Behavior and performance of emerging market investors: Evidence from China

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Abstract

We study brokerage account data from China to study investing behavior and trading performance in an emerging market. We find that Chinese investors exhibit behavioral biases (i.e., they seem overconfident, inclined toward a disposition effect, and exhibit a representativeness bias) and make poor ex post trading decisions. We also consider potential cross-sectional determinants of investing behavior. Specifically, we identify (1) investors who have accumulated relatively more years of investing experience, (2) middle-aged investors, (3) active investors, (4) investors with relatively more wealth, and (5) investors from the more cosmopolitan Chinese cities, to see if these investors are less prone to exhibiting behavioral biases. Oftentimes, the answer seems to be 'no.'

JEL classification: G10
Keywords: Investor behavior; Trading performance; China

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1. Introduction

Researchers have shown that individual investors in developed markets may succumb to heuristic simplification in their decision-making. As a result, individual investors seem to be overconfident, they suffer from a disposition effect (i.e., they hold onto their losers and they sell their winners), and they seem to be making ex post trading mistakes. These cognitive errors are said to stem from the brain's tendency to make mental shortcuts and to avoid longer analytical processing. With regard to investors from emerging markets, however, we know much less about their investing behavior. Are emerging market investors more or less inclined toward behavioral biases? Perhaps the larger question is, "are there any investor-types that are not prone to behavioral biases?" Given current literature, the answer to these two questions is that "we're not sure." Therefore, to address these two gaps in the literature, we study the investing behavior and trading performance of individual investors in China. Furthermore, we also differentiate these Chinese investors to try to identify differences in their behaviors. To conduct our analyses, we obtain data on 74,960 individual investor brokerage accounts from a brokerage firm in China. China's stock markets are quite new, and its society has only recently become more connected to the outside world. As such, our study should shed important insight into the behavior and performance of emerging market investors.

As previously stated, in addition to simply studying emerging market investors, we also conduct cross-sectional tests on investing behavior and performance. For example, researchers still do not know to what extent psychological biases can be mitigated with experience. Perhaps investors can 'learn' to become more rational. Or, is it possible that investing experience and/or other experiences exacerbate their tendencies toward behavioral biases, as investors may overweight or overestimate their own level of investing sophistication? Is there cross-sectional variation in Chinese investors' trading behaviors and abilities? If so, then who might be less inclined toward making trading mistakes?

We initially conduct four sets of empirical tests on Chinese investors. First, we identify trading performance by reporting the subsequent return of stocks sold versus stocks purchased. Second, we determine to what extent Chinese investors are disposed to holding poorly performing stocks (losers) while selling winners (i.e., the disposition effect). Third, we assess the extent to which they exhibit overconfident characteristics. Specifically, we examine their inclination toward portfolio diversification and trading activity. Finally, we identify the past performance of stocks that investors are purchasing to see if they are attracted to stocks that experience very recent run-ups (i.e., a representative bias). Overall, we find evidence that Chinese investors make poor ex post trading decisions (e.g., stocks that they sell subsequently outperform stocks that they buy), they are more disposed to selling their winners rather than losers, they exhibit overconfident tendencies (e.g., they under-diversify and trade frequently), and they exhibit a representativeness bias (i.e., they are purchasing stocks with recent large run-ups, perhaps thinking that these firms will continue to do well into the future).

Just as important, we conduct cross-sectional tests to see how different investors behave and perform. Specifically, we identify middle-aged investors, active investors, wealthier investors, experienced investors, and investors from the more cosmopolitan Chinese cities to see if they are less inclined toward making cognitive errors. Somewhat surprisingly, we find that with experience, investors oftentimes still cannot overcome behavioral biases. The overall message of our paper, therefore, is that emerging market investors make cognitive errors, and specific individual investors that one might think are savvier do *not* seem less inclined to making these errors.

The rest of our paper is organized as follows. The next section explores the literature on investing behavior, and it also discusses which investors *might be* less inclined toward behavioral biases. Section 3 describes our data and presents summary statistics. Section 4 presents and discusses our empirical findings. Conclusions are offered in the last section.

2. Investing behavior

2.1 Behavioral biases and trading performance

Investors may be inclined toward various types of behavioral biases, which lead them to make cognitive errors. Hirshleifer (2001) categorizes the different types of cognitive errors that investors can make. People may make predictable, non-optimal, choices when faced with difficult and uncertain decisions because of heuristic simplification. Heuristic simplification exists because constraints on cognitive resources (like memory, attention, and processing power) force the brain to shortcut complex analyses.

One outcome of heuristic simplification, self-deception, occurs because people tend to think that they are better than they really are (Trivers (1991)). Both the psychology and the recent finance literature characterize people with this type of behavior as being "overconfident." Investors who are overconfident believe they can obtain large returns, thus they trade often and they underestimate the associated risks (Benos (1998), DeLong, Shleifer, Summers, and Waldmann (1990), Kyle and Wang (1997), Odean (1998b) and Wang (1998, 2001)). Overconfidence can lead to the speculation that drives asset bubbles (Scheinkman and Xiong (2003)). Empirical evidence finds support for these conjectures. Barber and Odean (2000, 2001) and Odean (1999) find that U.S. individual investors trade excessively, expose themselves to a high level of risk, and make poor ex post investing decisions (i.e., the stocks that individuals sell outperform stocks that they buy).

One form of heuristic simplification is mental accounting, where the mind keeps track of gains and losses related to decisions (Thaler (1980)). According to Hirshleifer (2001), mental accounting may explain the "disposition effect." Simply stated, people want their good decisions to be recognized immediately in their mental accounts, but they postpone acknowledging their bad decisions. This behavioral bias has implications for investing behavior. That is, investors may sell stocks that have performed well so that they can feel good about themselves and boast to others about their ability to pick good stocks. At the same time, investors may hold on to their poorly performing stocks because they are not ready to acknowledge that they made a mistake, and because they are afraid that the stocks may recover (i.e., they wish to avoid regret) (Shefrin and Statman (1985)). Odean (1998a) finds empirical support. Specifically, he finds that U.S. individual investors are more willing to recognize paper gains than paper losses.

One mental shortcut, the representativeness bias, makes the assumption that certain qualities of an item must imply other qualities for that same (or related) item, often in a positively correlated way. For example, a clean used car is often thought to be a well-running car. This kind of bias can also affect investors (Shefrin (2000)). For example, investors may confuse a good company with a good investment. A good firm may be one that generates strong earnings, have high sales growth, and/or have quality management, but a good investment is a stock whose price increases more than other stocks (Solt and Statman (1989)). Investors also make this error when noting recent past stock returns. Investors might consider recent past returns to be representative of what they can expect in the future. Therefore, investors might buy stocks that have recently increased in price (i.e., they have a myopic focus). This is also known as momentum trading or positive-feedback trading. Dhar and Kumar (2005) investigate the price trends of stocks bought by more than 62,000 households at a discount brokerage during a five-year period. On average, these stocks increased by 0.6% during the week before the purchase. The increase was 1.2%, 2.2%, and 7.3% for the two weeks, one month, and three months before the purchase, respectively. The buying of past winners has also been identified by flows into equity mutual funds (Sirri and Tufano (1998)). Investors like to buy recent past winners because they believe that the past price trend is representative of the future price trend.

The above cognitive errors have been predominately studied in samples of U.S. investors. Other Western cultures, like Finland and Israel have been examined (Grinblatt and Keloharju (2000, 2001b) and Shapira and Venezia (2001), respectively). However, there may be important psychological differences between Chinese investors and investors in developed Western cultures. For example, some researchers suggest that Asians may be more overconfident than Westerners. Studies of risk perception find that people in Asian cultures (China, Japan, and Hong Kong were test groups) are less risk adverse then people in Western cultures (United States, Germany, and Poland were test groups) (see Kleinhesselink and Rosa (1991), Weber and Hsee (1998), and Keown (1989)). Differences between Chinese investors and Westerners may be further exacerbated as the Chinese may be less familiar with how equity markets work. For example, the Chinese may not be as familiar with stock price dynamics and trading as people from countries with more established stock markets. Because they are less familiar with stock investing, Chinese investors may view stocks as being very risky. This creates an interesting dichotomy: the Chinese may be less risk-adverse (i.e., they may be overconfident) in general, but they may view the stock market as being very risky because it is unfamiliar.

2.2 Potential cross-sectional determinants of investing behavior

Do all individual investors behave in the same way? Psychologists find that different groups of people experience different levels of cognitive biases. For example, men seem to be more overconfident investors than women (Lundeberg, Fox, and Puncochar (1994) and Barber and Odean (2001)). Additionally, different experiences seem to lead to different behaviors (Wolosin, Sherman, and Till (1973) and Gervais and Odean (2001)). Therefore, not all individuals might behave similarly when it comes to investing. Our study on emerging market investors should shed some light on how emerging market investors behave. However, in order to investigate how different investors might behave, we take it one step further. We identify five types of investors that we believe (albeit perhaps naively) will be less prone to behavioral biases and trading mistakes. Specifically, we identify experienced investors, middle-aged investors, active investors, wealthier investors, and investors from large cosmopolitan cities to see if they are less inclined toward making cognitive errors in their investing decisions.

Investors who have held their brokerage account for a relatively longer period of time might be less inclined to making mistakes. These investors have accumulated investing experience, so they may have learned to become more rational. Blume and Easley (1982) describe how traders can learn to become rational by recognizing and learning from their past mistakes. List (2003) provides some experimental evidence in support of the theory that traders can learn to become rational. We also identify middle-aged investors. In China, younger people tend to be the more educated and willing to participate in capital market activities. However, older people have more life experience. Therefore, the most sophisticated investors are likely to be young enough to have a market-oriented education, but old enough to have accumulated and learned from "life's lessons." Economic reforms in China began in 1978. A citizen who was 20 years old when the reforms began would be 40 years old at the beginning of our sample period. Therefore, we measure one's sophistication as a function of age using the absolute value of 40 minus the investor's age (i.e., |40-investor's age|, where if the investor is 35 or 45 years old, then this variable is equal to 5 for either case). A small number indicates an investor with a good mix of a capital-markets education and accumulated wisdom.

Third, we also identify traders who trade often. The more often an investor trades the quicker s/he gains trading experience. As mentioned above, an experienced trader may be less inclined toward behavioral biases in their trading decisions. A fourth type of investor is one with more wealth. Wealthier individuals may be more knowledgeable about finances than other individuals. However, it is also possible that wealthier individuals may be more overconfident. We use the value of the equity in the brokerage account as a proxy for an investor's wealth.

Fifth, and finally, we also consider the location in which the account is held to be indicative of investors. Accounts are located in six different cities: Wuhan, Urumuchi, Futian, Shekou, Shanghai, and Pudong. Futian and Shekou are communities of Shenzhen, and Pudong is a community of Shanghai. Among the cities in our study, Shanghai and Shenzhen may be considered the most cosmopolitan. Many of the major Chinese firms and many of the elite Chinese universities are located in Shanghai. As such, the overall technology level and education level are likely to be higher in Shanghai than in most other parts of China. Shenzhen, our other city that we consider to be cosmopolitan, was the first Special Economic Zone in China. It was created as an experimental city where capitalism was allowed to flourish. Today, Shenzhen is considered to be one of the main economies in China. Located in the center of China, Wuhan is one of the important industrial cities in China. It is also a transportation hinge (nerve center) for both railway and shipping (e.g., the famous Yangtse River passes through it).

Because Wuhan has good universities and some experience with business, its residents should be considered as moderately sophisticated. Urumuchi is in Xinjiang, which is a much more rural province. It is in the far northwest part of China. The region is not known for the existence of large companies, nor good education institutions. Therefore, investors who have accounts in Shanghai and Shenzhen may be 'better' investors than those from the more rural parts of China, like Urumuchi.

Our paper not only simply studies emerging market individual investors, but we also consider cross-sectional determinants of investing behavior. Two studies closest to ours are Dhar and Zhu (2005), who study the impact of demographics such as income and the type of employment on the disposition effect, and Feng and Seasholes (2005), who study the impact of investor experience on the disposition effect in China. Our main distinction from these works is that they are more narrowly focused on one cognitive error (the disposition effect) while we examine a broader range of behavioral biases and investing performance.

3. Data description

The Chinese stock markets are composed of two securities markets, the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), which were established in November 1990 and April 1991, respectively. The two exchanges are self-regulated, and cross listing is not allowed. The stock markets in China rely solely on limit-order placement. The SHSE and the SZSE are open from Monday to Friday, and each exchange has two trading sessions: the morning session opens at 9:30 and closes at 11:30, and the afternoon begins at 13:00 and ends at 15:00. These markets exhibited strong growth in the past decade and are currently the ninth largest in the world. At present, there are about 1,250 companies listed on the SHSE and the SZSE, with total market capitalization exceeding RMB4000 billion (about $500 billion). Meanwhile, there are more than 100 brokerage firms in China. The number of investor accounts is just over 70 million. Considering the population in China, the percentage of Chinese citizens with a brokerage account is small compared to that of developed countries.

There are several institutional differences between China and U.S. that are also important. China has no capital gains tax and margin trading is prohibited. Also, investors in China may open only one brokerage account (Feng and Seasholes (2003)), which is opened using their National Identity Card (NIC). With only one brokerage account, and a lack of 401(k) plans and other equity holdings, our paper is likely to be viewing investors' total investing behavior.[1] Also, the infrastructure for placing trades is not well developed for placing trades remotely. Instead, most orders are made from the brokerage location itself (Hertz (1998) and Feng and Seasholes (2004)), which promotes interaction between investors.

Our brokerage account data comes from a brokerage firm in China.[2] The complete data set includes 74,960 investor accounts. Not all of these accounts are useful for our study. We first delete the 17,172 accounts that only own government bonds. We also delete 5,720 accounts that have a zero (or negative) balance, or are institutional accounts. This leaves 52,068 individual investor accounts. We next delete trading accounts that only participate in the primary market. There is a high demand for buying IPOs in China. This may be due to their average underpricing of 272% (Chan et al. (2004)). Bidders for IPO shares are selected

[1] There are rumors that some of these rules are not followed. While margin trading is not legal, investors might borrow money external to the brokerage firm and buy equity with the capital. In addition, some investors may avoid the one stock-account rule by opening a second stock trading account with the use of a relative's name and NIC in order to increase their chances of obtaining IPOs, as they are distributed randomly to those who are interested. To the extent that this occurs, our personal characteristics data will be noisy. Therefore, we eliminate accounts that only participate in the IPO market. We will discuss this in more detail shortly. (Also, note that even if an investor does have multiple accounts in our sample, then it creates a bias against finding a correlation between psychological biases and personal characteristics.)

[2] As a condition for using its data, we promised anonymity to the brokerage firm.

randomly by the government (Gordon and Wei (2003)).[3] In order to increase the probability of obtaining shares and increase the number of shares purchased, investors will buy NIC numbers from citizens who are not interested in opening a brokerage account. The buyer will then open brokerage accounts with these NICs and use them to purchase the maximum number of shares in an IPO. Through these many accounts, one buyer (sometimes controlled by another public company) can acquire many shares of the IPO company. This is problematic for our study because it relies on the account owner (as noted by the NIC number) directing the decisions in the account. To reduce any noise, or bias, induced by this behavior, we delete all 5,099 accounts that have only primary market transactions. The final sample has 46,969 individual investor accounts.

The sample period for our accounts is from May 20, 1998 to September 30, 2002. During this time, the accounts show 1,308,596 stock purchase orders and 1,091,848 stock sales. We have data on the investor's age, the number of years that the investor has held the account, the investor's trading activities with regard to stocks bought and sold, the size of the investor's brokerage account, and the branch (city) in which the account is located. Chinese public companies have four types of shares; state-owned shares, legal-person shares, A-shares, and B-shares (Mei, et al. (2005)). Only A-shares and B-shares are publicly traded. This puts the float at only 30%. Of this float, approximately 25% is owned by individuals and 5% by institutional investors. A-shares are owned by Chinese citizens. Until February 28, 2001, B-shares were only owned by foreigners.[4] As such, only A-shares are included in our dataset. There are 1,139 stocks in the data sample, including 502 A-shares traded on the Shenzhen exchange and 637 A-

[3] This procedure came about because of a 1992 scandal in which Shenzhen insiders received most of the shares of a popular IPO. This caused a protest in the streets that was the largest social disturbance since the 1989 Tiananmen Square protest.

shares traded in Shanghai. To calculate stock returns, we use the monthly returns files of the China Stock Market & Accounting Research (CSMAR) Database, which is compiled and maintained at Hong Kong Polytechnic University. We omit the first month of stock returns issued in the primary market to avoid any bias due to equity issuance.

Summary statistics of our brokerage account database are presented in Table 1. Table 1 reports that the average stock account in our sample has been open for 3 years and 4 months. Interestingly, the mean value of accounts open less than three years is greater than the mean value of accounts open longer than 3 years. Most of the accounts are owned by people 29 to 49 years of age. The ten percent of the account holders that exhibit the greatest amount of trading turnover also have an account value greater than twice the value of the other accounts. The exchange rate during this time period was roughly 8 RMB to 1 USD. The mean value of the smallest third of accounts sorted by account value is 7,023 RMB (USD 878). The mean account value in the largest third of the accounts is USD 38,467. The greatest number of accounts (12,327) is in Urumuchi. However, there are 17,262 combined accounts in the two Shenzhen suburbs, Futian and Shekou. There are 12,608 accounts in the greater Shanghai area.

[Insert Table 1 about here]

4. Empirical methodology and findings

Our research approach is straightforward. First, we compute a behavioral or performance measure to determine (1) how Chinese investors perform in their trading activities, (2) whether or not Chinese investors are disposed to selling winners and holding onto losers, (3) to what degree Chinese investors are overconfident (are they under-diversified and do they trade a lot?), and (4) the myopic focus of Chinese investors (do they buy stocks with recent run-ups?). In each

[4] After February 28, 2001, Chinese investors were allowed to own B-shares (Karolyi and Li (2003)).

of these cases, we also conduct cross-sectional regression analysis to assess whether their personal characteristics (such as their experience, age, wealth, where they live, etc.) have an effect on their investing behavior and performance.[5] We divide the discussion of our results into four separate subsections.

4.1 Investor characteristics and trading performance

Individual investors have been shown to make poor trading decisions. This has been tested by comparing the subsequent performance of stocks that investors sold to the performance of stocks investors bought. Consider the investor who sells one stock and uses the proceeds to buy another stock. If the stock sold subsequently outperforms the stock bought, then the investor would have been better off holding the first stock. Making the trade was a poor decision, ex post.

Following Odean's (1999) methods, we identify the average subsequent returns of stocks that investors purchase and sell. We compute the total return for each stock during the four months (84 trading days), one year (252 trading days), and two years (504 trading days) after the trade. Table 2 presents these returns.

[Insert Table 2 about here]

Panel A of Table 2 shows that the subsequent return of the stocks purchased was 3.59% for the four-month period following the trade. This compares to a return of 5.57% for the stocks sold. The mean difference for each individual (-1.40%) is significant at the one percent level. For one and two years after the trades, the return difference between stocks purchased and stocks sold is -2.45% and -1.80%, respectively. In a sample of U.S. investors, Odean finds the difference in returns between stocks purchased and sold to be –1.36%, –3.31%, and –3.32%, for

[5] To assess the degree of multicollinearity in our models, we compute variance inflation factors (VIF) for each variable. The VIFs are all below 4.5, and thus suggest that multicollinearity is not a major problem.

the four month, one year, and two years periods, after the trades, respectively. Thus, the difference between bought and sold stocks in China, as compared to the U.S., are similar in the short-term (four months) and smaller in the long-term (one and two years). Overall, though, it appears that Chinese investors are making poor trading decisions similar to U.S. individual investors.

To examine the role that individuals' personal characteristics have on their poor trading performance, we regress personal characteristics onto the difference in purchase and sales returns. Specifically, the regression equation is as follows:

$$\text{Purchase-Sales Return} = \alpha + \beta_1(\text{Account Age}) + \beta_2(|\text{40-Investor's Age}|) + \beta_3\,(\text{Frequent Trading Dummy}) + \beta_4(\text{Account Value}) + \beta_5(\text{Urumuchi}). \quad (1)$$

The dependent variable is the difference between the returns of stocks just purchased and stocks sold using a subsequent four-month time period, a one-year time period, and a two-year time period. Account Age is the number of years the account has been open, |40-Investor's Age| is the absolute value of 40 minus the investor's age, Frequent Trading Dummy is a dummy variable that indicates when the account is in the top 10% with regards to trading activity, Account Value is the equity value of the brokerage account, and Urumuchi, the most rural city in our sample, is a dummy variable that indicates when the account is located there.

Panel B shows the regression estimates of equation (1). The reported adjusted-R^2 for the regressions show that between 0.8 to 3.1 percent of the variance in the return difference is explained by the individual investor's personal characteristics. The positive coefficient for the account age variable suggests that the longer a brokerage account has been open, the less stocks sold outperform stocks purchased. In this case, experience seems to lead to better investing performance. A positive coefficient for the investor age function is also found. However, this implies the opposite about investor sophistication: middle-aged individuals are not better investors.

The positive coefficient for the high trading frequency dummy variable means that high trading accounts perform better. This latter result is consistent with Odean (1999), who finds that low-trading U.S. accounts have a purchase-sale return difference of –4.28% for the year following the trades and that high-trading accounts experience a purchase-sales difference of only –2.69%. The coefficient in our regression suggests that the difference in China is 3.12% (versus 1.59% in the U.S.). The negative coefficient for the account value variable means that the largest accounts suffer poor trading performance the most.

As previously mentioned, the city of Urumuchi is considered to be a city where residents have less experience with capitalism compared to residents in Shenzhen and Shanghai. The negative coefficient on the dummy variable means that investors in that city have worse trading performance.

Overall, our results indicate that Chinese investors are making trading mistakes. More importantly, regression findings suggest that investors who are young or old compared with age 40, and who have a higher account value, are making poor trading decisions. In other words, middle-aged and wealthier investors are not better investors. However, Chinese investors who have held an account longer, trading in the top 10% of frequency, and not living in rural Urumchi seem to make fewer mistakes.

4.2 Investor characteristics and the disposition effect

Using U.S. investor brokerage accounts, Odean (1998a) shows that investors are reluctant to realize their losses. In Finland, Grinblatt and Keloharju (2001a) find that the larger the paper loss the less likely the investor is to sell the stock. Our data, and thus our methods, are similar to that of Odean's. When stocks are sold at a capital gain, we compute the proportion of gains realized to the total gains that *can* be realized (i.e., realized gains plus unrealized paper gains). Specifically, for stocks sold at a capital gain, we compute a PGR measure where:

$$\text{Proportion of Gains Realized (PGR)} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}} \quad (2)$$

Similarly, for stocks sold at a capital loss, a PLR measure is computed as the proportion of losses realized compared to the total loss that can be realized as follows:

$$\text{Proportion of Losses Realized (PLR)} = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}} \quad (3)$$

A large PGR relative to PLR indicates that investors have a tendency to sell their winners more than their losers. This behavior would be consistent with the disposition effect (Shefrin and Statman (1985)).

We compute the PGR and PLR for each transaction in the sample. Table 3, Panel A reports the mean PGR, PLR, and the difference between PGR and PLR for all transactions. From Panel A, we see that the PGR, at 0.519, is 0.209 larger than the PLR, at 0.310. The difference is statistically significant at the one percent level. These results suggest that Chinese investors are reluctant to realize their losses. In comparison, Odean's (1998a) results for U.S. investors report a mean PGR of 0.148 and PLR of 0.098. The disposition test ratios are much higher for Chinese investors than they are for US investor accounts. However, we should be careful in reading too much into a comparison between China and the U.S. The Chinese stock markets have only been open for a short period, which means that the proportion of unrealized gains and losses, i.e., the ratio denominator, is likely to be much smaller for Chinese accounts than for U.S. accounts. Nevertheless, note that the same disposition effect is illustrated in China (also see Feng and Seasholes (2005)) as it is in the U.S.

[Insert Table 3 about here]

To disentangle the multivariate effects of investors' personal characteristics, we re-estimate regression (1), but this time the dependent variable is PGR, PLR, or the difference (PGR-PLR). Panel B reports the coefficient estimates. The third regression, where PGR-PLR is the dependent variable, shows the disposition effect (i.e., the larger the difference, the greater is the individuals' disposition to sell winners and hold losers). The regression results suggest investors who trade often and investors who have larger accounts suffer *less* from a disposition effect. However, middle-aged investors and investors from cosmopolitan cities seem to suffer *more* from a disposition effect. Thus, the findings are mixed.

We also conduct a logit regression as a robustness check. Feng and Seasholes (2005) show that PGR and PLR measures are mechanically linked to right hand side variables in cross-sectional analysis (specifically, see Feng and Seasholes' Appendix D). Therefore, as in Grinblatt and Keloharju (2001a), we use a logit regression where the dependent variable is equal to one (zero) if PGR is greater (less) than PLR. The fourth model in Table 3, Panel B, shows the logit regression results. From this model, we see that investors with older accounts suffer more from a disposition effect, while account size is not related to the disposition effect. Therefore, the findings from the logit model are more consistent than the third regression model in showing that those investors one might think are savvier are *not* the ones that are less inclined toward a disposition effect.

Overall, we see that Chinese investors are inclined toward a disposition effect. That is, they are more likely to realize paper gains than paper losses. Just as important, our regression tests examining specific investor characteristics suggest that investors that we expected to be more savvy and sophisticated are often more prone to the disposition effect.

4.3 Investor characteristics and overconfidence

Overconfident investors feel certain about their knowledge and their investment skills. This overconfidence causes them to trade too much and hold under-diversified portfolios (Odean (1998b)). To measure trade frequency, we follow Barber and Odean (2001) and compute the mean monthly portfolio turnover for each brokerage account. To examine the potential for under-diversified portfolios, we report the mean number of stocks in each account.

We also measure each account's mean returns to get a sense of how the investors' portfolios are performing. To measure returns, we use the beginning-of-month position data for each account and we obtain their monthly stock returns from the CSMAR database. We assume that all transactions take place on the last day of the month. The monthly return of an account's portfolios, R_t^j, is calculated as follows:

$$R_t^j = \sum_{i=1}^{H_t^j} p_{it}^j R_{it} \tag{4}$$

where p_{it}^j is the beginning-of-month market value for the holding of stock *i* in account *j* in month *t* divided by the beginning-of-month market value of all stocks held in account *j*. R_{it} is the monthly return for stock *i* at month *t*. H_t^j is the number of stocks held in account *j* in month *t*.

Panel of A of Table 4 reports the mean number of stocks held in each account, the mean monthly turnover of each account, and the total mean monthly return of stocks held in each account. Several observations are noteworthy. First, we see that in general, Chinese investors own very few stocks. On average, they hold the stocks of only 2.60 different companies. In comparison, Zhu (2002) reports that US individual investors hold an average of 4 stocks. Also consider that Chinese investors can own only one brokerage account and do not have access to other ownership forms like pension plans. To compensate, Chinese investors should maintain diversification within their brokerage accounts. However, this does not seem to be the case. The average Chinese investor appears to be more under-diversified than the average US investor.

[Insert Table 4 about here]

Chinese investors also appear to be trading quite frequently. The mean monthly turnover is 27.3%, or 327% annually. It should be noted that a 27% monthly turnover when an investor holds only two stocks equates to trading (sell and then buy) a stock every other month. Zhu (2002) reports the monthly turnover of U.S. investors to be 7.59% (or 91% annually). The evidence that Chinese investors are trading at a rate almost four times higher than U.S. investors seems extraordinary. These comparisons between China and the U.S. are also consistent with the observations of Allen et al. (2005). They report that in 1999, the total turnover (expressed as a percentage of total market capitalization) for the year was 500% in China.[6] This is more then five times higher than the turnover of 87.7% on the NYSE during the same year. The high trading volume may be due to the lack of other investment vehicles in China. With regard to portfolio returns, they are discussed in conjunction with the individual's trading behavior below.

To examine the role for which individuals' personal characteristics have on their tendencies to be overconfident, we again estimate regression (1), but this time we use our overconfidence metrics (i.e., number of stocks held, turnover, and portfolio returns) as dependent variables. From Panel B, where the coefficient estimates are presented, we see that investors with older accounts own fewer stocks, have higher turnover, and a higher return. The estimates for investor age show that young and old investors trade more. Investors that trade very

[6] These volume estimates are actually understated because they do not include the trading in the large and illegal informal trading markets. Ti and Green (2003) describe these informal markets as trading non-listed shares of various equity types (i.e., employee shares and shares of non-sanctioned public companies).

frequently (top 10% of turnover) own 1.9 more stocks, on average, and earn 0.5% more return per month. Larger accounts also hold more stocks and trade less. However, they also earn a lower return. We see that Urumuchi accounts trade less.

Overall, the findings require careful interpretation. While middle-aged investors trade less, older accounts have more trading (an overconfidence characteristic), but also have better returns. Those who trade frequently are actually more diversified, but they also earn higher returns despite their frequent trading. Larger accounts exhibit the least overconfidence, as they are more diversified and trade less frequently, but they also earn less. The evidence suggests that when experience makes investors more overconfident, the overconfidence seems to be justified ex post, as these overconfident investors seem to earn higher returns.

4.4 Investor characteristics and the recent past performance of stocks purchased

Bange (2000) finds that U.S. investors purchase past winners. This is also known as momentum trading or positive-feedback trading. Investors might consider recent past returns to be representative of what they can expect in the future. This heuristic simplification is called the representativeness bias. Mutual fund investors also make this same extrapolating error (Sirri and Tufano (1998)). Even finance professors appear to be influenced by a representativeness bias. Welch (2000, 2001) has implemented several surveys of financial economics professors. The first series of surveys were implemented during the bull market of 1997 through 1999. Professors responded with their expected annual equity risk premium over the next 30 years at 7.2%. Professors also tended to lean toward the belief that the stock market mean reverts. Welch again surveys the profession in the bear market of 2001. Given the earlier expression that stock returns may exhibit mean reversion, one might expect respondents to express a higher equity premium estimate after a market decline. However, the mean expectation for the annual

30-year equity risk premium was only 5.5%, about 2% lower than the previous estimate. The responses are consistent with a representativeness bias.

Table 5 reports the past return for the stocks that Chinese investors purchased. Specifically, the prior 4-month return, prior 4-month abnormal return, prior 1-year return, and prior 1-year abnormal return are shown in the table. Abnormal returns are calculated as actual returns minus expected returns. Expected returns are estimated using a market model.

[Insert Table 5 about here]

Univariate analysis is shown in Panel A. Overall, investors purchased past winners. The return four months before the purchases was over 17% (a 32% abnormal return). The past one year return was only 2.9% (a 0.4% abnormal return). It appears that investors focus on the most recent short-term performance of the stocks they purchase. That is, investors appear to be myopic.

To examine the role that individuals' personal characteristics have on their tendencies to succumb to the representativeness bias, we again estimate regression (1), but this time we use prior abnormal performance (4-months and 1-year) as dependent variables. The coefficient estimates are presented in Panel B. From this panel, we see that investors with accounts open longer are less myopic (i.e., they do not buy recent winners). Middle-aged investors are also less myopic. However, people who trade more and have larger accounts have a higher tendency to buy recent past winners. These results suggest that experienced and active investors still buy stocks with recent run-ups. Individuals from Urumuchi seem to focus on the past one-year returns more than they do on the past 4-month returns, thus indicating that they are less myopic. Again, the mixed regression results indicate that investors whom one might think is less biased toward making cognitive errors are still making mistakes.

5. Conclusions

Recent research finds that individual investors are irrational (i.e., they are inclined toward behavioral biases) and that they make trading mistakes. However, might emerging market investors be more inclined or less inclined toward behavioral biases and trading mistakes, as compared to developed market investors? To address this question, we use brokerage account data from China. Because the Chinese stock markets are barely a decade old, the notion of investing and public ownership is relatively new to most Chinese investors. In empirical tests, we find that Chinese investors make trading mistakes (i.e., the stocks they sell outperform the stocks that they buy), they are reluctant to realize their losses (i.e., they suffer from a disposition effect), they tend to be "overconfident" (e.g., they seem to be under-diversified and they seem to trade often), and they exhibit a representativeness bias (buying recent short-term winners).

Just as important, we also conduct cross-sectional tests on investor behavior. Specifically, we identify middle-aged investors, active investors, wealthier investors, experienced investors, and those from cosmopolitan cities, to see if they are less inclined toward making cognitive errors. One might expect these investors to be 'better' investors. In empirical tests, however, we find that these investors are often unable to overcome behavioral biases. The overall message of our paper is that emerging market investors seem to make cognitive errors, and those individual investors who could be considered savvier investors are often *not* less inclined to make these errors.

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Table 1. Descriptive Statistics on Brokerage Accounts and Trades

This table reports descriptive statistics of Chinese individual investor brokerage accounts and buy/sell trades during the period from May 20, 1998 to September 30, 2002. The data is also differentiated by how long the account has been open (open < 3 years versus open ≥ 3 years), by the investor's age, by trading activity (frequent traders are those whose trading activity puts them in the top 10% of the sample), by account value in RMB (sample sorted into thirds), and by the city in which the account is located.

	Number of accounts	Mean value value of accounts	Mean yrs. account is open	Number of purchases	Number of sells	Mean transaction volume
All accounts	46,969	113,455	3.33	1,308,596	1,091,848	2,538.04
By account age:						
Open < 3 years	16,789	135,132	1.65	298,422	230,506	2,899.36
Open ≥ 3 years	19,984	116,874	4.74	689,128	587,867	2,553.56
By age of investor:						
18-28 years old	4,682	121,265	2.31	89,553	75,314	2,283.77
29-49 years old	31,391	101,272	3.49	857,417	717,814	2,515.53
50-75 years old	2,437	73,765	3.38	76,322	62,743	1,965.39
By trading activity:						
Frequent trading	4,694	224,959	4.18	639,578	572,459	2,762.58
Infrequent trading	42,275	101,075	3.24	669,018	519,389	2,309.04
By account value:						
Small	15,656	7,023	3.07	200,783	177,167	616.07
Medium	15,657	25,612	3.36	369,631	307,735	1,051.37
Large	15,656	307,737	3.57	738,182	606,946	3,826.72
By city:						
Wuhan	4,772	66,365	2.50	146,197	123,604	2,050.86
Urumuchi	12,327	56,001	3.08	242,174	197,112	1,518.21
Futian (Shenzhen)	5,271	313,712	3.07	156,788	135,211	5,675.71
Shekou (Shenzhen)	11,991	101,455	4.59	394,261	337,092	2,604.26
Shanghai	8,175	108,903	3.28	257,334	210,265	1,926.79
Pudong (Shanghai)	4,433	126,656	2.52	111,842	88,564	2,042.23

Table 2. Trading Performance

Panel A reports returns data of stock transactions that took place from May 20, 1998 to September 30, 2002 held in 46,969 Chinese brokerage accounts. The average subsequent returns of stocks that investors purchase and sell are computed for a four-month period (i.e., 84 trading days), a one-year period (i.e., 252 trading days), and a two-year period (i.e., 504 trading days). Panel B presents parameter coefficients of the following regression model:

$$\text{Purchase} - \text{Sales} = \alpha + \beta_1(\text{Account Age}) + \beta_2(|40\text{–Investor's Age}|) + \beta_3(\text{Frequent Trading Dummy}) + \beta_4(\text{Account Value}) + \beta_5(\text{Urumuchi}).$$

The dependent variable is the difference between Purchase returns and Sales returns using a four-month time period, one year time period, and a two-year time period. Account Age is the number of years the account has been open, |40-Investor's Age| is the absolute value of 40 minus the investor's age, Frequent Trading Dummy is a dummy variable that indicates when the account is in the top 10% with regards to trading activity, Account Value is the equity value of the brokerage account, and Urumuchi is a dummy variable that indicates when the accounts are located in the city of Urumuchi. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Univariate results

	4-month returns	1-year returns	2-year returns
Purchases	0.0359	0.1124	0.1064
Sales	0.0557	0.1371	0.1243
Purchase - Sales	-0.0140***	-0.0245***	-0.0180***
	(-182.58)	(-90.49)	(-41.87)

Panel B: Regression results

	Dependent variable: (Purchase – Sales) for:		
	4-month returns	1-year returns	2-year returns
Intercept	-0.0060**	-0.0548***	-0.2131***
	(-2.50)	(-17.83)	(-36.42)
Account Age	0.0038***	0.0052***	0.0181***
	(11.00)	(11.82)	(21.58)
| 40 – Investor's Age |	0.0002	0.0007***	0.0009**
	(1.37)	(3.49)	(2.27)
Frequent Trading Dummy	0.0031	0.0312***	0.0560***
	(1.41)	(10.98)	(10.34)
Account Value	-0.0059***	-0.0036***	-0.0039*
	(-6.34)	(-3.10)	(-1.76)
Urumuchi	-0.0036**	-0.0058***	-0.0104**
	(-2.09)	(-2.56)	(-2.46)
Adjusted R^2	0.0081	0.0147	0.0314

Table 3. The Disposition Effect

Panel A reports the mean proportion of gains and losses that are realized for stock transactions that took place from May 20, 1998 to September 30, 2002 held in 46,969 Chinese brokerage accounts. PGR is the ratio of realized gains to the sum of realized gains and paper gains. PLR is the ratio of realized losses to the sum of realized losses and paper losses. We also report the difference between PGR and PLR, along with a t-statistic indicating statistical significance. Panel B presents parameter coefficients of the following regression model:

$$\text{Dependent Variable} = \alpha + \beta_1(\text{Account Age}) + \beta_2(|40\text{–Investor's Age}|) + \beta_3\,(\text{Frequent Trading Dummy}) + \beta_4(\text{Account Value}) + \beta_5(\text{Urumuchi}).$$

Account Age is the number of years the account has been open, |40-Investor's Age| is the absolute value of 40 minus the investor's age, Frequent Trading Dummy is a dummy variable that indicates when the account is in the top 10% with regards to trading activity, Account Value is the equity value of the brokerage account, and Urumuchi is a dummy variable that indicates when the accounts are located in the city of Urumuchi. The first three models are OLS regressions and the fourth model is a logit model. *t*-statistics (chi-square statistics) are reported in parentheses for the OLS (logit) regression models. ***, **, and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Univariate results

	PGR	PLR	PGR – PLR (t-stat)
All Accounts	0.5190	0.3098	0.2092***
			(82.60)

Panel B: Results results

	Dependent variable:			
	PGR	PLR	PGR–PLR	=1 if PGR>PLR
Intercept	0.7007***	0.4662***	0.2345***	0.1213***
	(134.40)	(78.01)	(37.79)	(6.92)
Account Age	-0.0271***	-0.0301***	0.0030	0.0319***
	(-15.42)	(-14.95)	(1.44)	(4.18)
| 40 - Investor Age |	-0.0016***	-0.0010***	-0.0005***	-0.0044****
	(-13.52)	(-7.52)	(-4.12)	(-16.55)
Frequent Trading Dummy	-0.0747***	0.0061	-0.0808***	-0.9509***
	(-14.16)	(1.01)	(-12.88)	(-36.34)
Account Value	-0.0864***	-0.0771***	-0.0092***	-0.0146
	(-41.94)	(-32.65)	(-3.78)	(0.64)
Urumuchi	0.0080*	0.0316***	-0.0236***	-0.1063***
	(1.96)	(6.74)	(-4.84)	(-8.63)
Adjusted R^2	0.1297	0.0726	0.0117	

Table 4. Overconfidence

Panel A reports portfolio descriptive statistics of 46,969 Chinese brokerage accounts during the period from May 20, 1998 to September 30, 2002. We report the mean number of stocks owned in each account, the mean monthly turnover, and the mean monthly returns for the accounts. Panel B presents parameter coefficients of the following regression model:

$$\text{Dependent Variable} = \alpha + \beta_1(\text{Account Age}) + \beta_2(|40\text{–Investor's Age}|) + \beta_3(\text{Frequent Trading Dummy}) + \beta_4(\text{Account Value}) + \beta_5(\text{Urumuchi}).$$

The Dependent Variable is either the mean number of stocks owned in each account, the mean monthly turnover, or mean monthly returns for the accounts. Account Age is the number of years the account has been open, |40-Investor's Age| is the absolute value of 40 minus the investor's age, Frequent Trading Dummy is a dummy variable that indicates when the account is in the top 10% with regards to trading activity, Account Value is the equity value of the brokerage account, and Urumuchi is a dummy variable that indicates when the accounts are located in the city of Urumuchi. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Univariate results

	Mean # of stocks owned	Mean monthly turnover	Mean monthly returns
All accounts	2.60	0.2731	0.0042

Panel B: Regression results

	Dependent variable:		
	Mean # of stocks owned	Mean monthly turnover	Mean monthly returns
Intercept	1.4847***	0.2312***	-0.0062***
	(56.18)	(122.26)	(-15.05)
Account Age	-0.0023	0.0104***	0.0026***
	(-0.58)	(35.71)	(41.60)
| 40 – Investor's Age |	0.0007	0.0007***	0.0000
	(0.39)	(5.29)	(0.52)
Frequent Trading Dummy	1.9291***	0.0616***	0.0055***
	(61.53)	(27.49)	(11.16)
Account Value	0.8714***	-0.0093***	-0.0006***
	(78.44)	(-11.81)	(-3.81)
Urumuchi	0.0026	-0.0043***	-0.0001
	(0.12)	(-2.90)	(-0.54)
Adjusted R^2	0.3016	0.0711	0.0636

Table 5. Past Performance of Stocks Purchased

Panel A reports past returns and past abnormal returns of the 1,308,596 purchases in 46,969 Chinese brokerage accounts during the period from May 20, 1998 to September 30, 2002. We report the mean return for the 4-month period and the 1-year period before the stocks are purchased. Abnormal returns are computed using a market model. Panel B presents parameter coefficients of the following regression model:

$$\text{Past Performance} = \alpha + \beta_1(\text{Account Age}) + \beta_2(|40\text{–Investor's Age}|) + \beta_3\,(\text{Frequent Trading Dummy}) + \beta_4(\text{Account Value}) + \beta_5(\text{Urumuchi}).$$

The dependent variable is either the past 4-month abnormal return or the past 1-year abnormal return. Account Age is the number of years the account has been open, |40-Investor's Age| is the absolute value of 40 minus the investor's age, Frequent Trading Dummy is a dummy variable that indicates when the account is in the top 10% with regards to trading activity, Account Value is the equity value of the brokerage account, and Urumuchi is a dummy variable that indicates when the accounts are located in the city of Urumuchi. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Univariate results

	Past 4-month returns	Past 4-month abnormal returns	Past 1-year returns	Past 1-year abnormal returns
All accounts	0.1722	0.3250	0.0286	0.0043

Panel B: Regression results

	Dependent variable:	
	Past 4-month abnormal returns	Past 1-year abnormal returns
Intercept	-0.0149***	-0.0993***
	(-8.59)	(-37.48)
Account Age	-0.0023***	-0.0034***
	(-8.79)	(-8.50)
| 40 - Investor Age |	0.0007***	0.0010***
	(5.64)	(5.52)
Frequent Trading Dummy	0.0036	0.0128***
	(1.84)	(4.28)
Account Value	0.0087***	0.0192***
	(12.14)	(17.51)
Urumuchi	-0.0018	0.0089***
	(-1.34)	(4.29)
Adjusted R^2	0.0094	0.0155