely to trade more stocks. To ensure this possibility will not drive my results, I include several control variables that reflect the past trading behavior of investors (in the past year). These trading behavior control variables are (1) the average number of stocks in the beginning-of-month portfolios, (2) the logarithm of the average size of the beginning-of-month portfolios, and (3) the logarithm of the average of the monthly turnover rate calculated following Barber and Odean (2000).

3.3 Main results

Table 2 shows that retail investors significantly increase their trading activities in the following year of local IPO issuances. For columns (1) – (4), I use the ordinary least squares (OLS) model. Comparing the first four columns, adding extra controls and fixed effects does not change the local IPO number estimates much. The results are significant at the 1% level. All estimates are around 0.07. Column (4), for example, shows that one IPO in industry i in the previous year increases nearby household trading by 0.0795 trades. To put this number into perspective, the unconditional mean of household trading activity in one industry is 0.643. So, one IPO nearby increases the trading activity by households in the corresponding industry by 12.36 % (0.0795 /0.643) of the mean.

Columns (5)-(7) use non-linear models. These non-linear models are specifically designed for count data problems. All the estimates are reported as the average marginal effects (AME). Column (5) uses the Poisson regression with year and industry fixed effects. Compared with the OLS regression, the Poisson regression will always predict non-negative results for the number of trades. The Negative-Binomial model in column (6) addresses the overdispersion problem in the Poisson model. The key assumption in the Poisson model is that the conditional mean and conditional variance of independent variables should be equal ($\mathrm{Var}[y_i|x_i] = \mathrm{E}[y_i|x_i]$). However, in my data, most households trade a few times, and a few trade a lot, creating an overdispersion problem. Thus, this dataset does not meet the condition of the Poisson model (same mean-variance condition). Finally, my data contain excessive zeros, which can be addressed by the Zero-inflated Negative Binominal model in column (6). However, this model does not allow fixed effects. All three non-linear models yield significant results for the number of local IPOs. The first two models, (5) and (6), report an average marginal effect of 0.014 and 0.0167 trades. The estimates are similar in magnitude, around one-fifth of the OLS estimates. The estimate in column (7) is more than half of that in the OLS model, 0.0473 trades. Because of the straightforward interpretation and easy setups, I will use the OLS models in all other analyses.

4. Cross-sectional variation

My main results show that local IPOs induce households to trade more stocks in the same industry in the following year. However, my results rely on the assumption that local IPOs are saliant and retail investors pay attention to them. In this section, I provide more evidence to support this assumption.

4.1 Investor sophistication

Barber and Odean (2008) and Barber, Huang, Odean, and Chwarz (2021) suggest that naïve investors are more likely to trade attention-grabbing stocks. Da, Engelberg, and Gao (2011) also find that the google search volume index of IPO firms increases around the week of IPOs, indicating retail investors are paying attention to IPOs. If retail investors learn through noticing, I expect inexperienced investors to trade more since they do not have specific investments to focus on and be more likely to be attracted by stocks with salient features. I supplement the trading data with self-reported knowledge data to test this hypothesis. The brokerage firm collects the answer to a questionnaire on investment knowledge level when households open their account. There are four categories of knowledge sophistication: none, limited, high, and extensive. The data are partially available and not populated for all households.

I run the main regression with year and industry fixed effects for each knowledge group. The results in Table 3 show that both the magnitude and significance level of estimates decrease monotonically. For investors without knowledge of investments, one local IPO will increase their trading in the corresponding industry by 0.126 trades, equivalent to 20% (0.126/0.643) of the average trading number of the none-knowledge group. To compare the magnitude of estimate in each group, I include the marginal to means in the last row of Table3. There is a significant decline in the local IPO effect between the limited and the good knowledge groups. The magnitude of the decline is 48.5% [1-(0.089/0.173)]. The statistical significance level also decreases from the 1% to 5% level. From the good group to the extensive group, the effect magnitude declines by 38.2% [1-(0.055/0.089)].

Overall, the results show that local IPOs have a smaller effect on households with more investment knowledge. The evidence is consistent with the learning through noticing hypothesis. Households with more investment knowledge are more likely to have an investment focus in place. Thus, their attention is less likely to be directed by salient events. However, investors with limited knowledge typically do not have targeted stocks. Thus, they are more likely to investigate stocks attracting their attention.

4.2 IPO distance

Engelberg and Parsons (2011) find that investors respond strongly to local news coverage. Because people pay more attention to their surroundings, attention should decrease as news events become distant to investors. I hypothesize that the effect of local IPOs on retail investors decreases as the distance between the retail investor and the IPO firm's headquarters increases. To test this hypothesis, I run the main regression with industry and year fixed effects for four sub-samples with different distances between the households and IPO firms' headquarters.[1] For example, in column (1), I only include IPOs within 15 miles of households.

---

[1] The distance here is the distance between pairs of zip codes where IPO firm's headquarters and household beglong to. For more information, please refer to ZIP Code Distance Database on NBER website: https://www.nber.org/research/data/zip-code-distance-database.

According to Table 4, the influence of IPOs on household trading behavior decreases rapidly over distance. IPOs within 15 miles of households induce investors to make 0.094 more trades in the corresponding industry. IPOs within 100 miles induce investors to make 0.042 more trades, less than half the estimate in column (1). Because the effect of local IPOs declines quickly over a relatively short distance, the findings here should not be driven by local economic factors. The results are consistent with the salience-driven trading hypothesis.

5. More evidence on trade type and holdings

Previous results show households increase trading activities in the corresponding industry following local IPOs. There is a possibility that local IPOs serve as a proxy for industry clusters. For example, if we study investors in Silicon Valley, they are more likely to trade tech stocks because there are many tech companies around them. However, two hypotheses provide different predictions. Suppose local IPOs serve as a salient stimulus to make retail investors learn more related industry and invest. In that case, I expect retail investors to make more purchases as they venture into a new area. Thus, the learning by noticing hypothesis predicts that investors will buy more stocks in the same industry, and the effect should fade over time (learning curve decline). If retail investors trade simply because of local bias, there should not be any relationship between IPO timing and households' stock trading. In this section, I explore the effect of IPO timing on household trading and what type of trades IPOs induce.

5.1 Buy versus sell

If local IPOs serve as attention-grabbing events and induce households to trade, households should buy stocks in the corresponding industry right after IPOs issuance. However, if investors trade because they hold local stocks, there should not be any relationship between trade types and IPOs. I estimate the following two equations:

$$stock\ buy\ number_{hi,t} = \alpha + \beta * local\ IPOnumber_{hi,t-1} + \gamma * controls_{t-1} + \varepsilon_{hi,t} \qquad (2)$$

$$stock\ sell\ number_{hi,t} = \alpha + \beta * local\ IPOnumber_{hi,t-1} + \gamma * controls_{t-1} + \varepsilon_{hi,t} \qquad (3)$$

These two equations resemble equation (1). I change the dependent variable from the total trade number to the number of buys or sells. All the control variables are the same as in the main regression, and I include industry and year fixed effects.

Panel A of Table 5 reports the results. The estimate of the local IPO number in column (1) is not significant, and the estimate in column (2) is highly significant. Panel A shows that instead of inducing households to buy stocks in the corresponding industry, local IPOs induce people to sell their holdings. This result is not consistent with the predictions of both hypotheses. To ensure this result is general among investors, I run equations (2) and (3) again across different knowledge groups. Panel B reports the results of buys, and C reports the results of sells. Results in Panel B show that local IPOs induce households with none or limited knowledge to make more buys, while they marginally affect households with good knowledge and do not affect households with extensive knowledge. Panel C shows that local IPOs induce all households to sell their holdings in the corresponding industry, though the effect decreases as the knowledge level of households increases. The findings in Panels B and C are generally consistent with the results in A.

5.2 Possible explanations

In this section, I provide two possible explanations for why households engage in more sells in the corresponding industry one year after local IPOs. Then I examine the trading types and equity holdings in the corresponding industry in different time frames around the local IPOs to distinguish two explanations.

"Hot Market" Signal. Helwege and Liang (2004) show that IPOs can reflect the overall optimistic condition of the market. Thus, the number of IPOs can signal a "hot" market. In response to such a "hot" market signal, households will decrease their holdings in the corresponding industry. Therefore, local IPOs should be associated with household selling activities.

Under this explanation, several predictions can be made. First, households sell more and decrease their holdings after the local IPOs. Second, households should generate a stock return not significantly lower than the market return.

Learning By Trading. Another possibility is that investors learn about their ability and undo their initial investment decisions. Seru, Shumway, and Stoffman (2009) show that retail investors learn about their ability through trading and exit the market after they find their ability to trade is poor. Consider a retail investor who observes huge IPO returns and massive media coverage. He becomes optimistic about the IPO industry perspectives and rushes to invest in the same industry, but later finds out this is a mistake and decreases his holdings. In this scenario, households purchase more stocks around IPO issuances and decrease their holdings afterward.

There are three predictions under this explanation: First, households buy more stocks near the local IPO issuances and sell more afterward. Second, the general holdings of the local IPO industry should increase around IPO issuances and then decrease. Third, since this is an investment decision during the learning process, the stock return from purchases should be lower than the market return.

5.2.1 Timing of IPOs and household trading

To determine which explanation better fits the data, I explore the relationship between local IPO timing and household trading. In the previous section, I estimate the model according to equation (1). The time (*t*) in the dependent variable $trading\, number_{hi,t}$ and the independent variable $local\ IPOnumber_{hi,t-1}$ is at the annual level. To observe the more immediate effect, I change t to a shorter period, such as a quarter (3 months) or semiannual (6 months). Figure 2 shows an example of my method for quarterly estimation. I sum up the number of local IPOs in each quarter (or 6 months) and match them to household trading data in the following quarter (or half-year). Since IPOs can happen from month to month, I group them to reduce noise.

Table 6 provides the results of IPO timing and household trading activities. Panel A shows all stock trading activities, both buys and sells, for different periods following the local IPOs. The observations are at the quarter-household-industry level for column (1), the semiannual-household-industry for column (2), and the annual-household-industry for column (3). Column (3) is the annual estimates that are the same as those in Table 2 (column 2), and I include them for easy comparison. Panel A shows that the local IPO effect on trading decreases over time. The quarter estimate is about four times as large as the annual estimate. This result suggests that investors respond to IPOs strongly in the near term, supporting both explanations.

I split the total number of trades into sells and buys to distinguish the two explanations. Panel B shows results for the buy trades, and Panel C shows the sell trades. Generally, both panels show IPO effects decrease over time. However, the effect of local IPOs on stock purchases is stronger than on stock sells in the near term (three months and six months). The sell effect dominates buy effect one year after local IPO issuances. The results in Panels B and C are generally consistent with the learning through trading explanation. One might argue that looking at the number of trades may not reflect their equity holdings. Households can sell stocks many times but in small sizes and purchase stocks a few times but in big sizes. To rule out this possibility, I examine in more detail the portfolio holdings of households around the IPO issuances.

5.2.2 Equity holdings and local IPOs

I estimate the following two equations to see how households' portfolios change around local IPO issuance:

$$Equity\ holdings_{hi,t} = \alpha + \beta * local\ IPOnumber_{hi,t-1} + \gamma * control_{t-1} + \varepsilon_{hi,t} \tag{4}$$

$$Equity\ holdings_{hi,t-2} = \alpha + \beta * local\ IPOnumber_{hi,t-1} + \gamma * control_{t-1} + \varepsilon_{hi,t-2}. \quad (5)$$

The structure of equation (4) is similar to previous equations, but I replace the dependent variable with average monthly equity holdings (in \$) of households in industry i, at time period t. The t can be quarter, semiannual, and annual. The goal of equation (4) is to estimate the holding changes after local IPOs. Equation (5) is the same as equation (4), except the dependent variable $Equity\ holdings$ is at the time before IPO issuances. For equation (5), I only estimate the quarter result. Because IPO happens throughout the year, estimating longer periods will likely contaminate the results.

Table 7 reports the results of local IPOs and equity holdings. According to estimates in Table 7, the local IPOs induce investors to increase their holdings in the following quarter of the issuance. The economic magnitude is large. The unconditional holdings of households in any industry are around \$4150. In the following quarter, one local IPO induces households to increase their holdings in the corresponding industry by 50% of their average portfolio worth in the average industry. Households gradually decrease their holdings in the IPO industry over time. Within half-year, they decrease their average monthly holdings from \$2356 to \$1783, about a 25% reduction. Within one year, they further reduce holdings by another 55%, from \$1783 to \$806. From column (1), there are no significant holdings a quarter before IPO issuances. Also, the local IPO number estimate in column (4) is quite close to the estimate in column (1). This result shows that investors sell a significant amount of the holdings induced by local IPO within a year. The results are consistent with the predictions of the learning by trading hypothesis: investors increase their holdings immediately following local IPOs and then decrease them over time.

5.2.3 Implications on portfolio performance

Do IPO-induced trading activities benefit households? Two hypotheses give different answers. The "hot" market signal hypothesis assumes investors are rational and respond to the signal. Since households are informed, they should earn at least market returns. However, according to the learning through trading hypothesis, households do not know their ability and hold stocks after local IPOs. They will find their investment decision is not good and decrease holdings over time, performing worse than the market. In this section, I compare the performance of IPO-induced portfolios with several counterfactual portfolios to provide more evidence for a clear explanation.

Following Huang (2015), I construct several portfolios:

(1) IPO-induced stock portfolio: for each household-year pair, I pick the industry with the most local IPOs (non-zero) in the previous year to be the invested IPO industry. To form the portfolio, I

include all stocks purchased by households (in the year following IPO issuances) in the invested IPO industry.

(2) Actual portfolio: all stocks purchased by households.

(3) Beginning year portfolio: I assume investors hold the same stocks as they have at the beginning of the year. This portfolio mimics the results if investors do not change their portfolio throughout the year.

(4) Same IPO industry portfolio: I assume investors invest in the same industry as the invested IPO industry, but the stocks include all available stocks in the invested IPO industry.

I construct calendar-time portfolios according to the descriptions above. For each day, the calendar-time portfolio is constructed to include all stocks bought by households within the prior 21 trading days. For each stock-household (portfolio-household) pair, I use the weight based on the market value of equity for that stock from 10 trading days before. Then I accumulate the daily returns each week to obtain the weekly returns.

Table 8 reports the monthly abnormal returns of these portfolios, controlling for the Fama-French three factors (Fama and French, 1993) and the momentum factor (Jegadeesh and Titman,1993). I find that IPO-induced stock purchases produce significant negative weekly alpha, -0.00398 percentage points. The alpha is significant at the 10% level.

A general message we can learn from Table 8 is that purchasing IPO-induced stocks hurts households. Comparing the performance of the portfolio (1) with (2), I conclude that investors seem to profit from other stocks to compensate for the loss from induced IPO purchased stocks. However, the differences in returns between IPO-induced stocks and actual purchases are not statistically significant. Comparing portfolios (1) and (3), we can see that if the investors hold the portfolio the same as they have at the beginning of the year, they will perform much better. This result indicates that investors hurt their performance by trading. Finally, I get a small positive alpha for the same IPO industry portfolio. This result suggests that IPO industries do not perform worse after controlling for risks factors. The stocks households pick within IPO industries yield negative returns, reflecting inferior stock-picking abilities of investors. However, such inferior stock-picking abilities are restricted within the IPO industry: the general purchase portfolio does not perform worse than the market.

Overall, Table 8 suggests that households systematically pick the wrong stocks in the IPO industry. The return evidence is consistent with the learning through trading hypothesis. Right after the local IPO issuances, investors start to purchase stocks in the same industry as the IPO industry. However, such investment is a mistake for investors, as they get a significantly negative return after controlling for relevant risk factors. After paying the price, investors start to correct their mistakes by selling their positions induced by local IPOs.

6. Other features of induced purchases

Previous analyses suggest that local IPOs induce retail investors to trade stocks in the same industry. In this section, I explore whether local IPOs induce retail investors to purchase new stocks, local stocks, and stocks more related to local IPOs.

6.1 New stock purchases

Investors increase their trading activities in the IPO industry. However, learning by noticing hypothesis predicts that retail investors should also invest in new stocks. Table 9 provides the results of new stock purchases. The dependent variable in both columns is whether households own new stock (not owned in the past year) in one industry. The dependent variable equals one if households purchase new stock in one industry. Notice that I still use the OLS estimator in this test. Using fixed effect in Probit or Logit model will cause incidental parameters problem that leads to biased estimates.

The results of Table 9 are significant at the 1% level. A standard deviation increase in the number of IPOs (1.35) increases the probability of purchasing new stock by 0.464 percentage points (0.00344*1.35) for the model in column (1) or 0.653 percentage points (1.35*0.00484) in column (3). To put the number in perspective, the unconditional mean of purchasing new stock in one industry is about 7.66 percentage points. Therefore, a standard deviation increase in the number of local IPOs will increase the probability of purchasing new stock by 6.1% (0.464 /7.66) to 8.52% (0.653/7.66) relative to the mean. Thus, retail investors not only increase their current holdings but also purchase new stocks. The results imply that retail investors are more willing to venture into new investment opportunities following local IPOs. If we consider that the median household in the dataset only holds three stocks, local IPOs play an important role in increasing the investment choice set of households.

6.2 Geographic distribution of induced stocks

Up to this point, I have shown that retail investors are more likely to invest in the same industries as the industries of local IPOs. But which stocks should an investor pick? Previous literature suggests investors prefer local stocks. For example, Ivkovic and Weisbenner (2005) and Seasholes and Zhu (2010) show that individual investors overweight local stocks. Thus, in this section, I investigate whether "local IPO-induced" stocks are more likely to be local stocks.

I use the same methodology as in my return investigation. I calculate the average distance between households and several portfolios and compare these distances. I construct the following portfolios:

- Invested IPO industry stocks: for each household-year pair, I pick the industry with the most local IPOs (non-zero) in the previous year to be the invested IPO industry. To form the portfolio, I include all stocks purchased by households (in the year following IPO issuances) in the invested IPO industry.
- Other invested industry stocks: for each household-year pair, all industries other than the IPO industry. To form the portfolio, I include all stocks purchased by households (in the year following IPO issuances) in those industries.
- Market portfolios: include all stocks with non-missing zip code information.
- Same FF10 industry portfolio: include the stocks with non-missing zip code information in the industry same as the IPO industry.

I calculate the distance between the household zip code and the firm's headquarters zip code. Then, I average (equal weight) all household-year-stock pair distances to obtain an average distance for each portfolio. I perform a t-test for the distance differences between invested IPO industry stocks and other portfolios. I cluster the standard errors by zip code.

Table 10 report the results. The first row reports the differences in distances between invested IPO industry and invested other industries. The significant negative result implies that retail investors purchase more local stocks in the local IPO industry than in other industries following local IPOs. On average, IPO industry stocks are 319 miles closer to the household than those in other industries. Comparing the estimates of rows 1 and 2, we can conclude that retail investors are more likely to choose local stocks: both for invested IPO industry stocks and other invested industry stocks. A similar conclusion can be drawn from the estimates from row 3. My results illustrate that retail investors, besides purchasing stocks in the same category (industry), also choose stocks nearby their residences.

My findings in this section also imply a positive feedback loop for the local economy. Butler, Fauver, and Spyridopoulos (2019) show that local IPOs significantly improve local economic growth. After local IPOs, retail investors purchase more local stocks, signaling more confidence in future economic outlooks. Thus, managers may want to invest more and expand businesses.

6.3 More narrow industry?

I use the Fama-French 10-industry classification for all the analyses up to this point. Considering this classification system is coarse, a natural question is whether retail investors consider potential investment opportunities in more narrow industries. To answer this question, I repeat the same analyses for the main regressions but use the Fama-French 48 industry classification. The results are in Table 11. Comparing these results with the estimates from Table 2, I find both the economic magnitude and statistical significance decrease. The economic magnitude decreases by about one-fifth for each estimate, e.g., the estimate of column (2) in Table 11 is 0.0326 while the corresponding estimate in Table 2 is 0.0681 (column 2). It is not surprising to see such a reduction because trading and IPO activities in each industry will decrease significantly under a finer industry classification. Two facts can explain this phenomenon. First, households hold few stocks in their portfolios around the year: the median household holds only 3 stocks. Second, IPOs tend to cluster in a few locations while being quite sparse in most areas. However, I still find significant results under the Fama-French 48 industry classification, indicating that retail investors relate the local IPOs to potential investment opportunities in a finer industry category.

7. Conclusion

In this paper, I use a large panel of household trading data to show that retail investors respond to local IPOs by increasing their number of trades in the industries of local IPOs. The effect is concentrated among investors with less investment knowledge, and it fades over the distance. These results are consistent with the learning by noticing hypothesis. Also, I show that retail investors respond to local IPOs by increasing their holdings in the corresponding industries and then decreasing them over time. Given that the returns from the "induced purchases" underperform the market, investors seem to learn from their trading and actively correct their mistakes.

My research highlights how salient events induce investors to learn about related areas. Although I demonstrate that trading in related industries is induced by salience, I do not show how salience is transformed into the investment decision. For example, Laudenbach et al. (2016) show that increased local bankruptcies reduce risky shares of local retail investors. The local bankruptcies affect investors' behavior by temporarily changing their perceived risk and expectation of future stock prices. In this paper, there are three potential channels. First, investors may not know the return distribution of an industry and assume the returns from local IPOs are the typical returns people get from that industry. Second, investors may know the return distribution of an industry but might be overconfident in picking stocks and hoping to generate similar returns as the local IPOs. Finally, investors might become too optimistic about the economic outlook in an industry or general economy and thus increase their investment. Future researchers can use the expectation data to provide more insight into this issue.

References

Agarwal, Sumit, Vyacheslav Mikhed, and Barry Scholnick, 2020, Peers' Income and Financial Distress: Evidence from Lottery Winners and Neighboring Bankruptcies, *Review of Financial Studies* 33, 433–472.

Alok, Shashwat, Nitin Kumar, and Russ Wermers, 2020, Do Fund Managers Misestimate Climatic Disaster Risk, *The Review of Financial Studies* 33, 1146–1183.

Barber, Brad M., and Terrance Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773–806.

Barber, Brad M., and Terrance Odean, 2001, Boys will be Boys: Gender, Overconfidence, and Common Stock Investment*, *Quarterly Journal of Economics* 116, 261–292.

Barber, Brad M., and Terrance Odean, 2008, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21, 785–818.

Barber, Brad M., Xing Huang, Terrance Odean, and Christopher Schwarz, 2021, Attention Induced Trading and Returns: Evidence from Robinhood Users, *Journal of Finance, Forthcoming*

Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt, 2021 ,Rational inattention: a review, *working paper*

Branikas, Ioannis, Harrison Hong, and Jiangmin Xu, 2020, Location Choice, Portfolio Choice, *Journal of Financial Economics* 138, 74–94.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013, Salience and Consumer Choice, *Journal of Political Economy* 121, 803–843.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2020, Memory, Attention, and Choice*, *The Quarterly Journal of Economics* 135, 1399–1442.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2022, Salience, *Annual Review of Economics* 14, 521–544.

Butler, Alexander W., Larry Fauver, and Ioannis Spyridopoulos, 2019, Local Economic Spillover Effects of Stock Market Listings, *Journal of Financial and Quantitative Analysis* 54, 1025–1050.

Bushee, Brian, Matthew Cedergren, and Jeremy Michels, 2020, Does the media help or hurt retail investors during the IPO quiet period?, *Journal of Accounting and Economics* 69, 101261.

Célérier, Claire, and Boris Vallée, 2017, Catering to Investors Through Security Design: Headline Rate and Complexity*, *The Quarterly Journal of Economics* 132, 1469–1508.

Chaudary, Samra, 2019, Does salience matter in investment decision?, *Kybernetes* 48, 1894–1912.

Colaco, Hugh M J, Amedeo de Cesari, and Shantaram P Hegde, 2017, Retail Investor Attention and IPO Valuation, *European Financial Management* 23, 691–727.

Cosemans, Mathijs, and Rik Frehen, 2021, Salience theory and stock prices: Empirical evidence, *Journal of Financial Economics* 140, 460–483.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The Geography of Investment: Informed Trading and Asset Prices, *Journal of Political Economy* 109, 811–841.

Dessaint, Olivier, and Adrien Matray, 2017, Do managers overreact to salient risks? Evidence from hurricane strikes, *Journal of Financial Economics* 126, 97–121.

Engelberg, Joseph E., and Christopher A. Parsons, 2011, The Causal Impact of Media in Financial Markets, *Journal of Finance* 66, 67–97.

Engelberg, Joseph, Caroline Sasseville, and Jared Williams, 2012, Market Madness? The Case of "Mad Money," *Management Science* 58, 351–364.

Enke, Benjamin, 2020, What You See Is All There Is*, *The Quarterly Journal of Economics* 135, 1363–1398.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance* 51, 55–84.

Gabaix, Xaiver, 2019, Chapter 4: Behavioral inattention, *Handbook of Behavioral Economics,* Volume 2

Greenwood, Robin, and Stefan Nagel, 2009, Inexperienced investors and bubbles, *Journal of Financial Economics* 93, 239–258.

Grinblatt, Mark, and Matti Keloharju, 2001, What Makes Investors Trade?, *Journal of Finance* 56, 589–616.

Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein, 2014, Learning Through Noticing: Theory and Evidence from a Field Experiment *, *The Quarterly Journal of Economics* 129, 1311–1353.

Helwege, Jean, and Nellie Liang, 2004, Initial Public Offerings in Hot and Cold Markets, *Journal of Financial and Quantitative Analysis* 39, 541–569.

Huang, Xing, 2019, Mark Twain's Cat: Investment experience, categorical thinking, and stock selection, *Journal of Financial Economics* 131, 404–432.

Ivković, Zoran, and Scott Weisbenner, 2005, Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments, *Journal of Finance* 60, 267–306.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Jiang, Feng, Michelle B. Lowry, and Yiming Qian, 2022, Local IPOs and Household Stock Market Participation, *working paper*, *Available at SSRN: https://ssrn.com/abstract=3909980*

Kao, Lanfeng, Anlin Chen, and Cheng-Shou Lu, 2022, Retail investor attention and IPO prices with a pre-IPO market, *International Review of Economics & Finance* 82, 416–432.

Kaustia, Markku, and Samuli Knüpfer, 2008, Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions, *Journal of Finance* 63, 2679–2702.

Kaustia, Markku, and Samuli Knüpfer, 2012, Peer performance and stock market entry, *Journal of Financial Economics* 104, 321–338.

Kuchler, Theresa, and Basit Zafar, 2019, Personal Experiences and Expectations about Aggregate Outcomes, *Journal of Finance* 74, 2491–2542.

Laudenbach, Christine, Benjamin Loos, Jenny Pirschel, and Johannes Wohlfart, 2021, The trading response of individual investors to local bankruptcies, *Journal of Financial Economics* 142, 928–953.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Peress, Joel, 2014, The Media and the Diffusion of Information in Financial Markets: Evidence from Newspaper Strikes, *Journal of Finance* 69, 2007–2043.

Schwartzstein, Joshua, 2014, Selective Attention and Learning, *Journal of the European Economic Association* 12, 1423–1452.

Reme, Bjørn-Atle, Helene Lie Røhr, and Morten Sæthre, 2021, Inattention in Contract Markets: Evidence from a Consolidation of Options in Telecom, *Management Science* 68, 1019–1038.

Seasholes, Mark S., and Guojun Wu, 2007, Predictable behavior, profits, and attention, *Journal of Empirical Finance* 14, 590–610.

Seasholes, Mark S., and Ning Zhu, 2010, Individual Investors and Local Bias, *Journal of Finance* 65, 1987–2010.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by Trading, *Review of Financial Studies* 23, 705–739.

Merkoulova, Yulia, and Chris Veld, 2022, Stock return ignorance, *Journal of Financial Economics* 144, 864–884

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2009, Information Immobility and the Home Bias Puzzle, *Journal of Finance* 64, 1187–1215.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2010, Information Acquisition and Under-Diversification, *Review of Economic Studies* 77, 779–805.

APPENDIX

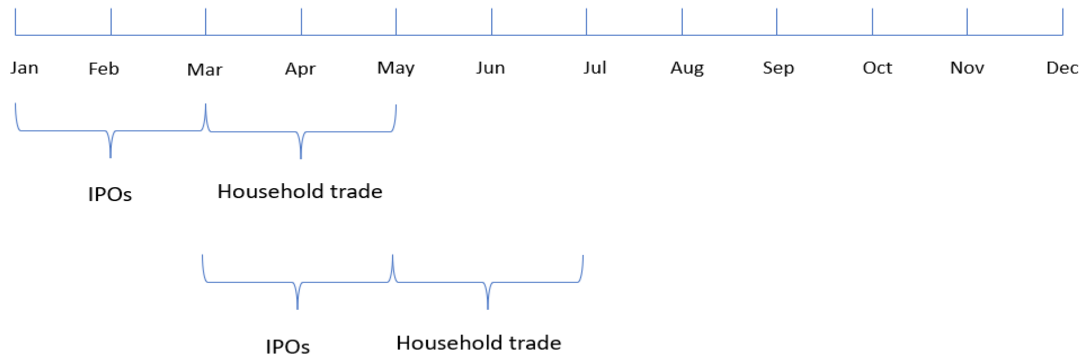

Figure 1. The methodology illustration.

Table 1: Summary Statistics

This table reports the summary of IPO distributions across different industries, trade types and number of trades made by retail investors across different industries, statistics of variables in main regressions, and the number of households across different sophistication groups. Panel A presents the number of IPOs from 1990 to 1995 across FF10 industries. Panel B displays the number of sells made by retail investors from1991 to 1996 across FF10 industries. Panel C displays the number of buys made by retail investors from 1991 to 1996 across FF10 industries. Panel D presents the number of trades (both sale and buy) by retail investors from1991 to 1996 across FF10 industries. Panel E presents Summary Statistics for variables used in main regressions. Panel F presents the number of households across different sophistication groups. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in a year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in a year. The *Average turnover rate* is calculated by averaging one year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t - 1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *IPO number* and the *number of trades* are at the year-household-industry level.

Panel A: Distribution of IPOs across different industries

Year	1990	1991	1992	1993	1994	1995	total
(1) Consumer Nondurables	6	24	34	46	27	24	161
(2) Consumer durables	3	6	14	21	20	11	75
(3) Manufacturing	15	24	33	78	66	47	263
(4) Oil, gas, and coal extraction and products	15	2	8	20	6	6	57
(5) High Technology	35	71	94	129	115	194	638
(6) Telephone and television transmission	0	5	15	28	21	22	91
(7) Wholesale, retail, and some services	19	57	77	87	63	51	354
(8) Health care, medical equipment, and drugs	31	93	109	54	60	65	412
(9) Utilities	1	4	3	4	2	1	15
(10) Others	90	105	186	313	211	114	1,014
N	215	391	573	780	591	535	3,080

Continued on next page

Table 1 Continued

Panel B: The number of sells by retail investors distribution across industries							
Year	1991	1992	1993	1994	1995	1996	Total
(1) Consumer Nondurables	4,986	4,788	5,574	4,761	5,226	4,507	29,842
(2) Consumer durables	2,901	4,147	4,044	2,754	3,517	3,290	20,653
(3) Manufacturing	8,495	7,562	8,342	7,124	9,053	8,494	49,070
(4) Oil, gas, and coal extraction and products	3,651	3,611	3,937	2,752	2,983	3,253	20,187
(5) High Technology	20,126	22,009	24,603	21,081	34,076	39,783	161,678
(6) Telephone and television transmission	3,702	4,296	4,844	4,131	5,158	4,394	26,525
(7) Wholesale, retail, and some services	10,108	10,057	10,598	8,614	10,630	10,667	60,674
(8) Health care, medical equipment, and drugs	11,735	13,449	12,633	10,184	11,349	10,953	70,303
(9) Utilities	3,402	3,590	3,776	3,343	3,747	3,470	21,328
(10) Others	20,077	15,991	18,452	14,014	16,192	15,649	100,375
Total	89,183	89,500	96,803	78,758	101,931	104,460	560,635

Panel C: The number of buys made by retail investors distribution across industries							
Year	1991	1992	1993	1994	1995	1996	Total
(1) Consumer Nondurables	7,947	6,711	7,046	5,105	4,915	5,369	37,093
(2) Consumer durables	4,221	4,590	3,471	4,276	3,887	3,241	23,686
(3) Manufacturing	10,708	8,954	8,130	7,463	10,376	10,440	56,071
(4) Oil, gas, and coal extraction and products	4,536	4,315	3,076	2,695	2,697	3,242	20,561
(5) High Technology	25,708	27,442	27,835	24,076	44,350	51,319	200,730
(6) Telephone and television transmission	5,812	5,016	5,489	5,981	5,153	4,728	32,179
(7) Wholesale, retail, and some services	14,215	13,925	13,539	11,125	11,479	10,771	75,054
(8) Health care, medical equipment, and drugs	19,891	22,603	18,122	10,619	10,445	11,706	93,386
(9) Utilities	5,299	5,384	3,953	5,354	2,832	2,500	25,322
(10) Others	27,198	18,079	19,999	16,166	16,141	16,749	114,332
Total	125,535	117,019	110,660	92,860	112,275	120,065	678,414

Panel D: The number of trades by retail investors distribution across industries							
Year	1991	1992	1993	1994	1995	1996	Total
(1) Consumer Nondurables	12,933	11,499	12,620	9,866	10,141	9,876	66,935
(2) Consumer durables	7,122	8,737	7,515	7,030	7,404	6,531	44,339
(3) Manufacturing	19,203	16,516	16,472	14,587	19,429	18,934	105,141
(4) Oil, gas, and coal extraction and products	8,187	7,926	7,013	5,447	5,680	6,495	40,748
(5) High Technology	45,834	49,451	52,438	45,157	78,426	91,102	362,408
(6) Telephone and television transmission	9,514	9,312	10,333	10,112	10,311	9,122	58,704
(7) Wholesale, retail, and some services	24,323	23,982	24,137	19,739	22,109	21,438	135,728
(8) Health care, medical equipment, and drugs	31,626	36,052	30,755	20,803	21,794	22,659	163,689
(9) Utilities	8,701	8,974	7,729	8,697	6,579	5,970	46,650
(10) Others	47,275	34,070	38,451	30,180	32,333	32,398	214,707
Total	214,718	206,519	207,463	171,618	214,206	224,525	1,239,0 49

Continued on next page

Table 1 Continued

Panel E: Summary Statistics for year-household-industry level variables						
	N	Mean	Std Dev	10th Percentile	50th Percentile	90th Percentile
Average number of stocks	995,868	4.83	5.37	1.00	3.00	10.27
Average portfolio size	995,868	47,844	165,628	3,458	16,960	96,239
Average turnover rate	988,497	0.07	0.12	0.00	0.03	0.20
Equal weighted industry return	1,445,526	0.17	0.31	-0.20	0.14	0.58
IPO number	1,445,526	0.1199	1.35	0	0	0
Number of trades	1,628,230	0.643	2.20	0	0	2

Panel F: Number of Households across different experience groups	
None	1,660
Limited	5,512
Good	7,527
Extensive	1,872
Total	16,571

Table 2: Local IPOs and the number of trades

This table reports the results of different models for main regressions. Columns (1)-(3) report the results of OLS regressions. Column (4) reports the results of the Poisson regression. Column (5) reports the results of the Negative Binominal regression. Column (6) reports the results of the Zero-Inflated Negative Binominal regression. All results of columns (4)-(6) are reported as the average marginal effects of independent variables. Each observation corresponds to a household-industry-year group, regardless of whether a household trades stocks in the industry. The dependent variable in regressions (1)-(6) is the total number of trades (both buy and sale) in an industry. The *Local IPO number* is the number of IPOs in one industry in the past year. The IPO firm's headquarters is within 25 miles of the household's residence. The *Equal weighted industry return* is the equal-weighted Fama-French 10 industry return in the past year. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in the past year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in the past year. The *Average turnover rate* is calculated by averaging the past year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t-1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *Average turnover rate* is calculated by averaging monthly turnover in a year. Industry fixed effects are defined at the Fama-French 10 industry classification level. Standard errors in parentheses are clustered by FF10 industry and year for the column (1)-(3). The standard errors are robust standard errors for columns (4)-(6). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	The number of trades in one industry						
	OLS	OLS	OLS	OLS	Poisson	Negative Binomial	Zero-Inflated Negative Binomial
Local IPO number	0.0637***	0.0681***	0.0772***	0.0795***	0.014***	0.0167***	0.0473***
	(0.0109)	(0.0100)	(0.0117)	(0.0115)	(0.000956)	(0.001)	(0.0014)
Equal weighted industry return		0.237*	0.236*	0.236*	0.199***	0.120***	0.399***
		(0.098)	(0.0975)	(0.0974)	(0.0128)	(0.011)	(0.0076)
log(Average portfolio size)		0.229***	0.210***	0.0783**	0.243***	0.217***	0.193***
		(0.017)	(0.015)	(0.024)	(0.0028)	(0.0026)	(0.0027)
Average number of stocks		0.0724***	0.0634***	0.0242*	0.0334***	0.0445***	0.0837***
		(0.005)	(0.004)	(0.011)	(0.0004)	(0.00052)	(0.00079)
log(Average turnover rate)		0.370***	0.297***	0.0175	0.365***	0.294***	0.314***
		(0.029)	(0.023)	(0.039)	(0.0031)	(0.0025)	(0.0027)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Zipcode FE	No	No	Yes	Yes	No	No	No
Household FE	No	No	No	Yes	No	No	No
Observations	1,445,526	709,101	709,101	709,101	709,101	709,101	709,101
R^2	0.0547	0.140	0.187	0.237	0.255	0.0835	~

Table 3: Variation in investor sophistication

This table reports the results of OLS regressions for a subgroup sample. The sample is divided into four groups based on investor's knowledge: None, Limited, Good, and Extensive. Each observation corresponds to a household-industry-year group, regardless of whether a household trades stocks in the industry. The dependent variable in columns (1)-(4) is the total number of trades (both buy and sale) in an industry. The *Local IPO number* is the number of IPOs in one industry in the past year. The IPO firm's headquarters is within 25 miles of the household's residence. The *Equal weighted industry return* is the equal-weighted Fama-French 10 industry return in the past year. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in the past year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in the past year. The *Average turnover rate* is calculated by averaging the past year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t-1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *Average turnover rate* is calculated by averaging monthly turnover in a year. Industry fixed effects are defined at the Fama-French 10 industry classification level. Standard errors in parentheses are clustered by FF10 industry and year. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	The number of trades in one industry			
Sophistication group:	None	Limited	Good	Extensive
Local IPO number	0.126**	0.106***	0.0720**	0.0603*
	(0.0300)	(0.0227)	(0.0174)	(0.0251)
Equal weighted industry return	0.304*	0.302**	0.285	0.326
	(0.118)	(0.0997)	(0.164)	(0.179)
log(Average portfolio size)	0.147***	0.160***	0.209***	0.192***
	(0.0309)	(0.0142)	(0.0372)	(0.0296)
Average num of stocks	0.0297**	0.0662***	0.0475***	0.0334*
	(0.00989)	(0.0107)	(0.00628)	(0.0120)
log(Average turnover rate)	0.124**	0.185***	0.267***	0.174***
	(0.0412)	(0.0246)	(0.0421)	(0.0355)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	27,522	87,714	146,817	41,364
R^2	0.224	0.229	0.241	0.260
Average total trading number	0.728	0.612	0.804	1.073
Marginal to means	0.173	0.173	0.089	0.055

Table 4: IPO distance variation

This table reports the results of OLS regressions for different distances from the IPO firm's headquarters to the household's residence. Each observation corresponds to a household-industry-year group, regardless of whether a household trades stocks in the industry. The dependent variable in columns (1)-(4) is the total number of trades (both buy and sale) in an industry in one year. The *Local IPO number* is the number of IPOs in one industry in the past year. The IPO firm's headquarters is within 25 miles of the household's residence. The *Equal weighted industry return* is the equal-weighted Fama-French 10 industry return in the past year. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in the past year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in the past year. The *Average turnover rate* is calculated by averaging the past year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t-1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *Average turnover rate* is calculated by averaging monthly turnover in a year. Industry fixed effects are defined at the Fama-French 10 industry classification level. Standard errors in parentheses are clustered by FF10 industry and year. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	The number of trades in one industry			
Different distance groups:	15 Miles	25 Miles	50 Miles	100 Miles
Local IPO number	0.0936***	0.0681***	0.0497***	0.0424**
	(0.0148)	(0.0100)	(0.00636)	(0.0126)
Equal weighted industry return	0.237*	0.237*	0.236*	0.236*
	(0.0978)	(0.0979)	(0.0981)	(0.0901)
Log (Average portfolio size)	0.229***	0.229***	0.229***	0.229**
	(0.0172)	(0.0172)	(0.0172)	(0.0709)
Average num of stocks	0.0724***	0.0724***	0.0723***	0.0723***
	(0.00485)	(0.00486)	(0.00485)	(0.0138)
Log (Average turnover rate)	0.370***	0.370***	0.369***	0.369**
	(0.0285)	(0.0286)	(0.0285)	(0.120)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	709,101	709,101	709,101	709,101
R^2	0.141	0.140	0.140	0.140

Table 5: Buy vs Sell

Panel A reports the results of OLS regressions for different trading types. Each observation corresponds to a household-industry-year group, regardless of whether a household trades stocks in the industry. In column (1), the dependent variable is the number of buys made by households in an industry in one year. In column (2), the dependent variable is the number of sells made by households in an industry in one year. Panel B reports the results of OLS regressions across different knowledge groups for buy trades. The sample is divided into four groups based on investor's knowledge: None, Limited, Good, and Extensive. The dependent variables across columns (1)-(4) are the number of buys made by households in an industry in one year. Panel C reports the results of OLS regressions across different knowledge groups for sell trades. The sample is divided into four groups based on investor's knowledge: None, Limited, Good, and Extensive. The dependent variables across columns (1)-(4) are the number of sell trades made by households in an industry in one year. The *Local IPO number* is the number of IPOs in one industry in the past year. The *Local IPO number* is the number of IPOs in one industry in the past year. The IPO firm’s headquarters is within 25 miles of the household's residence. The *Equal weighted industry return* is the equal-weighted Fama-French 10 industry return in the past year. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in the past year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in the past year. The *Average turnover rate* is calculated by averaging the past year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t-1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *Average turnover rate* is calculated by averaging monthly turnover in a year. Industry fixed effects are defined at the Fama-French 10 industry classification level. Standard errors in parentheses are clustered by FF10 industry and year. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Buy and Sell trades in one industry made by retail investors		
	(1)	(2)
Dependent variable:	Number of buys in one industry	Number of sells in one industry
Local IPO number	0.0314***	0.0372***
	(0.00486)	(0.00571)
Equal weighted industry return	0.189*	0.0484
	(0.0684)	(0.0395)
log(Average portfolio size)	0.123***	0.106***
	(0.00854)	(0.00897)
Average num of stocks	0.0374***	0.0348***
	(0.00269)	(0.00219)
log(Average turnover rate)	0.197***	0.173***
	(0.0154)	(0.0136)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	709,101	709,101
R^2	0.120	0.125

Continued on next page

Table 5: Continued

Panel B: Buy trades in one industry made by retail investors across different experience groups				
	(1)	(2)	(3)	(4)
Dependent variable:	The number of buys in one industry			
Sophistication group:	None	Limited	Good	Extensive
Local IPO number	0.0613**	0.0471**	0.0275*	0.0147
	(0.0208)	(0.0116)	(0.0101)	(0.0122)
Equal weighted industry return	0.248**	0.241**	0.232*	0.266*
	(0.0841)	(0.0711)	(0.0991)	(0.108)
log(Average portfolio size)	0.134***	0.107***	0.151***	0.152***
	(0.0191)	(0.0131)	(0.0200)	(0.0171)
Average num of stocks	0.0252**	0.0452***	0.0379***	0.0422***
	(0.00577)	(0.00700)	(0.00543)	(0.00488)
log(Average turnover rate)	0.216***	0.192***	0.239***	0.302***
	(0.0233)	(0.0172)	(0.0295)	(0.0250)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	27,522	87,714	146,817	41,364
R^2	0.122	0.125	0.137	0.147

Panel C: Sell trades in one industry made by retail investors across different experience groups				
	(1)	(2)	(3)	(4)
Dependent variable:	The number of sells in one industry			
Sophistication group:	None	Limited	Good	Extensive
Local IPO number	0.0566**	0.0529**	0.0331**	0.0296*
	(0.0138)	(0.0119)	(0.00884)	(0.0121)
Equal weighted industry return	0.0603	0.0630	0.0550	0.0543
	(0.0428)	(0.0320)	(0.0748)	(0.0867)
log(Average portfolio size)	0.115***	0.0925***	0.127***	0.124***
	(0.0169)	(0.0105)	(0.0195)	(0.0164)
Average num of stocks	0.0261**	0.0405***	0.0364***	0.0400***
	(0.00578)	(0.00618)	(0.00526)	(0.00366)
log(Average turnover rate)	0.187***	0.167***	0.210***	0.281***
	(0.0227)	(0.0151)	(0.0248)	(0.0237)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	27,522	87,714	146,817	41,364
R^2	0.133	0.129	0.143	0.151

Table 6: Different time frame

This table reports the results of OLS regressions on different time frames of Local IPOs and household trading activities. Panel A reports the results of local IPOs and the total number of trades in one industry across different time frames. For column (1), each observation corresponds to a household/industry/quarter group, regardless of whether the household trades stocks in the industry. The dependent variable is the number of trades made by the household within a quarter. The *Local IPO number* is the number of IPO in one industry in the past quarter. The IPO firm's headquarters is within 25 miles of the household's residence. All other control variables are averaged monthly variables of the past quarter. For column (2), each observation corresponds to a household/industry/semiannual group, regardless of whether the household trades stocks in the industry. The dependent variable is the number of trades made by the household within a half-year (6 months). The *Local IPO number* is the number of IPOs in one industry in the past half-year. The IPO firm's headquarters is within 25 miles of the household's residence. All other control variables are averaged monthly variables of the past half-year. For column (3), it is the same as the main regression. Each observation corresponds to a household-industry-year group, regardless of whether household trade stock in the industry. The dependent variable is the number of trades made by the household within a year. The *Local IPO number* is the number of IPOs in one industry in the past year. All other control variables are averaged monthly variables of the past year. Panel B reports the results of local IPOs and the number of buys in one industry across different time frames. Panel C reports the results of local IPOs and the number of sells in one industry across different time frames. Standard errors in parentheses are clustered by FF10 industry and quarter (1), semiannual (2), and year (3). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Total number of trades in one industry across different time frames			
	(1)	(2)	(3)
Dependent variable:		The number of trades in one industry	
	Quarter	Semiannual	Annual
Local IPO number	0.269***	0.226***	0.0681***
	(0.0574)	(0.0348)	(0.0100)
Equal weighted industry return	0.178	0.233**	0.237*
	(0.116)	(0.0944)	(0.0979)
log(Average portfolio size)	0.0747***	0.119***	0.229***
	(0.00337)	(0.00563)	(0.0172)
Average num of stocks	0.0225***	0.0398***	0.0724***
	(0.00120)	(0.00210)	(0.00486)
log(Average turnover rate)	0.114***	0.184***	0.370***
	(0.00548)	(0.0102)	(0.0286)
Industry FE	Yes	Yes	Yes
Quarter FE	Yes	~	~
Semiannual FE	~	Yes	~
Year FE	~	~	Yes
Observations	1,954,035	1,406,709	709,101
R^2	0.103	0.124	0.140

Continued on next page

Table 6: Continued

Panel B: The number of buys in one industry across different time			
	(1)	(2)	(3)
		The number of buys in one industry	
	Quarter	Semiannual	Annual
Local IPO number	0.136***	0.119***	0.0314***
	(0.0300)	(0.0177)	(0.00486)
Equal weighted industry return	0.116*	0.183**	0.189*
	(0.0663)	(0.0647)	(0.0684)
log(Average portfolio size)	0.0391***	0.0640***	0.123***
	(0.00191)	(0.00327)	(0.00854)
Average num of stocks	0.0116***	0.0208***	0.0374***
	(0.000639)	(0.00124)	(0.00269)
log(Average turnover rate)	0.0607***	0.0993***	0.197***
	(0.00310)	(0.00582)	(0.0154)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,954,035	1,406,709	709,101
R^2	0.0779	0.0987	0.120

Panel C: The number of sells in one industry across different time			
	(1)	(2)	(3)
		The number of sells in one industry	
	Quarter	Semiannual	Annual
Local IPO number	0.127***	0.107***	0.0372***
	(0.0269)	(0.0171)	(0.00571)
Equal weighted industry return	0.0548	0.0494	0.0484
	(0.0471)	(0.0315)	(0.0395)
log(Average portfolio size)	0.0332***	0.0544***	0.106***
	(0.00136)	(0.00259)	(0.00897)
Average num of stocks	0.0101***	0.0186***	0.0348***
	(0.000516)	(0.000898)	(0.00219)
log(Average turnover rate)	0.0503***	0.0841***	0.173***
	(0.00221)	(0.00448)	(0.0136)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,954,035	1,406,709	709,101
R^2	0.0763	0.101	0.125

Table 7: Local IPO number and equity holdings

This table reports the results of OLS regressions relating total stock equity holding and local IPOs across different time frames. Column (1) reports the result of household stock holdings($) one quarter before the local IPO issuances. Each observation corresponds to a household/industry/quarter group, regardless of whether the household trades stocks in the industry. The *Local IPO number* is the number of IPOs in one industry in the next quarter. The IPO firm's headquarters is within 25 miles of the household's residence. Column (2) reports the result of household stock holdings ($) one quarter after the local IPO issuances. Each observation corresponds to a household/industry/quarter group, regardless of whether the household trades stocks in the industry. The *Local IPO number* is the number of IPO firms in one industry in the past quarter. Column (3) reports the result of household stock holdings ($) half-year after the local IPO issuances. Each observation corresponds to a household/industry/semiannual group, regardless of whether the household trades stocks in the industry. The *Local IPO number* is the number of IPO firms in one industry in the past half-year. Column (4) reports the result of household stock holdings($) one year after the local IPO issuances. Each observation corresponds to a household-industry-year group, regardless of whether the household trades stocks in the industry. The *Local IPO number* is the number of IPO firms in one industry in the past year. Standard errors in parentheses are clustered by the FF10 industry and the corresponding time level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Total stock equity holdings($)			
	Pre-quarter	Quarter	Semiannual	Annual
Local IPO number	879.0	2356.0***	1782.9***	805.9***
	(965.5)	(524.0)	(308.8)	(131.2)
Equal weighted industry return	11434.7	11891.0	9054.5*	3697.3
	(8168.4)	(7079.2)	(4154.5)	(2522.6)
log(Average portfolio size)	31655.1***	14132.7***	28323.6***	24953.1***
	(1281.8)	(1067.8)	(1515.3)	(1442.6)
Average num of stocks	-150.7	345.8***	-7.729	176.3
	(148.5)	(112.1)	(147.7)	(175.6)
log(Average turnover rate)	3391.1***	187.6	2325.6***	1425.8**
	(334.2)	(177.9)	(390.7)	(455.8)
Industry FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	No	No
Semi-annual FE	No	No	Yes	No
Year FE	No	No	No	Yes
Observations	550,047	555,221	378,977	243,678
R^2	0.380	0.520	0.352	0.315

Table 8: Return performance: local IPO induced stocks vs other portfolios

The table reports the weekly abnormal returns of calendar-time portfolios controlling for the Fama-French three factors (Fama and French, 1993) and the Momentum factor (Jagadeesh and Titman,1993). The portfolios are formed as follows: (1) IPO-induced stocks: for each household-year pair, I pick the industry with the most local IPOs (non-zero) to be the IPO industry. To form the IPO-induced stocks portfolio, I include all stocks in the IPO industry within which households have bought during the prior 21 trading days; (2) Actual portfolio: for each day, the calendar-time portfolio of actual purchases is formed to include all stocks bought by households within the prior 21 trading days; (3) beginning-of-the-year portfolio: include the beginning-of-the-year portfolio for each purchase made by households during the prior 21 trading days; (4) Same FF10 industry with IPO industry but different stocks: to include all stocks on the market in the invested IPO industries. The portfolio returns are then accumulated each week to obtain weekly returns. The differences between returns of actual purchases and counterfactual portfolios are the weekly abnormal return of going long on the portfolio of actual purchases and short on the counterfactual portfolios. Standard errors are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Portfolio types	Portfolio 4-factor alpha	Difference (Induced stocks - Counterfactual)
(1) IPO-induced stocks	-0.00398* (0.00213)	
Counterfactual portfolios:		
(2) Actual portfolio	0.000532 (0.00542)	-0.00426 (0.00622)
(3) Beginning year portfolio	0.000830*** (1.436)	-0.00518*** (0.00195)
(4) Same ff10 industry with IPO industry but different stocks	0.00124* (0.000658)	-0.00489** (0.00207)

Table 9: Local IPO number and new stock purchase

This table reports the results of OLS regressions for whether local IPOs induce owning new stocks. Each observation corresponds to a household-industry-year group, regardless of whether the household previously owned stocks in the industry. The dependent variable in columns (1) and (2) is a dummy variable that equals one when a household purchases stock not previously owned in the industry. The *Local IPO number* is the number of IPOs in one industry in the past year. The IPO firm's headquarters is within 25 miles of the household's residence. The *Equal weighted industry return* is the equal-weighted Fama-French 10 industry return in the past year. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in the past year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in the past year. The *Average turnover rate* is calculated by averaging the past year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t-1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *Average turnover rate* is calculated by averaging monthly turnover in a year. Industry fixed effects are defined at Fama-French 10 industry classification level. Standard errors in parentheses are clustered by FF10 industry and year. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dependent variable:	Buy new stocks (not owned in the past year) in one industry		
Local IPO number	0.00344***	0.00478***	0.00484***
	(0.00042)	(0.00057)	(0.00056)
Equal weighted industry return	0.0555**	0.0555**	0.0555**
	(0.0199)	(0.0199)	(0.0199)
log(Average portfolio size)	0.0151***	0.0109***	-0.00748
	(0.0021)	(0.0018)	(0.0055)
Average num of stocks	0.00519**	0.00506***	-0.00460*
	(0.0011)	(0.00069)	(0.0019)
log(Average turnover rate)	0.0263***	0.0211***	-0.00347
	(0.00343)	(0.00328)	(0.00370)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Zipcode FE	No	Yes	Yes
Household FE	No	No	Yes
Observations	709,101	709,101	709,101
R^2	0.0758	0.0977	0.126

Table 10: Invested industry distance test

This table reports the results of t-tests on the distance of invested IPO industry stocks vs. other portfolios. For each household-year pair, I pick the FF10 industry with most local IPOs (Non-zero) as the invested IPO industry. I calculate the distance between the household zip code and the firm's headquarters zip code. Next, I average (equal weight) all household-year-stock pair distances to get an average distance between stocks and investors for each portfolio. The first row reports the t-test result of the average distance differences between invested IPO industry stocks and other invested industries stocks of the household. The second row reports the t-test result of the average distance differences between invested IPO industry stocks and the market portfolio. The final row reports the t-test result of the average distance differences between Invested IPO industry stocks and the universe of stocks in the same invested IPO industry category. Standard errors in parentheses are clustered at the zip-code level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Distance differences (in miles)	
Invested IPO industry stocks vs. other invested industry stocks	-318.7658*** (41.84849)
Invested IPO industry stocks vs. market portfolio	-585.7632*** (61.81015)
Invested IPO industry stocks vs. same ff10 industry portfolio	-486.9403*** (51.17639)

Table 11: Fama-French 48 industry test

This table reports the results of OLS regressions for main regressions but using Fama-French 48 industry classification. Each observation corresponds to a household-industry-year group, regardless of whether a household trades stocks in the industry. The dependent variable in columns (1)-(3) is the total number of trades (both buy and sale) in an industry. The *Local IPO number* is the number of IPO firms in one industry in the past year. The *Local IPO number* is the number of IPOs in one industry in the past year. The IPO firm's headquarters is within 25 miles of the household's residence. The *Equal weighted industry return* is the equal-weighted Fama-French 10 industry return in the past year. The *Average number of stocks,* the *Average portfolio size, and* the *Average turnover rate* are calculated using the beginning-of-month position data. The *Average number of stocks* is calculated by averaging the beginning-of-month number of stocks in the past year. The *Average portfolio size* is calculated by averaging the beginning-of-month total equities of stock holdings in the past year. The *Average turnover rate* is calculated by averaging the past year's monthly portfolio turnover rate. Monthly turnover is the beginning-of-month market value of shares purchased in month t-1(or sold in month t) divided by the total beginning-of-month market value of shares held in month t. The *Average turnover rate* is calculated by averaging monthly turnover in a year. Industry fixed effects are defined at the Fama-French 10 industry classification level. Standard errors in parentheses are clustered at industry and year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	Total stock trade number in one industry			
Local IPO number	0.0343***	0.0326**	0.0358**	0.0363**
	(0.00623)	(0.00729)	(0.00784)	(0.00805)
Equal weighted industry return		0.0440*	0.0440*	0.0440*
		(0.0197)	(0.0197)	(0.0197)
log(Average portfolio size)		0.0451***	0.0415***	0.0154**
		(0.00302)	(0.00266)	(0.00474)
Average num of stocks		0.0165***	0.0143***	0.00545*
		(0.00108)	(0.000660)	(0.00234)
log(Average turnover rate)		0.0776***	0.0618***	0.00293
		(0.00526)	(0.00406)	(0.00834)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Zipcode FE	No	No	Yes	Yes
Household FE	No	No	No	Yes
Observations	7,709,472	3,781,872	3,781,872	3,781,872
R^2	0.0516	0.0928	0.114	0.138

Vita

Guanhuan Wang spent most of his childhood in Hangzhou, China. After graduating Hangzhou High School, he attended Shaanxi Normal University, received a Bachelor of Economics degree in Finance. After college graduation, he attended Southern Methodist University and received Master of Finance degree. At the time of graduation, he knew he wanted to pursue a career as a researcher. He chose the University of Tennessee, Knoxville for his graduate studies to pursue a Doctor of Philosophy degree in Business Administration with a concentration in Finance. His research interests include the effects of salience on trading behaviors of retail investors and household finance. He is incredibly grateful for all the support throughout his studies from his family and friends.