Behavioral Bias of Traders: Evidence for the Disposition and Reverse Disposition Effect*

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Abstract

We present empirical evidence on the disposition effect not previously reported in the literature. We find evidence for the disposition effect for buy strategies, but a reverse disposition effect for sell strategies, besides a dependence of the disposition effect on the investor sophistication. The disposition effect also depends strongly on the time horizon of a trading strategy. We develop a model in which informed traders with a behavioral bias and rational traders interact to generate the reverse disposition effect for traders following a sell strategy as well as rational traders responding to the behavioral bias of other traders.

Keywords: Behavioral bias, investor characteristics, trading strategies
JEL Classification: G11, G14

1 Introduction

It is a widely accepted empirical fact that investors tend to hold on to loosing stocks for longer than to winning stocks. This observation was first reported by Shefrin and Statman (1985) and called the *disposition effect*, whose existence has been confirmed by a large number of empirical investigations, see e. g. Ferris et al. (1988), Odean (1998), Barber and Odean (1999), Grinblatt and Keloharju (2001), Boebel and Taylor (2000), Barber et al. (2003), Garvey and Murphy (2004), Kaustia (2004a), Frino et al. (2004), Shu et al. (2005), Locke and Onayev (2005), among others. While most of these investigations explore the behavior of all market participants on aggregate, regardless of their characteristics, market conditions or stock characteristics, few papers also attempt to find evidence for differences between traders. Conducting such investigations, Shapira and Venezia (2001) find that individual investors are more affected by the disposition effect than professional (i. e. institutional) investors, although both exhibit a disposition effect. Similarly, Dhar and Zhu (2002) and Feng and Seasholes (2005) find that the disposition effect reduces with investor sophistication and experience, a finding which is disputed for Chinese traders by Chen et al. (2004). Furthermore, Brown et al. (2005) find that traders with larger investments and those making more long-term investments are less affected by the disposition effect. Finally, Ranguelova (2001) find evidence that the disposition effect is only present for traders investing in large firms.

Investigations of the disposition effect are often held back by the amount of information that is available in databases, not only on the transactions of individual traders but in particular their characteristics. We have been given access to a unique database which does not only allow to trace the trading behavior of individual investors, but also record other characteristics explicitly, such as their age and gender, or implicitly, e. g. their trading activity or wealth. Using this database allows us to investigate the dependence of the disposition effect on a large number of these characteristics, which has so far not been conducted in the literature.

The origin of the disposition effect is commonly seen in prospect theory as developed by Kahnemann and Tversky (1979), see e. g. Odean (1998), Garvey and Murphy (2004) or Kyle et al. (2005) for a derivation of the disposition effect from prospect theory. The main idea is that the S-shaped value function induces risk aversion for winning stocks and risk seeking for loosing stocks, relative to a reference point which is usually the price at which the stocks have been bought. This risk aversion causes the trader to realize any profits quickly to avoid them turning into losses while risk seeking causes to let losses run in hope of a recovery, thus inducing the observed disposition effect. Recent evidence in Zuchel (2001) and Kaustia (2004b), however, suggests that prospect theory alone is insufficient to explain the observed patterns and we have to include mental accounting or other psychological factors for a full explanation. Regardless of the details of the origin of the disposition effect, there is a general agreement that it constitutes a behavioral bias.

Our paper develops in the coming section a simple model which introduces a behavioral bias into the demand of non-rational traders while a small fraction of rational traders exploit this bias. In contrast to other models of the disposition effect, it merely requires that traders tend to sell in rising markets and buy in falling markets, thus act as contrarians. In the case of buy strategies, introducing this bias causes the disposition effect for non-rational traders while for rational traders we observe a reverse disposition effect, i. e. a tendency to sell loosing stocks quicker than winning stocks. For sell strategies both traders exhibit a reverse disposition effect, albeit of a different magnitude.

We test our hypothesis with the help of a unique database recording not only the trades of individual traders, but also a large number of other characteristics such as their age or sex. It is found that not all traders exhibit a disposition effect as usually proposed in the literature. Not only is the strength of the disposition effect different among traders but also do some traders show a reverse disposition effect. These results are consistent with the model we develop in this paper and represent findings not previously reported in the literature.

The next section develops the theoretical model while section 3 describes the data and their treatment. The main empirical results are presented in section 4 before section 5 concludes the findings.

2 Rational response to the presence of biased traders

This section develops a model of traders exhibiting a behavioral bias and rational traders attempting to exploit this behavioral bias. We will show how this structure leads in some cases to the disposition and in other cases to the reverse disposition effect. Based on this model we develop four hypotheses which will be investigated empirically in this paper.

2.1 A model with biased and rational traders

We consider a market in which a single asset is traded in a single trading round before it is liquidated at the fundamental value. With the current price, i. e. the price prior to trading, being denoted p_0, all traders know the distribution of the fundamental value as $v \sim N(p_0, \sigma_v^2)$.

Let us assume two groups of traders to be present in the market, noise traders and informed traders. Noise traders submit orders of random sizes to the market, $u \sim N(0, \sigma_u^2)$, while informed traders exploit their perfect knowledge of the realization of the fundamental value v.

There are two types of informed traders, firstly we have fully rational risk neutral traders, who maximize their expected profits from trading using all available information. The second type of informed traders exhibit a behavioral bias which allows us to generate the disposition effect. We assume that the demand of these traders consists of two elements, a rational element and the bias. Suppose there are a fraction of γ informed traders with a bias. All traders of a group are behaving as a single trader, i. e. maximizing joint profits, allowing us to eliminate the effects of competing traders within types.

As in KYLE (1985) we propose that the price is a linear function of the excess demand, where x denotes the demand of informed traders and u the aggregate demand of noise traders:

$$p = \mu + \lambda(x + u) \tag{1}$$

and $x = \gamma x_B + (1-\gamma)x_R$ with x_B denoting the trading demand of the biased traders and x_R the trading demand of the fully rational traders. The trading demand of the fully rational traders is similar to KYLE (1985) assumed to be linear in the fundamental value:

$$x_R = \alpha + \beta v. \tag{2}$$

The demand of the biased traders is given as follows with p denoting the equilibrium price in the current trading round:

$$x_B = \xi(v - p_0) - \phi(p - p_0). \tag{3}$$

The first term in this expression captures the rational element of the demand while the second term captures the bias with $\phi \geq 0$ indicating the relative strength of this bias. If $\phi = 0$ the trading demand is consistent with the result in KYLE (1985) if we set the parameter ξ equal to the corresponding value there.

Suppose that $v > p_0$ and thus rational traders should hold a long position of the stock. Hence for $\phi > 0$ the demand of traders is reduced in rising markets ($p > p_0$) and increased in falling markets ($p < p_0$). If we assume that the traders' previous demands are random and have a mean of x_B^* and the *ex-ante* expectation of the demand is also x_B^*, we should observe that traders are more likely to sell (parts) of their holdings in rising markets as $Prob(x_B < x_B^*)$ is increasing with the bias, realizing profits with the sale. The trader will buy additional stocks in falling markets, not realizing losses because $Prob(x_B < x_B^*)$ is decreasing with the bias. These considerations clearly show that biased traders will exhibit a *disposition effect*.

In the case that $v < p_0$ rational traders should hold a short position of the stock. If $\phi > 0$ the demand of traders in rising markets ($p > p_0$) is reduced even further, hence using the same arguments as above, they are less likely to liquidate their short position and tend not to realize their gains. In falling markets ($p < p_0$) this effects is reversed, traders are more willing to liquidate their short position and realize any losses. We should thus observe traders more likely to realize losses than profits, showing a *reverse disposition effect*.

As our aim is to investigate trading strategies, we will have to interpret any long and short positions of traders relative to some benchmark holding, which we will choose as the holdings at the beginning of the trading strategy. Thus a long position will correspond to a holding exceeding this benchmark and a short position to a holding below the benchmark. Hence long positions are equivalent to buying additional shares and will thus also be referred to as *buy strategies*. Similarly short positions correspond to selling shares and will also be called *sell strategies*. This interpretation does not violate the assumption of rational traders in our model as it is reasonable to assume that multiple pieces of information are available with different time horizons. If the piece of information we consider in our model is relatively short-lived compared to another piece of information, we find that the initial position is determined by this long-lived information and the trader makes adjustments to exploit the short-lived information he has received. This interpretation allows us to obtain the above interpretation of long and short positions.

While we can characterize the behavior of biased traders from our assumptions as outlined above, we will now have to focus our attention on the behavior of the fully rational traders. These traders seek to maximize their profits from trading which are given by

$$\pi = (v - p)x_R, \tag{4}$$

and the trader seeks to maximize $E[\pi|v]$, his expected profits given the information he has received.

At first we have to note that the price equation as given in (1) is circular with the trading demand x contained in the price through x_B, hence we have to solve for the price in the first instance using (2):

$$p = \mu + \lambda(x + u) \tag{5}$$

$$
\begin{aligned}
&= \mu + \lambda \left(\gamma\xi(v - p_0) - \gamma\phi(p - p_0) + (1-\gamma)x_R + u\right) \\
p &= \frac{\mu}{1+\lambda\gamma\phi} + \frac{\lambda}{1+\lambda\gamma\phi}\left(\gamma\xi v - \gamma(\xi - \phi)p_0 + (1-\gamma)x_R + u\right).
\end{aligned}
$$

Inserting this expression into (4) and maximizing the expected profits gives the following first order condition:

$$
v - \frac{\mu}{1+\lambda\gamma\phi} - \frac{\lambda}{1+\lambda\gamma\phi}\left(\gamma\xi v - \gamma(\xi - \phi)\right) - 2\frac{\lambda}{1+\lambda\gamma\phi}(1-\gamma)x_R = 0, \tag{6}
$$

which can easily be solved as

$$
x_R = \frac{1+\lambda\gamma(\phi - \xi)}{2\lambda(1-\gamma)}v - \left(\frac{\mu}{2\lambda(1-\gamma)} - \frac{\gamma(\xi-\phi)}{2(1-\gamma)}p_0\right). \tag{7}
$$

By comparing coefficients with (2) we see that

$$
\begin{aligned}
\beta &= \frac{1+\lambda\gamma(\phi-\xi)}{2\lambda(1-\gamma)}, \\
\alpha &= \frac{\gamma(\xi-\phi)}{2(1-\gamma)}p_0 - \frac{\mu}{2\lambda(1-\gamma)}.
\end{aligned} \tag{8}
$$

We can now determine the expected trading demand of the fully rational traders:

$$
E[x_R] = \frac{p_0 - \mu}{2\lambda(1-\gamma)} \tag{9}
$$

We also find as a consequence of $E[v] = p_0$ that $E[x_B] = -\phi(E[p] - p_0)$ and we obtain

$$
\begin{aligned}
E[p] &= \mu + \lambda E[x] \\
&= \mu + \lambda\left(\gamma E[x_B] + (1-\gamma)E[x_R]\right) \\
&= \frac{\mu}{2} + p_0\left(\frac{1}{2} + \lambda\gamma\phi\right) - \lambda\gamma\phi E[p] \\
E[p] &= \frac{\mu + p_0(1+2\lambda\gamma\phi)}{2(1+\lambda\gamma\phi)},
\end{aligned} \tag{10}
$$

which in turn gives us

$$
E[x_B] = \phi\frac{p_0 - \mu}{2(1+\lambda\gamma\phi)}. \tag{11}
$$

Hence we have for the total expected trading demand

$$
\begin{aligned}
E[x] &= \gamma E[x_B] + (1-\gamma)E[x_R] \\
&= \frac{1+2\lambda\gamma\phi}{2\lambda(1+\lambda\gamma\phi)}(p_0 - \mu).
\end{aligned} \tag{12}
$$

The price is set such that given the order flow it reflects the belief of the fundamental value by uninformed traders:

$$\begin{aligned} p &= E[v|x+u] && (13) \\ &= E[v] + \frac{Cov[v, x+u]}{Var[x+u]}(x+u-E[x+u]) \\ &= p_0 + \frac{\beta\sigma_v^2}{\beta^2\sigma_v^2+\sigma_u^2}\left(x+u-\frac{1+2\lambda\gamma\phi}{2\lambda(1+\lambda\gamma\phi)}(p_0-\mu)\right). \end{aligned}$$

Comparing coefficients with (1) we see that

$$\begin{aligned} \lambda &= \frac{\beta\sigma_v^2}{\beta^2\sigma_v^2+\sigma_u^2}, && (14) \\ \mu &= p_0 - \lambda\frac{1+2\lambda\gamma\phi}{2\lambda(1+\lambda\gamma\phi)}(p_0-\mu) \\ &= p_0. \end{aligned}$$

This immediately enables us to solve for α as

$$\alpha = \frac{\lambda\gamma(\xi-\phi)-1}{2\lambda(1-\gamma)}p_0 = -\beta p_0. \tag{15}$$

We can also combine (14) and (8) to obtain explicit solutions for λ and β, which are of no relevance here.

The demand of fully rational traders is given by

$$x_R = \beta(v-p_0) = \frac{1+\lambda\gamma(\phi-\xi)}{2\lambda(1-\gamma)}(v-p_0). \tag{16}$$

The expected price of informed investors is from (5) determined as

$$\begin{aligned} E[p|v] &= \frac{p_0}{1+\lambda\gamma\phi} + \frac{\lambda}{1+\lambda\gamma\phi}\left(\gamma\xi v - \gamma(\xi-\phi)p_0 + (1-\gamma)x_R\right) && (17) \\ &= p_0 + \frac{\lambda}{1+\lambda\gamma\phi}\left(\gamma\xi + (1-\gamma)\beta\right)(v-p_0) \\ &= p_0 + \frac{1+\lambda\gamma(\phi+\xi)}{2(1+\lambda\gamma\phi)}(v-p_0) \end{aligned}$$

We can now use this result to compare the result in (16) with that of a biased trader. Suppose we also split the demand of the fully rational trader up into a rational and a biased part, where the rational part is identical to that of the biased trader

$$x_R = \xi(v-p_0) - \widehat{\phi}(E[p|v]-p_0). \tag{18}$$

The last term denotes the deliberate deviation from the rational demand due to the presence of biased traders. Combining (16)-(18), we obviously get the requirement that

$$\widehat{\phi} = -\frac{1+\lambda\gamma(\phi+\xi)-2\lambda\xi}{1+\lambda\gamma(\phi+\xi)}\frac{1+\lambda\gamma\phi}{\lambda(1-\gamma)}. \tag{19}$$

We see that for this term to be negative it is required that $\xi < \frac{1+\lambda\gamma\phi}{\lambda(2-\gamma)}$. Using the result from KYLE (1985) where $\xi = \frac{1}{2\lambda}$, we see that this relationship is always fulfilled. For $\gamma = 0$, i. e. the absence of any biased traders, the results collapse to that of KYLE (1985) as expected.

With $\widehat{\phi} < 0$ we observe a different behavior of rational investors compared to that of biased investors. It implies that for long positions ($v > p_0$) rational traders tend to increase their demand in rising markets ($p > p_0$) and decrease it in falling markets ($p < p_0$). In accordance with our previous interpretation we would thus observe a tendency to not realizing profits while realizing losses more easily. We should therefore observe a *reverse disposition effect* of rational traders.

For the case of short positions ($v < p_0$) the demand in rising markets ($p > p_0$) is reduced further while in falling markets ($p < p_0$) it actually increases. We thus also observe a *reverse disposition effect* for rational traders. As we obviously find $\widehat{\phi} \leq \phi$, we see that the disposition effect of rational traders is more pronounced than that of biased traders.

For the aggregate effect on the total trading demand we can use that $x = \gamma x_B + (1-\gamma)x_R$ and inserting from (3) and (16) we obtain by noting the result in (17) and the definition of β in (8):

$$\begin{aligned} x &= \gamma x_B + (1-\gamma)x_R \\ &= \gamma\xi(v-p_0) - \gamma\phi(p-p_0) + (1-\gamma)\beta(v-p_0) \\ &= (\gamma\xi - \beta(\gamma-1+\gamma\phi))(v-p_0). \end{aligned} \tag{20}$$

Dividing the aggregate demand into a rational part and a biased part as before, we can write this as

$$\begin{aligned} x &= \xi(v-p_0) - \widehat{\widehat{\phi}}(p-p_0) \\ &= (\xi - \widehat{\widehat{\phi}}\beta)(v-p_0). \end{aligned} \tag{21}$$

Comparing coefficients in (20) and (21) yields immediately that

$$\widehat{\widehat{\phi}} = \gamma\phi + (1-\gamma)\frac{\xi-\beta}{\beta}. \tag{22}$$

We observe that $\widehat{\widehat{\phi}}$ is positive if there are sufficient biased traders in the market:

$$\gamma > \frac{\xi-\beta}{\xi-\beta-\phi\beta}, \tag{23}$$

which is less than 1 as it is easy to show that $\xi - \beta \leq 0$. Assuming condition (23) to be fulfilled throughout the remainder of this paper we obtain a *disposition effect* for long positions and a *reverse disposition effect* for short positions for the aggregate demand as argued above.

2.2 Development of testable hypotheses

We can now use the model analyzed above to derive hypotheses which can be empirically tested. Even if we know the identity of traders and many characteristics of them, we will obviously not be able to derive directly whether they are rational or biased. It is reasonable, however, to suppose that the more experience traders have in the markets, the less likely they are to be affected by behavioral biases.

Using our inferences on the behavior of traders from the theoretical model in section 2.1 we can directly derive our first two hypotheses:

Hypothesis 1 Trading strategies encompassing long positions show a disposition effect for inexperienced traders and a reverse disposition effect for experienced traders.

Hypothesis 2 Trading strategies encompassing short positions show a reverse disposition effect for both inexperienced and experienced traders, where that for experienced is more pronounced.

With the result on the aggregate behavior of traders from equation (22), not distinguishing between experienced and unexperienced traders, we easily derive our third hypothesis:

Hypothesis 3 On aggregate we observe a disposition effect for trading strategies encompassing long positions and a reverse disposition effect for trading strategies encompassing short positions.

Our model for simplicity assumed that traders are either biased or rational. We would in reality, however, expect that traders are affected to different degrees by behavioral biases. If we reasonably assume that traders are less affected by behavioral biases and becoming more rational the more experienced they are, we should also observe an equivalent implication for the disposition effect, forming our final hypothesis:

Hypothesis 4 The more experienced a trader is, the smaller the disposition effect. For very experienced traders we should observe a reverse disposition effect.

With these hypotheses we can now proceed to empirically investigate the validity of the model hypotheses as derived here. It will only be necessary to define a measure for the disposition effect as well as a measure for the experience of the traders.

3 Data and Methodology

This section describes the institutional setting of the markets and trades analyzed. The Chinese stock market, which we investigate in this paper, has some relevant peculiar characteristics which are worth pointing out to readers not familiar with this market. We continue then to describe the contents of the database used before presenting a measure of the disposition effect.

3.1 Stock exchanges in China

The People's Republic of China (PRC) has two stock exchanges - the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), which were established in November 1990 and April 1991, respectively. Stocks are listed only on one exchange and not cross-listed. By the end of 2003 there were 1,278 companies listed on the SHSE and the SZSE with a total market capitalization of US$523 billion. The Chinese stock market has in the past been characterized by a strict segmentation between domestic and foreign investors. Companies issued category A shares to domestic investors and category B shares to foreign investors. These shares were subsequently traded separately and investors were restricted to their category of shares. These two categories have been partially merged by allowing domestic investors to trade either category since February 2001.

Both exchanges use an electronic open limit order system and offer continuous trading Mondays-Fridays from 9.30am to 11.30am and 1.00pm to 3.00pm, except on public holidays. Investors can submit their limit orders, market orders are not permitted, through computer terminals that show the current best five limit orders on both the bid and ask side. Orders to be exercised at the opening call auction are submitted between 9.15am and 9.25am. The opening price is calculated such that the transaction volume is maximal. Unexecuted orders are automatically stored in the limit order book for the continuous trading that begins at 9.30am. The closing price of each stock is the volume-weighted average price during the last minute of trading, or the price of the last trade if there is no trading during the last minute. The selling of stocks follows a "$T + 1$" rule, which means that once a stock is bought, it cannot be sold until the next trading day. Once a stock is sold, the income from this sale can be reinvested into the stocks on the same day, but it cannot be drawn out again until the next trading day.

3.2 Database overview

According to Chinese law an individual can open only one stock account on each stock exchange using his/her National Identity Card (NIC). Nevertheless, some large investors collect NICs from the public, e. g. family members or friends but also strangers, and open many stock accounts. Thus one investor may actually have multiple stock accounts, which effectively help them to escape from supervision and facilitate their trading. It allows them to buy and sell the same stock within a trading day, which formally is prohibited by the "$T + 1$" rule. One investor, however many stock accounts he/she has, can normally only have one fund account with a brokerage company. Thus we can identify the investor through the fund account rather than the stock account and eliminate any bias in the data that might be generated by relying on stock accounts.

The uniqueness of our database is that we have the records of these fund accounts from one brokerage house. We find around 12,500 stock accounts in the database, but only 4,700 fund accounts, which also denotes the number of investors in our database. About 400 fund accounts are associated with more than two stock accounts, controlling a total of 5,700 stock accounts, nearly half of the stock accounts in our database. Only through examining the fund accounts are we able to track the precise value and portfolio of investors at any time in the sample period and inquire into their trading behavior. Previous studies had to rely on stock account data and were thus not able to analyze the complete behavior of a single investor, which can easily give rise to biases in the observed effects. Our access to fund account data should significantly reduce any such bias.

After the investors open their fund account, they conduct all their transactions through the same branch of the brokerage company, buying and selling of shares as well as transferring cash in and out of the account, hence we have access to all relevant information about transactions the investor conducts. A typical investor in China is not able to invest outside the PRC and since mutual funds are relatively new in the PRC, we effectively know the investors' total investments in equity markets and all their trades conducted. Although investors could open accounts with multiple broker houses, this is only observed for large institutional investors in order to escape the supervision of the stock exchange and its effect can be neglected for our purpose.

The database includes many pieces of information on the trades of investors as well as personal characteristics:

Order submission For each order submitted by a trader we have recorded the time, price, stock code, quantity, bid/ask at the time of submission, associated fund account and stock account number of the investor. The database also includes information on the way the investor did submit the order, e. g. by telephone, internet or in the offices of the brokerage firm, and whether and when the limit order has been canceled.

Transactions Each transaction is timed, has the associated fund account number, stock account number, stock code, number of shares traded, purchase or sale price and transaction costs (fees and taxes).

Accounts The database contains all fund accounts and their corresponding stock accounts. The number of stocks in the investor's stock accounts after every transaction and the remaining cash in his fund account are recorded. The database also covers any other changes of these accounts through non-trading activities, e. g. withdrawal or transfer of cash.

Investor information The database has additional information on each investor associated with a fund account. For each individual investor we know his/her gender, age, and the date of opening the fund account.

Institutional investors Apart from individual investors there are also 84 institutional investors in our database. We distinguish between institutional and individual investors as follows: when opening a stock account, different types of investors are marked differently. At the SZSE, the stock accounts for institutional investors are marked by "08" for the first two characters of the account number; at the SHSE, the institutional stock accounts are marked "B" or "D" as the first character of the account number. If any stock account associated with a fund account implies it being an institutional trader, the trades in all stock accounts are deemed to be institutional trades, even if other stock accounts imply it to be an individual investor.

Aggregating the information on all stock accounts associated with each fund account, we can thus identify all orders submitted and trades conducted by an individual trader. We are also able to determine his total wealth invested into shares, as well as which shares he holds in what quantities at any point in time and the amount of cash held in the fund account.

Although our data are drawn from only a single branch of a brokerage house, there is no reason to doubt that it is not a representative sample of the investors trading in the market. Firstly, investors in China usually choose more or less randomly between brokerage houses and there are no significant differences between investors in different brokerage companies. Brokerage houses mainly play the role of allowing investors to trade on stock exchanges, their service quality could be evaluated by the speed and accuracy of information transfer, which are almost identical across different brokerage firms. Other auxiliary functions, such as providing computer terminals, are also widely spread and do not distinguish brokerage houses from each other. Thus brokerage in China is a fully competitive market and we should not expect any significant differences between them. The second argument for our database being representative is that the statistics of our database do not show any abnormal properties compared to the market as a whole. We are thus confident about it being representative of the market and its appropriateness for use in an academic study.

3.3 Data statistics

In detail, our database contains information on 4,619 investors from a major Chinese brokerage company in a large Chinese city. We find information on all trades of each investor in any of the 1,226 stocks between 8 September 1999 and 30 April 2003. The database allows us to identify each trader with its personal characteristics such as age, sex, total investments made into each stock, amount of cash deposited with the securities house, and number of stock accounts, among others. In total we record 556,174 trades for 2,886,734,942 shares with a total value of 39,227,195,202 RMB (approx 4.6bn US$), representing about 0.25% of the total trading volume of the two Chinese stock exchanges combined during that time period. Table 1 provides additional descriptive statistics of our database, split into institutional and private investors.

3.4 Data handling

In order to investigate the disposition effect it is essential that we are able to determine two key variables, the duration of a trade and the profits generated. Rather than focussing on individual trades, it would be more appropriate to analyze trading strategies as e. g. a large order is commonly split into a number of smaller orders to facilitate its exercise. We might also find that the trader wants to hide his intentions and thus might provide liquidity by posting repeatedly buy and sell orders such that only over time a position slowly builds up.

In the absence of any information on the motivations for trades, we determine the start and end points of a trading strategy by focussing on the holding of a specific stock (inventory). If the change in the inventory reverses, i. e. if it increases (decreases) after it previously has been decreasing (increasing), we record the time of this reversal as the starting point of a new trading strategy. The end point of the trading strategy is then determined by the first time the inventory reaches the same level as when the trading strategy started.

Using this methodology enables us to investigate the possibility that a trader might follow a number of trading strategies at the same time, e. g. he might have bought shares in the past in anticipation of a future increase and while the price slowly adjusts he conducts some trades to provide liquidity to the market, which would be a very short-term strategy complementing the more long-term strategy. Alternatively, he might also want to exploit any short-lived information he has acquired, while still pursuing his long-term strategy.

While this methodology only gives the total length of a trading strategy, our interest is the average length the stocks are held during a trading strategy. Using the first-in first-out methodology we therefore determine the length of each trade within the trading strategy and then take the weighted average of these lengths as the *duration* of the trading strategy. The weights we use are obviously given by the relative trade sizes.

With this definition of a trading strategy and its duration we can not only analyze the disposition effect for various characteristics of investors, stocks or market conditions, but also characteristics of the trading strategy itself. Most importantly, we will be able to distinguish strategies involving reducing the inventory (sell strategies, short positions in our theoretical model) and those increasing the inventory (buy strategies, long positions).

In order to determine whether a trading strategy has produced a profit or loss, we firstly calculate the profit the trading strategy has generated and then compare this with the profits a buy-and-hold strategy would have yielded on the average inventory. If the profits of the trading strategy exceed those of the buy-and-hold strategy, we call the trading strategy profitable, and loss-making otherwise. Out of the 96088 trading strategies identified in our sample, 48899 were profitable and 47189 loss-making, showing a reasonable balance between them and giving further evidence of the appropriateness of our measure.

In order to measure the disposition effect we have to compare the duration of trading strategies generating profits (D_+) with those generating losses (D_-). The size of the disposition effect we determine by

$$DISPO = 2\frac{D_- - D_+}{D_- + D_+}. \tag{24}$$

The larger this measure, the more pronounced the disposition effect and for negative values we find the reverse disposition effect. This measure now allows us to investigate our database empirically for the presence and relevance of the disposition effect. The only drawback of this measure of the disposition effect is the requirement to aggregate a number of trading strategies according to some criteria. Given the size of our database we do not expect this to be a serious limitation to our analysis.

4 Analysis of empirical results

This section analyzes the durations of trading strategies empirically with the aim to evaluate the model and hypotheses proposed in section 2. Throughout this section we aggregate all durations falling into a given category and then analyze the median duration within this category. We will first provide a graphical analysis of the results to gain some intuition for the outcomes before proceeding to a regression analysis in the second part.

4.1 Graphical analysis of results

Our results show very clearly that while buy strategies show the disposition effect, sell strategies are showing the reverse disposition effect as predicted by our model above, see figure 1. Statistical testing shows that the signs and differences between buy and sell strategies are highly significant. The effect that overall we observe a disposition effect can be traced back to the fact that long positions dominate the trading strategies with us observing 40067 (39915) profitable (loss-making) buy strategies against 8832 (7274) profitable (loss-making) sell strategies. Thus this graph confirms our hypothesis 3.

We furthermore observe from figure 2(a) that more active traders, i. e. those who trade more frequently, are less subject to the disposition effect. We can reasonably suppose that more active traders are more experienced. We also observe in figure 2(b) that institutional investors, usually regarded as more experienced, are subject to the reverse disposition effect while individual traders are subject to the disposition effect. Given that individual traders are much more common than institutional traders, the aggregate effect would again show a disposition effect. As before the described results show a high degree of significance in statistical tests and therefore support our hypothesis 4.

In order to evaluate hypotheses 1 and 2, we have to split our sample into buy and sell strategies. Figure 3(a) shows clearly that for buy strategies individual traders show a disposition effect while institutional investors exhibit a reverse disposition effect, in accordance with our hypothesis 1. For sell orders the same figure shows a reverse disposition effect for both, individual and institutional investors, where that of the institutional investors is stronger, as stated in hypothesis 2.

Using the trading frequency as a measure for the experience of traders we observe from figure 3(b) that with increasing experience the disposition effect reduces for buy strategies, as we would expect from combining hypotheses 3 and 4. While the results reported thus far satisfy any statistical test at a high significance level, for sell strategies the picture is very unclear and statistically not significant and we are not able to confirm easily the results. This disappointing outcome might be due to the fact that sell strategies are only rarely observed and thus our sample size is too small to yield more significant results. This, however, merely reflects the relatively rare use of sell strategies by traders, compared to buy strategies.

Another important observation is that most of the reverse disposition effect can be found for short-term trading strategies, lasting up to an hour, while a significant disposition effect can only be found for trading strategies that last more than three months. Trading strategies of intermediate length do not show any significant bias as shown in figure 4. This picture is consistent for individual and private investors. It is reasonable to assume that experienced traders are employing more short-term strategies in order to exploit new short-lived information they receive as well as the behavioral bias of less experienced traders. Our data show that institutional traders as well as active traders with a high trading frequency have a proportionally larger fraction of trades with a short duration. We can thus conclude that the reverse disposition effect for short duration is consistent with our hypothesis 4.

It is also possible to employ other measures of investor experience, such as their age and sex. We observe from figure 5(a) that female traders are more affected by the disposition effect than male traders. Furthermore, figure 5(b) shows younger traders are slightly less affected than older traders. We see here again the clear difference to institutional investors, who are included in both cases as the category labeled "NA". These differences in the disposition effect can easily be explained with the experience of these different categories of traders.

Besides those characteristics reported here, we also considered other variables that might be used as an indicator of their experience, such as their total capital with the brokerage firm, trading volume, trading activity as measure by the ratio of their trading volume and their capital, the number of stock accounts held by an investor, the time since the investor opened his fund account, the size of his position, or the size of the company. In most cases the relationships between those variables and the disposition effect was less clear than using the variables we used in the graphs above and we were not able to gain any further insights from using these variables.

The relationships established in this section are in agreement with our hypotheses as developed in section 2, but we might gain further insights by employing a regression analysis to explore the relative importance of the different variables. This would also enable us to take into account the possibility that several variables can be correlated, e. g. trading frequency and age might be strongly correlated and thus age does not provide additional information to explain the disposition effect. Therefore the coming subsection explores a regression analysis on our dataset.

4.2 Regression analysis

Using the ideas generated from the graphical analysis above we can now continue our analysis with a regression of the appropriate variables on the disposition effect (DISPO). We use the trading strategy (STRAT) which is 1 for a buy strategy and zero for a sell strategy, the trading frequency (FREQ) ranging from 1 for the highest decile to 10 for the lowest decile within our sample, the duration of the strategy (DURA) ranging from 1 for durations of less than an hour to 5 for durations of more than three months, the age of the investor (AGE) ranging from 1 for traders below 30 years to 5 for traders above 60 years, the sex (SEX) which 1 for male and zero for female, and whether the trader is an institutional investor or individual investor (INST). For institutional investors we set the age and sex equal to zero.

We first assigned each trading strategy into one of the $2 \times 10 \times 5 \times 5 \times 2 \times 2 = 2000$ categories we are able to generate from the division of our explanatory variables. For each of these categories we calculated the disposition effect

(DISPO). As not all categories had at least one profitable and one loss-making strategy, we were able to obtain data for 1019 categories, which is the sample size for our regression as reported in table 2. The disposition effect was estimated in each category by an average of 49 profitable strategies and 48 loss-making strategies.

The regression clearly confirms our hypothesis 4 by assigning a statistically significant negative sign to the coefficient of FREQ, the trading frequency, which we used before as a measure of experience. Other measures we had investigated, the age and whether we have an individual or institutional trader as well as the sex of the trader do not show any statistically significant coefficients. This result clearly indicates that experience is better expressed with other variables and the found relationships in the graphical analysis are arising simply as the consequence of a strong correlation between them rather than causality.

We also see that the coefficient of the trading strategy, STRAT, is significantly positive, confirming our hypothesis 3. We can thus rule out the possibility that the result was due to more unexperienced traders choosing buy over sell strategies.

A somewhat less obvious result of the regression is the relatively large positive coefficient of the duration (DURA). Although we had found the proposed relationship in figure 4, our hypothesis at that stage had been that there might be a strong correlation between the experience of traders and the duration. We see here, however, that the effect of the duration does not diminish greatly if we include the trading frequency (FREQ) into the regression as should be expected if our initial inferences had been correct. Our model does not allow for differences in the duration to impact on the disposition effect. Such an effect might, however, arise if we allow for investors to trade on multiple pieces of information with different time horizons. As we have not developed such a model, this interpretation must remain speculative and requires to develop an appropriate model for testing.

Although the obtained R^2 is in all cases very low, testing for overfitting of the data using the method in Foster et al. (1997) clearly rejected this hypothesis at a high level of significance, apart from the regression in table 3(a). In doing this test we assumed that there are 15 potential variables to explain the outcome, the number of variables we could obtain from our database for characteristics of investors, trading strategies, stocks, and market conditions. One contributory factor to these low R^2 is the classification of data to explain a continuous variable; this classification of data must necessarily reduce the quality of our regression. The rejection of overfitting and high significance of coefficients serves as a good indicator for the validity of our results.

In order to investigate hypothesis 1 and 2 we have to split our sample into those data arising from following a buy and those following a sell strategy. We obtained sample sizes of 547 and 472, respectively, and the estimation of the disposition effect is based on an average of 74 (75) profitable (loss making) trading strategies for buys strategies and for sell strategies on an average of 19 (16) such strategies. This obvious imbalance in the number of observations reflects the dominance of buy strategies over sell strategies as employed by traders in the market. The results of these two regressions are shown in table 3.

As we clearly see from table 3(a) the regression for buy strategies again shows a statistically significant negative coefficient associated with the trading frequency (FREQ), supporting hypothesis 1. The most important coefficient, however, turns out to be the duration of the trading strategy; the effect is even stronger than in the combined sample shown in table 2.

The regression for short positions or sell strategies as shown in table 3(b) shows no clear evidence in support of hypothesis 2. Although the coefficient for the trading frequency (FREQ) has the correct sign, it is statistically not significant. The only significant coefficient is the duration of the trading strategy, albeit with a negative sign in contrast to long positions where it was positive. Overall we struggle to reject an overfitting of the data with our model. One reason for this result might be the relatively small number of sell strategies employed by traders; they account for only about 17% of all trading strategies investigated. Given furthermore that the disposition effect is calculated only on an average of 35 observations, less than a quarter of that for long positions, we might lack sufficient data to properly evaluate these strategies.

We can summarize this section by stating that while our empirical investigation found strong support for hypotheses 3 and 4, the evidence for hypothesis 1 was much weaker and for hypothesis 2 inconclusive. We found clear evidence for the existence of a disposition effect for some traders while others showed a reverse disposition effect, which has thus far not been reported in the literature with the exception of Ranguelova (2001) for small companies. We found, however, no evidence that the size of the company, measured by its market capitalization, has any effect on our outcome. In that sense it provides a new finding to the literature. However, we found another explanatory variable, the duration of a trading strategy which has not been reported before and we are not able to explain the origin of this relationship with the model developed.

5 Conclusions

In this paper we found evidence for the dependence of the disposition effect and reverse disposition effect on characteristics of the traders and their trading strategies, results which have not been reported in the literature before. Access to a unique database which allows us to investigate a wide range of characteristics of investors enables us observe that traders following a buy strategy exhibit the disposition effect while those following a sell strategy show a reverse disposition effect. Without distinguishing between these two trading strategies we confirm the usual disposition effect of traders. Our data also provide evidence that the experience or sophistication of traders affects the size of the disposition effect in line with the established literature. Furthermore we find a strong influence of the length of a trading strategy on the disposition effect; short-term strategies yield the reverse disposition effect while long-term strategies the disposition effect.

We explain the differences between buy and sell strategies using a model based on the auction model developed in Kyle (1985), modifying it to allow for some informed traders to exhibit a behavioral bias which causes them to sell in rising markets and buy in falling markets, acting as contrarian investors. Rational investors will exploit this bias and together create the empirically observed outcome of the disposition and reverse disposition effect both being present in the market.

One result we obtain from our dataset is that the length of the trading strategy is an important factor for the determination of the disposition effect. Further research is required to find a reasonable explanation for this result which we cannot derive from the model developed in this paper. Our research also shows the importance of evaluating the characteristics of traders as well as their trading strategies when investigating the disposition effect, and most likely other behavioral biases alike. This suggests future research should pay more attention to these characteristics rather than looking only at aggregate data for all traders.

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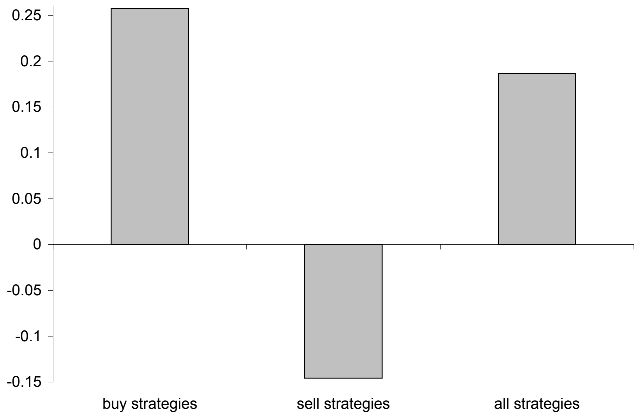
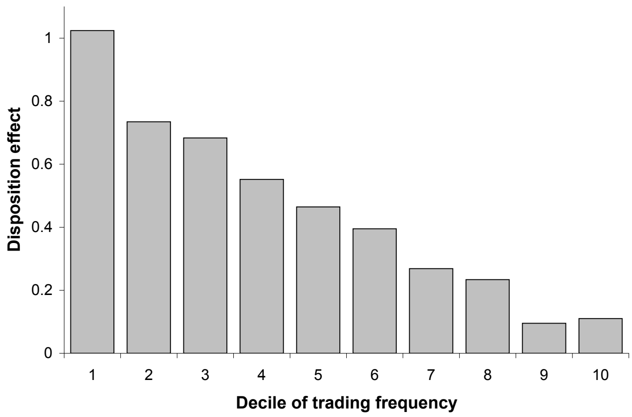
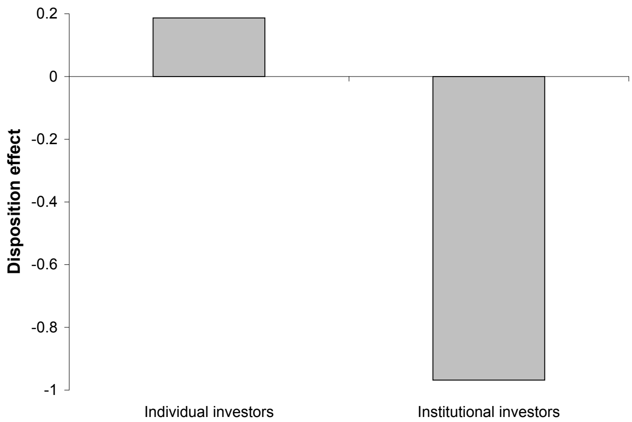


Figure 1: Disposition effect for different trading strategies.

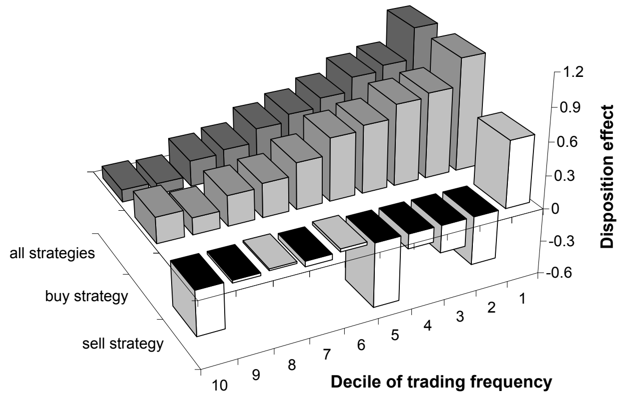


(a) Traders classified according to their frequency of trading.

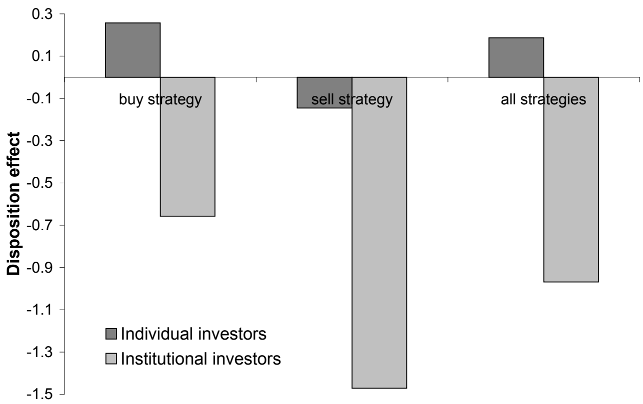


(b) Traders classified according to their type.

Figure 2: Disposition effect for differently experienced traders.



(a) Traders classified according to their frequency of trading.



(b) Traders classified according to their type.

Figure 3: Disposition effect for differently experienced traders, split up by trading strategy.

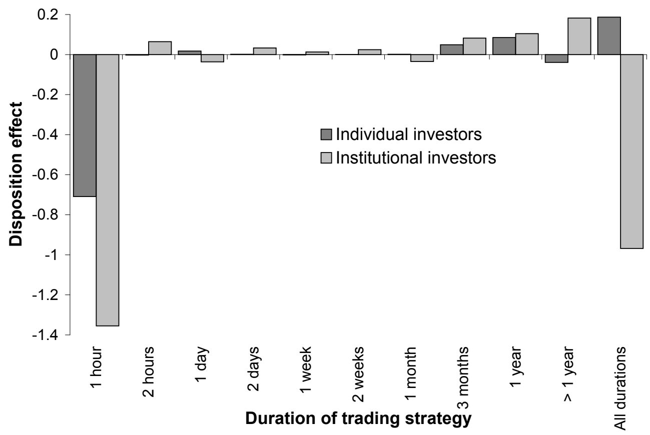
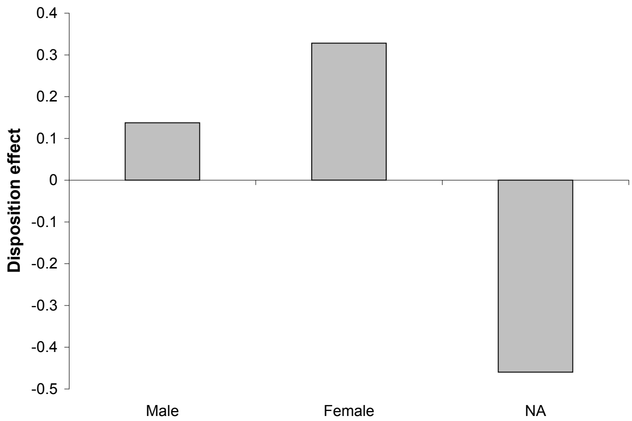
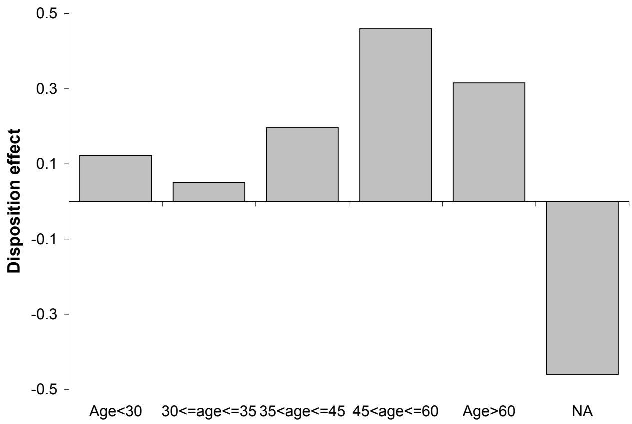


Figure 4: Disposition effect for trading strategies of different length.



(a) Traders classified according to their sex.



(b) Traders classified according to their age.

Figure 5: Disposition effect for investors of different sex and age.

Table 1: Descriptive statistics of data

	Institutional investors	Individual investors
Number of investors	77	4,542
Number of fund accounts	84	4575
Number of stock accounts	1958	10512
Number of male (female) investors		2108 (2078)
Average age of investors		40 years
Total number of trades	63,916	492,258
Total trading volume (shares)	617,476,167	2,269,258,774
Total trading volume (RMB)	9,530,495,153	29,696,700,049
Average capital (RMB)	20,201,406	715,942
Average fraction of capital invested into stocks	61%	79%
Average number of stocks held	6.22	2.98
Average time of holding shares	40.37 days	47.95 days

Table 2: Regression analysis of the disposition effect

The table below shows the coefficients from a number of regressions of the disposition effect (DISPO) on the trading strategy (STRAT) which is 1 for a buy strategy and zero for a sell strategy, the trading frequency (FREQ) ranging from 1 for the highest decile to 10 for the lowest decile, the duration of the strategy (DURA) ranging from 1 for duration of less than an hour to 5 for duration of more than 3 months, the age (AGE) ranging from 1 for traders below 30 years to 5 for traders above 60 years, the sex (SEX) which 1 for male and zero for female, and whether the trader is an institutional investor or individual investor (INST). For institutional investors we set the age and sex equal to zero.
$***$, $**$, $*$ denote significance of the coefficients at the 1, 5 and 10% level, respectively.

	1	2	3	4	5	6	7	8
CONST	-0.1046^{***}	0.0683^{***}	-0.0930^{***}	-0.0371	-0.1810^{***}	-0.0118	-0.1146^{***}	-0.0830^{**}
STRAT	0.1712^{***}			0.1660^{***}	0.1700^{***}		0.1653^{***}	0.1653^{***}
FREQ		-0.0135^{***}		-0.0108^{***}		-0.0126^{***}	-0.0099^{***}	-0.0099^{***}
DURA			0.02608^{***}		0.0250^{***}	0.0242^{***}	0.0238^{***}	0.0238^{***}
AGE×(1-INST)								-0.0094
SEX×(1-INST)								-0.0121
INST								-0.0215

Table 3: Regression analysis of the disposition effect for trading strategies involving long and short positions

The table below shows the coefficients of a number of regressions of the disposition effect (DISPO) on the trading frequency (FREQ) ranging from 1 for the highest decile to 10 for the lowest decile, the duration of the strategy (DURA) ranging from 1 for duration of less than an hour to 5 for duration of more than 3 months, the age (AGE) ranging from 1 for traders below 30 years to 5 for traders above 60 years, the sex (SEX) which 1 for male and zero for female, and whether the trader is an institutional investor or individual investor (INST).For institutional investors we set the age and sex equal to zero. $***$, $**$, $*$ denote significance of the coefficients at the 1, 5 and 10% level, respectively.

(a) Trading strategies with long positions (buy strategies)

	1	2	3	4
CONST	0.1398^{***}	-0.1661^{***}	-0.1043^{***}	-0.0855^{***}
FREQ	-0.0127^{***}		-0.0099^{***}	-0.0097^{***}
DURA		0.0751^{***}	-0.0735^{***}	0.0736^{***}
AGE×(1-INST)				-0.0041
SEX×(1-INST)				-0.0134
INST				-0.0329

(b) Trading strategies with short positions (sell strategies)

	1	2	3	4
CONST	-0.0534	-0.0057	0.0568	0.1039
FREQ	-0.0082		-0.009425	-0.0093
DURA		-0.0324^{**}	-0.0336^{***}	-0.0331^{**}
AGE×(1-INST)				-0.0156
SEX×(1-INST)				-0.0127
INST				-0.0190