Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability

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ABSTRACT

A previous study finds evidence to support selection ability among active fund investors for equity funds listed in 1982. Using a large sample of equity funds, I find evidence that funds that receive more money subsequently perform significantly better than those that lose money. This effect is short-lived and is largely but not completely explained by a strategy of betting on winners. In the aggregate, there is no significant evidence that funds that receive more money subsequently beat the market. However, it is possible to earn positive abnormal returns by using the cash flow information for small funds.

HAVING EXPERIENCED DRAMATIC GROWTH in the past two decades, the mutual fund industry plays an important role in the U.S. economy. As a major investment vehicle, open-end mutual funds at the end of the first quarter of 1998 managed about \$3.3 trillion in assets, a sum that exceeds all bank savings deposits. Due to the great number of funds in existence, evaluating managers' performance and selecting funds with relatively high risk-adjusted returns can be an especially difficult and challenging task. The growth of data companies such as Lipper, Morningstar, and Micropal and the explosion in the publication of books and articles on mutual funds both reflect investors' tremendous demand for detailed mutual fund information and investment advice. This huge demand suggests that many investors are making mutual fund investment decisions themselves and many of them study current and historical information about funds carefully during the decision-making process. With all the effort spent in selecting and evaluat-

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ing mutual funds, there is one natural question to ask: Can investors forecast mutual fund performance? This study investigates whether investors' purchasing and selling decisions are able to predict funds' future performance, and whether investors are smart in selecting funds.

A number of recent papers study the investment performance of mutual fund managers, yet only Gruber (1996) studies the ability of investors to select funds. Beginning with Jensen (1969), many researchers have examined the performance of different groups of mutual fund managers using various methods. Most find that managers on average underperform the market, but others find that managers display some management skill. Brown and Goetzmann (1995) and Carhart (1995) find that a value-weighted index of equity funds has a small positive risk-adjusted return that is slightly higher than that of an equally weighted index. This may be interpreted as evidence that the average dollar invested in U.S. equity funds beats the average mutual fund and the benchmark.

Do mutual fund investors display selection ability?[1] In other words, do revisions in the aggregate mutual fund portfolio forecast future returns? Gruber (1996) investigates this issue by examining the risk-adjusted returns of newly invested money in actively managed mutual funds. He reports monthly cash-flow-weighted alphas for 227 funds over the period of January 1985 through December 1994. His evidence shows that the return on new cash flows is higher than the average return for all investors in these funds.

In the present paper, I examine the statistical and economic significance of two effects on a large mutual fund database:

1. *Gruber's "smart money" effect:* whether investors are smart ex ante, in that they move to the funds that will perform better
2. *The information effect:* whether investors' moves have information that can be used to make abnormal returns.[2]

For the smart money effect to exist, the implementation of trading strategies is not required. For the information effect to exist, the strategies have to be implementable. I first apply a performance test introduced by Grinblatt and Titman (1993) to examine the smart money effect. This test was

[1] It is well documented that investors chase past positive performance and that performance persists on a short-term basis. Patel, Hendricks, and Zeckhauser (1990), Ippolito (1992), Sirri and Tufano (1998), Goetzmann and Peles (1993), Chevalier and Ellison (1995), Roston (1996), and others have reported that money flows into past good performers and flows out of past poor performers. Researchers have also provided strong evidence for performance persistence: Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown, Goetzmann, Ibbotson, and Ross (1992), Carhart (1997), Brown and Goetzmann (1995), Malkiel (1995), Elton, Gruber, and Blake (1996), and Grinblatt and Titman (1994) all suggest that performance persists. These two phenomena suggest that active fund investors may have selection ability and obtain high relative returns.

[2] The mutual fund database, which has fund data from 1961 to 1993, is provided by Mark Carhart, Eugene Fama, and Kenneth French, and is substantially broader than Gruber's sample. It includes defunct funds, merged funds, and newly opened funds.

initially proposed to measure the portfolio performance of mutual funds. The Grinblatt–Titman (GT) measure uses the portfolio weights in the preceding period as a benchmark and thus is less subject to the problems caused by inappropriate benchmarks. Since the GT measure is not implementable in practice, it does not provide information to study the information effect. To further investigate the practical implications of investors' buying and selling decisions, I form different trading strategies based on new money flows and examine the raw returns as well as the risk-adjusted returns realized by the constructed portfolios. From the trading strategies, I investigate both the smart money effect, whether new money flows predict future fund returns, and the information effect, whether aggregate new money flows have information that can be used to make abnormal returns.

To capture the time variation in mutual fund risks and risk premia, I adopt the conditional performance measure introduced by Shanken (1990), Ball, Kothari, and Shanken (1995), and Ferson and Schadt (1996). This measure allows for active strategies based on macroeconomic conditions and possible "style effects" (Ferson and Schadt (1996), Brown and Goetzmann (1994), Fama and French (1992)). According to the conditional measure, a portfolio strategy should not be regarded as having superior performance if it can be replicated using readily available public information. This conditional performance measure uses predetermined instruments for the time-varying expectations and controls common variation due to public information. In the context of the smart money effect, the conditional method allows us to determine whether the effect is due to a rational response to macroeconomic variables (e.g., interest rate variables) or to style variables such as dividend yield, size, and book-to-market ratio. The failure of this conditional method to explain away the effect suggests that investors use fund-specific information to make their mutual fund investment choices.

The results from the GT test support the smart money effect: investors are able to select funds by moving away from the poor performers and toward the good performers. The trading strategies suggest evidence that the raw returns as well as risk-adjusted returns for funds with positive new money flow are significantly higher than those with negative new money flow over the short term. This finding is consistent with the empirical evidence in Gruber (1996). The trading strategies, however, suggest that for the whole sample there are no significant positive abnormal returns over the market from constructing a portfolio of funds with positive new money. Thus there is no significant evidence that active investors in general can beat the market. Interestingly, there is evidence that active investors in small funds can beat the market. The trading strategies allowing some time delay in the cash flow information show that, for the whole sample, investors' cash flow moves cannot be used to earn abnormal returns; however, there is evidence for the information effect for small funds.

By comparing portfolios that follow new money signals with portfolios that follow performance signals, I find that the smart money effect cannot be completely explained by investors chasing past fund performance. However, a significant percentage of the performance variations in the smart money strategy is explained by the performance variations in the "repeat winner" strategy. I also find that superior returns are earned principally by new money flowing into and out of small funds rather than large funds. The fact that the above result is robust to both the unconditional and conditional measures indicates that the smart money effect is likely due to fund-specific information. The empirical tests of the conditional performance measure indicate a negative correlation between changes in the conditional beta and changes in net new money flows, which is consistent with results in Ferson and Warther (1996) and Ferson and Schadt (1996).

The paper is organized as follows. Section I presents the methodology and Section II describes the data. The empirical results are set forth in Section III. Section IV concludes.

I. Methodology

A. The Benchmark Free Aggregate Performance Measure

I apply a measure of portfolio performance introduced by Grinblatt and Titman (1993) to estimate aggregate investors' ability in selecting mutual funds and switching among them. The GT measure employs portfolio holdings and uses its own portfolio holdings in the preceding period as a benchmark.

$$\text{GT Measure}_t = \sum_{j=1}^{N} R_{j,t+1}(w_{jt} - w_{j,t-1}), \tag{1}$$

where w_{jt} is the portfolio weight for fund j at time t and $\mathrm{R}_{j,t+1}$ is the return of fund j between time t and time $t + 1$.

The GT measure in expression (1) represents the dollar return of a zero-cost portfolio. It also estimates the covariance between the proportional holdings of a particular fund and its subsequent returns. Under the null hypothesis that investors have no fund selection ability and that expected returns are constant over time, both current and past weights are uncorrelated with current returns and thus expression (1) converges to zero in large samples.[3] Under the alternative hypothesis that the investor has selection ability, expression (1) should be positive and converge to the covariance under the

[3] One potential concern about the GT measure is that it could be positive even if the investor is merely gradually increasing the systematic risk of the portfolio. As mentioned by Grinblatt and Titman (1993), this problem should not be severe for large samples. I further address the problem by regressing the dollar returns of the zero-cost portfolio on the market factors. The coefficient for the single factor model and those for the market factor and size factor of the three-factor model are not significantly different from zero. The coefficient for the book-to-market factor is significantly negative. Thus, there is no evidence that the systematic risk of the zero-cost portfolio increases over time. Implications of the GT measure can be further studied using simulated portfolios.

assumption that the $w_{j,t-1}$'s are uncorrelated with R_{jt}'s. Notice that the zero investment assumption implicitly assumes that the investor is shorting some assets to finance the purchase of others. Note also that Grinblatt and Titman use the average of expression (1) over time as their performance measure and they perform significance tests on a cross-section of mutual funds, whereas in this study I draw inferences on a time series of estimated values of expression (1).[4] Under the null hypothesis that the investors have no selection skill, estimates of expression (1) representing the dollar returns of a zero-cost portfolio are serially uncorrelated.

Instead of incorporating both selection and timing effects as in Gruber (1996), this aggregate performance measure examines investors' fund selection ability exclusively. The measure is not affected by the flow of aggregate money into and out of stock mutual funds because the weights are normalized each month.

Throughout the paper, I use a "follow the money" approach, introduced by Elton, Gruber, and Blake (1996b), to control for survivorship bias. If a fund merges into another, I assume the investors place money in the fund that continues to exist after the merger.[5] Thus mergers do not cause severe survivorship bias because my tests do not exclude defunct funds before they actually disappear. In the case where I cannot identify the new fund into which the old one is merged, I assume that the investors place money in the average surviving fund. By following this approach, I do not require a fund to survive for two quarters after it is included in the aggregate portfolio. However, this does not completely eliminate survivorship bias because the premerger return in the merging month is unknown. If merger is conditioned on performance, then the survivorship bias described by Brown et al. (1992) and Brown, Goetzmann, and Ross (1995) might obtain. Nevertheless, I control for survival biases to the extent possible.

B. Trading Strategies

In order to explore the practical implications of the aggregate investor's selection ability, I compare the returns and the risk-adjusted returns of different trading strategies, most of which are based on past new money flow (newly invested money) signals. The portfolios corresponding to the investment strategies are invested as follows:

[4] The mean of expression (1) is $\sum_{j=1}^{J} \sum_{t=1}^{T}[R_{jt}(w_{jt} - w_{j,t-k})]/T$.

[5] More than 95 percent of the mergers in my sample occur either at the beginning or at the end of the month according to my data set. For mergers that occur at the beginning of each month, I use returns of the merger partner for the merger month and forward in my portfolio calculation. For mergers that occur at the end of each month, I use the return of the merger fund for the merger month and the returns of the merger partner for the merger month forward in my portfolio calculation. For the mergers that occur on other dates of the month, I use either the return of the merger fund or the return of the merger partner for the month of the merger depending on whether the merger occurs before or after the 15th of each month. I do the same to calculate the alphas for the fund regression approach.

Portfolio 1: Equally in all available funds.

Portfolio 2: In all available funds and weighted by funds' current Total Net Assets.

Portfolio 3: Equally in all available funds with positive new money cash flow.

Portfolio 4: Equally in all available funds with negative new money cash flow.

Portfolio 5: In all available funds with positive new money cash flow and weighted by funds' new money.

Portfolio 6: In all available funds with negative new money cash flow and weighted by funds' new money.

Portfolio 7: Equally in all available funds with above-median new money cash flow.

Portfolio 8: Equally in all available funds with below-median new money cash flow.

I refer to portfolios 3 through 8 as new money portfolios, as they are constructed from the strategies based on new money signals. I refer to portfolios 3, 5, and 7 as positive portfolios and to portfolios 4, 6, and 8 as negative portfolios. Portfolios 3 through 6 are based on the sign of new money. Portfolios 7 and 8 break all funds equally into two groups according to the amount of newly invested money received by each fund, and thus control for the fact that there might be a disproportionate number of funds with positive and negative new money in some periods. I construct all trading portfolios at the beginning of each quarter based on the relevant information of the immediately preceding quarter. I hold these portfolios for three months, then re-form portfolios according to the same criteria at the beginning of the next quarter. For example, in order to construct the returns for portfolio 5 for July through September 1970, I first select funds with positive new money in the quarter that ends in June 1970. The July through September monthly returns of the selected funds are then weighted by their corresponding new money measure. The three weighted average numbers are the monthly returns earned by portfolio 5 for the three months desired. To calculate the monthly returns for the portfolio for October through December 1970, I reselect funds according to the new money data for the quarter that ends in September 1970 and repeat the previous procedure to get the weighted average returns for the three months.

I use two aggregate methods to calculate the risk-adjusted returns of the various portfolios. The first approach estimates time-series regressions for returns of the portfolios of mutual funds. Hereafter, I refer to this approach as the "portfolio regression approach." The second method used is comparable to the one in Gruber (1996), which estimates the one-factor and the Fama and French three-factor time-series regressions for each fund and calculates the performance measures for the portfolios cross-sectionally period by period. I refer to this as the "fund regression approach." In the next two paragraphs, we will see the obvious trade-offs between the two methods.

For the portfolio regression approach, I calculate a time series of raw returns for each of the eight portfolios and perform OLS regressions to estimate portfolio factor loadings and α measures from the following regressions:

$$R_{pt} - R_{ft} = \alpha_p^1 + \beta_p^1(R_{mt} - R_{ft}) + e_{pt}, \tag{2}$$

$$R_{pt} - R_{ft} = \alpha_p^3 + \beta_{p\mathrm{RMRF}}^3 \mathrm{RMRF}_t + \beta_{p\mathrm{SMB}}^3 \mathrm{SMB}_t + \beta_{p\mathrm{HML}}^3 \mathrm{HML}_t + e_{pt}, \tag{3}$$

where R_{pt} = the rate of return of portfolio p in month t, R_{ft} = the risk-free interest rate in month t, R_{mt} = the rate of return of the market in month t, RMRF_t = the excess market return in month t, SMB_t = the rate of return on the mimicking portfolio for the common size factor in stock returns in month t, HML_t = the rate of return on the mimicking portfolio for the common book-to-market equity factor in stock returns in month t, α = excess returns of the corresponding factor model, and β = factor loadings of the corresponding factors.

Only requiring mutual funds to have return information one month after the portfolio formation means that this approach is free of look-ahead bias, a survivorship bias conditioned on performance as discussed in Brown et al. (1992). The look-ahead bias occurs when we require the fund to survive for a longer period of time in order to be included in the test. However, this approach does not take into account that the portfolio compositions and their risk characteristics are time-varying.[6]

In contrast, the fund regression approach is able to pick up the portfolio variations through time, yet it suffers from look-ahead bias.[7] The α measures of this approach are obtained by averaging the α estimates for individual funds within the portfolio:

$$R_{it} - R_{ft} = \alpha_i^1 + \beta_i^1(R_{mt} - R_{ft}) + e_{it}, \tag{4}$$

$$R_{it} - R_{ft} = \alpha_i^3 + \beta_{i\mathrm{RMRF}}^3 \mathrm{RMRF}_t + \beta_{i\mathrm{SMB}}^3 \mathrm{SMB}_t + \beta_{i\mathrm{HML}}^3 \mathrm{HML}_t + e_{it}, \tag{5}$$

$$\alpha_{pt} = \sum (\alpha_i + e_{it}) * w_{it} / \sum w_{it}, \tag{6}$$

[6] According to Edwin Elton (personal communication), and the evidence in Fama and French (1996) and Ferson and Harvey (1997), the portfolio betas are unstable in multi-index models.

[7] The look-ahead bias is not a problem for the sample used by Elton, Gruber, and Blake (1996a,b) and Gruber (1996), once the mergers are treated using their "follow the money" method. However, the look-ahead bias is still present in my sample because of the existence of some new funds that do not have enough tracking history for the regression analysis.

where R_{it} = the rate of return of fund i in month t, α_{pt} = the excess return of the portfolio of mutual funds in month t, α_i = the excess return of individual mutual funds, and w_{it} = the portfolio weight of fund i in month t.

As I require a minimum of 30 months of return data to perform the time-series OLS estimation for each fund, some of the new funds and defunct funds included in the portfolio regression approach are excluded. The look-ahead bias may affect the accuracy of estimating the performance of new money and the actual effect of the bias can only be observed empirically.

Both approaches that calculate the time-series mean of the cross-section estimates give equal weight to each time period, thus avoiding the practice of assigning more weight to the recent years that incur much larger cash flow. They also recognize the fact that one dollar in 1970 is different from one dollar in 1993 by comparing only dollars within the same time period. Similar to the GT measure, the returns on the eight portfolios are not affected by the size of aggregate money flowing into and out of stock funds.

To evaluate the performance of the trading strategies, I use different measures of returns and risk-adjusted returns:

1. Raw returns
2. Excess return over the market: $R_{it} - R_{mt}$
3. Excess return from the single factor model:

$$R_{it} - R_{ft} = \alpha_i^1 + \beta_i^1(R_{mt} - R_{ft}) + e_{it} \tag{7}$$

4. Excess return from the Fama–French three-factor model:

$$R_{it} - R_{ft} = \alpha_i^3 + \beta_{i\mathrm{RMRF}}^3 \mathrm{RMRF}_t + \beta_{i\mathrm{SMB}}^3 \mathrm{SMB}_t + \beta_{i\mathrm{HML}}^3 \mathrm{HML}_t + e_{it} \tag{8}$$

5. Excess return from the conditional single factor model:

$$R_{it} - R_{ft} = \alpha_i^1 + \delta_{1i}^1(R_{mt} - R_{ft}) + \delta_{2i}^{1\prime}[z_{t-1} * (R_{mt} - R_{ft})] + e_{it} \tag{9}$$

6. Excess return from the conditional Fama–French three-factor model:

$$\begin{aligned} R_{it} - R_{ft} = {} & \alpha_i^3 + \delta_{1i\mathrm{RMRF}}^3 \mathrm{RMRF}_t + \delta_{1i\mathrm{SMB}}^3 \mathrm{SMB}_t + \delta_{1i\mathrm{HML}}^3 \mathrm{HML}_t \\ & + \delta_{2i\mathrm{RMRF}}^{3\prime}(z_{t-1} * \mathrm{RMRF}_t) + \delta_{2i\mathrm{SMB}}^{3\prime}(z_{t-1} * \mathrm{SMB}_t) \\ & + \delta_{2i\mathrm{HML}}^{3\prime}(z_{t-1} * \mathrm{HML}_t) + e_{it}, \end{aligned} \tag{10}$$

where δ = factor loadings of the conditional regression factors and z_{t-1} = a vector of lagged predetermined instruments.

To capture the time-varying property of portfolio risk and to determine whether the smart money effect is due to a rational response to macroeconomic variables, I use the conditional performance measure introduced by

Shanken (1990), Ball et al. (1995), and Ferson and Schadt (1996). The conditional measure views a portfolio strategy that only explores readily available public information as having no superior performance. By incorporating lagged information variables in the traditional factor model, the conditional models estimate time-varying conditional betas and control common variation due to public information. As explained by Ferson and Schadt, the δ_1''s in expressions (9) and (10) can be viewed as an average beta or the mean of the conditional beta. The δ_2''s are the response coefficients of the conditional beta with respect to the instrument variables of public information.

Following Ferson and Schadt (1996), the lagged information variables used are: (1) the level of the one-month Treasury-bill yield, (2) the dividend yield of the CRSP value-weighted NYSE and AMEX stock index, (3) a bond default premium provided by Ibbotson Associates, and (4) a bond horizon premium provided by Ibbotson Associates.

II. Data

The data sample used in this study is a subset of a comprehensive mutual fund database provided by Mark Carhart, Eugene Fama, and Kenneth French. Carhart (1995) has a detailed description of this data set, which reports open-end mutual fund data from December 1961 to December 1993 for funds of all investment objectives, including defunct funds.

This study uses all equity funds over the period of January 1970 through December 1993, during which quarterly fund total net asset values are available. The sample excludes sector funds, international funds, and balanced funds because these funds have different risk components and require additional factors to span the space covered by their investments. The sample includes both load and no-load funds, which enables the comparison of new money performance of load funds to that of no-load funds. In summary, the sample has a total of 1,826 fund-entities and 13,944 fund-years. During the time period examined, there are, on average, 478 funds in existence each month, with a minimum of 281 funds and a maximum of 1,196 funds.

In this study, I include all funds that existed in 1970 as well as all subsequently newly opened funds until December 1993. Thus the return on new investment is estimated using the newly invested money of all diversified equity funds available to investors, instead of only the new money in funds that are listed in Wiesenberger's *Mutual Fund Panorama* at the beginning of 1982 as in Gruber (1996). Since the sample in my study is closer to the opportunity set of equity mutual funds that investors faced in practice, the results based on this sample should provide a more realistic assessment of investors' aggregate fund selection ability.

I define new money or cash flow as the dollar change in total net assets (TNA) minus the appreciation in the fund assets and the increase in total assets due to merger. Two alternative definitions are stated below in expressions (11) and (12) with respect to different timing assumptions. The asset appreciation includes capital appreciation, income, and capital gains distributions. I use the dollar amount of new money instead of the percentage increase in fund assets in order to aggregate new money performance across funds from the perspective of investors. The latter is more appropriate from the perspective of the mutual fund industry. Huge changes in percentage can occur for small funds, but these are not necessarily economically meaningful when we examine the aggregate mutual fund flows. Nevertheless, to check the robustness of my results, I repeat all the tests defining new money as a percentage of a fund's TNA in the previous period. All the major conclusions remain unchanged.

Since we do not know exactly when cash flows occur within each quarter, I calculate new money differently under two extreme assumptions:

ASSUMPTION 1: *New money is invested at the end of each quarter:*

$$\text{Newmoney}_{it} = \text{TNA}_{it} - \text{TNA}_{i,t-1} * (1 + R_{it}) - \text{MGTNA}_{it}. \tag{11}$$

ASSUMPTION 2: *New money is invested at the beginning of each quarter:*

$$\text{Newmoney}_{it} = \text{TNA}_{it}/(1 + R_{it}) - \text{TNA}_{i,t-1} - \text{MGTNA}_{i,t-1}, \tag{12}$$

where MGTNA *is the increase in total net assets due to mergers*.

I perform tests involving new money under both assumptions. Since the empirical results show robustness of the tests to the different calculations of new money, I only report the test results assuming that new investment occurs at the end of each quarter.

III. Empirical Results

A. GT Measure

I calculate quarterly portfolio weights of the aggregate equity fund as the TNA of each fund divided by the sum of the TNA of all funds for each quarter from March 1970 to December 1993. The differenced weights (weights for quarter t minus weights for quarter $t-1$) are multiplied by the corresponding future monthly returns of the funds. For example, the July through September 1970 monthly returns are multiplied by the difference between portfolio weights on June 30, 1970 and the weights on March 31, 1970. By updating the differenced weights every three months and applying them to the monthly return data, I construct a time series of 282 monthly returns for a zero-investment portfolio.

Table I reports the GT performance estimates for the aggregate portfolio in all equity mutual funds. The time-series mean of the performance measure, significance statistics from the t-test, the t-statistics adjusted for autocorrelation using the Newey-West covariance matrix, and the significance level from the nonparametric Wilcoxon test are documented. If the monthly

Table I

GT Performance Estimates for the Aggregate Mutual Fund Portfolios: January 1970 to June 1993

GT Performance measure = $(\Sigma_j R_{j,t+1}(w_{jt} - w_{j,t-1})$, where $R_{j,t+1}$ is the return of fund j between time t and time $t-1$ and w_{jt} is the weight for fund j at time t. I calculate quarterly portfolio weights as the total net assets (TNA) of each fund divided by the sum of the TNA of all funds for each quarter from March 1970 to December 1993. The differenced weights (weights for quarter t minus weights for quarter $t-1$) are multiplied by the corresponding future monthly returns of the funds. For example, the July 1970 through September 1970 returns are multiplied by the difference between portfolio weights on June 30, 1970 and the weights on March 31, 1970. According to Grinblatt and Titman (1993), under the null hypothesis that investors have no selection ability, the GT measures are serially uncorrelated with mean zero. The t-statistic in column five is adjusted for autocorrelation using the Newey-West covariance matrix. The last column reports the probability that the absolute value of the Wilcoxon-Mann-Whitney Rank Z-statistic is greater than the observed Z-statistic under the null hypothesis. Performance measures are in percentage return per month.

	No. of Months	Performance Measure	t-Test Statistic	t-Test Newey-West	Wilcoxon Probability
All funds	282	0.567	4.57	3.41	0.00
Eliminating observations with absolute values greater than 5					
All funds	273	0.222	4.60	3.41	0.00

performance measures are autocorrelated, the Newey-West adjustment corrects the bias caused by the autocorrelation. If the distribution of portfolio returns is highly nonnormal, the nonparametric method provides a more appropriate significance measure.

The average performance for the entire sample period is 57 basis points per month, or approximately 6.84 percent per year, with a high statistical significance level indicated by the t-test with or without Newey-West adjustment, and the nonparametric method. This measure represents the return that aggregate active investors earn. Thus, the GT test results support the smart money effect that investors in aggregate show strong selection ability in mutual fund investment. However, because investors are normally not allowed to short sell funds, the GT measure is not implementable and the abnormal returns are unlikely to be realized by individual investors in practice. In other words, the results of the GT test do not suggest the presence of the information effect.

I examine the distribution of the time-series performance measure to make sure that the positive abnormal performance is not caused by several outliers. In fact, there are a few positive extreme values in my sample. To test the effect of these outliers on the performance measure, I eliminate nine observations for which the absolute value of the monthly measure is higher than 5 percent. All nine observations have positive signs originally. As we would expect, the performance measure becomes much smaller in magnitude, with a mean value of 2.66 percent per year. However, the t-statistic, 4.60, and that with the Newey-West adjustment, 3.41, and the nonparametric probability, 0.0001, all remain statistically significant, indicating that investors are informed about management skills. The performance measure is significantly positive even when I omit the observations with an absolute value higher than two.

As discussed in Grinblatt and Titman (1993), the GT performance measure can be positive for portfolios with increasing expected returns. An alternative performance measure is the intercept in the time-series regression of the dollar returns of the zero-cost portfolio on the market factors. The regression intercept is significantly positive using the one-factor and the three-factor models. Thus the modified measure, which adjusts for systematic risk, also suggests that mutual fund investors have fund selection ability.

Merger activities can bias this test because cash flows caused by mergers are not due to investors' choice. When I use the reported TNA values to construct the quarterly portfolio weights, I find that during the quarter of the event, funds that have cash inflow due to mergers are weighted more heavily than is appropriate. However, because the performance of these funds after mergers is slightly below the performance of the average fund, the bias is small and toward zero.

In short, the GT test suggests that equity mutual fund investors in aggregate display strong fund selection skills in making investment decisions.

B. Trading Strategies

To further explore the practical implications of investors' ability to pick mutual funds, I compare the performance of the eight constructed portfolios as discussed in Section II. The trading strategies study both the smart money effect and the information effect.

B.1. Simple Excess Returns

Table II, Panel A, reports the average monthly excess returns over the market. This performance measure is the same under both the portfolio regression approach and the fund regression approach.

There is no empirical evidence that the allocation of the aggregate portfolio is smart, although the aggregate active buying and selling decisions are. The mean monthly excess return on the average fund is negative during the testing period, indicating that, on average, mutual fund managers do not outperform the market. For the whole time period of 1970 to 1993, the excess return on the TNA-weighted portfolio is even lower than that on the average fund, indicating that invested money measured as stock is not smart for the whole time period. This does not necessarily conflict with the result from the GT test because the former test considers changes in the weights instead of the magnitude of the weights. The change in their weights measure is more similar to the new money measure as opposed to TNA values. In other words, the GT measure suggests that the buying and selling decisions of mutual fund investors are smart; however, it does not imply anything about the allocation of the aggregate portfolio.

The mean simple excess returns of different new money portfolios display the expected relative ranking under the alternative hypothesis that investors have fund selection ability and can outperform the average fund. The positive portfolios 3 and 5 have positive mean excess returns, and all the negative portfolios have negative mean excess returns. The mean excess returns on the positive portfolios are all higher than the return of the average fund, and the mean excess returns on the negative portfolios are all lower than that of the average fund. However, the positive excess returns on the positive portfolios are not statistically different from zero. Thus, for the whole sample there is no significant evidence that the positive new money flow can beat the market. Nevertheless, the excess return on portfolio 3, an equal investment in all funds that incur positive cash flow, is significantly higher than the excess return on the average mutual fund.[8] This finding supports the hypothesis that astute investors can do better than the average mutual fund. The mean excess return on negative portfolio 6 is negative and statistically different from zero. This finding suggests that this negative portfolio of funds underperforms the market. Thus there is some significant evidence that money flows out of funds that subsequently underperform the market.

The positive excess returns on the positive portfolios can be thought of as the excess returns earned by aggregate new money. The absolute value of the negative excess returns on the negative portfolios can be thought of as the excess returns earned by divesting, or by short-selling the fund and buying the market. Table II, Panel B, reports the excess returns earned by the long-short strategies, in which one buys the positive portfolios and sells the corresponding negative portfolios. The excess returns on the long-short strategies provide evidence of investors' ability to select funds by moving away from the poor performers and toward the good performers. For the three long-short trading strategies, all the positive portfolios outperform the negative portfolios. Portfolio 3 outperforms portfolio 4 significantly and portfolio 7 outperforms portfolio 8 significantly. For each performance measure hereafter, positive portfolio 3 always significantly outperforms negative portfolio 4. The above findings support the smart money effect—that investors have fund selection ability. The excess returns on the long-short strategies, however, do not correspond to implementable strategies because investors are normally not allowed to short sell funds in practice. Hence they do not provide evidence of the information effect—that investors can make abnormal returns by exploiting new money flow information. Moreover, as I consider both load and no-load funds at this stage, the actual returns of the portfolios should be adjusted by load charges. The results are virtually the same when the return series are adjusted for autocorrelation using Newey-West covariance matrix.

Should we expect a strengthening of the smart money effect over time, since investors today have access to more mutual fund information than they did previously? I break my sample into two subperiods: June 1970 to

[8] Note that the average mutual fund in this sample underperforms the market.

Table II

Performance of New Money Portfolios Estimated by Simple Excess Returns and Risk-Adjusted Returns Using the Portfolio Regression Approach: January 1970 to December 1993

The excess return is calculated as $R_{it} - R_{mt}$, where R_{it} is the return of portfolio i between time t and time $t-1$, and R_{mt} is market return, the return on a value-weighted portfolio of all stocks listed on the CRSP (Center for Research in Security Prices) database. The t-statistic in parentheses tests the performance difference between the particular portfolio and the average mutual fund. The t-statistics in brackets test the performance difference between the particular portfolio and the market. Alpha$_1$ is calculated from the time series regression of portfolio returns on the single factor model: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + e_{pt}$. R_{pt} is the rate of return of portfolio p in month t, R_{ft} is the risk-free interest rate in month t, α_p is the excess return of the model, and β_p is the factor loading of the market factor. The t-statistics in parentheses test whether alpha$_1$ is significantly different from zero. Alpha$_3$ is calculated from the time-series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: $R_{pt} - R_{ft} = \alpha_p + \beta_{p\mathrm{RMRF}}\mathrm{RMRF}_t + \beta_{p\mathrm{SMB}}\mathrm{SMB}_t + \beta_{p\mathrm{HML}}\mathrm{HML}_t + e_{pt}$. The excess market return, RMRF, is the difference between the return on a value-weighted CRSP stock portfolio and 1-month T-bill yields. SMB is the return on the mimicking portfolio for the common size factor in stock returns. HML is the return on the mimicking portfolio for the common book-to-market equity factor in stock returns. RMRF, SMB, and HML are constructed according to the descriptions in Fama and French (1993). β_p is the factor loading of the corresponding factor. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. New money = $\mathrm{TNA}_{it} - \mathrm{TNA}_{i,t-1} * (1 + \mathrm{R}_{it}) - \mathrm{MGTNA}_{it}$, where TNA is total net assets, and MGTNA is the increase in total net assets due to mergers. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero, and the t-statistics in brackets are adjusted for autocorrelation using the Newey-West covariance matrix. Performance measures are in percentage return per month.

Portfolios	Excess Return	Alpha$_1$	Alpha$_3$
Panel A: Portfolio Performance			
1. Average fund	−0.046	−0.025	0.009
	(NA)	(−0.40)	(0.19)
	[−0.72]		
2. Weighted by total net asset	−0.058	−0.042	0.001
	(−0.27)	(−1.15)	(0.03)
	[−1.58]		
3. Positive cash flow (EW)	0.025	0.035	0.074
	(1.97)	(0.56)	(1.71)
	[0.41]		
4. Negative cash flow (EW)	−0.074	−0.053	−0.027
	(−0.76)	(−1.09)	(−0.70)
	[−1.49]		
5. Positive cash flow (CW)	0.003	0.002	0.089
	(0.85)	(0.03)	(1.54)
	[0.04]		
6. Negative cash flow (CW)	−0.103	−0.077	−0.039
	(−1.13)	(−1.73)	(−0.92)
	[−2.23]		
7. Upper 50 percent of all cash flow (EW)	−0.003	0.008	0.039
	(1.28)	(0.13)	(0.96)
	[−0.05]		
8. Lower 50 percent of all cash flow(EW)	−0.084	−0.060	−0.022
	(−0.96)	(−1.26)	(−0.55)
	[−1.71]		

Table II—*Continued*

Panel B: Performance Difference between the Positive and Negative Portfolios	
	Excess Return Mean Difference
Portfolio 3 − Portfolio 4	0.099
	(2.93)
	[2.66]
Portfolio 5 − Portfolio 6	0.106
	(1.62)
	[1.48]
Portfolio 7 − Portfolio 8	80.081
	(2.37)
	[2.21]

March 1982 and April 1982 to December 1993.[9] I perform a two-sample t-test to examine whether the performance differences between the positive and negative portfolios are the same in the two subperiods. The t-test cannot reject the null hypothesis that the performance differences are the same for the two subperiods.[10] There is no evidence supporting the hypothesis that new money is smarter in the later period.

The positive and negative new money portfolios that can best predict performance are portfolios 3 and 6. The positive new money portfolio that earns the highest abnormal return invests equally in funds with positive cash flow. The difference between its performance and that of a money-weighted positive portfolio might be explained by the hypothesis that performance may drop for funds with huge cash inflow. It might be hard for these funds to quickly find enough good opportunities for all the money, and thus their subsequent returns would be diluted. The negative portfolio with the lowest abnormal return is the money-weighted negative portfolio. This supports the conjecture that funds with big cash outflows possibly suffer from forced liquidation and lack of economy of scale and thus continue to perform very poorly.

In summary, investors do display fund selection ability, because the evidence shows that the positive portfolios outperform the negative portfolios. The significance tests show some evidence that informed investors can beat the average fund. For the whole sample, there is no significant evidence that investors can beat the market by investing in funds with positive new money.

[9] The test result is robust to various ways of breaking the sample period.

[10] The t-statistics testing the performance differences according to α_3 for the two sample periods are −0.70, 0.53, and −1.30, respectively, for portfolio 3 minus portfolio 4, portfolio 5 minus portfolio 6, and portfolio 7 minus portfolio 8. Test results are similar using the excess returns or α_1.

B.2. The Portfolio Regression Approach

The performance measures of the portfolio regression approach are obtained by regressing the time series of portfolio raw returns against the benchmarks. The last two columns of Table II, Panel A, report the regression results for the constructed portfolios using the traditional one-factor model and the three-factor model, respectively. The relative performance ranking of the portfolios is very similar to that of the simple excess return. The mean α_1 on the average fund is negative and the mean α_3 on the average fund is positive. Both are insignificant. Although the risk-adjusted performance measures are sensitive to the choice of benchmarks, we observe the expected signs of the abnormal returns of the positive and negative portfolios clearly.

One possible explanation of the smart money effect, or investors' fund selection ability, is that investors respond rationally to publicly available macroeconomic information—for example, interest rate variables. If this is the case, the conditional method should be able to explain away the effect. Another possible explanation of the effect is that investors select superior styles instead of superior managers. There is clear evidence that certain styles of funds perform better at different times. For example, the small firm effect has displayed a secular trend. To address this, I use the Fama and French three-factor model in a conditional beta framework.

The regression results are basically unchanged by conditioning on macro variables and style variables using the Ferson and Schadt (1996) conditional regression method. This observation provides a clue as to the source of the smart money effect. The effect is due neither to responses to macroeconomic information nor to predictable style effects, but likely is due to fund-specific information. Compared to the traditional regression, two of the three positive portfolios have slightly higher abnormal returns and lower average betas, and all of the negative portfolios have slightly lower abnormal returns and higher average betas. This result is consistent with Ferson and Warther's (1996) finding that funds' betas are negatively correlated with funds' new money flows.

B.3. The Fund Regression Approach

Table III reports the portfolio α_1 and α_3 from the fund regression approach using the unconditional and conditional one-factor and three-factor models. As we observe, the relative performance ranking of the portfolios remains the same. Both α_1 and α_3 for portfolios 3 and 7 are significantly higher than the returns on the average mutual fund. The α_3 for portfolios 4 and 8 is significantly lower than the returns on the average mutual fund. However, the stronger selection ability of investors can be caused by excluding some short-lived funds and new funds from the sample, since the performance of these funds might be more difficult for investors to evaluate than the ones with relatively long track records.

According to the conditional regressions using the fund regression approach, the relative performance differences and rankings of portfolios are similar to the earlier results. Thus, the smart money effect obtains under the conditional regression approach. The mean and median abnormal returns are higher under the conditional regression than those under the traditional one. This is similar to the finding in Ferson and Schadt (1996) that using the conditional regression improves the performance measure of their sample. Again, we need to be cautious in interpreting the numbers because the discrepancy can be caused by the look-ahead bias in the fund regression approach, which does not include short-lived funds and very new funds. Since short-lived funds usually incur negative cash flow during their existence, had I included them in the test they more likely would have had higher betas and lower alphas under the conditional methods. Once these funds are left out, the look-ahead or survivorship problem can bias the conditional abnormal returns upward.

B.4. Persistence in Performance and the Smart Money Effect

Why is money smart? There is extensive evidence (see footnote 1) that past fund performance influences money flows and that performance persists. Thus the relationship between the smart money effect and performance persistence is worth examining.

As mentioned earlier, it is well documented that performance persists. Carhart (1997) suggests that the "hot hands" phenomenon is mostly driven by the one-year momentum effect of Jegadeesh and Titman (1993). Grinblatt, Titman, and Wermers (1999) document that the majority of mutual funds existing during the 1975–1984 period followed a momentum strategy in selecting stocks—that is, buying past winners and selling past losers. Wermers (1999) finds evidence of herding behavior among mutual funds. Wermers also reports that the stocks the funds bought as a herd had significantly higher abnormal returns during the following quarters than stocks the funds sold as a herd. One other potential explanation of the persistence phenomenon is that management ability is not included in the price of open-end funds, nor is it reflected in fees and expenses as documented in Elton et al. (1996b) and Gruber (1996).[11] As documented in footnote 1, there is also extensive evidence that past performance influences investor new money flows. Together, these findings imply that the smart money effect might be explained by investors forecasting future open-end fund performance using past performance information. How closely does the smart money effect relate to persistence in performance? Are smart investors simply exploiting the "repeat winner" phenomenon?

By comparing the component funds of the smart money strategy and the repeat winner strategy, I find significant differences in these strategies. Figure 1 examines the percentage of past winners in the above-median new money portfolio. If the smart money effect is simply a proxy for the "performance chasing" phenomenon, the percentage should be close to one. However, the figure shows that the average percentage is only slightly higher

[11] One possible explanation is that the labor market for fund managers is inefficient.

Table III

Performance of New Money Portfolios Estimated by Unconditional and Conditional Risk-Adjusted Returns Using the Fund Regression Approach: January 1970 to December 1993

Alpha$_1$ is calculated as the weighted average of the realized alphas of the individual funds obtained from the time-series regression: $R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + e_{it}$. R_{it} is the rate of return of fund i in month t; R_{mt} is market return, the return on a value-weighted portfolio of all stocks listed on the CRSP (Center for Research in Security Prices) database; R_{ft} is the risk-free interest rate in month t; α_i is the excess return of the model, and β_i is the factor loading of the market factor. Alpha$_3$ is calculated as the weighted average of the realized alphas of the individual funds obtained from the time-series regression: $R_{it} - R_{ft} = \alpha_i + \beta_{i\text{RMRF}}\text{RMRF}_t + \beta_{i\text{SMB}}\text{SMB}_t + \beta_{i\text{HML}}\text{HML}_t + e_{it}$. The excess market return, RMRF, is the difference between the return on a value-weighted CRSP stock portfolio and 1-month T-bill yields. SMB is the return on the mimicking portfolio for the common size factor in stock returns. HML is the return on the mimicking portfolio for the common book-to-market equity factor in stock returns. RMRF, SMB, and HML are constructed according to the descriptions in Fama and French (1993). β_i is the factor loading of the corresponding factor. The conditional alpha$_1$ is calculated as the weighted average of the realized alphas of the individual funds obtained from the time-series regressions: $R_{it} - R_{ft} = \alpha_i + \delta_{1i}(R_{mt} - R_{ft}) + \delta'_{2i}[z_{t-1} * (R_{mt} - R_{ft})] + e_{it}$. The conditional alpha$_3$ is calculated as the weighted average of the realized alphas of the individual funds obtained from the time series regressions: $R_{it} - R_{ft} = \alpha_i + \delta_{1i\text{RMRF}}\text{RMRF}_t + \delta_{1i\text{SMB}}\text{SMB}_t + \delta_{1i\text{HML}}\text{HML}_t + \delta'_{2i\text{RMRF}}(z_{t-1} * \text{RMRF}_t) + \delta'_{2i\text{SMB}}(z_{t-1} * \text{SMB}_t) + \delta'_{2i\text{HML}}(z_{t-1} * \text{HML}_t) + e_{it}$, where z is a vector of lagged predetermined instruments, and δ's are the factor loadings of the conditional regression factors. The t-statistic in parentheses tests the performance difference between the particular portfolio and the average mutual fund. The t-statistic in brackets tests the performance difference between the particular portfolio and the market. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. New money = $\text{TNA}_{it} - \text{TNA}_{i,t-1} * (1 + R_{it}) - \text{MGTNA}_{it}$, where TNA is total net assets, and MGTNA is the increase in total net assets due to mergers. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero and the t-statistics in brackets are adjusted for autocorrelation using the Newey-West covariance matrix. Performance measures are in percentage return per month.

Portfolios	Alpha$_1$	Alpha$_3$	Conditional Alpha$_1$	Conditional Alpha$_3$
Panel A: Portfolio Performance				
1. Average fund	−0.039	0.004	0.006	0.037
	(NA)	(NA)	(NA)	(NA)
	[−0.76]	[0.12]	[0.12]	[1.19]
2. Weighted by total net asset	−0.041	0.013	−0.023	0.039
	(−0.08)	(0.52)	(−1.01)	(0.11)
	[−1.33]	[0.30]	[−0.75]	[1.22]
3. Positive cash flow (EW)	0.047	0.072	0.083	0.088
	(4.31)	(4.57)	(4.01)	(3.73)
	[0.80]	[1.85]	[1.45]	[2.51]
4. Negative cash flow (EW)	−0.055	−0.020	−0.025	0.006
	(−1.27)	(−2.80)	(−2.40)	(−3.67)
	[−1.15]	[−0.57]	[−0.54]	[0.19]
5. Positive cash flow (CW)	0.016	0.059	0.027	0.079
	(1.32)	(1.70)	(0.55)	(1.48)
	[0.25]	[1.37]	[0.46]	[2.04]

Table III—*Continued*

Portfolios	$Alpha_1$	$Alpha_3$	Conditional $Alpha_1$	Conditional $Alpha_3$
Panel A: Portfolio Performance (*continued*)				
6. Negative cash flow (CW)	−0.087	−0.031	−0.072	−0.002
	(−1.55)	(−1.87)	(−2.54)	(−2.29)
	[−2.08]	[−0.90]	[−1.75]	[−0.07]
7. Upper 50 percent of all cash flow (EW)	0.015	0.041	0.057	0.064
	(3.63)	(3.55)	(3.42)	(2.63)
	[0.27]	[1.11]	[1.30]	[1.91]
8. Lower 50 percent of all cash flow (EW)	−0.065	−0.017	−0.038	0.008
	(−1.57)	(−2.01)	(−2.67)	(−2.84)
	[−1.40]	[−0.47]	[−0.86]	[0.26]
Panel B: Mean Difference between the Positive and Negative Portfolios				
Portfolio 3 − Portfolio 4	0.102	0.092	0.108	0.082
	(3.54)	(4.42)	(3.89)	(4.30)
	[3.29]	[4.04]	[3.54]	[3.82]
Portfolio 5 − Portfolio 6	0.103	0.090	0.099	0.081
	(1.95)	(2.40)	(1.97)	(2.39)
	[1.81]	[2.35]	[1.81]	[2.28]
Portfolio 7 − Portfolio 8	0.080	0.058	0.095	0.055
	(2.69)	(3.03)	(3.27)	(3.07)
	[2.56]	[2.87]	[3.07]	[2.89]

than 50 percent. The rank correlation between new money deciles and deciles formed on the basis of last period's performance is, on average, 0.27 for each time period.[12] These findings suggest that the smart money effect is related to but not equivalent to the "hot money" that chases past performance.

How do the returns of the new money portfolios compare to the returns of the portfolios based on past performance? To answer this question, I form eight performance-trading strategies based on performance signals instead of new money signals in the previous quarter. The results are reported in Table IV. The formation of the portfolios is similar to that of the new money portfolios. The portfolios are invested as follows:

Portfolio 1: Equally in all available funds.

Portfolio 2: In all available funds, weighted by funds' current Total Net Assets.

Portfolio 3: Equally in all available funds with positive excess returns.

Portfolio 4: Equally in all available funds with negative excess returns.

[12] When I aggregate through time, the correlation is 0.89. The discrepancy between the rank correlation for each time period and the rank correlation aggregating through time can be explained by the hypothesis that in months of heavy aggregate cash inflows, performance and flows are highly correlated, and in months of cash outflows or light cash inflows, performance and flows are not closely related.

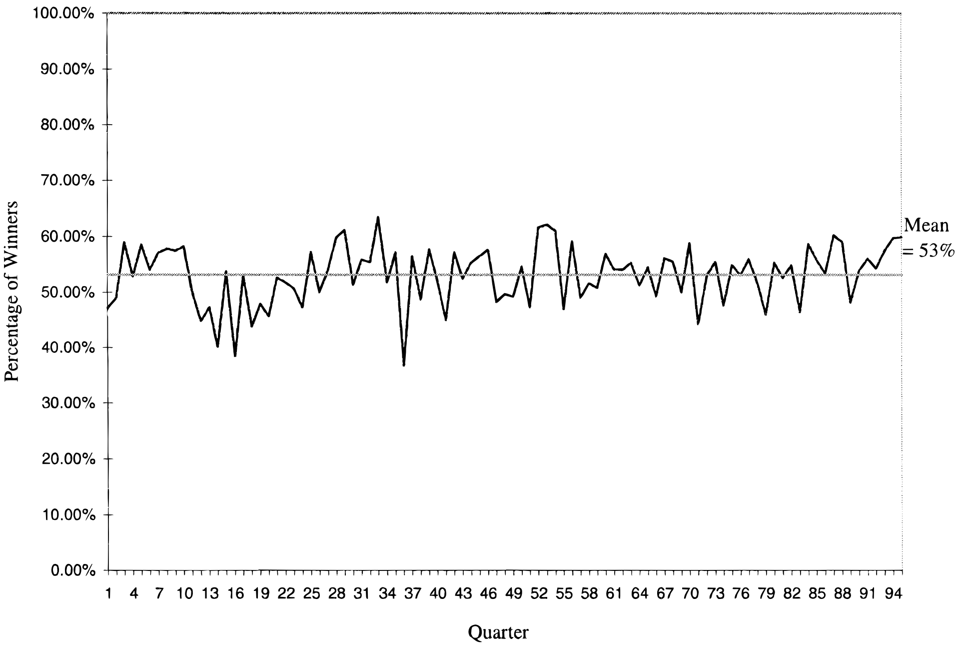

Figure 1. Percentage of past winners in the above-median new money portfolio. All funds are ranked by their returns and new money in the previous quarter. New money is defined as the dollar change in total net assets minus the appreciation in the fund assets and the increase in the total assets due to mergers. A fund is defined as a past winner if the return of the fund in the previous quarter is above the median performance of all funds in that same quarter. Otherwise, it is defined as a past loser. A fund belongs to the above-median new money portfolio if its amount of new money cash flow in the previous quarter is greater than the median cash flow of all funds in that same quarter. Otherwise, it belongs to the below-median new money portfolio. This figure plots the percentages of funds with above-median previous quarter returns in the above-median new money portfolio for each quarter from April 1970 to December 1993.

Portfolio 5: In all available funds with positive excess returns, weighted by funds' TNA.

Portfolio 6: In all available funds with negative excess returns, weighted by funds' TNA.

Portfolio 7: Equally in all available funds with above-median excess returns.

Portfolio 8: Equally in all available funds with below-median excess returns.

Table V reports the regression results of the risk-adjusted excess returns of the equally weighted new money portfolios on those of the equally weighted performance portfolios. The regression results suggest that the time series of α_3 on the two sets of trading strategies are significantly different from each other. On the other hand, a significant percentage of the variations in the risk-adjusted excess returns of the smart money strategy can be explained by the variations in the risk-adjusted excess returns of the repeat winner strategy. The coefficients on the risk-adjusted excess returns of the performance portfolios are significantly different from one. This observation indicates that we can reject the null hypothesis that the time series of risk-adjusted excess returns of these two strategies are identical. Nevertheless, the mean risk-adjusted excess returns of the new money portfolios are not significantly different from the mean risk-adjusted excess returns of the corresponding performance portfolios. As we observe, the coefficients on the risk-adjusted excess returns of the performance portfolios range from 83 percent to 88 percent, and R^2 ranges from 66 percent to 76 percent. The results are similar when I use the risk-adjusted excess returns over the average mutual fund instead of those over the market. These findings indicate that a significant percentage of the variations in the performance of the smart money strategy can be explained by the variations in the performance of the repeat winner strategy. Given the difference in the compositions of the portfolios of the two strategies, we can infer that some common factors may influence both. Brown and Goetzmann (1995), for instance, hypothesize that trends in the repeat winner phenomenon suggest that performance persistence is due to a common factor. One possible explanation is the momentum in stock returns. Carhart (1997) indicates that Jegadeesh and Titman's (1993) one-year momentum effect accounts for Hendricks et al.'s (1993) hot hands effect in mutual fund performance. Since the smart money effect is closely related to performance persistence, it is possible that momentum is the link between the findings that past returns influence flows and that investors make the right move ex ante. It would be interesting to investigate further whether the smart money effect can be explained by the momentum effect in stock returns.

B.5. Small Funds versus Large Funds

Does fund size affect investors' fund selection ability? Are investors more cautious when investing in small funds than in large funds? Is management skill more pronounced when a fund is small? If so, we would expect smart money to display some size effect.

Table VI reports the performance of the new money portfolios for small and large funds separately. Interestingly, small funds display a very strong smart money effect, but large funds display almost no such effect. For small funds, all the positive portfolios outperform the negative portfolios significantly. For large funds, none of the positive portfolios outperform the negative portfolios significantly. The highest abnormal return is earned by portfolio 5 of small funds which has a significant positive α_3 as high as 2.2 percent per year. The performance difference in α_3 between positive portfolio 5 and negative portfolio 6 is roughly 3.1 percent per year for small funds. More abnormal returns come from joining the positive portfolios than leaving the negative portfolios. This asymmetry is consistent with the hypothesis that investors are more cautious in buying small funds than in selling small funds. Within the small fund group, the trading strategies that

Table IV

Risk-Adjusted Returns of the Performance Portfolios: January 1970 to December 1993

The excess return is calculated as $R_{it} - R_{mt}$, where R_{it} is the return of portfolio i between time t and time $t - 1$, and R_{mt} is market return, the return on a value-weighted portfolio of all stocks listed on the CRSP (Center for Research in Security Prices) database. The t-statistic in parentheses tests the performance difference between the particular portfolio and the average mutual fund. The t-statistics in brackets test the performance difference between the particular portfolio and the market. Alpha$_1$ is calculated from the time series regression of portfolio returns on the single factor model: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + e_{pt}$. R_{pt} is the rate of return of portfolio p in month t; R_{ft} is the risk-free interest rate in month t; α_p is the excess return of the model, and β_p is the factor loading of the market factor. The t-statistics in parentheses test whether alpha$_1$ is significantly different from zero. Alpha$_3$ is calculated from the time-series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: $R_{pt} - R_{ft} = \alpha_p + \beta_{p\mathrm{RMRF}}\mathrm{RMRF}_t + \beta_{p\mathrm{SMB}}\mathrm{SMB}_t + \beta_{p\mathrm{HML}}\mathrm{HML}_t + e_{pt}$. The excess market return, RMRF, is the difference between the return on a value-weighted CRSP stock portfolio and 1-month T-bill yields. SMB is the return on the mimicking portfolio for the common size factor in stock returns. HML is the return on the mimicking portfolio for the common book-to-market equity factor in stock returns. RMRF, SMB, and HML are constructed according to the descriptions in Fama and French (1993). β_p is the factor loading of the corresponding factor. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. New money = $\mathrm{TNA}_{it} - \mathrm{TNA}_{i,t-1} * (1 + R_{it}) - \mathrm{MGTNA}_{it}$, where TNA is total net assets, and MGTNA is the increase in total net assets due to mergers. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero, and the t-statistics in brackets are adjusted for autocorrelation using the Newey-West covariance matrix. Performance measures are in percentage return per month.

Portfolios	Excess Return	Alpha$_1$	Alpha$_3$
Panel A: Portfolio Performance			
1. Average fund	−0.046	−0.025	0.009
	(NA)	(−0.40)	(0.19)
	[−0.72]		
2. Weighted by total net asset	−0.058	−0.042	0.001
	(−0.27)	(−1.15)	(0.03)
	[−1.58]		
3. Positive excess return (EW)	0.014	0.030	0.051
	(1.06)	(0.45)	(0.82)
	[0.21]		
4. Negative excess return (EW)	−0.140	−0.109	−0.073
	(−1.75)	(−1.76)	(−1.34)
	[−2.21]		
5. Positive excess return (CW)	−0.018	0.003	0.035
	(0.44)	(0.06)	(0.69)
	[−0.36]		
6. Negative excess return (CW)	−0.136	−0.103	−0.057
	(−1.36)	(−1.89)	(−1.05)
	[−2.39]		
7. Upper 50 percent of all excess return (EW)	0.014	0.026	0.050
	(1.15)	(0.38)	(0.84)
	[0.21]		
8. Lower 50 percent of all excess return (EW)	−0.138	−0.113	−0.072
	(−1.74)	(−1.65)	(−1.26)
	[−2.00]		

Table IV—*Continued*

Panel B: Performance Difference between the Positive and Negative Portfolios	
	Excess Return Mean Difference
Portfolio 3 − Portfolio 4	0.154
	(1.82)
Portfolio 5 − Portfolio 6	0.117
	(1.53)
Portfolio 7 − Portfolio 8	0.153
	(1.77)

use new money cash flow as weights do better than the trading strategies that use equal weights for all funds. This observation suggests that the size or relative size of cash flows helps to predict future fund returns within the sample of small funds.

Using an alternative definition of new money, I divide each new cash flow by the net asset value of the fund in the previous period so that new money represents percentage growth. By doing so, we give more weight to funds with small asset values. As the basic results are similar to those of Table VI, the size effect is even more obvious under this alternative definition of new money.

In summary, the smart money effect is caused primarily by money flowing into and out of small funds. The reasons for this size effect are worthy of further exploration.

B.6. Load Funds versus No-Load Funds

One chance we might have to test the different investment behavior of informed and uninformed investors is to investigate the portfolio performance of load and no-load funds separately. On one hand, the common view is that investors in load funds are not as well informed as investors in no-load funds. On the other hand, the higher cost of trading in load funds may make the new money flows of load funds seem smarter than their no-load counterparts. The empirical evidence in this paper supports the latter view.

I form portfolios according to the same strategies for load and no-load funds separately. Table VII presents the excess returns and α_3 for the two groups. As we observe, positive portfolios of load funds have abnormal returns higher than those of the corresponding no-load portfolios. This empirical finding is similar to the evidence in Gruber (1996). Although the above results are not statistically significant, the performance difference between the positive and negative portfolios is significant for the three pairs of buy-sell portfolios based on the new money of load funds, but only significant for portfolios 3 and 4 of no-load funds. This finding seems to be further evidence that investors have information about future fund performance. Note that these constructed returns have not been adjusted for load. Intuitively, in-

Table V

Regressions Examining the Relationship between the Risk-Adjusted Excess Returns of the New Money Portfolios and the Performance Portfolios

$$\alpha^3_{\text{newmoney},t} = a + \beta\alpha^3_{\text{performance},t} + e_t$$

$\alpha^3_{\text{newmoney},t}$ and $\alpha^3_{\text{performance},t}$ are calculated as the weighted average of the realized alphas of the individual funds obtained from the time-series regression: $R_{it} - R_{ft} = \alpha_i + \beta_{i\text{RMRF}}\text{RMRF}_t + \beta_{i\text{SMB}}\text{SMB}_t + \beta_{i\text{HML}}\text{HML}_t + e_{it}$. $\alpha^3_{\text{newmoney},t}$ is the risk-adjusted excess return of a portfolio of funds constructed according to their new money signals in the previous quarter. $\alpha^3_{\text{performance},t}$ is the risk-adjusted excess return of a portfolio of funds constructed according to their performance in the previous quarter. The t-statistics are in parentheses. The t-statistic for α tests whether it is different from zero and the t-statistic for β tests whether it is different from one.

Portfolios	α	β	R^2
Equally weighted positive new money portfolio on equally weighted positive performance portfolio	−0.000 (−0.28)	0.883 (−4.59)	0.70
Equally weighted negative new money portfolio on equally weighted negative performance portfolio	0.000 (1.56)	0.827 (−5.83)	0.66
Equally weighted above-median new money portfolio on equally weighted above-median performance portfolio	−0.000 (−1.39)	0.834 (−8.58)	0.76
Equally weighted below-median new money portfolio on equally weighted below-median performance portfolio	0.000 (2.09)	0.858 (−5.50)	0.68

vestors are reluctant to buy load funds unless they believe that they will be compensated by a return premium, and they are reluctant to sell load funds unless they believe that the fund performance is indeed bad and worth paying for the end-load. Thus, we expect the new money of load funds to have a stronger signal than that of no-load funds before deducting load charges. In fact, I observe a stronger smart money effect for load funds than for no-load funds.

B.7. Lagged New Money Portfolios

Can investors earn superior returns by following trading strategies that exploit the smart money effect? In other words, is there an information effect? The returns on the previous new money portfolios may not represent the returns that investors can earn in practice. One concern is that cash flow information is not available to the public in time for an investor to form and hold a new money portfolio for the immediate following quarter. To capture this delay in information, I modify my new money portfolios to allow for a delay in the cash flow signal.

Table VIII reports the abnormal returns of the new money portfolios delayed for a month and for a quarter. With a delay of a month, the smart money effect is only marginally significant. The difference in the abnormal returns of portfolio 3 and portfolio 4 is about 83 basis points per year and is statistically significant. However, the abnormal returns earned by investing

Table VI

Performance of the New Money Portfolios for Small Funds and Large Funds: January 1970 to December 1993

Small funds are funds for which the total net assets (TNA) are smaller than the median TNA. Large funds are funds for which the total net assets are greater than the median TNA. The excess return is calculated as $R_{it} - R_{mt}$, where R_{it} is the return of portfolio i between time t and time $t-1$, and R_{mt} is market return, the return on a value weighted portfolio of all stocks listed on the CRSP (Center for Research in Security Prices) database. Alpha$_3$ is calculated from the time-series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: $R_{pt} - R_{ft} = \alpha_p + \beta_{p\mathrm{RMRF}}\mathrm{RMRF}_t + \beta_{p\mathrm{SMB}}\mathrm{SMB}_t + \beta_{p\mathrm{HML}}\mathrm{HML}_t + e_{pt}$. The t-statistics in parentheses test the performance difference between the particular portfolio and the average mutual fund. The t-statistics in brackets test the performance difference between the particular portfolio and the market. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero. Performance measures are in percentage return per month.

	Small Funds		Large Funds	
Portfolios	Excess Return	Alpha$_3$	Excess Return	Alpha$_3$
Panel A: Portfolio Performance				
1. Average fund	−0.028	−0.009	−0.065	0.007
	(NA)	(NA)	(NA)	(NA)
	[−0.30]	[−0.25]	[−1.33]	[0.19]
2. Weighted by total net asset	−0.022	0.016	−0.061	0.009
	(0.14)	(3.49)	(0.16)	(0.34)
	[−0.55]	[0.38]	[−1.68]	[0.27]
3. Positive cashflow (EW)	0.077	0.099	−0.021	0.045
	(1.74)	(5.62)	(1.51)	(2.07)
	[1.07]	[2.24]	[−0.35]	[1.15]
4. Negative cashflow (EW)	−0.112	−0.064	−0.048	0.015
	(−1.36)	(−3.59)	(0.99)	(0.94)
	[−1.65]	[−1.61]	[−1.05]	[0.40]
5. Positive cashflow (CW)	0.202	0.181	−0.020	0.045
	(2.84)	(4.82)	(0.92)	(1.16)
	[2.32]	[3.17]	[−0.30]	[1.03]
6. Negative cashflow (CW)	−0.139	−0.077	−0.101	−0.028
	(−1.34)	(−1.58)	(−1.11)	(−1.91)
	[−1.53]	[−1.31]	[−2.23]	[−0.79]
7. Upper 50 percent of all cashflow (EW)	0.054	0.070	−0.048	0.029
	(1.41)	(5.06)	(1.01)	(2.10)
	[0.79]	[1.69]	[−0.87]	[0.76]
8. Lower 50 percent of all cashflow (EW)	−0.108	−0.051	−0.056	0.010
	(−1.27)	(−2.68)	(0.43)	(0.31)
	[−1.57]	[−1.22]	[−1.23]	[0.28]
Panel B: Mean Difference between the Positive and Negative Portfolios				
Portfolio 3 − Portfolio 4	0.189	0.163	0.027	0.031
	(4.65)	(5.50)	(0.65)	(1.23)
Portfolio 5 − Portfolio 6	0.342	0.258	0.081	0.073
	(4.55)	(4.51)	(1.19)	(1.86)
Portfolio 7 − Portfolio 8	0.163	0.121	0.008	0.019
	(4.30)	(4.35)	(0.24)	(0.95)

Table VII

Performance of the New Money Portfolios for Load and No-Load Funds: January 1970 to December 1993

The excess return is calculated as $R_{it} - R_{mt}$, where R_{it} is the return of portfolio i between time t and time $t-1$, and R_{mt} is market return, the return on a value weighted portfolio of all stocks listed on the CRSP (Center for Research in Security Prices) database. Alpha$_3$ is calculated from the time-series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: $R_{pt} - R_{ft} = \alpha_p + \beta_{p\text{RMRF}}\text{RMRF}_t + \beta_{p\text{SMB}}\text{SMB}_t + \beta_{p\text{HML}}\text{HML}_t + e_{pt}$. The t-statistics in parentheses test the performance difference between the particular portfolio and the average mutual fund. The t-statistics in brackets test the performance difference between the particular portfolio and the market. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero. Performance measures are in percentage return per month.

	Load Funds		No-Load Funds	
Portfolios	Excess Return	Alpha$_3$	Excess Return	Alpha$_3$
Panel A: Portfolio Performance				
1. Average fund	−0.050	0.010	−0.033	0.019
	(NA)	(NA)	(NA)	(NA)
	[−0.87]	[0.26]	[−0.42]	[0.54]
2. Weighted by total net asset	−0.050	0.021	−0.050	−0.004
	(−0.01)	(0.75)	(−0.81)	(−0.85)
	[−1.36]	[0.59]	[−1.36]	[−0.11]
3. Positive cash flow (EW)	0.038	0.091	0.016	0.058
	(3.05)	(4.89)	(0.90)	(1.66)
	[0.62]	[2.16]	[0.23]	[1.39]
4. Negative cash flow (EW)	−0.063	−0.006	−0.056	−0.010
	(−0.48)	(−1.76)	(−0.41)	(−2.05)
	[−1.29]	[−0.17]	[−0.98]	[−0.27]
5. Positive cash flow (CW)	0.058	0.109	−0.059	0.015
	(2.13)	(3.02)	(−0.32)	(−0.08)
	[0.87]	[2.34]	[−0.67]	[0.27]
6. Negative cash flow (CW)	−0.091	−0.019	−0.075	−0.027
	(−0.92)	(−1.29)	(−0.63)	(−1.45)
	[−1.97]	[−0.52]	[−1.27]	[−0.59]
7. Upper 50 percent of all cash flow (EW)	0.013	0.067	−0.011	0.028
	(2.48)	(5.26)	(0.45)	(0.53)
	[0.21]	[1.66]	[−0.16]	[0.74]
8. Lower 50 percent of all cash flow (EW)	−0.076	−0.011	−0.063	−0.001
	(−0.86)	(−1.83)	(−0.52)	(−1.22)
	[−1.58]	[−0.31]	[−1.12]	[−0.03]
Panel B: Mean Performance Difference between the Positive and Negative Portfolios				
Portfolio 3 − Portfolio 4	0.101	0.097	0.072	0.068
	(2.93)	(4.21)	(1.53)	(2.00)
Portfolio 5 − Portfolio 6	0.149	0.128	0.016	0.042
	(2.44)	(3.37)	(0.18)	(0.65)
Portfolio 7 − Portfolio 8	0.088	0.079	0.053	0.029
	(2.63)	(3.82)	(1.21)	(0.94)

Table VIII

Performance of the Lagged New Money Portfolios for All Funds and Small Funds: January 1970 to December 1993

Small funds are funds for which the total net assets are smaller than the median TNA. Large funds are funds for which the total net assets are greater than the median TNA. Alpha$_3$ is calculated from the time series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: $R_{pt} - R_{ft} = \alpha_p + \beta_{p\mathrm{RMRF}}\mathrm{RMRF}_t + \beta_{p\mathrm{SMB}}\mathrm{SMB}_t + \beta_{p\mathrm{HML}}\mathrm{HML}_t + e_{pt}$. The t-statistics in parentheses test the performance difference between the particular portfolio and the average mutual fund. The t-statistics in brackets test the performance difference between the particular portfolio and the market. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero. Performance measures are in percentage return per month.

	Alpha$_3$			
	All Funds		Small Funds	
Portfolios	Lagged for a Month	Lagged for a Quarter	Lagged for a Month	Lagged for a Quarter
Panel A: Portfolio Performance				
1. Average fund	0.008	0.015	−0.007	0.000
	(NA)	(NA)	(NA)	(NA)
	[0.23]	[0.44]	[−0.20]	[0.01]
2. Weighted by total net asset	0.013	0.009	0.019	0.016
	(0.41)	(0.03)	(3.04)	(3.28)
	[0.41]	[0.28]	[0.46]	[0.38]
3. Positive cash flow (EW)	0.063	0.047	0.079	0.056
	(3.52)	(1.95)	(4.39)	(2.66)
	[1.60]	[1.27]	[1.77]	[1.32]
4. Negative cash flow (EW)	−0.007	0.005	−0.034	−0.000
	(−1.62)	(−1.18)	(−1.68)	(−0.05)
	[−0.20]	[0.14]	[−0.86]	[−0.01]
5. Positive cash flow (CW)	0.044	0.011	0.149	0.137
	(1.10)	(−0.13)	(4.32)	(4.07)
	[1.00]	[0.26]	[2.70]	[2.51]
6. Negative cash flow (CW)	−0.006	0.012	−0.013	0.039
	(−0.73)	(−0.20)	(−0.13)	(1.11)
	[−0.17]	[0.32]	[−0.23]	[0.73]
7. Upper 50 percent of all cash flow (EW)	0.033	0.037	0.059	0.048
	(2.27)	(1.99)	(4.00)	(2.78)
	[0.88]	[1.00]	[1.42]	[1.19]
8. Lower 50 percent of all cash flow (EW)	0.002	0.007	−0.026	0.001
	(−0.60)	(−0.79)	(−1.15)	(0.04)
	[0.05]	[0.20]	[−0.63]	[0.02]
Panel B: Mean Performance Difference between the Positive and Negative Portfolios				
Portfolio 3 − Portfolio 4	0.069	0.042	0.113	0.056
	(3.23)	(1.95)	(3.81)	(1.84)
Portfolio 5 − Portfolio 6	0.050	−0.000	0.162	0.098
	(1.31)	(−0.01)	(3.06)	(2.01)
Portfolio 7 − Portfolio 8	0.031	0.030	0.086	0.047
	(1.61)	(1.58)	(2.98)	(1.61)

in a positive portfolio are insignificant. With a delay of a quarter, the smart money effect is hardly observable. Thus, for the whole sample there are no significant gains from constructing a portfolio of funds with positive new money, and new money does not have an information effect.

Since small funds display a much stronger smart money effect than all funds and large funds do, investors may want to follow a trading strategy based on the new money signal of small funds only. In the last two columns of Table VIII, I report the abnormal returns of the delayed new money portfolios for small funds. The smart money effect is significant with a delay of a month. The performance difference between the positive and negative portfolios is statistically significant. Portfolio 5 has a significant abnormal return of 1.8 percent per year. Thus, the gains from constructing a new money weighted portfolio of funds with positive cash flows are statistically and economically significant. With a delay of a quarter, the performance difference between portfolios 5 and 6 is still significant. Again, portfolio 5 significantly outperforms the market. In summary, there is statistically significant evidence supporting the information effect for the sample of small funds.

The abnormal returns in Tables VII and VIII are before deducting load charges. In reality, investors' realized returns should be the returns reported minus all load charges. In Table IX, I calculate the abnormal returns on the trading strategies for small load and small no-load funds separately. There is some evidence that the performance difference between the positive and negative portfolios is statistically significant for small load and small no-load funds either lagged for a month or without lags. Without lags in cash-flow information, portfolios 3 and 7 of small load funds and portfolios 3 and 5 of small no-load funds significantly beat the market. With a month lag, the positive abnormal returns on the positive portfolios of load funds are not statistically significant. However, the positive abnormal return on portfolio 5 of small no-load funds is about 2.2 percent per year and is statistically significant. Since there are no load charges for trading no-load funds, it is possible to realize the positive abnormal returns reported for the trading strategies. Thus there is some evidence supporting the information effect, that new money flow of small no-load funds contains information that can be used to make abnormal returns.

B.8. Holding Period

When I construct the new money strategies, I re-form my portfolios every three months. In reality, investors may have different holding periods. The performance of the portfolios can change dramatically if the investor alters the holding period. Figure 2 shows the performance of portfolios 5 and 6 for different holding periods up to 36 months. In general, the performance measures of the positive portfolio deteriorate through time, and the performance measures of the negative portfolio improve. Interestingly as we observe from the figure, when measured by alphas of the three-factor model the positive portfolio outperforms the negative one before month 30; in month 30 the

Table IX

Performance of the New Money Portfolios for Small Load and No-Load Funds: January 1970 to December 1993

Small funds are funds for which the total net assets are smaller than the median TNA. Alpha_3 is calculated from the time-series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: $R_{pt} - R_{ft} = \alpha_p + \beta_{p\text{RMRF}}\text{RMRF}_t + \beta_{p\text{SMB}}\text{SMB}_t + \beta_{p\text{HML}}\text{HML}_t + e_{pt}$. The t-statistics in parentheses test the performance difference between the particular portfolio and the average mutual fund. The t-statistics in brackets test the performance difference between the particular portfolio and the market. EW denotes equally weighted, and CW means that the individual fund returns are weighted by their corresponding new money amount. For Panel B, the t-statistics in parentheses test whether the performance difference between the positive and the negative portfolios is significantly different from zero. Performance measures are in percent return per month.

	Alpha_3			
	Small Load Funds		Small No-Load Funds	
Portfolios	Without Lags	Lagged for a Month	Without Lags	Lagged for a Month
Panel A: Portfolio Performance				
1. Average fund	−0.008	−0.007	0.027	0.025
	(NA)	(NA)	(NA)	(NA)
	[−0.20]	[−0.17]	[0.70]	[0.63]
2. Weighted by total net asset	0.007	0.005	0.042	0.050
	(1.62)	(0.99)	(2.16)	(1.89)
	[0.16]	[0.12]	[0.96]	[1.13]
3. Positive cash flow (EW)	0.103	0.087	0.122	0.108
	(4.52)	(4.09)	(2.99)	(2.05)
	[2.06]	[1.81]	[2.39]	[1.82]
4. Negative cash flow (EW)	−0.042	0.001	−0.062	−0.047
	(−1.72)	(0.40)	(−3.37)	(−2.68)
	[−0.95]	[0.03]	[−1.29]	[−0.96]
5. Positive cash flow (CW)	0.085	0.079	0.270	0.184
	(2.30)	(2.19)	(4.51)	(2.78)
	[1.41]	[1.38]	[3.80]	[2.42]
6. Negative cash flow (CW)	−0.045	0.009	−0.036	0.005
	(−0.70)	(0.32)	(−1.02)	(−0.32)
	[−0.68]	[0.14]	[−0.46]	[0.07]
7. Upper 50 percent of all cash flow (EW)	0.099	0.081	0.070	0.052
	(4.95)	(4.24)	(1.69)	(0.96)
	[2.11]	[1.76]	[1.54]	[1.08]
8. Lower 50 percent of all cash flow (EW)	−0.038	0.000	−0.025	−0.009
	(−1.42)	(0.36)	(−1.90)	(−1.16)
	[−0.80]	[0.01]	[−0.51]	[−0.18]
Panel B: Mean Performance Difference between the Positive and Negative Portfolios				
Portfolio 3 − Portfolio 4	0.145	0.086	0.185	0.155
	(3.73)	(2.37)	(3.79)	(2.74)
Portfolio 5 − Portfolio 6	0.130	0.070	0.306	0.179
	(1.83)	(1.05)	(3.70)	(2.16)
Portfolio 7 − Portfolio 8	0.137	0.081	0.095	0.062
	(3.55)	(2.31)	(2.03)	(1.21)

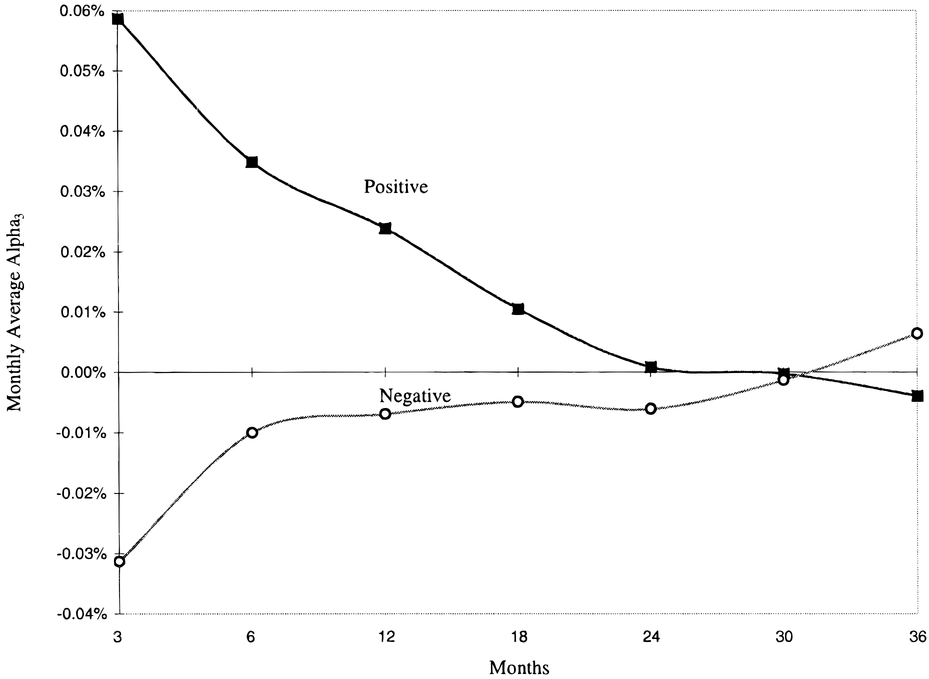

Figure 2. Performance of positive and negative portfolios for different holding periods. This figure plots the monthly average alpha$_3$ for portfolios 5 and 6 for different holding periods up to 36 months. Portfolio 5 invests in all available funds with positive new money cash flow and weights by funds' new money. Portfolio 6 invests in all available funds with negative new money cash flow and weights by funds' new money. Alpha$_3$ is calculated from the time-series regression of the excess portfolio returns on the excess market return and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors. Then the average monthly portfolio alpha$_3$ is calculated for different holding periods of 1 to 36 months after the portfolio formation.

two portfolios have very similar performance; and after month 30 the negative portfolio outperforms the positive portfolio. This mean-reversion phenomenon demonstrates the short-term property of investors' forecasts.

The smart money effect is short-lived. According to Figure 2, the performance ranking of the positive and negative portfolios reverses after month 30. Thus, the smart money effect is more short-lived than performance persistence.

B.9. Robustness Tests

All the portfolio returns reported in the earlier tests are based on the new money measure calculated under the end-of-quarter assumption. To test the robustness of the results to different timing assumptions of new money, I recalculate portfolio returns adopting the beginning-of-quarter assumption of new money. In summary, all earlier results are virtually unchanged.

I use an alternative definition of new money by dividing each new money flow by the net asset value of the fund in the previous period. This definition controls for the size effect of funds. Again, all the results remain virtually the same. With this approach, the difference in the smart money effect of small funds and large funds is even larger.

All major conclusions remain unchanged when I use different measures of risk-adjusted returns. Additionally, all t-test results are robust to the autocorrelation adjustment using the Newey-West covariance matrix.

IV. Conclusion

Despite the fact that performance evaluation is the most studied issue in mutual fund research, only one paper, Gruber (1996), has discussed the returns on new investment from the investors' point of view. As mutual funds are designed to serve the investment needs of common investors, it is as important to examine investors' ability to generate sensible returns using this investment vehicle as it is to study the individual managers' ability to beat the market. In the world of open-end mutual funds, where performance persistence exists and management skill is not priced, investors may improve their investment returns by exploiting persistence.

This paper studies the fund selection ability of the aggregate mutual fund investors' portfolio. Employing a test of performance introduced by Grinblatt and Titman (1993), the study finds that investors in aggregate are able to make buying and selling decisions based on good assessment of short-term future performance. To investigate the magnitude and practical implications of investors' fund selection skills, I examine returns on different strategies based on new money signals. The result from the trading strategies confirms the smart money effect that aggregate newly invested money in equity mutual funds is able to forecast short-term future fund performance, in that funds that receive more money subsequently perform significantly better than those that lose money. There is evidence that astute investors can outperform the average mutual fund. For the whole sample, there is no statistically significant evidence that investors can beat the market by investing in funds with positive new money flow. However, there is some evidence that the positive new money flow of small funds outperforms the market. For the sample of small funds, there is also evidence supporting the information effect; that is, new money flow has information that can be used to outperform the market. The smart money effect is short-lived: the performance ranking of the positive and negative portfolios reverses after 30 months.

To examine the source of the smart money effect, I explore the relation between the smart money strategy and the repeat winner strategy. Despite differences in the composition of the portfolios of the two strategies, a significant percentage of the performance variations in the smart money strategy can be explained by the performance variations in the repeat winner strategy. I also examine whether the smart money effect is due to investors exploiting changing macroeconomic conditions and predetermined style effects. Using a conditional method and style variables, I conclude that the smart money effect is not due to macroeconomic information or style effect, but likely is due to fund-specific information. This suggests that investors use fund-specific information in making their mutual fund investment decisions.

The empirical results of the paper provide some insight into the difference between investors' returns and the average mutual fund returns. The fact that investors can do better than the average fund systematically is related to performance persistence. The smart money effect, however, is not equivalent to investors chasing past performance. Smart money also displays a size effect in that superior returns are earned principally by new money flows into and out of small funds rather than large funds. It will be interesting to explore further the potential reasons for the smart money effect and the size effect.

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