Performance Persistence of Individual Investors*

Limei Che Øyvind Norli† Richard Priestley

January, 2008

Abstract

Using unique data on month-end stock market portfolios of all individual investors over an eleven year period, we find that a substantial number of investors exhibit economically and statistically significant performance persistence. Furthermore, a portfolio that is long in stocks previously favored by top performing investors earns a substantial risk adjusted return. These finding are robust to how we measure past performance, how often investors trade, and to the size of investors' portfolios. Unlike the evidence from mutual and pension funds, the persistence in performance of individual investors is not concentrated in portfolios with poor prior performance.

JEL classification: G11, D12, D14.
Keywords: Individual investors, performance, persistence.

*All authors are from the Norwegian School of Management (BI), Nydalsveien 37, N-0442 Oslo, Norway. Limei Che can be reached at +47 4641 0521 and limei.che@bi.no. Øyvind Norli can be reached +47 4641 0514 and oyvind.norli@bi.no. Richard Priestley can be reached at +47 4641 0515 and richard.priestley@bi.no. We are grateful to the Norwegian Central Securities Depository (VPS ASA) for providing the security ownership data. Øyvind Norli and Richard Priestley thank "Fondet til fremme av bank- og finansstudier" for providing financial support for this project. We thank Øyvind Bøhren, Wayne Ferson, Noah Stoffman (discussant), Russ Wermers and conference participants at the 2007 Northern Finance Association meetings for helpful comments. All remaining errors are ours.

†Corresponding author.

1 Introduction

Most of the evidence on the stock market performance of individual investors suggests that they make poor investment decisions. Individuals show a tendency to sell stocks that subsequently do well and buy stocks that subsequently perform poorly. Those who trade the most underperform relative to the market, relative to more sophisticated investors, and relative to less active investors.[1] This paper documents that the dismal stock market performance of some individual investors does not apply to individuals in general. Although we confirm earlier findings that very active investors underperform, we find that a sizeable fraction of all individuals who invest in stocks are able to consistently outperform the market. This performance persistence is both economically and statistically significant.

In contrast to many studies that rely on trading data from a brokerage account to study individual investors, our research is based on the entire portfolio holdings of *all* individuals that are active in the market that we study. For the period January 1993 through June 2003 we observe the month-end stock market portfolio of all individual investors who owned stocks on the Oslo Stock Exchange. The monthly frequency, the long time-series, and the access to all Oslo Stock Exchange investments of any individual creates a unique opportunity to measure long-term performance persistence at the portfolio level. Our main finding is that individuals who have done well over the past two to five years outperform a passive benchmark for as long as the next three years. This result is robust to different ways of measuring past and future performance. For instance, we regress future performance, measured using an investment-style adjusted benchmark, on past abnormal performance measured using Jensen's alpha. These regressions, which are performed at the individual portfolio level, show a strong positive relationship between past abnormal performance and future performance. In a second set of results, we isolate stocks that are held primarily by individuals that rank in the top past-performance decile and stocks that are held primarily by individuals ranked in the bottom performance decile. Portfolios of stocks favored by top-performers generate statistically significant alphas of between 72 and 125 basis

[1] See Odean (1998, 1999), Barber and Odean (2000, 2001), Grinblatt and Keloharju (2000), Barber, Lee, Liu, and Odean (2005)

points per month, depending on the holding period. A portfolio of stocks favored by bottom performers has an alpha close to zero. Our results demonstrate that some individuals have the ability to consistently outperform a risk adjusted benchmark in a way that is economically significant.

Analyzing individual investor performance persistence is important for at least three reasons. First, individual investors work in a different regulatory environment than other investors such as mutual funds and pensions funds. In particular, fund managers are often constrained in their ability to short sell and borrow on margin. In addition, fund managers typically have a mandate to follow a certain “investment style”—which further constrains their investable universe. As individuals are likely to be less constrained than institutional investors they may find it easier to execute profitable trading strategies.

Second, the behavioral finance literature has grown to become a significant provider of alternative ways of thinking about how assets are priced.[2] This literature largely understands asset pricing anomalies as rooted in behavioral biases held by individual investors. These behavioral biases are for the most part studied and documented in the cognitive psychology literature, often using laboratory experiments or relatively small samples. Our study is important since we are able to directly observe and investigate the portfolio choices made by the population, rather than a limited sample, of individual investors.

Third, professional fund managers who perform well often attract substantial inflows of new capital. Berk and Green (2004) point out that this process will lead to a lack of persistence in performance because managing more money drives costs up and returns down. If such a mechanism is at work in the mutual fund sector, uncovering anything other than very short run performance persistence using mutual fund data is unlikely (Bollen and Busse, 2004). Chevalier and Ellison (1999) offer an alternative explanation for why it is hard to find persistence in mutual fund performance. They find that well performing managers have a higher probability of surviving as managers and subsequently move to a bigger firm when compared to underperforming

[2] Hirshleifer (2001) surveys evidence and theories of the importance of investor psychology in security prices. Barberis and Thaler (2003) review the extensive evidence from cognitive psychology on behavioral biases. Baker, Ruback, and Wurgler (2005) survey how behavioral biases impact managerial decision making.

managers. If the best managers move around from fund to fund it will be difficult for a given fund to show persistence in performance. The strength of our paper is that we follow individuals, which first, guarantees that portfolio returns are linked to the same decision maker throughout and second, implies that returns are not influenced by fees and costs reacting to past performance. Since we show that a significant number of individual investors outperform the market consistently over time it would seem reasonable that a significant number of individuals hired as fund managers would possess some of the same ability. Thus, our findings can be interpreted as lending support to the view that some mutual fund managers have superior ability—but, that the rent from this ability is extracted by the mutual funds and not the investors in the funds. Berk and Green (2004) and Chevalier and Ellison (1999) suggest processes through which this rent extraction can happen.

This paper is related to a large literature on the stock market performance persistence of mutual fund managers. Early research documents significant performance persistence and interprets this evidence as being consistent with the view that fund managers have the ability to earn abnormal returns.[3] Carhart (1997) questions this interpretation and argues that performance persistence is driven by the momentum effect documented by Jegadeesh and Titman (1993). Carhart (1997) points out that managers who have done well in the past will, by definition, have stocks in their portfolios that have experienced high returns. Jegadeesh and Titman (1993) show that such stocks will outperform the market in a period of up to twelve months following the ranking month. Controlling for the momentum-effect, Carhart (1997) finds that only the worst performing funds display persistence.

As discussed briefly above, Berk and Green (2004) develop a model showing that competition among investors will drive future costs up and future returns down to the point where investors get returns that are commensurate with the risk of the fund. Thus, in the long-run, we should not expect a fund to be able to maintain a positive alpha. Bollen and Busse (2004) argue that the information advantage of a managers in the model of Berk and Green (2004) will be short lived and they use this to motivate an investigation of performance over a short horizon.

[3]See Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Brown and Goetzmann (1995) and Elton, Gruber, and Blake (1996).

They find that funds ranked in the top decile of past quarter performance generate an abnormal performance of 39 basis points per day over the quarter following the ranking period. The abnormal performance disappears if the holding period is extended beyond one quarter.

In a paper closely related to ours, Coval, Hirshleifer, and Shumway (2005) study performance persistence using data from a large discount brokerage firm. They observe trades from a large number of accounts but focus much of their analysis on the trades from about 17,000 accounts that are active traders over their seven year sample period. While we focus on long horizon performance, their paper focuses the analysis on short performance horizons. Looking at the five-day performance of stocks after they have been bought by an account (ignoring sales) Coval, Hirshleifer, and Shumway document strong performance persistence. Accounts that are classified as being in the top performance decile, based on past performance, obtain abnormal returns of between 12 and 15 basis points per day over the five-day holding period that follows the ranking period. They also document a similarly sized negative return for traders in the bottom performance decile. Coval, Hirshleifer, and Shumway (2005) also investigate the portfolio-performance (i.e., both purchases and sales) of the accounts. Ranking each account on performance over the first four years of the sample period, they construct two portfolios consisting of top decile performers and bottom decile performers. Following these portfolios over the next three years, using daily returns, the authors find that a portfolio long in the top performers and short in the bottom performers yields an annual return of about eight percent per year.[4]

Given the performance persistence evidence in Coval, Hirshleifer, and Shumway (2005) our results are interesting for several reasons. First, our investigation is based on access to the portfolio holdings of the population of Norwegian individuals that invest in stocks on the Oslo Stock Exchange. The portfolio holdings are observed monthly for a period of up to eleven years. This allow us to investigate the long-run performance persistence for individual investors in a way that previously has only been possible for mutual fund managers. Second, Coval, Hirshleifer, and Shumway use daily returns and focus their investigation on short horizon performance. Our study is based on monthly data, a longer time-series, and we focus on long horizon performance.

[4] The main findings of Coval, Hirshleifer, and Shumway (2005) are reinforced by Bauer, Cosemans, and Eichholtz (2007) using data from a Dutch online discount broker.

Third, the use of discount brokerage data raises the concern that it is not representative of investors' trading in the stock market and, as a result, it is not possible to draw more general conclusions about investor performance. Given that we are using all stock holdings of the population of individuals that trade on the Oslo Stock Exchange, independent of what account that is used to trade the stocks, this is not a concern with our data. Thus, the fact that we are able to corroborate the findings in Coval, Hirshleifer, and Shumway (2005) shows that the evidence from discount brokerage data may very well capture effects that generalize to the population of individual traders.

Our paper is also related to the literature on the investment decisions, trading behavior, and stock market performance of individual investors. A number of papers have found evidence consistent with a disposition effect, i.e., the tendency to sell winners too soon and hold on to losers too long, using trading records from a discount brokerage house.[5] There is also evidence that individuals who trade excessively underperform other investors. For example, Grinblatt and Keloharju (2006) find that investors who trade the most frequently are overconfident and are prone to sensation seeking. Barber and Odean (2000) also present evidence that overconfidence plays a role in the poor performance of individual investors. Finally, Odean (1999) shows that individual investors trade excessively which results in them underperforming. Although we also document bad performance for very active investors, we are able to show that some individual investors display consistent superior ability.

In a related strand of the literature that examines individuals' portfolio choices, Campbell (2006), Calvet, Campbell, and Sodini (2006) and Calvet, Campbell, and Sodini (2007) show that wealthier and more educated individuals behave more in line with the prediction of standard finance theory. Calvet, Campbell, and Sodini (2006) show that the welfare cost of portfolio inefficiencies such as underdiversification and nonparticipation are relatively modest. Focusing on the dynamics in individuals' portfolio choices, Calvet, Campbell, and Sodini (2007) document that individuals overall show a strong propensity to rebalance their portfolio in response to changes in the price of risky assets. On the other hand, there is ample evidence showing that

[5] See, for example, Odean (1998) and Grinblatt and Keloharju (2001).

individuals do not behave as predicted by standard finance theory. For example, Barber and Odean (2006) document that individual investors are net buyers of stocks that have caught their attention for exogenous reasons.

The rest of the paper is organized as follows. Section 2 provides the details on the methodology used to measure stock market performance. In section 3 we discuss our data and the sample selection. Section 4 explains how we measure performance persistence, presents our main results, and provides robustness tests of our main findings. Section 5 concludes the paper.

2 Measures of Stock Market Performance

This study relies heavily on various measures of stock market performance. We measure the performance of an individual investor's stock-market portfolio using (i) the Appraisal ratio, (ii) the Sharpe ratio, (iii) characteristic adjusted returns along the lines of Daniel, Grinblatt, Titman, and Wermers (1997), and (iv) a portfolio weight based measure similar to Grinblatt and Titman (1993).

Appraisal ratio. The Appraisal ratio of a portfolio is the Jensen's alpha (Jensen, 1968) of the portfolio normalized by the standard deviation of the error term from the regression used to estimate the alpha. We estimate the Jensen's alpha of portfolio p over months $t = 1, \ldots, T$ as the intercept α_p from the time-series regression:

$$r_{pt} = \alpha_p + \beta(R_{mt} - R_{ft}) + s\text{SMB}_t + h\text{HML}_t + m\text{MOM}_t + \epsilon_{pt}, \tag{1}$$

where r_{pt} is return on portfolio p in month t in excess of the risk-free return, R_{mt} and R_{ft} are returns on the proxy for the market portfolio and the risk-free rate, respectively. The three remaining variables captures returns related to market capitalization (size), book-to-market ratio, and stock return momentum. The size (SMB) and book-to-market factors (HML) are constructed following the approach of Fama and French (1993). The momentum factor (MOM) is constructed following the approach outlined on Ken French's web-site.[6] In particular, six value-weighted portfolios are constructed from the intersection of three portfolios formed using return momentum over months $t-12$ through month $t-2$ and two portfolios formed using market capitalization from month $t-1$. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. The Appraisal ratio of portfolio p is α_p normalized by the standard deviation of the error term ϵ_{pt}.

Christopherson, Ferson, and Glassman (1998) point out that using the Appraisal ratio has several advantages. First, using α_p as a normalized explanatory variable, along with normalizing all other variables, results in a Weighted Least Squares (WLS) regression. This reduces the cross-sectional differences related to variance which are likely to be important in our analysis because individual investors often hold stock-market portfolios that are not well diversified.

Second, Treynor and Black (1973) show that the Appraisal ratio is directly related to stock picking ability. In particular, they argue that when investors have stock-picking ability, the optimal portfolio choice can be thought of as a three-stage process (Treynor and Black, 1973, p. 74):

> ...the first stage is selection of an active portfolio to maximize the appraisal ratio, the second is blending the active portfolio with a suitable replica of the market portfolio to maximize the Sharpe ratio, and the third entails scaling positions in the combined portfolio up or down through lending or borrowing ...

Treynor and Black (1973) point out that Jensen's alpha is not invariant to the second stage. That is, Jensen's alpha varies with the balance between the active portfolio and the market portfolio. The implication for our study is important. The balance between the active portfolio and the market proxy is influenced by an investor's market expectations. Thus, Jensen's alpha is affected by market-timing ability while the Appraisal ratio is not. Thus, the Appraisal ratio is a better measure of ability related to picking individual securities.

[6] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Sharpe ratio. We measure the Sharpe ratio of portfolio p at time t as the average difference between the portfolio return and the risk-free return over the interval $t-T$ through $t-1$, divided by the standard deviation of the portfolio return over the same interval. This is a measure of ability that captures both stock picking skills and timing-ability.

Characteristic adjusted returns. We construct characteristic adjusted returns using an approach similar to Daniel, Grinblatt, Titman, and Wermers (1997). For a portfolio consisting of J stocks at time t, we construct a size and momentum matched portfolio by matching each of the J stocks in the portfolio with a stock of similar size and with similar stock return momentum. More specifically, for firm j in the portfolio of investor i at time t with market capitalization ME_{jit}, we identify all firms listed on the Oslo Stock Exchange with market capitalization in the interval $[0.7\text{ME}_{jit}, 1.3\text{ME}_{jit}]$. This set of firms is ranked according to stock return momentum measured over the six month period $t-6$ through $t-1$. The matching firm is the firm closest to firm j in the momentum rank. The characteristic adjusted returns on portfolio p is computed as the difference between the value-weighted return on portfolio p and the value-weighted return on a portfolio of the size and momentum matched stocks.[7]

Portfolio weight based performance. Grinblatt and Titman (1993) point out that from the perspective of an uninformed investor, expected returns are constant over time—implying that portfolio weights and future returns cannot be correlated for uninformed investors. In contrast, investors with stock picking ability can predict the return of certain stocks. This implies that ability will be reflected as a positive covariance between current portfolio weights and future returns. We follow Ferson and Khang (2002) and implement this idea for investor i (dropping the i subscript) as follows:

$$\Delta W_t(L, H) = \sum_{j=1}^{J} \left(w_{jt} - w_{jt}^b(L)\right) \left(R_{jt+1}(H) - E(R_j(H))\right), \tag{2}$$

[7]The number of stocks listed on the Oslo Stock Exchange is insufficient to create a matching portfolio using three or more characteristics. Thus, we are prevented from matching on book-to-market ratio in addition to size and momentum.

where w_{jt} is the portfolio weight on stock j at time t, $w^b_{jt}(L)$ is the benchmark weight computed as the weight stock j would have had in the portfolio at time t if the investor had followed a buy-and-hold strategy between month $t-L+1$ and month t, $R_{jt+1}(H)$ is the H-month buy-and-hold return starting with month $t+1$, and $E(R_j(H))$ is the expected H-month return used to demean the portfolio returns $R_{jt+1}(H)$.[8] The performance of investor i over a T-month period is measured as the average $\Delta W_t(L,H)$ over the period.

3 Data and Sample Selection

This paper studies individual investors who held common shares traded on the Oslo Stock Exchange between December 1992 and June 2003. At the end of June 2003, the Oslo Stock Exchange ranks 11th out of twenty-three European stock exchanges based on market capitalization and 12th based on the number of listed companies.[9] Thus, compared to other European exchanges, the Oslo Stock Exchange is close to the "median exchange" when it comes to market capitalization and number of shares listed. Looking at stock market turnover (measured as annualized electronic order book transactions), the exchange has the eighth highest turnover. Bøhren, Eckbo, and Michalsen (1997) show that the intensity of seasoned equity offerings is comparable to that of active markets like the New York Stock Exchange. In sum, the Oslo Stock Exchange is an established and mature market where liquidity and turnover are high enough to be an interesting laboratory to study investor behavior.

Our data source for the stock holdings of individual investors is the Norwegian Central Securities Depository (NCSD).[10] NCSD is a Norwegian company authorized to register rights to securities. Companies listed on the Oslo Stock Exchange are required by law to report to

[8] When implementing the portfolio weight based measure, we estimate the mean buy-and-hold returns for stock j using at most the past sixty months and at least twenty-four months. Ferson and Khang (2002) justify using demeaned returns because it implies that:

$$E\left(w_{jt} - w^b_{jt}(L)\right)\left(R_{jt+1}(H) - E(R_j(H)\right) = COV\left((w_{jt} - w^b_{jt}(L)), R_{jt+1}(H)\right)$$

even when $E(w_{jt} - w^b_{jt}(L)) \neq 0$.

[9] See www.fese.eu.

[10] The Norwegian name for the Norwegian Central Securities Depository (NCSD) is VPS ASA—or better known as "Verdipapirsentralen." The below description of the activities of NCSD borrows from www.vps.no/english.

a security register. During our sample period, all listed companies registered their shares with NCSD. All investors that invest in stocks registered at NCSD must have a NCSD-account. Our main data is the month-end holdings of stocks of all NCSD-accounts between December 1992 and June 2003. When securities are traded, NCSD performs the settlement by transferring the security from the seller's NCSD-account to the buyer's NCSD-account. The Norwegian Central Bank subsequently performs the cash settlement. The NCSD-registry is used by the Norwegian government for taxation of investors. Thus, the quality of the data is a very high.

We study the stock holdings of all individuals and sole proprietorships. Since the latter entity is a business that is only owned by one person, we will refer to these investors jointly as individual investors. The number of individual investors that were registered at least once during the sample period is 718,185—around 17% of the Norwegian population. Many NCSD-accounts held by individual investors must be considered as "stale" in the sense that the owner of the account practically never trades. We will follow Coval, Hirshleifer, and Shumway (2005), among others, and restrict our sample to accounts that are reasonably active. The next section describes the details of our sample selection procedure.

3.1 Sample Selection and Descriptive Statistics

Our sample selection procedure pertains to the inclusion of both stocks and investors. Regarding stocks, we restrict our sample by excluding the least liquid stocks on the Oslo Stock Exchange. In particular, for a given stock and a given month, the stock is only included in the sample if it has traded during the month. In other words, we are not computing returns from bid and/or ask prices. For a given month t, we also exclude "penny-stocks"—defined as a stock with a price below NOK 5.0 at time $t-1$.[11]

Table 1 reports descriptive statistics for the Oslo Stock Exchange. The Table reports numbers year-on-year, for the entire sample (1993-2003), and for the estimation period (1995-2003). The second column reports the number of listed stocks that satisfy the selection criteria each year. From a low of 132 stocks in 1993, the number of listed stocks peaked at 222 in 1998, before

[11] On April 23, 2007 NOK 5.0 is approximately USD 0.85.

steadily decreasing to 136 stocks in 2003. The averages over the sample and estimation period are 175 and 183, respectively. The third column reports the average market capitalization of the sample in NOK. The market capitalization is around three and a half times greater at the end of the sample than at the beginning of the sample, although there is not a monotonic increase in size over the sample period. In 1997, 1998 and 2003 the average market capitalization fell relative to the year before.

Analyzing performance persistence requires that we adjust portfolio performance for risk. This will, in part, be done using a four-factor model based on the three factors of Fama and French (1993) and the momentum factors of Carhart (1997). Using the stocks that satisfy our selection criteria, we construct a value-weighted market index, a size-factor, a book-to-market-factor, and a momentum factor for the Oslo Stock Exchange.[12]

The remaining columns of Table 1 report the factor premia on a monthly basis over the sample and estimation period. The market premium ($R_m - R_f$) is 0.61 percent per month over the sample period (1993–2003), but falls to 0.30 per cent over the estimation period (1995–2003). This sharp fall is due to the omission of 1993's extraordinarily high return of 3.70 percent per month. The next three columns report a SMB premium of 0.66 per cent per month, a HML premium of 0.50 per cent per month, and a MOM premium of 0.71% per month. These premia are very similar to those reported for the US.[13]

Panel B of Table 1 reports a correlation matrix of the factor risk premia and shows that the market premium is negatively correlated with the other three factors. These patterns, and the extent of the correlations, are the same as those observed in the US stock market with the exception of the the SMB premia which is positively related to the market premium. The data on factor risk premia reported in Table 1 illustrates that the Oslo Stock Exchange has very similar aggregate risk premia to that of other stock markets.

Although we have shown that the factors studied in Table 1 have similar risk premia to those in other stock markets, we have not yet shown that they can price stocks listed in the Oslo Stock

[12]Section 2 provides the details on how the factors are constructed.

[13]The corresponding US premia are, in per cent per month, $(R_m - R_f) = 0.61$, SMB = 0.22, HML = 0.42, MOM = 0.96.

Exchange. This is essential because we want to avoid the possibility that estimated alphas in the empirical analysis of performance are a result of model misspecification, rather than investor ability.

To this end, Table 2 reports results from asset pricing tests. We consider portfolio sorts based on size, book-to-market, and momentum. Because of the relatively small number of stocks in the sample we do not attempt double or triple sorts on these three characteristics, but rather form quintile based portfolios on each individual characteristic. Panel A reports results from regressing the five size sorted portfolios on the four risk factors discussed in Table 1. If these factors are adequate at capturing the cross-section differences in the size portfolios then the intercepts (alphas) should be zero. The factor loadings are sensible in that, along with the market betas, the size betas are all statistically and economically significant and vary cross-sectionally in a sensible manner. Loadings on the other two factors are not important in the pricing of the size portfolios. The intercepts are all small and never statistically significant.

Panel B reports the same analysis as panel A but using the book-to-market portfolios. Similar findings are observed for these portfolios: the loadings on the book-to-market factor are sensible and the intercepts are small and not statistically significant. Finally, panel C considers the portfolios formed on momentum returns and only in the case of the portfolio that includes the worst performing stocks is the intercept statistically different from zero. In summary, the four factors seem to be able to price the stocks traded on the Oslo Stock Exchange, except for the extreme past losers. In light of these findings the four factors should provide a reasonable risk adjustment for stocks traded on the Oslo Stock Exchange.

With regard to investors, our sample is restricted to individuals that are active. To be considered as an active investor in month t, an individual investor's portfolio must contain at least two stocks at $t-1$, have at least twenty-four non-missing return observation between month $t-60$ and $t-1$, and finally must have traded x times during the last twenty-four months. Table 3 reports average investor characteristics where each row corresponds to x lying between 0 and 6, 7 and 12, 13 and 18, 19 and 24, and considering all investors. For most of the analysis in the results section, we restrict investors to have traded at least six times during the last twenty-four months.

Panel A of Table 3 reports summary statistics for all months in the sample. The first row reports investor characteristics when there is no restriction on the number of trades in the past. Without this restriction the sample contains 177,010 individual investors that satisfy the other sampling criteria at least once during the sample period. Notice that this is a significant drop from the population of 718,185 individual investors. This is a reflection of the fact that the majority of individual investors hold just one stock. Considering the second column of Panel A, the number of investors falls as the sample represents more and more active investors. If an investor is required to have traded more than six times during the last twenty-four months the sample size drops to 65,848 investors. If we require at least 19 trades during the last 24 months the sample contains 10,330 investors. Thus, the data contains a significant number of reasonable active investors, but a smaller number of very active investors.

All numbers in Table 3 other than the numbers in the first two columns are cross-sectional averages. Consider the last column, "VW Return," as an example. First, for a given investor that satisfies our selection criteria for month t, we determine the value-weighted return for this investor's portfolio at time t. Second, using the time-series of months for which the given investor satisfies the selection criteria we compute a time-series average. The table reports the cross-sectional average of these time-series averages. Appendix A describes the details of how we compute all variables described in this table.

Table 3 shows that investor's purchase and sales turnover increases as the number of trades increases, as we would expect. However, they do not increase symmetrically since purchase turnover is much higher than sales turnover. We also report the number of stocks held by investors, and consistent with the asymmetry between purchase and sales turnover, we find that the number of stocks held by investors increases as the number of trades increases, as does the value of the investor's portfolio. In the column "Avg. Stock Value" we report the average size of the firms in the investor's portfolio. Interestingly, this decreases as the number of trades increases, suggesting that the most active investors are investing in smaller stocks.

What is perhaps the most striking feature of Table 3 is reported in the final column where we record the value weighted return on the investor's portfolio. There is a dramatic drop in returns as investors become more active. Without any restrictions on the number of months an investor trades over the last two years, the average return for the 177,010 investors in the sample is 0.81 per cent per month. This is close to the average return—as expected since in a large group of investors, their aggregate portfolio will mirror the market portfolio. However, the returns for individual investors are monotonically decreasing as the the number of trades increases. This finding is consistent with what is found using U.S. discount brokerage data (see, for example, Barber and Odean (2000), Odean (1999) and Barber and Odean (2001)).

Panels B and C of Table 3 explore the characteristics of investors' portfolios in months where the market returns are positive (Panel B) and negative (Panel C). All the investors' characteristics are basically the same in up and down markets except the return on the investors' portfolios. Here we see a dramatic difference in the average returns earned by investors depending on how much they trade. When considering months with positive returns in Panel B, investors who trade more earn higher return than investors who trade less. Panel C shows why the overall average return in Panel A falls as investor trade more: In down markets, investors who trade the most lose almost twice as much as investors who trade between 0 and 6 times. In sum, the most active investors seems to invest in small and risky stocks and their portfolio suffers big losses when the market drops. However, the large negative returns for active investors reported in Panel A are probably somewhat sample specific. From Table 1 we see that the average market return is less than -1.49 percent per month in three out of the eleven years. The tails of the return distribution have to be very fat for this to be a "normal" event during an eleven-year period.

4 Empirical Results

If some investors have the ability to consistently outperform the rest of the market, one would expect to find that these investors repeat as top performers over time. The literature has employed a variety of approaches to test this idea. One class of tests for performance persistence uses a cross-section of investors and regresses returns on measures of past performance. If performance persists, past performance should predict future performance. In a second class of tests, investors are first ranked based on some measure of past performance. Next, the future performance of the same investors are compared to a relevant benchmark. If performance persists, investors classified as top-performers in one period should outperform the benchmark in the following period. We present tests of the null hypothesis of no persistence in performance using both cross-sectional regressions and test based on performance-ranks.

4.1 Cross Sectional Tests

The first approach that we use to measure performance persistence is a predictive cross-sectional regression where we examine if future benchmark adjusted returns can be predicted by a measure of past performance. This method lends from the Fama and MacBeth (1973) methodology of testing asset pricing models and has been used in assessing mutual and pension fund performance persistence in Hendricks, Patel, and Zeckhauser (1993) and Christopherson, Ferson, and Glassman (1998).

We follow the spirit of this idea and run the following cross-sectional regression:

$$R_p(t, t+\tau) - R_b(t, t+\tau) = \theta_{t,\tau} + \gamma_{t,\tau} X_{pt-2} + \epsilon_p(t, t+\tau) \tag{3}$$

where $R_p(t, t+\tau)$ is compounded return for investor portfolio p for months t through $t+\tau$, $R_b(t, t+\tau)$ is compounded return on a benchmark portfolio for months t through $t+\tau$. The right-hand side variable, X_{pt-2}, is performance for portfolio p measured over months $t-61$ through $t-2$, using a minimum of 24 observations. Variables that measure past performance are described in section 2. Note that we are skipping a month to avoid capturing autocorrelations not related to performance persistence.

The approach outlined above differs from the extant literature in an important way. In particular, Christopherson, Ferson, and Glassman (1998) use future excess returns as the dependent variable and Jensen's alpha as the predetermined variable. Hendricks, Patel, and Zeckhauser

(1993) report results using a dependent variable that is adjusted using a constant-return benchmark as well as a CAPM based benchmark and define X_{pt} as a vector of past excess returns over different horizons. The approach we adopt uses measures of abnormal performance both as the dependent and the predetermined variables. However, to avoid the potential problem that the regression captures persistence in model-misspecification, we use the Appraisal ratio, the Sharpe ratio, and the portfolio weight based measure to capture past performance (dependent variables) and characteristic adjusted returns to measure future performance (independent variable).

The regression in (3) is performed at every month $t = 26, \ldots T$.[14] Using the time-series of $\hat{\gamma}_{t,\tau}$, we test the null hypothesis of no performance persistence using the average:

$$\gamma_\tau = \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_{t,\tau}.$$

We examine the predictability of future benchmark adjusted returns over horizons $\tau = 1$, 3, 6, 12, 18, 24, and 36 months. The null hypothesis that $\gamma_\tau = 0$ is tested using a t-statistic computed using Newey and West (1987) with $\tau - 1$ moving average terms. This accounts for the serial correlation induced by overlapping observations. When X_{pt} is measured using the Appraisal ratio, we divide all right-hand side variables in equation (3) by the standard deviation of the error-term from equation (1), effectively running a Weighted Least Squares (WLS) regression. As pointed out in section 2, this reduces the cross-sectional differences related to variance. Taking the cross-sectional variance into account is important in our analysis because individual investors' stock-market portfolios are not well diversified.

Table 4 reports a summary of the results from the cross-sectional regressions using the three different measures of past performance. The table is split into three panels based on how often an investor trades. We follow Christopherson, Ferson, and Glassman (1998) and only report t-statistics for this test. Panel A reports the t-statistics for the estimates of γ_τ for all investors (around 20,000) who traded at least six out of the last twenty four months. At the one-month horizon there is marginal evidence of a positive relationship between past performance using

[14]Since we require at least 24 observations to compute X_{pt} and since we skip a month, the first available date for running the cross-sectional regression is $t = 26$.

the Appraisal ratio and future benchmark adjusted returns, $t = 1.82$. However, as the horizon increases to three months and subsequently for all other horizons, the t-statistics reveal that the null hypothesis of no relationship between past performance and future benchmark adjusted returns is rejected at the 1% level. The results using the portfolio weight based measure of past performance are very similar to those using the Appraisal ratio. The relationship between past performance and future returns is a little weaker when the Sharpe ratio is employed as the past performance measure. A potential explanation for this finding is that the Sharpe ratio does not account for the systematic risk of a portfolio. Thus, an investor who holds high-beta stocks when the return on the market portfolio is high would tend to be classified as a top performer. If this investor has no ability to pick stocks that will outperform on a systematic risk-adjusted basis the Sharpe ratio should not predict future performance.

Panel B examines investors that have traded in at least twelve of the last twenty four months (around 7,000 investors) and finds results very similar to those in Panel A. In panel C we restrict the analysis to the investors who have traded in at least eighteen of the last twenty four months (around 2,500 investors). In this sample the results are weaker at the one month horizon, but otherwise confirm the results reported in panels A and B. Taken together, the results in Table 4 highlight a positive relationship between past performance and future benchmark adjusted returns which is robust to the choice of past performance measurement and to the extent of investor activity measured by frequency of trading. The relationship between past performance and future returns is stronger when we consider future returns at longer horizons. This result is consistent with the findings of Christopherson, Ferson, and Glassman (1998) who show that the persistence in performance of pension fund managers is stronger at longer horizons.

While there is clearly a strong link between past performance and future returns, it is not possible from Table 4 to know if this result is symmetric for investors whose past performance was poor and investors whose past performance was good. In particular, it is possible that the positive relationship between past performance and future returns is driven entirely by investors who in the past have performed poorly and in the future continue to perform poorly. Carhart (1997) and Christopherson, Ferson, and Glassman (1998) find that the positive relationship between past performance and future returns mainly is driven by the worst performing mutual fund and pension fund managers. To try and shed some light on this issue for individual investors, we split the sample of investors into quintiles based on past performance and examine the relationship between past performance and future abnormal returns for the top (best past performance) and bottom (worst past performance) quintiles.

Table 5 reports the findings from this exercise and shows, in Panel A, that the investors in the top past performance quintile have a statistically significant relationship between their past performance and future abnormal returns according to the Appraisal ratio and the Sharpe ratio. There is some evidence of a negative relationship at short horizons when using the portfolio weight based measure, before this turns positive at longer horizons. Panel B focuses on the bottom past performers and shows that there is also a strong positive relationship between past performance and future abnormal returns when measuring past performance with the Appraisal ratio and the portfolio weight based measure. Using the Sharpe ratio, there is a negative relationship between past performance and future abnormal returns.

Overall, the results using the cross-sectional regression method show that there is a strong positive relationship between the past performance of individual investors and the returns on their portfolios in the future—especially when past performance is measured using the Appraisal ratio. The strong effect for the Appraisal ratio may be related to the fact that this is a measure that is related to stock picking ability (Treynor and Black, 1973). The relationship between past and future performance is positive both for investors with good performance in the past and for investors with bad performance in the past. Because earlier papers on the performance persistence of fund managers find that any evidence of persistence is typically driven by the worst performing managers, our finding of persistently good performance of individual investors is especially interesting.

4.2 Top and Bottom Performing Portfolios

In the previous section we identified a positive relationship between past performance and future abnormal portfolio returns. In order to consider the economic significance of this relationship we now turn to an alternative methodology that ranks individuals into decile portfolios based on their past performance. Subsequently, we compare the abnormal returns earned by investors in the top and bottom performance deciles. This approach is similar to that used by Hendricks, Patel, and Zeckhauser (1993) who rank mutual funds by returns (net of fees) over an evaluation period and examine the return on the portfolio one quarter ahead.

We adopt the following methodology. For each month t all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month t are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. Investors are ranked based on their portfolio's Appraisal ratio, Sharpe ratio, and a portfolio weight based performance measure, $\Delta W(6,6)$. For all investors ranked in month t, we compute average abnormal portfolio return as the difference between the average portfolio return over horizon $t+1$ through $t+\tau+1$ less the average return over the same horizon for a portfolio of size- and momentum matched stocks. Next, these abnormal returns are averaged over all individuals ranked in month t. Using all available months, we obtain a time-series of abnormal returns for top- and bottom performing investors. We examine return horizons for $\tau = 1$, 3, 6, 12, 24, and 36 months.

Panel A of Table 6 reports average abnormal returns for the bottom and top performers when past performance is measured using the Appraisal ratio. At the one month horizon the top performers earn an abnormal return of 7.85% per month which falls to 5.20% at the thirty six month horizon. In sharp contrast, the bottom performers earn a negative abnormal return of −1.70% per month at the one month horizon which falls to −2.76% per month at the three month horizon, before increasing steadily as the horizon increases, but always remaining negative.

The row labeled "Top − Bottom" reports the time-series average of the differences between the abnormal returns for top performers and the abnormal return for bottom performers. This is always positive and is economically large, ranging from around 10% per month at horizons of up to six months and around 6% at the longest horizons. The row labeled "T-statistic" reports a Newey and West (1987) t-statistic which tests whether the difference between the abnormal returns on the top performing portfolio and the bottom portfolio are significantly different from zero. At the one month holding period we can reject the null hypothesis at the 5% level, while over all the remaining holding periods we can reject the null hypothesis at the 1% level.

Panel B presents the same analysis as in Panel A but using the Sharpe ratio as the measure of past performance. In this case the bottom performers earn a negative abnormal return at each horizon except at the twenty four and thirty six month horizons. The top performers always earn a positive abnormal return, irrespective of the horizon. The difference between the top and bottom performers is much smaller than when using the Appraisal ratio to measure past performance (around 0.5% per month at short horizons), and is only statistically significant at the three month horizon. However, Panel C shows that when using the portfolio weights based measure of past performance the differences in the top and bottom performers are statistically different from zero at all horizons, although smaller than those reported using the Appraisal ratio as the measure of past performance.

It is often argued that mutual funds cannot outperform a given benchmark consistently because they are too large. We assess whether the size of an individual's portfolio affects the relationship between past performance and future abnormal return. Table 7 presents results of the difference in the abnormal returns between top and bottom portfolios for the quartile of investors with small portfolio and the quartile of investors with large portfolios. Panel A records the findings using the Appraisal ratio as a measure of past performance. The differences between the abnormal returns of top and bottom performers tends to be larger for investors with small portfolios up to and including a holding period of six months. For longer holding periods investors with larger portfolio do better. Irrespective of whether the investor's portfolio is large or small, the difference between the abnormal returns of top and bottom performers is always statistically different from zero, except for large investors at the one month horizon (although economically the difference is large at 6.67% per month.)

Panel B reports findings using the Sharpe ratio as the measure of past performance. Recall from Table 6 that we found less evidence of a relationship between past performance using the Sharpe ratio and future abnormal returns. When we split investors by size there is a statistically and economically significant difference for large investors, but not for small investors. Panel C performs the same analysis but uses the portfolio weight based performance measure. This Panel shows that the difference between top performers and bottom performers tend to be larger, and more statistically significant, for investors with small portfolios than for investors with large portfolios.

The results in Tables 6 and 7 reinforce the findings from Table 4. Taken together, there exists a positive relationship between past performance and future returns for the individual investors observed in our data. This relationship tends to be stronger for investors that did well in the past and weaker for investors that were among the worst performers in the past. This relationship persists for both large and small investors.

4.3 Stocks Favored by the Best and the Worst Investors

In this section of the paper we form portfolios according to a trading strategy that attempts to exploit the ability of investors. We construct two portfolios, one that includes stocks favored in the past by investors whose past performance ranks them in the top performing decile, and another that includes stocks favored by investors whose past performance ranks them in the worst performing decile. If the top performing investors do well because they are able to include stocks that will do well in the future, we expect to observe that a portfolio of stocks favored by the top performing investors should outperform a passive benchmark.

We are not the first that try to exploit the stock-picking talent of successful investors. Cohen, Coval, and Pástor (2005) develop a new mutual fund performance measure that evaluates a manager's skill based on the degree of overlap between a manager's stock holdings and the stock holdings of other managers who have been successful in the past. Their measure is constructed by first defining the quality of a stock as the average skill (measured using Jensen's alpha) of all managers that hold the stock. A manager's skill is next defined as being proportional to the number of high quality stocks held in the portfolio. While Cohen, Coval, and Pástor (2005) use their measure to rank funds, Wermers, Yao, and Zhao (2007) use a similar measure to pick stocks. They construct a portfolio of stocks held by managers that have been successful in the past, where weights in the portfolio are determined by the size of each funds investment in the stock. Thus, a stock heavily held by successful managers get a large weight in the portfolio.

We follow the basic idea of Cohen, Coval, and Pástor (2005) and Wermers, Yao, and Zhao (2007). But, to deal with overlapping returns and to increase the power of our test we apply the portfolio formation approach used by Jegadeesh and Titman (1993). More specifically, we form portfolios as follows: For each month t all investors that have traded in at least six out of the last twenty-four months are ranked based on the performance of their portfolio over the period $t-60$ through $t-1$. Top performing investors for month t are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. Once we have have classified investors, we identify which stocks are held by top performing investors and which stocks are held by bottom performing investors. A stock is said to be favored by top-performing investors if the stock is held by twice as many top-performers as bottom-performers. The opposite is true for stocks favored by bottom-performers. We then construct a portfolio with an H-month holding period from stocks favored by top-performers as follows. For month t, the portfolio contains stock favored by investors that was classified as top-performers in months $t-H$ through $t-1$. Portfolio returns are computed as the weighted average of the returns on the stocks in the portfolio where the weight for stock j is number of top-performers holding stock j divided by total number of top-performing investors. Returns on a portfolio of stocks favored by bottom-performers are computed in a similar way.

Table 8 reports the average returns for the portfolios of stocks favored by top and bottom performers for monthly holding periods $H = 1$, 3, 6, 12, 18, 24, and 36 months. Using the Appraisal ratio to measure past performance we find that the portfolio of stocks favored by top performers earns 2.01% per month at the one month horizon while the return on the portfolio of stocks favored by bottom performers earns 0.29%. As the holding period increases the return difference between these two portfolios remains substantial. The remaining rows of Table 8 report results using the Sharpe ratio and the portfolio weight based measures of past performance. Consistent with the results in Panel A, we find that there are substantial portfolio return differences between the top performers and bottom performers irrespective of how past performance is measured.

Table 8 shows that a portfolio of stocks favored by top performing investors earns a substantially higher return than a portfolio of stocks favored by bottom performers. However, it is possible that these stocks have different risks and hence different returns. To assess this, Table 9 reports Jensen's alpha from a regression of the returns on the portfolios of stocks favored by individuals with the best past performance and individuals with the worst past performance on four risk factors. In Panel A we use the the Appraisal ratio to measure past performance. In this case, the portfolio of stocks favored by top performers has an economically and statistically significant alpha at all horizons. The statistical significance at the 24 and 36 month horizon is marginal, but, even here the economic significance is clear with a Jensen's alpha of 0.7% per month. The bottom performers have small alphas that are neither economically significant nor statistically different from zero.

Panels B and C of Table 9 repeat the analysis when the Sharpe ratio and the portfolio weight based measure are used to assess past performance. Using the Sharpe ratio gives results that are similar to the findings in Panel A. However, ranking investors based on the portfolio weight based measure does not generate significantly positive alphas. At the two longest horizons, the alphas are even negative and statistically significant for the top performers.

In summary, it appears that by forming a portfolio of stocks that are favored by top performing investors, especially if the Appraisal ratio and the Sharpe ratio are used to rank investors, it is possible to earn a statistically and economically significant risk adjusted return.

5 Conclusion

In this paper, we provide a novel analysis of stock market performance persistence for individual investors. We use a unique data set that includes all individual investors that at some point, during our eleven-year sample period, have owned stocks listed on the Oslo Stock Exchange. The monthly frequency of the data, the fact that we observe all the stock holdings of every individual investor, and the long time-series allow a unique opportunity to measure long-term performance persistence at the portfolio level. We analyze performance persistence using cross-sectional regressions and portfolio formation methods.

We find that a substantial number of investors exhibit economically and statistically significant performance persistence. This persistence is evident both for investors who did well in the past and for investors who did poorly in the past. The results that we report are robust to how persistence is measured. In addition, the findings are unaffected by how often investors trade and whether investors are small or large. We also show that forming a portfolio that is long in stocks previously favored by top performing investors earns a substantial risk adjusted return in the future.

One potential explanation for the finding that past performance is persistent, a finding that is absent in the mutual fund and pension funds literature, is that it is difficult to track successful professional fund managers over time. Chevalier and Ellison (1999) find that managers that perform well have a higher probability of surviving as managers and subsequently move to a bigger firm when compared to underperforming managers. An alternative explanation is offered by Berk and Green (2004). They develop a model showing that competition among investors to invest in the best performing funds will drive future costs up and future returns down to the point where investors get returns that are commensurate with the risk of the fund. Our data does not allow us to separate between these two explanations for the lack of performance persistence among mutual fund managers. We do, however, offer new insights into the performance of individual investors, a group of investors that generally have been viewed as one that makes poor investment decisions.

Appendix A

This appendix describes the details of how we compute the variables described in Table 3. Other than the first two columns in Table 3, all other columns contain cross-sectional averages. Consider the last column, "VW Return," as an example. First, to be included in the sample at time t an investor must have a portfolio that contains at least two stocks on $t-1$, have at least twenty-four non-missing return observation between month $t-60$ and $t-1$, and finally have traded x times during the last twenty-four months (time $t-24$ through $t-1$.) Table 3 reports results where each row corresponds to x lying between 0 and 6, 7 and 12, 13 and 18, 19 and 24, and considering all investors. If an investor satisfies the selection criteria, we determine the value-weighted return for this investor's portfolio at time t.

Second, using the time-series of months for which the given investor satisfies the selection criteria, and given we were able to determine the portfolio return, we compute a time-series average. Columns three through nine in Table 3 reports the cross-sectional average of these time-series averages.

The column labeled "Time-series obs." reports the average number of months in each investor's time-series. The column labeled "Purchase Turnover" reports the percent of the portfolio turned over due to purchases. Purchase turnover is value-weighted and is measured as the value of all stocks purchased during a period divided by the value of the portfolio at the end of the period:

$$\sum_{j=1}^{J_{it}} \frac{P_{jt-1}N_{ijt}}{V'_{it-1}} \times \frac{B_{ijt}}{N_{ijt}}$$

where $B_{ijt} = aN_{ijt} - N_{ijt-1}$ is the split adjusted number of stocks purchased by investor i in stock j during month t ($a \in [0,1]$ is the adjustment factor) and

$$V'_{it-1} = \sum_{j=1}^{J_{it}} aP_{jt-1}N_{ijt}.$$

The column labeled "Sales Turnover" reports the percent of the portfolio turned over due to sales. Sales turnover is value-weighted and is measured as the value of all stocks sold during a period divided by the value of the portfolio at the beginning of the period:

$$\sum_{j=1}^{J_{it}} \frac{P_{jt-1} N_{ijt}}{V_{it-1}} \times \frac{S_{ijt}}{N_{ijt}}$$

where $S_{ijt} = N_{ijt-1} - aN_{ijt})$ is the split adjusted number of stocks sold by investor i in stock j during month t. The column labeled "Number of Stocks" reports the number of stocks held by this investor at the end of month t. The column labeled "Portfolio Value" reports the value of the portfolio at time t in million Norwegian Kroner. The column labeled "Avg. Stock Value" reports the value weighted average firm size, in million Norwegian Kroner, over all firms in the portfolio at t:

$$\sum_{j=1}^{J_{it}} \frac{(P_{jt} N_{ijt})(P_{jt} N_{jt})}{V_{it}}$$

where J_{it} is the number of stocks in investor i's portfolio at time t, P_{jt} is the price of stock j at time t, N_{ijt} is the number of shares owned by investor i in stock j at time t, N_{jt} is the number of shares outstanding of stock j at time t, and

$$V_{it} = \sum_{j=1}^{J_{it}} P_{jt} N_{ijt}.$$

References

Baker, Malcolm, Richard S. Ruback, and Jeffery Wurgler, 2005, Behavioral corporate finance, in B. E. Eckbo, ed.: *Handbook of Corporate Finance: Empirical Corporate Finance* . chap. 4 (Elsevier/North-Holland, Handbooks in Finance Series).

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrence Odean, 2005, Who loses from trade? evidence from taiwan, Working Paper.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

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

——— , 2006, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, Forthcoming *Review of Financial Studies.*

Barberis, Nicholas, and Richard Thaler, 2003, A survey of behavioral finance, in George M. Constantinides, Milton Harris, and René M. Stulz, ed.: *Handbook of Economics of Finance*, vol. 1B of *Handbooks in Economics 21* . chap. 18, pp. 1053–1123 (Elsevier North-Holland: Amsterdam).

Bauer, Rob, Mathijs Cosemans, and Piet Eichholtz, 2007, The performance and persistence of individual investors: Rational agents of tulip maniacs?, Maastricht University Working Paper. http://ssrn.com/abstract=965810.

Berk, J. B., and R. C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Bøhren, Ø., B. E. Eckbo, and D. Michalsen, 1997, Why underwrite rights offerings?: Some new evidence, *Journal of Financial Economics* 46, 223–261.

Bollen, N. P. B., and J. A. Busse, 2004, Short-term persistence in mutual fund performance, *Review of Financial Studies* 18, 569–597.

Brown, Stephen J., and William N. Goetzmann, 1995, Performance persistence, *Journal of Finance* 50, 679–698.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2006, Down or out: Assessing the welfare costs of household investment mistakes, Working Paper.

——— , 2007, Fight or flight? portfolio rebalancing by individual investors, Working Paper.

Campbell, John Y., 2006, Household finance, *Journal of Finance* 61, 1553–1604.

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

Chevalier, J., and G. Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389–432.

Christopherson, J. A., W. E. Ferson, and D. A. Glassman, 1998, Conditioning manager alphas on economic information: Another look at the persistence of performance, *Review of Financial Studies* 11, 111–142.

Cohen, Randolph B., Joshua D. Coval, and Ľuboš Pástor, 2005, Judging fund managers by the company they keep, *Journal of Finance* 60, 1057–1096.

Coval, Joshua D., David A. Hirshleifer, and Tyler Shumway, 2005, Can individual investors beat the market, Harvard NOM Working Paper No. 02-45, HBS Finance Working Paper No. 04-025, http://ssrn.com/abstract=364000.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 1996, The persistence of risk-adjusted mutual fund performance, *Journal of Business* 69, 133–157.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 43, 3–56.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferson, W., and K. Khang, 2002, Conditional performance measurement using portfolio weights: Evidence for pension funds, *Journal of Financial Economics* 65, 249–282.

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

——— , 2001, What makes investors trade?, *Journal of Finance* 56, 589–616.

——— , 2006, Sensation seeking, overconfidence, and trading activity, NBER Working Paper 12223.

Grinblatt, Mark, and Sheridan Titman, 1992, The persistence of mutual fund performance, *Journal of Finance* 47, 1977–1984.

——— , 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 66, 47–68.

Hendricks, Darryl, Jayendu Patel, and Richard Zeckhauser, 1993, Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988, *Journal of Finance* 48, 93–130.

Hirshleifer, D., 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to bying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jensen, Michael C., 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389–416.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Odean, T., 1998, Are investors reluctant to realize their losses?, *Journal of Finance* 53, 1775–1798.

Odean, Terrance, 1999, Do investors trade too much?, *American Economic Review* 89, 1279–1298.

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

Wermers, Russ, Tong Yao, and Jane Zhao, 2007, The investment value of mutual fund portfolio disclosure, SSRN working paper, http://ssrn.com/abstract=891728.

White, H., 1980, Nonlinear regression on cross-section data (statistical techniques)., *Econometrica* 48, 721–746.

Table 1
Descriptive statistics for the Oslo Stock Exchange 1993–2003.

The table reports monthly averages and standard deviations (in parentheses) for the market risk-premium as well as risk-premia associated with firm size, book-to-market ratio, and stock return momentum. The size (SMB) and book-to-market factors (HML) are constructed following the approach of Fama and French (1993). The momentum factor (MOM) is constructed following the approach outlined in Ken French's web-site. In particular, six value-weighted portfolios are constructed from the intersection of three portfolios formed using return momentum over months $t-12$ through month $t-2$ and two portfolios formed using market capitalization from month $t-1$. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. The columns "$R_m - R_f$" through "MOM" reports the time-series average and standard deviation for the respective factors. The "Number of Securities" column report the time-series average number of common stocks that for a give month has a stock price that exceeded NOK 5.0 and is traded at least once during the month. The "Market Cap" column reports the time-series average market capitalization in NOK for the common stocks that satisfies the selection criterion. The sample period is January 1993 through June 2003.

	Number of Securities	Market Cap	$R_m - R_f$	SMB	HML	MOM
			A. Monthly averages and standard deviations			
1993	132 (9)	1,193 (140)	3.66 (5.4)	2.83 (5.4)	2.99 (4.2)	−1.64 (5.1)
1994	155 (3)	1,526 (52)	0.32 (5.8)	0.08 (3.0)	0.03 (2.4)	−0.71 (2.6)
1995	152 (5)	1,759 (68)	0.39 (3.6)	1.06 (2.3)	−1.24 (3.3)	2.16 (3.8)
1996	167 (5)	1,964 (158)	1.92 (3.0)	0.61 (2.4)	−0.34 (2.6)	−0.05 (3.6)
1997	196 (14)	2,639 (204)	2.08 (4.0)	−0.61 (1.8)	−0.18 (5.3)	1.93 (4.9)
1998	222 (5)	2,579 (450)	−2.60 (8.5)	−0.31 (5.5)	0.26 (4.1)	2.45 (5.7)
1999	209 (6)	2,563 (229)	2.60 (4.5)	1.33 (4.0)	−0.54 (4.9)	−0.71 (6.3)
2000	203 (3)	3,241 (240)	−0.28 (4.6)	1.15 (5.6)	1.07 (6.3)	0.25 (5.3)
2001	185 (9)	3,848 (356)	−1.49 (6.0)	0.48 (4.3)	0.25 (6.3)	1.24 (6.6)
2002	157 (14)	4,200 (341)	−2.70 (6.2)	0.28 (3.6)	2.40 (4.3)	4.21 (8.4)
2003	136 (3)	4,065 (430)	2.82 (6.4)	0.22 (3.5)	1.10 (3.4)	−2.74 (8.2)
1993–2003	175 (30)	2,634 (1009)	0.61 (5.6)	0.66 (3.9)	0.50 (4.5)	0.71 (5.7)
1995–2003	183 (27)	2,931 (882)	0.30 (5.6)	0.48 (3.8)	0.27 (4.7)	1.15 (6.0)
			B. Correlations 1993:01–2003:07			
$R_m - R_f$			1.0000			
SMB			-0.1936	1.0000		
HML			-0.1685	-0.3388	1.0000	
MOM			-0.2632	0.0154	0.0437	1.0000

Table 2
Pricing of stock portfolios sorted on size, book-to-market ratio, and six-month momentum, Oslo Stock Exchange 1995–2003.

The table reports intercept and factor sensitivities from the following time-series regression:

$$R_{pt} = \alpha_p + \beta(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mMOM_t + \epsilon_{pt},$$

where R_{pt} is the return on size, book-to-market ratio, or momentum-sorted portfolios, R_{mt} is the return on a value-weighted portfolio of all stocks listed on the OSE with price greater than NOK 5.00 and positive volume, and R_{ft} is the one-month NIBOR. The size (SMB) and book-to-market factors (HML) are constructed following the approach of Fama and French (1993). The momentum factor (MOM) is constructed following the approach outlined in Ken French's web-site. In particular, six value-weighted portfolios are constructed from the intersection of three portfolios formed using return momentum over months $t - 12$ through month $t - 2$ and two portfolios formed using market capitalization from month $t - 1$. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. The test assets are five size-sorted portfolios, five book-to-market ratio sorted portfolios, and five six-month momentum sorted portfolios. The sample period is January 1995 through July 2003, giving 103 observations. Parentheses contain p-values.

Portfolio	Intercept	$R_m - R_f$	SMB	HML	MOM	Adj. R-sq
			A. Size sorted portfolios			
Small	−0.17 (0.67)	0.90 (0.00)	0.86 (0.00)	−0.03 (0.78)	0.10 (0.19)	0.63
2	−0.20 (0.44)	1.00 (0.00)	0.90 (0.00)	−0.03 (0.72)	0.03 (0.59)	0.85
3	0.17 (0.44)	1.10 (0.00)	0.71 (0.00)	−0.01 (0.95)	−0.05 (0.24)	0.88
4	−0.01 (0.98)	1.17 (0.00)	0.48 (0.00)	0.08 (0.25)	0.06 (0.44)	0.78
Large	0.02 (0.87)	0.98 (0.00)	−0.18 (0.00)	−0.02 (0.50)	−0.04 (0.10)	0.98
			B. Book-to-market ratio sorted portfolios			
Low	−0.42 (0.21)	0.98 (0.00)	−0.04 (0.79)	−0.54 (0.00)	0.04 (0.59)	0.81
2	0.37 (0.24)	0.92 (0.00)	−0.18 (0.06)	−0.11 (0.16)	0.07 (0.16)	0.77
3	0.16 (0.63)	1.07 (0.00)	0.09 (0.33)	0.18 (0.02)	−0.01 (0.85)	0.76
4	0.39 (0.15)	1.01 (0.00)	0.06 (0.49)	0.20 (0.02)	−0.21 (0.00)	0.82
High	−0.12 (0.74)	1.27 (0.00)	0.28 (0.01)	0.63 (0.00)	−0.03 (0.70)	0.77
			C. Six-month momentum sorted portfolios			
Negative	−1.21 (0.02)	1.46 (0.00)	0.48 (0.01)	0.05 (0.76)	−0.38 (0.00)	0.76
2	0.13 (0.70)	0.96 (0.00)	0.22 (0.08)	0.06 (0.54)	−0.14 (0.05)	0.74
3	0.38 (0.16)	0.82 (0.00)	−0.21 (0.05)	0.02 (0.73)	−0.07 (0.21)	0.77
4	0.15 (0.56)	0.97 (0.00)	−0.13 (0.17)	−0.01 (0.84)	0.03 (0.64)	0.81
Positive	0.04 (0.91)	1.28 (0.00)	0.34 (0.13)	−0.17 (0.11)	0.32 (0.00)	0.72

Table 3
Descriptive statistics for individual investors

The table reports descriptive statistics for investors on the Oslo Stock Exchange. The numbers reported in columns 3 to 9 are cross-sectional averages and are computed as follows. For each investor we compute time-series averages from monthly observations. To be included in the time-series at month t the investor must satisfy the following criteria: The investor's portfolio must contain at least two stocks on $t-1$, have at least 24 non-missing return observation between month $t-60$ and $t-1$. In addition, in all but the first row of each panel, the cross-sectional average is computed over investors that have traded between 0 and 6 months, between 7 and 12, between 12 and 18, and between 19 and 24 times during the last 24 months. The first column of the table contains the number of trade intervals. The other columns are: "Number of Investors" is the number of investors used to compute the cross-sectional average value-weighted portfolio return, "Time-series obs." is the average number of months in each investor's time-series, "Purchase turnover" and "Sales turnover" are the percent of the portfolio turned over due to purchases and sales, respectively. "Number of stocks" and "Portfolio value" represent the value and the number of stocks in the portfolio. "Avg. stock value" is the average size (in million NOK) of firms in the portfolio. "VW return" is the percent average value-weighted monthly portfolio return. Appendix A provides more detail on these variables. Because our sampling require at least 24 non-missing return observation between month $t-60$ and $t-1$, the sample period is January 1995 through June 2003.

		Cross-sectional averages						
Trades	Number of Investors	Time-series obs.	Purchase Turnover	Sales Turnover	Number of Stocks	Portfolio Value	Avg. stock Value	VW Return
				A. All months				
All	177,010	41	2.39	1.75	3.46	0.292	21,563	0.81
0–6	164,794	33	1.19	1.31	2.65	0.129	23,646	1.07
7–12	65,848	18	3.67	2.67	4.66	0.443	17,670	0.28
13–18	26,233	17	7.85	3.72	6.80	0.900	12,355	-0.30
19–24	10,330	21	14.25	3.92	10.19	2.296	9,771	-0.62
				B. All months with positive market-index return				
All	171,278	24	2.16	1.81	3.43	0.292	20,760	4.94
0–6	158,447	20	0.98	1.37	2.66	0.133	22,559	4.77
7–12	62,432	10	3.61	2.79	4.77	0.468	17,001	5.22
13–18	24,719	9	8.13	3.98	6.96	0.979	12,041	5.91
19–24	9,651	11	15.17	4.03	10.35	2.413	9,524	6.24
				C. All months with negative market-index return				
All	171,505	18	2.68	1.68	3.50	0.292	22,577	-4.53
0–6	157,372	14	1.46	1.22	2.65	0.124	25,086	-3.95
7–12	60,654	9	3.74	2.52	4.54	0.414	18,442	-5.50
13–18	24,750	8	7.56	3.45	6.63	0.819	12,677	-6.76
19–24	9,760	11	13.35	3.80	10.04	2.183	10,009	-7.31

Table 4
T-values for measures of performance persistence for individual investors

The table reports t-values (Newey and West, 1987) for:

$$\gamma_\tau = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{t,\tau}$$

The estimates $\hat{\gamma}_{t,\tau}$, for $t = 1, \dots T$, are obtained by rolling forward the following cross-sectional regression:

$$R_p(t, t+\tau) - R_b(t, t+\tau) = \theta_{t,\tau} + \gamma_{t,\tau} X_{pt-2} + \epsilon_p(t, t+\tau) \quad p = 1, \dots, N$$

where $R_p(t, t+\tau)$ is compounded return for an investor's portfolio p for months t through $t+\tau$, $R_b(t, t+\tau)$ is compounded return for the size and momentum matched portfolio for months t through $t+\tau$. The return horizons are $\tau = 1, 3, 6, 12, 24$, and 36—corresponding to the columns in the table. The right-hand side variable, X_{pt-2}, is performance for portfolio p measured over months $t-61$ through $t-2$, using a minimum of 24 observations. Performance is measured using the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), Sharp ratio, and a portfolio weight based performance measure (ΔW(6,6).) Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

	Return horizon						
	1 month	3 months	6 months	12 months	18 months	24 months	36 months
Time-series obs.	102	100	97	91	85	79	67
A. Investors that traded at least 6 out of the 24 last months							
Cross-sectional obs.	21,151	20,934	20,533	19,515	18,273	16,926	13,881
Appraisal ratio	1.82	3.09	3.51	2.41	3.43	6.01	3.55
Sharpe ratio	1.42	2.55	2.62	1.86	2.12	1.01	0.58
ΔW(6,6)	1.98	3.38	3.60	4.57	5.20	3.74	3.56
B. Investors that traded at least 12 out of the 24 last months							
Cross-sectional obs.	7,342	7,273	7,140	6,772	6,264	5,679	4,337
Appraisal ratio	2.06	3.66	5.37	3.31	3.62	3.68	4.85
Sharpe ratio	1.56	2.73	3.44	2.34	1.96	1.57	1.94
ΔW(6,6)	1.60	3.07	3.87	4.68	4.55	4.06	2.46
C. Investors that traded at least 18 out of the 24 last months							
Cross-sectional obs.	2,599	2,580	2,542	2,423	2,237	2,011	1,473
Appraisal ratio	1.45	2.47	4.09	3.41	3.29	3.13	7.75
Sharpe ratio	1.13	1.89	2.83	2.11	1.45	1.01	1.61
ΔW(6,6)	1.17	2.47	3.09	2.72	3.29	3.54	4.13

Table 5
T-values for measures of performance persistence for individual investors that traded in at least 6 out of the 24 last months

The table reports t-values (Newey and West, 1987) on:

$$\gamma_\tau = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{t,\tau}$$

The estimates $\hat{\gamma}_{t,\tau}$, for $t = 1, \dots T$, are obtained by rolling forward the following cross-sectional regression:

$$R_p(t, t+\tau) - R_b(t, t+\tau) = \theta_{t,\tau} + \gamma_{t,\tau} X_{pt-2} + \epsilon_p(t, t+\tau) \quad p = 1, \dots, N$$

where $R_p(t, t+\tau)$ is the compounded return for an investor's portfolio p for months t through $t+\tau$, $R_b(t, t+\tau)$ is compounded return for the size and momentum matched portfolio for months t through $t+\tau$. The return horizons are $\tau = 1, 3, 6, 12, 24$, and 36—corresponding to the columns in the table. The right-hand side variable, X_{pt-2}, is performance for portfolio p measured over months $t-61$ through $t-2$, using a minimum of 24 observations. Performance is measured using the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, and a portfolio weight based performance measure (ΔW(6,6).) Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

	Return horizon						
	1 month	3 months	6 months	12 months	18 months	24 months	36 months
Time-series obs.	102	100	97	91	85	79	67
A. Top Quintile Performers							
Cross-sectional obs.	4,368	4,312	4,160	3,994	3,768	3,520	2,896
Appraisal ratio	1.646	3.108	4.001	5.157	5.166	4.762	4.373
Sharpe ratio	0.321	0.884	1.832	2.645	3.763	4.148	4.753
ΔW(6,6)	-1.237	-1.768	-2.424	-1.696	1.023	2.822	2.039
B. Bottom Quintile Performers							
Cross-sectional obs.	4,360	4,195	4,103	3,872	3,604	3,329	2,727
Appraisal ratio	1.865	3.086	4.967	7.007	7.664	5.809	7.575
Sharpe ratio	-0.040	-0.742	-1.767	-3.073	-2.565	-2.281	-2.474
ΔW(6,6)	0.976	2.140	3.429	3.953	3.949	3.965	2.525

Table 6
Average abnormal returns for portfolios of top and bottom performing individual investors, using investors that traded in at least 6 out of the 24 last months

For each month t all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t - 60$ through $t - 1$. Top performing investors for month t are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, and a portfolio weight based performance measure (ΔW(6,6).) For all investors ranked in month t, we compute the average abnormal portfolio return as the difference between the average return over horizon $t + 1$ through $t + \tau + 1$ less the average return, using returns from months $t + 1$ through $t + \tau + 1$, on a portfolio of size- and momentum matched stocks. These abnormal returns are averaged over all individuals ranked in month t. Using all available months, we obtain a time-series of abnormal returns for top and bottom performing investors. The return horizons are $\tau = 1, 3, 6, 12, 24$, and 36—corresponding to the columns in the table. The rows labeled "Bottom performers" and "Top performers"report the time-series average return using only bottom performing investors and top performing investors, respectively. The row labeled "Top − Bottom" reports the time-series average of the differences between the abnormal returns for top performers and the abnormal return for bottom performers. The rows labeled "T-statistic" report a Newey and West (1987) t-statistic. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

	Return horizon						
	1 month	3 months	6 months	12 months	18 months	24 months	36 months
Time-series observations	102	100	97	91	85	79	67
A. Past performance measured using the Appraisal ratio							
N	2,165	2,133	2,082	1,963	1,828	1,686	1,377
Top performers	7.85	7.44	7.68	6.13	4.95	4.32	5.20
Bottom performers	-1.70	-2.76	-2.02	-1.25	-1.52	-1.48	-0.77
Top − Bottom	9.55	10.20	9.70	7.39	6.47	5.80	5.96
T-statistic	2.13	3.54	4.14	3.73	3.96	3.97	4.50
B. Past performance measured using Sharpe ratio							
N	2,175	2,142	2,086	1,959	1,817	1,672	1,364
Top performers	0.35	0.34	0.31	0.21	0.14	0.13	0.21
Bottom performers	-0.10	-0.21	-0.14	0.01	-0.03	0.04	0.09
Top − Bottom	0.45	0.56	0.46	0.20	0.17	0.09	0.12
T-statistic	1.10	2.26	2.00	0.91	0.74	0.39	0.65
C. Past performance measured using a portfolio weigh based measure, ΔW(6,6)							
N	2,161	2,120	2,050	1,895	1,729	1,566	1,242
Top performers	-0.03	-0.05	-0.05	-0.04	-0.08	-0.08	-0.02
Bottom performers	-0.36	-0.39	-0.38	-0.31	-0.30	-0.25	-0.15
Top − Bottom	0.33	0.34	0.32	0.27	0.22	0.17	0.13
T-statistic	1.88	3.39	3.65	3.60	3.68	2.76	2.71

Table 7
Average abnormal returns for portfolios of top and bottom performing individual investors, using investors that traded in at least 6 out of the 24 last months, sorted by portfolio value

For each month t all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month t are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, and a portfolio weight based performance measure (ΔW(6,6).) For all investors ranked in month t, we compute the average abnormal portfolio return as the difference between the average return over horizon $t+1$ through $t+\tau+1$ less the average return, using returns from months $t+1$ through $t+\tau+1$, on a portfolio of size and momentum matched stocks. These abnormal returns are averaged over all individuals ranked in month t. Using all available months, we obtain a time-series of abnormal returns for top and bottom performing investors. The return horizons are $\tau = 1, 3, 6, 12, 24$, and 36—corresponding to the columns in the table. The rows labeled "Bottom performers" and "Top performers"reports the time-series average return using only bottom performing investors and top performing investors, respectively. The row labeled "Top − Bottom" reports the time-series average of the differences between the abnormal returns for top performers and the abnormal return for bottom performers. The rows labeled "T-statistic" report a Newey and West (1987) t-statistic. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

	Return horizon						
	1 month	3 months	6 months	12 months	18 months	24 months	36 months
A. Past performance measured using the Appraisal ratio							
Quartile of individual investors with small portfolios							
N	433	420	402	364	329	296	236
Top − Bottom	9.09	9.29	8.38	4.84	3.82	3.06	4.20
T-statistic	2.05	3.06	3.06	2.12	2.18	2.54	4.29
Quartile of individual investors with large portfolios							
N	421	419	416	402	380	357	294
Top − Bottom	6.67	7.79	8.25	7.32	7.32	6.95	6.97
T-statistic	1.21	2.08	2.51	2.56	2.93	3.36	3.73
B. Past performance measured using Sharpe ratio							
Quartile of individual investors with small portfolios							
N	522	508	487	444	406	371	306
Top − Bottom	0.35	0.46	0.49	0.07	0.06	-0.08	0.03
T-statistic	0.64	1.71	1.66	0.25	0.05	-0.24	0.15
Quartile of individual investors with large portfolios							
N	385	383	380	368	349	326	269
Top − Bottom	0.29	0.41	0.39	0.38	0.36	0.32	0.26
T-statistic	0.82	1.82	2.05	2.32	2.92	2.95	4.04
C. Past performance measured using a portfolio weigh based measure, ΔW(6,6)							
Quartile of individual investors with small portfolios							
N	530	513	486	431	383	340	265
Top − Bottom	0.37	0.42	0.41	0.41	0.34	0.20	0.04
T-statistic	1.56	2.83	2.75	2.61	2.55	1.57	0.37
Quartile of individual investors with large portfolios							
N	303	301	297	285	269	250	204
Top − Bottom	0.17	0.13	0.15	0.15	0.20	0.20	0.23
T-statistic	1.08	1.04	1.37	1.72	2.13	2.30	2.90

Table 8
Average returns for portfolios of stocks favored by top performing and bottom performing individual investors that traded in at least 6 out of the 24 last months

The table reports portfolio time-series average returns. The portfolio returns are constructed as follows. For each month t all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month t are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, performance relative to a portfolio of size and momentum matched stocks (style matched), and a portfolio weight based performance measure (ΔW(6,6).) A stock is favored by top-performing investors if the stock is held by twice as many top-performers as bottom-performers. The opposite is true for stocks favored by bottom-performers. We construct an H-month holding period portfolio, R^H_{pt}, from stocks favored by top-performers as follows. For month t, the portfolio contains stock favored by investors that was classified as top-performers in months $t-H$ through $t-1$. This way of populating a portfolio with stocks follows Jegadeesh and Titman (1993). Portfolio returns are computed as the weighted average of the returns on the stocks in the portfolio where the weight for stock j is number of top-performers holding stock j divided by total number of top-performing investors. Returns on a portfolio of stocks favored by bottom-performers are computed in a similar way. The columns report average returns for monthly holding periods H in $\{1, 3, 6, 12, 18, 24, 26\}$. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

	Return horizon						
	1 month	3 months	6 months	12 months	18 months	24 months	36 months
Time-series observations	101	99	96	90	84	78	66
A. Past performance measured using the Appraisal ratio							
Top performers	2.01	1.72	1.63	1.33	1.15	0.85	0.43
Bottom performers	0.29	0.22	0.38	0.73	0.16	0.19	-0.56
B. Past performance measured using Sharpe ratio							
Top performers	1.48	1.39	1.28	1.24	0.98	0.72	0.33
Bottom performers	0.93	0.40	0.49	0.91	0.03	0.48	-0.65
C. Past performance measured using a portfolio weigh based measure, ΔW(6,6)							
Top performers	0.72	1.16	1.08	0.79	0.47	0.14	-0.11
Bottom performers	-0.72	-0.50	-0.54	-0.62	-0.60	-0.62	-0.37

Table 9
Jensen's alphas for portfolios of stocks favored by top performing and bottom performing individual investors that traded in at least 6 out of the 24 last months

The table reports intercepts from the following time-series regression:

$$R_{pt}^{H} = \alpha_p + \beta(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mMOM_t + \epsilon_{pt},$$

where the right-hand side variables are described in Table 2. The portfolio returns on the left-hand side are constructed as follows. For each month t all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month t are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, performance relative to a portfolio of size and momentum matched stocks (Style matched), and a portfolio weight based performance measure (ΔW(6,6).) A stock is favored by top-performing investors if the stock is held by twice as many top-performers as bottom-performers. The opposite is true for stocks favored by bottom-performers. We construct an H-month holding period portfolio, R_{pt}^{H}, from stocks favored by top-performers as follows. For month t, the portfolio contains stock favored by investors that was classified as top-performers in months $t-H$ through $t-1$. This way of populating a portfolio with stocks follows Jegadeesh and Titman (1993). Portfolio returns are computed as the weighted average of the returns on the stocks in the portfolio where the weight for stock j is number of top-performers holding stock j divided by total number of top-performing investors. Returns on a portfolio of stocks favored by bottom-performers are computed in a similar way. The columns report Jensen's alphas for monthly holding periods H in $\{1, 3, 6, 12, 18, 24, 26\}$. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003. The parentheses contains White (1980) t-values.

	Return horizon						
	1 month	3 months	6 months	12 months	18 months	24 months	36 months
Time-series observations	101	99	96	90	84	78	66
A. Past performance measured using the Appraisal ratio							
Top performers	1.25 (3.25)	0.92 (2.55)	0.97 (2.58)	0.81 (2.21)	0.80 (2.07)	0.72 (1.83)	0.73 (1.66)
Bottom performers	0.07 (0.09)	−0.20 (−0.25)	0.08 (0.09)	0.45 (0.60)	0.04 (0.06)	0.26 (0.42)	−0.23 (−0.39)
B. Past performance measured using Sharpe ratio							
Top performers	0.77 (3.12)	0.63 (2.75)	0.67 (2.77)	0.71 (2.90)	0.59 (2.32)	0.51 (1.91)	0.45 (1.50)
Bottom performers	0.87 (0.72)	0.12 (0.11)	0.32 (0.28)	0.71 (0.75)	−0.09 (−0.12)	0.67 (0.97)	−0.22 (−0.29)
C. Past performance measured using a portfolio weigh based measure, ΔW(6,6)							
Top performers	−0.00 (−0.01)	0.36 (1.05)	0.24 (0.76)	−0.08 (−0.34)	−0.31 (−1.26)	−0.48 (−1.90)	−0.57 (−2.04)
Bottom performers	−0.61 (−0.53)	−0.43 (−0.37)	−0.46 (−0.40)	−0.67 (−0.58)	−0.46 (−0.41)	−0.39 (−0.35)	−0.19 (−0.16)