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

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Abstract

This paper analyzes 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; Shapira and Venezia, 2001; Weber and Camerer, 1998), our main objective is to identify differences in the disposition bias across individuals and explain this in terms of underlying investor characteristics. Building on the findings in experimental economics and social psychology, we hypothesize that differences in investor literacy about financial markets and trading frequency are responsible in part for the variation in individual disposition effect. Using demographic and socio-economic variables as proxies for investor literacy, we find empirical evidence that wealthier individuals and individuals employed in professional occupations exhibit a lower disposition effect. Consistent with experimental economics, trading frequency 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

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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 departures from what rational theory predicts. 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 behavioral finance have shown how systematic biases in investor behavior may impact asset prices (Barber, Odean and Zhu 2003, Hong and Stein 1999, Barberis and Shleifer, 1998).

In this paper, we focus on one of the most widely documented biases 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, Shapira and Venezia 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. First, if we find that trading heuristics are correlated with specific investor characteristics, this has clear implications for the dynamics of asset prices in bubbles and crashes (Ofek and Richardson 2003). Second, if we find that a certain type of individual 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. A third 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 paper differs from previous research in that we focus on the disposition effect at the level of each individual and the differences in disposition effect across investors. Most 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 the previous finding (Odean 1998, Grinblatt and Keloharju 2001b) that individual investors, on average, exhibit the disposition effect. The new results fall into three categories. First, we find that despite the significant disposition effect on average, about one fifth of the investors in our sample exhibit behavior opposite to the disposition effect. Second, we show that individual characteristics that correspond to greater literacy about investment products, such as their income and occupational status, attenuate the magnitude of the disposition effect. Specifically, we find that individuals who are wealthier and work in professional occupations show a significantly smaller disposition effect. The disposition effect for such investors is 10-20 percent smaller than that for investors with less investment knowledge. Further, such investors are 18-50 percent less likely to exhibit disposition effect than investors with less investment knowledge. Third, we find a negative relationship between trading frequency and the magnitude of the disposition effect. Specifically, individuals who trade frequently are more willing to sell their losers, implying that trading frequency might help investors trade "out of" the disposition bias. Our results remain unchanged with alternative measures of the disposition effect and various robustness checks.

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 individual investors become aware of this tendency and adjust their trading accordingly. Second, since a large fraction of individual investors are reluctant to realize their losses, we suggest that brokerage firms should try to educate their clients about the disposition effect. Better awareness of the disposition effect can motivate investors to sell their losers earlier, deduct trading loss in tax filing, and improve after-tax portfolio performance. This will increase the added value of brokerage firms' services. Finally, certain demographic and socio-economic groups show a greater disposition effect, which may

adversely affect their after-tax portfolio return. The increase in self-investing highlights the role of government agencies and non-profit organizations in making investors aware of their trading biases.

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

Section 2. Disposition Effect and Individual Differences

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 using 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 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 psychological 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 reference, the decision to sell a stock that has risen since purchase will be seen as a choice between a sure gain (if the stock were to be sold) and a risky gain (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, the decision to sell it would be seen as incurring a sure loss whereas holding onto the stock would be seen as preferring the risky outcome (Payne et al. 1984). Risk averse behavior for gains and risk seeking behavior for losses would then lead to the disposition effect.

The central focus of this paper is to examine whether and why the disposition bias might vary across individual investors. As Odean (2000) notes, the aggregate description of average investors will "mask considerable cross-sectional variation" in understanding individual investment behavior. A second 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) for 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. The focus on computing PGR, PLR and the disposition effect for each investor thus may sharpen the measurement of the effect.

We provide several reasons that might lead to a systematic difference in the disposition bias across individual investors. First, since the disposition effect depends on the degree to which the purchase price of the stock serves as the reference price, a question that naturally arises is whether such reference point varies across individuals depending upon their trading frequency. In theory, multiple reference points, from the purchase price of the stock to the highest and the lowest price since purchase, might combine together to produce a reference level (Heath, Larrick and Wu, 1999; Kahneman 1992). Investors who trade more frequently may also have a better appreciation for the concept of market efficiency. This greater understanding of the role of market forces in setting stock prices may lead these individuals to adjust the reference price of a security from the purchase price in the direction of the current price (i.e., the true value of a security is the price at which it is currently trading). It can be easily shown that the closer the reference price is to the current price, the smaller is the magnitude of the disposition effect (see Weber and Camerer 1998). Thus, there should be no difference in the tendency to sell winners or losers if the current price of the security serves as the reference point. We discuss below past research in other domains that examines whether the reference effect observed due to prospect theory is attenuated for the individuals that trade more frequently.

The early experimental economics literature examined the effect of repeated trials in selling prices for an identical good in the lab. 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". The data show that although individual bids show a large disparity between willingness-to-accept (WTA) and willingness-to-pay (WTP) at first, the ending bids submitted after a series of trials are similar (Coursey, Hovis, Schulze 1987). In contrast, critics of this approach contend that the evidence of learning is mixed (Knetsch and Sniden 1984). Camerer and Hogarth (1999) note that cognitive capital builds up slowly, over days or years, rather than in the short run of an experiment.

One way to resolve this debate is through the recent work of List (2003) who identifies trading frequency rather than the length of trading as the key variable. List (2003) uses data from sports card trading market to show that trading frequency can attenuate the endowment effect. Specifically, List

(2003) shows that for experienced non-dealers, the endowment effect is much smaller and nonexistent than for inexperienced non-dealers. The experience was measured as the number of trades in a typical month, which is similar to our focus on the effect of frequency of trading in the stock market. Further, List (2004) replicates the effect of trading frequency on reducing the endowment effect. Since the disposition bias for stocks is based on incomplete adaptation to prospect theory's reference point, the results of List (2003, 2004) suggests that the effect is likely to be weaker for individuals who trade more. Novemsky and Kahneman (in press) also note that experience in trading can reduce the reluctance to trade and the endowment effect. They speculate that this might occur because experience in trading provides individuals with enough repeated exposures to giving up an item that they learn that this reaction is less extreme than inexperienced
traders believe it to be.

Accordingly, we predict and find that individual investors who trade more frequently will have a lower disposition effect than investors who trade less.

Hypothesis 1: Trading frequency is negatively related to the magnitude of the disposition effect.

A second reason to expect differences in the disposition effect across individuals is based on differences across individuals in knowledge about investment products. There are two theoretical reasons for looking at the role of knowledge. First, the lack of knowledge about how investment valuation works inherently increases the reliance on the price paid in inferring value. Second, an awareness of situations in which one is more or less reluctant to trade is likely to lead to correcting mechanisms (Wegener and Petty 1995). Thus, individuals who are aware of the reluctance to sell losers can more completely account for the consequences of their decisions, leading to behavior modification. This line of thinking is also consistent with the thinking that while reference effects are "cognitive illusions" and hence not easy to eliminate through learning, individuals can still become aware about these illusions and correct for such biases by engaging in different behavior (Kahneman and Reipe 1998).

Accordingly, we propose that differences in knowledge about investments can also account for the variation in the reluctance to sell losers. Since we do not have direct data on individual knowledge about investments, we rely on demographic variables that have been shown to proxy differences in expertise in general and about investment products in particular. Accordingly, we

propose that demographic characteristics that have been shown to correlate with better access to information and understanding of stock investments will have a significantly lower disposition effect than other investors. Specifically, we test the effect of individuals' income and occupational status on the magnitude of the disposition effect. We motivate the specific reasons below.

There are several reasons to predict that individuals with higher income will have a lower disposition bias. First, the high-income individual investors are more likely to have access to financial advice such as financial and tax planners as they can afford value-added services. Second, wealthier individuals also have more investment at stake and therefore find it more worthwhile to utilize such services. Recent research that examined knowledge about investment products among individual investors supports this rationale. An NASD Investor Literacy survey (2003) that asked respondents ten basic knowledge questions (e.g., relationship among bond prices and interest rates, relationship between risk and return, etc.) finds that 51% of higher income individuals (>100k+) answered 7 of 10 questions correctly compared to 23% of lower income individuals (<$50k). This suggests that individuals with higher incomes have better knowledge about investments and hence should be less likely to show the disposition effect.

A second demographic variable that is likely to affect investment literacy is the educational background of the individual. Past research has found a link between the educational background and better decisions and performance in general (Krueger and Rouse 1998, Bailey et al. 2001) and financial decisions in particular (Chevalier and Ellison 1999, Golec 1996). In an analysis of the link between financial literacy and demographic characteristics (Alexander, Jones, and Nigro 1998), a survey of mutual fund investors found that college graduates were more knowledgeable about financial investment products. Since we do not have data on educational background, we use their occupational status as proxy for education. This is based on the notion that certain occupations are more likely to correspond to a higher level of education and consequently with higher financial literacy. Since individuals who work in "professional" occupations have on average higher education than those working as "non-professional" occupations, we expect them to exhibit smaller disposition effect. Based on the above categorization and discussion, we intend to test the following hypotheses:

Hypothesis 2a: Individual investors in "high-income" bracket will display smaller disposition effect than individual investors in 'low-income' bracket.

Hypothesis 2b: Individual investors who work in "professional" occupations will display smaller disposition effect than investors in "non-professional" occupations.

Section 3. Documenting the Disposition Effect at the Individual Level

Previous research has used several different constructs 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 the existence of the disposition effect at the aggregate level. In this study, we focus on calculating the Realized Gain, Realized Loss, Paper Gain, and Paper Loss for each individual, 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:

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

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

We count the number of "Realized Gain/Loss" and "Paper Gain/Loss" at each time an individual sells a stock. A sale is defined as a realized winner/loser if the selling price is higher/lower than the stock's average purchase price.[2] "Realized Gain/Loss" is defined as the number of winner/loser stocks sold in a portfolio. For other stocks that remain in the portfolio, if a stock's daily high and low price for that day is both higher/lower than its average purchase price at the time of calculation, it is considered a paper winner/loser.[3] If its average price lies between the daily high and low price, neither a gain nor loss is counted. The "Paper Gain/Loss" is defined as the number of paper

[2] Individual investors may have purchased the stock at different time and different prices.

[3] All prices are adjusted for distributions such as dividends and stock splits.

winner/loser stocks in an investor's portfolio (for further details, see Odean 1998).[4] The disposition effect is defined as the difference of each investor's PGR and PLR:

$$Disposition\ Effect(DE) = PGR - PLR \qquad (3)^{5}$$

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

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 1. There are three data files: a trade file, a position file and a demographics file. The trade file contains information on the stocks that each individual 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 individual's portfolio position at the end of each month during the same period. The demographic data contains information collected on certain demographic variables such as age, profession and income. This data was compiled by Infobase Inc. (as of June 8, 1997) and provided by the brokerage house and was not available for all individuals. The median age was 48 and the median annual household income was $50,000. 21 percent of the investors are female and the remaining 79 percent are male.

Trade data are available for 77,995 investors and we can calculate the disposition effect for 14,872 investors. Several reasons are responsible for the decrease in the usable number of observations: (1) 15,608 investors trade only mutual funds, fixed income securities, ADRs (American Deposit Receipts) or foreign equities whose prices are not available from CRSP (Center for Research on Securities Prices) data. As we focus on equity trading behavior, we only keep the remaining 62,387 investors who trade equities. (2) A large fraction of investors trade rather infrequently. We focus only

[4] For simplicity, we did not consider commission when counting gains or losses. commission should not have particular impact on individuals' realized winner or loser stocks. (Odean, 1998)

[5] We exclude observations if either PGR or PLR turns out undefined (i.e. an investor has never had a winner or loser in her portfolio).

on investors who, on average, trade no less than once every year during the six-year period. As a result, a further 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: 15,427 investors executed only buying trades or only selling trades during the studied period. Thus we cannot calculate the trade return or compute the number of realized gains or losses for such individuals. For other investors who have both buying and selling trades, we do not have the round-trip buy and sell trades for the same stock for 12,282 individuals and hence cannot identify their realized winner or loser. For example, an investor that sells a stock in the sample period had purchased the stock before our data starts or an investor that buys a stock in the sample period later sold the stock after our data ends. All of the above factors limit the analysis of disposition effect at the individual level to 14,872 investors.[6]

Demographic information is available on 7,965 of the 14,872 investors. The descriptive statistics of our final sample is shown in the right column of Table 1. 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=$15,620) than those of the entire data (mean=$35,629 and median=$13,869). Regarding demographics, our investors have moderately higher annual income (mean=$64,571) than average investors (mean=$59,097).

4. 2 Investor characteristics

To study how individual demographic characteristics contribute to variations in the disposition effect, we construct several "income" and "occupation" categories. For the "income" variable, we divide the investors into three categories, namely "high-", "medium-" and "low-income", if the income information is reported. 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 into the "high- income" category.

[6] Unavoidably, this procedure could pose potential selection bias by excluding investors who trade infrequently. This should not concern us because these inactive investors do not have significant impact on the overall behavior of the entire sample. We compute the disposition effect at the aggregate level for the sub-samples of

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 of annual income for our sample investors is $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 nation 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 assign individuals to "professional" and "non-professional" occupations, if the occupation information is reported. We classify individuals as working in "professional" occupations if they report working in "professional/technical" or "managerial/administrative" positions. We classify individuals as working in "non-professional" occupations if they report working in "white collar/clerical", "blue collar/craftsman" or "service/sales". 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 "blue collar" than "white collar" in the nature of their work. We hence classify "service/sales" as "non-professional'. [7] Because not all demographic information is available on all investors, it is possible that an individual investors does not belong to any income or occupation category.

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 the disposition effect (DE) in Table 2. 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 observe in

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62,387, 42,581, and 14,872 investors and the aggregate disposition effect are almost the same for respective sub-groups.

Panel 1 of Table 2 that the mean of PGR, PLR and the disposition effect is 0.38, 0.17 and 0.21, respectively. We also compute the disposition effect for 6,807 investors for whom we do not have demographic information. The PGR, PLR and DE of these investors are 0.39, 0.19, and 0.20, respectively.[8] The disposition effect for these individuals is highly significant and very similar to the disposition effect for the sample investors. Consistent with previous research (Odean 1998), the disposition effect is positive and significant. Interestingly, taxable and tax deferred accounts exhibit similar disposition effect. This result is similar to that of Odean (1998) and indicates that tax consideration does not change individual investors' behavior as predicted by theory (Constantinides, 1984). Panel 2 of Table 2 reports a significant median disposition effect among individual investors. The median PGR, PLR, and DE are 0.31, 0.17, and 0.11, respectively and the median disposition effect is the same for taxable and non-taxable accounts.

The disposition effect based on aggregating trades of all investors is 0.068. We note a significant difference between our individual measurement of 0.21 and the market level measurement of 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, the aggregation across all investors assigns more weight to the frequent traders who are predicted to have a lower disposition bias in our sample, thus reducing the magnitude of the effect.

We also present the distribution of DE in Figure 1. The disposition effect measure is widely distributed with minimum of -1 and maximum of 1. An interesting finding is that not all individuals exhibit the disposition bias. Specifically, 19.7 percent of individuals in our sample do not exhibit any disposition effect or exhibit behavior opposite to the prediction of the disposition effect. We consider this as a conservative measure given that 9,016 excluded individual investors (more than 20 percent of all individual investors) never realize any winning stocks in the sample period. While previous studies

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[7] Only about 2 percent of all sample investors report their occupation to be in "Service/Sales", among investors who report occupation information. An alternative classification measure that exclude investors working in 'service/sales' occupation produces the same results.

[8] The mean for the PGR, PLR and disposition effect for all months including December is 0.37, 0.18, and 0.19. The correlation coefficient between the DE measure using data between January and November and the DE measure using all months is 0.94 and significant at 1 percent. All of our results remain the same if we use the DE measure including December trades.

(Constantinides 1984) show that lower disposition effect during December can be due to tax benefits, our result shows that even for the period from January through November, there are a significant number of investors exhibiting negative disposition effect, meaning that they realize more losses than winners in their portfolios.

A preliminary way to test our hypotheses is to compare the characteristics of investors who exhibit disposition effect versus those who do not. We report the trading frequency, income, profession and age for investors who exhibit disposition effect and those who do not in Panel 3 of Table 2. Consistent with our hypotheses, the twenty percent of individuals exhibiting no disposition effect tend to have higher trading frequency, higher income, and work in professional occupations. The results provide some initial support for our conjecture before we formally test them.

As hypothesized in Section 2, we next examine the variation in the disposition effect across demographic characteristics. We report the disposition effect for different income and occupation groups in Panel 2 of Table 3. As predicted, the mean DE for the "high-income" (0.189) is lower than that for the "low-income" groups (0.211). The mean DE for the investors working in "professional" occupations (0.203) is lower than that for investors working in the "non-professional" occupations (0.245). The differences between individuals in "high-income" and "low-income" groups and between "professional" and "non-professional" occupations are both negative and significant. We recognize that individual disposition effect is not normally distributed and therefore also compare the median of each group in a similar fashion. The median for "high-income" and "low-income" disposition effect are 0.15 and 0.167 and the median for individuals in "professional" and "non-professional" occupation are 0.167 and 0.214. With Wilcoxon rank test, we show that the differences in the median between income and profession groups are also significant at 5% percent. We further performed the Kolmogrov-Simirnov test to compare the distribution of disposition effect for the respective pairs. The results are again consistent with our findings that individuals with "high-income" and working in "professional" occupations exhibit smaller disposition bias.

Since income and occupation are potentially correlated among individuals, it is possible that their effect are confounded. To address this issue, we calculate the disposition effect of different occupations within the same income group and similarly calculate the disposition effect for different income levels within the same occupation group. We report the results in Panel 3 of Table 3 and in Figure 2 and 3. The disposition effect for "high-income" individuals is smaller than the disposition

effect for “low-income” individuals for both types of occupations. The difference between income groups is much larger for individuals who are in the “non-professional” occupations. The difference between the disposition effect of individuals in “professional” and “non-professional” occupations is small and insignificant for the “high-income” group while it is much bigger and statistically significant for the “mid-income” and “low-income” groups. This is consistent with the notion that high-income individuals might get advice from financial planners and temper the bias regardless of their education and investment knowledge. Hence, the occupation difference has marginal influence on their disposition effect. The results confirm that income and occupation have separate impact on individual investor’s disposition effect.

One limitation of the DE measure in Equation (3) for interpreting differences across investor groups is that this measure can be affected by portfolio size and trading frequency (Odean 1998). For example, it can be shown that an investor with the same proportion of gain/loss trades will have a lower disposition effect using this measure if his portfolio size (i.e. the number of stock held in the portfolio) is larger. Our data shows that this should not be a concern. Despite a modest negative correlation between DE and portfolio size (correlation coefficient = -0.l58), the number of stocks held in portfolios for investors from different income and profession groups is very similar. The average number of stocks held by individuals categorized as high- and low-income is 4.7 and 4.2, and the average number of stocks held by individuals in “professional” and “non-professional” occupations is 4.4 and 4.2, respectively. This indicates that our findings are not driven by differences in portfolio sizes.

Second, the DE measure in Equation (3) would result in a higher disposition bias for individuals who trade more frequently but realize the same proportion of winners/losers. This should not be a problem because there is little difference in the trading frequency between the high-income and low-income individuals (58.0 Vs. 57.4 trades in the sample period). The individuals who work in professional occupations traded modestly more (on average 2 trades per year) than those working in non-professional occupations, which would not cause much change to the disposition effect measure. To better account for the impact of portfolio size and trading frequency on the disposition effect measure, we use alternative measures and perform additional robustness check in Section 4.5. and 4.6. None of the major results change.

4. 4. December Trades

As noted earlier, we analyze December trades separately for two reasons. First, Odean (1998) shows that individual investors have significantly smaller disposition bias for the month of December as they realize more losses for tax benefits. More importantly, the December trading pattern is especially interesting in our context as it allows us to test the assumption of knowledge about investment as the underlying driver of differences in disposition effect across demographics. Thus, if individuals with higher income and working in professional occupations are reasonable proxies for knowledge about investments as we assumed, we would expect individuals with these demographic characteristics to realize a greater proportion of their losers in December than the other individuals.

Of the 7,965 investors on whom we have demographics information, 5,206 have trading records in December. As there are far less trades in December than in the rest of the year, all demographic groups include less individuals, on whom we can calculate the disposition effect, than the rest of the year. Table 4 reports individual disposition effect in December. Consistent with Odean (1998), the disposition effect in December for each demographic group is much smaller than that in the rest of the year. Individuals with high income and working in professional occupations, who exhibit weaker disposition effect from January to November, also exhibit a significantly smaller disposition effect than the "low-income" and "non-professional" investors (significant at 5 and 10 percent), respectively. This further supports our premise that certain groups appear more knowledgeable about investment products and make better investment decisions.

4.5. Regression Analyses

As stated previously, the disposition effect measured in Equation (3) can be influenced by the trading frequency and demographic characteristics. To better understand the impact of trading frequency and investor characteristics, we perform regression analyses specified as follows:

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

where *DE* is the disposition effect as defined in Equation (3). The *D* matrix contains demographic variables of each individual, X includes individual trading pattern and portfolio characteristics and ε is the i.i.d error term. The *D* matrix includes dummy variables for "high-income", "low-income",

"professional", and non-professional" (the regression intercept is for individuals whose income and occupation information is missing or does not fall into the above categories). 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 the distribution of age is positively skewed. The *X* matrix is composed of the logarithm of the number of trades an individual has executed, the realized returns of winning and losing trades of each investor, and the average number of stocks held in an investor's portfolio. We use the logarithm of the number of trades because it is positively skewed. We include the returns of realized gains and losses because the past performance can potentially influence individuals' decisions to trade: investors with good/bad overall performance might be more/less likely to realize winners. The return of realized winning and losing trades can also proxy for an investor's overall portfolio performance and control these factors. Finally, we include the average number of stocks held in portfolios to explicitly control for portfolio size's potential impact on our results.

Table 5 reports the results of the DE regression. In the base model in column (1), consistent with Hypothesis H1, the coefficient for Ln(Numtrade) is negative and highly significant. An increase of 10 trades can decrease the disposition effect by 0.06 (30 percent from the mean DE). This supports the notion that trading frequency helps investors become more willing to sell losers, in turn reducing their disposition effect. The results also support the Hypothesis 2a and 2b. "High-income" group exhibits disposition effect 10 percent smaller than "low-income" group, even as we control for other investor and portfolio characteristics. Individual investors working in "non-professional" occupations exhibit 20 percent stronger disposition bias than individuals working in "professional" occupation.[9] Both results are consistent with our hypothesis 2. We also include the product of different income and occupation groups to handle the potential interaction between income and occupation. We do not report them as no interaction effect is significant. The coefficient for control variable "age" is significantly negative, indicating that older investors have smaller disposition effect.

One potential concern about the demographic variables is that income and occupation can be correlated. The correlation between 'high-income' and 'professional' dummies is modest (0.177). Further, the potential collinearity problem should bias us against finding significant impact of either

[9] All t-statistics in this study are computed by using White heteroskedasticity-consistent variance-covariance.

income or occupation, which is opposite to our current findings. We have also used instrument variable to separate the impact of income and occupation. Instead of using the income dummy variables in specification (1) of Table 5, we use income instrument. Specifically, we first regress the 'hi-income' and 'low-income' dummy on the two occupation dummy variables and then include the residuals from the first-stage regression into the regression that we run in Table 5. The results are entirely consistent with our main findings.

We next investigate the impact of portfolio performance and portfolio size on the disposition effect. In specification (2), we include the return of realized gains and realized losses and neither coefficient is significant. In specifications (3) and (4), we include the average number of stocks held in an investor's portfolio and the inverse of the average number of stocks held in an investor's portfolio to control for their effect on the DE measure. As expected, there is a significant negative relationship between the disposition effect as measured in Equation (3) and the portfolio size and a significantly positive relationship between the disposition effect and the inverse of the portfolio size. Nevertheless, including a proxy for portfolio size does not change any of our major findings: individual investors who are wealthier, work in professional occupations, and trade more frequently continue to exhibit a significantly weaker disposition effect.

To further test for robustness of our results, we adopt three other measures for the disposition bias. First, we implement the disposition effect measure proposed in Weber and Camerer (1998) which defines the disposition effect as $(S_{+}-S_{-})/(S_{+}+S_{-})$, where S_{+} and S_{-} are the number of sales of winners and losers, respectively. This measure considers investors' choice between winner and losers and does not depend on the portfolio size or trading frequency. The second measure was used by Odean (1998) to study the disposition effect of frequent versus infrequent traders and is defined as *PGR/PLR*.[10] Odean shows that this measure of disposition effect is less influenced by investor' trading frequency. Finally, we use an alternative measure defined as RG/RL-PG/PL, which also avoids the potential scaling bias in the measure defined in Equation (3). Our major findings remain unchanged using the three alterative measures. In Table 6, the coefficient for the trading frequency is

negative for all three alternative measures, although not significant for specification (3). Under all three alternative measures, the coefficient for "high-income" is significantly negative and the coefficient for 'non-professional' is significantly positive. This is completely consistent with our previous finding.

In summary, our main findings are as follows. We show that, despite the significant disposition effect at the aggregate level, there is wide variation in the size of the disposition effect across investors with different trade frequency and demographic characteristics. About one fifth of investors in our sample do not exhibit any disposition effect or exhibit behavior opposite to disposition effect. Consistent with our hypotheses and recent research on trading of sports card, trading frequency mitigates the disposition effect. Finally, demographic characteristics that are proxies for investment literacy, such as investor income and occupation, can also decrease the disposition effect. Our results hold when we use alternative means to measure the disposition effect.

4. 6. Robustness Tests

4.6.1. Distributional Property of Disposition Effect

One has to take caution interpreting the regression analyses because the dependent variable (the disposition effect) is not perfectly normally distributed. The disposition effect is by definition the difference between two ratios (PGR and PLR) and bounded by –1 and 1. Figure 1 reveals spikes toward the tails of the bell-shape histogram of individual investor disposition effect, indicating the results can be influenced by these extreme values and cut-offs. To make sure our results are robust, we performed two additional robustness tests.

We first remove observations where the absolute value of the disposition effect is bigger than 0.9. This filtering rule retains about 97% of the whole sample and addresses the problem that some investors exhibit disposition effect close to 1 or –1. The new sub-sample of disposition effect conforms closely to normal distribution. We replicate the specification (1) in Table 5 and report the results in specification (1) of Table 7. Consistent with our main findings, investor with higher trading frequency, higher income, and working in professional occupations exhibit significantly weaker disposition effect.

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[10] For this measure and the other alternative measure, we exclude observations when an investor never has a

Second, we create a binary variable based on the disposition effect and perform probit regression in specification (2) of Table 7. The new dependent variable takes the value of 1 if an investor's disposition effect is greater than 0 and the value of 0 if an investor's disposition effect is smaller than or equal to 0. The results of the probit regression indicate that an investor with 10 more trades is 20 percent less likely to exhibit disposition effect. Further, 'hi-income' investors are 18 percent less likely to exhibit disposition effect and individuals working in "non-professional" occupations are 50 percent more likely to exhibit disposition effect. All probit results are consistent with our main results using OLS regressions.

4.6.2. Sub-Sample of Different Account Size and Trade Number

To control for the potential impact that account size (number of stocks being held) and trading frequency have on the disposition effect measure, we divide our observations into sub-samples by their portfolio size and trading frequency respectively and re-run the regression in Section 4.3. The results in Table 8 show that most of our results remain within each sub-sample. This again indicates that difference in portfolio size is not driving our major findings and lends further support to our major findings.

4.6.3. Sub-Sample of Two Sub-Periods

To test our results' consistency over time, we run the same regression specified in Equation (4) again for two sub-periods: 1991-1993 and 1994-1996. Because splitting the data reduces the number of observations for each investor, we can compute the disposition effect for fewer investors during each sub-period. We report the results in Table 9. "Ln(Numtrade)" and "high-income" remain significant within the sub-periods while "professional' and "non-professional" variables hold directionally as in the regression for the entire data set yet become less significant.

4.6.4. Leverage Points

Regression results are sensitive to leverage points, observations that are far away from the linear regression lines. Given that we have many observations of 0.5 and 1 for our disposition effect

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paper or realized loss so that PLR is well defined.

measure, it is important that we check the robustness of our regression without those points. We perform the same regression as in Equation (4) in the last column Table 9 for the sub-sample in which observations are excluded if dependent variables equal to 0.5 or 1. Our main findings hold and the impact of income and profession indeed becomes stronger.

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 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 the differences in trading frequency and demographic characteristics that proxy for knowledge about investment products are 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 about investment products have a 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 individuals who are "low-income" and work in "non-professional" occupations show the highest disposition effect among all investors. It is particularly unfortunate as the changes in investment return may have the greatest adverse impact on such investors. This suggests that 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 advocates can help these investors pay closer attention to loser stocks in their portfolio and make them aware of tax benefits of realizing losers.

The findings are also valuable to various brokerage firms that help investors obtain higher returns. We believe that the brokerage firms will be more profitable if their clients enjoy higher rate of return in their investments. 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 effectively target “low-income” and “non-professional” clients who are most likely to suffer from the disposition effect.

Finally, we note that trading frequency helps reduce the disposition effect, which supports other findings showing that trading frequency 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 rather costly to alleviate disposition bias through trading. Rather than encouraging individuals to trade more frequently, the benefits of frequent trading need to be effectively communicated to all individuals.

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Table 1. Descriptive Statistics of Investor Sample

This table summarizes the data used in empirical studies. We use both investor trade file and the demographics file. 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 demographics and socio- economic information such as age, gender, income code, profession code, and residential location (zip code) for s sub-sample of individuals. Medians are provided in parentheses.

	Entire Dataset	Data in this paper
Panel 1: Sample size		
Number of Households	62,387	7,965
Number of Included Households	42,581	7,965
Panel 2: Investor portfolio position		
Average Portfolio Size	$35,629 ($13,869)	$39,446 ($15,620)
Average Number of Trades	41 (19)	58 (29)
Average Stocks in Portfolio	4 (3)	5 (3)
Panel 3: Investor trades		
Total Number of Trades	2,886,912	697,746
Trades in Common Stocks	1,854,776	458,419
December Stock Trades	128,983	34,536
Average Holding Period (Days)	187 (95)	122 (81)
Panel 4: Investor demographics		
Average Age	50 (48)	50 (48)
Average Income	$59,097 ($50,000)	$64,571 ($50,000)

Table 2. The Disposition Effect for Individual Investors

The disposition effect is calculated for each individual investor. In Panel 1, the mean of the disposition effect for all individuals are reported. In Panel 2, the median of the disposition effect for all individuals are reported. In Panel 3, characteristics for investors with and without disposition effect are reported. "Taxable" sub-sample includes cash accounts and margin accounts. "Non-taxable" sub-sample includes "IRA" and "Keogh" accounts. There are 7,965 households in the whole sample, 2,451 in the 'taxable' sub-sample and 5,514 in the 'non-taxable' sub-sample. T-statistics for equal mean of two samples and rank-sum z-statistics for equal median of two samples are reported in parentheses in Panel 1 and 3 and Panel 2, respectively.

	Whole Sample	Taxable	Non-Taxable	Difference (Tax-Non tax)
Panel 1: Disposition Effect (Mean)				
PGR	0.38	0.37	0.38	-0.01 (-0.57)
PLR	0.17	0.18	0.17	0.01 (0.13)
DE	0.21	0.19	0.21	-0.02 (-0.62)
Number of Trades	58.26	58.09	56.36	1. 73 (0.70)
Panel 2: Disposition Effect (Median)				
PGR	0.31	0.30	0.32	-0.02 (0.90)
PLR	0.17	0.16	0.17	-0.01 (0.77)
DE	0.11	0.11	0.11	0 (0.91)
Number of Trade	29	29	29	0 (0.49)
Panel 3: Characteristics of Investors with and without DE				
	Observation	Percent of Hi-income	Percent of Professional	Mean Trade
Positive DE	6,301	22.77	28.90	54.50
Non-Positive DE	1,664	25.94	29.52	58.36
Difference (Non-Pos.-Pos)		3.17 (2.42)**	0.62 (1.71)*	3.86 (1.42)

* means significant at 10% level; ** means significant at 5% level; *** means significant at 1% level

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 for different income and occupation categories. Panel 3 reports the disposition effect for income/occupation groups within the same occupation/income category. There 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. P-values from t-test, Wilcoxon z-test, and Kolmogrov-Simirnov z-test are provided in parentheses in Panel 2.

Panel 1: Sample decomposition by demographic groups

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

Panel 2: Difference between the disposition effect of demographic groups

	Summary Statistics			
	Mean	t-statistics (p-value)	Wilcoxon z-stat. (p-value)	KS z-statistics (p-value)
		Income		
High-Income	.189			
Low-Income	.211			
(High-Income)-(Low-Income)	-.022	-1.95*[a] (.051)	-2.02**[b] (.044)	-2.45** (.016)
		Occupation		
Professional Occupation	.203			
Non-professional Occupation	.245			
Professional-Non-professional	-.042	-2.20** (.028)	-2.67*** (.008)	-2.59** (.013)

Panel 3: Disposition effect of different demographic groups

	Professional Occupation	Non-Professional Occupation	'Prof'-'Non-Prof'	Group DE
High-Income	.1924	.1911	.0013	.189
Mid-Income	.2057	.2568	-.051**	.208
Low-Income	.2210	.2827	-.062**	.211
Hi-Low	-.0286**	-.0916**		-.022*
Group DE	.203	.245	-.042**	

* means significant at 10% level; ** means significant at 5% level; *** means significant at 1% level.

Table 4. Disposition Effect of December Trades

This table reports the PGR, PLR and Disposition Effect (DE) of December trades by individual investors belonging to various demographic categories. There are 1,245 "high-income", 1,580 "mid-income", and 503 "low-income" investors that sell in the month of December. There are 833 investors working in "professional" and 95 investors working in "non-professional" that sell in the month of December.

	The disposition effect			
	Hi-Income	Mid-Income	Low-Income	Hi-Low
PGR	.1613	.1644	.1671	
PLR	.1596	.1312	.1017	
DE	.0017	.0332	.0654	-.0637 (2.47)**
	Professional Occupation	Non-Professional Occupation		'Prof'-'Non-Prof'
PGR	.1734	.1748		
PLR	.1356	.1299		
DE	.0378	.0449		-.0071 (1.89)*

* means significant at 10% level and ** means significant at 5% level.

Table 5. 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 income categories, professional categories, the logarithm of the number of trades that each investor has executed, the logarithm of an investor's age, the return of realized gains, the return of realized losses, the average number of stocks held within an investor's portfolio, and the inverse of the average number of stocks within an investor's portfolio. White heteroskedasticity-consistent t-statistics are provided in parentheses.

	The disposition effect			
	(1)	(2)	(3)	(4)
Constant	0.77	0.55	0.76	0.73
	(12.76)	(9.35)	(11.44)	(11.28)
High-income	-0.021	-0.019	-0.025	-0.019
	(-2.27)**[a]	(-2.16)**	(-2.49)**	(-2.06)**
Low-income	0.004	0.001	0.003	0.0093
	(0.52)	(0.11)	(0.25)	(0.99)
Professional	-0.0059	-0.0042	-0.0049	-0.0045
Occupation	(-0.67)	(-0.47)	(-0.79)	(-0.53)
Non-professional	0.036	0.053	0.037	0.035
Occupation	(2.36)**	(3.64)***	(2.75)***	(2.22)**
Ln(Age)	-0.096	-0.068	-0.094	-0.091
	(-6.28)***	(-4.65)***	(-5.68)***	(-5.525)***
Ln(Numtrade)	-0.059	-0.032	-0.046	-0.052
	(-13.69)***[b]	(-7.82)***	(-10.03)***	(-12.53)***
Return of realized gains		-0.0019		
		(-1.21)		
Return of realized losses		0.032		
		(1.45)		
Portfolio size			-0.00068	
			(-6.69)***	
Inverse of portfolio size				0.19
				(5.02)***
R square	0.05	0.05	0.06	0.04

a: ** means significant at 5% level; b: *** means significant at 1% level

Table 6. The Impact of Control Variables on Alternative Measures of the Disposition Effect (DE)

The regression is specified as follows: $DE = \gamma D + \beta X + \varepsilon$. The dependent variable is the disposition effect (DE). In column 1, the disposition effect is defined as $(S_+-S_-)/(S_++S_-)$, where S_+ and S_- are the number of sales of winners and losers, respectively. In column 2, the disposition effect is defined as *PGR/PLR*. In column 3, the disposition effect is defined as *RG/RL-PG/PL*. Extreme values are excluded for disposition effect measure in Column 2 and 3. The independent variables include income categories, professional categories, the logarithm of the number of trades that each investor has executed, and the logarithm of an investor's age. White heteroskedasticity-consistent t-statistics are provided in parentheses.

	(1)	(2)	(3)
Constant	0.77	1.82	2.15
	(11.94)	(8.29)	(3.50)
High-income	-0.021	-0.095	-0.079
	(-2.45)**	(-2.76)***	(-1.93)*
Low-income	0.0058	-0.025	0.015
	(0.59)	(-0.77)	(0.39)
Professional	-0.0079	-0.025	0.046
Occupation	(-0.92)	(-0.84)	(0.55)
Non-professional	0.035	0.19	0.35
Occupation	(2.29)**	(3.40)***	(2.32)**
Ln(Age)	-0.090	-0.27	-0.59
	(-5.56)***	(-5.00)***	(-3.82)***
Ln(Numtrade)	-0.059	-0.45	-0.42
	(-3.72)***	(-1.96)**	(-0.24)
R square	0.05	0.05	0.03

a: * means significant at 10% level; b: ** means significant at 5% level; c: *** means significant at 1% level.

Table 7. The Impact of Control Variables on the disposition effect (DE) under alternative regression specifications.

In Column (1), linear regression $DE = \gamma D + \beta X + \varepsilon$ is performed. The dependent variable is the disposition effect (DE). The independent variables include dummy variables of different income categories, professional categories, the logarithm of the number of trades that each investor has executed, and the logarithm of an investor's age. All observations where the absolute value of the dependent variable is greater than 0.9 are excluded. In Column (2), probit model is performed where the depended variable equals to 1 if the disposition effect is larger than 0 and 0 if the disposition effect is zero or negative. The same independent variables are included. White heteroskedasticity-consistent t-statistics are provided in parentheses. Pseudo R-square is reported for the Probit regression.

	(1)	(2)
	OLS w/o extreme values	Probit
Constant	0.645	3.394
	(11.33)	(40.74)
High-income	-0.027	-0.179
	(-3.24)**	(-5.86)***
Low-income	0.004	-0.054
	(0.42)	(-0.49)
Professional	-0.006	-0.039
Occupation	(-0.01)	(-0.32)
Non-professional	0.038	0.497
Occupation	(2.75)***	(11.51)***
Ln(Age)	-0.084	-0.689
	(-5.78)***	(-25.97)***
Ln(Numtrade)	-0.036	-0.195
	(-9.70)***	(-30.98)***
R square	0.05	0.08

** means significant at 5% level ; *** means significant at 1% level

Table 8. The Impact of Control Variables on the Disposition Effect (DE) for Sub-Sample of Investors

The regression is specified as follows: $DE = \gamma D + \beta X + \varepsilon$

The dependent variable is the disposition effect (DE). In Column 2 and 3, we divide investors by half depending on the average number of stocks held in the portfolios. "Portfolio Size 1"/"Portfolio Size 2" are the sub-samples of investors holding a number of stocks smaller/larger than the median number of stocks held in individual portfolios during the sample period. In Column 4 and 5, we divide investors by half depending on their trading frequency. "Trading Frequency 1"/"Trading Frequency 2" are the sub-samples of investors with trading frequency smaller/larger than the median trading frequency during the sample period. The independent variables include income categories, professional categories, the logarithm of the number of trades that each investor has executed, the logarithm of an investor's age, and the average number of stocks held within an investor's portfolio. White heteroskedasticity-consistent t-statistics are provided in parentheses.

	The disposition effect			
	Portfolio Size 1	Portfolio Size 2	Trading Frequency 1	Trading Frequency 2
Constant	0.52	0.093	0.54	0.62
	(2.90)	(3.05)	(9.19)	(5.17)
High-income	-0.054	-0.020	-0.017	-0.024
	(-2.02)**	(-2.63)**	(-1.85)*	(-2.59)**
Low-income	0.033	0.033	0.0072	0.034
	(1.54)	(1.34)	(0.84)	(1.67)*
Professional	-0.087	-0.014	-0.0025	-0.010
Occupation	(-2.30)**	(-0.47)	(-0.33)	(-0.72)
Non-professional	0.017	0.077	0.031	0.044
Occupation	(0.76)	(1.99)**	(2.44)**	(1.89)*
Ln(Age)	-0.024	-0.032	-0.083	-0.079
	(-1.56)	(-1.83)*	(-5.05)***	(-2.55)***
Ln(Numtrade)	-0.50	-0.011	-0.020	-0.067
	(-4.13)***	(-0.71)	(-2.20)**	(-2.44)**
Portfolio size	-0.0012	-0.000044	-0.00065	-0.0014
	(-1.97)**	(-1.02)	(-5.09)***	(-4.97)***
R square	0.04	0.04	0.06	0.03

* means significant at 10% level; ** means significant at 5% level; *** means significant at 1% level

Table 9. The Disposition Effect Regression of Sub-sample 1991-1993 and 1994-1996

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 categories, professional categories, the logarithm of the number of trades that each investor has executed, and the logarithm of an investor's age,. We perform regression analysis for two sub-periods: 1991 to 1993 and 1994 to 1996 in Column 2 and Column 3. The last column includes a sub-sample of 6,082 investors for which the disposition effect does not equal to 1 or 0.5 (leverage points). White heteroskedasticity-consistent t-statistics are provided in parentheses.

	The Disposition Effect			
	1991-1993	1994-1996	1991-1996	1991-1996 No Leverage Points
Constant	0.55	0.43	0.77	0.51
	(6.52)	(4.21)	(12.76)	(9.04)
High-income	-0.029	-0.019	-0.021	-0.027
	(-2.18)**	(-1.05)	(-2.27)**	(-2.99)***
Low-income	0.003	0.0089	0.004	0.005
	(0.25)	(0.56)	(0.52)	(0.75)
Professional	-0.004	-0.025	-0.0059	-0.011
Occupation	(-0.021)	(-0.18)	(-0.67)	(-0.90)
Non-professional	0.011	0.023	0.036	0.039
Occupation	(1.09)	(1.15)	(2.36)**	(2.69)***
Ln(Age)	-0.059	-0.052	-0.096	-0.079
	(-2.75)***	(-2.06)**	(-6.28)***	(-5.15)***
Ln(Numtrade)	-0.040	-0.028	-0.59	-0.020
	(-7.20)***	(-4.33)***	(-13.69)***	(-4.74)***
N	3328	2229	7965	6082
R square	0.02	0.02	0.05	0.04

** means significant at 5% level; *** means significant at 1% level

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

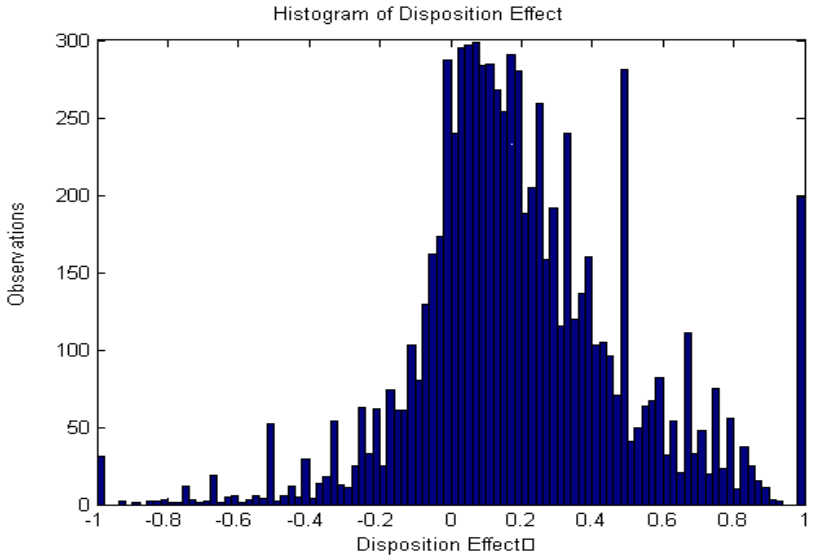

Figure 2. Disposition Effect of Different Income Groups

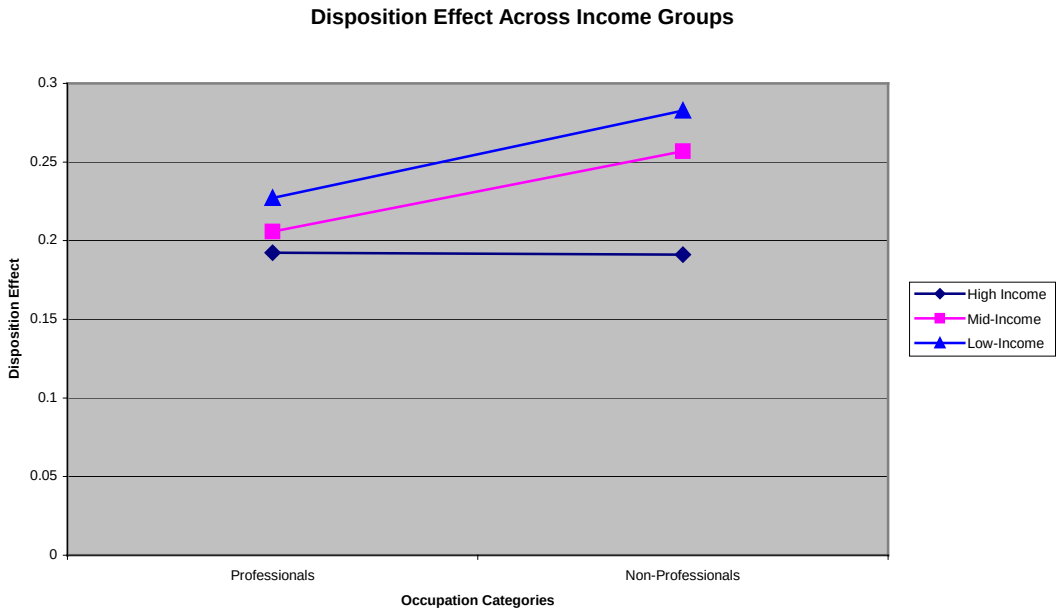

Figure 3. Disposition Effect of Different Occupation Groups