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ANALYSIS OF THE DISPOSITION EFFECT**

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Up Close and Personal: An Individual Level Analysis of the Disposition Effect

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**Up Close and Personal:
An Individual Level Analysis of the Disposition Effect**

In this paper, we analyze the trading records of a major discount brokerage house to investigate the disposition effect, the tendency to sell winners too quickly than losers. In contrast to previous research that has demonstrated the disposition effect by aggregating across investors (Odean, 1998), our main objective is to identify individual differences in the disposition bias and explain this in terms of underlying investor characteristics. Building on the findings in experimental economics and self-correction in psychology, we hypothesize that investors' sophistication about financial markets and trading experience is responsible in part for the variation in individual disposition effect. Using demographic and socio-economic data as proxies for investors' sophistication, we find empirical evidence that wealthier and individual investors in professional occupations exhibit less disposition effect. Consistent with experimental economics, trading experience also tends to reduce the disposition effect. We provide guidelines for investment advisors, regulators and investment communities to utilize our findings and help investors make better decisions.

Keywords: Disposition effect, Investor sophistication, Individual decision making.

JEL classification G10

The rational expectation paradigm assumes investors to be optimizing economic agents who make fully informed economic decisions. In contrast, a number of recent studies find that individual investors exhibit systematic behavior away from what rational theory predicts (Mullainathan and Thaler 2002, Barberis and Thaler 2002). Grinblatt and Keloharju (2001a) use Finnish data to show that individual investors tend to invest in stocks that are located closer to their residence and that have management speaking the same language, even though neither strategy appears to increase investment returns. Barber and Odean (2000) use individual investor data to show that investors trade too frequently even though doing so is costly, and thus harmful to their wealth. Using similar data, Goetzmann and Kumar (2001) show that individual investors' equity portfolios are much less diversified than predicted by portfolio theory. Theorists in behavior finance have shown how systematic biases in investor behavior may impact asset prices (Hong and Stein 1999, Barberis, Shleifer and Vishny 1998).

In this paper, we focus on one of the most widely documented bias in investor behavior, the disposition effect. The disposition effect refers to the tendency to sell previously purchased stocks that have appreciated in price ("winners") and the reluctance to sell those that are trading below their purchase price ("losers"). Starting with Shefrin and Statman (1985), a number of researchers have demonstrated the basic effect using different investor databases (Odean 1998, Venezia and Shapira 2001, Weber and Camerer 1998). This work clearly documents the existence of the disposition effect. Now that the existence question has been asked and answered, it is possible to explore the conditions under which the effect is prevalent, and what investor characteristics are correlated with the bias. These "How" and "When" questions are important for several reasons. If we find that trading heuristics are correlated with specific conditions, this has clear implications for the dynamics of asset prices in bubbles and crashes. Second, if we find that certain type of investor is more susceptible to biases, it will have welfare and regulatory implications. In particular, social security and retirement investment account reform depends in part on the assumption that individual economic choice is by and large rational. If we find

that this is true for some but not others, the regulation and reform will clearly have differential effects. Indeed, self investment choice may not be pareto-improving. Another implication of differential biased behavior is that rational agents may profit from the poor heuristic of irrational agents. This motivates theorists to accommodate investor heterogeneity in sophistication and style in their models (Barberis and Shleifer 2002). Our work in this paper takes a step toward determining which investors have advantages over other investors in the equity investor universe.

Our paper differs from previous research in that we investigate the disposition effect at the level of each individual. All evidence to date for the disposition effect has been demonstrated by aggregating the data across all trades and traders to arrive at the mean disposition effect for a representative investor in the market place. Recent research, for example Goetzmann and Massa (2002) and Dhar and Kumar (2002), find significant heterogeneity in investor beliefs and trading styles. Such systematic differences in trading heuristics across individuals imply that the mean value is not the whole story. This paper conducts a cross sectional study of the disposition effect that analyzes investor characteristics contributing to the heterogeneity in the tendency of investors to ride losers and sell winners.

Our analysis strongly confirms findings of previous studies (Odean 1998, Grinblatt and Keloharju 2001b) that individual investors, on average, exhibit the disposition effect. However, we find that despite the significant disposition effect on average, about one fifth of investors in our sample exhibit behavior opposite to the disposition effect. Consistent with our main hypotheses, we find that investor characteristics that correspond to greater sophistication such as investor income, profession and trading experience attenuate the magnitude of the disposition effect. Specifically, we find that wealthier and investors in professional occupations show a significantly smaller disposition effect. Furthermore, investors who trade frequently also have a smaller disposition effect, implying that repeated trading experience may help investors trade “out of” the disposition effect.

Our findings have important implications for policy makers as well as behavioral financial theorists. First, as certain investors are more susceptible to the

disposition effect than others, individual investor organizations should focus on helping early-stage investors become aware of this tendency and adjust their trading accordingly. Second, since a large fraction of individual investors never realize their losses, we suggest that brokerage firms should try to educate their clients of the disposition effect, thereby improving their clients' after tax portfolio performance and increasing the added value of their services. Finally, certain demographic and socio-economic groups show a greater disposition effect, which may adversely affect their portfolio return. The increase in self-investing highlights the role of government agencies and non-profit organizations in making investors aware of their trading heuristics and biases. We therefore suggest that government agencies should exist to better inform and educate low-income, non-professional and young investors.

The remainder of the paper is organized as follows: Section 2 reviews the literature; Section 3 motivates studying the disposition effect at individual investor level and across demographic groups; Section 4 presents the empirical results and Section 5 concludes and proposes policy recommendations.

Section 2 Literature Review

The tendency of investors to “sell winners too early and ride losers too long” was documented by Shefrin and Statman in 1985. More recently, Odean (1998) demonstrated the existence of the disposition effect with empirical evidence from a large sample of individual investors at a major discount brokerage firm. Heath et al (1998) report similar results using data on the option exercising behavior of over 50,000 employees at seven big companies. Internationally, Shapira and Venezia (2001) use data from Tel Aviv Stock Exchange to show that Israeli individual investors also display the disposition effect.

The principal explanation for the disposition effect is based on Kahneman and Tversky's Prospect Theory (1979), according to which gains and losses are often judged relative to a reference point and individuals exhibit risk-averse behavior for gains and risk seeking behavior for losses. Thus, if individuals do not adapt to price changes and use the purchase price of a stock as a natural reference point, prices of

stocks that have risen since purchase will be seen as a choice between a sure gain (if the stock is sold) and a risky gamble (if one continues to hold onto the stock), the domain in which people are often risk averse. In contrast, if the previously purchased stock is trading below its purchase price, selling it would be seen as incurring a sure loss whereas holding onto the stock would be seen as preferring the risky outcome. The tendency towards the disposition effect may be further moderated by loss aversion, the notion that losses are weighted more than equivalent gains (see Weber and Camerer 1998).

Since the disposition effect depends on the degree to which the purchase price serves as the reference price, a question that naturally arises is whether such reference point varies across individuals. In practice multiple reference points, from the purchase price to the highest and lowest price since purchase, might combine together to produce a reference level (Kahneman 1992). Sophisticated investors may have a better appreciation for the concept of market efficiency. This greater understanding of the role of market forces in setting prices may readily allow such investors to adjust the reference price of a security from the purchase price in the direction of the current price (i.e., the true price of a security is the price at which it is currently trading). Thus, there should be no disposition effect if the reference point is the current price of the security but the exact proportion of winners and losers realized will depend upon the likelihood and the subjective outcomes of the two gambles. More generally, it can be easily shown that the closer is the reference price to the current price, the smaller the magnitude of the disposition effect (see Weber and Camerer 1998).

Furthermore, while Kahneman and Tversky have often termed reference effects as “cognitive illusions” and hence not easy to eliminate, investors can still learn about illusions and help inhibit such biases by engaging in more critical or analytical thinking (Kahneman and Reipe 1997). A general awareness of situations in which one is more or less prone to sell is likely to lead to correcting mechanisms (Wegener and Petty 1995). Thus, for individuals who are aware of their reluctance to sell losers, they can more completely evaluate the consequences of their decisions over time, leading to modification of their behavior. Accordingly, we propose that

investors' differential opportunity to learn from information is partially responsible for such variation in the reluctance to sell losers. We show that investor groups with potentially better access to information and sophistication about the financial markets have a significantly lower disposition effect than other investors.

A related question that arises is whether investors learn from trading experience to correct for the disposition effect. A criticism by the experimental economics literature of psychology experiments is that many of the biases documented do not utilize repeated trials for individuals to familiarize themselves with the bias. As noted by Knez, Smith, and Williams (1985), "Most (but not all) experimental markets show some learning effects over time with equilibrium behavior quite different from start-up behavior". Experimental economists show that although individual bids show a large disparity between willingness-to-accept (WTA) and willingness-to-pay (WTP), ending bids submitted after a series of trials are similar (Coursey, Hovis, Schulze 1987, List 2002). For example, given that the disposition effect is basically a heuristic approach to trading (incomplete adaptation to current prices), the effect is likely to be weaker for more experienced traders as experience might attenuate such a behavioral bias. Accordingly, we predict and find that investors who trade more have a lower disposition effect than investors who trade less. This also provides support to our hypothesis that learning and experience help alleviate the disposition effect.

Section 3 Documenting the Disposition Effect at the Individual Level

Previous research differs in the construct used to measure the disposition effect. Shefrin and Statman (1985) and Shapira and Venezia (2001) calculate the length of the round-trip holding period for winners and losers in investors' portfolios. Odean (1998) calculates the disposition effect as the difference between investors' propensity to realize winner and loser stocks in their portfolios. We use the construct proposed by Odean (1998). By assuming individual trades or accounts are independent, Odean (1998) shows that there exists the disposition effect at the aggregate level. In this study, we focus on calculating the Realized Gain, Realized

Loss, Paper Gain and Paper Loss at individual investor level, which allows us to examine the cross sectional variation in the disposition effect for individuals with different characteristics.

Particularly, Proportion of Gain Realized (PGR) and Proportion of Loss Realized (PLR) are defined as:

$$PGR = \frac{\text{Realized Gain}}{\text{Realized Gain} + \text{Paper Gain}} \quad (1)$$

$$PLR = \frac{\text{Realized Loss}}{\text{Realized Loss} + \text{Paper Loss}} \quad (2)$$

“Realized Gain/Loss” is defined as the number of winner/loser stocks sold in a portfolio. If a stock’s price is higher/lower than its purchase price at the time of calculation, it is considered a winner/loser. The “Paper Gain/Loss” is defined as the number of winner/loser stocks in an investor’s portfolio at the time of calculation (for further details, see Odean 1998). The disposition effect is defined as the difference of each investor’s PGR and PLR:

$$\text{Disposition Effect}(DE) = PGR - PLR \quad (3)$$

A positive disposition effect is considered evidence that this particular investor is more likely to realize gains than losses in her portfolio. The bigger the disposition effect, the more likely one investor is to realize winners than losers.

There are several reasons why it may be useful to measure the disposition effect for each investor. First, as Odean (2000) notes, the aggregate description of average investors will “mask considerable cross-sectional variation” in understanding individual investment behavior. One limitation of calculating the disposition effect at aggregate level is that the PGR (Proportion of Gains Realized) of one investor does not necessarily correspond to the PLR (Proportion of Losses Realized) of the same investor. As a result, aggregating the total number of paper gains, paper losses, realized gains and realized losses is equivalent to treating all investors as one representative agent. This may blur the matching between PGR and PLR of each individual and disguise the difference in the disposition effect across investors. The

focus on computing PGR, PLR and the disposition effect for each investor thus may sharpen the measurement of the effect.

The inference about individual level disposition effect based on the calculation for the aggregate data may also be affected by any difference in their frequency of trading. To elaborate on the possible limitations of such an inference based on aggregate data, we offer a hypothetical example. The example in Table 1 reveals that even if the disposition effect is detected at an aggregate level, the majority of the investors in that market may not exhibit disposition effect. Imagine that there are only three investors within an economy. In this example, the market-aggregate level disposition effect is 0.18 while the disposition effect for three investors' portfolios are -0.08 , 0 , and 0.19 , respectively. Even though only one third of the investors display the disposition effect, the aggregate measurement leads us to conclude positively about the existence of the disposition effect.²

While the main focus of the paper is on establishing the disposition effect at the individual level and the corresponding investor characteristics, we also briefly look at the absolute magnitudes of PGR and PLR. Even for two investors with the same disposition effect, their investment behaviors are not necessarily the same. For example, one investor selling 90 percent of her winners and 80 percent of her losers exhibits a disposition effect of 0.1. On the other hand, another investor exhibiting disposition effect of 0.1 sells 20 percent of her winners and 10 percent of her losers. Although these two investors have the same disposition effect, they are quite different in their overall tendency to trade stocks. Hence, the disposition effect does not depict a complete picture about investors' overall tendency to sell winner and loser stocks. Measuring PGR and PLR at the individual level allows us to differentiate these investors by examining potential differences in investor characteristics.

In summary, an advantage of examining the disposition effect at the individual level is that we can identify variation in investor's Disposition Effect (DE). Second, it allows us to examine the role of investor characteristics in explaining the difference. Our primary hypothesis is that difference in investor sophistication is partly responsible for the variation in the disposition effect. The proposed link between

investor sophistication and the disposition effect (DE) is consistent with related findings (Grinblatt and Keloharju 2001b), which shows that investor classes with higher level of sophistication show lower tendency toward certain biases.³ Third, by calculating PGR and PLR for each investor, we can analyze the investor characteristics that might explain the relative differences in the proportion of winners and losers that are realized.

We expect sophisticated investors to have a lower disposition effect because they are less susceptible to reference effects and more aware of such tendency and hence likely to correct for it. As we expect some demographic variables to underlie investors' sophistication, we use them as proxies for the degree of sophistication. In particular, we test whether the more sophisticated demographic groups, which have better access to information or better understanding of market forces in setting prices, have a smaller disposition effect. Specifically, we test the moderating impact of investor income and occupation status on the magnitude of the disposition effect.

We argue that investor income can be considered as a proxy for the information quality and the ability to process information for the following reasons. First, high-income people are more likely to have access to financial advice such as financial and tax planners as they can afford value-added services. In addition, wealthier investors also have more investment at stake and therefore find it more worthwhile to utilize such services. Second, annual income is likely to be correlated with occupations such that high-income investors are also more likely to work in professional occupations. We discuss next why professionals have better ability to process information. Based on above argument, we expect wealthier investors to exhibit a smaller disposition effect.

Our second proxy for sophistication is occupation of the investor. We posit that certain occupations call for higher level of education and people working in such professions have better ability dealing with financial related and abstract decisions such as equity investment. Moreover, previous research (Chevalier and Ellison 1999) finds that education has a significant impact on professional money manager's investment performance. They find that fund managers with better education show

better performance. Since professionals have higher education than non-professionals, we expect them to exhibit smaller disposition effect.

Separate from demographic variables, investor experience is also likely to influence the disposition bias in that as people repeat doing things, they become more familiar with the objectives and can do better than those individuals who do the same thing less frequently. As List (2002) notes his experience in the sportscard market, “As my own trading experience intensified, I by passed fewer beneficial trade... In essence, I had learned to effectively trade, and any notion of an endowment effect was purely inconsequential, or severely attenuated.” We believe such a learning explanation also applies to investor behavior. Therefore, we expect the number of trades that each investor executed to decrease the disposition effect.

Based on above categorization and discussion, we intend to test following specific hypotheses:

Hypothesis 1: The majority of individual investors will display the disposition effect.

Hypothesis 2a: “High-income” investors will display smaller disposition effect than “low-income” investors.

Hypothesis 2b: “Professional” investors will display smaller disposition effect than “non- professional” investors.

Hypothesis 3: Trading frequency reduces the magnitude of the disposition effect.

Section 4 Empirical Results

4.1 Data Description

The data used in our research contains trading records of more than 50,000 individual investors from a large discount brokerage firm between 1991 and 1996. We present the descriptive statistics of our data in Table 2. There are three files with our data: a trade file, a position file and a demographics file. The trade file contains information on the stocks that each investor buys and sells, the prices at which stocks are bought or sold and the time of such trades. The position file contains information on each investor’s portfolio position at the end of each month during the same period. The demographic data contains information collected on investor’s key demographics

such as age, profession and income. Such information is not available for all investors.

We have information on the trading record of 79,995 investors in our sample. Due to incomplete trade record, we can calculate the disposition effect for 14,872 investors. Several reasons are responsible for such a decrease in the number of observations: (1) 17,608 investors trade only mutual funds, fixed income securities, ADR (American Deposit Receipt)s or foreign equities whose prices are not available from CRSP (Center for Research on Securities Prices) data. As we focus on equity trading behavior of investors, we only keep the remaining 62,387 investors who trade equities. (2) A large fraction of investors trade rather infrequently. We decide to focus on investors who, on average, trade no less than one trade every year during the six-year period. As a result, 19,806 investors are excluded from the data. (3) Even for the 42,581 investors who have more than 6 trades, we are not always able to calculate their disposition effect: Some investors only buy or sell stocks during the studied period and we cannot compute the number of realized gains or losses for such investors. For other investors who have both buy and sell trades, we sometimes cannot find the trade record that match what we observe in our data. An investor may have bought a stock that she sells in our data before our data starts or sell a stock that she buys in our data after our data ends. All of the above issues hinder us from computing individual's disposition effect and we finally manage to compute the disposition effect for 14,872 investors.

Out of the 14,872 investors, we have demographics information on 7,965 investors. The descriptive statistics of our final sample is included in Table 2. Due to our data selection criteria, the investors in our study generally have more trades (mean=58 and median=29) than the entire sample investors do (mean=41 and median=19). Investors in our sample also have larger portfolio values (mean=\$39,446 and median=\$16,520) than those of the entire data (mean=\$35,629 and median=\$13,869). Regarding demographics, our investors have higher annual income (mean=\$64,571) than average investors (mean=\$59,097).

4. 2 Investors characteristics

To study how individual investor characteristics contribute to variations in the disposition effect and PGR and PLR, we formulate an “income” and a “profession” variable. For the “income” variable, we divide the investors into three income categories, namely “high-”, “medium-” and “low-income”. We classify investors with annual income lower than \$40,000 dollars into the “low-income” category; investors with annual income between \$40,000 and \$100,000 into the “medium income” category and investors with annual income more than \$100,000 annual income into the “high- income” category.

We set our cut-off point at \$40,000 because we would like “low-income” investors to have income lower than the average income of all investors. The census data indicates that the median annual household income of 1994 is \$33,178 (US Bureau of Census 2000). The mean and median income of annual income in our sample investors are \$54,571 and \$50,000, respectively. Not surprisingly, individuals who open brokerage accounts have higher income than those who do not. Therefore, we choose \$40,000 as the cut-off point for our “low-income” group as it lies between the median annual household income of the nations and the average annual household income of our sample investors. We classify investors with annual income greater than \$100,000 as “high-income” investors because \$100,000 is a widely used benchmark for high-income people. Such a division also allows us to have a reasonable number of observations in each income groups.

The demographic data allows us to divide investors into “professional”, “non-professional” and “non-employed” categories by their occupations. We classify investors as “professional” if their occupations are either “professional/technical” or “managerial/administrative”. We classify investors as “non-professional” if their professions are “white collar/clerical”, “blue collar/craftsman” or “service/sales”. Investors who are farmers or retired are classified as “non-employed”. The reason why we put “service/sales” into “non-professional” category is that according to Bureau of Labor Statistics (2000), more than 80 percent of the people in service/sales

category are actually service people, which we believe are more similar to “white collar” and “blue collar” in the nature of their work. ⁴

4.3 Individual disposition effect

Our main focus is on the existence of the disposition effect for each of the 7,965 investors and we report the descriptive statistics of DE in Table 3. Because investors’ trading in the month of December is affected by tax selling considerations (Odean 1998), we exclude December trades initially and only examine the trades between January and November. We also present the distribution of DE in Figure 1. The disposition is widely distributed with minimum of -1 and maximum of 1. We observe that the mean of disposition effect is 0.19. Consistent with previous research (Odean 1998), the disposition effect is positive and significant.

The disposition effect at aggregate market level is 0.068. We notice a significant difference between our individual measurement 0.19 and the market level measurement 0.068 (p -value=0.01). We believe two reasons are responsible for this. First, as discussed above, it is due to the fact that aggregate disposition effect does not capture the idiosyncratic difference between PGR and PLR for each individual investor. Second, since aggregating across all investors assigns more weight to the frequent traders who are predicted to have a lower disposition bias in our sample, it reduces the magnitude of the effect.

An interesting finding is that not all investors exhibit disposition effect. As a matter of fact, 19.7 percent of investors in our sample do not exhibit any disposition effect or exhibit behavior opposite to the prediction of disposition effect. Odean (1998) finds that investors exhibit negative disposition effect during December and that is because investors try to take advantage of the tax benefits from realized losses towards year-ends (Constantinides 1984). Our result shows that even for the period from January through November, where the tax-selling impact is marginal, there are a significant number of investors exhibiting negative disposition effect, meaning that they realize more losses than winners in their portfolios.

As discussed in Section 3, we expect the disposition effect to vary among investors due to differences in sophistication and trading experience. Particularly, we next test whether different disposition effect is moderated by investor demographics and frequency of trading.

We report the disposition effect of each demographic group in Panel 2 of Table 3. As predicted, the mean of “high-income” and “low-income” groups are 0.189 and 0.211, respectively. The mean of “professional” and “non-professional” are 0.203 and 0.245, respectively. The differences between “professional” and “non-professional” groups and between “high-income” and “low-income” groups are both negative and significant. We understand that individual disposition effect is not normally distributed and therefore also report the median of each group in a similar fashion. The medians of “high-income” and “low-income” group’s disposition effect are 0.15 and 0.167 and the medians of “professional” and “non-professional” investors’ disposition effect are 0.167 and 0.214. With Wilcoxon rank test, we show that the differences between income and profession groups are significant at 5% percent. We further perform Kolmogorov-Smirnov test comparing the distribution of disposition effect in each group. The results are again consistent with our findings from measuring the means that “high-income” and investors in “professional” occupations exhibit weaker disposition effect.

Since income and occupation are correlated among investors, it is possible that we may have confounded the income and occupation effect when comparing the disposition effect of different income and occupation groups. To address this issue, we calculate the disposition effect of different occupations within the same income groups and similarly calculate the disposition effect of different income levels within the same occupation. Such an approach will reveal the sole effect of income and occupation.

We illustrate the result in Figure 2 and 3. The disposition effect for “high-income” investors is smaller than the disposition effect for “low-income” investors for all three categories of professions. The difference is much bigger for investors from “non-professional” group. Similarly, “professional” investors consistently have

smaller disposition effect than “non-professional” investors. The difference between the disposition effect of “professional” and “non-professionals” is small and insignificant for the “high-income” group while it is much bigger and statistically significant for “low-income” group. This shows that income and occupation have separate impact on individual investor’s disposition effect. As high-income investors are on average more capable of processing information or getting advice from financial and tax planners, the occupation difference has marginal influence on their disposition effect. On the other hand, low-income investors working in a professional occupation have a lower bias as well suggesting that our these investors in our sample are likely to be early stage investors as opposed to low-income blue-collar workers.

We note that “non-employed” investors have a much lower disposition effect than employed investors. Ex post, there are two possible explanations for such a finding. First, it is possible that “non-employed” investors spend more time collecting and analyzing information regarding investment and therefore suffer less from the disposition effect. Second and more likely, since most of “non-employed” individuals in our database are retired and older (mean of age=61), they are more likely to have been from professional occupation as well as more experienced investors. Our regression analysis below will examine this in greater detail.

We perform a regression analysis to elaborate on the impact of investor characteristics on the disposition effect. The regression function is specified as follows:

$$DE = \gamma D + \beta X + \varepsilon \quad (4)$$

where DE is the disposition effect. The D matrix contains demographic variables of each investor. Particularly, it includes dummy variables of “high-income”, “low-income”, “professional”, “non-professional” and “non-employed”. We also include the logarithm of age in the demographic matrix to control for age difference among investors. We take the logarithm of age because age is skewly distributed. The X matrix is composed of information on each investor’s idiosyncratic trading pattern. In our current specification, X includes the logarithm of the number of trades an investor

has executed and the realized returns of winning and losing trades of each investor. Again, we use the logarithm of the number of trades due to its skewed distribution. ε is the i.i.d error term.

We report the result of the DE regression in Table 4. The result shows that “high-income” group exhibits lower disposition effect than “low-income” investors. “Non-professional” investors exhibit a significantly larger disposition effect than “professional” investors. Both results are consistent with our hypothesis 2. In addition, the coefficient for “non-employed” investors becomes insignificant as we control for the age of investors. It supports our previous premise that “non-employed” investors have significantly lower disposition effect because they are generally more senior in age. We also include the product of different income and occupation groups to handle the potential correlation between income and occupation. We do not report them as no cross product is significant. Finally, the coefficient for $\ln(\text{Numtrade})$ is negative and highly significant. This supports the notion that trading frequency helps investors accumulate experience and become more sophisticated about selling losers. Such experience, in turn, helps reduce their disposition effect. The coefficient for control variable “age” is significantly negative, meaning that older investors have smaller disposition effect.

One limitation of the DE measure as constructed is that it can be affected by the amount of trading relative to the size of the investor portfolio (Odean 1998, Weber and Camerer 1998). For example, if investors have a large portfolio, this leads to lower PGR and PLR, and hence to lower DE.⁵ Since it is likely that higher income investors have a larger portfolio, we include proxies for portfolio sizes into the same regression to ensure that our findings are not driven by the fact that investors with different demographic characteristics also have systematically different portfolio sizes. Specifically, we include average number of stocks within an investor’s portfolio every month and its inverse into separate regressions. We consider the inverse of portfolio sizes because the relationship between portfolio size and the disposition effect may not be linear.

Our results remain unchanged. We report the regression results in column 4 and 5 of Table 4, respectively. There is a significantly negative relationship between the disposition effect and portfolio size and a significantly positive relationship between the disposition effect and the inverse of portfolio size. Nevertheless, including proxy for portfolio size does not change any of our major findings: investors who are wealthier, professional, older and more experienced still exhibit significantly weaker disposition effect.

We further examine the correlation between portfolio size and the disposition effect. As stated previously, the disposition effect is negatively correlated with portfolio size (correlation coefficient=-0.158) and positively correlated with the inverse of portfolio size (correlation coefficient=0.086). The correlation coefficients, however, are both very low. One possible reason is that a majority of sample investors moderate number of stocks in their portfolios (mean=4 and median=3) and only 4.3 percent of sample investors hold an average of 10 stocks within their portfolio. We therefore believe that our major findings are not driven by differences in portfolio sizes.⁶

In summary, we find that there is wide variation in the size of the disposition effect across investors. We confirm previous findings that on average, there is disposition effect at the aggregate level and our measurement approach renders stronger disposition effect than previously reported. We also find that about one fifth of investors in our sample do not exhibit any disposition effect or behavior opposite to disposition effect. Consistent with our hypothesis, investor's sophistication about financial information influences her disposition effect. Proxies for sophisticated investors, such as wealthier, professional, older and more experienced investors, exhibit smaller disposition effect. These results hold up after we control for investors' portfolio sizes.

4.4 Individual Proportion of Gain Realized (PGR) and Proportion of Loss Realized (PLR)

We next explore the difference in overall tendency to trade as measured by PGR and PLR for each investor following the above definition. The mean and median of PGR are 0.38 and 0.24 while the mean and median of PLR are 0.19 and 0.11, respectively. To compare our results with that obtained in Odean's research, we also calculated the PGR and PLR by aggregating the buy and sell trades across all investors. The PGR and PLR are 0.132 and 0.064, respectively, both smaller than those calculated with our approach. 4.7 percent of investors never realize their winner stocks within the studied period while 21.5 percent of investors never sell any loser stocks in their portfolios. This presents an additional piece of evidence that investor behavior is asymmetric when it comes to what stocks to sell.

Figure 4 and Figure 5 show the distribution of PGR and PLR. Both PGR and PLR are widely distributed between 0 and 1, indicating that investors vary a lot in their overall tendency to trade as well as their attitudes toward winner and loser stocks in their portfolios. There is greater variance in PGR (standard deviation=0.279) than PLR (standard deviation=0.211), which is consistent with previous study (Weber and Camerer 1998). As investors are more homogeneous in their aversion to selling loser stocks, their PLR tends to show less variance.

As stated previously, we are interested in exploring the impact of investor characteristics in the variability of PGR and PLR, the difference of which determines the magnitude of the disposition effect. We perform the regression analysis specified as follows:

$$Y = \gamma D + \beta X + \varepsilon \quad (5)$$

where Y is PGR or PLR and all other variables are defined as in Equation (4). Different from the disposition effect regression that includes return of both realized gains and losses, PGR regression only includes the return of realized gains and PLR regression only includes the return of realized losses.

The results are reported in Table 5. For the PGR regression, "professional" dummy is negative and significant, meaning that investors in "professional"

occupations generally realize a smaller fraction of their winning stocks. The coefficients for “ln(age)” and “ln(numtrade)” are negative and highly significant, indicating that older and more experienced investors have lower tendency to realize their winners. The coefficient for return of realized gains is negative and highly significant. One possibility is that investors with higher realized returns are more confident about their investment ability and therefore likely to hold on to their winning stocks longer. Another possibility is that investors first sell the stocks with the highest overall returns and the proportion of stocks sold is determined by other factors.

We ran a similar regression for PLR. For the PLR regression, “high-income” dummy is positive and significant, meaning that “high-income” investors realize a higher fraction of their loser stocks. A decreasing tendency to sell winners combined with an increasing tendency to sell losers is responsible for the decrease in high-income investor’s disposition effect. The coefficient for “non-professional” is negative and significant, indicating investors in non-professional occupations realize a smaller fraction of their loser stocks. Again, the coefficients for “age” and “ln(numtrade)” are negative and significant. The coefficient of return of realized losses (-0.207) is both statistically and economically significant. One possible explanation is that investors with bigger realized losses also have poorer overall portfolio performance. As the losses are so deep, investors do not expect further downside risk in their losing stocks and therefore decide not to sell them. A second possibility is that investors first sell the losing stocks with the highest negative returns and the proportion of losers sold is exogenously determined by stock returns. Therefore, the more negative the realized returns for an investor, the lower is the PLR. In addition, we notice that the R-square increases from 0.04 to 0.15, indicating that the magnitude of the realized losses has a significantly explanatory power for investors’ tendency of selling loser stocks.

4. 5 December Trades

Odean (1998) shows that investors have significantly smaller disposition effect in December as investors realize more losses for tax benefits. We did a similar analysis to see whether such a pattern also exists in our sample. The December trading pattern is especially interesting in our context as they are closely related to investor sophistication. Due to tax loss motivations outlined in previous research (Constandinides 1984), we expect more sophisticated investors to be less reluctant to sell their losers for tax benefits toward year-ends. As “high-income” and investors in “professional” occupations are our proxies for more sophisticated investors, we expect them to realize a greater proportion of their losers.

For the 7,965 investors on whom we have demographics information, 5,206 have trading records in December. As some investors have very limited number of trades in December, we cannot calculate the December disposition effect for each individual. Instead, we calculate the December disposition effect for all investors from each demographic group. Consistent with Odean (1998), the disposition effect in December for each demographic group is much smaller than that in the rest of the year. For some demographic groups such as “High-Income” and “Non-Employed”, the disposition effect completely disappears.

The evidence from December trades is consistent with our hypothesis that some investors are better able to deal with their losses, which is driver of the differences in the disposition effect. Panel 1 of Table 6 shows that, disregarding losers or winners, higher proportion of “high income” and “professional” investors (67.5% and 36%) sell stocks in comparison to the “low income” and “non professional” investors (39% and 30.5%), respectively. More importantly, Panel 2 of Table 6 reports that investors with high income and in professional occupations exhibit a significantly smaller disposition effect than the “low-income” and “non-professional” investors (significant at 5 and 10 percent, respectively), although the differences for all groups are much smaller for the December trades. This further supports our premise that certain groups are more sophisticated about their ability to deal with losses and understand price setting mechanism. We also notice in Panel 2 that the disposition effect becomes marginal or non-existent during December, indicating that

investors realized a similar proportion of their winners and losers. This is consistent with Odean's analysis of December trades (1998).

4. 6 Robustness of Sub-Periods

To test our results' consistency over time, we do the same regression specified in Equation (4) again for two sub-periods: 1991-1993 and 1994-1996. As splitting the data reduces the number of observations for each investors, we can compute the disposition effect for fewer investors during each sub-period. We report the results in Table 7. "High-income", "Ln(Age)" and "Ln(Numtrade)" remain significant within the sub-periods while other coefficients remain in the same direction as in the regression for the entire data set and become less significant.

Section 5. Discussion and policy recommendation

This paper studies the disposition effect with individual trading records from a large discount brokerage firm. We show that there is wide dispersion in the proportion of gain realized (PGR), proportion of loss realized (PLR) and the disposition effect (DE) across individual investors. While our results confirm previous findings of the existence of the disposition effect on average, we also show that one fifth of investors in our sample do not exhibit disposition effect. We find support for our main proposition, namely that investor sophistication is in part responsible for the variation in the disposition effect. Such heterogeneity induces different levels of behavioral bias among individual investors, which casts further questions about who should trade on their own.

Our paper shows that certain demographic characteristics that correspond to lower sophistication have higher disposition effect. Due to tax considerations, investors with high disposition effect will have lower after tax returns than what they could possibly obtain without suffering from the disposition effect. The bigger the disposition effect, the greater an investor could suffer from this bias. We show that "low-income" and "non-professional" investors have the highest disposition effect among all investors. It is particularly unfortunate as the changes in investment return

may have the greatest adverse impact on them. We recommend policy makers and non-profit organizations such as Individual Investor Association (IIA) should try to make investors aware of such biases, especially those at the lower income levels and engaged in non-professional occupations. Such advocate can help these investors pay closer attention to loser stocks in their portfolio, make them aware of tax benefits of realizing losers toward year-end and motivate them to switch from direct investment to other investment vehicles such as mutual funds.

Our findings are also valuable to various brokerage firms, which dedicate themselves to helping investors make better investments. We believe that the brokerage firms will be more profitable if their clients enjoy higher rate of return in their investment for the long run. As a result, it is in the brokerage firms' own interests to better inform their clients of the existence of the disposition bias and its implications. With demographic information, the brokerage firms could also effectively target "low-income" and "non-professional" clients who are most likely to suffer from the disposition effect.

Finally, we find that trading experience seems to help reduce the disposition effect, which supports other findings showing that experience can eliminate some market anomalies (List 2002). However, trading frequently has also been shown to be hazardous to investors' wealth (Barber and Odean 2000), indicating that it is a rather costly to alleviate behavioral bias through trading. Brokerage firms and investment clubs should use newsletters and reminders to educate investors of such biases and help them make better investments.

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Table 1. Disposition Effect in Hypothetical Economy

Table 1 offers a hypothetical example illustrating the limitation of measuring the disposition effect at an aggregate level. There are three investors in an economy, with disposition of -0.08 , 0 and 0.19 , respectively. The mean disposition effect of the economy is 0.04 , indicating the existence of disposition effect while only one third of all investors exhibit disposition effect.

	Investor 1	Investor 2	Investor 3	Mean of all investors ¹	Market aggregate ²
Gains					
Realized Gain	1	10	30		41
Paper Gain	10	50	50		110
PGR	0.09	0.17	0.38	0.21	0.27
Losses					
Realized Loss	1	20	20		41
Paper Loss	5	100	100		205
PLR	0.17	0.17	0.17	0.17	0.16
The disposition effect					
Disposition Effect	-0.08	0	0.19	0.04	0.11

¹The mean of all investors is the mean of the PGR, PLR and the disposition effect of all three investors.

² Market aggregate approach first aggregates the number of realized gain (RG), paper gain (PG), realized loss (RL) and paper loss (PL) of all investors and then compute PGR, PLR and DE at the market level.

Table 2 Descriptive Statistics of Investor Sample

This table summarizes the data used in empirical studies. We use both investor trade file and the demographics files. The investor trade file comes from a large discount brokerage firm and contains each investor's trade record during the period from January 1991 to November, 1996. A total number of 10,486 common stocks were traded and we can find the price information on 9,893 stocks of them. The demographic file contains information on each investor demographics and socio- economic information such as age, gender, income code, profession code and residential location (zip code).

	Summary Statistics	
	Entire Dataset	Data used in this paper
<i>Sample size</i>		
Number of Households	62,387	7,965
Number of Households used in this study	41,039	7,965
<i>Investor portfolio position</i>		
Average Portfolio Size	\$35,629 (Median=\$13,869)	\$39,446 (Median=\$15,620)
Average Number of Trades	41 (Median=19)	58(Median=29)
Average Number of Stocks in the Portfolio	4 (Median=3)	5 (Median=3)
<i>Investor trades</i>		
Total Number of Trades	2,886,912	697,746
Trades in Common Stocks	1,854,776	458,419
Total Number of December Trades in Common Stocks	128,983	34,536
Average Holding Period	187 Trades Days (Median=95 days)	122 Trading Days (Median=81 days)
<i>Investor demographics</i>		
Average Age	50 (Median=48)	50 (Median=48)
Average Income	\$59,097 (Median=\$50,000)	\$64,571 (Median=\$50,000)

Table 3 Descriptive Statistics of Investor Disposition Effect

Panel 1 reports the number of investors belonging to each demographic category. Panel 2 reports the disposition effect of each category of investors. Panel 3 reports the significance of the difference in disposition effect with different measurement methods (p-values are reported in parentheses). We have a total number of 102,924 realized gains, 53,443 realized losses, 679,286 paper gains, and 782,033 paper losses. Aggregating trades across all investors, PGR equals 0.132 and PLR equals 0.064. Disposition effect calculated this way equals 0.068. In Panel 2 and Panel 3, p-values are provided in parentheses.

Panel 1 Sample decomposition

	Number of observations			Sum
	Professional	Non-Professional	Non-Employed	
High-Income	807	83	173	1846
Mid-Income	1270	154	461	3833
Low-Income	236	73	248	1291
Sum	2315	311	887	

Panel 2 Disposition effect of different demographic groups

Income	
High- Income	.189
Mid-Income	.208
Low-Income	.211
‘High-Income’ - ‘Low-Income’	-.022 (.051)*
Profession	
Professional	.2029
Non-Professional	.2450
Non-Employed	.1738
‘Professional’ - ‘Non-Professional’	-.042 (.028)**

* indicates significance at 10% level

** indicates significance at 5% level

Panel 3 Difference between the disposition effect of demographic groups

Summary Statistics				
	Mean	t-statistics (p-value)	Wilcoxon rank (p-value)	komogrov- simirnov test
Income				
High-Income	.189			
Low-Income	.211			
(High-Income)- (Low-Income)	-.022	-1.95 ^{*a} (.051)	-2.02 ^{**b} (.044)	.056 (.016)
Profession				
Professional	.203			
Non-professional	.245			
Professional- Non-professiona	-.042	-2.20 ^{**} (.028)	-.267 ^{**} (.008)	.095 ^{**} (.013)

a: * means significant at 10% level

b: ** means significant at 5% level

Table 4 The Impact of Control Variables on the Disposition Effect (DE)

The regression is specified as follows:

$$DE = \gamma D + \beta X + \varepsilon$$

The dependent variable is the disposition effect (DE). The independent variables include demographic dummy variables of different income, professional category, the logarithm of an investor's age, the logarithm of the number of trades that each investor has executed, the return of realized gains, the return of realized losses, the average number of stocks within an investor's portfolio, and the inverse of the average number of stocks within an investor's portfolio.

	The disposition effect			
	(1)	(2)	(3)	(4)
Constant	0.75 (11.88)	0.52 (8.46)	0.70 (10.84)	0.73 (11.28)
High-income	-0.020 (-2.16)**b	-0.014 (-1.92)*	-0.019 (-2.10)**	-0.019 (-2.06)**
Low-income	0.006 (0.69)	0.000 (0.005)	0.009 (0.097)	0.0093 (0.992)
Professional	-0.0069 (-0.82)	-0.0048 (-0.59)	-0.0046 (-0.54)	-0.0045 (-0.53)
Non-professional	0.03 (1.95)*a	0.050 (3.36)***	0.034 (2.16)**	0.035 (2.22)**
Non-employed	-0.014 (-1.052)	-0.018 (-1.39)	-0.0086 (-0.625)	-0.011 (-0.764)
Ln(Age)	-0.056 (-5.56)***	-0.061 (-3.952)***	-0.08 (-4.88)***	-0.091 (-5.525)***
Ln(Numtrade)	-0.17 (-13.69)***	-0.031 (-7.81)***	-0.045 (-10.33)***	-0.052 (-12.53)***
Return of realized gains		-0.0019 (-1.23)		
Return of realized losses		0.032 (1.49)		
Portfolio size			-0.00066 (-7.69)***	
Inverse of portfolio size				0.19 (5.02)***
R square	0.05	0.05	0.05	0.04

a: * means significant at 10% level

b: ** means significant at 5% level

c: *** means significant at 1% level

Table 5 PGR and PLR Regressions

The regression is specified as follows:

$$Y = \gamma D + \beta X + \varepsilon$$

The dependent variables of various regressions are Proportion of Gain Realized (PGR), Proportion of Loss Realized (PLR). The independent variables include demographic dummy variables of different income, professional category, the logarithm of an investor's age and the logarithm of the number of trades that each investor has executed, the return of realized gains, and the return of realized losses.

	PGR		PLR	
	(1)	(2)	(1)	(2)
Constant	1.21 (22.00)	0.89 (47.93)	0.45 (10.35)	0.60 (34.97)
High-income	-0.012 (-1.39)	-0.0058 (-0.75)	0.08 (1.86) ^a	0.014 (-2.01) ^{**b}
Low-income	0.011 (1.36)	0.012 (1.54)	0.006 (0.88)	0.0053 (0.82)
Professional	-0.031 (2.42) ^{**}	-0.0084 (-1.17)	-0.002 (-0.38)	-0.0003 (-0.054)
Non-professional	-0.017 (-1.38)	0.013 (0.997)	-0.016 (-1.56)	-0.023 (-2.13) ^{**}
Non-Employed	0.017 (1.36)	-0.03 (-1.56)	-0.015 (-1.59)	-0.011 (-1.17)
Ln(Age)	-0.13 (-8.81) ^{***c}	-0.12 (-8.08) ^{***}	-0.043 (-2.88) ^{***}	-0.040 (-3.48) ^{***}
Ln(Numtrade)	-0.10 (-28.04) ^{***}	-0.11 (-31.88) ^{***}	-0.19 (-15.64) ^{***}	-0.083 (-28.12) ^{***}
Return of realized gains		-0.0063 (-4.43) ^{***}		
Return of realized losses				-0.207 (-13.14) ^{***}
R square	0.13	0.16	0.04	0.15

a: * means significant at 10% level

b: ** means significant at 5% level

c: *** means significant at 1% level

Table 6 December Trades

Panel 1 reports the descriptive statistics of December trades of investors of different demographic categories. Panel 2 reports the PGR, PLR and Disposition Effect (DE) of December trades of various demographic categories.

Panel 1 Percentage of investors of demographic groups selling stocks in December

	Summary statistics		
	Hi-Income	Mid-Income	Low-Income
Number of Accounts	1846	3833	1291
Number of accounts that sell in December	1246	1580	503
Percentage of accounts that sell in December	0.675	0.412	0.390
	Professional	Non-Professional	Non-Employed
Number of accounts	2315	311	887
Number of accounts that sell in December	833	95	256
Percentage of accounts that sell in December	0.360	0.305	0.289

Panel 2 December disposition effect of different demographic groups

	The disposition effect		
	Hi-Income	Mid-Income	Low-Income
PGR	.1589	.1712	.1582
PLR	.1448	.1299	.1279
DE	.0013	.0511	.0617
	Professional	Non-Professional	Non-Employed
PGR	.1734	.1748	.1397
PLR	.1356	.1299	.1360
DE	.0378	.0449	.0036

**Table 7 The Disposition Effect Regression of
Sub-sample 1991-1993 and 1994-1996**

The regression is specified as follows

$$DE = \gamma D + \beta X + \varepsilon$$

We perform regression analysis for two sub-periods: 1991 to 1993 and 1994 to 1996. All variables are defined the same as in Table 4.

	The Disposition Effect		
	1991-1993	1994-1996	1991-1996
Constant	0.55 (6.21)	0.391 (3.68)	0.752 (11.88)
High-income	-0.041 (-2.20)**b	-0.021 (-0.93)	-0.020 (-2.16)**
Low-income	0.009 (0.69)	0.015 (0.652)	0.006 (0.69)
Professional	-0.001 (-0.016)	-0.01 (-0.45)	-0.0069 (-0.82)
Non-professional	0.009 (0.50)	0.016 (0.72)	0.03 (1.95)*a
Non-Employed	-0.003 (-0.15)	-0.025 (-1.04)	-0.014 (-1.05)
Ln(Age)	-0.047 (-2.56)**c	-0.035 (-1.55)	-0.056 (-5.56)**
Ln(Numtrade)	-0.124 (-7.20)**	-0.093 (-4.37)**	-0.168 (-13.69)**
N	3328	2229	6462
R square	0.02	0.02	0.05

a: * means significant at 10% level

b: ** means significant at 5% level

c: *** means significant at 1% level

Figure 1. Distribution of disposition effect (DE) of all investors

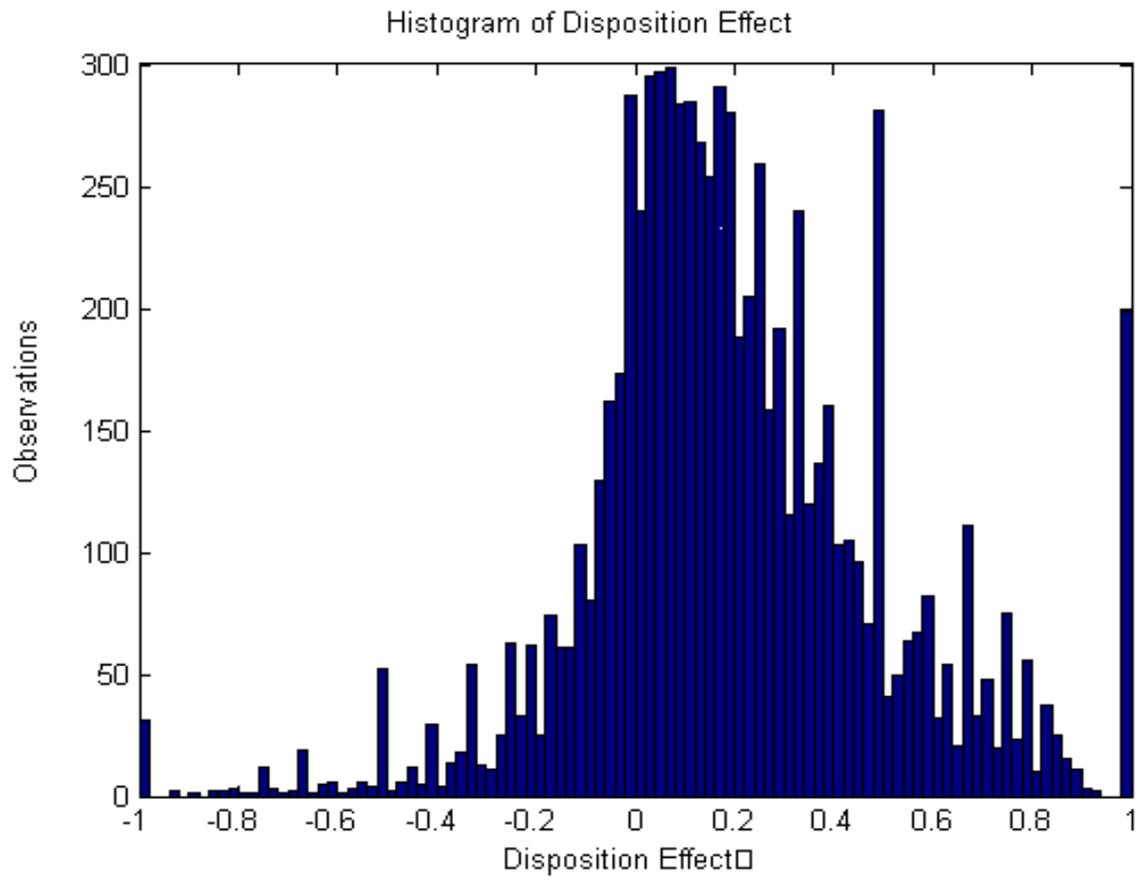


Figure 2 Disposition Effect of Different Income Groups

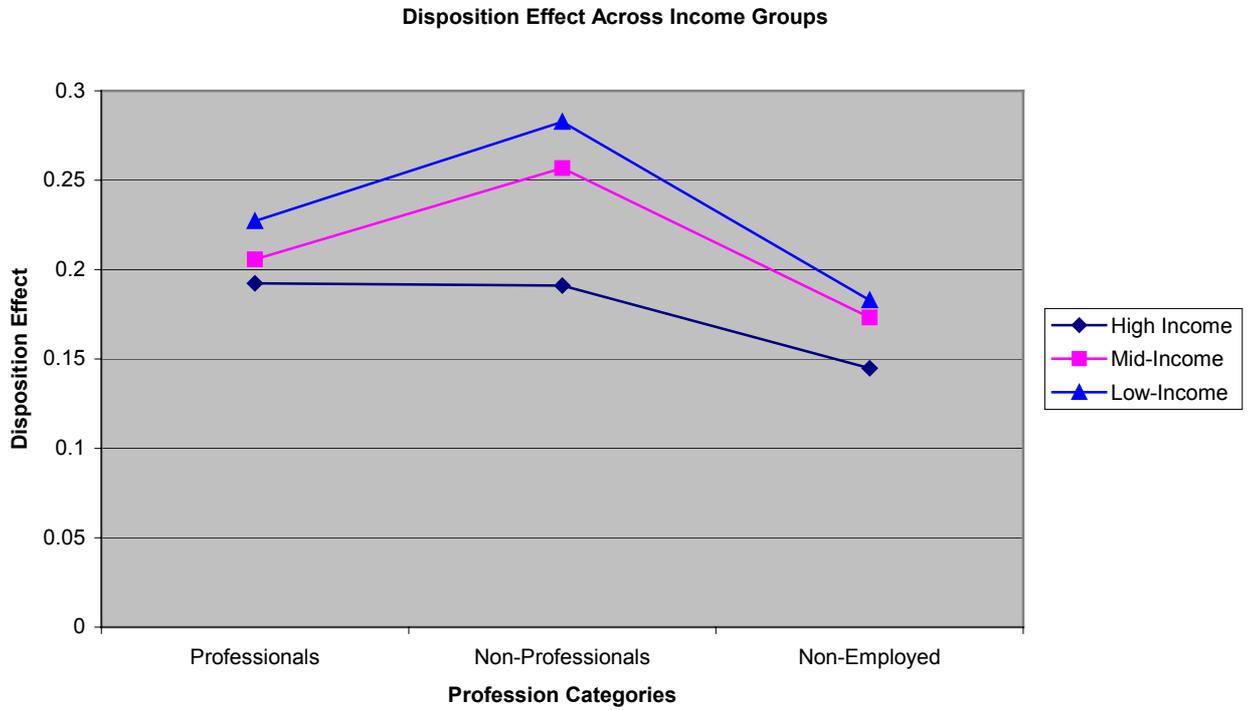


Figure 3 Disposition Effect of Different Profession Groups

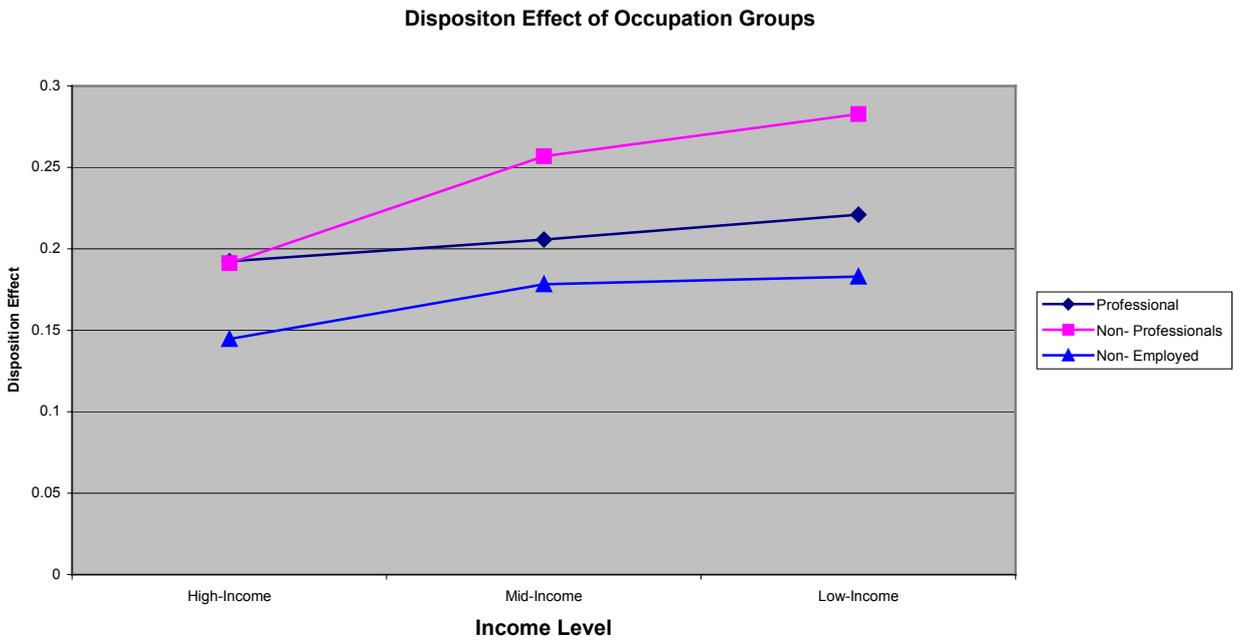


Figure 4 Distribution of proportion of gain realized (PGR) of all investors

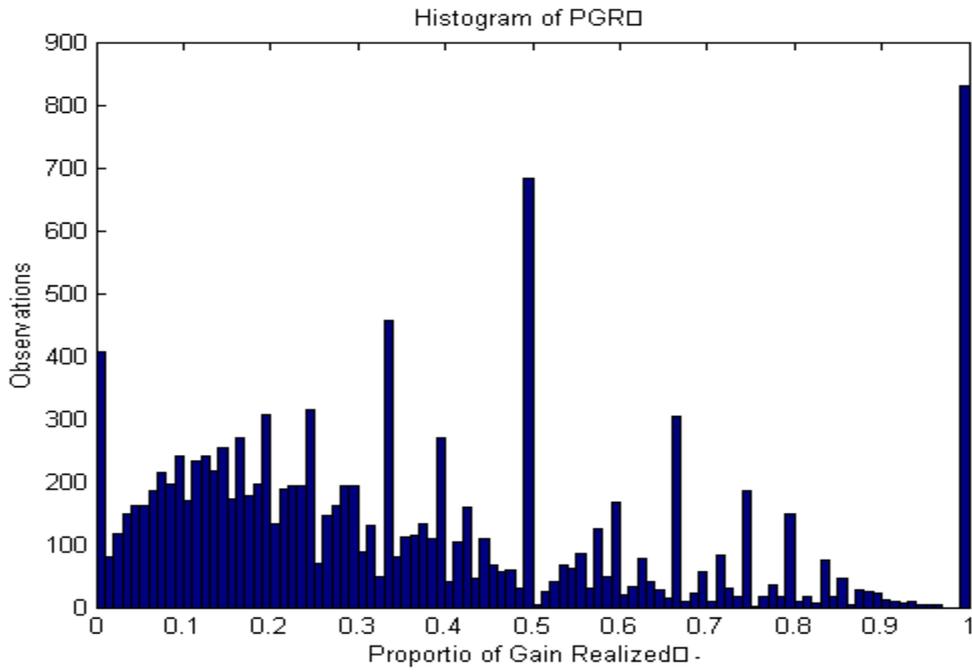
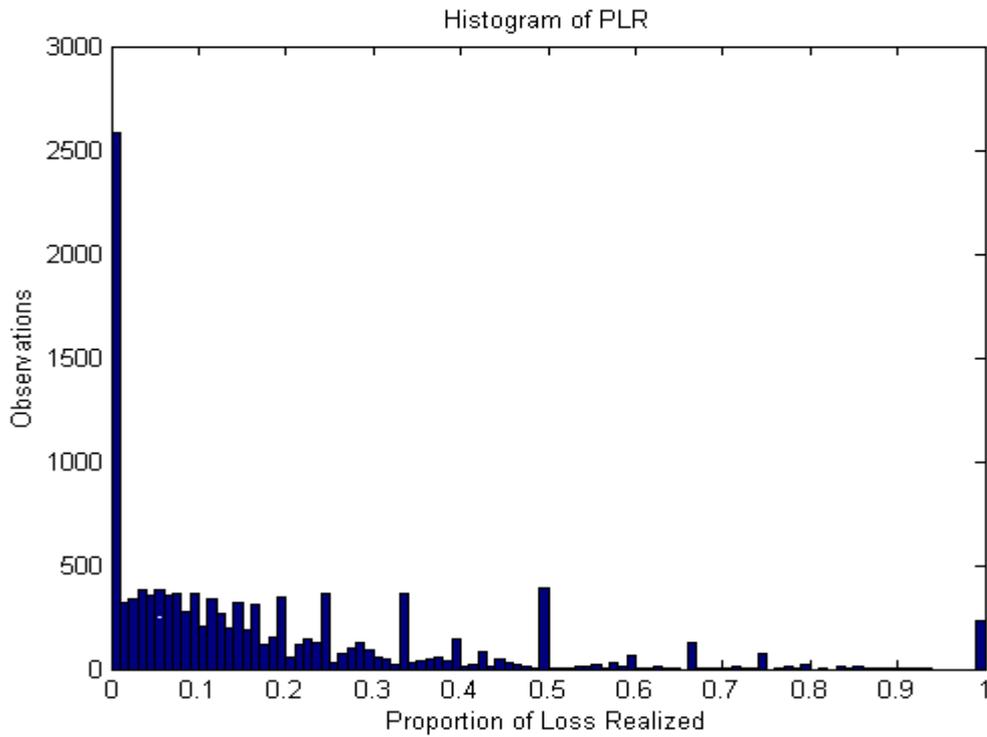


Figure 5 Distribution of proposition of loss realized (PLR) of all investors.



2 The disposition effect of each account can depend on each account's portfolio size and number of trades. We explore this in Section 4.

3 Shapira and Venezia (2000) show that professional investors exhibit weaker disposition effect than individual investors investing on their own.

4 Information on occupation is unavailable for some investors. All occupation dummy variables are zero for these investors.

5 We thank Terrance Odean and Martin Weber for pointing this out.

6 We also calculated normalized disposition effect for each individual as proposed by Weber and Camerer (1998), in order to control for portfolio size's impact on the disposition effect. The results are very similar to those in Table 4 and are not reported.