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Does Stock Return Momentum Explain the "Smart Money" Effect?

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ABSTRACT

Does the "smart money" effect documented by Gruber (1996) and Zheng (1999) reflect fund selection ability of mutual fund investors? We examine the finding that investors are able to predict mutual fund performance and invest accordingly. We show that the smart money effect is explained by the stock return momentum phenomenon documented by Jegadeesh and Titman (1993). Further evidence suggests investors do not select funds based on a momentum investing style, but rather simply chase funds that were recent winners. Our finding that a common factor in stock returns explains the smart money effect offers no affirmation of investor fund selection ability.

Do investors make smart choices when selecting mutual funds? Studies by Gruber (1996) and Zheng (1999) suggest that investors have selection ability, a finding that has been dubbed the "smart money" effect. Using a sample of 227 stock mutual funds during the period 1985–1994, Gruber (1996) shows that the risk-adjusted return on new cash flows to funds is higher than the average return for all investors in the funds. Subsequent work by Zheng (1999) analyzes a sample of 1,826 stock mutual funds during the period 1970–1993 and also finds that the short-term performance of funds that experience positive new money flow is significantly better than those that experience negative new money flow.

One possible explanation for the smart money effect is that investors base their investment decisions on fund-specific information, or in other words, they have an ability to identify superior managers and invest accordingly. An important implication of such an interpretation is that it provides a rationale for investing in actively managed mutual funds, as argued by Gruber (1996).[1] This is not, however, the only plausible explanation for the smart money effect. In particular, we note that in benchmarking fund performance neither Gruber nor Zheng accounts for the well-known Jegadeesh and Titman (1993) stock return

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[1] Beginning with Jensen (1968), a large number of studies have shown that the average actively managed fund fails to outperform the relevant benchmarks after expenses. Gruber (1996) suggests that the smart money effect explains the puzzling fact that actively managed funds have witnessed significant growth despite the unfavorable evidence on their performance.

momentum phenomenon. Carhart (1997) demonstrates that momentum is an important common factor in explaining stock returns. Furthermore, he shows that the previously documented evidence of persistence in mutual fund performance is not robust to the momentum factor.[2] In light of Carhart's findings, a natural question that arises is whether the smart money effect is really due to fund-specific information as suggested by Gruber (1996) and Zheng (1999), or whether it can be explained by exposure to momentum.[3] Specifically, suppose that fund investors merely chase past performance. Then funds that happen to hold high concentrations of recent winner stocks would, on average, receive more investor cash while also benefiting more than other funds from the effects of return momentum. This, in turn, could lead to the finding of a smart money effect, despite the absence of any ability on the part of investors to select superior fund managers.

We first explore this question by reexamining the smart money effect while explicitly controlling for momentum. If investors are indeed able to identify superior managers, then new cash flows should continue to earn positive abnormal returns even after controlling for the effect of mechanical styles such as momentum strategies. Our test uses the complete universe of diversified U.S. equity mutual funds for the period 1970–2000 in the CRSP Survivor-Bias Free U.S. Mutual Fund Database. Following Gruber and Zheng, we form two new-money portfolios at the beginning of each quarter. The first portfolio includes all funds that realize positive net cash flow during the last quarter, and the second portfolio includes all funds that realize negative net cash flow. We then examine the subsequent performance of each portfolio using the Carhart (1997) benchmark model that includes the three Fama and French (1993) factors, but unlike either Gruber (1996) or Zheng (1999), we also include a momentum factor.

If the performance benchmark model does not account for exposure to momentum, we find that there is evidence of an apparent smart money effect. For instance, a strategy that mimics investor fund flows by going long in the (cash-flow-weighted) positive cash-flow portfolio and short in the negative cash-flow portfolio produces a statistically and economically significant annual alpha of 2.09% over the period 1970–2000. Similar findings have led previous

[2] A number of earlier studies (e.g., Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and Elton, Gruber, and Blake (1996)) find performance persistence over short-term horizons of 1 to 3 years.

[3] While neither Gruber nor Zheng explicitly examines the source of the smart money effect, they offer some conjectures in this regard. Gruber notes that his findings are consistent with the existence of (a) superior management skill that is not reflected in the net asset values of mutual funds, thus allowing for performance to be predictable, and (b) a group of sophisticated investors who recognize this fact and correctly identify superior fund managers. Similarly, Zheng (1999) interprets her findings as evidence that ". . . the smart money effect is likely due to fund-specific information" (p. 904). At the same time, Zheng recognizes, "One possible explanation is the momentum in stock returns . . . . 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" (p. 921).

researchers to conclude that investors have the ability to identify superior performing funds. We show, however, that the Jegadeesh and Titman (1993) stock return momentum phenomenon explains the smart money effect. Using a performance benchmark that includes a momentum factor, we find that the adjusted excess return (alpha) on the flow of money is essentially zero. Furthermore, after we control for a portfolio's momentum exposure, the return earned by the flow of money into funds is unable to outperform the return on the average dollar invested in the fund universe.

Our finding that a common factor in stock returns explains the smart money effect offers no affirmation that investors are identifying superior fund managers. Furthermore, the finding that momentum accounts for the smart money effect begs a new question: Are investors then chasing funds with momentum styles, or are they just naively chasing funds with large past returns? It could be that investors base their decisions on certain observable fund characteristics or styles that are common to a group of funds. If investors chase funds with momentum styles in an effort to exploit return momentum, then the smart money effect may have an explanation consistent with a group of sophisticated fund investors taking advantage of cheap momentum strategies. This implies that preference for a particular style leads investors to implement a mechanical fund selection rule. Alternatively, it may be that investors are not basing their investment decisions on fund style, but are instead naively chasing recent winners and incidentally benefiting from the momentum effect. Distinguishing between these two possible explanations is important because the former yet provides a rationale for the growth in actively managed mutual funds, potentially solving a prominent puzzle in finance, while the latter leaves this puzzle unexplained.[4]

To address the above questions, we first explore the determinants of cash flows to funds within a cross-sectional regression framework. We find that cash flows to funds are strongly correlated with recent returns, but not to fund momentum loadings. This effectively demonstrates that fund investors appear to be chasing recent large returns rather than identifying momentum-style funds. Second, we examine whether investors do, in fact, pursue a deliberate strategy of investing in momentum funds by ranking funds based on momentum loadings. Specifically, we examine whether funds with high momentum exposure persistently enjoy positive cash flows, as would be the case if investors were successful in identifying fund managers that follow momentum styles. We rank funds at the start of each quarter in the sample period into deciles based on their exposure to the momentum factor and then examine the proportion of funds within each decile that experiences positive net cash flows during the formation quarter and during the next four quarters. We find that only 49% of the funds in the top momentum decile enjoy positive net cash flows in the

[4] Berk and Green (2002) suggest an alternative interpretation of the evidence on the performance of active fund managers. They show that in a model with decreasing returns to scale in active portfolio management, the absence of superior performance is a consequence of a competitive market for capital provision to mutual funds.

formation quarter, and this proportion declines to 34% after four quarters. This further illustrates that cash flows do not consistently track a momentum investing style.

The evidence demonstrates that investors do not follow a deliberate strategy of selectively investing in momentum funds. They appear instead to naively chase funds that are recent winners and, in doing so, they unwittingly benefit from the momentum effect in the short term. This leads mechanically to the observed apparent selection ability in terms of the three-factor benchmark. Hence, our results show not only that fund investors are unable to identify superior managers with their cash flows, but they also do not identify momentum investment styles. A common factor in stock returns, rather than selection ability, or "smartness," on the part of mutual fund investors, is responsible for the apparent favorable performance of new-money portfolios documented in the literature. Since Gruber's (1996) explanation for the puzzling growth in actively managed mutual funds rests upon sophisticated investors being able to identify superior managers and invest accordingly, an important implication of our findings is that the puzzle noted by Gruber still begs an answer.

The rest of this paper is organized as follows. Section I discusses the mutual fund data sample and the methods used to measure cash flows and the performance of new-money portfolios. Section II provides evidence on the performance of the new-money portfolios. Section III examines the determinants of net cash flows to funds. Section IV presents evidence on whether investors are successful at identifying funds with momentum styles, and Section V concludes.

I. Data and Methodology

A. Sample Description

We use data from the CRSP Survivor-Bias Free U.S. Mutual Fund Database. Our sample includes all domestic common stock funds that exist at any time during the period 1970–2000 for which quarterly total net assets (TNA) values are available. We exclude international funds, sector funds, specialized funds, and balanced funds because these funds may have risk characteristics that are not spanned by the factors driving the returns of most other mutual funds. The final sample contains 5,882 fund-entities comprising 29,981 fund-years.[5]

Table I presents descriptive statistics for the mutual fund sample. The average fund size measured by TNA is $324 million. However, the sample is somewhat skewed by larger funds, since the median fund size is only $291 million. The average quarterly new cash flow (described below) into funds is a positive $2.9 million. If we normalize cash flow by the prior quarter TNA, the average quarterly net cash flow is 16.6% of fund assets. We also see that the average

[5] Elton, Gruber, and Blake (2001) point out that the fund returns in the CRSP database have a slight upward bias in cases where a fund makes a capital gain distribution and a dividend distribution on the same day. We have, therefore, applied the correction suggested by them to eliminate this bias.

Table I

Descriptive Statistics for Mutual Fund Sample

The table presents summary statistics on the mutual fund sample obtained from the CRSP Survivor-Bias Free U.S. Mutual Fund Database. The sample includes all U.S. equity mutual funds that existed at any time during January 1970 to December 2000 for which quarterly TNA values are available. We exclude sector funds, international funds, specialized funds, and balanced funds. The final sample consists of 5,882 fund-entities comprising 29,981 fund-years. The dollar quarterly net cash flow ($NCF_{i,t}$) for fund i during quarter t is measured as $NCF_{i,t} = TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t}) - MGTNA_{i,t}$. In this equation, the terms $TNA_{i,t-1}$ and $TNA_{i,t}$ represent the TNA for the fund at the end of quarter $t{-}1$ and t respectively, $r_{i,t}$ represents the fund's return in month t, and $MGTNA_{i,t}$ represents the increase in the fund's TNA due to mergers during quarter t. The normalized quarterly cash flow for a fund during a quarter is computed as the dollar quarterly cash flow for the fund divided by the TNA at the beginning of the quarter. Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA, maximum front-end load is the maximum percent charges applied at the time of purchase, maximum total load fee is the sum of maximum front-end load fees and maximum sales charges paid when withdrawing money from the fund, and expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. For each item, we first compute the cross-sectional averages in each year from 1970 to 2000. The reported statistics are computed from the time series of the 31 annual cross-sectional average figures for each item.

	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
TNAs ($ millions)	323.63	290.66	167.04	460.80	164.99
Quarterly net cash flow ($ millions)	2.92	1.86	−2.11	7.45	6.86
Normalized quarterly net cash flow (%)	16.59	3.83	1.20	16.03	37.33
Turnover (%/year)	73.93	76.88	65.72	82.51	13.35
Maximum front-end load fee (%)	3.75	3.94	1.97	5.30	1.72
Maximum total load fee (%)	4.05	4.02	2.58	5.32	1.45
Expense ratio (%/year)	1.10	1.00	0.98	1.31	0.19

fund had an annual portfolio turnover rate of 74% and an expense ratio of 1.10%.

B. Measurement of Cash Flows and Performance

We analyze the fund selection ability of fund investors by examining the performance of new-money portfolios formed on the basis of fund net cash flow. At the beginning of each quarter, we group the mutual funds into two portfolios. The positive cash-flow portfolio includes all funds that realized positive net cash flow during the previous quarter, and the negative cash-flow portfolio includes all funds that realized negative net cash flow during the previous quarter. The net cash flow to fund i during quarter t is measured as follows:

$$TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t}) - MGTNA_{i,t}. \tag{1}$$

Here $TNA_{i,t}$ refers to the TNA at the end of quarter t, $r_{i,t}$ is the fund's return for quarter t, and $MGTNA_{i,t}$ is the increase in the TNA due to mergers during quarter t. For some of the analysis, we employ the normalized cash flow, defined as the quarterly net cash flow divided by the TNA at the beginning of the quarter. The net cash-flow measure described in equation (1) implicitly assumes that existing investors reinvest their dividends and that the new money is invested at the end of each quarter. We also replicate our analysis under the alternative extreme assumption that the new money is invested at the beginning of each quarter. Our results are nearly identical under this assumption and, hence, we only report results based on the assumption inherent in equation (1). We employ Gruber's "follow the money" approach that assumes that investors in merged funds place their money in the surviving fund and continue to earn the return on the surviving fund. This mitigates survivorship bias, since defunct funds are not excluded from the sample before they disappear. We compute monthly returns for the two sets of new-money portfolios using two portfolio-weighting schemes. First, we compute cash-flow-weighted returns for the portfolio using the cash flows realized during the previous quarter by the funds within the portfolio. Additionally, we compute equally weighted returns for the new-money portfolios. For purposes of comparison, we also report the returns on a TNA-weighted portfolio of all funds in the sample.

Table II reports the descriptive statistics for the new-money portfolios for the period 1970–2000. The table presents the mean monthly returns in excess of the 1-month T-bill return (as well as the median and the 25^{th} and 75^{th} percentiles), the standard deviation, and the Sharpe ratio for the positive cash-flow and the negative cash-flow portfolios. The data are presented for the equally weighted and cash-flow-weighted new-money portfolios. For comparison, the table also shows the corresponding statistics for a TNA-weighted portfolio as well as an equally weighted portfolio of all funds in the sample. We note that the positive cash-flow portfolios have a higher average return and a higher Sharpe ratio compared to the negative cash-flow portfolios. For example, a comparison of the cash-flow-weighted portfolios reveals that the positive cash-flow portfolio has a mean excess return of 0.51%, compared to a mean excess return of 0.43% for the negative cash-flow portfolio. The average excess return on the market portfolio for the same period was 0.54%.

We evaluate the performance of the positive and the negative cash-flow portfolios using a four-factor model as in Carhart (1997). Specifically, the benchmarking model is given by:

$$r_{p,t} = \alpha_p + \beta_{1,p} RMRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + e_{pt}. \quad (2)$$

Here, $r_{p,t}$ is the monthly return on a portfolio of funds in excess of the 1-month T-bill return; RMRF is the excess return on a value-weighted market portfolio; and SMB, HML, and UMD are returns on zero-investment factor-mimicking portfolios for size, book-to-market, and 1-year momentum in stock returns.[6] Pioneering work by Carhart (1997) has shown that the four-factor model, which includes a momentum factor, is superior to both the CAPM and the Fama–French three-factor model in explaining the cross-sectional variation in fund

[6] We wish to thank Ken French for making available the data on RMRF, SMB, HML, and UMD.

Table II

Descriptive Statistics for Mutual Fund Portfolio Excess Returns

The sample of mutual funds is described in Table I. This table presents summary statistics for monthly returns in excess of the risk-free rate on portfolios of mutual funds for the period January 1970 to December 2000. Also presented are the corresponding Sharpe ratios for the portfolios. The first row gives statistics for a TNA-weighted portfolio of all funds in the sample. The second row describes an equally-weighted portfolio of all funds in the sample. Also shown are the summary statistics for portfolios formed on the basis of quarterly net new cash flows. Each quarter funds are grouped into either the positive cash-flow portfolio or the negative cash-flow portfolio based on the sign of the net cash-flow experienced by each fund during the previous quarter. These portfolios are either equally-weighted across funds or cash-flow-weighted, and are rebalanced quarterly. Summary statistics are also given for the market factor, labeled RMRF. RMRF represents the excess return on the value-weighted market index of all NYSE, AMEX, and NASDAQ stocks. The risk-free rate is the 1-month Treasury bill rate. Returns are expressed in percent per month.

	Mean	Median	25^{th} Percentile	75^{th} Percentile	Standard Deviation	Sharpe Ratio
TNA-weighted average fund portfolio	0.465	0.693	−2.247	3.541	4.472	0.104
Equally-weighted average fund portfolio	0.510	0.785	−2.299	3.668	4.591	0.111
(Equally-weighted) positive cash-flow portfolio	0.551	0.871	−2.325	3.773	4.697	0.117
(Equally-weighted) negative cash-flow portfolio	0.484	0.811	−2.234	3.521	4.518	0.107
(Cash-flow-weighted) positive cash-flow portfolio	0.505	0.778	−2.316	3.622	4.902	0.103
(Cash-flow-weighted) negative cash-flow portfolio	0.427	0.753	−2.241	3.384	4.448	0.096
Market factor (RMRF)	0.542	0.810	−2.240	3.780	4.616	0.117
Monthly risk-free rate	0.539	0.480	0.390	0.640	0.216	—

returns. The model represented by equation (2) may be interpreted as a performance attribution model. We test for fund selection ability on the part of investors by examining the difference between the alphas of the positive and the negative cash-flow portfolios. In order to provide a comparison to previous studies that have not incorporated a momentum factor in the performance benchmark, we also report the portfolio alphas based on a three-factor model that excludes the momentum factor.

II. Performance of New-Money Portfolios

A. Portfolio Regressions

We begin our analysis by examining whether investors are able to earn superior returns based on their investment decisions. Panel A of Table III presents results for equally weighted new-money portfolios. The first three columns of Panel A present results using the three-factor model for the positive cash-flow,

Table III

Performance of New-Money Portfolios

Each quarter from January 1970 to December 2000, mutual funds are grouped into either the positive cash-flow portfolio or the negative cash-flow portfolio based on the sign of the net cash flow experienced by each fund during the previous quarter. Portfolio performance is evaluated based on the estimated portfolio alpha. The four-factor portfolio alpha is calculated as the intercept from the monthly time series regression of portfolio excess returns on the market excess return (RMRF) and mimicking portfolios for size (SMB), book-to-market (HML), and momentum (UMD) factors: $r_{p,t} = \alpha_p + \beta_{1,p} RMRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + e_{pt}$. The three-factor alpha is based on a model that excludes the momentum factor. Panel A of the table reports estimates of portfolio alphas and factor loadings for the new-money portfolios formed using equally-weighted fund returns. Estimates are also presented for an average fund portfolio that is equally-weighted in all available funds. Panel B reports estimates for the new-money portfolios formed using cash-flow-weighted fund returns. Estimates are also presented for an average fund portfolio representing the TNA-weighted portfolio of all available funds. Each panel also reports the difference in alphas between (a) the positive cash-flow portfolio and the negative cash-flow portfolio, and (b) the positive cash-flow portfolio and the average portfolio. Alphas are reported as percent per month. The t-statistics based on the Newey–West covariance matrix are reported in parenthesis. Statistical significance is denoted only for alphas.

	Three-Factor Model					Four-Factor Model				
				Difference in Alphas					Difference in Alphas	
	Positive Cash-Flow Portfolio	Negative Cash-Flow Portfolio	Average Portfolio	Positive vs. Negative	Positive vs. Average	Positive Cash-Flow Portfolio	Negative Cash-Flow Portfolio	Average Portfolio	Positive vs. Negative	Positive vs. Average
	Panel A: Equally-Weighted Portfolios									
Alpha	0.071	−0.041	0.008	0.112	0.063	−0.003	−0.031	−0.015	0.028	0.012
	(1.73)*	(−0.96)	(0.23)	(1.89)*	(1.17)	(−0.07)	(−0.65)	(−0.38)	(0.44)	(0.21)
RMRF	0.925	0.943	0.936			0.930	0.942	0.937		
	(59.42)	(66.36)	(69.72)			(64.46)	(69.13)	(74.32)		
SMB	0.222	0.120	0.162			0.225	0.119	0.163		
	(10.36)	(4.13)	(7.15)			(9.98)	(4.14)	(6.87)		
HML	−0.070	0.020	−0.029			−0.042	0.016	−0.020		
	(−2.70)	(0.64)	(−1.12)			(−1.97)	(0.58)	(−0.90)		
UMD						0.063	−0.009	0.020		
						(3.46)	(−0.41)	(1.12)		
Adj. R^2	0.973	0.969	0.977			0.975	0.969	0.978		

Panel B: Cash-Flow-Weighted Portfolios

Alpha	0.068	−0.106	−0.027	0.174	0.095	−0.071	−0.086	−0.050	0.015	−0.021
	(1.27)	(−2.10)**	(−0.97)	(2.37)**	(1.57)	(−1.27)	(−1.57)	(−1.63)	(0.19)	(−0.33)
RMRF	0.936	0.950	0.941			0.945	0.949	0.943		
	(46.76)	(52.47)	(90.86)			(55.00)	(53.35)	(96.21)		
SMB	0.191	0.026	0.033			0.195	0.026	0.034		
	(6.48)	(0.74)	(2.15)			(9.11)	(0.73)	(2.15)		
HML	−0.176	0.037	−0.044			−0.124	0.030	−0.035		
	(−5.12)	(1.11)	(−2.32)			(−4.78)	(1.05)	(−2.14)		
UMD						0.118	−0.017	0.020		
						(5.63)	(−0.65)	(1.61)		
Adj. R^2	0.963	0.960	0.985			0.966	0.960	0.985		

*Significant at 10% level; **significant at 5% level.

negative cash-flow, and average portfolios, respectively. The results are similar in spirit to those reported by Zheng (1999). The positive cash-flow portfolio has a statistically significant alpha of 7.1 basis points per month, or 85.2 basis points annually. This contrasts with the insignificant three-factor alpha of 0.8 basis points (i.e., 9.6 basis points annually) earned by the average dollar invested in mutual funds over this time period. The alpha of the negative cash-flow portfolio is an insignificant −4.1 basis points per month. It is instructive to look at the difference in alphas between a trading strategy that is long in the positive cash-flow portfolio and short in the negative cash-flow portfolio. It should be noted, however, that any strategy that would require the short selling of mutual funds cannot be implemented in practice, as most funds forbid short selling of their shares. These comparisons merely show the extent to which aggregate mutual fund cash flows appear able to predict future performance. When we take the difference between the positive cash-flow and negative cash-flow portfolio alphas, we get 11.2 basis points per month, or 134.4 basis points annually, which is significant at the 10% level. Hence, the so-called smart money effect.

Judging from the placement of their new cash, investors appear to have fund selection ability. However, notice from the first column under the heading "Four-factor model" in Panel A that when we control for return momentum, the alpha for the positive cash-flow portfolio shrinks to an insignificant −0.3 basis points per month. The corresponding four-factor alpha for the average fund portfolio equals an insignificant −1.5 basis points. Similarly, the negative cash-flow portfolio's four-factor alpha continues to be insignificant at −3.1 basis points per month. Note also from the four-factor model estimates that the momentum loading of the negative cash-flow portfolio is in fact negative, in contrast to the positive momentum loading of the positive cash-flow portfolio. Finally, we note that the difference in alphas between the positive cash-flow and negative cash-flow portfolios is essentially zero after accounting for momentum. In summary, the results for the equally weighted new-money portfolios show that the abnormal performance obtained under the three-factor benchmark disappears after accounting for momentum.

We next examine the performance of cash-flow-weighted new-money portfolios, reported in Panel B of Table III. Unlike an equal-weighting scheme, a cash-flow-weighting scheme has the benefit of placing greater emphasis on funds experiencing the largest absolute cash flows. As can be seen, there is evidence in support of the smart money effect when we do not control for momentum. The positive cash-flow portfolio has a three-factor alpha of 6.8 basis points per month which, though insignificant, contrasts with the corresponding three-factor alphas of the average portfolio (−2.7 basis points per month) and the negative cash-flow portfolio (−10.6 basis points per month). Note, however, that a very different picture emerges when we account for the portfolios' momentum exposure. The positive cash portfolio's four-factor alpha is negative, though not significantly different from zero, at −7.1 basis points per month, or −85.2 basis points annually. This is in fact lower than the corresponding four-factor alpha of the average portfolio, which equals −5.0 basis points per month (i.e., −60.0 basis points per year).[7] We also note that the evidence on the performance of the negative cash-flow portfolio suggests that investors may be able to identify poor performing funds. This result, while interesting, is not too surprising because public indicators such as high expense ratios and load fees have been shown to be bellwethers of poor performance.

We next examine the difference in alphas between the positive cash-flow portfolio and the negative cash-flow portfolio. A hypothetical strategy of going long in the positive cash-flow portfolio and short in the negative cash-flow portfolio yields a statistically and economically significant three-factor alpha of 17.4 basis points per month, or 2.09% annually. However, once we control for return momentum, the gain to this strategy shrinks to an insignificant 1.5 basis points per month. Overall, the results for the cash-flow-weighted portfolios confirm the previous findings with regard to the equally weighted portfolios. The inclusion of a momentum factor completely explains the alphas of the new-money portfolios.

In summary, the three-factor benchmark results show limited evidence of a smart money effect. Trading strategies that go long on either equally weighted or cash-flow-weighted positive cash-flow portfolios and short on the corresponding negative cash-flow portfolios would appear to capture significant alpha gains. However, once we account for return momentum in our performance benchmark, the apparent difference in performance is eliminated in every case. Furthermore, a comparison of the performance of positive and negative cash-flow portfolios with the average portfolio shows that there is no difference in the performance of the flow of money and that of the existing stock of money once we control for momentum exposures. Hence, the smart money effect is completely explained by return momentum.

As an alternative to the portfolio regression approach described above, we also employ a fund-regression approach similar to Gruber (1996) to analyze the performance of new cash flows. Although not reported here, the results are qualitatively similar to those presented in Table III. In each case, the smart money effect is explained by exposure to stock return momentum. We also confirm that our results are robust to a number of checks, including controls for the possible non-normal distributions of the alphas using a bootstrap procedure, the use of a conditional performance evaluation framework as in Ferson and Schadt (1996), the use of different subperiods, and controls for fund size and load charges. Details of these tests are available from the authors upon request.

B. Discussion

Our results indicate that, consistent with previous studies, there is evidence of a smart money effect based on a three-factor model. We further show, however,

[7] This figure is comparable to the average alpha of −5.4 basis points reported by Gruber (1996) for a sample of 270 equity mutual funds over the period 1985–1994. Gruber's estimate is based on a four-factor benchmark model that includes a bond factor in addition to a market factor and factors for size and growth/value.

that investor fund flows do not earn superior returns and do not outperform the existing stock of money, after we account for momentum exposure. The lack of positive alphas after controlling for momentum suggests that investors do not identify fund managers with superior ability. How then do we interpret the cash-flow decisions of investors? There are two potential interpretations of the role of momentum in explaining the performance of the new-money portfolios, each with competing implications for the selection ability of fund investors.[8]

The first interpretation is that investors are aware of the momentum effect and, therefore, purposely seek out actively managed funds that consistently follow momentum strategies. Since the inclusion of a momentum factor in the performance benchmark adjusts for this type of investment style, the apparent excess returns disappear. According to this story, even though investors are unable to identify managers with superior ability, they are smart in the sense of being able to identify managers who follow momentum styles. Hence, investors choose to invest in actively managed funds in order to have access to cheap momentum strategies, rather than because they have the ability to identify superior managers.

An alternative interpretation of the role of the momentum factor in adjusting for new-money portfolio returns is that the combination of return momentum and the fact that investors *naively* chase funds with recent high returns leads mechanically to the observed selection ability documented in Gruber (1996) and Zheng (1999). According to this story, funds with high recent returns happen by chance to contain winner stocks that continue to perform well. This, in fact, is the conclusion reached by Carhart (1997). If investors naively chase recent winner funds, whatever causes the momentum effect also causes fund investors to have apparent selection ability relative to a three-factor model. However, the four-factor alphas of the new-money portfolios are insignificantly different from zero because the inclusion of a momentum factor in the performance benchmark model removes the mechanical effects of momentum in stock returns. Under this interpretation, investors do not even have selection ability based on investment style, and the puzzle of why investors put money in actively managed funds remains. In the analysis that follows, we distinguish between these two possible interpretations of the role of momentum in explaining the smart money effect.

III. Determinants of Cash Flows to Mutual Funds

If investors are in fact identifying momentum styles, then we would expect fund momentum loadings to have significant explanatory power for fund cash flows. However, if investors are merely chasing recent large returns without any ability to identify fund styles, we would expect lagged fund returns to be the primary determinant of fund cash flows.[9] We examine the explanatory power

[8] We are grateful to the referee for his or her extensive comments and suggestions in this regard.

[9] The positive correlation between past fund performance and subsequent cash flows is well established in the literature. We confirm this stylized fact in our sample, where the rank correlation between percentage cash flows and prior quarter return deciles is 0.99.

of both momentum factor loading and lagged fund return for fund cash flows through a set of cross-sectional regressions.

Based on previous studies, we would expect that several other factors may also influence net cash flows to funds (see, e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998), Jain and Wu (2000)). These include fund size, portfolio turnover, load fees charged by the fund, and the expense ratio of the fund. Since larger funds have more existing assets and presumably greater visibility to potential investors, we would expect that these funds experience larger dollar cash flows than smaller funds. A high portfolio turnover implies an increased hidden cost in the form of transactions costs, and also increases the fund's "tax inefficiency." Funds that advertise more heavily would be expected to have higher expense ratios on average, because these costs are frequently deducted from fund assets in the form of 12b-1 fees. Since information on asset turnover and fund fees is publicly available to investors, these characteristics may have some impact on investor fund flows.

We use a fund's quarterly normalized net cash flow as the dependent variable in our cross-sectional regression framework. The independent variables include the prior quarter return for a fund, the logarithm of TNA at the end of the prior quarter, the normalized cash flow from the prior quarter, fund asset turnover, fund expenses, and the maximum load fees charged by the fund. We also include as a regressor the fund's momentum factor (UMD) loading from a four-factor model estimated over the prior 36 months of fund returns. Table IV presents the estimated coefficients from these regressions. The reported coefficient estimates are time series averages of 112 quarterly cross-sectional regression estimates over the period from January 1973 to December 2000. We also report a cross-sectional R^2 statistic as a goodness of fit measure.[10]

The first column of Table IV presents results for the model in which the prior quarter's return is the sole explanatory variable used. We see that cash flows are significantly positively correlated with the previous quarter's return, confirming the findings of previous studies. Model II employs a fund's UMD loading as an explanatory variable, in addition to the prior quarter's return. Results from this model show that although the UMD loading is positively related to cash flows, it is not a significant predictor. At the same time, the prior quarter's return continues to be significantly positively related to cash flows. This suggests that cash flows are primarily influenced by past returns rather than by fund momentum exposure. Estimates from Model III show that fund size is negatively correlated with percentage cash flows, reflecting the fact that smaller funds attract proportionately larger net cash flows compared to bigger funds.[11] In Models IV and V, we use the prior quarter normalized net cash flow as an additional explanatory variable to account for any persistence in cash

[10] The cross-sectional R^2 follows Jagannathan and Wang (1996) and Lettau and Ludvigson (2001) and is computed as $[\mathrm{Var}(\bar{C}_i) - \mathrm{Var}(\bar{\varepsilon}_i)]/\mathrm{Var}(\bar{C}_i)$, where $\bar{\varepsilon}_i$ is the average cross-sectional residual for fund i, $\bar{C}_i$ is the average percentage net cash flow for fund i, all variances are cross-sectional, and variables with bars over them denote time-series averages.

[11] In unreported tests, we find there is a positive relation between fund size and dollar net cash flows.

Table IV

Determinants of Fund Cash Flows

This table presents the coefficients from regressions of realized quarterly normalized cash flow for a fund against the fund's total return in the previous quarter, the momentum (UMD) loading, the logarithm of TNA, the normalized cash flow during the prior quarter, turnover, expense ratio, and maximum front-end load fees. The normalized quarterly cash flow for a fund during a quarter is computed as the dollar quarterly cash flow for the fund divided by the TNA at the beginning of the quarter. Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA; expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses; and the maximum front-end load fees are the maximum percent charges applied at the time of purchase. The reported coefficients are averages of 112 quarterly cross-sectional regressions from 1973 to 2000. The t-statistics based on the Newey-West covariance matrix are reported in parenthesis, except for coefficients on UMD loading, for which the reported t-statistics are adjusted for the error-in-variables bias using the correction suggested by Shanken (1992). The cross-sectional R^2 is computed as $[\mathrm{Var}(\bar{C}_i) - \mathrm{Var}(\bar{\varepsilon}_i)]/\mathrm{Var}(\bar{C}_i)$, where $\bar{\varepsilon}_i$ is the average cross-sectional residual for fund i, $\bar{C}_i$ is the average percentage net cash flow for fund i, all variances are cross-sectional, and variables with bars over them denote time-series averages. The initial sample has a total of 5,882 fund-entities comprising 29,981 fund-years and is described in Table I. Due to the requirement of a minimum 30 months of prior data for calculating factor loadings, regressions containing UMD loading include 3,733 fund-entities comprising 26,407 fund-years.

	Model				
Explanatory Variables	I	II	III	IV	V
Intercept	−0.80	−0.51	−0.45	−0.39	−0.38
	(−5.92)	(−6.59)	(−6.28)	(−5.74)	(−5.51)
Previous quarter's return	0.81	0.50	0.49	0.42	0.42
	(5.86)	(6.59)	(6.78)	(6.10)	(6.00)
UMD loading		0.005	0.001	−0.002	0.0003
		(0.38)	(0.10)	(−0.13)	(0.26)
Logarithm of TNAs			−0.01	−0.01	−0.01
			(−6.00)	(−6.67)	(−5.94)
Previous quarter's net cash flow				0.22	0.22
				(4.36)	(4.34)
Turnover					0.0002
					(0.38)
Expense ratio					−0.001
					(−0.23)
Maximum front-end load					−0.0003
					(−0.70)
Cross-sectional R^2	0.028	0.030	0.034	0.107	0.118

flows due to fund reputation or visibility. The coefficient on prior quarter net cash flow is positive and highly significant in both models, suggesting that cash flows tend to be persistent. Results from Model V also confirm that the past performance of the fund has significant explanatory power for explaining net cash flows, even after controlling for a number of other fund characteristics, whereas momentum factor loading does not. Finally, we note that the marginal impact of fund turnover, expenses, and load fees on net cash flow is insignificant.

In summary, the evidence from Table IV shows that cash flows to funds are consistently positively related to the fund's near-term performance, but not to fund momentum loadings. These findings suggest that investors are primarily chasing recent large returns rather than identifying momentum-style funds. To further examine whether investors appear to identify and invest in momentum-style funds, in the next section, we track the net cash flows over time for funds classified by momentum exposure.

IV. Persistence of Cash Flows to Momentum Funds

The evidence suggests that investor fund flows are attracted to funds with recent high returns, rather than being explained by the funds' momentum exposures. To further explore this issue, we test whether investors do in fact implement momentum investing strategies. Specifically, we examine whether funds with high momentum exposure persistently enjoy positive cash flows, as would be the case if investors were successful in identifying fund managers that follow momentum styles. We rank funds at the start of each quarter in the sample period into deciles based on their exposure to the momentum factor. We then analyze the proportion of funds within each decile that experiences positive net cash flows during the formation quarter and during the next four quarters. Results are presented in Table V. The reported figures represent the average proportions over the 112 quarters from 1973 to 2000. Interestingly,

Table V
Persistence of Cash Flows to Funds Based on Momentum Factor Rankings

Mutual funds are sorted each quarter from 1973 to 2000 into decile portfolios based on momentum (UMD) factor loadings estimated from individual fund four-factor regressions that use data from the prior 36 months. Funds not having at least 30 months of prior data are excluded. This yields a sample of 3,733 fund-entities comprising 26,407 fund-years. The table reports for each momentum decile the percentage of funds which experience positive net cash flow during the formation quarter and during each of the following four quarters.

	Percentage of Funds with Positive Net Cash Flow After				
UMD Factor Loading Decile	Formation	1 Quarter	2 Quarters	3 Quarters	4 Quarters
1 Contrarian	36	34	31	28	26
2	37	34	32	29	27
3	39	36	33	30	28
4	43	39	37	34	30
5	45	41	37	34	32
6	44	41	37	34	31
7	44	42	37	34	31
8	48	43	40	36	34
9	48	44	40	36	33
10 Momentum	49	45	41	37	34
Average	43	40	36	33	31

we find that less than half of the "momentum" funds enjoy positive net cash flows during the formation quarter, and the proportion diminishes to 34% after four quarters. This illustrates that investors do not appear to be deliberately pursuing a strategy of investing in momentum-style funds.[12]

We perform a similar exercise where we rank funds into deciles based on past quarter return and examine the percentage of funds that experience positive net cash flows during the formation quarter and the next four quarters. Results, which are not reported, show that 58% of funds in the top performance decile experience positive net cash flows. This proportion tapers off to 40% four quarters after formation. This analysis further highlights the greater sensitivity of cash flows to past returns, as opposed to fund momentum loading.

In summary, the evidence presented in this section shows that investors appear unable to consistently select funds based on a momentum investing style. Together with our earlier findings, this suggests that a combination of momentum and investors *naively* chasing funds with recent high returns leads mechanically to the observed selection ability documented in Gruber (1996) and Zheng (1999).

V. Conclusion

Two recent studies by Gruber (1996) and Zheng (1999) examine whether mutual fund investors have the ability to predict future fund performance and invest accordingly. Both studies find evidence of a "smart money" effect—investors appear to invest in funds that subsequently perform better than funds from which investors divest. These studies suggest that investors as a group possess fund selection ability. Furthermore, Gruber claims that the finding that investors can select actively managed funds that subsequently generate superior performance solves a prominent puzzle in the investments literature—namely "Why do investors put money in actively managed funds when their performance on average has been inferior to passive benchmarks?" However, neither the Gruber nor the Zheng study adopts a momentum factor for benchmarking returns or specifically investigates the link between the smart money effect and return momentum. Our paper addresses this omission and shows that the smart money effect is an artifact of stock return momentum.

When we assess performance with a three-factor benchmark model that does not control for momentum exposure, we find some evidence of a smart money effect: a strategy of investing in the positive cash-flow portfolio and short selling the negative cash-flow portfolio appears to yield significant alpha gains. However, when we control for stock return momentum, the smart money effect

[12] Interestingly, Carhart (1997) examines the ability of funds to maintain their momentum rankings over time and finds that fund managers appear unable to consistently implement a momentum strategy. Carhart argues that returns to funds with high momentum loadings are, therefore, the result not of fund managers consciously following a momentum strategy, but rather of funds holding last year's winners by chance. In results not reported, we also examine the consistency of fund momentum rankings over time and confirm his findings in our larger sample.

disappears. The lack of positive alphas after controlling for momentum suggests that investors do not identify fund managers with superior ability. We then examine whether investors appear to be actively identifying momentum-style funds or naively chasing large recent returns. Evidence on fund net cash flows from both a cross-sectional regression analysis and investment patterns over time indicates that investors are simply responding to large recent returns.

An important implication of our findings is that the puzzle posed by Gruber (1996) still begs an answer: Why do investors put money in actively managed funds? As a group, actively managed funds do not offer superior performance, but charge management fees that could be avoided in a passive benchmark fund. Gruber's explanation hinges upon sophisticated investors being able to identify skilled fund managers and invest accordingly. Yet, our findings suggest that investors are naively chasing past returns, not identifying skilled fund managers. Therefore, the puzzle remains.

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