The Performance and Persistence of Individual Investors: Rational Agents or Tulip Maniacs?

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Abstract

We examine the performance and persistence of individual investors trading at a Dutch online broker. We use a unique database consisting of more than 68,000 accounts and eight million trades in stocks, bonds and derivatives. The average investor earns negative gross and net returns after accounting for risk and style tilts. The main driver of this result is the underperformance of investors trading derivatives, due to bad market timing and expensive trading. Other significant determinants of cross-sectional variation in investor performance are turnover, gender and account size. We find strong evidence of performance persistence among individual investors, which is only partly driven by persistence in trading costs. Women are more likely to be persistent winners than men and successful investors hold larger accounts with lower turnover.

JEL classification: G11, G12, G14, G24

Keywords: individual investor performance, investor behavior, performance persistence, Internet brokerage, derivatives trading

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1. Introduction

Over the last decade, Internet brokerage has dramatically changed the investment landscape all over the world. Banks and brokers now offer their individual clients Internet based trading systems that embody such features as real-time trading, investment decision tools and streaming price information. Trading costs have fallen over time due to technological innovations and increasing competition. Furthermore, individuals are becoming more and more responsible for their own retirement provision. As a result, professional traders who used to dominate financial markets now find themselves accompanied by a much larger and more diverged crowd: individual investors.

In order to gain a better insight into the trading behavior of individual investors, financial economists have examined their performance using trading records and position statements obtained from brokerage firms.[1] Studies have focused among others on the link between excessive trading and performance (Odean (1998, 1999); Barber and Odean (2000)), the relation between gender and performance (Barber and Odean (2001)), the determinants of portfolio turnover (Statman, Thorley and Vorkink (2006)) and performance persistence of individual investors (Coval, Hirshleifer and Shumway (2005)). However, all these studies focus on investor performance in the United States. Although some studies have looked at the trading behavior of individual investors in Germany (Dorn and Huberman (2005)); Glaser and Weber (2005, 2006)), Finland (Grinblatt and Keloharju (2000, 2001)) and Sweden (Anderson (2005)), the number of accounts in these data sets is small compared to US databases or the sample period is short.

We contribute to this literature by analyzing the relation between individual investor performance and turnover, gender, account value and age in a different market and more recent time period. Furthermore, we extend previous work by comparing the performance of derivatives and non-derivatives traders. This gives us the opportunity to shed light on the question whether individual investors understand the risk and return characteristics of these more complex securities and are able to apply them successfully. Finally, we examine whether individual investor performance is persistent, i.e. are some investors able to consistently earn abnormal returns and, if so, what are the characteristics of these investors and their portfolios?

[1] Although the first studies on the performance of individual investors date back to the end of the seventies (Schlarbaum, Lewellen and Lease (1978a, 1978b)), the topic started to receive widespread attention at the end of the nineties when large databases became available. A comprehensive overview of recent studies on investor behavior is given by Barberis and Thaler (2003).

We use a unique and comprehensive database consisting of more than 68,000 accounts and eight million trades in stocks, bonds, options and futures at the largest online discount broker in the Netherlands. We examine investor performance from January 2000 to March 2006. This time period covers the top of the recent stock market boom in 2000, the large fall in stock prices during its aftermath (2001-2003) and the stage of recovery (2003-2006). We are therefore able to examine whether changes in market movements affect trading behavior and investor performance. Thus, our data set enables us to provide out-of-sample evidence both in the time-series (sample period) dimension and in the cross-sectional (international) dimension.

The Dutch market is also interesting to analyze for historical reasons, since the Amsterdam stock exchange is regarded as the oldest exchange in the world, being established in 1602. Soon futures and options were being traded and in 1978, the Amsterdam Stock Exchange launched the European Options Exchange, the first options exchange in Europe. Kindleberger (2000) describes the long history of financial speculation by Dutch investors, best illustrated by the famous Tulip mania in 1636. Since online trading has attracted many individual investors to financial markets, we examine whether Dutch investors have learned their lesson from history. In particular, do they act like rational agents or tulip maniacs?

We also make several methodological contributions to the literature on individual investor performance. First, in order to adjust returns for risk and style tilts we use the Carhart (1997) four-factor model and a multifactor model in the spirit of Agarwal and Naik (2004). Their model builds on the theoretical framework developed by Glosten and Jagannathan (1994) and includes both traditional buy-and-hold factors and option-based factors designed to capture the nonlinear payoffs of options. In addition, in contrast to existing work on individual investor performance we allow for time variation in risk loadings and style exposures. This is motivated by a large body of empirical evidence showing that systematic risk of stocks and investment styles of funds change through time (see, for example, Franzoni (2006) and Ferson and Schadt (1996)). We estimate time-varying factor exposures using a Kalman filter approach. A recent application of this technique is given by Brunnermeier and Nagel (2004) who use the Kalman filter to estimate the dynamic exposure of hedge funds to the technology sector.

Our empirical analysis shows that the average individual investor earns negative gross and net returns after correcting for risk and style tilts. This finding is mainly driven by investors trading derivatives, as gross alphas for non-derivatives traders are close to zero. The poor performance of derivatives traders is due to bad market timing and high trading costs. Derivatives traders bet on a further market decrease when markets start to recover. Other significant determinants of cross-sectional variation in investor performance are turnover, gender and account value. While the majority of investors do not trade every month, a subset of investors trades very actively. Gross returns of the most active traders are higher than those of less active traders but the picture reverses in terms of net performance. We show that women earn higher net returns than men, partly due to higher trading costs incurred by men. Women outperform men particularly in the period of stock market decline, consistent with the notion that women are more risk averse. Account value is positively related to performance. Investors with large accounts have higher gross returns and their performance is hurt less by trading. Investor age does not seem to be related to performance differentials.

In general, portfolios of individual investors in our sample are tilted towards high market beta securities and small stocks. Furthermore, portfolios exhibit a significant positive exposure to an IT index, particularly during the tech bubble. Factor loadings in the dynamic performance evaluation models show considerable time variation. We also document substantial differences in factor exposures across groups of investors.

We find strong evidence of performance persistence among individual investors. Investors who belong to the top decile based on past one-year performance continue to outperform investors in the bottom decile by 1.5% (gross alpha) and 2.8% (net alpha) per month. Spearman rank correlation coefficients between formation period ordering and evaluation period ranking are significant at the 1% level. Persistence in trading costs explains only part of total performance persistence. None of the decile portfolios manages to beat the market consistently. Gross alphas for the top deciles are close to zero. Net alphas are negative for all portfolios and significant for the bottom three deciles. Losers have significantly higher exposures to the market, SMB, UMD and IT factors than winners. Furthermore, the bottom deciles tend to consist of small accounts with high turnover that are predominantly held by men. Investors in the bottom decile portfolio lose more than 90% of value between 2000 and 2005. Performance persistence is somewhat weaker on shorter horizons but still significant for 6-month periods. We find no evidence of persistence on three-month horizons.

The paper proceeds as follows. Section 2 gives a brief overview of related literature. Section 3 describes the data set and in section 4 we explain our methodology. Section 5 provides empirical evidence on the relation between investor characteristics and performance and section 6 investigates performance persistence. Concluding remarks are offered in section 7.

2. Individual Investor Performance and Behavior: Empirical Evidence

Our work relates to a growing literature on the performance and behavior of individual investors. A puzzling finding of prior research is excessive trading (Odean (1998, 1999)). Barber and Odean (2000) show that excessive trading reduces performance substantially because of high transaction costs. Active investors are not able to offset high trading costs by superior investment returns. Anderson (2005) confirms that most individual investors lose by trading. He finds that investors with a high fraction of total financial wealth invested in the online portfolio have highest turnover and highest losses. Importantly, these investors also have lowest total wealth. He therefore concludes that 'trading losses are mainly carried by those who can afford them the least'. This highlights the need to educate individual investors in financial decision making.

Given the negative impact of trading on performance, many studies attempt to explain excessive trading by individual investors. As pointed out by Black (1986), in perfectly rational markets there will be very little trading in individual securities in equilibrium. In a world where it is known that everyone is rational, investors will be reluctant to trade because if it is rational for the counterparty to trade, the investor must be wrong and loses. Portfolio choice theory asserts that it is optimal for all investors to hold the market portfolio of risky assets, for instance by investing in index mutual funds. Black attributes the observed frequent trading in individual stocks to noise traders. Some investors interpret the noise they trade on as information.[2] Investors with real pieces of information are likely to have different beliefs than the noise traders and, consequently, they are willing to trade.

Odean (1998) relates the concept of noise trading to overconfidence. In particular, he shows in a theoretical framework that investors can become noise traders because they are too confident about the information and the beliefs they have. In turn, the heterogeneity in beliefs leads to excessive trading between investors. Barber and Odean (2001) use gender as a proxy for overconfidence, motivated by psychological evidence that men are generally more overconfident about their financial decision making ability than women. Therefore, they interpret their findings that men trade more often than women, thereby significantly lowering their net returns, as evidence for the overconfidence story of overtrading. Daniel, Hirshleifer and Subrahmanyam

[2] Alternatively, Black points out that investors trade on noise just because they like to trade. Empirical support for this conjecture is given by Grinblatt and Keloharju (2005), who show that investors most prone to sensation seeking trade more frequently. Furthermore, they show that this excessive trading does not lead to higher gross returns and due to transactions costs, overconfident and sensation seeking investors underperform in terms of net return. Anderson (2005) suggests that online investors gamble by frequently making small and unprofitable trades.

(1998) develop a theoretical model of dynamic overconfidence, in which the degree of overconfidence depends on past returns. Statman, Thorley and Vorkink (2006) provide empirical support for dynamic overconfidence models. They find that share turnover is positively related to past returns, which they interpret as evidence of biased self-attribution. After past investment success, individual investors tend to become overconfident about the value of active trading and start trading more frequently. Using questionnaire data, Glaser and Weber (2006) find that investors who think they are superior in terms of investment skills or past performance trade more. In another paper, Glaser and Weber (2005) show that the impact of past portfolio returns on trading volume is stronger for investors who are better able to estimate own past performance.

Although the majority of individual investors lose by trading, Barber and Odean (2000) document considerable cross-sectional variation in market-adjusted performance across investors. In addition, Barber, Lee, Liu and Odean (2004) find strong evidence of performance persistence among a small group of day traders in Taiwan. These successful investors make enough money to cover transaction costs. Coval, Hirshleifer and Shumway (2005) document that some individual investors in the US have 'hot hands', i.e. they are consistently able to beat the market. However, they also identify a group of investors who continue to underperform. Coval et al. show that the performance differential between persistent winners and losers cannot be explained by well-known size, value or momentum strategies. They conclude that skillful investors seem to be able to exploit some other market inefficiencies.

3. Data Description

We use a unique data set of individual investor accounts at the largest Dutch online discount broker. The raw data set contains all individual investor accounts that existed between January 2000 and March 2006. Due to various trading restrictions, accounts owned by minors (age < 18 years) are excluded from the analysis. Accounts that were opened or closed during the time period we investigate are included in the sample for those months in which they were open. Thus, our sample is free from survivorship bias. We impose two restrictions on the sample. First, dormant accounts (accounts that are empty or only consist of cash) are excluded for those months in which they are dormant. In addition, we exclude accounts with a beginning-of-the-month value less than €250. Imposing these restrictions leaves 66,146 accounts and more than two million monthly portfolio overviews.

Table I presents descriptive statistics for the sample of accounts we use in the empirical analysis. The age of accountholders ranges from 18 (due to the exclusion of minors) to 106 years and is on average equal to 45 years. The majority of accounts are held by men (62%). Female accountholders make up 10% of the sample and 28% of all accounts are held jointly by a man and woman. The mean (median) number of trades per account per month is 3.47 (0). The large discrepancy between mean and median indicates that the distribution of trades is skewed. The average number of trades per month equals 3.64 for men and only 2.45 for women, consistent with results documented by Barber and Odean (2001) that men trade more frequently.

Although the majority of investors (65%) do not trade on a monthly basis, a small group trades very often. When only considering investors who are active in a given month the average (median) number of trades is close to 10 (4). Splitting the number of trades into non-derivatives (stocks, bonds) and derivatives (options and futures) shows a striking feature of our sample: the high level of derivatives trading. Out of the total of 8 million trades more than half are trades in derivatives: almost 4 million trades in options (49%) and half a million trades in futures (6%). The remaining 3.5 million trades are in non-derivatives, mainly in stocks.

Also reported in table I are statistics for monthly turnover per account, defined as the average of the value of all security purchases and sales divided by beginning-of-the-month account value. Although average turnover is 32.5%, median turnover is 0%, which shows that the distribution is skewed to the right. Restricting the sample to active accounts, average (median) turnover is 91.6% (24%). Splitting turnover into derivatives and non-derivatives reveals that more than a quarter of turnover is due to derivatives trading. Trading activity in our sample is much higher than in the sample of US accounts analyzed by Barber and Odean (2000) but comparable to results reported by Glaser and Weber (2005) for individual investors in Germany. An important difference between these data sets is that the investors considered by Barber and Odean (2000) do not trade via the Internet. Barber and Odean (2002) show that after switching online investors significantly increase portfolio turnover. High turnover drives transaction costs. Average monthly transaction costs per account are equal to €90 when all accounts are considered and equal to €252 when only active investors are included. Average monthly transaction costs per trade per account equal € 24.34. Average transaction costs for derivatives trades are higher than for non-derivatives trades. Mean (median) account value is €32,327 (€5,370). The distribution of account value shows that although many accounts are relatively small, a few large accounts have a big impact on average account value.

4. Methodology

4.1 Measuring Investor Performance

We define investor performance as the relative change in the combined market value of all assets in the investor's account, taking into account trading of assets and associated transaction costs and deposits and withdrawals of cash and securities. Since we measure performance on a monthly basis we have to make an assumption concerning the timing of deposits and withdrawals. In particular, in order to be conservative we assume that deposits are made at the beginning of the month while withdrawals take place at the end of the month. In appendix A we show that our results are robust to this assumption. In contrast to Barber and Odean (2000, 2001), who assume that all assets are bought or sold on the last day of the month and ignore any intramonth trading, we account for the exact timing of all trades. End-of-the-month account value is net of transaction costs the investor incurred during the month. Thus, performance in terms of returns net of trading costs is calculated as follows

$$R_{jt}^{net} = \frac{(V_{jt} - V_{jt-1} - NDW_{jt})}{(V_{jt-1} + D_{jt})}, \tag{1}$$

where R_{jt}^{net} is the net return on account j in month t, V_{jt} is the account value at the end of month t, NDW_{jt} is the net of deposits and withdrawals during month t and D_{jt} are the deposits during month t. Note that by deriving returns from beginning and end-of-the-month values we implicitly calculate value-weighted returns.

Gross returns are obtained by adding back transaction costs incurred during month t, TC_{jt}, to end-of-the-month account value,

$$R_{jt}^{gross} = \frac{(V_{jt} - V_{jt-1} - NDW_{jt} + TC_{jt})}{(V_{jt-1} + D_{jt})}. \tag{2}$$

In line with Barber, Lee, Liu and Odean (2004) we only consider direct transaction costs (commission) and ignore indirect transaction costs (market impact, bid-ask spread). Individual investor trades are relatively small, so their market impact is likely to be limited. In addition, Keim and Madhavan (1998) point out that quoted bid-ask spreads may be imprecise estimates of the true spread, because trades are often executed inside the quoted spread. Barber and Odean

(2000) therefore estimate the bid-ask spread using transaction prices and closing prices. The drawback of this approach, however, is that the estimate of the spread includes the intraday return on the day of the trade, which can be substantial in the case of derivatives. We calculate gross and net monthly returns for the average investor as

$$\overline{R}_t^{gross} = \frac{1}{N_t}\sum_{j=1}^{N} R_{jt}^{gross} \text{ and } \overline{R}_t^{net} = \frac{1}{N_t}\sum_{j=1}^{N} R_{jt}^{net}, \tag{3}$$

respectively, where N_t denotes the total number of accounts at time t.

4.2 Performance Attribution

The performance of investor portfolios is attributed to different factors in order to obtain the abnormal performance, which is the return left unexplained by the risk factors in the model. However, it is not clear which model should be used to control for risk. Many studies have used the Capital Asset Pricing Model (CAPM) as a benchmark but it is well-known that this model is misspecified. Indeed, as pointed out by Fama and French (2004), positive abnormal returns relative to the predictions of the CAPM can be obtained by investors with no special ability for selecting winners by exploiting return anomalies that have been discovered over the past decades, including the size effect, value premium and momentum effect.

Therefore, in order to make a fair comparison between the performance of different groups of investors style differences should be taken into account. The Fama-French (1993) three-factor model extends the CAPM by including two factors, SMB and HML, related to size and book-to-market (value) effects in returns. In order to account for the momentum effect, Carhart (1997) adds a momentum factor to the three-factor model. Apart from the Carhart model, we also use an extended version of the model to deal with the specific risk/return characteristics of individual investor portfolios. In particular, most investors in our sample not only invest in stocks but also in bonds and options. We therefore include factors designed to capture the exposure from investments in these non-equity assets. We add a bond factor to account for the risk related to fixed income investments. In order to characterize the nonlinear exposure from options we build on the theoretical framework developed by Glosten and Jagannathan (1994). They propose to add option-based factors to models used for performance attribution. Agarwal and Naik (2004) implement this approach to characterize the risk exposure of hedge funds and find that many funds use strategies that result in option-like payoffs. Finally, we add an index of technology stocks to capture possible tech-related style tilts, since several economists argue that the technology bubble was fed by irrational euphoria among individual investors (Brennan (2004); Shiller (2005)). We label this extended Carhart model that consists of eight factors the "Agarwal" model. The general time series model we estimate to obtain risk and style adjusted returns is

$$R_{jt} = \alpha_j + \sum_{k=1}^{K} \beta_{jk} F_{kt} + \varepsilon_{jt}, \tag{4}$$

where R_{jt} denotes the month t return on portfolio j in excess of the risk-free rate, β_{jk} is the loading of portfolio j on factor k and F_{kt} is the month t excess return on the k'th factor mimicking portfolio. The intercept α_j is Jensen's (1968) alpha, which measures abnormal performance with respect to the factors included in the model. The loadings on the factors indicate whether a given portfolio is tilted towards a particular investment style or risk factor.

The factors are constructed for the Dutch market, since the investors in our sample invest predominantly in Dutch assets.[3] In order to characterize the market risk of the equity component of the portfolio returns we include the value-weighted excess return on all stocks in the Worldscope universe for the Netherlands. We choose the Worldscope universe because of its broader market coverage than other indices like the MSCI Netherlands equity index. In addition, following the methodology of Fama and French (1993), we construct the factor mimicking portfolios SMB and HML using the Worldscope universe of Dutch stocks. We also construct our own momentum factor (UMD) according to the procedure outlined by Kenneth French.[4] In order to capture the risk related to bond investments we add the excess return on the 10-year Dutch government bond index (BOND) to the model.[5] Finally, we include the excess returns on liquid at-the-money (ATM) European call and put options on the Dutch AEX market index to capture the nonlinear systematic risk exposure of investors' portfolios. We adopt a procedure similar to that described by Agarwal and Naik (2004) to construct these factors. In particular, at the end of each month an ATM index option that expires two months later is bought. Furthermore, the index option that was bought at the end of the previous month is sold. For the ATM option we select the option whose strike price is closest to the current index value. This rolling strategy of buying

[3] In terms of transaction volume (value) almost 95% (85%) of all trades are transactions in Dutch securities. This suggests the presence of a home bias among Dutch investors, which has previously been documented by French and Poterba (1991) for the US, Japan and UK.

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[5] Since the investors in our data set predominantly invest in Dutch government bonds, we do not add a factor based on a corporate bond index to capture credit risk. Our results are robust to this choice.

and selling calls and puts on the index produces a time series of returns on ATM call and put options. We use the value-weighted index of Dutch stocks from the MSCI IT and Telecommunications sector to capture investors' exposure to the tech sector.

Summary statistics for all factors are provided in table II. Panel A reveals that the return on HML is the only significant factor premium at a 5% level. The average market premium, SMB and UMD are all negative during our sample period, reflecting the large stock market decline from 2000 to 2002. The bond factor is positive and close to significance at the 5% level. The option-based factors are much larger in magnitude than the other factors and very volatile. In line with Agarwal and Naik (2004), we scale the option factors by a factor of 100 to account for the size of option contracts and use the scaled option returns for performance attribution. Panel B of table II shows factor correlations. Naturally, the option-based factors are highly correlated with the market premium and negatively related to each other. The IT factor exhibits strong correlation with the market premium and the two option factors. In our empirical analysis we therefore orthogonalize the option factors and the IT factor with respect to the other factors in the model.

Most existing studies on individual investor performance assume that factor loadings remain constant over time, i.e. unconditional or static models are used for performance attribution. However, a large body of empirical evidence shows that systematic risk of stocks varies substantially over time as a function of the business cycle (see, for example, Franzoni (2006)). Furthermore, in a dynamic world it is unlikely that investors keep their exposure to risk and style factors constant over time. Ferson and Schadt (1996) therefore argue that fluctuations in factor exposures should be taken into account when measuring portfolio performance.

Time variation in loadings can be modeled in several ways. A commonly used approach proposed by Shanken (1990) is to model betas as a function of a set of publicly available conditioning variables (see, for instance, Ferson and Schadt (1996) and Christopherson, Ferson and Glassman (1998)). In order to implement this approach, the factors in the unconditional asset pricing model are scaled with instruments that contain information that is likely to be important for summarizing variation in conditional moments. An important practical problem that arises when using this approach is that the investor's information set is unobservable. Another drawback of this method is that many parameters need to be estimated, especially if the model includes a large number of factors and conditioning variables. This is particularly important since our sample period consists of only 75 months. Other commonly used approaches to estimating time-varying betas are short-window regressions or rolling regressions, in which conditioning variables need not be specified. However, short-window regressions assume that betas remain constant within a given time window while rolling regressions use overlapping observations. In both cases the number of data points used is limited, which reduces estimation precision.

Given the drawbacks of the aforementioned methods for modeling time variation in factor loadings, we employ a different technique. In particular, instead of using conditioning variables, rolling regressions or short-window regressions, we treat the time-varying betas as latent state variables and infer them directly from portfolio returns. Conditional betas are estimated using a Kalman filter approach, explained in appendix B. The following random walk process is assumed for the latent conditional betas:

$$R_{jt} = \alpha_j + \sum_{k=1}^{K} \beta_{jkt} F_{kt} + \varepsilon_{jt} , \qquad \varepsilon_{jt} \sim N(0, \sigma_{j\varepsilon}^2) \tag{5}$$

$$\beta_{jt} = \beta_{jt-1} + \eta_{jt} . \qquad \eta_{jt} \sim N(0, Q) \tag{6}$$

where ε_{jt} and η_{jt} are normally distributed mean zero shocks orthogonal to each other and with variance $\sigma_{j\varepsilon}{}^2$ and diagonal covariance matrix Q, respectively. The state-space representation consists of two equations: eq. (5) is the measurement or signal equation and eq. (6) represents the transition or state equation. The parameters in the model are estimated using maximum likelihood. The restriction Q = 0 corresponds to the null hypothesis of constant parameters, which we test by calculating a likelihood ratio statistic.

5. Empirical Results

5.1 Average Investor Performance

We first discuss performance and factor exposures for the average investor. Table III reports results for this analysis in which accounts are weighted equally. Panel A shows that the average monthly gross return for the full period equals -1.14%, which is economically large but statistically insignificant from zero at conventional levels. In order to shed more light on the poor performance we split the sample period in two sub periods. The sub sample analysis reveals that an average monthly return of -3.46% is earned during the period January 2000 through December 2002, which includes the large stock market decline after the burst of the tech bubble. In the second sub period, from January 2003 to March 2006, the market recovers from the crash and the average monthly return on investor portfolios is 1%. Correcting for risk exposure and style tilts explains part of the negative returns. Specifically, the risk-adjusted monthly return (alpha) obtained from the unconditional Carhart model estimated over the full sample period is -0.58%. The alpha obtained from the Agarwal model is closer to zero and also insignificant.

Obviously, when transaction costs are taken into account performance deteriorates. In particular, the average net return for the full sample period is -1.76% per month, which is just significant at a 5% level. The monthly difference between gross and net returns equals 0.62%, which is substantial given that most investors do not trade every month. Adjusting net returns for risk and style exposures leaves significant alphas of -1.20% and -1.10% for the Carhart and Agarwal models, respectively.

In panel B portfolio returns are adjusted for risk and style tilts by dynamic factor models, in which betas are estimated using the Kalman filter.[6] Alphas obtained from the conditional models are 10 basis points closer to zero than those produced by the static models. Panel C reports OLS beta estimates for the static Agarwal model and Kalman smoothed betas for the dynamic specification of the model.[7] Striking in the static model are the high and significantly positive loadings on the market premium, the SMB factor, the BOND factor and the IT index. This suggests that the portfolio of the average investor is tilted towards small IT stocks with a high exposure to the market. The preference of individual investors for small stocks is consistent with results of Barber and Odean (2000). The high adjusted R^2 indicates that the Agarwal model explains a large part of time variation in portfolio returns.

The sub sample analysis reveals that investors have lowered their exposure to the market, UMD, BOND and IT in the second sub period, indicating a shift away from high-beta, high momentum IT stocks towards a portfolio with lower risk exposures. These fluctuations in exposures are picked up by the dynamic model. This is illustrated by figure 1, which traces the evolution of Kalman smoothed factor loadings.[8] The plot shows that investors often adjust their exposures too late. For instance, individual investors tend to have a high exposure to the market in the first sub period when it is falling and reduce market risk in the second sub period when it recovers. Furthermore, investors reduce their exposure to the IT sector only after the burst of the Internet bubble. Interestingly, Brunnermeier and Nagel (2004) find that hedge funds, which are generally considered to be sophisticated investors, were also riding the technology bubble but

[6] We do not estimate the dynamic models for the sub periods due to the limited number of observations.
[7] All factor loadings we report in this paper are based on gross returns. Loadings are very similar for net returns.
[8] The initial instability in some plots is due to the small number of observations at the start of the recursive estimation procedure.

reduced their exposure to the technology sector before prices collapsed. Finally, the likelihood ratio equals 19.96, rejecting the null hypothesis that all factor loadings are constant at a 1% level. This supports the use of dynamic models for performance evaluation.

5.2 Cross-Sectional Analysis of Investor Performance

The previous section treats individual investors as a homogenous group. However, it is likely that performance differs considerably across different types of investors. In this section we therefore relate investment returns to investor characteristics. We examine the relation between gross and net returns and investor characteristics by applying the cross-sectional methodology developed by Fama and MacBeth (1973). In particular, each month we run a cross-sectional regression of gross or net portfolio returns on investor characteristics,

$$R_{jt} = \gamma_{0t} + \sum_{l=1}^{7} \gamma_{lt} Z_{j,l,t} + v_{jt} , \qquad (7)$$

where R_{jt} denotes gross or net month t excess portfolio return and Z_{jlt} is the value of characteristic l for investor j at time t. Subsequently, we calculate the Fama-MacBeth (FM) estimator for the characteristics, which is the time-series average of the monthly cross-sectional parameter estimates. The standard error of the FM estimator is calculated from the time series of these monthly estimates.

We use the following characteristics as independent variables: $derivatives_{jt}$ and $both_{jt}$, which are two dummy variables equal to one if investor j trades in month t only in derivatives or in both non-derivatives and derivatives, respectively; monthly portfolio $turnover_{jt}$ and $woman_j$ and $joint_j$, which are two gender dummy variables (one indicating woman or an account held by a man and woman jointly, respectively). Furthermore, we include account value at the end of the previous month, $value_{jt-1}$, and age of the primary accountholder, age_{jt}. Because the descriptive statistics in table I reveal that the distributions of turnover and account value display considerable skewness we decide to trim these characteristics at the 99th percentile and use their logarithmic transformations in the cross-sectional regressions. Panel A of table IV presents the correlation matrix for these investor characteristics. All pairwise correlations are below 0.30 in absolute value. The highest correlations are between account value and age (ρ = 0.29) and between the dummy variable for jointly held accounts and age (ρ = 0.25). Because most other correlations are much smaller the regressions do not suffer from serious multicollinearity problems.

Results from the Fama-MacBeth regressions are reported in panel B of table IV. In the first three columns the dependent variable is gross return while in the last three columns net return is the regressant. We run the cross-sectional regressions for the full sample period and the two sub periods defined before, i.e. January 2000 - December 2002 and January 2003 - March 2006, to assess the stability of the relationships between performance and investor characteristics in different market conditions.

The results show that over the full period turnover, gender and account value are significant determinants of gross returns. Specifically, turnover and account value are positively related to returns and accounts held by a woman or a man and woman jointly outperform accounts held by a man only. Controlling for other characteristics, women outperform men by 0.35% a month. However, their outperformance is mainly limited to the first sub period, the period of stock market decline. Thus, women are hurt less by the stock market crash, which could be due to a higher degree of risk averseness. Investor age is insignificant in the regressions and the dummy variable indicating whether an investor only trades derivatives is only significant in the second sub period.[9] The coefficient on this dummy variable implies that derivatives traders underperform non-derivatives traders by 2.55% a month in the period January 2003 - March 2006 even though they outperformed in the first sub period by 0.95% a month.

While in terms of gross returns derivatives traders underperform non-derivatives traders only in the second sub period, after transaction costs are taken into account they underperform over the full period by more than 4% a month. However, the bad performance of derivatives traders is still mainly driven by the second sub period. Furthermore, since turnover drives transactions costs, when net return is used as dependent variable the positive relation between turnover and performance vanishes and turns significantly negative in the second sub period. The two gender dummies and account value are still significant. In fact, coefficients on these variables have increased, which indicates that the outperformance of women and large accounts grow when net return is used as a measure of performance. Given the results from the Fama-MacBeth analysis, we dig further into the relation between performance and derivatives trading, turnover, gender and account size in the next sections.

[9] A univariate sort on age shows that young investors underperform older investors due to expensive trading. However, in the cross-sectional regressions the effect of age is picked up by the variables turnover, value and joint.

5.3 Derivatives versus Non-Derivatives

Table V compares the performance of investors trading only derivatives, non-derivatives or both derivatives and non-derivatives. At the end of each month investors are sorted into three groups based on whether they traded derivatives, non-derivatives or both during that month. Subsequently, for each of these groups we calculate the gross and net performance for the particular month. Confirming the results from the Fama-MacBeth analysis, the most important finding is that the difference in performance between derivatives and non-derivatives traders is huge. In terms of gross raw returns derivatives traders underperform non-derivatives traders by on average -1.73% per month (panel A). Accounting for risk and style differences has a marginal effect on the difference. Gross alphas for derivatives traders are negative and significant at a 1% level. In contrast, alphas for non-derivatives traders and investors trading both derivatives and non-derivatives are close to zero and insignificant. Thus, non-derivatives traders do not underperform risk and style benchmarks when transaction costs are ignored.

Looking at net performance shown in panel B, the picture for derivatives traders becomes even gloomier. In terms of raw returns, the difference between derivatives and non-derivatives traders almost doubles. Focusing on alphas derivatives traders underperform their counterparts by more than 2% a month. This can partly be explained by the transaction cost structure. Trading costs for derivatives consist of a specific amount per contract, whereas trading costs for non-derivatives are based on a fixed amount and a variable part that depends on transaction value. Individual investors tend to trade many small derivatives contracts, which makes the relative cost of trading options higher than trading stocks or bonds, as shown in table I.

Panels C and D indicate that allowing for time variation in risk and investment styles does not reduce the relative underperformance of derivatives traders. Panel E reveals that in terms of factor exposures derivatives traders differ from other investors. Specifically, their loadings on the market and SMB factors are significantly lower than those of the other two groups. As expected, their exposure to the call option factor is higher and significant. The coefficient on the put option factor is insignificant, suggesting that derivatives traders predominantly use calls rather than puts. Finally, the low adjusted R^2 for the derivatives-only group indicates that the Agarwal model has some trouble explaining variation in their portfolio returns even though the option-based factors have considerable explanatory power, increasing the adjusted R^2 by 7 percentage points.[10]

[10] It is known from the literature on hedge fund performance that linear factor models have less explanatory power for portfolios with a large option component due to non-linearities in option payoffs (e.g. Fung and Hsieh, 2001).

In order to shed more light on the large underperformance of derivatives-only traders we also examine the two sub periods defined before (results are not reported to save space). In line with results of the Fama-MacBeth regressions, in terms of gross raw return and Agarwal alpha derivatives traders outperform non-derivatives traders by 0.25% a month in the first sub period. In the second sub period, however, derivatives traders do not profit from the general recovery of financial markets and lose on average more than 3% per month relative to non-derivatives traders, who earn a positive return of 1.84% a month. Correcting for risk and style differences reduces the performance gap between the two groups only to a small extent. In terms of net returns derivatives traders also underperform non-derivatives traders in the first sub period, by on average 1% per month. In the second sub period the return difference widens to 5% per month.

The relative underperformance of derivatives traders when the general market movement is upward suggests that they have bad market timing skills. After the large stock market decline in 2001 and 2002 investors were bearish about market prospects and expected a further fall. However, it is important to realize that clients of the brokerage firm cannot sell stocks short. The only way to speculate on a market decrease is through the use of derivatives. Figure 2 displays the return on the market index, the gross return difference between non-derivatives and derivatives traders and the ratio of derivatives positions speculating on a market increase and positions taken in anticipation of a market decrease, which we call the “Hausse-Baisse ratio”. This ratio is calculated as the sum of the value of call options bought and put options sold divided by the sum of the value of put options bought and call options sold. The plot indicates that this ratio is below one for most months in 2003 and 2004, which is exactly the time when the market started to recover from the downfall. The gross return difference between non-derivatives and derivatives traders grows considerably in this period.

In sum, these results suggest that after the market collapse in 2001 and 2002, derivatives traders speculated on a further decline of the market. As a result, they missed the recovery of the market from 2003 to 2006 and underperformed other investors. Although derivatives can also be used to hedge other positions, it is unlikely that the investors in our sample use derivatives for hedging purposes. In an online survey among 1500 clients of the Internet brokerage firm, more than 80% of the investors indicate that they use options predominantly for speculation. Furthermore, investors seem to lack knowledge about the use of derivatives. Only 10% of investors participating in the survey uses option Greeks when trading options.

5.4 Turnover and Performance

In section 5.1 we noted that the difference between gross and net performance for the average investor is considerable. This seems surprising since the descriptive statistics in table I indicate that most investors do not trade every month. We now analyze this finding in more detail by comparing the performance of investors sorted on trading activity. Specifically, at the end of each month we form three quantiles of investors who traded during the month based on turnover and compare their risk and return characteristics.[11] Note that we exclude accounts with no turnover here because the number of accounts in this group would be much larger than the number of investors in other segments.[12] Average monthly turnover breakpoints are 15% and 75%.

Results presented in table VI show that accounts with highest turnover outperform the other two quantiles in terms of gross performance by more than 2% per month. In fact, the high turnover segment is the only group that manages to earn positive alphas. However, in terms of net performance the most active investors rank last. Transaction costs reduce the performance of the highest turnover quantile by on average 3.50% per month. In contrast, for the low and medium turnover quantiles, the difference between gross and net returns is only 0.20% and 0.75% per month, respectively. Accounting for time variation in risk loadings and style exposures (panel C and D) does not change these conclusions.

In short, although most investors do not trade every month, a small group trades very frequently, thereby incurring high transaction costs. While accounts with high turnover outperform in gross terms, they underperform the other two quantiles after taking transactions costs into account. In contrast, Barber and Odean (2000) find that those who trade most do not earn higher gross returns than less active investors. Our results suggest that the trades of active traders seem to be motivated by some information signals, since they generate positive gross alphas. Nevertheless, these gains are insufficient to offset trading costs. This conclusion is in line with findings of Barber, Lee, Liu and Odean (2004), who document that although heavy traders earn gross profits, these are not large enough to cover transaction costs.

5.5 Men versus Women

The Fama-MacBeth regressions in table IV show that accounts held by a woman or by a man and woman jointly outperform accounts held by a man only. In this section we dig further into

[11] Using number of trades as a measure of trading activity does not alter the conclusions.

[12] Gross performance of accounts with no turnover is comparable to that of the quantile with lowest turnover while net performance is 0.20% higher, both in terms of raw returns and risk and style adjusted returns.

the relationship between investor performance and gender by analyzing the risk and return characteristics of portfolios sorted on gender. Panel A of table VII confirms that women earn significantly higher gross returns than men. The difference in raw return is 0.39% per month and the difference in alphas produced by the static Carhart and Agarwal models is 0.31% and 0.26%, respectively. Panel B reports net returns and shows that the outperformance of women relative to men increases to 0.67% a month, which implies that due to more expensive trading men reduce their returns more than women. Although in terms of alpha the difference is smaller it is significant at the 1% level. As expected, the performance of the third group, i.e. accounts jointly held by men and women, is in between the performance of the two other groups.

Panels C and D present gross and net alphas produced by dynamic specifications of the Carhart and Agarwal models. On average, these alphas are 10 basis points per month higher than those obtained from the unconditional models. However, the conclusion that women outperform men in terms of gross and net performance remains unchanged. Finally, panel E shows that accounts held by men load significantly higher on the market, SMB, BOND, ATMC and IT factors than those held by women or a man and woman jointly. The higher exposures of men to the risk factors is consistent with the notion that men are less risk averse than women.

5.6 Small versus Big

Account value is the last significant determinant of the cross-section of individual investor returns identified by the Fama-Macbeth regressions. Barber and Odean (2000) partition investors into quintiles based on the value of their portfolio of stocks. They find that small portfolios earn higher gross returns than large portfolios but the difference is not statistically significant. After accounting for transaction costs and risk, the return difference between small and large accounts diminishes further. These results contrast the positive relation between portfolio value and trading performance documented by Anderson (2005) for a sample of Swedish investors.

In order to investigate the relation between account value and performance in our sample we group investors into quintiles based on the total value of their account at the end of month *t-1*. Subsequently, we calculate portfolio returns for every quintile for month *t*. Results shown in panel A of table VIII indicate that gross returns and alphas increase uniformly with account size. On average, the largest size quintile outperforms the smallest quintile by 1% per month. These results are in line with those documented by Anderson (2005) but inconsistent with the findings of Barber and Odean (2000). Correcting for differences in risk and style exposures reduces the performance gap only slightly. When transaction costs are accounted for (panel B) returns continue to increase with account size. In fact, the difference in terms of net performance between the largest and smallest quintile has doubled. The quintile of largest accounts outperforms the smallest quintile by almost 2% per month in terms of net returns and 1.5% in terms of net alpha, which is significant at a 1% level.

Although the differences in alphas between large and small accounts become somewhat smaller when time variation in risk and style loadings is modeled they remain significant. Panel E indicates that investors with large accounts have significantly lower exposures to the market factor, SMB, BOND and the IT factor than investors with small accounts.

6. Performance Persistence of Individual Investors

The previous sections have shown that on average individual investors underperform relevant risk and style benchmarks, particularly due to excessive trading and investments in derivatives. However, our analysis also shows that the group of individual investors is extremely heterogeneous. In addition, Barber and Odean (2000) show that, although the majority of individual investors lose by trading, the top quartile of investors in their data set beats the market by six percent a year, after accounting for transaction costs. Therefore, in this section we perform persistence tests in order to identify investors who consistently earn positive or negative alphas, i.e. persistent winners or losers.

Barber, Lee, Liu and Odean (2004) identify a small group of individual day traders in Taiwan who are able to consistently earn profits sufficiently large to cover transaction costs. Empirical evidence of individual investor performance persistence in the United States is provided by Coval, Hirshleifer and Shumway (2005). They show that some individual investors are consistently able to beat the market, i.e. these investors seem to have ‘hot hands’. However, they also identify a group of investors who underperform the market persistently. In particular, to examine long horizon performance persistence, Coval et al. sort investors into deciles based on characteristic adjusted performance in the first half of their sample (1990 - 1993) and evaluate the performance of these deciles in the second half of the sample (1994 - 1996). They find that investors in the top past performance decile outperform those in the bottom decile by almost 8 percent per year, which is statistically significant at low levels. Because the return differential cannot be explained by size, value or momentum strategies, Coval et al. suggest that skillful individual investors are able exploit some other market inefficiencies.

At first sight it seems surprising that some individual investors can persistently outperform the market, given the mixed evidence of performance persistence for mutual funds, which are generally considered to be more sophisticated investors[13]. Coval et al. note that while it is unlikely that individual investors are better informed than mutual fund managers, they are better able to exploit superior information for two reasons. First, individual investors usually trade smaller positions and consequently, the price impact of their trades is less. Second, individual investors face fewer constraints when deciding on their asset allocation, as they are not required to hold a diversified portfolio or track a specified benchmark.

Given the evidence of performance persistence documented by Barber et al. (2004) and Coval et al. (2005), we examine whether we can confirm their finding for a different market using a more recent data set that incorporates derivatives trading. Following Carhart (1997), we sort investors into decile portfolios based on raw returns during a ranking period. Carhart motivates ranking on the basis of raw returns instead of alphas by pointing out that if the same asset pricing model is used for sorting and evaluating, performance will be affected by any model bias between ranking and formation periods. Another reason for sorting on raw return instead of alpha is that over time investors enter and drop out of the sample. As a result, the number of investors present in the data set for the entire sample period is limited. Estimating the performance attribution models for a given investor using a small number of time series observations would lead to imprecise estimates.

Subsequently, we calculate returns for each of these deciles over a post-ranking period. Repeating the ranking procedure using non-overlapping intervals, we obtain a time series of post-ranking returns for each decile. In line with Carhart, accounts that drop out of the data set during the evaluation period are included in the decile portfolios until they disappear, after which portfolio weights are readjusted. We use the time series of returns as dependent variable in the Carhart and Agarwal models to compute risk and style adjusted returns. We test whether past winners (losers) continue to outperform (underperform) by performing a t-test on the performance difference between decile 1 (past winners) and decile 10 (past losers). Furthermore, we calculate Spearman rank correlation coefficients between the formation period ranking and the evaluation period ranking. The null hypothesis of the nonparametric Spearman test is that there is no relation between formation and evaluation period ranking.

[13] Evidence of persistence in mutual fund performance is documented by Grinblatt and Titman (1992), Hendricks, Patel and Zeckhauser (1993), Brown and Goetzmann (1995), Elton, Gruber and Blake (1996) and Busse and Irvine (2006). However, Carhart (1997) shows that most of the persistence is related to expenses and momentum strategies.

In order to examine whether persistence, if any, is due to persistence in transaction costs we perform the analysis for both gross and net returns. In particular, if we find evidence of performance persistence when sorting on net returns but no sign of persistence in gross returns, we conclude that persistence is related to costs. We consider three-month, six-month and twelve-month ranking and evaluation periods. This choice is based on evidence reported in the mutual fund literature that performance persistence is usually short term (Busse and Irvine, 2006). Moreover, using longer periods implies that fewer investors can be included in the analysis, because we require an account to be present in the sample during the complete ranking period and at least one month of the evaluation period. On the other hand, results for periods shorter than three months are likely to be dominated by noise and luck.

Table IX presents average monthly returns and Carhart and Agarwal alphas for portfolios of investors formed on past one-year return. Results in the columns labeled 'gross' ('net') refer to deciles formed and evaluated on gross (net) performance. The results indicate that the top decile continues to outperform the bottom decile in the year subsequent to the formation year by on average 1.20% per month in terms of gross return and 2.39% in terms of net return. A substantial part of the performance differential is driven by the bad performance of past losers. Gross and net returns for decile 10 are 0.73% and 1.38% lower, respectively, than for decile 9. However, it is noteworthy that in the evaluation period decile 1 is no longer the best performing segment. As we will see later, this result also holds for other performance measures and ranking and evaluation periods. Nevertheless, the Spearman rank correlation is significant at the 1% level for both gross and net returns, indicating a strong relation between formation and evaluation period ranking.

The large spread in returns across deciles is illustrated by figure 3, which plots post-formation cumulative net returns for the ten deciles and the Worldscope Netherlands index. The figure identifies three clusters of investors: top performers (decile 1, 2 and 3), average performers (decile 4, 5 and 6) and losers (decile 7, 8, 9 and 10). Only investors in the top deciles of the ranking period manage to stay close to the market return in the evaluation period. In contrast, investors in decile 10 lose 90% of their initial account value in the five-year period from December 2000 to December 2005.

The large performance differential between past winners and past losers in the evaluation period also shows up when Carhart and Agarwal alphas are used to measure performance. Investors in decile 1 earn gross and net alphas that are 1.5% and 2.8% higher, respectively, than those earned by investors in decile 10. These differences are significant at the 1% level.

Spearman rank correlation coefficients exceed 0.9 and are significant at the 1% level, providing strong evidence of performance persistence among individual investors. Decile 1 and 2 manage to earn positive but insignificant gross alphas. All other deciles earn negative but insignificant gross alphas. Net alphas are negative for all deciles and significant for the bottom three (Carhart) or four (Agarwal) deciles. The losses of decile 10 investors are substantial. In terms of gross alpha decile 10 loses -1.5% per month while in terms of net alpha this even doubles to -3%. These results suggest that many investors would be better off by investing in an index mutual fund, which is expected to produce a gross alpha close to zero and a net alpha of approximately -0.10% a month due to fees.

Finally, table IX reports factor loadings for the decile portfolios in the Agarwal model. Winner deciles tend to have significantly lower loadings on the market, SMB, UMD and IT factors than loser deciles. In particular, the high exposure of decile 10 investors to the market (1.93), the SMB factor (1.86), and the IT factor (0.80) reveal strong style tilts in their portfolios towards high market beta stocks, small caps and tech stocks.

Results for six-month and three-month ranking and evaluation periods are presented in table X. The general picture is that performance persistence is somewhat weaker on short horizons. However, Spearman correlation coefficients for the six-month periods are still significant at the 5% level. Decile 1 gross returns are 1.2% higher than those of decile 10 while net returns of the top decile exceed those of the bottom decile by 2.4%. While these differences are smaller than those reported for the one-year period they are still significant at a 1% level. The difference is again partly driven by the underperformance of decile 10 relative to all other deciles. Adjusting for risk and style differences by the Carhart and Agarwal models reduces the performance difference to 0.8% and 0.5%, respectively, in gross terms and 2% and 1.7%, respectively, in net terms. Gross alphas for the top deciles are again close to zero. Net alphas are negative for all deciles but only significant for the bottom four deciles. The six-month ranking and evaluation period therefore confirms the conclusion from table IX that the top decile investors are able to match the performance of the market. However, a large group of investors continues to lose substantially, thereby dragging down performance of the average investor in our sample.

In contrast to the findings for the one-year and six-month periods, results for the three-month formation and evaluation period do not provide significant evidence of performance persistence. Spearman correlation coefficients for deciles formed and evaluated on gross performance are positive but below 0.2. When net performance is used for ranking and evaluating the correlation is around 0.5, which is insignificant at conventional levels. However, the difference between the rank correlation for gross and net performance indicates that persistence on short term horizons, if any, is driven by persistence in transaction costs. Despite the absence of significant persistence on short horizons, the bottom decile continues to underperform the other deciles.

Given the significant evidence of performance persistence on one-year and six-month horizons, we investigate whether performance differentials between winner and loser decile portfolios are related to heterogeneity in investor characteristics. Table XI presents characteristics for portfolios of investors sorted on past one-year net return. Also shown are Spearman rank correlations that measure the relation between rank ordering in the formation period based on net return and ranking in the evaluation period based on the characteristic, where the decile portfolio with the highest value for the characteristic is ranked decile 1 in the evaluation period. Median account value decreases uniformly with ranking, i.e. the top decile consists of the largest accounts while the smallest investors dominate the bottom decile. Furthermore, while for most of the top deciles (except decile 1) derivatives turnover is only 5%, for the bottom deciles it is much higher, with decile 10 having derivatives turnover of more than 40% a month. These results are consistent with those of section 5.3 where the underperformance of derivatives traders was highlighted. Variation in non-derivatives turnover across top deciles is larger but once again bottom deciles have much higher turnover than top deciles, which explains part of their low net returns. Table XI also reveals that in the bottom deciles a higher percentage of accounts are held by a man than in the top deciles. Approximately 10% of accounts in the top deciles are held by a woman compared to 5% of accounts in the bottom deciles. The proportion of accounts held by a man and woman jointly is also somewhat higher in the top deciles (not reported). Finally, age of the investor does not seem to be related to performance persistence. In sum, accounts with high value, low turnover and held by a woman tend to perform best.

7. Conclusion

We provide new evidence on the performance, persistence and behavior of individual investors. We analyze returns earned on stock, bond and derivatives investments of more than 68,000 investors trading at the largest Dutch online discount broker. Our sample period ranges from January 2000 to March 2006, which covers both the burst of the Internet bubble and the subsequent recovery of financial markets. We show that the average investor earns negative returns after adjusting for risk and style tilts. Individual investors not only underperform in terms of net performance but also earn negative gross returns. These results are mainly driven by the performance of investors trading derivatives, as gross alphas for non-derivatives traders are close to zero. Due to bad market timing derivatives traders underperforms other investors by on average 1.60% per month in gross terms and 3.30% in terms of net return. Derivatives traders incur higher transaction costs than other investors and speculate on a market decrease when markets start to recover. Furthermore, we document that while the majority of investors do not trade every month, a subset of investors trades very actively. Although gross returns of the most active traders are significantly higher than those of less active traders, the picture is opposite in terms of net performance. The large losses from excessive trading and investments in derivatives stress the need to educate individual investors in financial decision making.

When sorting investors according to gender we confirm the finding of Barber and Odean (2001) that women earn higher net returns than men due to higher trading costs incurred by men. However, in contrast to Barber and Odean we find that women also outperform in terms of gross performance. In addition, we show that investors with large accounts have higher gross returns than small accounts and their performance is hurt less by trading. Investor age is not a significant determinant of individual investor returns after controlling for other factors.

In general, portfolios of individual investors in our sample are tilted towards high market beta stocks and small firms. Furthermore, portfolios exhibit a significant positive exposure to the IT sector, particularly during the tech bubble. Factor loadings in the dynamic performance attribution models, estimated using a Kalman filter approach, show considerable time variation. Our analysis also reveals substantial differences in factor exposures between groups of investors.

We find strong evidence of performance persistence among individual investors. Investors ranked in the top decile portfolio based on past one-year performance continue to outperform investors in the bottom decile by 1.5% (gross alpha) and 2.8% (net alpha) per month over the next year. Persistence in trading costs explains only part of performance persistence. Net alphas are negative for all portfolios and significant for the bottom three deciles. Losers tend to have significantly higher exposures to the market, SMB, UMD and IT factors than winners. Furthermore, the bottom deciles tend to consist of small accounts that have high turnover and are predominantly held by men. Performance persistence is somewhat weaker on shorter horizons but still significant for 6-month periods. In general, our results show that the group of individual investors is extremely heterogeneous and we confirm the theoretical prediction of Black (1986) that most investors would be better off by investing in an index fund.

Appendix A: Timing Assumption of Deposits and Withdrawals

As explained in section 4, in order to be conservative we make the assumption that deposits are made at the beginning of the month while withdrawals take place at the end of the month, which follows the approach of Anderson (2005). This ensures that returns can only be generated by funds the investor actually has. In this appendix we show that our results are robust to this assumption. Here we assume that deposits and withdrawals are made halfway the month. Performance in terms of returns net of trading costs is then calculated as follows[14]

$$R_{jt}^{net} = \frac{(V_{jt} - ½NDW_{jt}) - (V_{jt-1} + ½NDW_{jt})}{(V_{jt-1} + ½NDW_{jt})}, \tag{A1}$$

where R_{jt}^{net} is the net return on portfolio *j* in month *t*, V_{jt} is the account value at the end of month *t*, and NDW_{jt} is the net of deposits and withdrawals during month *t*.

Gross returns are obtained by adding back transaction costs incurred during month *t*, TC_{jt}, to the end-of-the-month account value,

$$R_{jt}^{gross} = \frac{(V_{jt} - ½NDW_{jt} + TC_{jt}) - (V_{jt-1} + ½NDW_{jt})}{(V_{jt-1} + ½NDW_{jt})}. \tag{A2}$$

The main conclusions drawn in the text do not change when the analysis uses returns calculated according to this approach.[15]

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[14] As an example, suppose that the beginning-of-the month account value is 1000, the end-of-the-month value is 2000, deposits during the month amount to 500 and withdrawals equal 100. The net return is then equal to [(2000-½(500-100)) – (1000 + ½(500-100))]/ (1000 + ½(500-100)) = 50%.

[15] Results are available upon request from the authors.

Appendix B: Kalman Filter[16]

For ease of exposition we repeat the state space model introduced in section 4.2 here:

$$R_{jt} = \alpha_j + \sum_{k=1}^{K} \beta_{jkt} F_{kt} + \varepsilon_{jt} , \qquad \varepsilon_{jt} \sim N(0, \sigma^2_{j\varepsilon}) \tag{B1}$$

$$\beta_{jt} = \beta_{jt-1} + \eta_{jt} . \qquad \eta_{jt} \sim N(0, Q) \tag{B2}$$

The Kalman filter is a recursive algorithm for sequentially updating the one-step ahead estimate of the state mean and variance given new realizations of the dependent variable R_t in the measurement equation (B1). It calculates maximum likelihood estimates of the model parameters σ^2_ε and Q along with optimal (minimum mean-square error) estimates of the state variables β_t, i.e. the factor loadings in our case.[17] The procedure consists of two stages, the prediction phase and the updating phase. In the prediction phase first $\beta_{t|t-1}$ is calculated, which is the expected value of β at time t using information up to $t-1$. Then $R_{t|t-1}$ is computed, the dependent variable in the measurement equation. After one observation (one month) the 'true' value of R_t becomes known. It is then possible to compare the estimate, $R_{t|t-1}$, with the realized value, R_t, to obtain the one-step ahead forecast error, $n_{t|t-1}$, and its variance, $f_{t|t-1}$. This information is used to update the estimates of the state variables, i.e. to obtain $\beta_{t|t}$ and its variance $P_{t|t}$. These updated estimates are a weighted average of the initial estimate $\beta_{t|t-1}$ and the prediction error $n_{t|t-1}$. Thus, the transition equation (B2) projects forward (*a priori*), while the measurement equation (B1) receives the feedback (*a posteriori*). This prediction and updating sequence is summarized in eqs. (B3) - (B8).

$$\beta_{t|t-1} = \beta_{t-1|t-1} , \tag{B3}$$

$$P_{t|t-1} = P_{t-1|t-1} + Q , \tag{B4}$$

$$n_{t|t-1} = R_t - R_{t|t-1} = R_t - F_t \beta_{t|t-1} \tag{B5}$$

$$f_{t|t-1} = \sigma^2_\varepsilon + F_t P_{t|t-1} F_t' \tag{B6}$$

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1} F_t' f^{-1}_{t|t-1} n_{t|t-1} , \tag{B7}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1} F_t' f^{-1}_{t|t-1} F_t P_{t|t-1} . \tag{B8}$$

[16] Hamilton (1994) and Durbin and Koopman (2001) provide a thorough derivation of the Kalman filter.
[17] For notational simplicity we omit the cross-section subscript *j* here.

The first four equations represent the prediction phase while the last two equations refer to the updating procedure. The second term on the right hand side in eq. (B7) that is multiplied by the one-step ahead prediction error $n_{t|t-1}$ is known as the *Kalman gain*, which denotes the adjustment of $\beta_{t|t-1}$ to reflect the disclosure of the prediction error. We set the initial one-step ahead predicted values for the states, $\beta_{1|0}$, equal to the OLS estimates from the static model. In the dynamic Carhart model we treat the initial one-step ahead predicted value of the diagonal covariance matrix Q as diffuse, setting it to an arbitrarily large number. To ensure unique identification of the parameters in the Agarwal model we use the variance estimates of the state variables from the Carhart model as initial predicted values for the variances of the loadings on R_M, SMB, HML and UMD and initialize the variance for the other states using diffuse priors. Under the normality assumption of the disturbances in the measurement equation and the transition equation, the log-likelihood function for the state space model can be written as

$$\log L = -\frac{1}{2}\sum_{t=1}^{T}\left[\log(2\pi f_{t|t-1}) + \frac{n_{t|t-1}^{2}}{f_{t|t-1}}\right]. \tag{B9}$$

Maximizing this function results with respect to σ_{ε}^{2} and Q produces a series of one-step ahead forecasts of the state and its variance, $\beta_{t|t-1}$ and $P_{t|t-1}$, the filtered estimate of the state and its variance, $\beta_{t|t}$ and $P_{t|t}$, and the smoothed estimates of the state and its variance, $\beta_{t|T}$ and $P_{t|T}$. The difference between the filtered and the smoothed estimates is that the former are conditioned on the information set from the *current* period while the latter are conditioned on information from the *complete* sample period. Smoothed estimates are obtained by using a smoothing algorithm, described by eqs. (B10) and (B11), which is iterated backward in time to obtain $\beta_{t|T}$ and $P_{t|T}$ for any time t = 1, ..., T.

$$\beta_{t|T} = \beta_{t|t} + P_{t|t}P_{t+1|t}^{-1}(\beta_{t+1|T} - \beta_{t|t})\,, \tag{B10}$$

$$P_{t|T} = P_{t|t} + P_{t|t}P_{t+1|t}^{-1}(P_{t+1|T} - P_{t+1|t})P_{t+1|t}^{-1\prime}P_{t|t}^{-1}\,. \tag{B11}$$

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Table I

Descriptive Statistics on Individual Investor Accounts and Trades

This table presents descriptive statistics for a sample of 68,146 individual investor accounts at a large Dutch online brokerage firm from January 2000 to March 2006. Age is the age of the primary accountholder. Trades are the number of trades per account per month. This is split into trades of non-derivatives (stocks, bonds) and derivatives (options and futures contracts). Turnover is the average of the value of all purchases and sales in a given month per account divided by the beginning-of-the-month account value. TC all are monthly transaction costs in euros per account based on all accounts. Trades active, turnover active, and TC active are based on all accounts that trade in a given month. TC/trade are monthly transaction costs in euros per trade per account. This is split into trades in non-derivatives, options and futures contracts. Account value is the market value of all assets in the investor's account. For each variable the mean, median, standard deviation as well as 1st, 5th, 25th, 75th, 95th and 99th percentile values are reported.

	Mean	Median	Std. Dev.	1st	5th	25th	75th	95th	99th
Age (years)	44.67	43	12.38	21	26	35	54	66	75
Trades (#)	3.47	0	15.96	0	0	0	2	17	52
Non-derivatives	*1.55*	*0*	*6.43*	*0*	*0*	*0*	*1*	*8*	*25*
Derivatives	*1.92*	*0*	*13.99*	*0*	*0*	*0*	*0*	*9*	*37*
Trades active (#)	9.78	4	25.63	1	1	2	10	37	90
Non-derivatives	*4.36*	*2*	*10.21*	*0*	*0*	*1*	*4*	*17*	*45*
Derivatives	*5.42*	*0*	*23.09*	*0*	*0*	*0*	*4*	*24*	*70*
Turnover (%)	32.53	0	211.93	0	0	0	10.13	123.51	561.97
Non-derivatives	*23.68*	*0*	*184.96*	*0*	*0*	*0*	*2.38*	*83.33*	*425.42*
Derivatives	*8.85*	*0*	*100.83*	*0*	*0*	*0*	*0*	*25.60*	*172.63*
Turnover active (%)	91.67	24	347.92	0.08	1.01	7.95	63.99	344.57	1203.60
Non-derivatives	*66.73*	*12*	*305.94*	*0*	*0*	*0.22*	*42.70*	*247.49*	*987.80*
Derivatives	*24.94*	*0*	*167.77*	*0*	*0*	*0*	*8.35*	*95.42*	*427.24*
TC all (€)	89.56	0	521.03	0	0	0	31.34	390.65	1,470.78
TC active (€)	252.18	69.00	851.01	0.13	12	26.53	204.00	968.33	2,878.40
TC/trade (€)	24.34	15.60	40.09	0.13	10.83	13.03	24.38	61.24	143.91
Non-derivatives	*21.78*	*14.71*	*27.31*	*1.72*	*10.50*	*12.00*	*22.42*	*53.68*	*118.04*
Derivatives	*31.85*	*16.25*	*73.08*	*5.00*	*13.50*	*13.50*	*28.13*	*86.57*	*262.50*
Account Value (€)	32,327	7,773	145,726	297	510	2,376	24,682	123,693	387,625

Table II

Summary Statistics of Factor Premia

This table presents summary statistics for 75 months from January 2000 through March 2006. Panel A reports the monthly mean, standard deviation and t-statistic of the mean for factors included in multifactor models for performance evaluation. These factors are the market premium (R_M), the Fama-French (1993) factor mimicking portfolios SMB and HML, a momentum factor (UMD), a government bond factor (BOND), excess returns on at-the-money call and put index options, ATMC* and ATMP*, respectively, constructed according to the procedure outlined in section 4, and IT*, the excess return on a value-weighted MSCI IT and Telecommunications Index for the Netherlands. In the factor models we use orthogonalized versions of the option factors and the IT index denoted by ATMC, ATMP and IT, respectively. Panel B shows pairwise correlations between all factors.

	R_M	SMB	HML	UMD	BOND	ATMC*	ATMP*	IT*
	Panel A: Summary Statistics							
Mean	-0.49	-0.55	1.14	-0.16	0.31	-9.60	-4.27	-1.53
Std. dev.	6.42	3.71	4.28	7.27	1.40	83.67	108.56	11.11
t(Mean)	-0.67	-1.28	2.30	-0.20	1.95	-0.99	-0.34	-1.20
	Panel B: Correlation Matrix							
R_M	1							
SMB	-0.01	1						
HML	0.39	-0.07	1					
UMD	-0.49	0.10	-0.50	1				
BOND	-0.42	-0.02	-0.13	0.15	1			
ATMC*	0.80	0.09	0.20	-0.25	-0.39	1		
ATMP*	-0.90	0.03	-0.32	0.36	0.33	-0.70	1	
IT*	0.70	0.51	0.24	-0.22	-0.26	0.62	-0.64	1

Table III

Raw and Risk- and Style-Adjusted Returns and Factor Loadings for the Average Investor

This table reports gross and net monthly returns for 68,146 equally-weighted individual investor accounts over the period January 2000 through March 2006. Panel A shows average raw returns and returns adjusted for risk and style tilts using the Carhart four-factor model and Agarwal eight-factor model with fixed factor loadings. Raw returns and alphas are presented for the full sample period as well as for two sub periods, the first from January 2000 to December 2002 and the second from January 2003 to March 2006. T-statistics are in parentheses and computed using Newey-West heteroskedasticity and autocorrelation robust standard errors. Parameters significant at the 5% level are printed bold. In panel B returns are corrected for risk and style tilts using the Carhart and Agarwal model with time-varying factor exposures estimated by a Kalman filter approach. Finally, panel C reports in the second, third and fourth columns estimated factor loadings in the static Agarwal model for the full period and both sub periods, respectively. In the fifth column average factor loadings in the dynamic Agarwal model are shown with standard deviations of the conditional betas in parentheses. The last line reports the adjusted R^2 in the static Agarwal model and the likelihood ratio statistic (LR) for the null hypothesis that factor loadings are constant.

Panel A: Static Models

	Gross			Net		
	2000 - 2006	2000 - 2002	2003-2006	2000 - 2006	2000 - 2002	2003-2006
Raw	-1.14	**-3.46**	1.00	**-1.76**	**-4.12**	0.42
	(-1.26)	(-2.16)	(1.26)	(-1.96)	(-2.60)	(0.53)
Carhart	-0.58	0.05	-0.30	**-1.20**	-0.62	**-0.88**
	(-1.51)	(0.06)	(-0.76)	(-3.85)	(-0.85)	(-2.30)
Agarwal	-0.48	-0.12	-0.36	**-1.10**	-0.81	**-0.96**
	(-1.63)	(-0.18)	(-0.79)	(-3.85)	(-1.25)	(-2.18)

Panel B: Dynamic Models

	Gross	Net
	2000 - 2006	2000 - 2006
Carhart	-0.42	**-1.02**
	(-1.44)	(-3.66)
Agarwal	-0.38	**-1.00**
	(-1.02)	(-2.81)

Panel C: OLS Betas and Kalman Smoothed Betas

	Static				Dynamic
	2000-2006	2000-2002	2003-2006		2000-2006
R_M	**1.35**	**1.47**	**1.15**		1.27
	(15.46)	(10.26)	(7.25)		(0.15)
SMB	**0.72**	**0.61**	**0.66**		0.75
	(6.08)	(5.92)	(4.17)		(0.10)
HML	0.12	**0.20**	0.04		0.14
	(1.74)	(2.59)	(0.27)		(0.04)
UMD	0.10	**0.21**	-0.05		-0.01
	(1.27)	(2.37)	(-0.73)		(0.13)
BOND	**0.44**	**0.77**	0.20		0.29
	(2.23)	(2.50)	(0.78)		(0.16)
ATMC	0.78	1.49	1.09		1.17
	(1.61)	(1.05)	(1.81)		(0.04)
ATMP	-0.25	-0.09	-0.29		-0.10
	(-0.32)	(-0.09)	(-0.27)		(0.03)
IT	**0.38**	**0.40**	**0.23**		0.31
	(8.40)	(4.80)	(2.02)		(0.06)
Adj. R^2	91.4%	92.6%	84.6%	LR	**19.96**

Table IV

Fama-MacBeth Regressions of Gross and Net Performance on Investor Characteristics

Panel A presents pairwise correlations between investor characteristics. *Derivatives* is a dummy variable equal to one in a given month when an investor only traded derivatives that month. Similarly, *both* is a dummy variable equal to one if the investor traded both derivatives and non-derivatives in a particular month. *Turnover* is defined as the average of the value of all purchases and sales of an investor in a given month divided by beginning-of-the-month account value. *Woman* and *joint* are dummy variables equal to one if the account is held by a woman or by a man and woman jointly, respectively. *Value* is total account value and is lagged by one month. *Age* is the age of the primary acountholder. Panel B reports Fama-MacBeth coefficient estimates. In the first three columns gross portfolio returns are the dependent variable while in the last three columns net returns are used. We estimate the Fama-MacBeth regressions for the full period, January 2000 - March 2006, as well as for two sub periods, January 2000 to December 2002 and January 2003 to March 2006. The independent variables are the investor characteristics defined in table XII. Adj. R^2 is the time-series average of the monthly adjusted R^2. T-statistics based on Newey-West heteroskedasticity and autocorrelation robust standard errors are in parentheses.

Panel A: Correlation Matrix of Investor Characteristics

	Derivatives	Both	ln Turnover	Woman	Joint	ln $Value_{t-1}$	Age/10
Derivatives	1						
Both	-0.09	1					
ln Turnover	-0.13	0.05	1				
Woman	-0.01	-0.02	-0.01	1			
Joint	-0.01	0.00	-0.03	-0.20	1		
ln $Value_{t-1}$	0.05	0.21	-0.21	0.01	0.09	1	
Age/10	0.02	0.06	-0.07	0.02	0.25	0.29	1

Panel B: Fama-MacBeth Estimates

	Gross Return			Net Return		
	2000-2006	2000-2002	2003-2006	2000-2006	2000-2002	2003-2006
Intercept	**-3.98**	**-7.54**	-0.69	**-6.21**	**-10.01**	**-2.71**
	(-2.44)	(-2.53)	(-0.51)	(-3.84)	(-3.40)	(-2.05)
Derivatives	-0.87	0.95	**-2.55**	**-4.07**	-1.87	**-6.10**
	(-1.37)	(0.89)	(-4.23)	(-6.33)	(-1.74)	(-10.49)
Both	-0.25	-0.43	-0.07	**-2.32**	**-2.35**	**-2.29**
	(-0.76)	(-0.77)	(-0.21)	(-7.42)	(-4.41)	(-6.51)
ln Turnover	**0.55**	**0.76**	**0.36**	-0.04	0.18	**-0.24**
	(4.41)	(3.21)	(3.80)	(-0.31)	(0.81)	(-2.67)
Woman	**0.35**	**0.62**	0.10	**0.43**	**0.69**	0.19
	(2.80)	(3.02)	(0.73)	(3.57)	(3.51)	(1.40)
Joint	**0.18**	0.18	**0.18**	**0.26**	**0.27**	**0.26**
	(3.22)	(1.77)	(3.50)	(4.80)	(2.66)	(5.18)
ln $Value_{t-1}$	**0.34**	**0.44**	**0.24**	**0.54**	**0.65**	**0.43**
	(3.63)	(2.45)	(3.55)	(5.92)	(3.73)	(6.62)
Age/10	0.00	0.04	-0.04	0.00	0.04	-0.05
	(-0.12)	(0.69)	(-1.26)	(-0.08)	(0.76)	(-1.31)
Adj. R^2	1.95%	2.25%	1.68%	2.76%	2.58%	2.93%

Table V

Derivatives - Raw and Style-Adjusted Returns and Factor Loadings

This table shows gross (panel A and C) and net (panel B and D) monthly returns for accounts sorted on derivatives trading. In panel A and B returns are adjusted for style tilts using static Carhart and Agarwal models and in panel C and D dynamic versions of these models are estimated. Panel E reports factor loadings for the static Agarwal model. T-statistics based on Newey-West heteroskedasticity and autocorrelation robust standard errors are in parentheses.

	Deriv	Non	Both	Deriv - Non	Deriv - Both	Non - Both
			Panel A: Gross Performance Static			
Raw	**-2.30**	-0.57	-0.77	-1.73	**-1.53**	0.20
	(-3.32)	(-0.49)	(-0.72)	(-1.95)	(-2.28)	(0.70)
Carhart	**-1.66**	0.04	-0.09	**-1.70**	**-1.57**	0.12
	(-2.80)	(0.07)	(-0.18)	(-2.88)	(-4.35)	(0.45)
Agarwal	**-1.45**	0.15	0.07	**-1.60**	**-1.52**	0.08
	(-2.66)	(0.36)	(0.17)	(-2.75)	(-4.19)	(0.29)
			Panel B: Net Performance Static			
Raw	**-4.96**	-1.57	**-2.83**	**-3.39**	**-2.13**	**1.26**
	(-7.65)	(-1.35)	(-2.70)	(-3.80)	(-3.20)	(3.98)
Carhart	**-4.35**	**-0.96**	**-2.16**	**-3.39**	**-2.19**	**1.20**
	(-7.49)	(-2.02)	(-4.69)	(-5.84)	(-6.58)	(4.10)
Agarwal	**-4.17**	**-0.86**	**-2.03**	**-3.31**	**-2.14**	**1.17**
	(-7.71)	(-2.20)	(-5.08)	(-5.52)	(-6.13)	(3.87)
			Panel C: Gross Performance Dynamic			
Carhart	**-2.26**	0.06	-0.22	**-2.45**	**-2.06**	0.40
	(-4.28)	(0.14)	(-0.55)	(-5.23)	(-6.32)	(1.83)
Agarwal	**-1.65**	-0.01	-0.09	**-1.64**	**-1.47**	0.23
	(-3.34)	(-0.02)	(-0.17)	(-3.40)	(-4.71)	(0.78)
			Panel D: Net Performance Dynamic			
Carhart	**-4.94**	-0.76	**-2.31**	**-4.09**	**-2.62**	**1.48**
	(-9.63)	(-1.84)	(-6.05)	(-9.31)	(-8.96)	(5.68)
Agarwal	**-4.48**	-1.02	**-2.23**	**-3.41**	**-2.15**	**1.35**
	(-8.84)	(-1.76)	(-4.95)	(-7.14)	(-7.73)	(4.34)
			Panel E: Factor Loadings Static Agarwal Model			
R_M	**0.99**	**1.55**	**1.60**	**-0.56**	**-0.61**	-0.05
	(4.85)	(17.81)	(13.75)	(-3.23)	(-5.53)	(-0.68)
SMB	0.30	**0.99**	**0.79**	**-0.69**	**-0.49**	**0.20**
	(1.32)	(7.17)	(4.50)	(-4.92)	(-5.95)	(3.02)
HML	-0.13	**0.23**	0.11	-0.36	-0.24	0.12
	(-0.63)	(2.38)	(1.04)	(-1.62)	(-1.78)	(1.30)
UMD	0.17	0.01	0.07	0.15	0.09	-0.06
	(1.34)	(0.16)	(0.73)	(1.73)	(1.81)	(-1.45)
BOND	0.51	**0.51**	**0.63**	0.00	-0.12	-0.11
	(1.27)	(2.23)	(2.45)	(-0.01)	(-0.49)	(-0.80)
ATMC	**3.77**	0.67	**1.65**	**3.10**	**2.11**	**-0.98**
	(3.60)	(0.98)	(2.24)	(3.82)	(3.67)	(-2.99)
ATMP	0.50	-0.05	0.56	0.55	-0.06	-0.61
	(0.33)	(-0.05)	(0.43)	(0.58)	(-0.12)	(-1.01)
IT	**0.30**	**0.41**	**0.39**	-0.11	-0.09	0.02
	(2.63)	(7.31)	(5.39)	(-1.06)	(-1.41)	(0.43)
Adj. R^2	56.3%	89.2%	88.3%	60.8%	73.8%	20.4%

Table VI

Turnover - Raw and Style-Adjusted Returns and Factor Loadings

This table shows gross (panel A and C) and net (panel B and D) monthly returns for accounts sorted on portfolio turnover. In panel A and B returns are adjusted for style tilts using static Carhart and Agarwal models and in panel C and D dynamic versions of these models are estimated. Panel E reports factor loadings for the static Agarwal model. T-statistics based on Newey-West heteroskedasticity and autocorrelation robust standard errors are in parentheses.

	Low	Medium	High	Low-Medium	Low-High	Medium-High
	Panel A: Gross Performance Static					
Raw	-1.41	**-2.27**	0.41	**0.86**	**-1.82**	**-2.67**
	(-1.64)	(-2.42)	(0.35)	(5.25)	(-3.10)	(-5.45)
Carhart	**-1.00**	**-1.67**	1.26	**0.67**	**-2.26**	**-2.92**
	(-3.27)	(-4.46)	(1.63)	(4.72)	(-4.13)	(-6.08)
Agarwal	**-0.94**	**-1.64**	**1.61**	**0.70**	**-2.55**	**-3.25**
	(-3.54)	(-5.37)	(2.48)	(4.80)	(-5.13)	(-7.55)
	Panel B: Net Performance Static					
Raw	-1.63	**-3.02**	**-3.09**	**1.39**	**1.46**	0.07
	(-1.90)	(-3.25)	(-2.73)	(8.65)	(2.69)	(0.15)
Carhart	**-1.21**	**-2.42**	**-2.28**	**1.21**	**1.07**	-0.14
	(-3.97)	(-6.54)	(-3.06)	(8.49)	(2.07)	(-0.31)
Agarwal	**-1.17**	**-2.41**	**-1.99**	**1.24**	0.83	-0.41
	(-4.34)	(-7.89)	(-3.14)	(8.45)	(1.71)	(-1.01)
	Panel C: Gross Performance Dynamic					
Carhart	**-0.81**	**-1.44**	0.59	**0.71**	**-1.29**	**-2.01**
	(-3.22)	(-4.85)	(0.82)	(5.39)	(-2.81)	(-4.78)
Agarwal	**-0.84**	**-1.57**	1.36	**0.71**	**-1.96**	**-2.69**
	(-2.74)	(-4.20)	(1.65)	(4.71)	(-3.38)	(-5.88)
	Panel D: Net Performance Dynamic					
Carhart	**-1.06**	**-2.20**	**-3.16**	**1.24**	**1.57**	**0.96**
	(-4.36)	(-7.27)	(-4.76)	(9.06)	(2.99)	(2.70)
Agarwal	**-1.09**	**-2.34**	**-2.45**	**1.24**	**1.60**	0.33
	(-3.48)	(-6.43)	(-3.13)	(6.98)	(2.82)	(0.81)
	Panel E: Factor Loadings Static Agarwal Model					
R_M	**1.36**	**1.45**	**1.42**	**-0.10**	-0.07	0.03
	(23.97)	(21.56)	(9.97)	(-2.90)	(-0.60)	(0.28)
SMB	**0.49**	**0.69**	**1.12**	**-0.20**	**-0.63**	**-0.43**
	(7.78)	(9.19)	(7.03)	(-5.41)	(-5.01)	(-3.96)
HML	**0.13**	0.08	0.13	0.05	0.00	-0.05
	(2.08)	(1.08)	(0.84)	(1.37)	(-0.02)	(-0.49)
UMD	**0.09**	**0.10**	0.06	-0.01	0.03	0.03
	(2.19)	(2.01)	(0.62)	(-0.33)	(0.32)	(0.48)
BOND	0.35	**0.48**	0.54	-0.13	-0.19	-0.06
	(1.89)	(2.20)	(1.16)	(-1.24)	(-0.52)	(-0.18)
ATMC	0.08	0.26	**3.57**	-0.19	**-3.49**	**-3.31**
	(0.16)	(0.46)	(2.93)	(-0.66)	(-3.64)	(-3.98)
ATMP	-0.16	-0.42	0.66	0.26	-0.81	-1.08
	(-0.30)	(-0.68)	(0.50)	(0.88)	(-0.79)	(-1.21)
IT	**0.28**	**0.32**	**0.55**	-0.04	**-0.27**	**-0.23**
	(6.54)	(6.34)	(5.15)	(-1.73)	(-3.25)	(-3.17)
Adj. R^2	93.1%	91.7%	76.4%	34.4%	40.5%	36.5%

Table VII

Gender - Raw and Style-Adjusted Returns and Factor Loadings

This table shows gross (panel A and C) and net (panel B and D) monthly returns for accounts sorted on gender. In panel A and B returns are adjusted for risk and style tilts using the static Carhart and Agarwal models and in panel C and D dynamic versions of these models are estimated. Panel E reports factor loadings for the static Agarwal model. T-statistics based on Newey-West heteroskedasticity and autocorrelation robust standard errors are in parentheses.

	Men	Women	Joint	Men-Women	Men-Joint	Women-Joint
			Panel A: Gross Performance Static			
Raw	-1.26	-0.86	-0.99	**-0.39**	**-0.27**	0.13
	(-1.35)	(-1.06)	(-1.12)	(-2.55)	(-2.87)	(1.36)
Carhart	-0.67	-0.36	-0.47	**-0.31**	**-0.20**	0.11
	(-1.59)	(-1.09)	(-1.33)	(-2.36)	(-2.35)	(1.52)
Agarwal	-0.56	-0.30	-0.38	**-0.26**	**-0.17**	0.08
	(-1.76)	(-1.29)	(-1.52)	(-2.04)	(-2.33)	(0.93)
			Panel B: Net Performance Static			
Raw	**-1.98**	-1.31	-1.46	**-0.67**	**-0.52**	0.16
	(-2.15)	(-1.61)	(-1.67)	(-4.55)	(-5.74)	(1.75)
Carhart	**-1.39**	**-0.80**	**-0.94**	**-0.59**	**-0.45**	**0.14**
	(-3.40)	(-2.47)	(-2.72)	(-4.75)	(-5.57)	(2.08)
Agarwal	**-1.28**	**-0.74**	**-0.85**	**-0.54**	**-0.43**	0.12
	(-4.17)	(-3.31)	(-3.50)	(-4.53)	(-5.95)	(1.40)
			Panel C: Gross Performance Dynamic			
Carhart	**-0.63**	-0.27	-0.41	**-0.31**	**-0.19**	0.12
	(-2.00)	(-1.21)	(-1.61)	(-2.57)	(-2.37)	(1.75)
Agarwal	-0.49	-0.08	-0.30	**-0.27**	-0.15	0.10
	(-1.18)	(-0.21)	(-0.79)	(-2.24)	(-0.98)	(1.58)
			Panel D: Net Performance Dynamic			
Carhart	**-1.33**	**-0.70**	**-0.87**	**-0.58**	**-0.44**	**0.15**
	(-4.36)	(-3.23)	(-3.49)	(-4.94)	(-5.85)	(2.16)
Agarwal	**-1.22**	-0.53	**-0.77**	**-0.54**	**-0.37**	**0.19**
	(-2.95)	(-1.50)	(-2.05)	(-5.32)	(-3.94)	(3.37)
			Panel E: Factor Loadings Static Model			
R_M	**1.37**	**1.24**	**1.33**	**0.14**	**0.04**	**-0.09**
	(14.59)	(16.29)	(16.99)	(5.18)	(2.25)	(-7.19)
SMB	**0.76**	**0.61**	**0.66**	**0.15**	**0.10**	-0.05
	(5.86)	(7.36)	(6.05)	(2.86)	(4.18)	(-1.55)
HML	0.13	0.10	0.12	0.03	0.00	-0.02
	(1.68)	(1.50)	(1.89)	(0.90)	(0.15)	(-1.32)
UMD	0.10	0.09	0.08	0.01	0.02	0.01
	(1.29)	(1.38)	(1.12)	(0.68)	(1.82)	(0.96)
BOND	**0.49**	**0.32**	**0.37**	**0.17**	**0.11**	-0.06
	(2.28)	(2.02)	(2.25)	(2.10)	(1.96)	(-1.44)
ATMC	0.92	0.49	0.61	**0.43**	**0.32**	-0.11
	(1.73)	(1.28)	(1.40)	(2.09)	(2.21)	(-0.87)
ATMP	-0.14	-0.55	-0.33	0.41	0.19	-0.22
	(-0.16)	(-0.94)	(-0.50)	(1.15)	(0.78)	(-1.24)
IT	**0.40**	**0.32**	**0.35**	**0.08**	**0.04**	**-0.04**
	(7.96)	(8.93)	(8.92)	(3.73)	(3.75)	(-2.67)
Adj. R^2	90.3%	93.7%	92.9%	52.5%	41.4%	53.8%

Table VIII

Account Size - Raw and Style-Adjusted Returns and Factor Loadings

This table shows gross (panel A and C) and net (panel B and D) monthly returns for accounts sorted into size quintiles. In panel A and B returns are adjusted for risk and style tilts using static Carhart and Agarwal models and in panel C and D dynamic versions of these models are used. Panel E shows factor betas for the static Agarwal model.

	Account Size Quintiles					
	Small	2	3	4	Large	Large- Small
	Panel A: Gross Performance Static					
Raw	-1.67	-1.33	-1.13	-0.93	-0.65	**1.02**
	(-1.58)	(-1.36)	(-1.23)	(-1.09)	(-0.86)	(2.38)
Carhart	-1.01	-0.75	-0.57	-0.41	-0.15	**0.85**
	(-1.72)	(-1.65)	(-1.52)	(-1.26)	(-0.58)	(1.96)
Agarwal	-0.82	-0.62	-0.47	-0.34	-0.14	0.68
	(-1.86)	(-1.83)	(-1.71)	(-1.46)	(-0.68)	(1.85)
	Panel B: Net Performance Static					
Raw	**-2.82**	**-2.07**	-1.65	-1.34	-0.91	**1.91**
	(-2.71)	(-2.13)	(-1.81)	(-1.59)	(-1.21)	(4.57)
Carhart	**-2.15**	**-1.49**	**-1.10**	**-0.83**	-0.42	**1.73**
	(-3.81)	(-3.37)	(-2.97)	(-2.56)	(-1.58)	(4.10)
Agarwal	**-1.97**	**-1.36**	**-0.99**	**-0.75**	**-0.41**	**1.56**
	(-4.55)	(-4.15)	(-3.69)	(-3.30)	(-1.97)	(4.23)
	Panel C: Gross Performance Dynamic					
Carhart	-0.90	**-0.72**	-0.52	-0.36	-0.06	**0.77**
	(-1.94)	(-2.16)	(-1.94)	(-1.48)	(-0.27)	(2.23)
Agarwal	-0.80	-0.61	-0.42	-0.23	0.06	**0.83**
	(-1.31)	(-1.40)	(-1.20)	(-0.65)	(0.18)	(2.10)
	Panel D: Net Performance Dynamic					
Carhart	**-2.05**	**-1.44**	**-1.03**	**-0.76**	-0.31	**1.64**
	(-4.67)	(-4.43)	(-3.89)	(-3.12)	(-1.50)	(4.98)
Agarwal	**-1.95**	**-1.35**	**-0.93**	-0.64	-0.20	**1.67**
	(-3.40)	(-3.19)	(-2.72)	(-1.84)	(-0.62)	(4.91)
	Panel E: Factor Loadings Static Agarwal Model					
R_M	**1.50**	**1.42**	**1.37**	**1.29**	**1.18**	**-0.32**
	(12.62)	(15.07)	(15.45)	(16.92)	(17.52)	(-4.79)
SMB	**0.87**	**0.82**	**0.74**	**0.65**	**0.51**	**-0.36**
	(4.28)	(5.86)	(6.75)	(7.41)	(7.59)	(-2.28)
HML	0.13	**0.17**	0.14	**0.12**	0.06	-0.08
	(1.25)	(2.15)	(1.85)	(2.04)	(0.90)	(-0.86)
UMD	0.15	0.10	0.09	0.08	0.07	-0.08
	(1.55)	(1.25)	(1.14)	(1.11)	(1.09)	(-1.59)
BOND	**0.75**	**0.53**	**0.40**	0.29	0.21	**-0.54**
	(2.26)	(2.47)	(2.24)	(1.91)	(1.51)	(-2.09)
ATMC	0.97	0.81	0.67	**0.85**	0.61	-0.36
	(1.30)	(1.43)	(1.46)	(2.02)	(1.95)	(-0.68)
ATMP	0.53	-0.03	-0.28	-0.62	-0.85	-1.38
	(0.46)	(-0.03)	(-0.36)	(-1.03)	(-1.76)	(-1.78)
IT	**0.55**	**0.44**	**0.37**	**0.31**	**0.21**	**-0.33**
	(7.88)	(8.40)	(8.12)	(7.72)	(6.35)	(-5.49)
Adj. R^2	84.5%	90.2%	92.4%	93.7%	93.8%	49.1%

Table IX

Decile Portfolios of Individual Investors Sorted on Past One-Year Return

At the end of every year from 2000 to 2004 investors are ranked into equal-weight decile portfolios based on returns earned over the year. Each portfolio is held one year and subsequently rebalanced. This table shows average monthly raw returns, alphas produced by the Carhart and Agarwal models and factor loadings in the Agarwal model for each decile portfolio. Decile 1 contains investors with the highest return during the formation period and decile 10 includes the worst 10% performers in the ranking period. Columns labeled 'gross' ('net') refer to deciles formed and evaluated based on gross (net) returns. R^2 is the adjusted R^2 produced by the Agarwal model. T-statistics based on Newey-West heteroskedasticity and autocorrelation robust standard errors are in parentheses. Rank ρ is the Spearman rank correlation coefficient that measures the relation between formation period ranking and evaluation period ranking. ** denotes its significance at the 1% level.

	Raw Return		**Carhart Alpha**		**Agarwal Alpha**		**Factor Loadings**								
Decile	Gross	Net	Gross	Net	Gross	Net	R_M	SMB	HML	UMD	BOND	ATMC	ATMP	IT	R^2
1	-0.20	-0.42	0.06	-0.15	0.02	-0.19	**1.07**	**0.38**	0.08	**-0.08**	0.29	0.57	-0.04	**0.09**	95.3
	(-0.23)	(-0.50)	(0.23)	(-0.63)	(0.08)	(-0.90)	(28.84)	(5.27)	(1.42)	(-2.18)	(1.68)	(1.38)	(-0.11)	(3.00)	
2	-0.12	-0.26	0.14	-0.01	0.15	-0.00	**0.95**	**0.46**	0.01	-0.04	0.13	0.26	0.35	**0.11**	95.0
	(-0.17)	(-0.35)	(0.77)	(-0.03)	(0.90)	(-0.01)	(27.69)	(8.80)	(0.26)	(-1.26)	(1.05)	(0.80)	(0.78)	(4.03)	
3	-0.28	-0.36	-0.07	-0.15	-0.05	-0.11	**0.96**	**0.44**	0.08	-0.02	0.04	0.27	-0.04	**0.19**	96.7
	(-0.37)	(-0.48)	(-0.33)	(-0.71)	(-0.28)	(-0.64)	(23.62)	(9.23)	(1.54)	(-0.47)	(0.40)	(1.29)	(-0.08)	(7.57)	
4	-0.41	-0.66	-0.18	-0.45	-0.11	-0.40	**1.10**	**0.55**	**0.12**	0.02	0.04	0.27	-0.09	**0.24**	95.8
	(-0.47)	(-0.77)	(-0.63)	(-1.63)	(-0.55)	(-1.92)	(23.54)	(9.97)	(2.08)	(0.37)	(0.27)	(0.86)	(-0.20)	(7.70)	
5	-0.42	-0.64	-0.18	-0.39	-0.07	-0.33	**1.12**	**0.68**	0.11	-0.02	0.09	0.57	-0.26	**0.29**	95.2
	(-0.46)	(-0.69)	(-0.58)	(-1.17)	(-0.31)	(-1.40)	(23.66)	(10.76)	(1.53)	(-0.37)	(0.65)	(1.80)	(-0.50)	(8.31)	
6	-0.48	-0.63	-0.17	-0.33	-0.09	-0.20	**1.31**	**0.96**	0.05	0.05	0.08	0.75	0.29	**0.42**	92.1
	(-0.45)	(-0.60)	(-0.36)	(-0.70)	(-0.26)	(-0.60)	(20.28)	(10.05)	(0.54)	(0.77)	(0.35)	(1.74)	(0.38)	(9.48)	
7	-0.57	-0.94	-0.32	-0.68	-0.24	**-0.61**	**1.40**	**1.11**	0.11	0.12	0.30	0.29	0.59	**0.47**	94.1
	(-0.52)	(-0.85)	(-0.71)	(-1.49)	(-0.85)	(-2.09)	(20.42)	(12.96)	(1.21)	(1.92)	(1.42)	(0.57)	(0.87)	(10.47)	
8	-1.01	-1.43	-0.69	**-1.11**	-0.50	**-0.96**	**1.55**	**1.28**	0.10	0.14	0.08	0.42	0.41	**0.54**	92.0
	(-0.81)	(-1.14)	(-1.19)	(-1.96)	(-1.17)	(-2.21)	(19.92)	(9.89)	(0.94)	(1.76)	(0.28)	(0.64)	(0.41)	(10.15)	
9	-1.02	-1.94	-0.74	**-1.71**	-0.67	**-1.66**	**1.60**	**1.40**	0.14	**0.26**	0.42	0.03	0.50	**0.63**	90.0
	(-0.83)	(-1.53)	(-1.14)	(-2.66)	(-1.40)	(-3.75)	(13.73)	(10.85)	(0.94)	(2.51)	(1.49)	(0.05)	(0.44)	(8.75)	
10	-1.73	**-3.20**	-1.53	**-2.98**	**-1.48**	**-2.96**	**1.93**	**1.86**	0.25	**0.39**	0.54	-0.48	0.46	**0.80**	87.6
	(-1.08)	(-2.04)	(-1.84)	(-3.69)	(-2.54)	(-4.98)	(10.99)	(6.47)	(1.19)	(2.49)	(1.33)	(-0.41)	(0.26)	(7.46)	
1 - 10	1.53	**2.77**	**1.59**	**2.84**	**1.50**	**2.76**	**-0.86**	**-1.48**	-0.17	**-0.47**	-0.25	1.05	-0.49	**-0.71**	74.5
	(1.57)	(2.87)	(2.27)	(4.02)	(2.98)	(5.20)	(-5.31)	(-5.88)	(-0.89)	(-3.25)	(-0.68)	(1.08)	(-0.30)	(-6.94)	
9 - 10	0.72	**1.25**	**0.78**	**1.27**	**0.81**	**1.29**	**-0.32**	**-0.46**	-0.11	-0.14	-0.12	0.51	0.05	**-0.16**	34.1
	(1.58)	(2.94)	(2.28)	(3.81)	(2.46)	(3.57)	(-2.96)	(-2.03)	(-0.99)	(-1.30)	(-0.42)	(0.59)	(0.05)	(-2.05)	
Rank ρ	0.99**	0.92**	0.94**	0.94**	0.95**	0.92**									

Table X

Decile Portfolios of Individual Investors Sorted and Evaluated on Six and Three-Month Performance

This table shows average monthly raw returns and alphas produced by the Carhart and Agarwal models for equal-weight decile portfolios of investors sorted on past returns. Decile 1 contains investors with the highest return during the formation period and decile 10 includes the worst 10% performers in the ranking period. Columns labeled 'gross' ('net') refer to deciles formed and evaluated based on gross (net) returns. The first six columns present results for six-month ranking and evaluation periods while the last six columns are for three-month periods. T-statistics based on Newey-West heteroskedasticity and autocorrelation robust standard errors are in parentheses. Rank ρ is the Spearman rank correlation coefficient. * and ** denote its significance at the 5% and 1% level, respectively.

	Six-Month Ranking and Evaluation Period						Three-Month Ranking and Evaluation Period					
	Raw Return		**Carhart Alpha**		**Agarwal Alpha**		**Raw Return**		**Carhart Alpha**		**Agarwal Alpha**	
Decile	Gross	Net	Gross	Net	Gross	Net	Gross	Net	Gross	Net	Gross	Net
1	-1.09	-1.33	-0.17	-0.45	-0.22	-0.51	-1.65	**-2.29**	-0.55	**-1.20**	-0.56	**-1.19**
	(-1.03)	(-1.31)	(-0.31)	(-0.97)	(-0.57)	(-1.54)	(-1.60)	(-2.24)	(-0.99)	(-2.29)	(-1.48)	(-3.42)
2	-0.61	-0.99	0.13	-0.30	0.16	-0.24	-1.13	-1.34	-0.27	-0.51	-0.21	-0.49
	(-0.66)	(-1.08)	(0.34)	(-0.82)	(0.62)	(-0.94)	(-1.16)	(-1.39)	(-0.63)	(-1.27)	(-0.65)	(-1.63)
3	-0.72	-0.81	-0.09	-0.22	-0.06	-0.19	-1.09	-1.34	-0.29	-0.53	-0.14	-0.39
	(-0.81)	(-0.97)	(-0.29)	(-0.74)	(-0.27)	(-0.90)	(-1.16)	(-1.46)	(-0.68)	(-1.35)	(-0.49)	(-1.39)
4	-0.65	-1.03	-0.04	-0.37	0.02	-0.34	-0.95	-1.22	-0.24	-0.58	-0.16	**-0.53**
	(-0.77)	(-1.18)	(-0.14)	(-1.18)	(0.13)	(-1.71)	(-1.05)	(-1.41)	(-0.67)	(-1.76)	(-0.62)	(-2.38)
5	-0.84	-1.08	-0.09	-0.30	-0.03	-0.20	-0.88	-0.93	-0.27	-0.33	-0.17	-0.24
	(-0.88)	(-1.17)	(-0.27)	(-0.81)	(-0.13)	(-0.80)	(-0.99)	(-1.06)	(-0.84)	(-1.10)	(-0.81)	(-1.06)
6	-0.87	-0.99	-0.15	-0.27	-0.09	-0.24	-0.80	-1.25	-0.14	-0.55	-0.06	**-0.48**
	(-1.01)	(-1.10)	(-0.48)	(-0.78)	(-0.35)	(-0.92)	(-0.93)	(-1.40)	(-0.44)	(-1.61)	(-0.27)	(-1.96)
7	-1.13	-1.85	-0.31	**-1.03**	-0.24	**-1.00**	-0.89	-1.36	-0.12	-0.59	-0.05	-0.53
	(-1.12)	(-1.84)	(-0.70)	(-2.62)	(-0.68)	(-3.56)	(-0.95)	(-1.45)	(-0.34)	(-1.64)	(-0.20)	(-1.90)
8	-1.49	-1.83	-0.60	**-0.91**	-0.55	**-0.79**	-1.36	-1.78	-0.48	**-0.85**	-0.42	**-0.79**
	(-1.41)	(-1.69)	(-1.25)	(-1.96)	(-1.69)	(-2.22)	(-1.32)	(-1.73)	(-1.08)	(-2.01)	(-1.33)	(-2.41)
9	-1.56	-2.34	-0.48	**-1.23**	-0.35	**-1.13**	-1.42	**-2.38**	-0.46	**-1.36**	-0.39	**-1.30**
	(-1.30)	(-1.89)	(-0.85)	(-2.05)	(-0.80)	(-2.53)	(-1.36)	(-2.16)	(-0.91)	(-2.67)	(-1.02)	(-3.60)
10	-2.28	**-3.72**	-1.00	**-2.45**	-0.75	**-2.24**	**-2.63**	**-4.26**	**-1.38**	**-2.97**	-0.98	**-2.56**
	(-1.90)	(-3.14)	(-1.52)	(-3.86)	(-1.25)	(-3.75)	(-2.17)	(-3.55)	(-2.06)	(-4.38)	(-1.50)	(-3.80)
1 - 10	**1.20**	**2.39**	**0.83**	**2.00**	0.54	**1.73**	**0.98**	**1.97**	0.83	**1.77**	0.42	**1.37**
	(3.01)	(5.64)	(2.26)	(5.19)	(1.27)	(3.83)	(2.11)	(4.03)	(1.93)	(3.91)	(0.86)	(2.60)
9 - 10	**0.73**	**1.38**	**0.51**	**1.21**	0.40	**1.11**	**1.21**	**1.88**	**0.92**	**1.61**	0.60	**1.26**
	(2.37)	(4.36)	(1.99)	(4.28)	(1.42)	(4.03)	(3.03)	(4.50)	(2.48)	(4.07)	(1.36)	(2.81)
Rank ρ	0.81**	0.76*	0.79**	0.66*	0.77*	0.72*	0.18	0.47	0.15	0.56	0.18	0.50

Table XI

Characteristics of Portfolios of Individual Investors Sorted on Past One-Year Net Return

This table reports time-series averages of monthly cross-sectional averages of investor characteristics for decile portfolios of individual investors formed on the basis of past one-year return. As an exception, numbers reported for account value are time-series averages of monthly cross-sectional median account value. Decile 1 contains investors with the highest return during the formation period and decile 10 includes the worst 10% performers in the ranking period. Account value is the market value of all assets in the investor's account. (Non-)Derivatives turnover is the average value of (non-)derivatives sales and purchases divided by beginning-of-the-month account value. Men (%) and Women (%) are the percentages of accounts held by a man or woman only, respectively. Age is the age of the primary accountholder. Rank ρ is the Spearman rank correlation coefficient that measures the relation between formation period net performance ranking and evaluation period characteristic ranking. * and ** denote its significance at the 5% and 1% level, respectively.

Decile	Account Value (€)	Derivatives Turnover (%)	Non-Derivatives Turnover (%)	Men (%)	Women (%)	Age (years)
1	20,547	9.6	25.8	61.9	9.49	44.1
2	20,489	4.7	13.2	54.2	10.07	44.6
3	18,660	4.9	11.9	54.6	8.47	44.7
4	15,654	4.6	24.0	51.2	10.65	45.5
5	12,351	4.6	28.4	54.8	8.85	45.9
6	8,825	4.7	23.6	62.5	8.62	43.8
7	7,881	7.1	36.2	59.7	7.98	44.2
8	4,630	10.6	52.6	64.5	6.02	42.7
9	3,975	15.5	90.5	62.9	5.88	42.0
10	3,429	41.7	123.2	67.2	5.13	43.8
1 - 10	17,118	-32.13	-97.36	-5.3	4.4	0.3
9 - 10	546	-26.21	-32.70	-4.3	0.7	-1.8
Rank ρ	1.00**	-0.61	-0.82**	-0.75*	0.86**	0.63

Figure 1

Kalman Smoothed Betas for the Average Individual Investor

This figure plots the evolution of Kalman smoothed factor loadings in the Agarwal model for the average individual investor over the period January 2000 through March 2006.

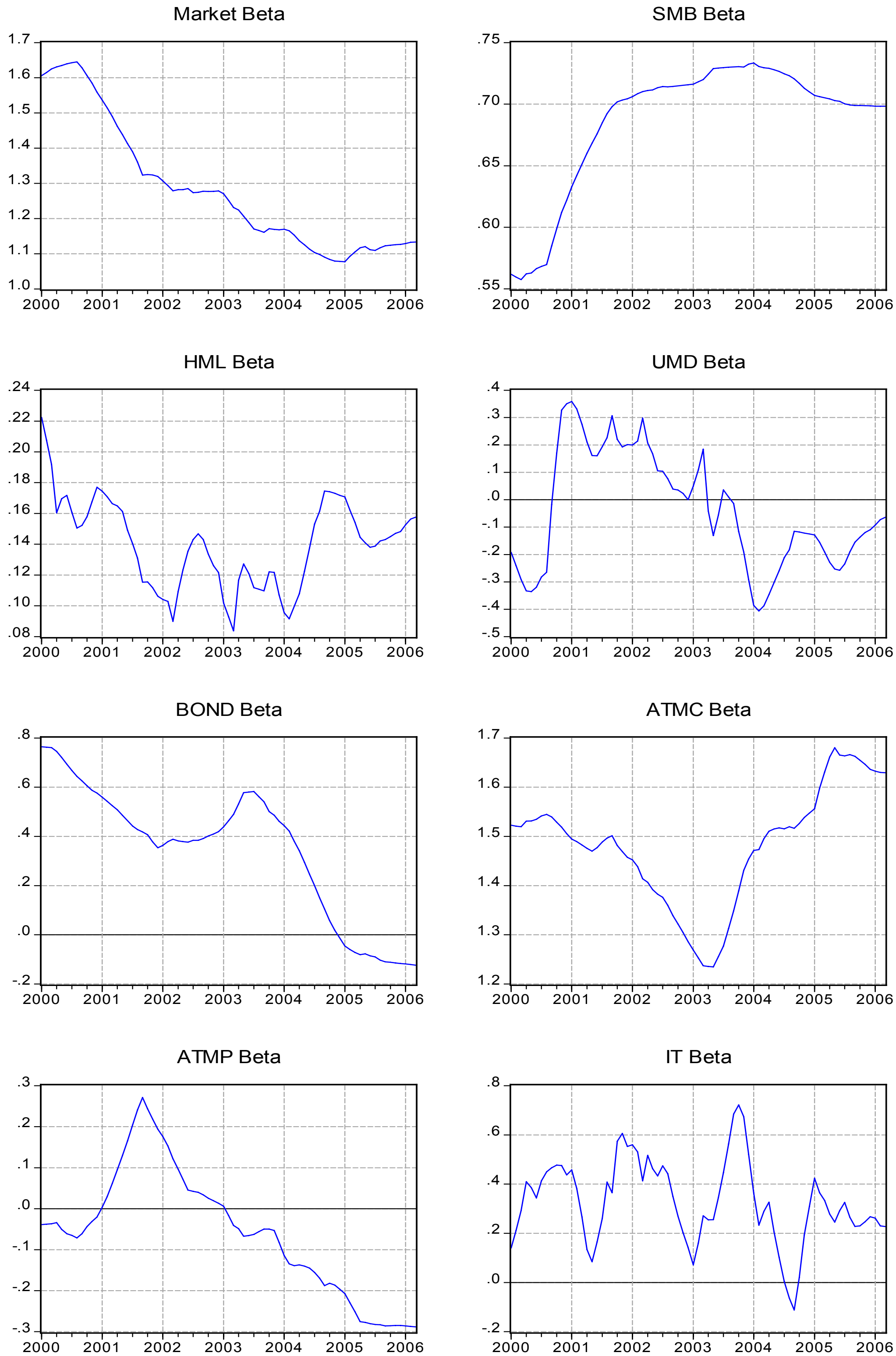

Figure 2

Hausse-Baisse Ratio and Gross Return Difference Derivatives and Non-Derivatives Traders

This figure plots the evolution through time of the monthly Hausse-Baisse ratio, the return on the Worldscope Netherlands equity universe and the gross return difference between derivatives traders and non-derivatives traders. The Hausse-Baisse ratio is calculated as the sum of the value of call options bought and put options sold divided by the sum of the value of put options bought and call options sold.

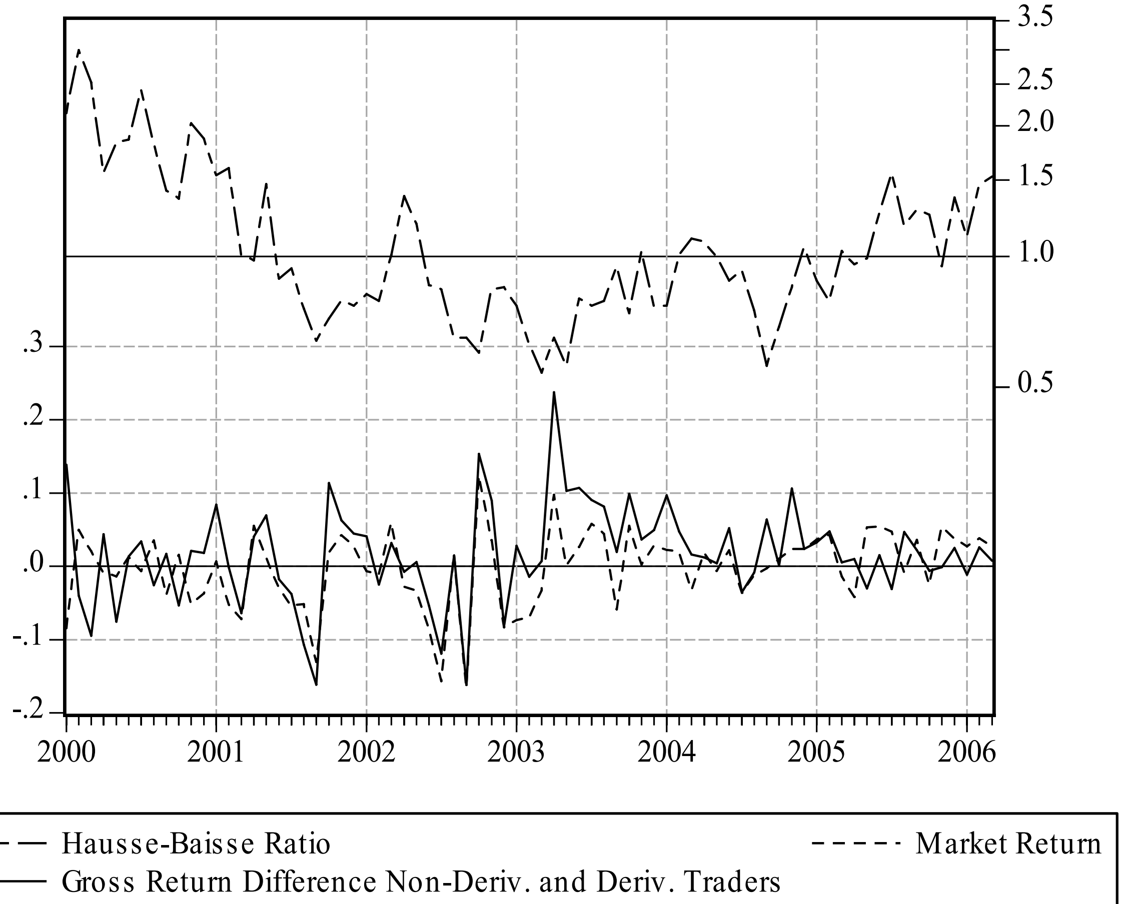

Figure 3

Post-Formation Cumulative Net Performance of Decile Portfolios of Individual Investors Sorted on Past One-Year Net Return

At the end of every year from 2000 to 2004 investors are ranked into equal-weight decile portfolios based on net returns earned over the year. This figure plots the cumulative net performance of these deciles in the year subsequent to the formation year and the monthly level of the Worldscope total return index for the Netherlands, scaled to one at the end of December 2000. Decile 1 contains investors with the highest return during the formation period and decile 10 includes the worst 10% performers in the ranking period.