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Abstract

We study the impact of derivatives trading on the investment performance of individual investors and examine whether investor performance is persistent. Using a sample of more than 68,000 accounts and nine million trades, we find that the average investor earns negative gross and net alphas, mainly because of substantial losses on derivatives investments. The underperformance of derivatives traders is due to bad market timing that results from overreaction to past stock market movements. We also find strong evidence of performance persistence among individual investors. Women are more successful investors than men and persistent winners hold larger accounts with lower turnover.

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Over the last decade, Internet brokerage has dramatically changed the investment landscape. Banks and brokers now offer their individual clients Internet-based trading systems that integrate features such as real-time trading, research and other investment decision tools, and streaming price information. At the same time, commissions have fallen over time due to technological innovations and increasing competition. Furthermore, individuals are becoming more and more responsible for making their own financial decisions, for instance on the investments in their pension plans. As a result, the professional traders who used to dominate financial markets now find themselves surrounded by a much larger and more divergent crowd: individual investors. Motivated by this change and to gain a better insight into the trading behavior of the increasing numbers of individual investors, financial economists are examining their performance, using trading records and position statements obtained from brokerage firms.

We study the impact of derivatives trading on investor performance. Doing so gives us the opportunity to shed light on the question of whether individual investors understand the risk and return characteristics of these more complex securities, and if they are able to apply these instruments successfully. We also investigate whether individual investor performance is persistent, i.e., whether some investors are able to consistently earn abnormal returns. We then analyze the characteristics and trading strategies of these successful and unsuccessful investors. We further examine whether we can extend the results that Barber and Odean (2000, 2001) document for the United States on the relation between investor performance and turnover, age, gender, and account value to a different market and more recent time period.

To perform our investigation we use a unique database comprising more than 68,000 accounts and nine million trades in stocks, bonds, options, and futures at the largest online discount broker in the Netherlands. In terms of size, our sample is comparable to data sets used in studies for the United States. We examine investor performance from January 2000 to March

2006. This period covers the top of the recent stock market boom in 2000, the subsequent bust in stock prices in 2001 and 2002, and the recovery from 2003 to 2006. Thus, we are able to examine whether major market movements affect trading behavior and investor performance.

We use several methods to deal with the specific risk and return characteristics of individual investor portfolios. First, to adjust returns for risk and style tilts, we use a multifactor model in the spirit of Agarwal and Naik (2004) to capture the nonlinear payoffs of options. In addition, we use a Kalman filter approach to allow for time variation in risk loadings and style preferences. Finally, to identify the determinants of cross-sectional variation in investor performance, we introduce an approach that allows us to control for risk and style exposures even when the number of time series observations for some investors is small.

Our empirical analysis shows that the average individual investor earns negative gross and net alphas. This finding is mainly driven by investors trading derivatives, since the gross alphas for non-derivatives traders are close to zero. We attribute the poor performance of derivatives traders to bad market timing that results from overreaction to past stock market movements. Expensive trading and a lack of knowledge also have a detrimental impact on the return on derivatives investments. Other significant determinants of cross-sectional variation in investor performance are turnover, gender, and account value. Active investors outperform inactive investors in terms of gross returns, but the picture reverses when we look at net performance. Women outperform men, especially in the period of stock market decline, because they incur lower trading costs and hold less risky portfolios than men. Account value is positively related to performance.

We find strong evidence of performance persistence among individual investors. Investors who are in the top decile portfolio based on past one-year performance continue to outperform investors in the bottom decile portfolio over the next year in terms of both gross and net alphas. Performance persistence is somewhat weaker on shorter horizons but still significant for six-month periods. Persistence in trading costs explains only part of total performance persistence. Although gross alphas for investors in the top deciles are close to zero, the net alphas are negative for investors in all deciles and significant for those in the bottom three deciles. Differences in factor exposures show that losers hold riskier portfolios than winners. We further find that the bottom deciles tend to consist of small accounts with high turnover, which are predominantly held by men.

The paper proceeds as follows. Section I gives a brief overview of related studies. Section II describes the data set and in Section III we explain our methods. In section IV we provide empirical evidence on the relation between investor characteristics and performance, and in Section V we investigate performance persistence. Section VI concludes.

I. Individual Investor Performance Literature

Our work relates to the growing number of studies on the performance and behavior of individual investors. Perhaps the most puzzling finding of prior research is excessive trading (Odean (1999)). Barber and Odean (2000) show that excessive trading by individual investors substantially reduces performance because of high transaction costs. Anderson (2005) finds that investors with the highest fraction of total financial wealth invested in an online portfolio suffer most from overtrading. Because these investors also have lowest total wealth, Anderson concludes that "trading losses are mainly carried by those who can afford them the least."

Since portfolio choice theory states that it is optimal for all investors to hold the market portfolio of risky assets, many studies attempt to explain why individual investors trade so excessively. Black (1986) attributes frequent trading in individual stocks to noise traders, who interpret the noise they trade on as information. Investors with real pieces of information are likely to have different beliefs than the noise traders, and consequently, they are willing to trade.

Alternatively, Black points out that investors trade on noise because they enjoy trading. Grinblatt and Keloharju (2005) provide empirical support for this conjecture by showing that the investors most prone to sensation seeking trade more frequently.

Odean (1998) relates excessive trading to overconfidence. Using a theoretical framework, he shows that investors can become noise traders when they are too confident about their information and beliefs. To test this hypothesis, Barber and Odean (2001) use gender as a proxy for overconfidence. This choice is motivated by psychological evidence that men are generally more overconfident about their financial decision-making ability than are women. Therefore, these authors interpret their finding that men trade more frequently than women as evidence for the overconfidence explanation of overtrading.

Recent studies also present evidence of investor irrationality in option markets. Poteshman and Serbin (2003) find that customers of discount brokers regularly engage in irrational early exercise of stock options. Mahani and Poteshman (2005) document that discount clients act irrationally by entering option positions that load up on growth stocks a few days before earnings announcements, even though at earnings announcements value stocks outperform substantially. Lakonishok et al. (2007) show that a large fraction of individuals' option activity is motivated by speculation on the direction of future stock price movements. Hedging against adverse price movements and trading the volatility of underlying stocks are less important determinants of option volume. Lakonishok et al. (2007) also highlight that discount customers speculated heavily on a further increase in the price of growth stocks during the tech bubble. We extend these studies by explicitly linking option trading to investor performance.

Although the majority of individual investors lose by trading, Barber, Lee, Liu, and Odean (2004) present strong evidence of performance persistence among a small group of successful day traders in Taiwan. Coval, Hirshleifer, and Shumway (2005) document that some individual investors in the U.S. have hot hands, i.e., they are consistently able to beat the market. These authors further show that the difference in performance between persistent winners and losers cannot be explained by well-known size, value or momentum strategies. We test whether we can confirm the finding of performance persistence among individual investors when we incorporate derivatives trading and account for transaction costs.

II. Data Description

We use a data set of individual investor accounts held at the largest Dutch online broker. The raw data set contains all individual investor accounts that existed between January 2000 and March 2006. Due to various trading restrictions, we exclude accounts owned by minors (age < 18 years) from our analysis. We impose two restrictions on the sample. First, we exclude dormant accounts, which we define as those accounts that are empty or consist only of cash. Second, we exclude accounts with a beginning-of-the-month value of less than €250 to reduce the impact of outliers. Imposing these restrictions leaves 68,146 accounts and more than two million monthly portfolio overviews. On average, investors are present in the sample for 36 months.

Table I presents summary statistics for our sample. The average (median) age of investors is 45 (43) 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 positively skewed. The average number of trades per month equals 3.64 for men and only 2.45 for women, which is consistent with Barber and Odean's (2001) finding that men trade more frequently than women.

Although the majority of investors (65%) does not trade on a monthly basis, a small group trades very often. When we consider only those investors who are active (i.e., who trade) in a given month, the average (median) number of trades is close to ten (four). When we split the number of trades into non-derivatives (stocks and bonds) and derivatives (options and futures), we see a striking feature of our sample: the high level of derivatives trading. Out of the total of nine million trades, more than half are trades in derivatives: 4.3 million trades in options (48%) and half a million trades in futures (6%). More than 33 million option contracts are traded, which, based on historical statistics retrieved from NYSE Euronext Liffe, is 7.2% of all option contracts traded at the Amsterdam options exchange during our sample period. The remaining 3.5 million trades are in non-derivatives, mainly in stocks.

Table I also reports statistics for monthly turnover per account, which we define as the average of the value of all security purchases and sales divided by beginning-of-the-month account value. Although the average turnover is 32.5%, the median turnover is zero, which shows that the distribution is positively skewed. When we restrict the sample to active accounts, we find that the average (median) turnover is 91.6% (24%). Splitting turnover into derivatives and non-derivatives shows that more than a quarter of the total turnover is due to derivatives trading. Trading activity in our sample is much higher than in the sample of U.S. accounts analyzed by Barber and Odean (2000). However, an important difference between the Barber and Odean (2000) data set and ours is that the investors they study do not trade via the Internet. Barber and Odean (2002) show that investors increase portfolio turnover after switching to online trading. High turnover drives transaction costs. Average monthly transaction costs per account are equal to €90 when we consider all accounts and equal to €252 when we include only active investors. The mean (median) account value is €32,327 (€7,773). The distribution of account value shows that a few large accounts have a big impact on average account value.

III. Methods

A. Measuring Investor Performance

We define investor performance as the relative change in the combined market value of all assets in the investor's account. In doing so we take into account both the 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. To be conservative, we assume that deposits are made at the beginning of the month and that withdrawals take place at the end of the month. This ensures that returns can only be generated by funds the investor actually possesses. We also performed our analysis under the assumption that deposits and withdrawals are made halfway the month and can confirm that our results are robust to this timing assumption. End-of-the-month account value is net of transaction costs the investor incurred during the month. Thus, we calculate performance in terms of returns net of trading costs as

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

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 made during month t.

We obtain gross returns by adding back transaction costs incurred during month t, TC_{jt}, to end-of-the-month account value,

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

Following Barber, Lee, Liu, and Odean (2004), we consider only direct transaction costs (commissions) and do not add back any indirect transaction costs (market impact and bid-ask spreads). The trades of most individual investors 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. Therefore, Barber and Odean (2000) estimate the bid-ask spread using transaction prices and closing prices. However, this approach is inappropriate for our purposes because the resulting 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 follows:

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

where N_t denotes the total number of investors at the end of month t.

B. Performance Attribution

We attribute the returns on investor portfolios to different risk and style factors to obtain the abnormal performance, i.e., the return left unexplained by the factors. However, it is not clear which model should be used to control for risk. Many studies use the Capital Asset Pricing Model (CAPM) as a benchmark, but Fama and French (2004) note that investors with no special ability for selecting winners can earn positive abnormal returns relative to the predictions of the CAPM by exploiting return anomalies that have been discovered over the past decades. Therefore, if we wish to make a fair comparison between the performance of different groups of investors, we must take style differences 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. To account for the momentum effect, Carhart (1997) adds a momentum factor to the three-factor model. We construct these factors for the Dutch market, since the investors in our sample mainly invest in Dutch securities.[1] To characterize the market risk of the equity component of the portfolio returns, we include the value-weighted average excess return on all stocks in the Worldscope Netherlands universe. We choose the Worldscope universe because it has broader market coverage than indexes such as the MSCI Netherlands index. We form the factor-mimicking portfolios SMB, HML, and UMD according to the procedure outlined by Kenneth French.[2]

We also use an extended version of the Carhart (1997) model to deal with the specific risk and return characteristics of individual investor portfolios. Because many investors in our sample not only trade stocks, but also bonds and options, we include factors designed to capture the exposure from investments in these non-equity assets. For capturing the risk related to fixed-income investments, we add the excess return on the ten-year Dutch government bond index to the model. Since most of the fixed-income investments in our sample are in Dutch government bonds, we do not add a factor to capture credit risk exposure. Our results are robust to this choice.

To characterize the nonlinear exposure from options, we build on the theoretical framework developed by Glosten and Jagannathan (1994), who propose adding option-based factors to performance attribution models. 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. Following these studies, we include the excess returns on liquid at-the-money (ATM) European call and put options on the Dutch AEX stock market index to capture the nonlinear systematic risk exposure of investors' portfolios. In particular, at the end of each month ATM call and put index options that expire two months later are bought. These index options are sold one month later and new index options are purchased. As a proxy for ATM options we select options whose strike prices are closest to the current index value. This rolling strategy of buying and selling index calls and puts produces a time series of returns on ATM calls and puts that we add to the performance attribution model. We scale the option factors by a factor of 100 to account for the size of option contracts.

We further include the value-weighted average return on Dutch stocks from the MSCI IT and Telecommunications sector to capture possible tech-related style tilts, since many economists, including Shiller (2005), argue that the technology bubble was fed by irrational euphoria among individual investors. Because the option-based factors and the IT factor are highly correlated with the market premium we orthogonalize them with respect to the excess market return. We call this extended Carhart model consisting 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. The factor loadings indicate whether a portfolio is tilted towards a particular investment style.

Other studies on individual investor performance assume that factor loadings remain constant over time, i.e., they use unconditional or static models for performance attribution. However, a large body of empirical evidence shows that the systematic risk of stocks varies substantially over time as a function of the business cycle (see, for example, Ferson and Harvey (1999)). Moreover, in a dynamic world it is unlikely that investors keep their exposure to risk and style factors constant over time. Empirical support for this conjecture is provided by Kumar (2006), who finds that individual investors exhibit time-varying style preferences, driven by past style returns and earnings differentials. Hence, Ferson and Schadt (1996) argue that fluctuations in factor exposures should be taken into account when measuring portfolio performance.

We treat the time-varying factor loadings as latent state variables and infer them directly from portfolio returns using the Kalman filter. We assume a random walk process for the latent conditional betas. Specifically, we consider the following state-space representation:

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

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

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. We test the null hypothesis of constant betas, which corresponds to the restriction that the diagonal elements of Q are zero, using a likelihood ratio test. Equation (5) is the observation equation and equation (6) is the state equation. The Kalman filter is a recursive algorithm for sequentially updating the one-step ahead estimate of the state mean and variance. We use it to calculate maximum likelihood estimates of the model parameters $\sigma_{j\varepsilon}^2$ and Q along with minimum mean-square error estimates of the state variables β_{jt}.

We set the initial one-step-ahead predicted values for the states equal to the OLS estimates from the static model. In the Carhart model, we treat the initial one-step-ahead predicted values of the covariance matrix Q as diffuse, setting them equal to arbitrarily large numbers. 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 variances for the other states using diffuse priors. We use a smoothing algorithm to obtain Kalman smoothed estimates, which are conditioned on information from the full sample period (see Hamilton (1994)).

IV. Empirical Evidence on Investor Performance and Behavior

A. Average Investor Performance

In Table II, Panel A shows that during our sample period the average investor earns a monthly gross return of -1.14%, which is economically large but not statistically significant from zero at conventional levels. To shed more light on the poor investor performance we split the sample in two subperiods. The subsample analysis shows that during the period from January 2000 to December 2002, which includes the huge stock market decline after the burst of the tech bubble, investors earn an average monthly return of -3.46%. In the second subperiod, from January 2003 to March 2006, the market recovers from the crash and the average monthly return on investors' portfolios is 1%. However, accounting for general market movements by adjusting returns for risk exposures and style tilts explains only part of the poor performance: the monthly alpha from the unconditional Carhart model estimated over the full period is -0.58% and the Agarwal alpha is -0.48%. We further note that in terms of alpha, the underperformance of investors is concentrated in the second subperiod.

Obviously, when we take into account transaction costs, performance deteriorates. We see that the average net return for the full sample period is -1.76% per month, which is marginally 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 alphas of -1.20% and -1.10% for the Carhart and Agarwal models, respectively, which are economically large and statistically significant at a 1% level.

In Panel B, we adjust the portfolio returns for time-varying risk and style exposures, using the Kalman filter. We do not estimate the dynamic models for the subperiods because of the small number of time series observations. The alphas we obtain from the conditional models are 10 basis points closer to zero than are those produced by the static models.

Panel C reports beta estimates for the static Agarwal model and Kalman smoothed betas for the dynamic specification of the model. These betas are based on gross returns but loadings based on net returns are similar. Noteworthy in the static model are the high and significantly positive loadings on the market premium and the SMB and IT factors. These estimates imply that, on average, investors' portfolios have a high exposure to the market and are tilted towards small caps and technology stocks.

The subsample analysis shows that investors lower their exposure to R_M, UMD, BOND, and IT in the second subperiod, which reinforces Kumar's (2006) finding that individual investors exhibit time-varying style preferences. The likelihood ratio for testing whether factor loadings are constant in the Agarwal model is 19.96, rejecting the null hypothesis that betas are constant at a 1% level. Figure 1, which traces the evolution of Kalman smoothed factor loadings, 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 subperiod when it falls, and reduce market risk in the second subperiod when the market recovers. Furthermore, investors reduce their exposure to the IT sector only after the burst of the Internet bubble. In contrast, Brunnermeier and Nagel (2004) show that hedge funds, which are considered to be managed by sophisticated investors, were also riding the bubble but reduced their exposure to the IT sector before stock prices collapsed.

B. Cross-Sectional Analysis of Investor Performance

Although the previous section treats individual investors as a homogeneous group, it is likely that performance differs considerably across investors. Therefore, here we relate returns to investor characteristics. We examine the relation between gross and net performance and investor characteristics by applying the cross-sectional approach of Fama and MacBeth (1973). Each month we run a cross-sectional regression of portfolio returns on investor characteristics:

$$R_{jt} = \gamma_{0t} + \sum_{l=1}^{7} \gamma_{lt} Z_{jlt} + v_{jt} \, , \tag{7}$$

where R_{jt} denotes gross or net month t portfolio return and Z_{jlt} is the value of characteristic l for investor j at time t. We then calculate the Fama-Macbeth estimator for the characteristics, which is the time series average of the monthly cross-sectional parameter estimates. We calculate the standard error of the Fama-Macbeth estimator from the time series of these monthly estimates. We run the cross-sectional regressions for the full sample period and the two subperiods, January 2000 to December 2002 and January 2003 to March 2006, to assess the stability of the relations between performance and characteristics in different market conditions.

We use the following characteristics as independent variables: $derivatives_{jt}$ and $both_{jt}$, which are two trade type dummy variables equal to one if investor j trades only derivatives or both non-derivatives and derivatives, respectively, in month t; monthly portfolio $turnover_{jt}$; $inactive_{jt}$, a dummy variable equal to one if monthly portfolio turnover is zero; and $woman_j$ and $joint_j$, which are two gender dummy variables equal to one if the account is held by a woman or jointly by a man and woman. We also include account value at the end of the previous month, $value_{jt-1}$, and age of the primary accountholder, age_{jt}. Because the statistics in Table I show that the distributions of turnover and account value are skewed, we decide to trim these characteristics at the 99$^{\text{th}}$ percentile and use their logarithmic transformations in the cross-sectional regressions.

Table III reports results from the Fama-MacBeth regressions. Panel A shows that turnover, gender, account value, and trade type are significant determinants of gross returns. Turnover and account value are positively related to returns, and accounts held by a woman or jointly by a man and woman outperform accounts held by a man only. Investors who do not trade earn lower gross returns than active traders. In contrast, Barber and Odean (2000) find that those who trade most do not earn higher gross returns than do less active investors. The dummy variable that indicates whether an investor trades only derivatives is significant in the second subperiod. Derivatives investors underperform non-derivatives traders by 3.24% a month in this period.

Controlling for other characteristics, women outperform men by 0.41% a month. However, their outperformance is concentrated in the first subperiod, which is the period of stock market decline. A univariate sort on gender shows that the portfolios held by women have significantly lower risk exposures than do those held by men. Thus, it seems that women are hurt less by the stock market crash than men partly because of their higher degree of risk aversion.

After we take into account the transaction costs, we find that derivatives investors underperform non-derivatives traders by more than 3.5% a month over the full sample period. This underperformance can be partly explained by the brokerage firm's commission fee structure. Trading costs for derivatives consist of a specific amount per contract, but trading costs for non-derivatives are based on a fixed amount and a variable part that depends on the value of the transaction. Individual investors tend to trade many small derivatives contracts, which makes the relative cost of trading derivatives higher than trading stocks or bonds.

Furthermore, since turnover drives transaction costs, the positive relation between turnover and performance vanishes when we take costs into account. Opposite to the results for gross performance, inactive investors significantly outperform active investors in terms of net return. Thus, the trading gains of active investors are insufficient to offset trading costs. After incorporating costs, women continue to outperform men and investors who hold large accounts still earn higher returns than those with small accounts.

The cross-sectional analysis above does not consider risk and style differences across investor portfolios. The standard approach to identifying the determinants of cross-sectional variation in risk- and style-adjusted returns has two steps. First, for every portfolio time series regressions of returns on risk and style factors are run to obtain alphas. Second, a cross-sectional regression of these alphas on investor characteristics is estimated.

The main drawback of this approach is the errors-in-variables problem that arises because the factor loadings in the first-stage time series regression are estimated with error. Particularly when the number of time series observations is small, it can be difficult to estimate the model parameters consistently. Therefore, we introduce a new method that allows us to control for risk and style exposures even when the number of return observations for some investors is small. Our approach is based on a purged estimator used in the asset pricing literature by Brennan, Chordia, and Subrahmanyam (1998).

Each month, we first run the cross-sectional regression (7) of returns on characteristics. We then regress the vector of monthly cross-sectional coefficients γ_{lt} for each of the l characteristics on a constant and the time series of risk and style factor realizations F_{kt},

$$\gamma_{lt} = \delta_{l0} + \sum_{k=1}^{K} \delta_{lk} F_{kt} + \omega_{lt} \ . \qquad (8)$$

In the appendix we show that the intercept in this regression, δ_{l0}, is an unbiased estimate of the cross-sectional relation between characteristic l and risk- and style-adjusted returns. The standard error of δ_{l0} is the standard error of the purged estimator. Brennan, Chordia, and Subrahmanyam (1998) note that, intuitively, the time series regression (8) purges the cross-sectional coefficients of their factor dependent component. Thus, we obtain an unbiased estimate of the relation between alpha and characteristics without the need to estimate first-stage time series regressions for every investor.

Panel B in table III presents the results of this analysis. We use the Agarwal model here to adjust the cross-sectional coefficients for risk and style differences across investor portfolios.[3] Compared to the results for raw returns in panel A, we see that taking risk and style exposures into account does not alter the main conclusions from the cross-sectional analysis. The most important determinants of cross-sectional variation in alphas continue to be derivatives trading, trading activity, gender, and account value. Thus, differences in risk and style exposures cannot explain the relative net underperformance of derivatives traders, active investors, male accountholders, and investors with small accounts.

C. Characteristics and Trades of Derivatives Investors

Here, we dig further into the underperformance of derivatives traders by examining their trades and characteristics. Since the number of futures transactions is relatively small, we focus on option trades. During our sample period 26,266 investors trade options, which corresponds to 38.5% of all investors in the data set. The statistics further show that on average, option traders are 2.5 years older than other investors. The proportion of men and women among option investors is similar to that in the full sample of investors. Hence, when we take gender as a proxy for overconfidence, we do not find any relation between overconfidence and option trading. Furthermore, option traders hold larger accounts than do other investors. Thus, accounts held by option investors do not seem to be small gambling portfolios.

Table IV classifies all opening option trades into purchased and written calls and purchased and written put positions. The table also shows the proportion of trades in each category and splits them between trades in AEX index options and stock options. Panel A displays the number of opening transactions per category. When we look at all options, most transactions are purchased call options, followed by purchased put, written call, and written put positions. The finding that call positions are more prevalent than put positions is consistent with results documented by Lakonishok et al. (2007).

Panel B reports the value of options traded in each category. Also in terms of value purchased call positions dominate, followed by purchased put, written put, and written call option contracts. When we differentiate between index options and stock options, we find that almost two thirds of option investments are in stock options. Call options dominate for index options but put positions are more prevalent for stock options. In fact, almost half of the value invested in index options is in purchased call positions, and the smallest amount of money is invested in long put positions.

We consider three alternative explanations for the substantial underperformance of derivatives traders. First, it is possible that investors use derivatives for hedging the downward risk of their stock portfolio. However, it is unlikely that hedging motives are an important reason that investors in our sample trade derivatives. In a survey among 1,500 clients of the Internet brokerage firm, more than 80% indicate that they use options primarily for speculation.

Lakonishok et al. (2007) provide further evidence that most investors do not use options for hedging. These authors show that little options volume can be attributed to hedging, apart from written calls. They point out that, given the low prevalence of short sales of common stocks, it is unlikely that investors use purchased call and written put positions for hedging short-stock positions. Table IV shows that these two positions account for more than half of all the option activity in our sample. Lakonishok et al. (2007) find that for the discount brokerage database analyzed by Barber and Odean (2000), covered call writing is the dominant option strategy. Although written calls can be used for hedging, the protection they provide against a price decline of the underlying asset is limited to the option premium. In Table IV, panel B shows that in our sample written call options are the least important of the four possible option positions. Purchased puts can also be used to hedge a long position in the underlying stock, but Lakonishok et al. (2007) find that naked purchased puts are five times as frequent as protective put purchases.

A second possible reason for the losses suffered by derivatives investors is a lack of knowledge about the risk and return characteristics and the use of derivatives instruments. For instance, it is possible that investors do not use options for hedging due to a lack of knowledge. Some evidence supporting this hypothesis is that only 10% of the clients of the brokerage firm participating in the survey indicate that they use the option Greeks when trading options. A lack of knowledge about derivatives can also partly explain why derivatives investors only underperform during the second half of our sample period, since it is likely that the early online investors were more sophisticated investors.

The last explanation we consider here for the relative underperformance of derivatives traders when the general market movement is upward, is bad market timing due to overreaction. We expect market timing skills to be especially important in the derivatives market, because, due to the leverage they provide, derivatives are effective instruments for betting on market moves. Our earlier finding that most option activity is generated by speculation on changes in underlying stock prices supports this conjecture. We argue that after the stock market decline in 2001 and 2002, investors became bearish about market prospects and expected a further fall. We note that the online broker restricts the ability of the investors to sell stocks short to the 50 largest and most liquid Dutch stocks. Furthermore, the broker allows only intraday short selling, and strict margin requirements apply. For these reasons most clients use options to speculate on a market decrease. Therefore, we expect that at the end of 2002 investors took bearish positions in options.

We examine this explanation in figure 2, which plots the return on the market index, the gross return difference between non-derivatives and derivatives traders, and the ratio of short-term (three months to expiration or less) option positions that are used to speculate on a market increase and positions taken in anticipation of a market decrease. We calculate this ratio, which we call the “Hausse-Baisse ratio,” 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. We argue that option traders are negative about market prospects if this ratio is smaller than one.

Figure 2 indicates that the ratio is below one for most months in 2003 and 2004. The plot further shows that this is exactly the period in which stock markets started to recover. This supports our hypothesis that, after the stock market crash in 2001 and 2002, derivatives traders speculated on a further decline of the market. As a result, they missed part of the recovery of the market and consequently, the gross return difference between non-derivatives and derivatives investors grows considerably.

Our conclusion that option traders overreact to past stock market movements is in line with results of Lakonishok et al. (2007). These authors find that discount clients decreased their open interest in purchased puts at the height of the Internet bubble but sharply cut their bets that prices would increase after the burst of the bubble. In contrast, clients of full-service brokers and firm proprietary traders did not use the option market to speculate on rising prices during the boom.

V. Performance Persistence of Individual Investors

The cross-sectional analysis shows that the group of individual investors in our sample is extremely heterogeneous. Further, Barber and Odean (2000) find that, although the majority of investors loses by trading, the top quartile of investors in their data set beats the market by 6% a year. Here, we perform persistence tests in order to identify those investors who consistently earn positive or negative returns, i.e., persistent winners or losers.

At first sight, it seems unlikely that some individual investors can consistently outperform the market, given the mixed evidence of performance persistence among mutual funds, which are generally considered to be managed by more sophisticated investors.[4] Coval, Hirshleifer, and Shumway (2005) note that although 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, so the price impact of their trades is limited. Second, individual investors face fewer asset allocation constraints, since they are not required to hold a diversified portfolio or track a specified benchmark.

We examine whether we can confirm the finding of Coval, Hirshleifer, and Shumway (2005) of performance persistence among individual investors when we incorporate derivatives trading and account for transaction costs. Following Carhart (1997), we sort investors into decile portfolios based on raw returns earned during a ranking period. We then calculate returns for each of these deciles over a post-ranking period. By repeating the ranking procedure using nonoverlapping intervals, we obtain a time series of post-ranking returns for each decile. We include investors that drop out of the sample during the evaluation period in the portfolios until they disappear, after which we readjust the portfolio weights. We test whether past winners continue to outperform past losers by performing a t-test on the return difference between decile 1 (past winners) and decile 10 (past losers). We also 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, i.e., no performance persistence.

To examine whether consistency in returns, if any, is due to persistence in transaction costs, we consider both gross and net returns. If we find evidence of performance persistence when we sort on net returns, but no sign of persistence in gross returns, then we can conclude that persistence is related to costs. We consider three-, six-, and 12-month ranking and evaluation periods. This choice is based on mutual fund studies showing that performance persistence is usually short term (e.g., Busse and Irvine (2006)). Using longer periods also means that we can include fewer investors in the analysis, because we require an investor to be present in the sample during the complete ranking period and at least one month in the evaluation period. On the other hand, results for periods shorter than three months are likely to be dominated by noise and luck.

Table V presents post-formation returns and alphas for portfolios of investors sorted on past one-year return. The figures in the columns labeled “gross” (“net”) refer to deciles formed and evaluated on the basis of gross (net) performance. The results indicate that on average, investors in the top decile continue to outperform those in the bottom decile in the year subsequent to the formation year by 1.2% per month in terms of gross return and 2.4% in terms of net return. The consistency in gross returns indicates that persistence in costs can only explain part of total performance persistence. A substantial part of the performance differential is driven by the bad performance of investors in decile 10. Gross and net returns for these investors are 0.73% and 1.38% lower, respectively, than for those in decile 9. The Spearman rank correlation is significant at the 1% level, indicating a strong relation between formation and evaluation period ranking.

Figure 3 illustrates the large spread in returns across deciles. The figure plots post-formation cumulative net returns for each of the ten deciles, a hypothetical index fund that we base on the Worldscope Netherlands index, assuming 5 basis points management fees per month, and a hypothetical equity mutual fund, assuming a net monthly alpha of -0.15%, based on Carhart (1997). Since we rebalance the decile portfolios annually, the figure indicates an investor’s cumulative net return in case he or she would remain in the same decile for the entire period.

The figure shows that only investors in the top deciles earn cumulative net returns that are close to those on the index and mutual funds. Specifically, 90% of investors underperform the index fund and 80% of investors also underperform the mutual fund. Investors who remain in the bottom decile from December 2000 to December 2005 lose 90% of their initial investment in this five-year period. Thus, most investors would have been better off by holding an index fund or a mutual fund.

The difference in performance between past winners and losers also shows up when we use the Carhart and Agarwal alphas to measure performance in the evaluation period. 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 a 1% level. Spearman rank correlation coefficients exceed 0.9 and are significant at the 1% level, thus providing strong evidence of performance persistence among individual investors. Although gross alphas for investors in the top deciles are close to zero, the net alphas are negative for all investors and significant for those in the bottom three deciles. The losses of decile 10 investors are substantial. In terms of gross alpha, those in decile 10 lose 1.5% per month, but in terms of net alpha this loss even doubles to 3%.

Table V further reports the exposures of the returns on the decile portfolios to the factors in the Agarwal model. Loser deciles tend to have significantly higher loadings on the R_M, SMB, UMD, and IT factors than winner deciles. The high exposures of investors in decile 10 to the market premium (1.93), the SMB factor (1.86), and the IT factor (0.8) indicate strong style tilts in their portfolios towards high market beta stocks, small caps, and tech stocks.

The picture that emerges from the results for the three- and six-month ranking and evaluation periods (not reported to save space) is that performance persistence is still significant on six-month horizons but absent for shorter periods. Spearman correlation coefficients are significant at the 5% level for the six-month periods but not significant for the three-month periods.

We investigate whether the return difference between winner and loser portfolios is related to heterogeneity in investor characteristics. Table VI presents the characteristics of the investors in the decile portfolios formed on past one-year net returns. We find that the median account value decreases uniformly with ranking, i.e., the top decile consists of investors who hold the largest accounts. Furthermore, although derivatives turnover is only 5% for accounts in most of the top deciles, for the bottom deciles it is much higher, with investor portfolios in decile ten having derivatives turnover of more than 40% a month. Accounts in the bottom deciles also have much higher non-derivatives turnover than those in the top deciles. Table VI further shows that in the bottom deciles men hold a higher proportion of the accounts than in the top deciles. Finally, investor age appears to be unrelated to performance persistence.

VI. Conclusion

By studying the impact of derivatives trading on portfolio returns and by examining whether individual investor performance is persistent, we provide new evidence on the investment performance and behavior of individual investors. We analyze returns earned on stock, bond, and derivatives investments of more than 68,000 investors who trade 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 after adjusting for risk and style tilts, the average investor earns negative gross and net returns. This result is mainly driven by the performance of investors trading derivatives, who underperform other investors by almost 1.5% a month in gross terms and 3.5% in terms of net return. We attribute the poor performance of derivatives traders to bad market timing due to overreaction to past stock market movements. In particular, after the collapse of the Internet bubble, derivatives traders speculated on a further market decrease when markets started to recover. Expensive trading and a lack of knowledge also contribute to the detrimental effect of derivatives trading. Furthermore, we find that active investors cannot offset high trading costs by superior investment returns. Although gross alphas of the most active traders are significantly higher than those of less active traders, the picture is opposite in terms of net performance.

In addition, we find strong evidence of performance persistence among individual investors. Those investors ranked in the top decile portfolio based on past one-year performance continue to outperform investors in the bottom decile over the next year by 1.5% a month in terms of gross alpha and 2.8% in terms of net alpha. Persistence in trading costs explains only part of the performance persistence. The bottom deciles tend to consist of small accounts with high turnover, which are predominantly held by men. Performance persistence is somewhat weaker on shorter horizons, but still significant over six-month periods.

Taken together, our results demonstrate that the group of individual investors is extremely heterogeneous. We further confirm the prediction of modern portfolio theory that most investors are better off by holding an index fund. Most importantly, the substantial losses from excessive trading and investments in derivatives highlight the need to educate investors in financial decision making. Measuring the effect of financial education on investor behavior and performance is a fruitful area for future research.

Appendix: Cross-Sectional Risk and Style Adjustment

In this appendix we show that we can obtain an unbiased estimate of the relation between alphas and characteristics without estimating first-stage time series regressions for every investor. Each month, we estimate a cross-sectional regression of returns on investor characteristics. We then regress the vector of monthly cross-sectional coefficients γ_{lt} for each of the l characteristics on a constant and the time series of risk and style factor realizations F_{kt},

$$\gamma_{lt} = \delta_{l0} + \sum_{k=1}^{K} \delta_{lk} F_{kt} + \omega_{lt} \ . \tag{A1}$$

To see that the intercept δ_{l0} in this time series regression is an unbiased estimate of the cross-sectional relation between alpha and characteristic l, consider the following. Suppose that portfolio returns are generated by the factor model

$$R_{jt} = \alpha_j + \sum_{k=1}^{K} \beta_{jk} F_{kt} + \varepsilon_{jt} \ . \tag{A2}$$

We are interested in the cross-sectional relation between α_j and Z_{jlt}, the value of characteristic l for investor j at time t. We denote the true coefficient vector of this relation between alphas and the characteristics by $\boldsymbol{\delta}$. The cross-sectional regression of portfolio returns in month t on investor characteristics produces the following coefficient vector

$$\boldsymbol{\gamma}_t = (\mathbf{Z}_t'\mathbf{Z}_t)^{-1}\mathbf{Z}_t'\mathbf{R}_t = \boldsymbol{\delta} + \mathbf{F}_t[(\mathbf{Z}_t'\mathbf{Z}_t)^{-1}\mathbf{Z}_t'\boldsymbol{\beta}]. \tag{A3}$$

Therefore, as noted by Brennan, Chordia, and Subrahmanyam (1998), the intercept δ_0 from the time series regression of the monthly cross-sectional parameter estimates γ_{lt} on the vector of factor realizations $\mathbf{F}_t$ is an unbiased estimate of $\boldsymbol{\delta}$ if the factor premia are serially uncorrelated. The coefficients on the factor premia $\mathbf{F}_t$ are unbiased estimates of $[(\mathbf{Z}_t'\mathbf{Z}_t)^{-1}\mathbf{Z}_t'\boldsymbol{\beta}]$ and measure the relation between factor loadings and investor characteristics.

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Notes

[1] In terms of transaction volume (value) almost 95% (85%) of all trades are transactions in Dutch securities. Consequently, we find that Dutch versions of the factor-mimicking portfolios lead to a better model fit than do international factors.

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

[3] Cross-sectional results for the Carhart (1997) model are similar and omitted to conserve space.

[4] 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.

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. Our sample period is from January 2000 to March 2006. We define our variables as follows: Age is the age of the primary accountholder. Trades are the number of trades per account per month. This variable 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. We base trades active, turnover active, and TC active on all accounts that trade in a given month. TC/trade are monthly transaction costs in euros per trade per account. This variable is split into trades in non-derivatives and derivatives. Account value is the market value of all assets in the investor's account. For each variable we report the mean, median, and standard deviation, as well as 1^{st}, 5^{th}, 25^{th}, 75^{th}, 95^{th} and 99^{th} percentile values.

	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

Raw Returns, Alphas, and Factor Loadings for the Average Individual 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 constant factor loadings. We present raw returns and alphas for the full sample period and for two subperiods, 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. In panel B, we adjust returns for risk and style tilts by the Carhart and Agarwal models with time-varying factor exposures estimated using the Kalman filter. Panel C reports the estimated factor loadings in the static Agarwal model for the full period and for both subperiods. In the last column we show the average factor loadings in the dynamic Agarwal model with the standard deviations of the loadings in parentheses. The last row reports the adjusted R^2 of the static Agarwal model and the likelihood ratio (LR) for the null hypothesis that factor loadings are constant in the dynamic Agarwal model.

	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 III

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

This table reports Fama-MacBeth (1973) coefficient estimates. In the first three columns gross portfolio returns are the dependent variable and in the last three columns we use net returns. Panel A shows results for raw returns and panel B refers to Agarwal alphas. We estimate the Fama-MacBeth regressions for the full period, January 2000 to March 2006, and for two subperiods, January 2000 to December 2002 and January 2003 to March 2006. The independent variables are investor characteristics. Derivatives is a dummy variable equal to one if an investor only traded derivatives in a given month. Both is a dummy variable equal to one if the investor traded both derivatives and non-derivatives in a particular month. We define turnover 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. Inactive is a dummy variable equal to one if an investor does not trade in a given month. Woman and joint are dummy variables equal to one if the account is held by a woman or jointly by a man and woman, respectively. Value is total account value and is lagged by one month. Age is the age of the primary accountholder. *t*-statistics are in parentheses.

	Gross			Net		
	2000 - 2006	2000 - 2002	2003-2006	2000 - 2006	2000 - 2002	2003-2006
			Panel A: Raw Returns			
Derivatives	-1.49	0.41	-3.24	-3.51	-1.29	-5.55
	(-2.10)	(0.36)	(-4.27)	(-4.92)	(-1.12)	(-7.60)
Both	-0.94	-1.01	-0.86	-1.65	-1.64	-1.66
	(-4.22)	(-2.73)	(-3.34)	(-7.39)	(-4.53)	(-6.05)
ln(Turnover)	0.61	0.79	0.44	-0.15	0.05	-0.33
	(4.36)	(3.10)	(3.50)	(-1.14)	(0.22)	(-2.85)
Inactive	-0.99	-0.86	-1.10	0.99	1.09	0.89
	(-2.36)	(-1.35)	(-1.99)	(2.48)	(1.80)	(1.68)
Woman	0.41	0.66	0.17	0.40	0.65	0.16
	(3.72)	(3.58)	(1.52)	(3.67)	(3.59)	(1.44)
Joint	0.19	0.18	0.20	0.25	0.25	0.24
	(3.52)	(1.80)	(4.24)	(4.62)	(2.50)	(5.27)
ln($Value_{t-1}$)	0.30	0.41	0.20	0.57	0.68	0.46
	(2.99)	(2.14)	(2.47)	(5.80)	(3.69)	(5.94)
Age/10	0.00	0.04	-0.04	-0.01	0.04	-0.05
	(-0.04)	(0.63)	(-1.10)	(-0.25)	(0.67)	(-1.60)
			Panel B: Agarwal Alphas			
Derivatives	-1.36	0.87	-2.47	-3.45	-0.93	-4.96
	(-2.57)	(0.94)	(-3.31)	(-6.63)	(-1.00)	(-7.06)
Both	-0.90	-0.56	-0.89	-1.63	-1.25	-1.72
	(-4.13)	(-1.37)	(-2.83)	(-7.39)	(-3.05)	(-5.12)
ln(Turnover)	0.77	1.15	0.42	-0.01	0.37	-0.42
	(6.08)	(4.56)	(2.66)	(-0.10)	(1.44)	(-2.70)
Inactive	-1.39	-1.40	-0.54	0.78	0.60	1.51
	(-3.98)	(-2.38)	(-0.89)	(2.10)	(1.01)	(2.69)
Woman	0.36	0.61	0.23	0.35	0.58	0.22
	(4.13)	(3.93)	(2.07)	(4.02)	(3.76)	(1.86)
Joint	0.16	-0.01	0.16	0.22	0.06	0.20
	(3.34)	(-0.10)	(2.61)	(4.58)	(0.63)	(3.35)
ln($Value_{t-1}$)	0.24	0.28	0.17	0.51	0.57	0.44
	(2.99)	(1.79)	(1.66)	(6.56)	(3.76)	(4.42)
Age/10	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.95)	(-1.05)	(-1.40)	(-2.25)	(-1.02)	(-1.85)

Table IV

Descriptive Statistics on Option Trades

In this table we classify all opening option trades into purchased call, written call, purchased put, and written put positions. Panel A reports the number of opening transactions and panel B shows the value in millions of euros of option contracts traded in each category. The table also shows the proportion of trades in a given category relative to the total of call and puts traded. Furthermore, we make a split between trades in index options and stock options.

		Call			Put			Call+Put
		Purchased	Written	Total	Purchased	Written	Total	Total
		Panel A: Option Transactions						
All	#	877,105	541,906	1,419,011	557,720	520,647	1,078,367	2,497,378
	%	35.1	21.7	56.8	22.3	20.8	43.2	100
Index	#	336,887	198,030	534,917	403,838	209,393	613,231	1,148,148
	%	29.3	17.2	46.6	35.2	18.2	53.4	100
Stock	#	540,218	343,876	884,094	153,882	311,254	465,136	1,349,230
	%	40.0	25.5	65.5	11.4	23.1	34.5	100
		Panel B: Option Value Traded						
All	€	1839.7	905.2	2744.9	1504.1	1103.8	2608.0	5352.9
	%	34.4	16.9	51.3	28.1	20.6	48.7	100
Index	€	916.9	337.7	1254.5	175.5	419.8	595.3	1849.8
	%	49.6	18.3	67.8	9.5	22.7	32.2	100
Stock	€	922.8	567.6	1490.4	1328.7	684.0	2012.7	3503.1
	%	26.3	16.2	42.5	37.9	19.5	57.5	100

Table V

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

At the end of every year from 2000 to 2004 we rank investors into equal-weight decile portfolios based on returns earned over the year. Each portfolio is held for one year and subsequently rebalanced. This table shows the average monthly raw returns, alphas produced by the Carhart and Agarwal models, and factor loadings in the Agarwal model for each decile portfolio in the post-formation period. Decile 1 contains the 10% of investors with the highest return during the ranking 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.

	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 VI

Characteristics of Decile Portfolios of 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 investors formed on the basis of past one-year return. As an exception, the numbers we report for account value are time series averages of monthly cross-sectional median account values. Decile 1 contains the 10% of investors with the highest return during the ranking 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 in a given decile portfolio held by a man or woman, respectively. Age is the age of the primary accountholder.

Decile	Account Value (€)	Derivatives Turnover (%)	Non-Derivatives Turnover (%)	Men (%)	Women (%)	Age (years)
1	20,547	9.6	25.8	61.9	9.5	44.1
2	20,489	4.7	13.2	54.2	10.1	44.6
3	18,660	4.9	11.9	54.6	8.5	44.7
4	15,654	4.6	24.0	51.2	10.7	45.5
5	12,351	4.6	28.4	54.8	8.9	45.9
6	8,825	4.7	23.6	62.5	8.6	43.8
7	7,881	7.1	36.2	59.7	8.0	44.2
8	4,630	10.6	52.6	64.5	6.0	42.7
9	3,975	15.5	90.5	62.9	5.9	42.0
10	3,429	41.7	123.2	67.2	5.1	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	0.8	-1.8

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.

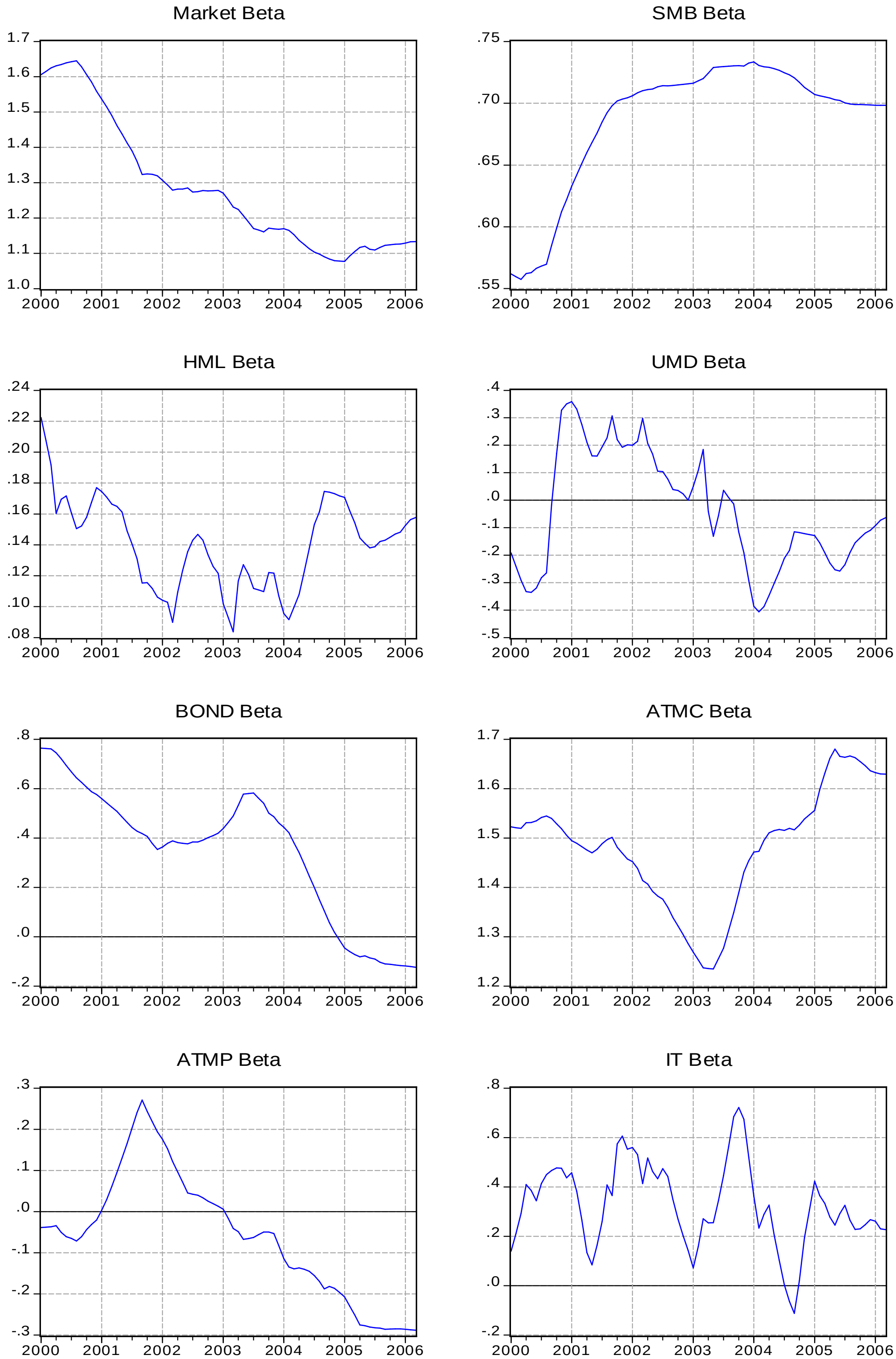

Figure 2

Hausse-Baisse Ratio and Gross Return Difference Non-Derivatives and 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 non-derivatives and derivatives traders. We calculate the Hausse-Baisse ratio as the sum of the value of short-term (3 months to expiration or less) call options bought and put options sold divided by the sum of the value of put options bought and call options sold.

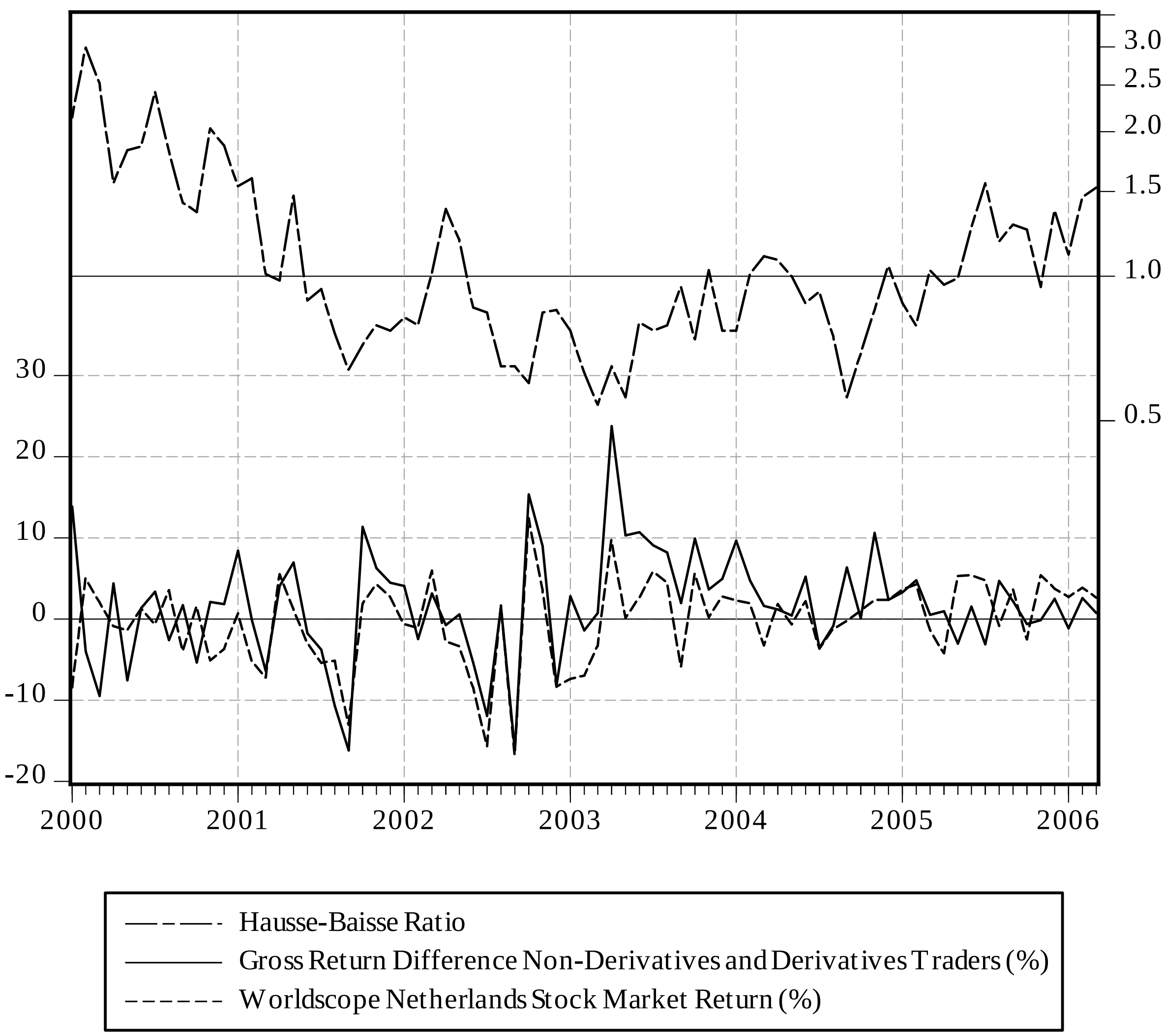

Figure 3

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

At the end of every year from 2000 to 2004 we rank investors into equal-weighted decile portfolios based on net returns earned over the year. This figure plots the cumulative net return of these deciles in the year subsequent to the formation year, scaled to one at the end of December 2000. The figure also shows the cumulative net return on a hypothetical index fund based on the Worldscope Netherlands index, assuming 5 bp fees per month, and on a hypothetical mutual fund, assuming a net monthly alpha of -0.15% based on Carhart (1997). Decile 1 (10) contains the 10% of investors with the highest (lowest) return during the ranking period.