Is Money Really "Smart"? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence

Russ Wermers*
Department of Finance
Robert H. Smith School of Business
University of Maryland
College Park, MD 20742-1815
(301) 405-0572

November 2003

*Internet: rwermers@rhsmith.umd.edu. Web address: http://www.rhsmith.umd.edu/Finance/rwermers/. In particular, I thank Nick Bollen, Naveen Daniel, Wayne Ferson, Mark Grinblatt, George Oldfield, Hans Stoll, Sheridan Titman, Wanda Wallace, Lu Zheng, and Xinge Zhao as well as finance workshop participants at the College of William and Mary; Penn State University; Stockholm School of Economics; Stockholm University; Tilburg University (CentER); the University of Amsterdam; the University of California, Los Angeles; the University of Maryland; the University of Southern California; the University of Texas at Austin (AIM Investment Center Conference on Mutual Funds); the University of Vienna (Gutmann Center); and Vanderbilt University for helpful comments. Also, I gratefully acknowledge research support from INQUIRE-Europe for this project. Excellent research assistance was provided by Bill Ding and Inchul Suh at the University of Colorado, and by Carl Ullrich at the University of Maryland. This paper was formerly entitled, "Predicting Mutual Fund Returns."

Is Money Really "Smart"?
New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence

Abstract

Mutual fund returns strongly persist over multi-year periods–that is the central finding of this paper. Further, consumer and fund manager behavior both play a large role in explaining these long-term continuation patterns–consumers invest heavily in last-year's winning funds, and managers of these winners invest these inflows in momentum stocks to continue to outperform other funds for at least two years following the ranking year. By contrast, managers of losing funds appear reluctant to sell their losing stocks to finance the purchase of new momentum stocks, perhaps due to a disposition effect. Thus, momentum continues to separate winning from losing managers for a much longer period than indicated by prior studies.

Even more surprising is that persistence in winning fund returns is not entirely explained by momentum–we find strong evidence that flow-related buying, especially among growth-oriented funds, pushes up stock prices. Specifically, stocks that winning funds purchase in response to persistent flows have returns that beat their size, book-to-market, and momentum benchmarks by two to three percent per year over a four-year period. Cross-sectional regressions indicate that these abnormal returns are strongly related to fund inflows, but not to the past performance of the funds–thus, casting some doubt on prior findings of persistent manager talent in picking stocks. Finally, at the style-adjusted net returns level, we find no persistence, consistent with the results of prior studies. On balance, we confirm that money is smart in chasing winning managers, but that a "copycat" strategy of mimicking winning fund stock trades to take advantage of flow-related returns appears to be the smartest strategy.

Eighty-eight million individuals now hold investments in U.S. mutual funds, with over 90 percent of the value of these investments being held in actively managed funds. Further, actively managed equity funds gain the lion's share of consumer inflows–flows of net new money to equity funds (inflows minus outflows) totalled \$309 billion in 2000, pushing the aggregate value of investments held by these funds to almost \$4 trillion at year-end 2000.

While the majority of individual investors apparently believe in the virtues of active management in general, many appear to hold even stronger beliefs concerning the talents of subgroups of fund managers–they appear to believe that, among the field of active managers, superior managers exist that can "beat the market" for long periods of time. In particular, *Morningstar* and *Lipper* compete vigorously for the attention of these true believers by providing regular fund performance rankings, while popular publications such as *Money Magazine* routinely profile "star" mutual fund managers. In addition, investor dollars, while not very quick to abandon past losing funds, aggressively chase past winners (see, for example, Sirri and Tufano (1998)).

Are these "performance-chasers" wasting their money and time, or is money "smart"? Several past papers have attempted to tackle this issue, with somewhat differing results. For example, Grinblatt and Titman (1989a, 1993) find that some mutual fund managers are able to consistently earn positive abnormal returns before fees and expenses, while Brown and Goetzmann (1995; BG) attribute persistence to inferior funds consistently earning negative abnormal returns. Gruber (1996) and Zheng (1999) examine persistence from the viewpoint of consumer money flows to funds, and find that money *is* "smart"–that is, money flows disproportionately to funds exhibiting superior future returns. However, the exact source of the smart money effect remains a puzzle–does smart money capture manager talent or, perhaps, simply momentum in stock returns?[1]

More recently, Carhart (1997) examines the persistence in net returns of U.S. mutual funds, controlling for the continuation attributable to priced equity styles (see, for example, Fama and French (1992, 1993, 1996), Jegadeesh and Titman (1993), Daniel and Titman (1997), and Moskowitz and Grinblatt (1999)). Carhart finds little evidence of superior funds that consistently outperform their style benchmarks–specifically, Carhart finds that funds in the highest net return decile (of the CRSP mutual fund database) during one year beat funds in the lowest decile by about 3.5 percent during the following year, almost all due to the one-year momentum effect documented

[1] Sapp and Tiwari (2002) find evidence that, at the net return level, the smart-money effect can be explained by momentum and not by manager talent, while Teo and Woo (2001) find evidence of a "dumb money" effect–that is, high inflow funds underperform low inflow funds over multi-year time periods.

by Jegadeesh and Titman (1993) and to the unexplained poor performance of funds in the lowest prior-year return decile.[2] Thus, Carhart (1997) suggests that money is not very smart.

Recent studies find somewhat more promising results than Carhart (1997). Chen, Jegadeesh, and Wermers (1999) find that stocks most actively purchased by funds beat those most actively sold by over two percent per year, while Bollen and Busse (2002) find evidence of persistence in quarterly fund performance. Wermers (2000) finds that, although the average style-adjusted net return of the average mutual fund is negative (consistent with Carhart's study), high-turnover funds exhibit a net return that is significantly higher than low-turnover funds. In addition, these high-turnover funds pick stocks well enough to cover their costs, even adjusting for style-based returns. This finding suggests that fund managers who trade more frequently have persistent stockpicking talents. All of these papers provide a more favorable view of the average actively managed fund than prior research, although none focus on the persistence issue with portfolio holdings data.

This study examines the mutual fund persistence issue using both portfolio holdings and net returns data, allowing a more complete analysis of the issue than past studies. With these data, we develop measures that allow us to examine the roles of consumer inflows and fund manager behavior in the persistence of fund performance. Specifically, we decompose the returns and costs of each mutual fund into that attributable to (1) manager skills in picking stocks having returns that beat their style-based benchmarks (selectivity), (2) returns that are attributable to the characteristics (or style) of stockholdings, (3) trading costs, (4) expenses, and (5) costs that are associated with the daily liquidity offered by funds to the investing public (as documented by Edelen (1999)). Further, we construct holdings-based measures of momentum-investing behavior by the fund managers. Together, these measures allow an examination of the relation between flows, manager behavior, and performance persistence.

In related work, Sirri and Tufano (1998) find that consumer flows react about as strongly to one-year lagged net returns as to any other fund characteristic. In addition, the model of Lynch and Musto (2002) predicts that performance repeats among winners (but not losers), while the model of Berk and Green (2002) predicts no persistence (or weak persistence) as consumer flows compete away any managerial talent. Consistent with Sirri and Tufano (1998), and to test the competing viewpoints of Lynch and Musto (2002) and Berk and Green (2002), we sort funds on their one-year lagged net returns for most tests in this paper. While other ways of sorting funds are attempted,

[2] A good deal of recent media attention has been given to the alleged underperformance of actively managed mutual funds, too. See, for example, Clements (2001), who bases his arguments on the CRSP database used by Carhart.

we find that one-year lagged net returns explain persistence patterns as well as any other variable.

Our findings are as follows. When all domestic equity funds are ranked on their net returns of one year, top quintile funds beat bottom quintile funds by five percent during the following year, as well as beating the S&P 500 index by two percent. As shown by Carhart (1997), winning funds, by default, hold winning stocks which provide momentum-based returns that explain a portion of this spread. However, we expose another strong influence–the reaction of consumers to fund performance, and the resulting behavior of managers. As shown by Sirri and Tufano (1998), consumers strongly invest cash in funds having high prior-year returns, and (weakly) disinvest in funds having low prior returns. While most of the fund managers in our sample buy stocks on momentum, winning managers use their large cash inflows (20-30 percent of assets per year) to implement momentum strategies more strongly than losing managers. Losing managers, in fact, appear reluctant to sell their low return stocks to replace them with new momentum stocks–thus, momentum works against them because they hold on to losers that continue to be losers. While this reluctance to sell low return stocks may be an avoidance of trade-related costs, it is also consistent with a disposition effect among mutual fund managers. This evidence adds to the findings of Grinblatt and Han (2002), who show that momentum appears to be related to a reluctance to sell losing stocks–we show that mutual fund managers may play a role in this effect.[3]

Most surprisingly, our paper presents strong evidence that flow-related buying pushes up stock prices, controlling for momentum-based returns. Fama-MacBeth cross-sectional regressions indicate that fund performance (adjusted for size, book-to-market, and momentum) is strongly correlated with both contemporaneous and past flows, but not with past performance. Further analysis shows that flow-related additions to existing positions impact prices, but not flow-related purchases of newly added stocks. Thus, winning managers, having correlated holdings, appear to push up stock prices through their flow-related purchases of the same stocks. These results also cast some doubt on past findings of style-adjusted skill among growth-fund managers (e.g., Daniel, Grinblatt, Titman, and Wermers (1997)), indicating that flow-related buying may be pushing performance, and not persistent stockpicking skills.

Finally, we find a strong reputation effect in consumer flows, especially for growth-oriented

[3]Consistent with Badrinath and Wahal (2002), we find that all mutual fund managers implement momentum more strongly when establishing new stock positions (i.e., they buy winners not already held) than they do when adding to existing positions. Winning managers, for the most part, use their inflows to buy larger allocations of new momentum stocks than other managers, but they do not underweight their existing low-return stocks to increase the weights of their existing high-return positions. Thus, interestingly, winning managers also exhibit a disposition effect.

funds–consumers continue to disproportionately invest new cash into growth-fund winners during the second and third years after the return ranking period, although the spread in returns diminishes. This reputation effect in consumer flows explains why Zheng (1999) found that the smart money effect is not completely captured by the chasing winners (momentum) effect. Consumer money flows to winners over a longer period (two to four years) than the period of the momentum effect (one year), and these high-inflow funds continue to perform well due to their flow-related purchases. However, it is noteworthy that these persistent inflows also have a negative effect on the net returns of winning funds, as inflows push winning managers temporarily away from being fully invested in stocks with momentum-based returns.

After controlling for this flow-related drag on net returns, we find that the style-adjusted net return of the average dollar invested in past winning funds is not very different from that invested in past losing funds (although the style-adjusted return on stockholdings and the unadjusted net returns are very different). This result is consistent with the model of Berk and Green (2002), where money strongly chases performance, and performing managers capture the entire rents from their performance. However, our results indicate that persistent performance may be more related to flow-related trades than to persistent manager talent.[4]

Overall, while we find strong persistence in performance, at the stockholdings level, we do not find strong evidence of a tradeable strategy in style-adjusted net returns. This suggests that a "copy-cat" strategy (Myers, Poterba, Shackelford, and Shoven (2002) and Wermers (2001)) may be the smartest money of all.

The remainder of this paper is organized in four sections. The construction of our database is discussed in Section I, while our performance-decomposition methodology is discussed in Section II. We present empirical findings in Section III, and conclude the paper in Section IV.

I Data

We merge two major mutual fund databases for our analysis of mutual fund performance. Details on the process of merging these databases is available in Wermers (2000).

The first database contains quarterly portfolio holdings for all U.S. equity mutual funds existing at any time between January 1, 1975 and December 31, 1994; these data were purchased from

[4]We note that Kosowski, Timmermann, Wermers, and White (2003) find that ranking funds on their three-year style-adjusted net returns results in weak performance persistence.

Thomson/CDA of Rockville, Maryland. The CDA dataset lists the equity portion of each fund's holdings (i.e., the shareholdings of each stock held by that fund) along with a listing of the total net assets under management and the self-declared investment objective at the beginning of each calendar quarter. CDA began collecting investment-objective information on June 30, 1980; we supplement these data with hand-collected investment objective data from January 1, 1975.

The second mutual fund database is available from the Center for Research in Security Prices (CRSP) and is used by Carhart (1997). The CRSP database contains monthly data on net returns, as well as annual data on portfolio turnover and expense ratios for all mutual funds existing at any time between January 1, 1962 and December 31, 2000. Further details on the CRSP mutual fund database are available from CRSP.

These two databases were merged to provide a complete record of the stockholdings of a given fund, along with the fund's turnover, expense ratio, net returns, investment objective, and total net assets under management during the entire time that the fund existed during our the period of 1975 to 1994 (inclusive).[5] Finally, stock prices and returns were obtained from the CRSP stock files.

In this study, we limit our analysis to funds that predominantly hold diversified portfolios of U.S. equities. Specifically, during each quarter, we include only mutual funds having a self-declared investment objective of "aggressive growth," "growth," "growth and income," "income," or "balanced" at the beginning of that quarter.[6] We exclude all other funds, which include international funds, bond funds, gold funds, real estate funds, and all other sector funds, as these types of funds generally hold and trade minimal quantities of domestic equities (if any).

In this paper, we decompose mutual fund returns into several components to analyze the costs and benefits of active mutual fund management. The next section describes the measures we use to decompose the returns generated by the stocks held by a mutual fund. In addition, we describe our method for estimating trading costs for each mutual fund during each quarter.

[5]In a small number of cases, we could not find a match between funds in the CDA and CRSP files. However, these are mainly very small mutual funds. Since this paper focuses on fund returns, weighted by the total net assets under management, these omitted funds will not materially bias our study. See Wermers (2000) for further details on the missing funds.

[6]See Grinblatt, Titman, and Wermers (1995) for a description of the types of investments made by funds in each category.

II Performance-Decomposition Methodology

In this study, we use several measures that quantify the ability of a mutual fund manager to choose stocks, as well as to generate superior performance at the net return level. These measures, in general, decompose the return of the stocks held by a mutual fund into several components in order to both benchmark the stock portfolio and to provide a performance attribution for the fund.

The measures used to decompose fund returns include:

1. the portfolio-weighted return on stocks currently held by the fund, in excess of returns (during the same time period) on matched control portfolios having the same style characteristics (selectivity)

2. the portfolio-weighted return on control portfolios having the same characteristics as stocks currently held by the fund, in excess of time-series average returns on those control portfolios (style timing)

3. the time-series average returns on control portfolios having the same characteristics as stocks currently held (style-based returns)

4. the execution costs incurred by the fund

5. the expense ratio charged by the fund

6. the net returns to investors in the fund, in excess of the returns to an appropriate benchmark portfolio.

The first three components of performance, which decompose the return on the stocks held by a given mutual fund before any trading costs or expenses are considered, are briefly described next.[7] We estimate the execution costs of each mutual fund during each quarter by applying recent research on institutional trading costs to our stockholdings data–we also describe this procedure below. Data on expense ratios and net returns are obtained directly from the merged mutual fund database. Finally, we describe the Carhart (1997) regression-based performance measure, which we use to benchmark-adjust net returns.

---

[7] These measures are developed in Daniel, Grinblatt, Titman, and Wermers (1997), and are more fully described there. In that paper, the authors argue that decomposing performance with the use of benchmark portfolios matched to stocks on the basis of the size, book-to-market, and prior-year return characteristics of the stocks is a more precise method of controlling for style-based returns than the method of decomposing performance with factor-based regression techniques that is used by Carhart (1997).

A The Characteristic Selectivity (CS) Measure

The first component of performance measures the stock-picking ability of the fund manager, controlling for the particular style used by that manager.[8] This measure of stock-picking ability, which is called the "Characteristic-Selectivity" measure (CS) is computed during quarter t as

$$CS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-1}(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}}), \tag{1}$$

where $\tilde{w}_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\tilde{R}_{j,t}$ is the quarter t buy-and-hold return of stock j, and $\tilde{R}_t^{b_{j,t-1}}$ is the quarter t buy-and-hold return of the characteristic-based benchmark portfolio that is matched to stock j at the end of quarter $t-1$.

To construct the characteristic-based benchmark portfolio for a given stock during a given quarter, we characterize that stock over three characteristics–the size, book-value of equity to market-value of equity ratio, and past returns of that stock. Benchmarking a stock proceeds as follows–this procedure is based on a modification of Daniel, Grinblatt, Titman, and Wermers (1997). First, all stocks (listed on NYSE, AMEX, or Nasdaq) having at least two years of book value of equity information in Compustat, and stock return and market capitalization of equity data in CRSP, are ranked, at the end of each June, by their market capitalization. Quintile portfolios are formed (using NYSE size quintile breakpoints), and each quintile portfolio is further subdivided into book-to-market quintiles, based on their most recently available book-to-market data as of the end of the December immediately prior to the ranking year. Here, we modify the DGTW approach to use a different industry normalization of book-to-market.[9] Finally, each of the resulting 25 fractile portfolios are further subdivided into quintiles based on the 12-month past return of stocks through the end of May of the ranking year. This three-way ranking procedure results in 125 fractile portfolios, each having a distinct combination of size, book-to-market, and momentum

[8] This study does not take a position on whether fund managers should be rewarded for holding stocks with certain characteristics (e.g., momentum stocks) during long periods of time when those stocks outperform the market. However, we provide an accurate decomposition of the returns of winners and losers into style-based returns and style-adjusted returns to allow the reader (and investors) to draw their own conclusions.

[9] Specifically, we compute the book-to-market characteristic as $\frac{\ln(BTM_{i,t}^j)-\ln(BTM_t^j)}{\sigma_j\left[\ln(BTM_{i,t}^j)-\ln(BTM_t^j)\right]}$, where $BTM_{i,t}^j$ is the book-to-market ratio of stock i, which belongs to industry j on June 30th of year t and $\ln(BTM_t^j)$ is the log book-to-market ratio of industry j (the aggregate book-value divided by the aggregate market value). Also, $\sigma_j\left[\ln(BTM_{i,t}^j)-\ln(BTM_t^j)\right]$ is the cross-sectional standard deviation of the adjusted book-to-market ratio across industry j. This approach was suggested by Cohen and Polk (1998), as well as by discussions with Christopher Polk.

characteristics.[10] The three-way ranking procedure is repeated at the end of June of each year, and the 125 portfolios are reconstituted at that date. In an extension of this procedure that we use later in this paper, we reconstitute these portfolios at the end of each calendar quarter. While the annual sort is closer to an implementable strategy that is an alternative to holding the manager's portfolio, the quarterly sort allows us to more accurately separate the influence of the manager's style-based trades from her stockpicking talents. For example, a manager that strongly purchases new momentum stocks each quarter will exhibit CS performance with the annual sort, but not with the quarterly sort on characteristics.

Value-weighted returns are computed for each of the 125 fractile portfolios, and the benchmark for each stock during a given quarter is the buy-and-hold return of the fractile portfolio of which that stock is a member during that quarter. Therefore, the benchmark-adjusted return for a given stock is computed as the buy-and-hold stock return minus the buy-and-hold value-weighted benchmark return during the same quarter. Finally, the Characteristic Selectivity measure of the stock portfolio of a given mutual fund during quarter t, CS_t, is computed as the portfolio-weighted benchmark-adjusted return of the component stocks in the portfolio, where the stock portfolio is normalized so that the weights add to one.

B The Characteristic Timing (CT) Measure

The above stock-selectivity measure does not capture the ability of the fund manager to time the various stock styles. Indeed, fund managers can generate additional performance if size, book-to-market, or momentum strategies have time-varying expected returns that the manager can exploit by "tilting" portfolio weights toward stocks having these characteristics when the return on the characteristics are the most profitable. Thus, our second component of performance measures a fund manager's success at timing the different investment styles; this component is termed the "Characteristic Timing" (CT) measure. The quarter t component of this measure is

$$CT_t = \sum_{j=1}^{N} (\tilde{w}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{w}_{j,t-5} \tilde{R}_t^{b_{j,t-5}}). \tag{2}$$

Note that the portfolio weight of stock j at the end of quarter $t-5$ is multiplied by $\tilde{R}_t^{b_{j,t-5}}$, the quarter t return of the characteristic-based benchmark portfolio that is matched to stock j at the

[10] Thus, a stock belonging to size portfolio one, book-to-market portfolio one, and prior return portfolio one is a small, low book-to-market stock having a low prior-year return.

end of quarter $t-5$.

C The Average Style (AS) Measure

To measure the returns earned by a fund because of that fund's tendency to hold stocks with certain characteristics, we employ our third performance component, the "Average Style" (AS) return measure. The quarter t component of this measure is

$$AS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-5} \tilde{R}_t^{b_{j,t-5}}. \tag{3}$$

Each stock held by a fund at the end of quarter $t-5$ is matched with its characteristic-based benchmark portfolio of that date. The quarter t return of this benchmark portfolio is then multiplied by the end of quarter $t-5$ portfolio weight, and the resulting product is summed over all stocks held by the fund at the end of quarter $t-5$ to give the quarter t AS component. Note that by lagging weights and benchmark portfolios by one year, we eliminate returns due to timing the characteristics. For example, a fund that successfully buys high book-to-market stocks when returns to such a strategy are unusually high will not exhibit an unusually high AS return, since this strategy will most likely involve moving into stocks within a year before the unusually high book-to-market return. However, a fund that systematically holds high book-to-market stocks to boost its portfolio return (without trying to time the effect) will exhibit a high AS Return. Note that the sum of the CS, CT, and AS measures for a given quarter (by Equations (1), (2), and (3) equals the total portfolio-weighted return of the stocks held by a given fund (we also call this the "gross return" of the fund).[11] Note, also, that computations of the AS and CT measures begin in 1976 instead of 1975, as we must use one-year lagged portfolio weights to compute these measures.

D Execution Costs

Following Wermers (2000), we use the following equation (which is based on Keim and Madhavan (1997)) for estimating the total cost of executing a purchase of stock i during quarter t, as a

[11]In practice, this equivalence is only approximately true because of the additional requirement that a stock be listed in Compustat to be included in the calculation of the CS, CT, and AS measures for a fund.

percentage of the total value of the trade, $C_{i,t}^B$:

$$C_{i,t}^B = Y_t^k \cdot \left[1.098 + 0.336 D_{i,t}^{Nasdaq} + 0.092 Trsize_{i,t} - 0.084 Logmcap_{i,t} + 13.807 \left(\frac{1}{P_{i,t}}\right)\right].$$

$D_{i,t}^{Nasdaq}$ is a dummy variable that equals one if the trade occurs on Nasdaq, and zero otherwise, $Trsize_{i,t}$ is the ratio of the dollar value of the purchase to the market capitalization of the stock, $Logmcap_{i,t}$ is the natural log of the market capitalization of the stock (expressed in $thousands), and $P_{i,t}$ is the stock price at the time of the trade. Finally, Y_t^k is the year t trading cost factor for market k (k=NYSE/AMEX or Nasdaq). This factor captures the year-to-year changes in average trading costs over our time period in the different markets–these factors are based on Stoll (1995). Similarly, our equation for estimating the percentage cost of selling stock i during quarter t, $C_{i,t}^S$, is

$$C_{i,t}^S = Y_t^k \cdot \left[0.979 + 0.058 D_{i,t}^{Nasdaq} + 0.214 Trsize_{i,t} - 0.059 Logmcap_{i,t} + 6.537 \left(\frac{1}{P_{i,t}}\right)\right].$$

Details on the development of these equations are provided in Wermers (2000).

E The Carhart Measure

Carhart (1997) develops a four-factor regression for estimating mutual fund performance at the net return level. This four-factor model is an extension of the Fama and French (1993) three-factor model, and is described as,

$$R_{j,t} - R_{F,t} = \alpha_j + b_j \cdot RMRF_t + s_j \cdot SMB_t + h_j \cdot HML_t + p_j \cdot PR1YR_t + e_{j,t} \ . \tag{4}$$

Here, $R_{j,t} - R_{F,t}$ equals the net return, in excess of T-bills, of fund j during month t; $RMRF_t$ equals the month t excess return on a value-weighted aggregate market proxy portfolio; and SMB_t, HML_t, and $PR1YR_t$ equal the month t returns on value-weighted, zero-investment factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns. We use the Carhart (1997) regression measure of performance, α, to estimate the performance of mutual funds from their net return time-series data. This approach is useful in completing the performance attribution when combined with our stockholdings-based measures described previously.

F The Ferson-Schadt Measure

Ferson and Schadt (FS, 1996) develop a conditional performance measure at the net returns level. In essence, this measure identifies a fund manager as providing value if the manager provides excess net returns that are significantly higher than the fund's matched factor benchmarks, both unconditional and conditional. The conditional benchmarks control for any predictability of the factor return premia that is due to evolving public information. Managers, therefore, are only labeled as superior if they possess superior private information on stock prices, and not if they change factor loadings over time in response to public information.

FS also find that these conditional benchmarks help to control for the response of consumer cashflows to mutual funds. For example, when public information indicates that the market return will be unusually high, consumers invest unusually high amounts of cash into mutual funds, which reduces the performance measure, "alpha," from an unconditional model (such as the Carhart model). This reduction in alpha occurs because the unconditional model does not control for the negative market timing induced by the flows. Edelen (1999) provides further evidence of a negative impact of flows on measured fund performance. Using the FS model mitigates this flow-timing effect.

The version of the FS model used in this paper starts with the unconditional Carhart four-factor model and adds a market factor that is conditioned on the five FS economic variables. This model is described as,

$$R_{j,t} - R_{F,t} = \alpha_j + b_j \cdot RMRF_t + s_j \cdot SMB_t + h_j \cdot HML_t + p_j \cdot PR1YR_t + \sum_{i=1}^{5} B_{j,i}[z_{i,t-1} \cdot RMRF_t] + e_{j,t} \ ,$$

where $z_{i,t-1}$ is the deviation of information variable i from its unconditional (time-series) mean at time $t-1$, and $B_{j,i}$ is the response of fund manager j's loading on the market factor, $RMRF_t$, in response to the observed realization of $z_{i,t-1}$.[12,13] The intercept of the model, α_j, is the FS performance measure for fund j.

[12]The public information variables of FS include (1) the lagged level of the one-month T-bill yield, (2) the lagged dividend yield of the CRSP value-weighted NYSE and AMEX stock index, (3) a lagged measure of the slope of the term structure, (4) a lagged quality spread in the corporate bond market, and (5) a dummy variable for January.

[13]Note that, to maintain model simplicity, we use only the market equity premium to construct conditional factors. However, it is likely that the majority of public information concerns the return on the broad market, versus the return premia due to various styles.

G Measuring "Momentum Investing"

Finally, our study examines the role of momentum investing in the persistence of mutual fund performance. In particular, Grinblatt, Titman, and Wermers (GTW; 1995) show that the majority of mutual funds use a momentum investing strategy as part of their stock-picking approach. For the most part, we use the contemporaneous measure of momentum investing of GTW, which computes the covariance of quarterly portfolio weight changes with contemporaneous stock returns. Specifically, we use the "buy momentum" ($BMOM$) and "sell momentum" ($SMOM$) measures of GTW, which are computed during quarter t as

$$BMOM_t = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1})(\tilde{R}_{j,t} - \overline{R}_j) \ , \quad \text{and} \tag{5}$$

$$SMOM_t = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}<\tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1})(\tilde{R}_{j,t} - \overline{R}_j), \tag{6}$$

where $\overline{R}_j$ is the expected return for stock j. We use the average return of stock j during the year beginning with quarter $t + 4$ as a proxy for this expected return (i.e., we skip one year to avoid the one-year momentum effect; also, we do not use past returns as a proxy, as fund strategies are often correlated with past returns). $BMOM$ measures whether a fund manager increases weights of stocks that have recently experienced abnormally high returns, while $SMOM$ measures whether weights have decreased in stocks recently experiencing abnormally low returns. Following GTW, we modify the portfolio weights used in Equations (5) and (6) so that a buy-and-hold manager will exhibit $BMOM$ and $SMOM$ measures of zero. Specifically, the beginning and end of quarter t weights for each stock are computed using the average of the beginning- and end-of-quarter prices for that stock.[14] In some of the applications of these measures, we use end-of-quarter prices to compute both beginning- and end-of-quarter weights, following the buy-and-hold approach used by Ferson and Khang (2000). Although these results are not reported, all are qualitatively similar to the average price approach.

Also, in implementing some of our tests, we use the version of the GTW momentum measure that lags returns one quarter. For example, the one-quarter lagged buy momentum measure ($BMOML$)

[14]End-of-quarter stockholdings and stock prices are adjusted to reverse the effect of stock splits and other stock dividends.

is computed as

$$BMOML_t = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t} > \tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1})(\tilde{R}_{j,t-1} - \overline{R}_j) \ . \tag{7}$$

The one-quarter lagged sell momentum measure ($SMOML$) is computed by similarly modifying $SMOM$.

III Results

A One-Year Return Persistence in Stocks Held by Mutual Funds

We begin with an analysis of the one-year return persistence in the stockholdings of individual mutual funds. This approach exposes persistence at the stockholdings level, before trading costs and expenses muddy the picture. If we do not find persistence at this level, then we can rule out manager talent, and look for lower expenses and other costs as a source of persistence in net returns.

In particular, we compute the hypothetical yearly fund "gross returns" by applying CRSP stock returns to quarterly fund portfolio holdings data. Then, we compare the gross returns of funds with the highest and lowest prior-year gross returns to determine whether these gross returns persist. We note that holdings of non-stock securities by mutual funds are not available in our database. Therefore, we compute the gross return for each mutual fund only over the equity portion of the portfolio (normalizing portfolio weights to add up to one), both during the ranking year and the test year.

Our ranking procedure is as follows. Starting on December 31, 1975, we rank all domestic equity mutual funds existing for the entire prior year on their average monthly gross returns of that year. For a given fund, this gross return is computed for each month of 1975 by assuming that the most recent stockholdings that are available in our database represent the actual holdings of the fund during that month. Although this hypothetical portfolio only provides an estimate of the actual portfolio holdings, we believe that, if anything, the use of hypothetical portfolio weights reduces any return difference that we might find between prior-year winners and losers.[15] Funds

[15] As we will show in a later section of this study, funds with higher levels of turnover generate more extreme returns (both positive and negative) during a given year. For these funds, our use of hypothetical portfolio weights imposes the largest bias, since "stale" portfolio holdings misrepresent actual holdings more when turnover is high. Thus, using hypothetical holdings reduces the return difference during a given year between funds with the highest and lowest prior-year returns. A complete description of the limitations of the holdings data is available in Wermers (1999).

having gross returns in the top past-year quintile are labeled "Past-Year Winners," while those in the bottom past-year quintile are labeled "Past-Year Losers."

To compute the following year gross returns for winners and losers, we first compute the quarterly buy-and-hold return for the funds existing during the first quarter of that year, regardless of whether those funds survived past that quarter. Portfolios of funds are rebalanced at the end of the first quarter (using weights described below), and the process is repeated for the second quarter (the third and fourth quarters are computed similarly). Finally, the annual return is computed by compounding these quarterly rebalanced, buy-and-hold returns. This procedure minimizes any survival bias, as it includes all funds existing during any given quarter.

Table I presents the following year gross returns of mutual fund winners and losers, during each year of the period 1975 to 1994. Also presented are these following-year returns, averaged across longer time periods. Results are presented for two different fund weighting appraches: funds are weighted both by their total net assets (TNA), and by using an equal weighting (EW) across all funds.

The results show a strong level of persistence in gross fund returns. In particular, the average dollar invested in past-year winners earns a gross return of 19.2 percent over the following year, while the average dollar invested in past-year losers earns 13.3 percent (see TNA-average results). The results for the average fund (instead of the average dollar) are similar–past-year winners hold stocks that beat past-year losers by almost 6 percent per year during the following year (see EW-average results). The persistence in gross returns is much stronger than that found by Chen, Jegadeesh, and Wermers (CJW; 2000), which indicates that our more restrictive sample has somewhat different stockholdings strategies than the full sample of funds examined by CJW.[16] In addition, the gross return achieved by past winners beats the return on both the S&P 500 and CRSP indexes (both with dividends reinvested) by about 5 percent per year. In contrast, past-year losers hold portfolios of stocks that underperform market indexes by about 1 percent per year.

B One-Year Persistence in Mutual Fund Net Returns

While the persistence in returns to the portfolios of stocks held by mutual funds may provide reassurance to fans of active fund management, it is possible that this spread between past winners

[16]Specifically, CJW examine the aggregate U.S. stockholdings of all U.S. mutual funds (including sector funds, international funds, etc.) over the 1975 to 1994 period, while we examine only funds with an investment objective consistent with holding a diversified portfolio of U.S. equities.

and losers might be erased by differences in expenses and trading costs between winners and losers. To address this concern, we replicate the one-year ranking procedure described in Section A, except that mutual fund net returns to shareholders are used as the ranking (and measurement) variable. Specifically, Table II shows the yearly net return accruing to a strategy of holding funds, in the highest (or lowest) prior-year net return quintile. These yearly returns are presented for portfolios of funds weighted by their total net assets (TNA) as well as for equal-weighted (EW) portfolios of funds.

For example, the return accruing to a strategy of holding, during 1976, funds in the highest net return quintile during 1975 is 30.2 percent (see the 1976 TNA-average net return). Similarly, the net return during 1976 that accrues to holding the quintile of prior-year losing funds is 14.8 percent.

The results over the entire time period (1976 to 1994) show an average net return spread between prior-year winners and losers of 4.8 percent (16.2 minus 11.4 percent) and 5.3 percent (16.8 minus 11.5 percent), respectively, for the TNA-weighted and EW portfolios of funds. These results compare to a gross return spread of 5.9 and 5.7 percent (shown in Table I), for TNA-weighted and EW portfolios, respectively. Thus, while the spread is reduced somewhat when we examine the net returns actually realized by investors, a substantial spread is still present. In addition, the table shows that prior-year winners handily beat the returns on market indexes. For example, the TNA-weighted past winner portfolio exhibits an average yearly return of 16.2 percent, while the S&P 500 and CRSP VW portfolios (both with dividends reinvested) exhibit average returns of 14.2 and 14.5 percent, respectively.

Also noteworthy is that the spread in *average* mutual fund returns between top and bottom prior-return quintiles (EW results) is only marginally higher than the spread in the return on the average *dollar invested* in the top and bottom quintiles (TNA-weighted results). As argued in Wermers (2000), using a TNA-averaging method minimizes the impact of any potential biases in our mutual fund dataset. Thus, the remainder of this paper uses such a weighting system.[17]

The spread between the returns of prior-year winners and the market indexes, about two percent

[17]Specifically, biases in mutual fund databases are usually most problematic with small funds. For example, the tendency of all databases to omit the records of very small funds that exist only for a short time causes survival bias in studies using these data. Most other biases are related to fund size, as well. These biases are greatly reduced by weighting fund results by the total net assets (TNA) under management instead of using an equal-weighting. Although we believe that the vast majority of small funds are covered by our data, we avoid this problem by using a TNA-weighting.

per year, indicates that abnormal returns can be obtained by simply buying last-year's highest return funds. However, it is not clear whether the higher returns from past winners are simply due to the characteristics of the stocks held by these funds, or if managers of these funds also having stockpicking talents. In particular, buying last-year's top funds is clearly an indirect play on momentum–high past-return funds hold high past-return stocks. Of interest is whether this return boost from passively holding high past-return stocks explains the entire spread between winning funds and market indexes, as well as between winning and losing funds–Carhart (1997) analyzes net returns to support this viewpoint. In the next section, we provide a complete decomposition of the returns and costs of portfolios of winner and loser mutual funds to precisely locate the source of persistence.

C Decomposing the Persistence in Mutual Fund Returns

Sirri and Tufano (1998) find that consumer flows react about as strongly to one-year lagged net returns as to any other fund characteristic. In addition, the model of Lynch and Musto (2002) predicts that performance repeats among winners (but not losers), while the model of Berk and Green (2002) predicts no persistence (or weak persistence) as consumer flows compete away any managerial talent. Consistent with Sirri and Tufano (1998), and to test the competing viewpoints of Lynch and Musto (2002) and Berk and Green (2002), we sort funds on their one-year lagged net returns for the majority of tests in the remainder of this paper. When appropriate, we provide results for other sorting approaches as well.

Section III.B shows that winners (and losers) strongly repeat from one year to the next. However, there are many possible reasons for this spread in net returns. For example, winning funds may systematically hold stocks with higher expected returns, or losing funds may simply generate higher trading costs and charge higher expenses. This section formally investigates the winner-loser patterns by decomposing the returns and costs of funds to provide an in-depth analysis of the drivers of net return persistence at a one-year frequency. We start by analyzing the investing characteristics of winners vs. losers, followed by a decomposition of mutual fund returns and costs. As a preview of our results, we will show that consumer flows to winning funds, as well as the resulting investment behavior of fund managers, plays a large role in the persistence of mutual fund returns, as predicted by Berk and Green (2002).

C.1 The Characteristics of Winning vs. Losing Funds

Panel A of Table III shows the characteristics of each fractile portfolio of funds, ranked by their prior-year net returns. We use a ranking method similar to that described in Section III.B, except that we reconstitute prior-year net return sorted portfolios every calendar quarter–thus, creating overlapping test years.[18] The reader should also note that all results in Table III are based on a TNA-weighted average across funds (for each fractile). The characteristics presented, for each fractile, include the number of funds, the average total net assets of these funds, stock holdings as a percentage of total fund holdings, the loadings from a regression of the fractile excess net returns on the four Carhart factors, and the TNA-average (over all event years): buy- and sell-momentum investing measures ($BMOM$ and $SMOM$, respectively), net cash inflows as a percent of beginning of period assets, buy- and sell-turnover levels, and the percentage of stock purchases that represent additions to stocks already held (versus purchases of new stocks). Note that net cash inflows are computed, for each fund during a given year, as the percentage change in shares outstanding of the fund from the beginning to the end of that year.[19]

Some results stand out in the panel. First, winning mutual funds exhibit significantly higher loadings on the SMB and PR1YR factors than losing funds, which indicates that they hold more small-capitalization and high past-return stocks. In addition, winners have a slightly higher market exposure (RMRF) and book-to-market exposure (HML). Consistent with the higher RMRF loading, funds in the highest past-return fractiles hold somewhat higher percentages of stocks in their portfolios than funds in the lowest past-return fractiles (see "Stocks").[20]

The substantially higher exposure of winning funds to momentum is to be expected, since we rank funds on their prior-year net returns–winning funds hold winning stocks. However, since these funds make portfolio revisions during the year following the ranking, it may also follow that they modify the momentum exposure of their portfolios during year one. $BMOM$ and $SMOM$ measure the active portfolio revisions (buy and sell revisions, respectively) that are made by a fund manager in the same direction as contemporaneous-quarter stock returns relative to expected returns. The proxy for the expected return for each stock during a given quarter (quarter t) is the

[18] All time-series inference tests in this table, as well as the following tables, are adjusted for overlapping observations.

[19] This approach counts reinvested capital gains and dividends as cash inflows.

[20] It is noteworthy that all of these higher factor loadings are consistent with winners holding stocks with higher expected returns than losers–thus, we would naturally expect that winners exhibit continued higher portfolio returns during this test year. We examine this in the next section.

average quarterly return of that stock after skipping one year (i.e., quarters $t+5$ to $t+8$) after the end of that quarter. The panel shows that winning managers actively buy stocks on momentum, as indicated by their $BMOM$ measure, but do not sell stocks on momentum, as indicated by their $SMOM$ measure. Although losing fund managers also buy stocks on momentum, they do not implement this strategy as strongly as winning managers (see the Top-Bottom results for $BMOM$). For example, winners in the top decile exhibit a buy momentum investing measure, 3.2 percent per year, that is roughly twice the momentum investing level of bottom-decile losers, 1.5 percent per year.

In unreported results, we partition the $BMOM$ measure into two further measures. The first measure, $BMOM^{new}$, computes $BMOM$ only across stocks newly added by the manager to her portfolio during a quarter. The second measure, $BMOM^{same}$, computes $BMOM$ only across stocks for which the manager is adding to an already established position. Consistent with Badrinath and Wahal (2002), we find that all fund managers (winners and losers) implement $BMOM$ strategies mainly in new stock purchases. However, we further find that winning managers (having larger buy turnover levels) buy new winners to a greater degree than losing managers. Specifically, the $BMOM^{new}$ measure for the top quintile of funds, ranked by their one-year lagged net returns, equals 2.6 percent per year, while it equals 1.8 percent per year for bottom quintile funds. By comparison, $BMOM^{same}$ equals 0.3 and -0.1 percent per year for winners and losers, respectively. Larger differences between $BMOM^{new}$ measures are present for more extreme funds: top and bottom decile funds exhibit measures of 3.0 and 1.9 percent per year, respectively, while top and bottom ventile funds exhibit measures of 3.7 and 2.0 percent per year. Again, these extreme funds do not show much of a tendency to use momentum in adding to existing positions. Thus, while most funds use momentum chiefly in adding new stocks to portfolios, it is significant that winning managers implement these strategies more strongly than losing managers.

Further insight is gained by looking at the large differences in consumer cashflows between past winners and losers. Specifically, the quintile of past winners experiences yearly inflows that average 20.3 percent of beginning-of-year fund assets. In contrast, cashflows to the average fund are only 8.9 percent, while the quintile of past losers experiences a cash *outflow* of 1.9 percent. Cashflow statistics for funds with more extreme prior-year returns are much more dramatic–for example, funds in the highest ventile of prior-year returns gather 31.3 percent cashflows per year, while those in the lowest ventile experience outflows of 5.9 percent per year. This evidence, along with the difference in the $BMOM$ measure between past winners and losers, shows that past winners invest their substantial new cash inflows in new momentum stocks. While managers of losing funds could add new momentum stocks by selling off some of their losing stocks (which they hold in abundance), they do not appear to be willing to do this, as shown by our evidence on sell turnover levels. Specifically, the winning quintile of funds sell an average of 48 percent of their stocks during the year, and use the proceeds, along with their inflows, to add 75 percent in new positions (either adding to existing or purchasing new stocks). By contrast, the losing quintile, sell almost the same fraction of their portfolios, 49 percent, to finance the purchase of 58 percent in new positions. It should be noted that the prior cashholdings of these funds provide a buffer, so that they manage to purchase more stocks than they sell, even in the absence of inflows.

Somewhat offsetting this effect is that winning fund managers, when they buy stocks, add more shares to existing stock positions than losing managers (43 percent vs. 37 percent of purchases are same-stock purchases, respectively). In a later section of this paper, we will show that this difference is insignificant during the ranking year, indicating a strategy shift by winning and/or losing managers following the ranking year. This finding may be consistent with winning fund managers exhibiting overconfidence–that is, they may attribute lucky high returns to their stock-picking skills. Alternatively, winning managers may continue to add to existing holdings because they have developed unique skills in following these stocks. We will address which view appears to hold in a later section of this paper.

In unreported tests, we examine the reaction of consumer flows to short-term returns–flows were measured for funds with the highest and lowest three-month past net returns. The results indicated that inflows for three-month prior winning funds are higher than those for three-month losers, but the difference is not as dramatic as the reaction of flows to past one-year returns. Thus, consumers pay more attention to returns over at least a one-year period.

C.2 Decomposing Returns on Stockholdings

We next decompose the return on stocks held by winning vs. losing mutual funds. This decomposition helps us to understand whether fund managers have talents in finding stocks that beat other stocks with similar characteristics (or styles), or whether the return of the fund is due simply to the return premia that accrues to the characteristics of the stockholdings. While we might reward a manager for using style investing during a time period when that particular style experienced high returns, we might look even more favorably on the manager who can pick the best stocks within a given style category.

Table III, Panel B, breaks down the TNA-average gross returns of the past net-return sorted fractiles of funds described previously. The table presents the gross return, as well as the decomposition of gross return into its characteristic selectivity (CS), characteristic timing (CT), and average style (AS) components. As mentioned in Section II, the CS and CT measures capture the ability of the manager to select stocks that beat other stocks having the same characteristics, and to time the characteristics, respectively. The AS measure captures the style- (or characteristic-) based returns of the fund manager's portfolio.

The results show that funds having the highest prior-year net returns exhibit significant CS measures, indicating that such fund managers can successfully pick stocks–this component contributes 1.5 percent per year to the gross return of the top quintile of funds, and 2.1 percent per year for the top 5 percent of funds. Meanwhile, low past-return funds exhibit no abilities to pick stocks, as their CS measures are small and (in general) insignificant. Past winners also have a significantly higher AS measure than the lowest prior-year return funds, which reflects the prior-mentioned fact that high past-return funds hold stocks with characteristics associated with higher expected returns, during the following year, than their low past-return counterpart funds. In particular, the spread in the AS component contributes 3.8 percent per year to the spread in gross returns between the top and bottom quintiles of funds. Results for the CT measure show that none of the portfolios of funds–past winners, past losers, or funds in between, have the ability to successfully time the styles. It is important to note, however, that the CT measure captures short-term style-timing ability, and does not capture the ability of fund managers to time styles over longer periods.

Our findings of this section, therefore, indicate two different sources of the gross return spread between past winners and losers. First, the winner-loser spread in stockpicking skills (between the top and bottom quintiles of funds) is 1.2 percent, while the spread in characteristic-based returns is 3.8 percent. The total spread in gross returns is 5.1 percent.[21]

[21] As mentioned in Section III, the sum of the CS, AS, and CT components only approximately equals the gross return, as these components are computed only across stocks having Compustat data available during a given time period.

C.3 Decomposing Costs

We also present a decomposition of costs for past winners and losers in Panel B. We examine the spread in two types of costs between winners and losers–the expenses charged and the trading costs incurred by each of these categories of funds. The results show that spreads in expenses and trading costs between past winners and losers are quite small. Thus, our results seemingly run contrary to the findings of Carhart (1997), who finds that the worst-return funds charge much higher expenses than the best.[22] The result of the spread in gross returns and this very small spread in costs is that the winner-loser spread in net returns is 4.8 percent per year, which is roughly the same level as the winner-loser spread in gross returns.

C.4 Style-Adjusted and Liquidity-Adjusted Net Returns

While our results in Subsection C.2 indicate that past winners having stock-picking talents within their style specialization, it is also informative to examine performance measured at the net return level. In particular, performance achieved at the stockholdings level may not translate to performance at the net returns level, due to expenses, trading costs, and the performance of the non-stock holdings relative to stocks.

In Panel B, we present the four-factor alpha of Carhart (1997)–labelled $\alpha^{Net}_{Carhart}$. Interestingly, this measure of performance shows results that are dramatically different from the CS measure of performance that is also shown in the panel for the various fractiles. Specifically, last-year's winners exhibit significantly *negative* Carhart alphas, while last-year's losers do not.

At first blush, this discrepancy seems difficult to understand, especially given the insignificant spread in expenses and trading costs between winners and losers. However, it is important to note that another cost is present in net returns–the cost of providing daily liquidity to investors. For example, Edelen (1999) shows how fund inflows and outflows from investors negatively impact fund performance at the net return level. Edelen shows that consumers appear to invest greater amounts of cash into mutual funds when they expect market returns to be abnormally high–the result is that the level of fund cashholdings are positively correlated with the equity premium level of the market (since there is a delay until the new cash can be invested in stocks). This cashholdings "drag" on performance is worse for funds experiencing higher cash inflows, which, of course, are

[22]However, this discrepancy appears to be due to the differences in weightings of the two studies. Specifically, while our study uses a TNA weighting across funds, Carhart uses an equal-weighting, which (especially in the lowest past-return fractiles) places a higher weight on very small funds having very high expense ratios.

the best performing funds.

To control for the negative effect of flows on style-adjusted performance at the net return level, we also present results for the Ferson and Schadt conditional alpha. Specifically, Ferson and Schadt (FS; 1996) advocate a conditional factor model that controls for changes in a fund's loading on the market portfolio that is related to changing public information on economic variables. Since FS indicate that shareholder flows are related to this public information, the FS measure, labeled $\alpha^{Net}_{Ferson-Schadt}$, can be interpreted as the performance of a fund, at the net return level, that controls for both return predictability based on public information as well as the impact on returns of consumer cashflows into and out of funds.

The results show that no fractile of funds (other than the portfolio of "All Funds") exhibits a significant FS alpha. This result is interesting, since our FS measure controls for style-based returns as well as the costs of liquidity. The FS measures of winners, for example, indicates that these funds pick stocks just well enough to cover their costs. Also, note the similarity in Carhart and FS alphas for funds that are not past winners—the two alpha measures are quite similar for these fractiles, which reflects the more moderate cash inflows that are directed to these funds.

It is also interesting that the spread in FS alphas is insignificant between prior-year winners and losers, while the spread in the CS measure is positive and significant (although it is small, 1.2 percent during the year). As DGTW argue, measuring performance at the stockholdings level using characteristic-matched portfolios is a more precise method of measuring performance–the FS alpha is insignificant due to the large amount of noise in this measure.

C.5 The Longer-Term Performance of Winning vs. Losing Funds

Our results show strong evidence of one-year persistence in mutual fund net returns, as well as in benchmark-adjusted returns. However, this invites the question: how long does performance persist? Besides finding whether funds that consistently beat their benchmarks exist, this issue is also of great interest to those investors who chase winning mutual funds. If managers beat their benchmarks over longer time periods, then this minimizes the need for smart money to trade excessively.

To address this issue, we present the second-year decomposition in returns and costs for the funds in Panel C. The results show that past winners continue to exhibit superior CS performance during year two, although the winner-loser spread is lower than the first-year spread (and the spread is not significant). Note, also, that a significant winner-loser spread is still present at the net returns level–winners beat losers by about three percent per year. Less than one-third of this spread (between quintile portfolios of winners and losers) can be attributed to the spread in CS performance, while the remaining amount can be attributed to the spread in the AS component. In unreported tests, we find that winners have a substantially higher loading on the Carhart momentum factor than losers during the second year (Year 2) following the performance ranking year (Year 0). This "echo effect" of momentum indicates that winners actively invest their new cashflows into high past-return stocks to refresh momentum in their portfolios. We will present evidence in a later section that this effect has strong implications for the long-term persistence of net returns of winners relative to losers.

Another result of interest is present in the second-year performance attribution of the panel. Note that the Carhart alphas for all fractile portfolios–winners as well as losers–are insignificant. This result indicates that the cash inflows to winners–while remaining much higher than those for losers–create less of a drag on performance than during the first year.

The figure illustrates the persistence of domestic equity funds by showing the percentage of winners that repeat. To create this figure, we rank funds as in our previous ranking procedure, except that funds are ranked only once per year (at the end of that year) and fractile portfolios are formed. Then, we measure the percentage of ranking year (Year 0) top fractile funds that are members of the Year +1 top fractile–the ranked funds in Year +1 include new entrants to our fund universe. To be conservative, if a Year 0 fund disappears from our sample, we assume that it performed poorly and did not make the top fractile before it disappeared, thus eliminating concerns about survival bias. We also show the percentage of Year 0 top funds that are members of Year +2 through +5 top fractiles.

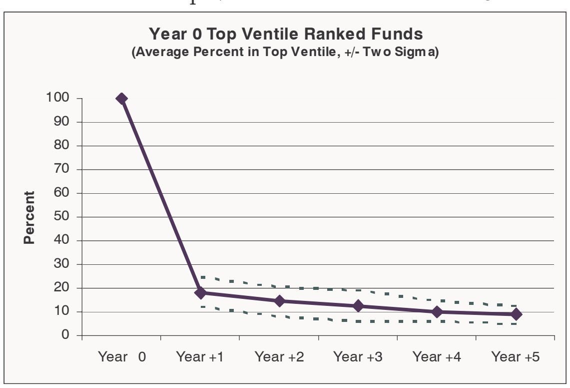
For example, Panel C shows that 32.4 percent of Year 0 top quintile funds have net returns in the top quintile during Year +1, on average over all event years, with a two sigma range of 25.6 to 39.1. Thus, net returns persist for one year at greater than the 95 percent confidence level. During Years +2 through +5, the persistence rates drop to 28.5, 24.5, 23.9, and 22.9–eventually, the persistence rate is statistically indistinguishable from its expected level of 20 percent, given random performance patterns. Only Years +1 and +2 exhibit statistically significant persistence of Year 0 quintile funds.

Panels A, B, and D show qualitatively similar results for top ventile, decile, and top half rated funds of Year 0. Interestingly, top ventile funds persist through Year +5 at the 95 percent confidence level. Of course, as shown previously, part of this persistence in net returns is based on CS (style-adjusted) performance, and part is based on AS (style-based) returns.

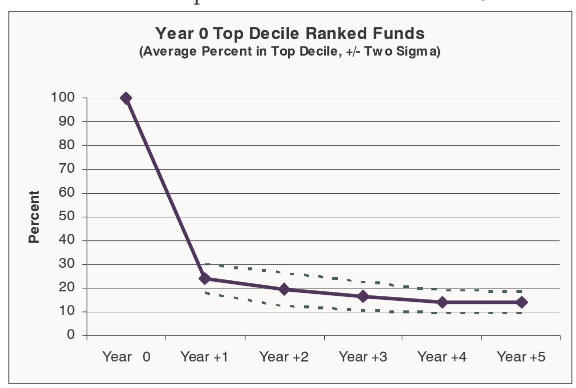
Figure. Rate of Recidivism of Top Funds

At the end of each calendar year, starting December 31, 1975 and ending December 31, 1993, we rank all domestic equity mutual funds that existed during that entire year (Year 0) on their average monthly net return of that year. We re-rank all funds during each of the following five years (Years 1 through 5) on their average monthly net return of each of those years, including new funds that enter the sample. A fund is included in the calculations for one of these years even if it does not survive that year (nonsurvivors are assumed to have dropped out of the fractile to avoid survival bias). The figure presents, of the funds in a top fractile during Year 0, the percentage that repeated their top fractile performance during each of the following years. For example, Panel A shows the percentage of top ventile Year 0 funds that were a member of the top ventile during each of the following years. In addition, estimated time-series standard deviations are used to illustrate the two-sigma bands in each panel.

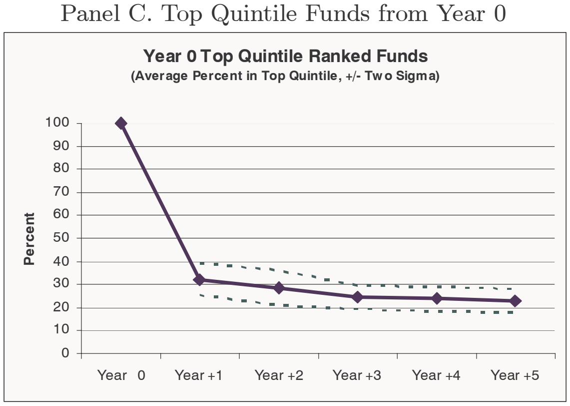
Panel A. Top Ventile Funds from Year 0



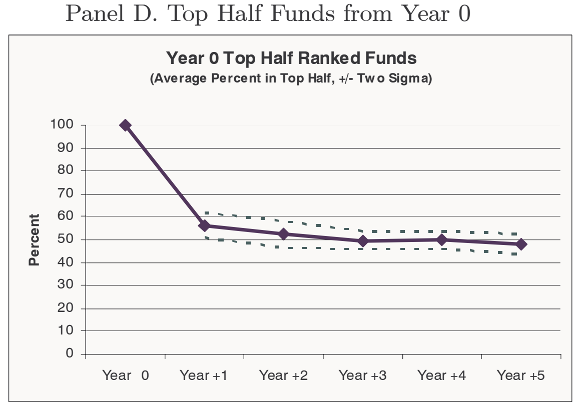
Panel B. Top Decile Funds from Year 0



Panel C. Top Quintile Funds from Year 0



Panel D. Top Half Funds from Year 0



C.6 Ranking on Longer-Term Returns

Many investment advisory services advocate the use of a 3- or 5-year ranking period for consumers to judge the relative merits of funds.[23] Following this advice, we next ranked mutual funds by their

[23] *The Mutual Fund Cafe*, a former website that collected fund information on mutual funds for consumers, reported that the majority of mutual fund complexes actively promote a three-year past return ranking window.

net return over the past three years, rather than over the past year. Specifically, on January 1, 1978, we sort all mutual funds by their three-year average net return over the 1975 to 1977 period. Again, funds in the highest past-return fractiles are labeled "winners," while those in the lowest past-return fractiles are "losers." Panel A of Table IV presents a performance decomposition for each fractile.

Our results show that the a 3-year ranking method substantially increases the accuracy of identifying funds with a significant CS measure. To be specific, funds in the top five percentile hold stocks that beat their style benchmarks by 3.3 percent during the following year. However, using a three-year ranking period reduces the characteristic-based return spread in half–the spread in AS returns between the top and bottom quintiles of funds is now 1.7 percent per year (and insignificant), compared to 3.8 percent per year using a one-year ranking period. Note that this three-year ranking procedure provides a slightly better prediction of resulting consumer inflows (see the column labeled "Inflows" in Table IV) than the one-year ranking of the prior section (see the corresponding column in Panel A of Table III). However, for the remainder of the tests in this paper, we use a one-year net return ranking procedure to maintain consistency with Carhart (1997), as well as to increase the size of our sample (since a fund needs only a one-year return record to be included in our tests).[24]

C.7 Ranking with Other Variables

We repeated our tests above, using the lagged characteristic selectivity (CS) measure of funds as the ranking variable, instead of the lagged net return of funds. Lag periods of both one and three years were used, and the results (which are unreported) are qualitatively similar to the results from our net return tests. For example, the top five percent of funds, ranked on their lagged three-year CS measure, have a TNA-average CS measure of 3.0 percent during the following year, compared to our finding of 3.3 percent using net returns as the ranking variable (which is shown in Table IV).

D The Persistence of Growth vs. Value Funds

Past studies indicate that managers of growth-oriented funds have better stockpicking skills than managers of income-oriented funds. For example, Chen, Jegadeesh, and Wermers (2000) find that

[24]Sirri and Tufano (1998) show that consumer inflows to mutual funds are most sensitive to one-year past returns, when both one-year and other past return windows are included in regression tests.

growth funds buy stocks with significantly higher characteristic-adjusted returns than stocks they sell from their portfolios, over the first year following the stock trades. In contrast, stocks purchased by income funds do not outperform those stocks that are sold.

Of interest is whether this apparent stockpicking talent of growth funds persists over longer time periods. We investigate this issue in this section by repeating the ranking procedure that was conducted in the prior section, except that we limit our tests to include only growth-oriented funds. To be specific, a fund is included in the prior-year ranking procedure only if the fund has a self-declared investment objective of either "aggressive-growth" or "growth" at the end of the ranking year. Table V shows the results of this ranking procedure, where we present results only for: net returns, consumer flows, stockpicking talents (CS measure), and the tendency to use momentum investing strategies (MOM). These measures, which are TNA-averaged in the table, are shown for the ranking year as well as the four years following the ranking year.

Panel A shows that the net return spread between winners and losers remains between two and four percent per year over the first four years after the ranking year, while Panel B shows that consumer flows to winners remain much higher than flows to losers over this four-year period. A strong reputation effect appears to be present among both winners and losers–winners, while outperforming losers by only a few percent per year during the years following the ranking period, still collect the vast majority of new consumer inflows. This result is likely due to fund ranking services, such as Morningstar, which assign ratings based on three-, five-, and 10-year net return records of funds. Thus, a fund newly receiving, for example, a Morningstar five-star rating–due to a very high one-year return–will likely keep that rating for at least a couple additional years.

Panels C and D add further insight–these panels present results on the spread in CS measures and in the tendency to invest on momentum between winners and losers. Notably, the spread in CS measures remains at about one percent per year over each of these four years (the spread between the quintiles of winners and losers is statistically significant during three of the four years). These results are somewhat stronger than the results across all mutual funds, which was shown in Table III. This indicates that persistence in stockpicking talents are concentrated in growth funds.

Note, also, that all fractiles of growth funds strongly use momentum strategies (see Panel D), but that winning funds exhibit a higher tendency to use these strategies than losing funds. It is interesting that winning funds exhibit a significantly higher momentum investing measure during the ranking year and Year +1, but not during later years. This finding again suggests that winning funds use their abnormally high cash inflows to purchase high past-return stocks, which helps them to maintain their net return advantage over past losing funds.

Table VI shows results for similar tests conducted over value-oriented funds. These results stand in stark contrast to the results for growth funds–value funds exhibit only short-lived persistence in the winner-loser net return spread (Panel A), although the spread in consumer flows is persistent (Panel B). However, flows do not chase performance among value funds to the extent that they chase winning growth funds.

Also, value funds as a group exhibit weak style-adjusted performance–their dollar-weighted CS measure is only 0.30 percent per year during the first year following the ranking (see the "All Funds" row during Year +1). In addition, the spread in CS measures between winners and losers is insignificant for all test years. Finally, value funds as a group exhibit no tendency to invest using momentum strategies (Panel D), except for the top five percentile of past-winners. The reluctance of value funds to use active momentum strategies is not entirely surprising, as it involves buying stocks with rising price-to-earnings ratios.

E A Decomposition of Momentum Investing Behavior

To gain further insight into the investing behavior of fund managers, the $BMOM$ measure is further partitioned into two categories, as we did in a previous section of this paper. The first category measures buy momentum investing, only over additional purchases of stocks already held by a fund ($BMOM^{same}$), while the second measures buy momentum investing only over new positions initiated during a quarter ($BMOM^{new}$).

This decomposition, which is not fully reported, shows that $BMOM^{same}$ is only 0.5 and 0.03 percent per year for top and bottom quintile funds, respectively. By contrast, $BMOM^{new}$ is 3.7 and 2.4 percent per year, respectively–reinforcing our prior findings for the universe of mutual funds that momentum strategies are chiefly implemented through initiating new stock positions rather than adding to shares already owned. Also, both the levels and the spread in momentum measures are larger among growth-oriented funds than for the universe of mutual funds.

Further insight into the behavior of mutual fund managers can be gained by modifying the buy momentum investing measures, $BMOM$, $BMOM^{same}$ and $BMOM^{new}$, to adjust for the level of turnover of a fund. For growth-oriented funds, we compute quarter t turnover-adjusted measures of momentum buying of all stocks, of additional shares of stocks already held, and of new positions in stocks, $TABMOM$, $TABMOM^{same}$ and $TABMOM^{new}$, as:

$$TABMOM_t = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1})(\tilde{R}_{j,t-1} - \overline{R}_j) / \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1}) \ , \tag{8}$$

$$TABMOM_t^{same} = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}>0}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1})(\tilde{R}_{j,t-1} - \overline{R}_j) / \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}>0}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1}) \ , \text{ and} \tag{9}$$

$$TABMOM_t^{new} = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}=0}}^{N} \tilde{w}_{j,t}(\tilde{R}_{j,t-1} - \overline{R}_j) / \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}=0}}^{N} \tilde{w}_{j,t} \ . \tag{10}$$

A fund manager buying extreme past winning stocks, but in small amounts (proportionate to the total portfolio value), would exhibit turnover-adjusted measures–Equations (8), (9) and (10)– that are higher than similar measures for a manager buying larger (proportionate) amounts of equities, but with less regard to their past returns. This result contrasts with the unadjusted measures, $BMOM^{same}$ and $BMOM^{new}$, which would likely be higher for the latter manager. These turnover-adjusted measures add further insight into the behavior of winning vs. losing fund managers.

Panel A of Table VII shows the turnover-adjusted buy momentum investing measures of the fractiles of growth-oriented funds, ranked by their one-year past net returns. The top past return quintile of funds exhibits a very high turnover-adjusted buy momentum measure, $TABMOM$, during the ranking year. This measure, 25.5 percent (compounded over all four quarters of the ranking year) indicates that winning managers exhibit a very strong tendency to bias their investments to their very recent well-performing stocks, while losing managers do not. Thus, adjusting for the higher buy-turnover levels of winning managers brought about by their large cash inflows, these managers also change their behavior to buy very high return stocks. During the following four years (Years +1 to +4), this winner-loser spread in turnover-adjusted momentum measures decreases, until their is no appreciable difference during Year +4. In unreported results, we find that the winner-loser spread in the tendency to consider past returns when adding stocks already owned (adjusted for turnover; $TABMOM^{same}$) is 4.5 percent during Year +1, while the spread in buying new stocks on (turnover-adjusted) momentum ($TABMOM^{new}$) is 2.4 percent.[25] Thus, winners and losers both implement momentum strategies more strongly in buying new stocks (as shown previously), but the difference in momentum investing between winners and losers is more pronounced when adding to existing positions.

One may, however, attribute the higher momentum investing measures (e.g., MOM) and turnover-adjusted momentum investing measures (e.g., $TABMOM$) to the idea that winning managers have a much greater opportunity to buy high past return stocks than losing managers. Clearly, this is true when adding to existing positions, since winning managers have a large number of extremely high past return stocks in their portfolios. However, it may also be true when initiating new positions, if managers are constrained to stay within their investment styles or sectors–winning managers can add new positions from their currently hot sector or style category, while losing managers cannot without potentially taking the risk of violating their investment constraints. To address whether this possibility explains why winning managers pick higher past return stocks than losing managers, we modify our turnover-adjusted measures to gauge the momentum of a stock as its return compared to the same-quarter return of the median return stock in the manager's portfolio. For example, $TABMOM$ is modified to create the median-adjusted $TABMOM$,

$$MTABMOM_t = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1})(\tilde{R}_{j,t-1} - R_{j,t-1}^{median}) / \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t}>\tilde{w}_{j,t-1}}}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1}) \ , \qquad (11)$$

which measures the tendency of the fund manager to add high past return stocks to the portfolio, compared to the median return among all stocks already held. A decomposition of $MTABMOM$ (Equation (11)) into same-stock ($MTABMOM^{same}$) and new-stock ($TABMOM^{new}$) median- and turnover-adjusted buy momentum is also performed.

Panel A of Table VII shows that, while somewhat lower than $TABMOM$, the $MTABMOM$ measure is still significantly different between winners and losers. This result indicates that winning fund managers change their behavior during and after their high return year, tilting their purchases increasingly toward extreme high past return stocks. Thus, the combination of having more cash available and tilting toward more extreme past return stocks allows past winning

[25]The corresponding $TABMOM_t^{same}$ of past winners and losers is 4.6 percent and 0.1 percent per year, respectively, while the corresponding $TABMOM_t^{new}$ is 17.2 and 14.9 percent per year, respectively. Thus, momentum is mostly implemented by buying new stocks with much higher past returns than stocks already held, although past winning funds also add to the positions of extreme winners already held.

funds to outperform past losing funds for several years. Further results for $MTABMOM^{same}$ and $MTABMOM^{new}$ show analogous results–although somewhat weaker than the results for $TABMOM^{same}$ and $TABMOM^{new}$ (i.e., which use the returns from year +2 as the proxy for expected return), these measures show that winning managers buy more extreme high past return stocks, compared to the median stock in their portfolios, than losing managers, both when adding to existing holdings and when initiating new positions.

To sum up, we have established that winning fund managers implement momentum investing strategies by buying more extreme past return stocks as well as by using their inflows to buy larger positions in these stocks. Of great interest is whether these winning managers push stock prices up through their potentially correlated momentum buying–the next section explores this issue.

F Why is Money "Smart"?

As shown in Panel B of Table V, consumer flows are large and persistent for winning growth-oriented funds, even as their net returns (Panel A) and selectivity measures (Panel C) revert toward the mean. For example, the top quintile of funds (ranked on one-year lagged net returns) attract inflows that decline only slightly from 26 percent of year-beginning assets to 19 percent over the four years following the ranking year. Simultaneously, their net return spread above prior-year losing funds drops by more than half, as shown by Panel A of that table (see the row labeled "Top-Bottom 20%"); in addition, the spread in their selectivity measure (above prior-year losing funds) decreases slightly from 1.1 to 0.9 percent per year (see the same row in Panel C). Panels A and B of Table VI show similar, although much less pronounced results for value-oriented funds. These persistent flows indicate that consumers are attracted by a reputation effect that persists over time, long past the period of highest performance–perhaps this is due to the tendency of Morningstar and other ratings firms to use a 3–5 year window as a large part of their performance evaluation system. Since we find persistence in the selectivity measure of growth-oriented funds over the four-year period, this reputation effect on flows explains the finding by Zheng (1999) that the smart-money effect is somewhat different from a pure strategy of chasing the highest past return funds. That is, inflows continue to move toward funds with a positive and significant selectivity measure, long after these funds have dropped out of the highest past-return fractiles.

The strong persistence in inflows among growth-oriented funds suggests that, perhaps, flows push up the prices of stocks through the resulting purchase activity of winning fund managers, perhaps through their herding into the same stocks or the same sectors. Boyer and Zheng (2002) find evidence suggestive of mutual fund flows impacting the overall market return, but perhaps they have an even stronger influence on individual stocks or sectors. In the next section, we decompose the characteristic selectivity measures of growth-oriented funds in order to determine whether new money simply finds managers with superior stockpicking skills, or whether flows potentially impact stock prices through the trades of fund managers. Then, in the following section, we implement multivariate regression tests to more precisely separate flow-related performance from true stockpicking skills.

F.1 A Decomposition of the Characteristic Selectivity Measure

Our decomposition of the characteristic selectivity measure proceeds as follows. We compute this measure for each mutual fund over two distinct subportfolios of stocks that are actively purchased by the fund manager during a given quarter. The first subportfolio consists of those stocks purchased by the manager during a given quarter to add to an already existing position. This selectivity component, CS^{same}, is measured during quarter t as

$$CS_t^{same} = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t-2}>0 \\ j:\Delta S_{j,t-1}>0}}^{N} \tilde{w}_{j,t-1}(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}}) / \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t-2}>0 \\ j:\Delta S_{j,t-1}>0}}^{N} \tilde{w}_{j,t-1}, \tag{12}$$

where $\tilde{w}_{j,t-2} > 0$ indicates that the manager held a position in stock j at the beginning of quarter $t-1$ (the end of quarter $t-2$), and where $\Delta S_{t-1} > 0$ indicates that the manager increased shareholdings of stock j during quarter $t-1$, adding to the already-existing position during the quarter.[26] The second subportfolio consists of those stocks purchased by the manager during a given quarter to establish a new position. This selectivity component, CS^{new}, is measured during quarter t as

$$CS_t^{new} = \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t-2}=0 \\ j:\Delta S_{j,t-1}>0}}^{N} \tilde{w}_{j,t-1}(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}}) / \sum_{\substack{j=1 \\ j:\tilde{w}_{j,t-2}=0 \\ j:\Delta S_{j,t-1}>0}}^{N} \tilde{w}_{j,t-1}. \tag{13}$$

By isolating the selectivity measure for stocks actively purchased by fund managers, we can examine whether fund flows appear to impact stock prices through these purchases. By further

[26] In computing $\Delta S_{t-1} \equiv S_{t-1} - S_{t-2}$, we adjust the end of quarter $t-1$ shareholdings of stock j, S_{t-1}, to eliminate the effects of any exogenous changes, such as stock dividends. Therefore, the computed value of ΔS_{t-1} is positive only if the fund manager actively purchased shares during the quarter.

decomposing the measure into same-stock vs. new-stock purchases, we provide insight into whether flows differentially impact the prices of stocks already owned, relative to the prices of stocks that are newly added to a mutual fund portfolio.

For the characteristic selectivity measures of this section, we reconstitute DGTW (1997) benchmarks more frequently than we did in our prior tests of this paper. Specifically, instead of a yearly sort of all CRSP stocks based on their size, book-to-market, and momentum characteristics, we perform a quarterly sort on these characteristics.[27] A quarterly sort provides a benchmark that more precisely controls for the changing characteristics of a fund's stockholdings–this is important, given our prior evidence that fund managers, especially winning managers, strongly implement active momentum strategies. Such strategies can result in changing fund characteristics from one quarter to the next.

Thus, the selectivity measures computed in this section are free of any influence on returns of the changing characteristics of fund stockholdings, since we reconstitute these benchmarks at the same frequency that the fund holdings are updated. For example, we compute the characteristic selectivity measure for the March 31, 1975 portfolio holdings of the Fidelity Magellan fund, during April 1 through June 30, 1975, using benchmarks that are formed based on the characteristics of stocks on March 31. Thus, the manager of the Magellan fund would not be able to game our benchmarks by purchasing stocks with high first-quarter 1975 returns. Similarly, benchmarks for the June 30, 1975 holdings (which are used to analyze July 1 through September 30, 1975) are formed at June 30, 1975. Our goal in this section is to measure the impact of flows on the prices of fund portfolios, while carefully controlling for changing portfolio characteristics.

Panel A of Table VIII shows the overall characteristic selectivity measures (computed across all stockholdings, as in prior sections of this paper) of one-year lagged net return sorted fractiles of growth-oriented funds. A comparison of this panel with Panel C of Table V (which uses annual-reconstituted DGTW benchmarks) shows that the majority of the performance of winning fund managers can be attributed to these managers adding new momentum stocks to their portfolios during the evaluation year. For example, the CS measure of the top quintile of fund managers drops from about two percent per year, during years +1 to +3, to below 1.5 percent per year. This confirms our findings in earlier sections of this paper that manager trading, in reaction to cash

[27]The book-to-market characteristic is only updated once per year, to reflect the availability of the fiscal year-end book value data for each company in CRSP/Compustat. However, the industry membership of a company may change from one quarter to the next, therefore, the industry-normalized book-to-market characteristic is updated each quarter.

inflows, substantially influences the performance of winning funds. Although we still find some evidence that winning fund managers beat their benchmarks, this evidence is much weaker using quarterly reconstituted benchmarks.

Chen, Jegadeesh, and Wermers (2000) suggest that we should examine the trades of managers to find the strongest evidence of performance, since they find that managers hold stocks beyond the period that they perform well, relative to their benchmarks. Panel B analyzes trades by showing the tendency of managers to add to already existing stock positions in their portfolios when they buy stocks. This panel shows the percentage of dollars spent on adding to existing positions, relative to dollars spent on all purchases (which include purchases of new positions). The panel shows that winning (and losing) fund managers change their behavior somewhat after they achieve their top fractile (bottom fractile) ranking. Specifically, the difference in same-stock purchases between winning and losing funds is insignificant during the ranking year; however, this difference is six to eight percent (and significant) during each of the four years following the ranking year. This tendency for winning managers to add to existing stocks to a greater degree than losing managers may be due to the desire to limit the "style drift" of their portfolios as they add significant new positions. Alternatively, it may be due to winning managers exhibiting overconfidence in their beliefs about their prior stock picks–the high returns of their portfolios may reinforce the notion that they have made the correct stock picks.

Panels C and D show the characteristic selectivity measures of same-stock and new-stock purchases for each fractile, respectively, as given by Equations (12) and (13). The performance of both same-stock and new-stock purchases in these panels is substantially higher than the performance of all stockholdings, shown in Panel A. In addition, the large benchmark-adjusted performance of stocks purchased by funds in the very top fractiles (the top five percent and 10 percent fractiles) indicates that the large purchases resulting from the large inflows to these funds may be pushing up the prices of the stocks that are purchased. For example, stocks purchased by the top decile of funds, whether adding to an existing position (Panel C) or establishing a new position (Panel D), beat their benchmarks by more than two percent during the majority of test years. However, it is also possible that these managers have persistent stockpicking talents, or the "hot hands" of Hendricks, Patel, and Zeckhauser (1993). We will address these two possibilities in the next section.

Since the very top fractiles (the top ventile and decile) consist of relatively small numbers of funds (an average of 13 and 26 funds, respectively), we next analyze the performance of stocks purchased by the top quintile of funds. Our results for this fractile shows that managers exhibit significant CS measures both for same-stock and new-stock purchases, but the performance of new stocks is roughly double that of same stocks. Results for the second quintile (labeled "2nd 20%") are qualitatively similar. These results suggest that flow-induced price pressure, if present, may not entirely account for the performance of winning managers, at least for their new stock purchases. Thus, the purchase of a new position by a winning fund manager is likely a much stronger signal than that manager adding to an already existing position.

Losing fund managers, however, do not appear to add any performance through their stock purchases–neither the CS^{same} nor the CS^{new} are significant for any loser fractile. Overall, we find that winning fund managers exhibit strong benchmark-adjusted performance in their purchases of stocks. However, it still remains to be seen whether winning managers have stockpicking talents or whether flow-related purchases are impacting stock prices.

F.2 Multivariate Fama-MacBeth Regressions

To separate the influence of flow-related trading from manager stockpicking talent, we implement the following model to explain the cross-section of CS measures, across the funds in our database during a given year:

$$CS_{j,t} = a_t + c_t \cdot CS_{j,t-1} + f_t \cdot Flows_{j,t} + g_t \cdot Flows_{j,t-1} + m_t \cdot BMOML_{j,t} + e_{j,t} \ ,$$

where $CS_{j,t}$ = the characteristic selectivity measure for fund j during year t, $Flows_{j,t}$ = inflows to fund j during year t, and $BMOML_{j,t}$ = the buy momentum measure for fund j during year t, using one-quarter lagged returns. This modified buy momentum measure, developed by Grinblatt, Titman, and Wermers (1995), uses one-quarter lagged returns to measure the momentum implied by current quarter portfolio weight changes. We use this measure in our model to avoid any spurious correlation between $CS_{j,t}$ and the buy momentum measure that might arise if weight changes and excess returns are measured contemporaneously. That is, especially for funds with a high $CS_{j,t}$ measure during a given quarter, it may be true that measuring weight changes and excess returns contemporaneously might pick up performance.

To implement this regression, we first sort funds on their one-year net returns, as in prior sections. Then, we form twenty ranked fractiles, each weighted by the total net assets of funds that are members of that fractile. We measure the following year CS measure, $Flows$, and $BMOML$

for each of these fractiles, as well as the ranking year CS measure and $Flows$. The cross-sectional regression above is implemented across the 20 TNA-weighted variables during that year–the regression is performed across weighted fractiles to avoid any strong influence from funds that are outliers, which are usually small funds. Next, we step ahead one quarter and repeat this procedure–thus, we end up with overlapping regressions. Finally, the time-series average coefficients and the overlapping-observation adjusted standard deviations are computed across all event dates to complete the Fama-MacBeth type regressions.

If manager stockpicking talent is persistent, then we will see a positive coefficient on the lagged CS measure. However, if $Flows$ or momentum investing ($BMOML$) tend to push stock prices, then we will observe a positive coefficient on $BMOML$ and on contemporaneous $Flows$, and (possibly) a negative coefficient on lagged $Flows$.

Table IX presents the results of these regressions. Regressions 1 through 4 apply the model using the overall CS measure as the dependent variable. Regression 1 indicates that lagged CS measure explains current CS measure, which suggests that manager talent persists. However, regression 2 shows that, when we add $Flows$, the past CS measure has no explanatory power. Thus, the past performance variable was simply a proxy for current year flows–flows go to funds with high past-year performance.

Regression 3 shows that lagged flows have a negative effect on current CS measure, which further supports the finding that flow-related purchases impact prices. That is, flows push up prices only temporarily, and, if abnormally high flows do not continue, then stock prices decrease. Regression 4 shows that higher levels of momentum investing also impact the CS measure, independent of flows.

Regressions 1A through 4A implement the model on the subportfolio of stocks that the manager purchased to add to an already existing position. The results of these regressions are very similar to those of regressions 1 through 4: flows impact performance, as does buy momentum investing behavior. Finally, regressions 1B through 4B indicate that our model does not explain the CS measure for new stock purchases. Neither past manager talent nor flows explains differential patterns in the ability of fund managers to initiate new stock positions that beat their style benchmarks.

Our finding that flows impact same stock purchases, but not other purchases indicates that winning managers are holding high correlated portfolios of stocks. Their flow-related purchases likely pushes them to "herd" into many of the same stocks and sectors, although a clear test of this is left for future research. However, our finding that performance does not seem to persist, controlling for flows, casts doubt on some prior studies that find that managers have talents in choosing stocks that beat their benchmarks.

IV Conclusion

In this paper, we studied the persistence in performance of mutual funds over the 1975 to 1994 period with a new database. This database was created by merging a database of mutual fund holdings with a database of mutual fund net returns, expenses, turnover levels, and other characteristics. With the database, we are able to address issues that have plagued studies of persistence–most importantly, we were able to investigate whether fund managers have persistent skills in picking stocks, both before and after fund expenses and trading costs.

We show that mutual fund net returns are strongly predictable. Investing in growth-oriented funds with the highest prior-year net returns is a strategy that beats holding the market portfolio by about 2 to 3 percent over the first year following the ranking, and by almost that much over the second year. This net return spread is due to the better style-adjusted returns of stocks held by prior-year winning funds relative to prior-year losers, as well as to winners holding stocks with higher style-related returns (i.e., due to momentum in their portfolios). In addition, consumer flows to these winners is strong and persistent.

We also present evidence that highlights the role of consumer flows in patterns of performance persistence. First, inflows are highest for funds with the best past performance, which temporarily reduces the equity exposure of these funds. This serves to reduce momentum-based and other equity performance benefits provided by the stockholdings of these funds. However, offsetting this effect is that managers of these top funds eventually invest inflows in stocks with high future returns. At least a part of these returns are due to these top managers buying additional stocks with high past returns–thus, large cash inflows allow top-performing funds to augment the return boost provided by passively holding their past winners with another boost provided by actively trading on momentum–this momentum investing mostly happens with winning managers adding new momentum stocks to their portfolios rather than increasing an existing position in a momentum stock.

To sum up, at least a portion of the persistence in mutual fund returns can be attributed to the tendency of consumers to aggressively chase mutual funds with high past returns, which results in fund managers chasing stocks with high past returns. The multi-year persistence in performance can be traced, in part, to the persistence in flows over multiple years–thus, consumers expectations of future performance are, to some extent, self-fulfilling. Finally, we also find strong evidence that consumer flows push stock prices.

Bibliography

[1] Badrinath, S. G., and Sunil Wahal, 2002, "Momentum Trading by Institutions," *Journal of Finance*, 57, pp. 2449-2477.

[2] Berk, Jonathan B., and Richard C. Green, "Mutual Fund Flows and Performance in Rational Markets," Working Paper.

[3] Bollen, Nicolas and Jeffrey Busse, 2002, "Short-Term Persistence in Mutual Fund Performance," Working Paper.

[4] Brown, Stephen J. and William N. Goetzmann, 1995, "Performance Persistence," *Journal of Finance*, 50, pp. 679-698.

[5] Brown, Stephen J., William N. Goetzmann, Roger G. Ibbotson, and Stephen A. Ross, 1992, "Survivorship Bias in Performance Studies," *Review of Financial Studies*, 5, pp. 553-580.

[6] Carhart, Mark, 1997, "On Persistence in Mutual Fund Performance," Journal of Finance, 52, pp. 57-82.

[7] Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 1999, "The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers," *Journal of Financial and Quantitative Analysis*, forthcoming.

[8] Clements, Jonathan, 2001, "Resisting the Lure of Managed Funds," *Wall Street Journal*, February 27, page C1.

[9] Cohen, Randolph B. and Christopher K. Polk, 1998, "The Impact of Industry Factors in Asset-Pricing Tests," Working Paper.

[10] Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *Journal of Finance*, 52, pp. 1035-1058.

[11] Daniel, Kent and Sheridan Titman, 1997, "Evidence on the Characteristics of Cross-Sectional Variation in Common Stock Returns," *Journal of Finance*, 52, pp. 1-33.

[12] Edelen, Roger, 1999, "Investor Flows and the Assessed Performance of Open-End Mutual Funds," *Journal of Financial Economics*, 53, pp. 439-466.

[13] Fama, Eugene F. and Kenneth R. French, 1992, "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47, pp. 427-465.

[14] Fama, Eugene F. and Kenneth R. French, 1993, "Common Risk Factors in the Returns on Stocks And Bonds," *Journal of Financial Economics,* 33, pp. 3-56.

[15] Fama, Eugene F. and Kenneth R. French, 1996, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance*, 51, pp. 55-84.

[16] Fama, Eugene F. and James D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81, pp. 607-636.

[17] Ferson, Wayne E. and Kenneth Khang, 2000, "Conditional Performance Measurement Using Portfolio Weights: Evidence for Pension Funds," Working Paper.

[18] Ferson, Wayne E. and Rudi W. Schadt, 1996, "Measuring Fund Strategy And Performance In Changing Economic Conditions," *Journal of Finance*, 51, pp. 425-461.

[19] Grinblatt, Mark and Bing Han, 2002, "The Disposition Effect and Momentum," Working Paper.

[20] Grinblatt, Mark and Sheridan Titman, 1989, "Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings," *Journal of Business*, 62, pp. 394-415.

[21] Grinblatt, Mark and Sheridan Titman, 1992, "The Persistence of Mutual Fund Performance," *Journal of Finance*, 47, pp. 1977-1984.

[22] Grinblatt, Mark and Sheridan Titman, 1993, "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns," *Journal of Business*, 66, pp. 47-68.

[23] Grinblatt, Mark and Sheridan Titman, 1994, "A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques," *Journal of Financial and Quantitative Analysis*, 29, pp. 419-444.

[24] Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," *American Economic Review*, Volume 85 (5), pp. 1088-1105.

[25] Gruber, Martin J., 1996, "Another Puzzle: The Growth in Actively Managed Mutual Funds," *Journal of Finance*, 51, pp. 783-810.

[26] Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, "Hot Hands in Mutual Funds: The Persistence of Performance, 1974-88," *Journal of Finance*, 48, pp. 93-130.

[27] Jegadeesh, Narasimhan and Sheridan Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, 48, pp. 65-91.

[28] Keim, Donald B. and Ananth Madhavan, 1997, "Transactions Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades," *Journal of Financial Economics*, 46, pp. 265-292.

[29] Lynch, Anthony W., and David K. Musto, "How Investors Interpret Past Fund Returns," Working Paper.

[30] Moskowitz, Tobias and Mark Grinblatt, 1999, "Do Industries Explain Momentum?" *Journal of Finance*, 54, pp. 1249-1290.

[31] Myers, Mary M., James M. Poterba, Douglas A. Shackelford, and John B. Shoven, "Copycat Fund: Information Disclosure Regulation and the Returns to Active Management in the Mutual Fund Industry," Working Paper.

[32] Sapp, Travis R. A. and Ashish Tiwari, 2002, "Does Stock Return Momentum Explain the 'Smart Money' Effect?" Working Paper.

[33] Sirri, Erik R. and Peter Tufano, 1998, "Costly Search And Mutual Fund Flows," *Journal of Finance*, 53, pp. 1589-1622.

[34] Stoll, Hans R., 1995, "The Importance of Equity Trading Costs: Evidence from Securities Firms' Revenues," in R. Schwartz, ed.: *Global Equity Markets: Technological, Competitive, and Regulatory Challenges*, Irwin.

[35] Teo, Melvyn and Sung-Jun Woo, 2001, "Persistence in Style-Adjusted Mutual Fund Returns," Working Paper.

[36] Treynor, Jack L. and Kay K. Mazuy, 1966, "Can Mutual Funds Outguess The Market?" *Harvard Business Review*, 44, pp. 131-136.

[37] Wermers, Russ, 1997, "Momentum Investment Strategies of Mutual Funds, Performance Persistence, and Survivorship Bias," University of Colorado working paper.

[38] Wermers, Russ, 1999, "Mutual Fund Herding and the Impact on Stock Prices," *Journal of Finance*, 54, pp. 581-622.

[39] Wermers, Russ, 2000, "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses," *Journal of Finance*, 55, pp. 1655-1695.

[40] Wermers, Russ, 2001, "The Potential Effects of More Frequent Portfolio Disclosure on Mutual Fund Performance," *Investment Company Institute Perspective,* 7 (June).

[41] Zheng, Lu, 1999, "Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability" Journal of Finance, 54, pp. 901-933.

Table I
One-Year Persistence in Mutual Fund Gross Returns

Mutual fund returns are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases. The CDA database, purchased from CDA Investment Technologies, Inc., includes periodic (usually quarterly) portfolio holdings of equities for all mutual funds between 1975 and 1994 (inclusive). The CRSP database, purchased from the Center for Research in Securities Prices, contains data on mutual fund net returns, load fees, expense ratios, and other fund characteristics during the same time period. Separate shareclasses of a single fund listed in CRSP are combined based on the relative total net assets of the various shareclasses before they are matched to a single CDA fund. This table provides, each year, the S&P 500 and CRSP yearly returns, both value-weighted with dividends reinvested. Also, gross returns (on the stock portion of mutual fund portfolios only) are provided for the mutual fund universe for each year, for the quintile of funds having the highest prior-year gross returns, and for the quintile having the lowest prior-year gross returns. Average gross returns are weighted both by the total net assets (TNA) and by using an equal-weighting (EW) across all mutual funds (weights are updated at the beginning of each quarter). For the universe of funds ("All Funds"), every fund existing during a given quarter is included in the computation of that quarter's return measures, even if the fund does not survive past the end of that quarter. These quarterly buy-and-hold returns are compounded to give the annual returns reported below. A fund must have at least a 12-month history of gross returns to be included in either the past-year winner or loser category. During the following year, all funds existing during a given quarter are included in the computation of that quarter's returns measures (and, these quarterly returns are compounded into an annual return). In all statistics in this table, we limit our analysis to funds having a self-declared investment objective of "aggressive growth," "growth," "growth and income," "income," or "balanced" at the beginning of the listed year. Note, also, that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (this data was hand-collected from printed sources).

				TNA-Avg Gross Retn (pct/year)			EW-Avg Gross Retn (pct/year)		
Year	**S&P 500 Return**	**CRSP VW Return**	**No**	**All Funds**	**Past-Year Winners**	**Past-Year Losers**	**All Funds**	**Past-Year Winners**	**Past-Year Losers**
1975	37.2	37.4	241	38.1	—	—	40.1	—	—
1976	23.8	26.8	241	26.7	34.3	15.3	28.0	34.4	18.8
1977	-7.2	-3.0	226	-3.0	-0.9	-4.0	0.2	3.0	-1.2
1978	6.6	8.5	222	11.3	17.6	8.6	12.9	20.4	9.1
1979	18.4	24.4	219	27.9	44.7	22.5	32.9	46.5	22.9
1980	32.4	33.2	364	37.8	56.3	29.4	40.1	55.0	28.8
1981	-4.9	-4.0	365	-4.2	-12.4	4.2	-2.3	-9.7	5.9
1982	21.4	20.4	362	24.0	32.0	18.3	25.6	32.4	20.8
1983	22.5	22.7	347	23.6	27.3	22.8	23.9	26.6	22.6
1984	6.3	3.3	372	0.3	3.7	-2.1	-0.6	3.0	-2.8
1985	32.2	31.5	391	32.0	32.4	28.9	32.4	33.6	29.3
1986	18.5	15.6	418	17.7	18.9	14.8	15.8	17.6	10.5
1987	5.2	1.8	483	3.4	3.3	-0.6	2.1	2.9	-1.4
1988	16.8	17.6	543	18.7	13.1	22.5	18.2	13.0	22.5
1989	31.5	28.4	589	29.4	23.8	33.4	29.2	26.0	31.1
1990	-3.2	-6.0	637	-7.4	-2.4	-15.7	-7.4	-4.1	-11.6
1991	30.5	33.6	679	37.5	46.1	34.7	41.0	48.4	42.1
1992	7.7	9.0	815	9.1	4.1	10.7	10.0	7.8	10.5
1993	10.0	11.5	949	15.2	22.1	9.4	13.9	20.2	10.5
1994	1.3	-0.6	1,279	-0.4	0.06	0.2	-0.8	-1.3	-1.2
1976-1979	10.4	14.2	241	15.7	23.9	10.6	18.5	26.1	12.4
1980-1984	15.5	15.1	459	16.3	21.4	14.5	17.3	21.5	15.1
1985-1989	20.8	19.0	676	20.2	18.3	19.8	19.5	18.6	18.4
1990-1994	9.3	9.5	1,567	10.8	14.0	7.9	11.3	14.2	10.1
1976-1994	14.2	14.5	1,788	15.8	19.2	13.3	16.6	19.8	14.1

Table II
One-Year Persistence in Mutual Fund Net Returns

Mutual fund returns are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases. The CDA database, purchased from CDA Investment Technologies, Inc., includes periodic (usually quarterly) portfolio holdings of equities for all mutual funds between 1975 and 1994 (inclusive). The CRSP database, purchased from the Center for Research in Securities Prices, contains data on mutual fund net returns, load fees, expense ratios, and other fund characteristics during the same time period. Separate shareclasses of a single fund listed in CRSP are combined based on the relative total net assets of the various shareclasses before they are matched to a single CDA fund. This table provides, each year, the S&P 500 and CRSP yearly returns, both value-weighted with dividends reinvested. Also, reported mutual fund net returns are provided for the mutual fund universe for each year, for the quintile of funds having the highest prior-year average monthly net returns, and for the quintile having the lowest prior-year net returns. A fund must have a complete history of monthly returns during the prior calendar year to be included in the return computations for a given year in all columns of this table. The table reports average net returns during the following year, weighted both by the total net assets (TNA) and by using an equal-weighting (EW) across all mutual funds (weights are updated at the beginning of each quarter). All funds existing during a given quarter of this following year are included in the computation of that quarter's returns measures, regardless of whether the fund survived past that quarter-end. These quarterly buy-and-hold returns are compounded to give the annual returns reported below. In all statistics in this table, we limit our analysis to funds having a self-declared investment objective of "aggressive growth," "growth," "growth and income," "income," or "balanced" at the beginning of the listed year. Note, also, that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (this data was hand-collected from printed sources).

				TNA-Average Net Return (pct/year)			EW-Average Net Return (pct/year)		
Year	S&P 500 Return	CRSP VW Return	No	All Funds	Past-Year Winners	Past-Year Losers	All Funds	Past-Year Winners	Past-Year Losers
1975	37.2	37.4	241	30.9	—	—	31.5	—	—
1976	23.8	26.8	241	23.3	30.2	14.8	24.0	32.8	16.5
1977	-7.2	-3.0	226	-1.9	0.2	-4.8	0.4	4.5	-3.1
1978	6.6	8.5	222	9.2	15.1	8.3	10.1	16.1	7.9
1979	18.4	24.4	219	22.7	37.2	13.8	26.1	36.1	15.8
1980	32.4	33.2	364	31.3	45.1	21.0	31.9	41.7	18.6
1981	-4.9	-4.0	365	-2.8	-9.8	4.1	-1.0	-6.0	4.9
1982	21.4	20.4	362	24.7	29.6	21.8	25.9	29.4	23.3
1983	22.5	22.7	347	20.5	21.2	20.9	20.3	22.2	19.1
1984	6.3	3.3	372	-0.2	0.1	-2.4	-0.7	-0.2	-4.0
1985	32.2	31.5	391	28.1	27.9	25.9	27.9	28.1	26.0
1986	18.5	15.6	418	15.8	19.3	10.9	13.9	16.0	6.7
1987	5.2	1.8	483	2.2	2.3	-1.7	1.5	2.1	-1.9
1988	16.8	17.6	543	15.8	10.1	19.1	14.4	10.8	17.8
1989	31.5	28.4	589	25.3	23.2	29.3	24.7	23.8	24.8
1990	-3.2	-6.0	637	-5.3	-3.1	-11.0	-5.5	-4.4	-7.7
1991	30.5	33.6	679	33.0	37.3	31.1	35.7	39.3	38.8
1992	7.7	9.0	815	8.1	3.3	10.4	9.2	9.4	8.6
1993	10.0	11.5	949	14.1	20.2	8.2	13.3	19.3	8.7
1994	1.3	-0.6	1,279	-1.5	-1.2	-2.0	-1.7	-1.0	-1.8
1976-1979	10.4	14.2	241	13.3	20.7	8.0	15.2	22.4	9.3
1980-1984	15.5	15.1	459	14.7	17.2	13.1	15.3	17.4	12.4
1985-1989	20.8	19.0	676	17.4	16.6	16.7	16.5	16.2	14.7
1990-1994	9.3	9.5	1,567	9.7	11.3	7.3	10.2	12.5	9.3
1976-1994	14.2	14.5	1,788	13.8	16.2	11.4	14.3	16.8	11.5

Table III
A Decomposition of One-Year Persistence in Mutual Fund Returns

A decomposition of mutual fund returns and costs is provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases. At the end of each calendar quarter, starting December 31, 1975 and ending December 31, 1993, we rank all mutual funds in the merged database that existed during the entire prior 12-month period (and had a complete data record during that year) on their average monthly net return of that year (the "ranking year"). Then, fractile portfolios are formed, and we compute average return measures (e.g., net returns) for each fractile portfolio during the following year (the "test year"). In computing the average return measure for a given test year, we first compute quarterly buy-and-hold returns for each fund that exists during each quarter of the test year, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA) average quarterly buy-and-hold return across all funds for each quarter of the test year. Finally, we compound these returns into an annual return that is rebalanced quarterly. Panel A presents several characteristics of these sorted fractiles during the first year following the ranking year: the number of funds in each fractile, the average total net assets of funds in each fractile, the percentage of assets held in stocks, the coefficients from a time-series regression of the TNA-average excess net return on the four Carhart factors, and the TNA-average (over all event years): BMOM (buy) and SMOM (sell) quarterly momentum investing measures (compounded across all test-year quarters, for each fund, to percent per year); net cash inflows as a percent of beginning of period total net assets; buy and sell turnover (defined as the quarterly dollar purchases or sales of stocks, respectively, divided by the beginning-of-quarter total stockholdings, in dollars, compounded across all test-year quarters); and percent of stock purchases (in dollars) that represent increases in positions in stocks already owned (as opposed to new positions) at the beginning of each calendar quarter of the test year (averaged across all four quarters). Panels B and C present a decomposition of fund returns and costs during the first and second years following the ranking year, respectively. Specifically, presented in these panels are the TNA-average annual: pre-trade cost and pre-expense return on the stock portfolio of the funds (Gross Return), characteristic selectivity measure (CS), characteristic timing measure (CT), average style measure (AS), expense ratio, estimated transactions costs, net reported return, Carhart net return alpha, and Ferson and Schadt net return alpha. The table presents test year statistics, averaged over all event years. In forming all portfolios in this table, we limit our analysis to funds having a self-declared investment objective of "aggressive growth," "growth," "growth and income," "income," or "balanced" at the beginning of the test year. Note, also, that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Autocorrelation-adjusted time-series inference tests are presented, where appropriate.

Panel A. Fractile Characteristics (Year 1)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA ($millions)	Stocks (pct)	RMRF	SMB	HML	PR1YR	BMOM (%/yr)	SMOM (%/yr)	Inflows (%/yr)	Buy Turnover (%/yr)	Sell Turnover (%/yr)	Buys^{Same} (%)
Top 5 %	19	278	86.5	0.99***	0.46***	-0.07*	0.33***	3.7***	0.1	31.3	86.4	49.5	42.9
Top 10 %	37	328	85.0	0.96***	0.40***	-0.05	0.27***	3.2***	0.02	26.6	80.4	48.9	43.4
Top 20 %	74	439	84.4	0.94***	0.35***	-0.03	0.24***	2.7***	-0.2	20.3	74.7	48.0	43.0
2nd 20 %	74	612	82.3	0.88***	0.11***	0.01	0.10***	1.7**	-0.3	12.2	60.3	43.2	44.1
3rd 20 %	74	477	82.6	0.89***	0.10***	-0.03*	0.03**	1.5*	-0.3	7.8	56.8	42.0	44.5
4th 20 %	74	354	82.0	0.89***	0.04*	-0.04*	-0.04**	1.3**	0.1	4.4	56.7	44.8	41.1
Bottom 20 %	74	225	81.1	0.90***	0.06**	-0.12***	-0.12***	1.5*	0.2	-1.9	58.3	49.1	37.3
Bottom 10%	37	157	77.1	0.85***	0.08**	-0.21***	-0.18***	1.5*	0.1	-3.7	57.7	52.2	35.8
Bottom 5%	19	146	76.0	0.88***	0.12**	-0.24***	-0.23***	1.6	-0.4	-5.9	57.8	54.7	33.7
Top-Bottom 5%	19	—	10.4*	0.11**	0.34***	0.17**	0.56***	2.1*	0.5	37.1***	28.6***	-5.2**	9.2***
Top-Bottom 10%	37	—	7.9	0.11***	0.32***	0.16**	0.45***	1.7*	-0.04	30.4***	22.7***	-3.4	7.6***
Top-Bottom 20%	74	—	3.3	0.04	0.28***	0.09*	0.36***	1.2	-0.4	22.2***	16.4***	-1.1	5.7**
All Funds	367	473	82.8	0.90***	0.11***	-0.04***	0.03***	1.6**	-0.1	8.9	59.7	44.4	43.3

Table III (continued)

Panel B. Performance Attribution (Year 1)

Ranking Variable = Net Return Fractile	Avg No	Gross Return (%/yr)	CS (%/yr)	CT (%/yr)	AS (%/yr)	Expense Ratio (%/yr)	Trans. Costs (%/yr)	Net Return (%/yr)	$\alpha^{Net}_{Carhart}$ (%/yr)	$\alpha^{Net}_{Ferson-Schadt}$ (%/yr)
Top 5 %	19	21.0	2.13*	0.36	18.2	0.99	1.32	17.9	-2.2*	-0.8
Top 10 %	37	19.9	1.75*	0.30	17.6	0.90	1.13	17.4	-1.9*	-0.8
Top 20 %	74	18.7	1.54*	0.08	16.9	0.87	1.03	16.2	-2.2**	-1.4
2nd 20 %	74	16.2	0.54*	-0.40	15.8	0.77	0.71	14.4	-1.4**	-0.5
3rd 20 %	74	16.0	1.09**	0.06	14.7	0.74	0.66	14.2	-0.6	-0.1
4th 20 %	74	15.6	0.76**	0.25	14.1	0.77	0.69	13.4	-0.2	0.1
Bottom 20 %	74	13.7	0.39	0.26	13.1	0.86	0.83	11.4	-0.8	-1.1
Bottom 10%	37	14.6	0.92*	0.80	13.5	0.98	1.14	11.4	0.3	0.3
Bottom 5%	19	13.0	0.16	0.87	13.2	1.03	1.36	9.6	-0.6	-0.5
Top-Bottom 5%	19	8.0**	1.97*	-0.51	5.1**	-0.04	-0.04	8.3**	-1.6	-0.3
Top-Bottom 10%	37	5.3*	0.83*	-0.50	4.1**	-0.08*	-0.01	6.0*	-2.2	-1.1
Top-Bottom 20%	74	5.1**	1.15*	-0.18	3.8***	0.01	0.20	4.8**	-1.4	-0.3
All Funds	367	15.8	0.78***	0.02	14.8	0.78	0.74	13.8	-1.0***	-0.6*

Panel C. Performance Attribution (Year 2)

Ranking Variable = Net Return Fractile	Avg No	Gross Return (%/yr)	CS (%/yr)	CT (%/yr)	AS (%/yr)	Expense Ratio (%/yr)	Trans. Costs (%/yr)	Net Return (%/yr)	$\alpha^{Net}_{Carhart}$ (%/yr)	$\alpha^{Net}_{Ferson-Schadt}$ (%/yr)	Inflows (%/yr)
Top 5 %	17	19.4	1.49**	-0.52	17.7	0.95	1.17	16.8	1.1	1.5	25.7
Top 10 %	34	18.7	1.29***	-0.39	17.1	0.90	1.06	16.2	-0.1	0.4	22.0
Top 20 %	68	17.7	1.27***	0.01	16.2	0.87	1.02	15.1	0.3	-0.1	21.9
2nd 20 %	68	16.6	0.81***	-0.14	15.6	0.76	0.69	14.6	-0.5	-0.7	12.7
3rd 20 %	68	16.0	0.91***	-0.06	14.8	0.75	0.63	14.1	-0.3	-0.5	8.0
4th 20 %	68	15.7	0.83***	0.05	14.4	0.78	0.66	13.7	-0.1	-0.2	4.0
Bottom 20 %	68	14.9	0.66**	0.26	13.7	0.87	0.82	12.7	-0.9	-0.8	-2.2
Bottom 10%	34	16.4	0.95***	0.22	14.8	0.96	0.99	13.5	-1.8	-0.5	-0.5
Bottom 5%	17	16.8	0.48	0.05	15.7	1.08	1.25	13.6	-0.5	0.5	-0.4
Top-Bottom 5%	17	2.6	1.01	-0.57	1.9**	-0.13	-0.08	3.2*	1.6	1.0	26.1***
Top-Bottom 10%	34	2.3	0.34	-0.60**	2.3***	-0.06**	0.08	2.7*	1.8	0.9	22.5***
Top-Bottom 20%	68	2.8**	0.60	-0.26	2.6***	-0.003	0.19**	2.5**	1.2	0.7	24.1***
All Funds	339	15.2	0.76***	-0.08	14.3	0.78	0.69	13.2	-1.0***	-0.7	10.4

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table IV
A Decomposition of Mutual Fund Returns Using a Three-Year Ranking Period

A decomposition of mutual fund returns and costs is provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases. At the end of each calendar quarter starting December 31, 1977 and ending December 31, 1993, we rank all mutual funds in the merged database that existed during the entire prior 36 months (and had a complete data record during that period) on their average monthly net return of those months (the "ranking period"). Then, fractile portfolios are formed, and we compute cross-sectional average return measures (e.g., net returns) for each fractile portfolio during the year following the ranking period (the "test period"). In computing the average return measure for a given test year, we first compute quarterly buy-and-hold returns for each fund that exists during each quarter of the test year, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA-weighted) average quarterly buy-and-hold return across all funds during that quarter. This process is repeated for each quarter of a test year. Finally, we compound these returns into a yearly return that is rebalanced quarterly for a test year. Specifically, presented in this table are the TNA-average annual: return on the stock portfolio of the funds (Gross Return), characteristic selectivity measure (CS), characteristic timing measure (CT), average style measure (AS), expense ratio, estimated transactions costs, net reported return, and Carhart net return alpha (the table also shows the time-series average number of funds within each fractile portfolio). The table presents test year statistics, averaged over all (overlapping) event years. In forming all portfolios in this table, we limit our analysis to funds having a self-declared investment objective of "aggressive growth," "growth," "growth and income," "income," or "balanced" at the beginning of the test year. Note, also, that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Autocorrelation-adjusted time-series inference tests are presented, where appropriate.

Performance Attribution (Year 1)

Ranking Variable = 3-Year Net Return Fractile	**Avg No**	**Avg TNA**	**Gross Return (pct/year)**	**CS (pct/year)**	**CT (pct/year)**	**AS (pct/year)**	**Expense Ratio (pct/year)**	**Trans. Costs (pct/year)**	**Net Return (pct/year)**	$\alpha^{Net}_{Carhart}$ **(pct/year)**	**Inflows (pct/yr)**
Top 5 %	13	530	22.1	3.27**	-0.19	18.5	0.92	1.22	19.4	-0.01	40.2
Top 10 %	27	580	20.5	2.50**	-0.17	18.1	0.90	1.10	18.7	-0.4	32.9
Top 20 %	54	640	18.8	1.59**	-0.16	17.2	0.84	0.95	16.7	-1.1	27.0
2nd 20 %	54	570	17.9	1.15**	-0.15	16.7	0.73	0.71	16.0	-1.0*	14.0
3rd 20 %	54	419	16.6	0.11	-0.16	16.5	0.75	0.68	14.5	-1.4**	8.8
4th 20 %	54	388	16.5	0.61	0.02	16.0	0.73	0.64	14.1	-1.0	3.7
Bottom 20 %	54	160	16.2	0.54	0.01	15.5	0.84	0.87	13.9	-1.2	-3.6
Bottom 10%	27	125	17.0	0.50	0.22	15.8	0.89	1.00	13.6	-1.3	-5.9
Bottom 5%	13	101	18.7	0.45	0.68	16.3	1.07	1.32	13.2	-0.7	-8.1
Top-Bottom 5%	13	—	3.4	2.82*	-0.87	2.2	-0.15*	-0.10	6.2	0.7	43.0***
Top-Bottom 10%	27	—	3.5	2.00*	-0.39	2.3	0.01	0.10	5.1	0.8	38.9***
Top-Bottom 20%	54	—	2.6	1.05	-0.17	1.7	-0.001	0.08	2.9	0.09	30.6***
All Funds	267	518	17.2	0.73*	-0.18	16.5	0.75	0.72	15.1	-1.0**	11.4

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table V
Persistence in Mutual Fund Returns
Ranked on Prior 1-Year Net Return
(Growth-Oriented Funds)

Selected mutual fund measures are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases, for growth-oriented funds only. At the end of each calendar quarter starting December 31, 1975 and ending December 31, 1993, we rank all mutual funds in the merged database that existed during the entire prior 12-month period, had an investment objective at the end of that year of "aggressive-growth" or "growth," and had a complete data record during that year, on their average monthly net return of that year (the "ranking year"). Then, fractile portfolios are formed, and we compute average measures (e.g., net returns) for each fractile portfolio during the following year (the "test year"). In computing the average measure for a given test year, we first compute the quarterly buy-and-hold measure for each fund that exists during each quarter of the test year, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA) cross-sectional average quarterly buy-and-hold measure across all funds for each quarter of the test year. Finally, we compound these measures into an annual measure that is rebalanced quarterly. Presented in this table are the TNA-average annual: net return (Panel A), net consumer flows (Panel B), characteristic selectivity measure (Panel C), and momentum-investing measure (Panel D). The table presents test year statistics over years 1-4 following the ranking year, averaged over all (overlapping) event dates. The table also shows the time-series average number of funds within each fractile portfolio. Note that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Autocorrelation-adjusted time-series inference tests are presented, where appropriate.

Panel A. Net Returns (percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	37.7	17.0	16.5	16.2	17.1
Top 10 %	26	257	33.0	17.1	17.3	16.2	16.4
Top 20 %	53	299	28.7	17.0	16.6	16.6	15.9
2nd 20 %	53	375	19.7	15.6	15.8	15.9	16.0
3rd 20 %	53	347	14.8	14.4	15.0	15.4	15.0
4th 20 %	53	272	10.4	13.3	14.6	15.0	14.8
Bottom 20 %	53	169	3.4	13.2	13.5	14.3	14.4
Bottom 10%	26	128	-0.3	12.7	14.4	13.8	13.9
Bottom 5%	13	108	-3.9	12.5	14.5	12.2	13.6
Top-Bottom 5%	13	—	41.6	4.5***	2.0	4.0**	3.5***
Top-Bottom 10%	26	—	33.3	4.3***	2.9**	2.5*	2.5***
Top-Bottom 20%	53	—	25.3	3.8***	3.0***	2.3**	1.5**
All Funds	265	305	14.8	14.7	14.4	15.5	15.3

Panel B. Flows (percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	41.2	40.4	24.4	17.9	20.9
Top 10 %	26	257	28.8	32.5	23.4	18.1	20.1
Top 20 %	53	299	20.3	26.4	20.6	18.0	18.8
2nd 20 %	53	375	10.4	12.2	13.0	12.7	13.2
3rd 20 %	53	347	7.1	6.3	9.0	10.1	10.6
4th 20 %	53	272	5.4	2.1	4.7	7.0	7.3
Bottom 20 %	53	169	1.7	-2.7	0.9	4.1	4.8
Bottom 10%	26	128	-0.9	-4.5	-0.1	4.2	4.2
Bottom 5%	13	108	-3.0	-5.4	0.3	2.3	2.4
Top-Bottom 5%	13	—	44.1***	45.8***	24.1***	15.6***	18.5***
Top-Bottom 10%	26	—	29.7***	37.0***	23.5***	14.0***	15.9***
Top-Bottom 20%	53	—	18.6***	29.1***	19.7***	13.9***	14.0***
All Funds	265	305	8.8	8.9	9.1	11.0	11.5

Table V (continued)

Panel C. Characteristic Selectivity Measure (percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	12.6	2.9***	1.4**	1.2**	2.1***
Top 10 %	26	257	10.0	2.1**	2.0***	1.8***	1.5***
Top 20 %	53	299	7.4	1.8**	1.9***	2.1***	1.5***
2nd 20 %	53	375	3.2	1.2**	1.8***	1.7***	1.7***
3rd 20 %	53	347	1.2	1.2**	1.5***	1.5***	1.0***
4th 20 %	53	272	-0.6	0.8	1.8***	1.0***	1.0***
Bottom 20 %	53	169	-3.9	0.7	1.1***	0.5	0.6*
Bottom 10%	26	128	-5.9	0.8	1.4***	0.2	0.8
Bottom 5%	13	108	-7.6	0.5	1.2*	-0.6	0.7***
Top-Bottom 5%	13	—	20.2	2.4***	0.2	1.8**	1.4
Top-Bottom 10%	26	—	15.9	1.3	0.6	1.6**	0.7
Top-Bottom 20%	53	—	11.3	1.1	0.8*	1.6***	0.9**
All Funds	265	305	1.3	1.0*	1.4***	1.4***	1.3***

Panel D. Buy Momentum Investing Measure (BMOM; percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	8.4***	4.8***	4.5***	3.4***	3.7**
Top 10 %	26	257	6.8***	4.2***	3.7***	2.9**	3.2***
Top 20 %	53	299	5.8***	4.1***	3.5***	3.4***	2.9***
2nd 20 %	53	375	4.2***	2.7***	2.9**	3.1***	2.9***
3rd 20 %	53	347	3.1***	2.4**	2.2***	2.2**	3.0**
4th 20 %	53	272	2.1**	1.8**	2.1**	2.1**	2.9**
Bottom 20 %	53	169	1.3*	2.2**	2.3**	2.3**	2.9**
Bottom 10%	26	128	1.3	2.4***	2.6**	2.7**	3.0**
Bottom 5%	13	108	1.0	3.1***	2.7***	3.4**	3.2**
Top-Bottom 5%	13	—	7.4***	1.7*	1.9	-0.01	0.5
Top-Bottom 10%	26	—	5.3***	1.8**	1.1	0.2	0.2
Top-Bottom 20%	53	—	4.6***	1.8**	1.2	1.0	0.03
All Funds	265	305	3.2***	2.6***	2.6***	2.7***	2.8***

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table VI
Persistence in Mutual Fund Returns
Ranked on Prior 1-Year Net Return
(Value-Oriented Funds)

Selected mutual fund measures are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases, for value-oriented funds only. At the end of each calendar quarter starting December 31, 1975 and ending December 31, 1993, we rank all mutual funds in the merged database that existed during the entire prior 12-month period, had an investment objective at the end of that year of "growth-income," "income," or "balanced," and had a complete data record during that year, on their average monthly net return of that year (the "ranking year"). Then, fractile portfolios are formed, and we compute average measures (e.g., net returns) for each fractile portfolio during the following year (the "test year"). In computing the average measure for a given test year, we first compute the quarterly buy-and-hold measure for each fund that exists during each quarter of the test year, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA) cross-sectional average quarterly buy-and-hold measure across all funds for each quarter of the test year. Finally, we compound these measures into an annual measure that is rebalanced quarterly. Presented in this table are the TNA-average annual: net return (Panel A), net consumer flows (Panel B), characteristic selectivity measure (Panel C), and momentum-investing measure (Panel D). The table presents test year statistics over years 1-4 following the ranking year, averaged over all (overlapping) event dates. The table also shows the time-series average number of funds within each fractile portfolio. Note that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Autocorrelation-adjusted time-series inference tests are presented, where appropriate.

Panel A. Net Returns (percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	6	431	28.8	13.3	12.8	13.2	13.5
Top 10 %	13	663	24.0	13.6	13.0	13.8	13.9
Top 20 %	26	835	22.2	13.8	14.7	14.1	14.3
2nd 20 %	26	765	19.8	14.0	14.2	14.3	14.7
3rd 20 %	26	749	13.2	14.1	15.0	14.4	13.8
4th 20 %	26	505	9.4	13.5	15.2	14.2	13.6
Bottom 20 %	26	239	1.2	12.0	14.6	14.0	13.9
Bottom 10%	13	195	-0.5	12.0	13.8	13.9	14.0
Bottom 5%	6	161	-5.5	11.5	13.0	13.1	14.2
Top-Bottom 5%	6	—	34.3	1.9	-0.2	0.1	-0.7
Top-Bottom 10%	13	—	24.5	1.6	-0.8	-0.1	-0.1
Top-Bottom 20%	26	—	21.0	1.8**	0.1	0.1	0.4
All Funds	126	656	14.0	13.7	14.7	14.1	14.0

Panel B. Flows (percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	6	431	25.5	28.7	20.1	14.5	13.5
Top 10 %	13	663	23.4	22.6	17.8	13.3	13.4
Top 20 %	26	835	20.8	19.6	12.5	12.7	12.9
2nd 20 %	26	765	9.5	12.4	12.3	12.1	12.8
3rd 20 %	26	749	5.5	9.2	11.3	10.7	12.1
4th 20 %	26	505	0.5	4.8	5.1	9.0	10.9
Bottom 20 %	26	239	-0.5	-1.2	-0.2	2.5	9.8
Bottom 10%	13	195	-2.2	-4.2	-0.3	2.1	5.7
Bottom 5%	6	161	-4.5	-7.5	-0.5	2.0	5.5
Top-Bottom 5%	6	—	30.0***	36.1	20.6	12.5	8.0
Top-Bottom 10%	13	—	25.6***	26.8***	18.1***	11.2***	7.7
Top-Bottom 20%	26	—	21.3***	20.8***	12.7***	10.2***	3.1
All Funds	126	656	7.5	10.1	11.6	11.9	12.5

Table VI (continued)

Panel C. Characteristic Selectivity Measure (percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	6	431	4.59	-0.11	0.20	-0.11	0.05
Top 10 %	13	663	3.58	-0.10	-0.11	0.12	0.21
Top 20 %	26	835	2.17	0.20	0.33	0.18	0.15
2nd 20 %	26	765	1.48	0.14	0.11	0.22	-0.05
3rd 20 %	26	749	0.59	0.64***	0.23	0.25	0.24
4th 20 %	26	505	0.22	0.43*	0.33	0.18	-0.01
Bottom 20 %	26	239	-0.30	0.02	-0.13	0.05	-0.05
Bottom 10%	13	195	-1.55	0.28	-0.15	-0.11	-0.08
Bottom 5%	6	161	-2.65	0.33	0.05	-0.12	-0.10
Top-Bottom 5%	6	—	7.24	-0.44	0.15	0.01	0.15
Top-Bottom 10%	13	—	5.13	-0.38	0.04	0.23	0.29
Top-Bottom 20%	26	—	2.47	0.18	0.46	0.13	0.20
All Funds	126	656	0.35	0.30**	0.28*	0.27*	0.29*

Panel D. Momentum Investing Measure (MOM; percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	6	431	1.88	2.24***	1.15*	0.80	0.75
Top 10 %	13	663	1.08	1.18	0.89	0.77	0.67
Top 20 %	26	835	0.55	0.21	0.25	0.22	0.25
2nd 20 %	26	765	0.20	-0.01	-0.05	-0.07	-0.02
3rd 20 %	26	749	-0.10	-0.03	-0.10	-0.07	0.01
4th 20 %	26	505	-0.55	0.11	0.10	-0.05	0.01
Bottom 20 %	26	239	-0.56	0.38	0.05	0.01	0.05
Bottom 10%	13	195	-0.55	0.07	0.02	-0.04	-0.05
Bottom 5%	6	161	-0.60	-0.25	0.01	-0.10	-0.15
Top-Bottom 5%	6	—	2.48***	2.49***	1.16*	0.90	0.90
Top-Bottom 10%	13	—	1.63***	1.10*	0.87	0.81	0.72
Top-Bottom 20%	26	—	1.11*	-0.16	0.20	0.21	0.20
All Funds	126	656	0.01	0.02	-0.10	0.08	0.05

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table VII
Turnover-Adjusted Buy Momentum Investing Measures
(Growth-Oriented Funds)

The buy-momentum investing measure, adjusted for the level of turnover during each quarter for a given fund (TABMOM) is provided below for growth-oriented funds only. In addition, the buy-momentum investing measure, relative to the median stock return in the fund's portfolio during each quarter (MTABMOM) is presented, as well as the same-stock and new-stock decompositions of each of these two measures ($TABMOM^{same}$ and $TABMOM^{new}$; $MTABMOM^{same}$ and $MTABMOM^{new}$, respectively). To form these measures, at the end of each calendar quarter starting December 31, 1975 and ending December 31, 1993, we rank all mutual funds in the merged database that existed during the entire prior 12-month period, had an investment objective at the end of that year of "aggressive-growth" or "growth," and had a complete data record during that year, on their average monthly net return of that year (the "ranking year"). Then, fractile portfolios are formed, and we compute the buy momentum investing measure for each fund, across all stocks, and across only the subportfolio of stocks falling within a certain category, during the following year. The categories are (1) stocks already owned, that a fund purchased during a given calendar quarter of that year to increase its position and (2) stocks not already owned, that a fund newly purchased during a given calendar quarter of that year. These measures are normalized by the level of turnover, each quarter, of a fund. These fund subportfolio buy-momentum measures are then averaged over the following year (the "test year"), across all funds falling within a given fractile portfolio. In computing the average measure for a given test year, we first compute the quarterly buy-and-hold measure for each fund that exists during each quarter of the test year, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA) cross-sectional average quarterly buy-and-hold measure across all funds for each quarter of the test year. Finally, we compound these measures into an annual measure that is rebalanced quarterly. The table also shows the time-series average number of funds within each fractile portfolio. Note that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Autocorrelation-adjusted time-series inference tests are presented, where appropriate.

Panel A. Turnover-Adjusted Momentum-Investing Measure, All Stocks
(time-series average $TABMOM_t$, percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	34.6***	14.3*	13.9*	9.9	10.6
Top 20 %	53	299	25.5***	11.0*	10.5	10.0	10.7*
Middle 20 %	53	347	10.2*	7.8	7.1	8.9	10.1
Bottom 20 %	53	169	1.0	6.5	7.1	7.8	8.9
Bottom 5%	13	108	-4.6	6.0	8.9*	7.2	8.1
Top-Bottom 5%	13	—	39.2***	8.3	4.9	2.7	2.4
Top-Bottom 20%	53	—	24.5***	4.5	3.4	2.2	1.8

Panel B. Median- and Turnover-Adjusted Momentum-Investing Measure, All Stocks
(time-series average $MTABMOM_t$, percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	14.4***	13.0***	12.5***	10.6***	11.7***
Top 20 %	53	299	12.3***	11.0***	10.5***	9.4***	9.6***
Middle 20 %	53	347	8.4***	8.2***	8.0***	8.4***	8.3***
Bottom 20 %	53	169	7.8***	8.8***	8.0***	9.3***	8.5***
Bottom 5%	13	108	7.7***	9.4***	9.1***	10.3***	9.2***
Top-Bottom 5%	13	—	6.7***	3.6	3.4	0.3	2.5
Top-Bottom 20%	53	—	4.5***	2.2*	2.5	0.1	1.2

* Significant at the 90% confidence level.

** Significant at the 95% confidence level.

*** Significant at the 99% confidence level.

Table VIII
Decomposition of Characteristic Selectivity (CS) Performance Measure
(Growth-Oriented Funds)

A decomposition of the characteristic selectivity (CS) performance measure (using quarterly reconstituted DGTW (1997) benchmarks) is provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases, for growth-oriented funds only. At the end of each calendar quarter starting December 31, 1975 and ending December 31, 1993, we rank all mutual funds in the merged database that existed during the entire prior 12-month period, had an investment objective at the end of that year of "aggressive-growth" or "growth," and had a complete data record during that year, on their average monthly net return of that year (the "ranking year"). Then, fractile portfolios are formed, and we compute the CS measure for each fund, across only the subportfolio of stocks falling within a certain category, during the following year. The categories are (1) stocks already owned, that a fund purchased during the calendar quarter to increase its position and (2) stocks not already owned, that a fund newly purchased during the calendar quarter. These fund subportfolio CS measures are then averaged over the following year (the "test year"), across all funds falling within a given fractile portfolio. In computing the average measure for a given test year, we first compute the quarterly buy-and-hold measure for each fund that exists during each quarter of the test year, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA) cross-sectional average quarterly buy-and-hold measure across all funds for each quarter of the test year. Finally, we compound these measures into an annual measure that is rebalanced quarterly. The table also shows the time-series average number of funds within each fractile portfolio. Note that self-declared investment-objective data are available from CDA starting June 30, 1980, so the 1980 figures are as of that date. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Autocorrelation-adjusted time-series inference tests are presented, where appropriate.

Panel A. Overall Selectivity Measure
(time-series average CS_t, percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	11.5	2.2^{**}	1.1	1.0	1.0
Top 10 %	26	257	9.1	1.7^{**}	1.1	1.3	1.2
Top 20 %	53	299	6.7	1.4^{*}	1.1	1.4^{**}	1.1^{*}
2nd 20 %	53	375	2.8	0.9	1.3^{**}	1.0^{*}	0.9
3rd 20 %	53	347	0.8	1.0^{*}	1.1^{*}	0.9^{*}	0.7
4th 20 %	53	272	-1.1	0.6	1.3^{**}	0.5	0.8
Bottom 20 %	53	169	-4.5	0.6	0.9	0.6	0.3
Bottom 10%	26	128	-6.7	0.9	1.1	0.2	0.2
Bottom 5%	13	108	-8.4	0.4	0.8	-0.3	0.6
Top-Bottom 5%	13	—	19.8	1.7^{*}	0.3	1.3	0.5
Top-Bottom 10%	26	—	15.9	0.8	0.03	1.1	0.9
Top-Bottom 20%	53	—	11.4	0.8	0.3	0.8	0.9
All Funds	265	305	0.8	0.8	1.1^{*}	0.9^{*}	0.8

Panel B. Purchases of Same Stocks
($ percentage of all purchases)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	36.8	40.6	41.1	41.3	41.9
Top 10 %	26	257	37.6	40.3	40.9	41.4	42.9
Top 20 %	53	299	39.1	41.2	41.7	42.3	43.1
2nd 20 %	53	375	40.2	40.8	41.3	41.3	41.3
3rd 20 %	53	347	39.1	39.4	39.5	40.4	39.3
4th 20 %	53	272	39.7	39.7	38.8	38.4	37.8
Bottom 20 %	53	169	37.9	35.6	36.3	35.6	34.9
Bottom 10%	26	128	38.0	36.3	35.4	34.1	33.3
Bottom 5%	13	108	39.3	34.3	34.8	34.7	33.6
Top-Bottom 5%	13	—	-2.5	6.3^{***}	6.3^{*}	6.5	8.3^{**}
Top-Bottom 10%	26	—	-0.2	6.2^{***}	5.5	6.5^{**}	8.0^{**}
Top-Bottom 20%	53	—	1.2	5.6^{***}	5.1^{**}	6.7^{**}	8.2^{***}
All Funds	265	305	40.4	40.7	40.9	41.1	41.0

Table VIII (continued)

Panel C. Selectivity Measure for Same-Stock Purchases
(time-series average CS_t^{same}, percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	13.8	4.9***	1.0	1.6	2.5
Top 10 %	26	257	11.3	3.0***	0.5	2.2**	2.7**
Top 20 %	53	299	8.3	1.5**	0.3	1.9***	2.4**
2nd 20 %	53	375	3.6	1.1*	2.2**	1.4**	1.1
3rd 20 %	53	347	1.0	1.3*	2.0*	1.5	0.2
4th 20 %	53	272	-1.3	1.3**	1.6	0.8	0.3
Bottom 20 %	53	169	-6.0	0.03	0.9	0.6	1.1
Bottom 10%	26	128	-7.8	-1.1	0.4	-0.2	1.9
Bottom 5%	13	108	-10.1	-2.1	1.0	-2.6	1.6
Top-Bottom 5%	13	—	24.1	7.0***	-0.1	4.3**	1.0
Top-Bottom 10%	26	—	19.3	4.1***	0.01	2.4	0.8
Top-Bottom 20%	53	—	14.3	1.5	-0.5	1.3	1.3
All Funds	265	305	1.1	1.0	1.4*	1.4*	1.3

Panel D. Selectivity Measure for New Stock Purchases
(time-series average CS_t^{new}, percent per year)

Ranking Variable = Net Return Fractile	Avg No	Avg TNA	Ranking Year	Year +1	Year +2	Year +3	Year +4
Top 5 %	13	257	9.6	1.2	3.8	6.3***	5.4**
Top 10 %	26	257	7.5	1.0	2.2	4.4***	4.1***
Top 20 %	53	299	7.4	2.7**	2.6*	3.0***	3.7***
2nd 20 %	53	375	3.5	1.6**	2.6*	2.3*	1.1
3rd 20 %	53	347	0.8	1.2	0.5	1.1	1.1
4th 20 %	53	272	0.1	2.0***	0.5	0.6	0.2
Bottom 20 %	53	169	-4.5	1.1	2.1*	-1.0	0.1
Bottom 10%	26	128	-6.5	1.4	3.6*	-0.7	1.8
Bottom 5%	13	108	-8.8	1.8	3.4	-0.6	2.0
Top-Bottom 5%	13	—	18.5	-0.6	0.4	6.9***	3.4
Top-Bottom 10%	26	—	14.0	-0.3	-1.4	5.0***	2.3
Top-Bottom 20%	53	—	11.9	1.6	0.5	4.0***	3.6**
All Funds	265	305	1.2	1.3	1.6*	1.5*	1.2

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table IX
Fama-MacBeth Regressions of the Impact of Flows on Stock Returns

At the end of each quarter, beginning December 31, 1975 and ending December 31, 1993, all growth-oriented domestic equity mutual funds are ranked on their average net return of the prior 12 calendar months and separated into 20 ranked, TNA-weighted fractiles. A fund must have complete monthly net returns data during the prior year to be included in these sorts, and the fund is considered growth-oriented if its self-declared investment objective is either "aggressive growth" or "growth" at the end of a ranking quarter. Before 1980, funds are classified by their investment objectives as of January 1, 1975 (these data were hand-collected from printed sources). Then, for each of these overlapping ranking periods, a cross-sectional regression (across these 20 fractiles) of the TNA-average characteristic selectivity performance measure during the following year on various regressors is implemented. For regressions 1 through 4, the dependent variable is the overall characteristic selectivity measure, computed using quarterly reconstituted DGTW (1997) benchmarks, across fractiles ($CS_{Year\ +1}$), while the regressors are chosen from the characteristic selectivity performance measure ($CS_{Year\ 0}$) and consumer inflows ($Flows_{Year\ 0}$) during the ranking year; and consumer inflows ($Flows_{Year\ +1}$) and the buy momentum measure using lagged returns ($BM0ML_{Year\ +1}$) during the following year. $BM0ML_{Year\ +1}$ modifies the normal buy-momentum measure (BM0M) to multiply current-quarter weight changes by prior quarter excess returns (raw returns minus one-year ahead returns for each stock) to avoid any spurious relation between $CS_{Year\ +1}$ and the buy momentum measure that might arise if weight changes and excess returns are measured contemporaneously. For regressions 1A through 4A, the dependent variable is the TNA-average characteristic selectivity measure computed only over nonzero positions that a manager adds to during a given quarter of the year following the ranking year ($CS^{Same}_{Year\ +1}$), while the same variable during the ranking year ($CS^{Same}_{Year\ 0}$) as well as the buy momentum measure computed only over nonzero positions added to ($BM0ML^{Same}_{Year\ +1}$) replace their counterparts in regressions 1 through 4 as regressors. For regressions 1B through 4B, the dependent variable is the TNA-average characteristic selectivity measure computed only over newly initiated stock positions during a given quarter of the year following the ranking year ($CS^{New}_{Year\ +1}$), while the same variable during the ranking year ($CS^{New}_{Year\ 0}$) as well as the buy momentum measure computed only over newly initiated stock positions ($BM0ML^{New}_{Year\ +1}$) replace their counterparts in regressions 1 through 4 as regressors. After the cross-sectional regressions are computed, their time-series means and t-statistics are computed and presented below. Standard errors used to compute t-statistics are adjusted for overlapping observations.

	Dependent	Regressors								
Regression	**Variable**	**Intercept**	$\mathbf{CS}_{Year\ 0}$	$\mathbf{CS}^{Same}_{Year\ 0}$	$\mathbf{CS}^{New}_{Year\ 0}$	$\mathbf{Flows}_{Year\ +1}$	$\mathbf{Flows}_{Year\ 0}$	$\mathbf{BM0ML}_{Year\ +1}$	$\mathbf{BM0ML}^{Same}_{Year\ +1}$	$\mathbf{BM0ML}^{New}_{Year\ +1}$
1	$\mathbf{CS}_{Year\ +1}$	0.011**	0.076*							
2		0.009**	-0.033			0.048***				
3		0.008*	-0.024			0.068***	-0.045**			
4		0.007	-0.021			0.066***	-0.036**	0.097*		
1A	$\mathbf{CS}^{Same}_{Year\ +1}$	0.013		0.029						
2A		0.004		-0.062		0.068***				
3A		0.0002		-0.063		0.110***	-0.082**			
4A		0.0003		0.050		0.082***	-0.067**		0.599*	
1B	$\mathbf{CS}^{New}_{Year\ +1}$	0.019**			0.025					
2B		0.010			0.009	-0.016				
3B		0.009*			0.005	-0.048	0.018			
4B		0.007			0.004	-0.057	0.023			0.071

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.