Is Online Trading Gambling with Peanuts?

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Abstract

If individuals derive a small utility from gambling, we should observe high turnover in portfolios that are of only marginal importance to them. By the use of detailed individual financial data, as well as trades from a Swedish online broker, I measure the frequency and cost of online trading in the cross-section, and find the opposite relation. Those who have online portfolios that constitute a large share of risky assets trade more aggressively, but have lower trading performance. These results can be explained by a simple Treynor-Black portfolio model where investors suffer from biased self-assessment, rather than possessing true investment skill. The overall result suggests that the cost of online trading can be substantial. The top quintile of investors who have the highest share of their total financial assets in stocks invested at the brokerage firm under study loose 3.70% of their financial wealth annually, which corresponds to 1.38% of aggregate income within this group. These investors do not only have lower overall wealth and income, but also have the highest aggregate trading losses. Therefore, trading losses are mainly carried by those who can afford them the least. Across individuals, annual losses for 36% of investors exceed 1% of their financial wealth, and 17% lose more than 5%.

Keywords: Investor behavior; performance evaluation; online trading; overconfidence.

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1 Introduction

It is an established fact in the theory of decision making that individuals behave differently to small versus large sized gambles. Markowitz (1952b) notes that most individuals are risk seeking or neutral for small-stake gambles, say choosing a 10% chance of winning \$10 over a \$1 for certain. However, as stakes are increased, most people find it less attractive to gamble, and very few would choose a risky 10% chance of winning \$1,000,000, faced with a certain \$100,000. Prelec and Loewenstein (1991) dub this phenomena the "peanuts effect". The results from small-sized bets are difficult to interpret, as people may be simply indifferent to small stakes, or "peanuts". Conlisk (1993) suggests that individuals derive some positive utility from gambling itself that, locally, can dominate risk aversion. One would then expect people to always gamble with peanuts, but then it is unclear what the welfare implications are and how important the problem is for economic analysis. Shiller (1998) points out that the enjoyment of gambling is more complicated than can be captured by standard utility functions. Gambling is usually confined to specific areas, or favorite games, where individuals feel that they are especially skillful or lucky. Clotfelter (2000) finds that lottery expenditure is relatively stable across income groups, such that poor individuals devote a larger proportion of their budget to gambling. Brenner and Brenner (1990) argue that people gamble in the aspiration to become richer. Lotteries are particulary attractive to those who are poor, older, or have experienced a sudden drop in income, because such individuals are more likely to be dissatisfied about their future prospects.

Investing in financial markets is very different from gambling – at least in theory. Standard, normative advise is to avoid high trading costs and hold diversified portfolios. In direct contradiction stand the two most important stylized facts in the literature of investor behavior: investors trade too much, as evidenced by Barber and Odean (2000)), and they hold poorly diversified portfolios, as documented by Goetzmann and Kumar (2005) and Polkonichenko (2004)). Kumar (2005) finds that investors with similar socioeconomic background as those preferring lottery-tickets also prefer stocks with positively skewed payoffs (e.g. poor, less educated men, living in urban areas). Given the low diversification and high trading frequency, it is only natural to ask if poor trading performance really is economically important to investors, or if it is to be regarded as some form of entertainment.

This paper aims to document to which extent trading is related to significant amounts for individuals. If the peanuts effect is present in data, investors derive some constant utility from trading that dominates risk-aversion. This implies that it is mainly those who have proportionally small amounts of their wealth invested in their online portfolios who trade. As an alternative hypothesis, I present a portfolio choice problem with overconfidence that gives the opposite prediction. Investors who believe that they are better traders, allocate a higher share of financial assets to their traded portfolio. This is a much sharper test of overconfidence than found in most other studies, because it gives a strong cross-sectional prediction. People who trade more will do so with higher stakes, even if they are no better traders than other investors. The two features taken together directly implies that utility losses from trading can be substantial.

Unlike other performance studies, this paper makes explicit use of individual trading data from an online broker, as well as detailed individual financial tax reports in order to answer these questions. The *active weight* proxies for the investors belief in their trading capability, and is defined as each individuals stock portfolio value at the broker account divided by the value of all risky assets (financial wealth excluding holdings of cash and money market funds), measured at first year-end of trading. The cumulative distribution of the active portfolio for the 10,600 investors in sample is displayed in Figure 1, normalized either by risky assets or total financial assets. As expected, online portfolios constitute a relatively small part of financial wealth for many people. Around 25% of the individuals have stocks worth 5% or less of their total financial assets; around 50% of the investors 20% or less. For 50% of the individuals, the online portfolio weight of risky assets is less than 34%, which means that these investors hold more than 76% of their risky assets in other financial instruments than stocks at the online broker. At the top of the distribution, 17% of the investors have 75% or more of their financial wealth invested into stocks at the online account, and this constitute all of their holdings in risky assets. These results show that there is a wide dispersion of how much trading can effect investors utility, even if returns from trading were constant.

If losses from trading are mainly associated with "unimportant" portfolios at the left side of Figure 1, the documented results on trading performance can be seriously misleading. To the contrary, it is found that investors with a larger share of their wealth at stake (at the right side of Figure 1) are both more likely to trade, and have a higher turnover when they do trade. There is also a negative relationship between investors' online portfolio weight and trading performance. In regressions that control for turnover, as well as portfolio size, wealth, diversification, financial occupation, risk, age, education, and gender it is found that the main channel for this underperformance is through increased trading, and not lower average trading ability. The results adds evidence to the previous literature on investor behavior and overconfidence, since it is shown not only that investors who trade more, lose more on average, but are also more willing to place larger sized bets. The peanuts hypothesis can therefore forcefully be rejected.

In conclusion, it is found that the top quintile of investors who have the highest active weight loose 3.70% of financial wealth annually, which corresponds to 1.38% of aggregate income within this group. These investors do not only have lower overall wealth and income, but also have the highest aggregate trading losses. Therefore, losses are mainly carried by those who can afford them the least. The latter result have been inferred before from self-reported data by Barber and Odean (2001) and Kumar (2005), and is stressed by Vissing-Jorgensen (2003) and Calvet, Campbell, and Sodini (2006): Private investors may constitute a small part of the stock market, but investment mistakes can potentially have a large impact on individual utility. In the cross-section of individuals, 36% of investors loose more than 1% of their financial wealth due to trading, and 17% of the investors loose more than 5%, measured in annualized terms compared to the own-benchmark. It follows from the concentration of low weighs to the online portfolio in Figure 1 that a large part – 49% of investors – have trading revenues that constitute between plus and minus 1% of their financial wealth. Even if almost two-thirds of the investors lose from trading, there are also those who earn sizable amounts. About 8% of the investors gain more than 5% compared to their benchmark portfolio, measured as a fraction of their financial wealth on an annual basis.

The paper is organized into six sections. Section two explains how trading and portfolio selection is related in a stylized version of the Treynor-Black model. Section three presents the data, section four derives a method of measuring trading revenue and return. Section five presents the results, and section six concludes.

2 A simple portfolio model with overconfidence

Empirical work by Barber and Odean (2000) suggest that individual investors trade far more than can be justified by rational agents within a standard expected utility framework. Active investors earn lower returns due to fees and bid-ask spreads, but also due to unprofitable trading strategies, as found by Grinblatt and Keloharju (2000). Such irrational trading can be explained by overconfidence. In market settings, it is usually enough to model overconfident investors by assuming miscalibration in order to generate trading. More precisely, some investors understate the riskiness of assets as in, e.g., Kyle and Wang (1997), Odean (1998), and Hong, Scheinkman, and Xiong (2005).[1] The psychological literature gives a broader meaning to overconfidence. In the survey of Dunning, Heath, and Suls (2004), they summarize it as follows:

> ...on average, people say that they are above average in skill (a conclusion that defies statistical possibility), overestimate the likelihood that they will engage in desirable behaviors and achieve favorable outcomes, furnish overly optimistic estimates of when they will complete future projects, and reach judgements with too much confidence.

[1] Trading can also occur without private information in models of differences in opinion as in, e.g., Harris and Raviv (1993) and Varian (1989). Even if the models in this category generally are silent about the reason for disagreement, all of them share the feature that greater disagreement leads to increased trading.

Therefore, flawed self-assessment is not only the propensity to understate risks, but to hold an overly optimistic view of ones true capabilities. There is some evidence that this distinction of overconfidence is important to explain trading behavior. Using data from several UBS/Gallup Investor surveys, Graham, Harvey, and Huang (2005) find that investors who respond that they regard themselves to be competent in the area of investing both trade more frequently and diversify more widely. Glaser and Weber (2004) surveyed online investors and found a robust relation between their measure of the "better-than-average" effect and trading activity, but no relation between a traditional measure of miscalibration and trading. In order to formalize the alternative hypothesis to the peanuts effect, and to better understand the different concepts of overconfidence, consider a portfolio problem with a mean-variance investor. With standard quadratic utility, the investor maximize utility by allocating the weight

$$w_{P^*} = \frac{E\left(R_P^*\right) - R_F}{\gamma Var(R_P^*)}, \tag{1}$$

to the risky asset P. Ex ante, the investor believe he or she has an ability to outperform the market by trading individual stocks that generate an excess return of $\widehat{\alpha} \geq 0$ over and above the market, on average. Let there be some uncertainty about this ability denoted T. The investment decision as to which stocks to buy (or short sell) is not modeled explicitly, but the implicit assumption is that the investor will deviate from a predetermined benchmark to some other portfolio with higher expected return, which necessarily involves trading. The expected ability to generate such trading returns can be perfectly rational if the investor really is better on average, and the case of updating such beliefs if they turn out to be wrong is left to the end of this section. The benchmark have a mean return of $\overline{M}$ with a stochastic term M which is independent of T. We allow investors to be miscalibrated such that they underweight the true risk of the benchmark portfolio with a parameter $0 < c \leq 1$. The model also allows for investors to be miscalibrated about the variance of their ability $\widehat{\alpha}$ with a parameter $0 < d \leq 1$.[2] Assuming normality, we have

$$
\begin{aligned}
R_M &= \overline{M} + cM,\ cM \sim N(0, c^2\sigma_M^2), \\
R_T &= R_M + \widehat{\alpha} + dT,\ dT \sim N(0, d^2\sigma_T^2).
\end{aligned}
$$

The optimal investment in the trading asset, w_{T^*}, is given by maximizing the Sharpe-ratio of a portfolio of R_M and R_T. The solution is

$$
w_T^* = \frac{\widehat{\alpha}/d^2\sigma_T^2}{\left(\overline{M} - R_F\right)/c^2\sigma_M^2}, \tag{2}
$$

which is the standard solution to the model of Treynor and Black (1973), as the weight to the traded portfolio is increasing in the appraisal ratio in the numerator. The miscalibration parameters scales variance between the portfolios. When $c \neq d$, it is impossible to identify $\widehat{\alpha}$ unless it is zero. Note, however, that a positive allocation to the portfolio T is crucially dependent on investors self-assessed ability to outperform the benchmark. Miscalibration here only determines the magnitude. Substituting (2) into (1), factorizing, and simplifying the expression gives

$$
\begin{aligned}
w_{P^*} &= \frac{\left(\frac{\widehat{\alpha}/d^2\sigma_T^2}{\left(\overline{M}-R_F\right)/c^2\sigma_M^2}\right)\widehat{\alpha} + \overline{M} - R_F}{\gamma\left[\left(\frac{\widehat{\alpha}/d^2\sigma_T^2}{\left(\overline{M}-R_F\right)/c^2\sigma_M^2}\right)^2 d^2\sigma_T^2 + c^2\sigma_M^2\right]} = \\
&= \frac{\left(\overline{M} - R_F\right)^2\left(1 + \frac{c^2\sigma_M^2\alpha^2}{d^2\sigma_T^2\left(\overline{M}-R_F\right)^2}\right)}{\gamma c^2\sigma_M^2\left(\overline{M} - R_F\right)\left(1 + \frac{c^2\sigma_M^2\alpha^2}{d^2\sigma_T^2\left(\overline{M}-R_F\right)^2}\right)} = \\
&= \frac{\overline{M} - R_F}{\gamma c^2\sigma_M^2}.
\end{aligned} \tag{3}
$$

Therefore, the weight to the risky asset is only a function of the risk-premium and variance of the benchmark, risk aversion, and miscalibration of the risky benchmark return. Most notably, it is independent of $\widehat{\alpha}$, σ_T^2, and miscalibration over the self-assessed ability, d. The intuition for this result is that, due to independence, the allocation to trading scales linearly in mean and variance. The investor allocates more to trading for a higher

[2] Allowing for different parameters of miscalibration adds little to the analysis that follow, and is merely included for completeness.

$\widehat{\alpha}$, but keeps the allocation to risky assets at the whole constant. This independence cannot be generalized to arbitrary chosen utility functions, and is not the result to be stressed here. The model shows that it is possible to break the link between investors perception of risk in general, and the choice to reallocate their portfolio. Increased trading does not necessarily imply that investors are more risk-tolerant.

This becomes clear in the case when $c < 1$ and $\widehat{\alpha} = 0$. It is then impossible to discriminate between risk aversion and miscalibration because the parameters are not identified. Such an investor will have a higher weight to the risky portfolio P at any level of risk aversion, but will not allocate to the trading portfolio T. The implication of this stylized model is therefore that turnover is predicted by the weight in the traded portfolio among the set of tradable risky assets, but unrelated to the level of risk aversion and miscalibration. Since the weight to trading is given by the investors' perceived appraisal ratio, it will be correlated with their true stock-picking ability, but also reflect how optimistic they are about their capabilities. In this static model, investors can believe ex-ante that they have such ability, while ex-post, they do not. Such behavior may seem difficult to maintain with updating and realigning expectations, but consider the simplest case of an updating rule as follows. Suppose the true trading ability α have the distribution $N(\alpha, \sigma_T^2)$. Investors have at date 0, a prior with the distribution $N(\widehat{\alpha}_0, d^2\sigma_T^2)$. If the individual evaluates his or her trading performance for t trading periods, and accumulates the signal

$$\overline{\alpha}_t = \frac{1}{t}\sum_{i=1}^{t}\widehat{\alpha}_i,$$

it is straightforward to show that the posterior mean follows

$$\widehat{\alpha}_t = \left[\frac{d^2\sigma_T^2}{d^2\sigma_T^2 + \sigma_T^2/t}\right]\overline{\alpha}_t + \left[\frac{\sigma_T^2/t}{d^2\sigma_T^2 + \sigma_T^2/t}\right]\widehat{\alpha}_0. \quad (4)$$

Investors who have a biased prior of trading ability will rationally adjust their expectation over time as they discover their true α. Equation 4 shows that this process is a weighted average of the variances and the number of evaluation periods, and therefore does not need to be instantaneous. Except for the miscalibration term d, which make convergence slower, the updating rule is rational.[3]

3 Data

The data were made available by an online broker and cover all transactions since the start in May 1999 up to and including March 2002. The data covers 324,736 transactions in common stocks that are distributed over 16,831 investors who enter sequentially over time.[4] From this sample, investors are selected that have been active for at least 12 months and from whom there is complete data on wealth and income. The remaining sample is 10,600 investors who made 224,964 common stock transactions distributed over 241,118 investor portfolio months.[5] The average investor is therefore active approximately 24 months.

In addition to trading data, the sample has been matched to *Statistics Sweden* database with detailed background information of the investors. These data include exact information on investors market value of total portfolio at each year-end. More importantly, all Swedish financial institutions are by law required to report the market value of all individual's financial instruments as well as bank holdings directly to the Swedish Tax Authority. This means that each investor's total portfolio is observable at yearly intervals, and can be matched to those stocks that is held at the particular online broker under study. Furthermore, there is information of housing wealth (taxable), total liabilities, capital insurance, and income. It is also possible to retrieve information if income originates from employment in the financial sector - something that may be indicative of better training in financial decision making. Combined, this allows for a quite detailed analysis of how different investor and portfolio characteristics affect portfolio performance, and in particular–detailed controls–when studying turnover performance in the cross-section.

Some features of the data and matching is worth describing in more detail. Income is

[3]Gervais and Odean (2001) use a biased updating rule in order to generate endogenous overconfidence. Daniel, Hirshleifer, and Subrahmanyam (1998) model the dynamics of overconfidence by miscalibration, but are mainly concerned with pricing implications.

[4]See Anderson (2004) for a more comprehensive summary of this data.

[5]Total transactions include 120,734 purchases, 82,846 sales, and 21,384 deposits and redemptions of stocks.

measured as the first observed year-end disposable income adjusted for net capital gains. Turnover is calculated as the total value of all trades each month divided by two times the portfolio value at the beginning of the month. Finance is an indicator variable if the main source of working income has been earned in the financial sector during the year. Similarly, University takes the value one if the individual have at least one year of completed university studies. Wealth is broken up into three major components: Financial, Real Estate, and Debt. Financial wealth is in turn broken up into bank holdings, money market funds, bonds, stocks, equity and mixed mutual funds, other financial instruments, capital insurance, and other financial wealth. All financial wealth is measured at market values, except for the last component that includes non-listed instruments, private equity, promissory notes, and self-reported values of chattels.[6] The market value for Real Estate is not observable, but is measured as an adjusted value liable for taxation. In general, the tax value should reflect 75% of the market value, but is sometimes understated in regions of high price increases (i.e. urban areas, or popular areas of recreation). The reported values are conservatively adjusted by multiplying all real estate by the factor 1.33.

Three wealth measures are used. Financial wealth, already defined, Risky assets, and Total wealth. Risky assets includes all financial wealth, except bank holdings and money market funds. This measure of risky wealth is quite wide, but have the advantage that it is clearly defined. Total wealth is Real and Financial assets net of liabilities, but it is assumed that individuals can only borrow on real assets. If market values are indeed understated in spite of the correction, liabilities are assumed to be associated with real estate only, and calculated as the maximum of real estate minus liabilities, and zero.[7] At the heart of the analysis is the investors active weight. The proxy used here is investors' observed online portfolio value at first year-end, divided by risky assets. Even though real assets also can be regarded as being risky, it is assumed that the part of wealth that is investable consists only of financial wealth, which is in accordance with the model in section 2. In order to

[6]Swedish tax law requires individuals to state the value of private property, such as cars, boats, and jewellery. It is, however, doubtful how close these are to market values since it is virtually impossible to enforce.

[7]This maximum rule was imposed on 3% of investors in sample.

make sure that it is not only individuals that have overall low exposure to the stock and bond market who engage in trading, a separate risk measure is used for control. Trading can also be dependent of risk aversion in a dynamic context, where a given shock to the economy can generate different levels of portfolio rebalancing. A crude measure of risk is calculated as the total holdings of risky financial wealth divided by total net wealth. This variable therefore captures the more general propensity for investors to hold risky assets, and the rank correlation with the active weight is but 9%. There are several reasons for this low correlation. Around 46% of the investors in sample had stocks at other accounts at the year of matching, but equally important, around 64% also held an equity mutual fund. In addition, almost 65% of the investors also own real estate, which is the most important part of total wealth. In sample, financial wealth constitutes around 34% of total wealth including liabilities, which is typical for Swedish citizens.

The measure of active weight brakes the link between the overall preference for risk, and self-assessed trading ability. It is not necessary that a low active weight implies a preference for lower stock market risk, because risky assets may constitute a large portion of overall wealth. Further, an active weight equal to one means that the individual have all her risky financial wealth invested at the broker account, but this may represent a small part of total wealth if the value of safe assets or real estate is substantial. Investors may trade stocks at other accounts, but the model in section 2 predicts that the allocation and trading decision go hand in hand, such that we should expect a higher concentration of financial wealth allocated to undiversified stock portfolios where turnover is high. It is impossible to discard that individuals with small amounts allocated to their online portfolio also trade extensively in some other assets, or at some other brokerage account where they may choose to concentrate their financial assets. This would, however, only reinforce the main results of this paper, as long as their trading performance is uncorrelated over the accounts they are trading.

Table 1 display the data sorted into quintiles and highest decile with respect to turnover. Turnover is skewed, where around 15% of investors never trade and the top ten percent of investors turnover around 55% of their portfolio per month (about 6.6 times per year). The average yearly turnover is 113%, which means that the investor buy and sell their portfolio roughly once a year. There is a strong correlation between turnover and active weight. Those in the lowest quintile of turnover, who basically never trade, have about half the active weight as those in the top turnover quintile. This generally rejects the peanuts hypothesis as a motivation for trading. Portfolio size is, however, also positively correlated with turnover, which is indicative of that the absolute value of investment also may be a powerful determinant of turnover and that these variables may be interrelated. Diversification is low, where the average investor holds around 3 stocks, and the median investor only 2. Table 1 show that the investors in the lowest quintile of turnover have smaller portfolios and are less diversified. A possible explanation is that these investors refrain from trading due to high trading costs. This measure of diversification only consider stocks held at the brokerage firm. A wider, and maybe better, measure of overall diversification is the share of equity mutual funds of investors total equity investment. Investors in the lowest trading quintile have 36% of their equity invested in funds, and this proportion is twice as high as for those in the top quintile. This is also evidence that a larger proportion of financial assets is concentrated into the trading portfolio for the most active group.

Income and wealth is highly positively correlated. Investors in the top turnover quintile have somewhat lower income and wealth, but the difference is only statistically significant for income. The difference in risk between low and high turnover investors is significant, where those who trade the most have a larger proportion of their overall wealth invested into stocks. There is a clear and monotonic negative relationship between the amount of females and turnover quintiles. This broadly confirms the results of Barber and Odean (2001), who argue that women are less overconfident compared to men, and therefore also trade less. It is not clear that younger investors trade more than older. The average age in the top decile is about the same as the bottom quintile. The same pattern is observed for those with financial occupation. The representation of this group is more pronounced in the group that trade the least, but also the group that trade the most.

It is worth commenting how the data on wealth, income, and portfolio values relate to Swedish nationals in general. The average portfolio size is skewed with an average at SEK 86,183, the minimum SEK 1,000 and maximum exceeding SEK 19 million. The median stock portfolio in sample is therefore much lower at SEK 18,091. This is, however, approximately what is found for Swedes in general. *Statistics Sweden* report that the median for the whole country is SEK 20,000 and SEK 15,000 at the end of 1999 and 2001. Similarly, diversification is also low for most Swedes. The median Swede only hold one stock. Calvet, Campbell, and Sodini (2006), who documents portfolio holdings in Sweden during a similar time period, shows that stock market participants have around 20% higher income and 40% higher financial wealth than non-participants. The data under consideration matches income, net wealth, and stock portfolios quite well to participants in the Swedish population. For example, the average portfolio value for all Swedes is around SEK 82,145, and median income is SEK 277,088 compared to a portfolio value of SEK 86,183 and income SEK 315,249 in sample. Even if investors self-select into online trading, they do not appear to differ in any substantial way in the income and wealth dimension. They are, however, both younger and a have longer education than Swedes who hold stocks in general.

4 Turnover performance

It is difficult to find a proper benchmark when investors hold undiversified portfolios. The now standard extensions of Markowitz's (1952a) single-index model proposed by Fama and French (1992) and Carhart (1997) may fail to capture specific preferences of, for example, skewness that may be desirable to individual investors.

In the spirit of Grinblatt and Titman (1993), we let the investors instead self-select a benchmark portfolio at the beginning of each month, which is taken as given to reflect the desirable return profile. Ruling out liquidity motives, rational investors with correct expectations of future returns should on average only trade if deviations from the self-selected benchmark is profitable. Even in the presence of ”mechanical” motives to trade, such as liquidity and risk management, these costs are expected to be small. If investors trade for liquidity reasons, most investors can either sell or buy a mutual fund (as there are very few funds that have loading and exit fees in Sweden) or lend, alternatively borrow cash. If the investor is constrained, such that this is not applicable, it would still not be rational to trade too frequently at high costs, compared to trading once and store some cash at a bank account. In any of these cases, it is difficult to see why rational investors trade excessively at high costs. In addition, the ”constraint motivation” for trading does not square easily with the *positive* correlation between turnover and portfolio size found in data.

The approach defining monthly payoffs and returns is as follows. Since the cash account is unobservable on a monthly basis, it is assumed that investors hold unlevereged portfolios and the capital base used when calculating returns is only increased if the transactions involve a net increase in funding. Therefore, it is important to take the exact timing of trades into account. A sale that precedes a purchase need not affect the capital base, but the reverse transaction will. Furthermore, the interest for any cash balance that is either needed for financing or for storing cash must be properly accounted for.[8] A detailed description of how the trading payoff and return is calculated is given below.

4.1 Calculating trading returns

Let $x_{n,i,t}$ be the number of shares of a stock n held by the individual i at the end of month t. A transaction d during month t is denoted by $x_{n,i,d}$, and super-indices B and S indicate whether it is a buy or a sell transaction. Similarly, associated actual purchasing and sales prices including fees are denoted $p^B_{n,i,d}$ and $p^S_{n,i,d}$ for each of these transactions. In what follows, we also need the closing price for stock n on the last day of month t, which is

[8] The approach here is related to that of Linnainmaa (2005) who investigates daytrades, but he only analyzes individual daily stock returns which is different as it avoids the issues involved considering whole portfolios.

labelled $p^C_{n,t}$. The stock position for individual i at the end of month t is

$$x_{n,i,t} = x_{n,i,t-1} + \sum_{d \in t} \left(x^B_{n,i,d} - x^S_{n,i,d} \right), \tag{5}$$

which is the position at the beginning of month t plus the sum of buys and sells during the month, hereafter net purchases for short. In what follows, we will impose the restriction that $x_{n,i,t} \geq 0$, meaning that investors are not allowed to have outstanding negative positions at month-end.

4.1.1 Payoffs

Trading, position and total payoffs for each stock and individual are as follows. The position payoff is defined as

$$\Pi^P_{n,i,t} = x_{n,i,t-1} \cdot (p^C_{n,t} - p^C_{n,t-1}), \tag{6}$$

which is simply the position at the beginning of the month times the change in price. The trading payoff in stock n for individual i during month t is given by

$$\Pi^T_{n,i,t} = \sum_{d \in t} p^S_{n,i,d} \cdot x^S_{n,i,d} - \sum_{d \in t} p^B_{n,i,d} \cdot x^B_{n,i,d} + \sum_{d \in t} \left(x^B_{n,i,d} - x^S_{n,i,d} \right) p^C_{n,t}. \tag{7}$$

The first and second component of (7) states the net sales revenue of stock n during month t, which is the value of sells minus buys at actual transacted prices. This value needs to be adjusted if the number of stocks sold exceeds sales, or vice versa. The third component of (7) adjusts payoffs by the value of net purchases that are already accounted for by (6). Deposits of stocks are assumed to be transacted at the beginning of the month and redemptions at the end. Therefore, $x_{n,i,t-1}$ also includes all deposits of stocks made during the month. Investors are allowed to short-sell their stock with these definitions because the summation is invariant to the ordering of purchases and sales. The restriction only means that there must be a positive holding of each stock at the end of the month.[9]

[9]In the sample, this proved to be a minor problem as there were only 34 instances where it was needed to cover open short positions at month's end. This was done by dating the corresponding buy transaction at the beginning of the following month, $t+1$, as belonging to t.

Total payoff for each investor i in stock n is the sum of trading and position payoff

$$\Pi_{n,i,t} = \Pi^T_{n,i,t} + \Pi^P_{n,i,t}. \tag{8}$$

To find the payoff for the whole portfolio, we sum over n to obtain total portfolio payoff for individual i in month t

$$\Pi_{i,t} = \sum_n \Pi_{n,i,t} = \sum_n \Pi^T_{n,i,t} + \sum_n \Pi^P_{n,i,t}. \tag{9}$$

4.1.2 Capital components

Similar to payoffs, we distinguish between position and trading capital as follows. Position capital is defined as

$$C^P_{i,t} = \sum_n \left(x_{n,i,t-1} \cdot p^C_{n,t-1} \right), \tag{10}$$

which is simply the value of all stocks in the portfolio at the beginning of the month.

The amount of capital engaged in trading is determined by sorting each transaction in calendar time. The traded value of any sale or purchase at any day is

$$TV_{i,d} = \left\{ \begin{array}{c} p_{i,d} \cdot x^J_{i,d} \text{ if } J = S \\ -p_{i,d} \cdot x^J_{i,d} \text{ if } J = B \end{array} \right\},$$

such that it represents the revenue of any sales and cost of any purchase. The trade values are ordered during the month from beginning to end for each investor regardless of which stock is traded, and the cash balance is calculated at each point in time. The lowest cumulative cash balance in month t is the minimum amount needed to finance the portfolio without leverage, and is written

$$C^T_{i,t} = -\min_d \left[\sum_{d \in t} TV_{i,d}, 0 \right], \tag{11}$$

and is expressed as a positive number since we pick out the largest negative cash balance.

Total capital is the sum of position capital and trading capital,

$$C_{i,t} = C^P_{i,t} + C^T_{i,t}. \tag{12}$$

Therefore, the capital base is only increased if trading incurs additional funding. But this is exactly what we want, because the investor who reallocates her investment without using additional funds will have the same capital base.

4.1.3 Excess returns

Excess returns are created as follows. It is assumed that the investor can borrow and deposit cash at the available 30-day T-bill rate, r^F_{t-1}, in order to finance the portfolio. The interest that is attributable to the position component, $I^P_{i,t}$, is calculated as the cost of borrowing the value of the portfolio at the beginning of the month, i.e the first part of equation (12).

If trading occurs, we seek the net interest paid for trading capital during the month. Interest is calculated for each transaction and summed over the month creating the revenue $I^T_{i,t}$ that corresponds to the interest that is attributable to the actual timing of purchases and sales.[10]

The excess return is therefore

$$R_{i,t} = \frac{\Pi_{i,t} + I^P_{i,t} + I^T_{i,t}}{C_{i,t} - \min\left[I^T_{i,t}, 0\right]}, \tag{13}$$

where $I^P_{i,t}$ is always 0 or negative and $I^T_{i,t}$ is negative if there is a net cost of financing the monthly transactions. When trading capital is 0 but the investor is net selling, $I^T_{i,t}$ represents the interest earned on investments that is sold out of the portfolio. In this way, timing of the sale is properly accounted for since positive interest is added to the return measure. Both trading capital and $I^T_{i,t}$ can be positive if the investor only draws cash for a short time and for a small amount in comparison to sales revenues in a month.

The interest on trading capital is only added to the capital base if it is negative. This is because it is assumed that interest earned is paid out at the end of the month, but any costs must be covered by capital at the beginning of the month. It therefore ensures that returns are bounded at -1. In the case of no trading, $I^T_{i,t} = 0$, we obtain the familiar

[10] Two assumptions apply: the borrowing and lending rates are the same and the effect of compounding during the month is ignored.

definition of excess returns, which is

$$R_{i,t} = \frac{\Pi_{i,t} + I^P_{i,t}}{C^P_{i,t}} = r_{i,t} - r^F_{t-1}.$$

4.1.4 Passive returns

The idea of comparing investor performance with their own-benchmark was originally proposed by Grinblatt and Titman (1993). Here, the passive return captures the same intuition and is defined as

$$R^P_{i,t} = \frac{\Pi^P_{i,t} - I^P_{i,t}}{C_{i,t}}, \tag{14}$$

which is the position payoff divided by total capital corrected for interest. As the own-benchmark return measures the return of the portfolio since there was no trading during the month, we see that (13) and (14) are exactly the same, because then we have that

$$\Pi_{i,t} = \Pi^P_{i,t}.$$

The passive return measure uses total capital as a base. It is therefore assumed that whatever funds used for net investments during the month are invested at the risk-free rate. The investors can only deviate from the benchmark by trading. During the month, investors can move in and out of the market as a whole or switch allocation between stocks. If these tactical changes in risk and reallocations are profitable, investors earn a higher excess return on the traded portfolio than on the static own-benchmark. Trading return is therefore defined

$$R^T_{i,t} = R_{i,t} - R^P_{i,t}, \tag{15}$$

and a the cost of trading per unit of turnover. Turnover cost is

$$TOC_i = \frac{\sum_t (\Pi^T_{i,t} - I^T_{i,t})}{\sum_t \sum_d TV_{i,d,t}}, \tag{16}$$

and measures trading profit per unit of turnover value.

5 Results

Table 2 summarizes many of the key results of this paper, where the means for the turnover costs and trading returns are partitioned into quintiles of the active weight. Investors with the highest proportion of risky assets invested at the online broker trade more, have larger portfolios, but also lower trading returns. This pattern is clearest for the difference between the fifth and first quintile, which is highly statistically significant. Compared to investors in the bottom quintile of active weight, the top quintile investors loose 18 basis points per month on average. The turnover cost is somewhat U-shaped, but the difference between the top and bottom quintile of investors is around 0.74%. This means that the flow of money that is traded cost less for investors in the top quintile, but does not compensate enough for their higher turnover. The turnover cost is proportional to the portfolio size, since lower portfolio size is associated with smaller transactions and higher percentage fees.[11] Investors with the highest active weight have considerably larger portfolios, but size does not explain the average performance *after* fees which is 8 basis points lower compared to the same group. Since the returns are measured to an own-benchmark defined at the beginning of month, the residual is completely due to stock selection and market timing.

The remainder of the analysis of trading performance is conducted in three steps. First, the propensity to trade conditional on the observed characteristics is estimated on the full sample in order to determine the profile of those who trade. This includes taking the marginal probability of those who do not trade into account when calculating the overall effect of investor characteristics on turnover. The second step estimates the relationship between the same characteristics and trading returns, conditional on turnover being positive. The analysis of trading performance is therefore confined to those who actually trade, but concerns the cross-sectional differences in performance of these investors. Finally, the ex-post distribution of trading losses is analyzed.

[11] Anderson (2004) investigate this relationship in more detail.

5.1 Who is trading?

The first step is to determine who is trading, based on the characteristics data. The expectation of average monthly turnover for each individual, TO_i, conditional data $\mathbf{X}_i$ can be written

$$\begin{aligned} E(TO_i|\mathbf{X}_i) &= P(I=0|\mathbf{X}_i)\cdot 0) + P(I=1|\mathbf{X_i})\cdot E(TO_i|\mathbf{X}_i, I=1) \\ &= P(I=1|\mathbf{X}_i)\cdot E(TO_i|\mathbf{X}_i, I=1), \end{aligned} \tag{17}$$

where the indicator variable I takes the value one if turnover is observed. Following a version of the corner solution model considered in Wooldridge (2002), assume that if turnover is observed, it obeys

$$E(TO_i|\mathbf{X}_i, I=1) = \mathbf{X}_i\beta. \tag{18}$$

where the error term of the regression is normally distributed. Then the probability that turnover is observed follows a Probit model

$$P(I=1|\mathbf{X}_i) = \Phi(\mathbf{X}_i\lambda). \tag{19}$$

The models (18) and (19) can be consistently be estimated separately from data. It follows that the marginal effects are

$$\frac{dE(TO_i|\mathbf{X}_i)}{d\mathbf{X}_i} = \beta\Phi(\mathbf{X}_i\lambda) + \mathbf{X}_i\beta\phi(\mathbf{X}_i\lambda)\lambda, \tag{20}$$

where the first part can be thought of as an "turnover" effect, and the second part a "participation" effect, since a given change in $\mathbf{X}_i$ will affect both the probability to trade as well as the magnitude of turnover. Table 3 display the estimation results as well as the marginal effects of the model.

The active weight, portfolio size, and diversification increase the probability to trade. Evaluated at the functional mean, the marginal effects on turnover are about equal around 4%. The positive relation between portfolio size and the decision to trade is not surprising. It is likely that some investors are unwilling to trade in very small portfolios, since trading costs in percentage terms can be high in presence of minimum cost of fees.[12] The probability to trade is significantly decreasing in the level of wealth, risk, female, and age, where overall risk is most important. Investors with high wealth and high stock market risk exposure are less likely to trade, which supports the notion of them being more experienced and better trained in financial decisions.

The OLS estimation generally follows the same pattern, except for diversification and age. Less diversified, as well as younger investors, are less likely to trade, but those who do trade, trade significantly more. There is a strong and positive effect of portfolio size and the active weight. Investors who have a larger share of their financial wealth invested at the online account have both a higher probability to trade, as well as higher turnover when they do trade.

The last column of Table 3 shows the effect on turnover of a positive one standard deviation shock to the dependent variable, evaluated at the turnover mean of 9.44%. The most important effect on turnover is portfolio size, which increases turnover by almost 5%, followed by active weight of around 3%. The gender effect is evaluated binary, and shows that the expected turnover of women is 3% lower than that compared to men. University educated investors have almost 2% lower turnover than the other half of the sample with less education. The overall effect of risk and wealth on turnover is relatively small compared to the other measured effects.

5.2 Who looses from trading?

So far, it is established that the trading return on average is decreasing in the active weight, and that certain characteristics can be associated with more or less turnover (TO). The next step is to relate this evidence to turnover performance by the regression

$$R_i^T = a_0 + b_0 \cdot log(1 + TO_i) + \sum_k b_k \cdot X_{k,i} + \varepsilon_i, \tag{21}$$

where R_i^T denote the average individual trading return, data $X_{k,i}$ denote the characteristic variables with associated coefficients b_k. The reason for the log transformation of turnover

[12]The minimum cost per trade was SEK 89, or roughly USD 10, during the sample period.

is that it fits the data somewhat better. The results are very similar in an untransformed specification. When turnover is excluded among the independent variables, b_k measures the gross effect of the characteristics on performance. This regression disregards that turnover itself varies systematically over investors characteristics. When controlling for turnover, b_k measures the average performance for investor types. The point estimates in (21) coincides with OLS, but the variance-covariance matrix is estimated with GMM, using asymptotically robust errors as in White (1980). The results are presented in Table 4.

The regression coefficient for the active weight is significantly negative. The size of the portfolio is a very important determinant for investor performance, since high turnover in small portfolios are associated with higher transaction costs due to fees.[13] When controlling for portfolio size in the second column of Table 4, the point estimate for active weight almost doubles. An increase of 10% in the active weight is associated with a 2.2 basis point drop in monthly trading performance. The negative effect drops, but survives when controlling for other investor characteristics. When turnover is excluded, we neglect that turnover varies systematically over characteristics. The difference between the third and fourth column of Table 4 disentangle these effects. The coefficient for active weight is much lower when controlling for turnover, because investors with high active weights trade more, on average. Therefore, the main channel of underperformance is through increase trading, and not lower average trading ability. Similarly, female investors trade less on average, so the positive effect of 10 basis points higher average performance is almost halved, but still significant at 6 basis points. Furthermore, when fees are excluded from the dependent variable, the effect is insignificant. This suggests that the females in sample have higher trading performance compared to men, but this is due to that they were more careful in taking direct trading costs into account.

The negative effect of diversification on performance is statistically significant, but the economic effect is very small. Investors with one more stock in their portfolio have around 1 basis point less performance. The inclusion of the risk measure ensures that the

[13]As shown by, e.g., Anderson (2004).

negative effect of the active weight is unrelated to the overall risky portfolio in relation to total wealth. Rather, higher overall risk-taking is associated with positive trading performance, since a one standard deviation increase in risk improves performance by about 4 basis points per month. The effect of investors having financial occupation is positive, but insignificant. One of the most economically important determinants of performance is education. University educated investors experience almost 10 basis point higher trading performance per month compared to the roughly equally large population in the sample with lower education. This effect is not only due to lower turnover within this group, because it remains when controlling for both turnover and fees. University educated investors have 7 basis points higher performance per month on average, even after fees. The gross effect translates to over 1.4% per year on average, and after controlling for turnover and fees, 0.8%. If wealth and age could proxy for investor experience, these variables give contradicting results. The effect of higher wealth is positive, but age is negative. Both effects are statistically and economically important. A one standard deviation change in these variables represent 10 and 4 basis points in performance.

The economically most important negative effect on performance comes from increased trading alone. A one standard deviation positive shock to turnover above the mean (which corresponds to a turnover level of around 27%) implies an additional 31 basis points in negative trading performance per month–i.e. equally as much as the mean underperformance estimated by the intercept.

5.3 How much is lost from trading?

The previous section found that investors with portfolios that constitute a large part of financial wealth do not perform better than average. It follows directly that there are investors who loose substantial amounts in relation to their financial wealth. But it has not yet been documented how many these investors are, and how much they loose. The gross trading performance is aggregated for gains and losses separately within the quintiles of active weight and displayed in Table 5. Similarly, financial wealth, total net wealth, and income are also aggregated and net losses expressed as fractions of these measures of investor prosperity. The results from returns carry over to this table, since wealthier investors with lower stakes at the brokerage account both trade less and are better traders on average when they do trade. The sixth row of Table 5 reveals that the investors who are in the lowest quintile of active weight are over three times as wealthy compared to the twenty percent in the top, and possess over ten times as much financial wealth. In addition, the net trading loss is much larger for the fifth than the first quintile. Therefore, the loss incurred by trading is carried by those who can afford them the least. In the fifth quintile sorted on active weight, trading losses represents 3.70% of financial wealth and 1.38% of yearly income. As a comparison, Swedish households with similar income spend 14.6% of their annual disposable income on recreational activities, on average.[14] They spend 1.2% on sports and other hobbies, 2.4% on books and newspapers, around 2% on alcohol, and 2.6% on dining in restaurants. Trading losses are therefore far from negligible in this context.

Compared to gambling, Clotfelter (2000) reports that lottery expenditure is fairly constant over income groups, and so constitutes a much larger share of the budget for those earning less. Lottery expenditure is between 0.8% to 1.2% of income for those earning less than $15,000 per year, but only 0.04% for those earning more than $50,000. Online investors in sample have considerably higher income, and longer education than those who are regarded as being "poor" and have low education in the gambling literature. It is therefore not obvious how to compare these results. Nevertheless, *within* the group of online investors, it seems that many of the same characteristics that drive lottery purchases correlate with the driving forces of gambling behavior.[15] Based on the estimates in this sample, the economic loss of online trading is at least five times higher the cost of lottery purchases, on average.

The aggregated results do not display how trading gains and losses are distributed on an individual basis. Figure 2A display the cumulative distribution of net gains normalized by financial wealth and net wealth. The sharp curvature around 0 imply that the

[14]Matched to the 7th income decile in the 1999 Household Budget Survey, Statistics Sweden.
[15]This is what is also found by Kumar (2005).

trading revenue constitute a small share of wealth for the majority of investors–which is a direct consequence of the distribution for the online portfolio shown in Figure 1. About half, or 49% of the individuals have trading losses and gains representing 1% of their financial wealth. Two thirds of the investors loose from trading, where 36% of them loose more than 1% of financial wealth, and 17% more than 5%. The distribution is skewed, so there are fewer who gains from trading. Still, about 8% of investors gain more than 5% from rebalancing their portfolio to their self-selected benchmark, measured as a share of total financial wealth. The effect is similar, but less sharp when trading revenue is normalized with total net wealth: 20% loose more than 1%, and around 9% more than 5%. Even if fees are an important determinant for returns, Figure 2B shows that these are mainly associated with smaller trading losses. Without fees, 29% of investors loose more than 1% of their financial wealth, compared to 36% when fees are included.

6 Conclusion

Many online investors trade too frequently and most of them loose compared to holding their self-selected benchmark portfolio. This activity is difficult to rationalize with normative financial theory, and attempts have been made to explain this behavior. Most importantly, investors may suffer from overconfidence and illusion of control, as suggested by Barber and Odean (2002), and biased self-assessment as evidenced from Glaser and Weber (2004) and Graham, Harvey, and Huang (2005). They may be sensation-seeking, as proposed by Grinblatt and Keloharju (2005), or simply just untrained in financial decision making such that they are unaware of the common traps of stock investment. All the above explanations lean towards the conclusion that investors are uniformed or irrational. A straightforward rational explanation for excessive trading is that investors enjoy trading a small part of their portfolio for their entertainment, as suggested by Conlisk (1993), or they may find it rational to learn about financial markets with small bets before entering with larger investments.

This paper documents that the most active individuals do not gamble with small stakes. When the online portfolio constitutes a large share of risky assets, both the probability to trade increases, and turnover is also increasing in the share of risky assets held at the online account. Furthermore, these investors do not perform better. There is in fact a negative relationship between the share of financial wealth traded and the trading return, measured from a self-selected benchmark. This relation disappears when controlling for turnover, so the main channel of increased underperformance goes through increased trading, and not lower trading ability. High portfolio value and wealth improves trading performance, and wealthier people trade less. This means that the investors who are the least equipped to carry losses, i.e. those with low wealth, are actually those who have the poorest trading performance. In order to assess the importance of the costs across individuals, it is found that two thirds loose from trading, and over one third of the investors loose more than 5% of their financial wealth on an annual basis.

The results do not exclude the possibility that individuals trade for their amusement. If they do, however, the expected utility of gambling must be quite high for many investors. In particular, it must be considerably higher than playing, for instance, lottery games. A simpler, and very plausible alternative explanation forwarded here is that investors who believe themselves to be better on average engage more heavily in trading. A slightly modified Treynor-Black portfolio allocation model predicts that this relation can be independent of the overall level of financial risk-taking and how much the individual under-weights the true riskiness of the stock market. The empirical evidence supports this proposition, as the active weight is one of the strongest predictors of turnover, but there is a very weak link between overall financial risk-taking and trading. The evidence from the performance regressions suggest that biased self-assessment is mainly an idiosyncratic phenomena. Investors who tilt their risky portfolio to stocks at their online portfolio trade more, but are no better traders, than other investors.

References

Anderson, Anders, 2004, All guts, no glory: Trading and diversification among online investors, Working Paper, Swedish Institute for Financial Research.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 60, 773–806.

———, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

———, 2002, Online investors: Do the slow die first?, *Review of Financial Studies* 15, 455–487.

Brenner, Reuven, and Gabrielle A. Brenner, 1990, *Gambling and Speculation: A Theory, a History, and a Future for Some Human Decisions* (Cambridge University Press: Cambridge).

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2006, Down or out: The welfare costs of houshold investment mistakes, Working Paper, Stockholm School of Economics.

Carhart, Mark M., 1997, On persistance in mutual fund performance, *Journal of Finance* 52, 57–82.

Clotfelter, Charles T., 2000, Do lotteries hurt the poor? Well, yes and no, Working Paper, Terry Sanford Institute of Public Policy, Duke University.

Conlisk, John, 1993, The utility of gambling, *Journal of Risk and Uncertainty* 6, 255–275.

Daniel, Kent, David A. Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security under- and overreactions, *Journal of Finance* 53, 1839–1885.

Dunning, David, Chip Heath, and Jerry M. Suls, 2004, Flawed self-assessment, *Psychological Science in the Public Interest* 5, 69–106.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1–27.

Glaser, Markus, and Martin Weber, 2004, Overconfidence and trading volume, Working Paper, University of Mannheim.

Goetzmann, William N., and Alok Kumar, 2005, Why do individuals hold under-diversified portfolios?, Working Paper, Yale School of Management.

Graham, John R., Campbell R. Harvey, and Hai Huang, 2005, Investor competence, trading frequency, and home bias, Working Paper, Duke University.

Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43–67.

——— , 2005, Sensation seeking, overconfidence, and trading activity, Working paper, Helsinki School of Economics.

Grinblatt, Mark, and Sheridan Titman, 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 66, 47–68.

Harris, Milton, and Artur Raviv, 1993, Differences of opinion make a horse race, *Review of Financial Studies* 6, 473–506.

Hong, Harrison, Jos Scheinkman, and Wei Xiong, 2005, Asset float and speculative bubbles, Working paper, Princeton University.

Kumar, Alok, 2005, Who gambles in the stock market?, Working Paper, University of Notre Dame.

Kyle, Albert S., and Albert Wang, 1997, Speculation duopoly with agreement to disagree: Can overconfidence survive the market test?, *Journal of Finance* 52, 2073–2090.

Linnainmaa, Juhani, 2005, The individual day trader, Working Paper, The Anderson School at UCLA.

Markowitz, Harry, 1952a, Portfolio selection, *Journal of Finance* 7, 77–91.

——— , 1952b, The utility of wealth, *Journal of Political Economy* 60, 151–158.

Odean, Terrance, 1998, Volume, volatility, price, and profit when all traders are above average, *Journal of Finance* 53, 1887–1934.

Polkonichenko, Valery, 2004, Household portfolio diversification: A case for rank dependent preferences, Working Paper, University of Minnesota.

Prelec, Drazen, and George Loewenstein, 1991, Decision making over time and under uncertainty: A common approach, *Management Science* 37, 770–786.

Shiller, Robert, 1998, Human behavior and the efficiency of the financial system, NBER Working Paper No. 6375, Cambridge, M.A.

Treynor, Jack L., and Fischer Black, 1973, How to use security analysis to improve portfolio selection, *Journal of Business* 46, 66–86.

Varian, Hal R., 1989, Differences of opinion in financial markets, in Courtenay C. Stone, ed.: *Financial Risk: Theory, Evidence, and Implications* . pp. 3–37 (Kluwer Academic Publishers: Boston).

Vissing-Jorgensen, Annette, 2003, Perspectives on behavioral finance: Does "irrationality" disappear with wealth? Evidence from expectations and actions, in Mark Gertler, and Kenneth Rogoff, ed.: *NBER Macroeconomics Annual 2003* . pp. 139–208 (MIT Press: Cambridge, Massachusetts).

White, Halbert, 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica* 48, 817–838.

Wooldridge, Jeffrey M., 2002, *Econometric Analysis of Cross Section and Panel Data* (MIT Press: Cambridge, Massachusetts).

Table 1: Mean statistics sorted on turnover

The 10,600 investors are sorted into quintiles (and tenth decile) based on turnover, defined as the sum of monthly purchases and sales divided by two times portfolio value. Portfolio size is the value of the portfolio at the end of the first month of trading, which is also when Age and the number of different stocks held, Diversification, is determined. All other variables are defined at first observed year-end. The active weight is the online portfolio value divided total risky financial wealth. Income is disposable income net of capital gains. Wealth includes financial wealth and the maximum of adjusted housing wealth net of liabilities. Risk is measured as risky assets divided by wealth. Females and Finance measures the frequency of women and those who earned income from financial occupation. All reported values are means, unless stated otherwise. Under the sample period, USD 1 corresponds to about SEK 9.

	Turnover quinitles					Decile 10	All	Diff. Q5-Q1[1]	Test-statstic[2]
	1 (Low)	2	3	4	5 (High)				
Turnover, %	0.06	1.49	3.56	7.25	34.86	54.84	9.44	34.80	41.97***
Active weight, %	32.62	40.84	43.24	48.80	58.62	64.29	44.82	26.00	22.77***
Portfolio size, SEK	60 272	91 217	73 821	72 286	133 321	175 795	86 183	73 049	6.74***
Div., no. of stocks	2.18	3.25	3.27	3.29	2.99	2.87	3.00	0.81	11.41***
Div., funds vs. stocks, %	36.18	34.02	32.41	27.46	18.47	14.81	29.71	-42.22	-18.19***
Income, SEK (median)	336 397	321 395	316 357	307 919	296 025	301 491	315 249	-49 772	-3.60***
Wealth, SEK (median)	761 931	658 746	674 697	589 036	654 482	627 020	663 379	-50 165	-0.52
Risk, % (median)	23.14	26.93	25.66	24.71	29.13	30.02	25.97	3.39	3.02***
Females, %	23.35	20.42	20.05	14.43	11.89	11.13	18.03	-11.46	-9.82***
Age, years	39.21	37.97	38.15	37.55	38.36	39.27	38.25	-0.85	2.39**
Finance occupation, %	3.40	2.12	3.16	3.02	3.68	3.40	3.08	0.28	-0.50
University education, %	52.08	53.92	51.98	52.83	47.78	46.04	52.72	-6.04	-2.80***

1) Difference in means between first and fifth quintile. 2) t-test of difference in means (or proportions where applicable). Asterisks ***, **, and * denote significance on the 1%, 5%, and 10% percent level.

Table 2: Trading returns and turnover costs

Investors are sorted into quintiles of active weight, which is the online portfolio value divided by total risky assets at first year-end. The rows display the mean trading return, with and without fees, the turnover cost defined in the main text, average turnover, and portfolio size.

Variable means	Quintiles by Active weight 1 (Low)	2	3	4	5 (High)	All	Difference Q5-Q1
Active weight, %	1.96	11.36	35.00	75.93	99.87	44.82	97.91
Trading return, %	-0.23*** (-11.13)	-0.23*** (-11.61)	-0.21*** (-10.48)	-0.25*** (-11.16)	-0.41*** (-12.61)	-0.26*** (-25.20)	-0.18*** (-4.61)
Trading return (w/o fees), %	-0.07*** (-3.37)	-0.07*** (-3.76)	-0.04*** (-2.59)	-0.07*** (-3.58)	-0.15*** (-5.11)	-0.08*** (-8.48)	-0.08** (-2.36)
Turnover cost, %	-3.12*** (-10.22)	-2.80*** (-10.35)	-2.23*** (-10.58)	-1.51*** (-9.54)	-2.38*** (-11.68)	-2.41*** (-22.83)	0.74** (2.01)
Turnover, %	4.59*** (22.57)	6.86*** (20.34)	8.17*** (21.19)	13.28*** (23.85)	14.33*** (21.67)	9.44*** (45.37)	9.74*** (14.08)
Portfolio size, SEK	32,165*** (7.19)	46,694*** (13.53)	91,909*** (8.38)	156,780*** (15.83)	103,368*** (11.75)	86,183*** (23.42)	71.203*** (7.26)

Significance of a t-test (test statistics within parenthesis) are marked by ***, **, and *, indicating rejection at the 1%, 5%, and 10% level.

Table 3: Estimates of the determinants of turnover

The table display the parameters of a probit-estimation on the whole sample, and associated slope coefficients calculated at the functional mean. The OLS regression is specified over the 9,053 investors with non-zero turnover, defined as the sum of monthly purchases and sales divided by two times portfolio value. Portfolio size is the value of the portfolio at the end of the first month of trading, which is also when Age and the number of stocks held, Diversification, is determined. All other variables are defined at first year-end. Active weight is the online portfolio value divided by total risky financial assets. Income is disposable income without realized net capital gains. Wealth includes financial wealth and the maximum of adjusted housing wealth net of liabilities. Risk is measured as the value of risky assets divided by total wealth. Female and Finance are indicator variables for women or if income has been earned from financial occupation. The marginal effects for the combined model is decomposed into the marginal effect on turnover and participation. The last column reports the effect on turnover of a one standard deviation shock to the independent variable. Intercepts are suppressed.

Model	Probit 10,600 obs.		OLS 9,053 obs.	Marginal effects[1]			Turnover, one std. dev. shock to[2]
Dependent var:	Trading (1/0)	Slope	Turnover	Total	Trading	Participation	
Active weight	0.209*** (3.78)	0.035	8.080*** (8.61)	7.694*** (9.08)	7.322*** (8.78)	0.373*** (3.76)	2.947
Log Portfolio Size	0.213*** (13.92)	0.036	3.252*** (11.83)	3.327*** (13.16)	2.947*** (11.84)	0.380*** (13.73)	4.938
Diversification	0.255*** (19.00)	0.043	-1.145*** (-6.20)	-0.582*** (-3.54)	-1.037*** (-6.23)	0.455*** (17.42)	-1.537
Log Wealth	-0.066*** (-4.52)	-0.011	-0.155 (-0.66)	-0.259 (-1.11)	-0.141 (-0.59)	-0.118*** (-4.63)	-0.478
Risk	-0.104 (-1.62)	-0.018	2.004* (1.81)	1.630 (1.55)	1.816* (1.73)	-0.186 (-1.63)	0.594
Female	-0.145*** (-3.53)	-0.024	-3.153*** (-6.52)	-3.115*** (-7.13)	-2.857*** (-6.68)	-0.258*** (-3.21)	-3.115
Log Age	-0.102* (-1.69)	-0.017	5.642*** (6.18)	4.931*** (5.92)	5.112*** (6.21)	-0.204* (-1.71)	1.508
Finance	-0.114 (-1.24)	-0.019	2.089 (1.00)	1.689 (0.90)	1.893 (1.02)	-0.204 (-1.31)	1.689
University	-0.019 (-0.56)	-0.003	-1.894*** (-3.96)	-1.750*** (-4.02)	-1.717*** (-3.98)	-0.033 (-0.53)	-1.750
(Quasi) R-squared	0.139		0.079				

Reported t-statistics within parenthesis are based on Whites heteroscedastic standard errors. Asterisks *, **, and *** denote significance on 1%, 5%, and 10% level. 1) Marginal effects evaluated at the regression mean, bootstrapped errors. 2) Estimated effect to turnover of one standard deviation shock to the independent variable, except for "Female", "Finance", and "University", evaluated for binary values.

Table 4: Estimates of the determinants of trading return

The table display the linear regression coefficients from various specifications with the trading return as the dependent variable. Turnover is defined as the sum of monthly purchases and sales divided by two times portfolio value. Portfolio size is the value of the portfolio at the end of the first month of trading, which is also when Age and the number of different stocks held, Diversification, is determined. All other variables are defined at first year-end. The active weight is the online portfolio value divided by total value risky financial assets. Income is disposable income net of capital gains. Wealth includes financial wealth and the maximum of adjusted housing wealth minus liabilities. Risk is measured as risky financial wealth divided by wealth. Female and Finance are indicator variables for women or if income has been earned from financial occupation. The first five columns regress the trading return including fees directly on the independent variables, where the fifth column also condition them on turnover. The previous analysis is repeated in the last column, but with turnover return excluding fees as the dependent variable. All independent variables have been centralized.

Dependent variable	Trading return				Excl. fees
Intercept	-0.310*** (-25.35)	-0.310*** (-25.57)	-0.310*** (-25.68)	-0.310*** (-26.13)	-0.094*** (-8.54)
Active weight	-0.122*** (-3.39)	-0.221*** (-5.81)	-0.113** (-2.48)	-0.023 (-0.51)	-0.015 (-0.38)
Log Portfolio Size	-	0.105*** (12.61)	0.076*** (6.87)	0.112*** (9.80)	0.026*** (2.48)
Diversification	-	-	-0.001 (-0.21)	-0.014** (-2.42)	-0.003** (-0.48)
Log Wealth	-	-	0.060*** (4.07)	0.058*** (4.03)	0.020* (1.68)
Risk	-	-	0.098** (1.99)	0.120*** (2.46)	0.021 (0.48)
Female	-	-	0.095*** (3.37)	0.058** (2.06)	0.039 (1.57)
Log Age	-	-	-0.175*** (-3.51)	-0.115** (-2.33)	-0.098** (-2.23)
Finance	-	-	-0.003 (-0.05)	0.013 (0.17)	0.045 (0.66)
University	-	-	0.118*** (4.85)	0.097*** (4.10)	0.071*** (3.19)
Log Turnover	-	-	-	-1.556*** (-7.84)	-0.681*** (-3.69)
R-squared	0.016	0.019	0.027	0.061	0.027

Reported t-statistics within parenthesis are based on Whites heteroscedastic standard errors.
Asterisks ***, **, and * denote significance on 1%, 5%, and 10% level.

Table 5: Aggregate trading losses

Then 10,600 investors in sample are sorted into quintiles and top decile of active weight, which is the observed portfolio value observed at first year-end divided by total financial wealth. The net trading payoff for each investor is aggregated into total losses and gains for each of the two groups. The four bottom rows display and normalizes net gains with total financial wealth, total wealth, and income net of capital gains for each investor group. Values are in thousands of Swedish crowns (tSEK), where USD 1 roughly corresponds to SEK 9.

Aggregate trading revenue and wealth	Quintiles by Active weight					All
	1 (Low)	2	3	4	5 (High)	
Total losses, tSEK	-4,773	-6,495	-8,740	-25,258	-17,446	-62,712
Total gains, tSEK	3,260	4,574	7,395	15,950	8,047	39,226
Net gains, tSEK	-1,513	-1,921	-1,345	-9,308	-9,399	-23,486
Financial wealth, tSEK	2,721,510	715,594	529,765	542,274	254,310	4,763,453
Net gains / fin. wealth, %	-0.06	-0.27	-0.25	-1.72	-3.70	-0.49
Wealth, tSEK	5,503,150	2,403,157	2,162,958	2,056,789	1,537,862	13,663,916
Net gains / wealth, %	-0.03	-0.08	-0.06	-0.45	-0.61	-0.17
Income, tSEK	921,176	768,121	763,074	713,012	678,759	3,844,142
Net gains / income, %	-0.16	-0.25	-0.18	-1.31	-1.38	-0.61

Figure 1: The online portfolio weight

The cumulative frequency distribution of the online portfolio weight is plotted for the 10,600 investors in sample. The online portfolio is defined as portfolio value at first, observable year-end, divided by either total market value of risky assets or total financial wealth.

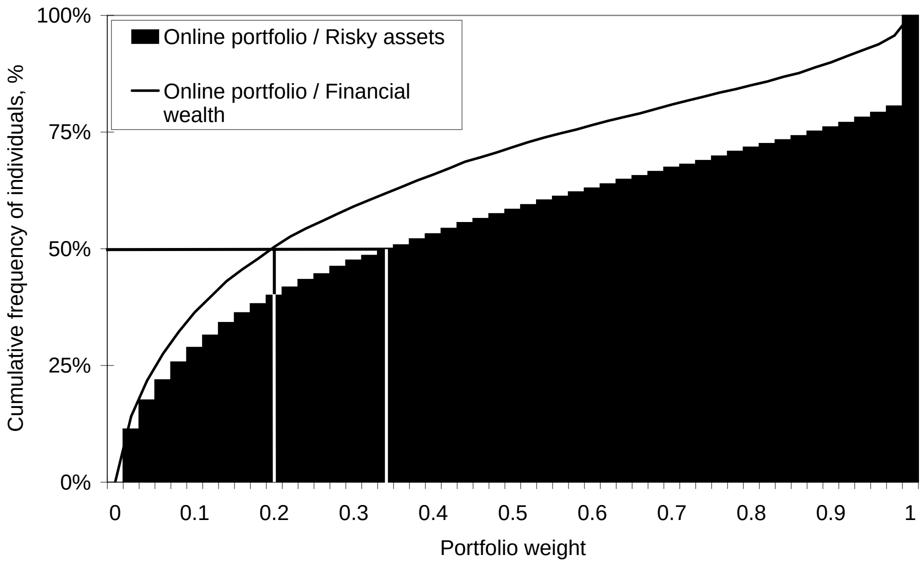

Figure 2: Cumulative frequency distributions of net gains as a share of wealth

Figure 2A depicts the cumulative frequency distribution for the net annualized gains of 10,600 investors in sample, measured as a share of financial wealth as well as total wealth. Figure 2B display net annualized gains divided by financial wealth with and without fees.