# Which Money Is Smart?

# Mutual Fund Buys and Sells of Individual and Institutional Investors

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**ABSTRACT**

Gruber (1996) and Zheng (1999) report that investors channel money towards mutual funds that subsequently perform well. Sapp and Tiwari (2004) find that this "smart money" effect no longer holds after controlling for stock return momentum. While prior work uses quarterly U.S. data, we employ a British data set of monthly fund inflows and outflows differentiated between individual and institutional investors. We document a robust smart money effect in the U.K. The effect is caused by buying (but not selling) decisions of both individuals and institutions. Using monthly data available post-1991 we show that money is comparably smart in the U.S.

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Can investors identify superior mutual funds? The first studies to address this question (Gruber (1996), Zheng (1999)) find, that indeed, funds that receive greater net money flows subsequently outperform their less popular peers. This pattern was termed the "smart money" effect. More recent research, however, finds that after fund performance is adjusted for the momentum factor in stock returns, greater net flows no longer lead to better performance (Sapp and Tiwari (2004)).

In this paper we reexamine the smart money issue with U.K. data. Due to data constraints, all of the above studies work with aggregate money flows to funds: All investors are aggregated, and sales are offset by repurchases. Further, not having access to exact net flows, these papers approximate such flows using fund total net assets (TNA) and fund returns. Lastly, the approximate net flows that these studies use are at the quarterly frequency. Our data allow us to conduct a stronger test for the smart money effect by using monthly data on exact fund flows, and to gain greater insight into investors' decisions by considering separately the sales and purchases of individual and institutional investors.

The smart money hypothesis states that investor money is "smart" enough to flow to funds that will outperform in the future, that is, that investors have genuine fund selection ability.[1] Research into smart money in the mutual fund context was initiated by Gruber (1996). His aim is to understand the continued expansion of the actively managed mutual fund sector despite the widespread evidence that on average active fund managers do not add value. To test whether investors are more sophisticated than simply being chasers of past performance, he examines whether investors' money tends to flow to the funds that subsequently outperform. Working with a subset of U.S. equity funds, he finds evidence that the weighted average performance of funds that receive net inflows is positive on a risk-adjusted basis. Thus, money appears to be smart.

Zheng (1999) further develops the analyses of Gruber (1996), expanding the data set to cover the universe of all equity funds between 1970 and 1993. She finds that funds that enjoy positive net flows subsequently perform better on a risk-adjusted basis than funds that experience negative net flows. She also examines whether a trading strategy could be devised based on the predictive ability of net flows and finds evidence that information on net flows into small funds could be used to make risk-adjusted profits.

The more recent research of Sapp and Tiwari (2004), however, argues that the smart money effect documented in prior studies is an artifact of these studies' failure to account for the momentum factor in stock returns. Their argument can be synthesized as follows. Stocks that perform well tend to continue doing well (Jegadeesh and Titman (1993)). Investors tend to put their money into ex-post best-performing funds. These funds necessarily have disproportionate holdings of ex-post best-performing stocks. Thus, after buying into winning funds, investors unwittingly benefit from momentum returns on winning stocks. To test this reasoning, Sapp and Tiwari calculate abnormal performance following money flows with and without accounting for the momentum factor, and find that inclusion of the momentum factor in the performance evaluation procedure eliminates outperformance of high flow funds. Additionally, they show that investors are not deliberate in seeking to benefit from stock-level momentum: More popular funds do not have higher exposure to the momentum factor at the time they are selected. Wermers (2003) further contributes to this discussion by examining fund portfolio holdings and establishing that fund managers who have recently done well try to perpetuate this performance by investing a large proportion of the new money they receive in stocks that have recently done well.

All of the research work above is conducted with U.S. data. This fact is not surprising, given that the U.S. mutual fund marketplace is by far the largest in the world (Khorana, Servaes, and Tufano (2005)). However, there are a number of advantages to examining the smart money effect in fund management using our U.K. mutual fund data. First, our money flow data are monthly rather than quarterly. Second, we observe exact flows rather than approximations based on fund values and fund returns. Third, we can distinguish between institutional and individual money flows. Fourth, we can distinguish between purchases and sales.

A further advantage is that we are able to examine mutual fund investor behavior in a different institutional setting from that of the U.S. For example, unlike U.S. mutual funds, U.K. funds compete within well-defined peer groups, which may facilitate investors' decision-making. Also, the tax overhang issue (Barclay, Pearson, and Weisbach (1998)) does not apply to U.K. mutual funds, which means that investors' decisions are not complicated by the dependence of their future tax liability on the interaction of fund flows and fund performance.

In addition to testing for the presence of smart money, the disaggregated nature of our fund flow data allows us to examine two key hypotheses with respect to mutual fund investor behavior. Specifically, we are in a position to compare the quality of fund selection decisions made by individual and institutional investors, and likewise to compare fund buying and selling decisions. While institutions should benefit from both better information and more sophisticated evaluation techniques, we would expect individual investors to have greater incentives to make good investment decisions given the superior alignment of their payoffs with their investment returns (Del Guercio and Tkac (2002)). In the absence of further guidance on the relative importance of the two arguments, our prior about the relative smartness of institutional versus individual money flows remains neutral. With regard to the direction of money flows, there are at least two reasons to believe that investors' fund sells have a weaker association with future performance than their fund buys. First, the disposition effect discussed in Odean (1998) suggests that sell decisions are generally not optimally made. Second, fund redemptions are more likely than fund purchases to be due to factors unrelated to future performance, such as liquidity needs or taxes.

We find that portfolios in which funds are weighted by their money inflows outperform portfolios in which funds are weighted by TNA: New money beats old money. We also find that high net flow funds outperform low net flow funds. Thus, within the universe of actively managed funds, new investors tend to choose the better ones: Money is smart. This result holds for both individual and institutional investors, and is driven by investors' fund buys rather than sells. The smart money effect is not explained by the Chen et al. (2004) fund size effect, performance persistence, or the impact of annual fees on fund performance, nor is it concentrated in smaller funds. Although the effect is statistically significant, its economic significance is modest.

Given that Sapp and Tiwari (2004) challenge the Gruber (1996) and Zheng (1999) smart money effect in the U.S., how do our U.K. findings relate to the previous literature? To answer this question, we follow a two-pronged approach. First, we reduce the precision of our U.K. data to the level used in the U.S. studies. Aggregating monthly flows to the quarterly frequency reduces the smart money effect somewhat (regardless of whether momentum is controlled for); switching from actual flows to approximate ones implied by fund TNA, whether at the monthly or the quarterly frequency, has little impact. Next, we turn to U.S. data, noting that monthly fund TNA are available for the U.S. from 1991 onwards. Using these monthly data, we document a statistically significant smart money effect in the U.S. whose magnitude is comparable to that of the U.K. However, even at the quarterly data frequency, the post-1990 period is suggestive of the presence of smart money in the U.S. (whereas the 1970 to 1990 period is not). These conclusions hold irrespective of whether the momentum factor is taken into consideration. Thus, Sapp and Tiwari's results are due to the weight they put on the pre-1991 period, and to their use of quarterly data. The conclusions of Gruber and Zheng about the presence of smart money in mutual fund investing hold for both the U.S. and the U.K.

The remainder of this paper is organized as follows. Section I describes our mutual fund data in the context of the U.K. institutional environment. Section II reports on the determinants of the different components of money flows to funds. Section III examines whether funds favored by investors generate better performance than those not favored, and establishes the smart money effect in the U.K. Section IV investigates the pervasiveness of the effect and the possible reasons for it. U.K. and U.S. findings are reconciled in Section V. Section VI discusses our results and their implications. Section VII concludes.

## I. Data and Institutional Background

### *A.The U.K. Mutual Fund Industry*

The first open-ended mutual funds (called "unit trusts," because formally investors buy units in a fund) appeared in the United Kingdom in the 1930s, or about a decade later than in the United States.[2] At the end of 2000 (which coincides with the end of our sample period), 155 fund families ran 1,937 mutual funds managing £261 billion (or $390 billion) in assets,[3] making the U.K. mutual fund industry one of the largest outside the U.S. (Khorana, Servaes, and Tufano (2005)). While the U.S. and U.K. mutual fund environments are quite similar in many respects, we note two institutional differences, both of which likely make investor fund choice more complicated in the U.S. than in the U.K.

First, in the U.S. there is no single, official classification system for fund objectives. This allows funds to mislead investors about their objectives (Cooper, Gulen, and Rau (2005)), suggesting that ambiguous classification complicates investors' fund picking. By contrast, in the U.K. the Investment Management Association (IMA) classifies funds into sectors on the basis of the funds' asset allocation, and the official IMA classification system is used by the funds themselves, by information providers, and by brokers.[4] This reduces the potential for confusion on the part of any investors whose fund selection process requires breaking down the fund universe into groups of comparable funds.

The second difference has to do with the tax treatment of capital gains. In the U.K., the system is simple: Investors only pay capital gains tax when they sell their shares in a fund. In the U.S., however, investors face an additional form of capital gains tax. U.S. mutual funds must distribute net capital gains realized by the fund, and when they do so, their investors are liable for tax on these distributions. While existing investors prefer their fund managers to defer realization of capital gains, the resulting tax overhang is likely to deter new investors (Barclay, Pearson, and Weisbach (1998)). U.K. investors therefore face a simpler asset allocation problem than their U.S. counterparts, as they need not be concerned with how any pre-existing fund-level tax liability may affect their own after-tax returns.

### *B. The Population of Funds*

[Table I here]

Unlike in the U.S., unfortunately there does not exist a survivorship bias-free electronic database of U.K. mutual funds. Therefore, to round up the population of funds over the period we study, we manually collect and link across years data from consecutive editions of the annual *Unit Trust Year Book* corresponding to year-end 1991 through year-end 1999. This data set additionally contains fund fees, management style (active or passive), and the fund sector assignment. Like earlier literature on the smart money effect, we focus on funds investing in domestic equities. Unlike the earlier papers, which all examine U.S. funds, we can select these funds unambiguously by retaining only those funds whose official sector definitions correspond to a U.K. equity mandate. Panel A of Table I shows the evolution of this group of funds. The number of domestic equity funds grows from 425 at the start of 1992 to 496 at the start of 2000 (averaging 461 per year), while assets under management increase almost four-fold over the same period to £115 billion. Since our interest lies in whether investors can identify superior funds, next we drop passively managed ("index tracker") funds. This leaves us with 432 eligible funds per year on average.

### *C. Data on Funds' Money Flows*

Our money flow data come from the IMA and give monthly mutual fund flows over the 1992 to 2000 period. Thus, unlike other studies of mutual fund investor behavior, which back out net flows from data on fund values and fund returns, we observe the exact amount of money injected by investors into each mutual fund. Further, in our data set these net flows are disaggregated into their component parts, namely, sales to individual investors, sales to institutional investors, repurchases from individual investors, and repurchases from institutional investors.

The IMA obtains money flow information directly from its member companies every month.[5] Not all management groups report this information; however, since information is collected live and historical information is not discarded, there is no bias towards surviving funds in the data collection process. We manually link these money flow data to the data set constructed from consecutive editions of the *Unit Trust Year Book* to obtain our final mutual fund sample. Panel B of Table I shows that our sample averages 311 funds per year with an annual attrition rate of 6.3%. Whether on the basis of assets under management or on the basis of the number of funds, our sample covers roughly three-quarters of the population of eligible funds that we identified earlier.[6]

The remainder of Panel B reports total money flows as well as their components parts. The net aggregate money flow is positive in every year except 2000, and averages £1,805 million annually. As it turns out, this amount masks an annual inflow of £6,617 million and an outflow of £4,812 million. This fact indicates that research based on approximations of net money flows observes (with noise) only a fraction of investors' capital moving through mutual funds.

As mentioned earlier, fund management companies report to the IMA not only the total sales and repurchases for each fund, but also whether these flows took place through retail channels and thus originated from individual clients, or whether they came from the fund's institutional clients. Over the full sample period, net flows from institutions are £311 million per year, as compared with £1,493 million from individuals. Even on a year-by-year basis, it is clear that individual and institutional investors do not behave alike. For example, the year 2000 had the lowest net flow of any year from institutions, but one of the higher annual net flows from individuals.

The remainder of Table I presents a further disaggregation of annual money flows by direction and by client type. Once again it can be seen that major capital movements are masked by the netting of sales and repurchases: For example, in 1999 the mere £3 million net flow from institutions is the result of them buying £3,299 million worth of fund units and selling £3,296 million worth of fund units.

Before we can start working with our flow data at the fund-month level, we address several data issues. First, we eliminate fund-months without any recorded money flow. This leaves 32,615 fund-months. Second, we set to "missing" retail (institutional) flows for fund-months without any retail (institutional) client sales or repurchases. This is because the fund universe we study includes funds that are open only to retail (institutional) investors, as well as funds that are open to both investor types. There are 15,541 fund-months with both retail and institutional activity, 15,307 fund-months with retail activity only, and 1,767 fund-months with institutional activity only. Third, we "clean" our data, so that highly unusual flows do not drive our results. In particular, unusual flow activity can take place for very young funds or for funds about to be closed down. Rather than setting a common normalized flow cutoff for all funds, we use a filtering procedure that takes into account a fund's flow volatility.[7] We begin by dropping funds with fewer than 10 months of flow data. Next, we calculate normalized net flows, that is, we divide the net monetary flow into a fund in a given month by the fund's size at the start of the month.[8] We then drop fund months with normalized net flows that are more than five standard deviations away from the fund's average.[9] We iterate the last two steps until no more fund-months are dropped. This leaves us with a final sample of 30,666 fund-months.[10] Of these, 29,030 fund-months experience retail activity, 16,169 experience institutional activity, and 14,533 experience both institutional and retail activity. Table II reports on the distribution of net flows and their components for these fund-months.

[Table II here]

In Panel A of Table II we show moments of the distribution of normalized flows, averaged across the 108 monthly cross-sections. The first row describes the flow estimate that is implied by fund total net assets (TNA) and return data alone. This is the variable used in the existing smart money literature and is calculated as $\frac{TNA_t - TNA_{t-1}(1+r_t)}{TNA_t}$ (fund subscripts are suppressed).[11] It is instructive to compare its distribution to that of the actual net money flow. While the mean net flow is 0.65% of fund value, corresponding to roughly 8% growth per year, the growth rate estimate based on implied flows averages 0.42% per month or about 5% annually. The noise in implied flows is also clear from observing that they vary more than actual net flows: the standard deviation of implied flows is more than 10% greater than that of actual flows, and the interquartile range for implied flows is over 40% wider than the one for actual net flows. More evidence on the quality of the implied flow estimate is in Panel B of Table II, which shows correlations between our flow variables. The table shows that the average correlation between implied and actual net flows equals 0.847. The practical implication of implied flows being an approximation of actual flows is that when portfolios are formed on the basis of implied flows, many funds will be assigned to the wrong portfolios. For example, in our sample of 30,666 fund-months, implied flows have the wrong sign for 5,424 fund-months, or 17.7% of the time.

The remainder of Panels A and B shows time-series averages of moments and correlations for components of the net aggregate money flow. First and most important, note the low average correlation between institutional and retail flows. For net flows, the correlation equals 0.251; for inflows the correlation equals 0.273 and for outflows it is 0.137. This leaves much scope for the possibility – which the remainder our paper explores in detail – that the behavior of aggregate net flows studied in the existing smart money literature could belie very different behaviors by investors, depending on whether they are buying into a fund or taking money out, and depending on who the investors are.

The correlations between inflows and corresponding outflows are also telling. In aggregate (for both individual and institutional investors), the correlation averages 0.118, and is similar for individual investors (0.141) and institutional investors (0.113). The fact that these correlations are positive, albeit small in magnitude, indicates that funds with low sales are not necessarily the funds with high withdrawals – and vice versa. We briefly examine the determinants of the different money flow components in Section II.

### *D. Performance Measurement*

Our fund return data are survivorship bias-free and come from Quigley and Sinquefield (2000), who collect monthly returns for domestic equity funds over the 1975 to 1997 period, and subsequently extend this data set to the end of 2001. As in the U.S. studies, our returns are gross of taxes but net of management fees.[12]

As the debate over the smart money effect in the U.S. shows, proper performance measurement is paramount. Like Sapp and Tiwari (2004), we measure fund performance using the Carhart (1997) four-factor model, which we adapt to the U.K. setting. Specifically, we estimate the regression model

$R_{it} - RF_t = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{UMD} UMD_t + e_{it}$, where $R_{it}$ is the rate of return on investment *i* in month *t*, $RF_t$ is the risk-free interest rate in month *t*, $MKT_t$ is the return on the market portfolio in excess of the risk-free rate, and $SMB_t$, $HML_t$, and $UMD_t$ are returns on the size, value, and momentum factor mimicking portfolios, respectively. Our monthly Fama and French (1992, 1993) size and value factor realizations come from Dimson, Nagel, and Quigley (2003), who confirm the size and value effects in the U.K. Our monthly momentum factor is constructed following Carhart (1997). Specifically, each month we rank all U.K. firms listed on the London Stock Exchange on their 11-month returns lagged by one month, and calculate the difference between the average returns of the highest and the lowest 30% of firms.[13]

## II. Determinants of Money Flows

In order to understand better how different types of investors make their fund buying and selling decisions, we briefly present evidence on the determinants of mutual fund money flows in the U.K. Our dependent variables are net flows and their components that are expressed as a proportion of fund value at the start of the month. For the sake of parsimony, we report on only two explanatory variables that past work has shown to be strong predictors of net mutual fund flows: Past flows and past performance (unreported control variables are logarithms of fund TNA and fund age, as well as initial and annual fees).

[Table III here]

The past flow measure we use for each flow component is the value of that flow component 12 months earlier. This is a simple way to account for seasonalities in investors' decisions (which may be due, for example, to regularly scheduled fund purchases). Since using lagged flows costs us a year of data, there are 96 monthly regressions corresponding to the period from January 1993 through December 2000. Our results, based on the time series of cross-sectional regression coefficient estimates (the Fama-Macbeth approach) are shown in Table III. Past performance is measured as the Carhart (1997) four-factor alpha, averaged over the 12 months preceding the money flow. The reported coefficients are averages of the monthly coefficient estimates, and *p*-values are based on the time-series standard deviations of these estimates.

The table indicates that our flow variables are persistent: Coefficient estimates for lagged flows are always positive and significant. The much higher coefficient estimate for actual net aggregate flow than for implied flow (0.142 vs. 0.062) is clearly due to the noise inherent in estimating the implied flow. The patterns of coefficient estimates further tell us that retail flows are more persistent than institutional flows, and that inflows are more persistent than outflows.

There exists overwhelming evidence in U.S.-based work that investors "chase" high returns (Chevalier and Ellison (1997), Sirri and Tufano (1998), Del Guercio and Tkac (2002)). Our data show that U.K. investors do likewise. The coefficient of 1.397 for net aggregate flows suggests that on the whole, a 1% increase in monthly alpha results in an additional inflow of more than 1% of fund value. Since the levels of the normalized flow variables that we examine are different, estimates of their sensitivity to past returns are not directly comparable. Nonetheless, it is clear that inflows increase with past performance while outflows tend to do the opposite; further, the reaction of inflows to past performance is markedly more pronounced than that of outflows both for individuals and for institutions. The asymmetry in investor reaction to good and bad performance is well known (Sirri and Tufano (1998)). However, previous researchers have not been able to observe this reaction for in- and outflows directly. Whether such differences in the behavior of our money flow measures translate into differences in fund selection ability is examined in the next section.

## III. Performance of Money Flow Based Portfolios

### *A. Money-Weighted Portfolios*

So, do investors benefit from their fund selection process? A simple way to address this question is to evaluate the performance of all "new money" put into mutual funds by investors. A natural benchmark against which to measure the success of these new investments is the performance of "old money," that is, of assets already in place before the latest round of investments.

Our data allow us to define what constitutes new money in several ways. First, we can measure it using the implied net money flow, as would a researcher with access to fund size and return data only. In addition, we can use actual net aggregate flows from our data set. Finally, we can use inflows or outflows from individual or institutional investors (or from both investor categories combined). A hypothetical portfolio of new money is then constituted from all eligible funds weighted in proportion to their value of the flow measure in the preceding month. Performance evaluation of our new money-weighted portfolios gives us the performance of the average pound (dis)invested in U.K. mutual funds in the past month. Similarly, we can form a portfolio of funds on the basis of the funds' total net assets excluding money put in during the last month ("old money"). Comparing the performance of new and old money-weighted portfolios tells us whether recent investing decisions outperform the mutual fund industry as a whole.

Note, however, that as a result of this portfolio formation scheme, when performance is evaluated on the net money flow basis, funds with negative net flows would be assumed sold short in our hypothetical portfolio. Because short-selling is generally a practical impossibility for mutual funds, and because a performance comparison between a portfolio including such short selling and the fund universe would be misleading, when dealing with net flows we contrast positive and negative money flow funds; this is done in Table V. If, on the other hand, portfolios are formed on the basis of either sale or repurchase activity, there are of course no negative weights; we report on the performance of such portfolios in Table IV, contrasting this performance with the performance of the fund universe.

[Table IV here]

In Table IV, we characterize our fund portfolios using what Zheng (1999) calls the fund-level approach. Specifically, each month we conduct a Carhart (1997) four-factor regression for every fund using the preceding 36 monthly returns to obtain our four estimated factor loadings.[14] We then subtract from that month's fund return the product of each factor realization and its estimated loading to obtain that month's alpha for each fund. These alphas and the fund-level regression estimates are used to compute the money-weighted average across funds for each month. The table reports the time-series average of the monthly averages. In the last two columns, it also reports the difference between the money-weighted alpha obtained in this way and the similarly obtained fund value-weighted alpha, as well as the associated *p*-values that are computed from the time series of the monthly averages.

Before discussing the performance of our new money-weighted portfolios, we first turn to the value-weighted portfolio in row 7 of the table, where all actively managed domestic equity funds are represented in proportion to their TNA. This corresponds to the performance of "old" money (specifically, of assets in place excluding the previous month's round of investments).[15] This portfolio's four-factor alpha averages -9.6 basis points per month over the full 1992 to 2000 period. We additionally evaluate an equally weighted portfolio of actively managed domestic equity funds, whose four-factor alpha averages -7.2 basis points per month (the last two columns of the table show this alpha to be insignificantly different from the value-weighted portfolio's alpha). As a further reference, in the last row of the table we summarize the performance of an equally weighted portfolio of low cost passively managed domestic equity funds;[16] its alpha, at -5.1 basis points per month, is insignificantly different from that of the value-weighted portfolio.

The first row of Table IV shows the performance of a portfolio of funds weighted by their aggregate (i.e., individual and institutional investors combined) inflows of money. While the factor loadings for this portfolio are quite similar to those of the value-weighted portfolio, its four-factor alpha, -2.2 basis points per month, is a highly significant 7.4 basis points higher than that of the actively managed fund universe. This is a first result indicating that U.K. mutual fund investors can and do choose funds that subsequently deliver above-average performance.

The second row of the table shows that the performance of U.K. funds weighted in proportion to their outflows of investor money is virtually indistinguishable from the value-weighted fund population. In other words, money withdrawn from funds, unlike that invested, is not smart.

In the next four rows, we separately examine inflows and outflows due to individual and institutional investors. Of those, only individual inflows perform significantly differently from the fund universe, beating it by 8.8 basis points per month. While institutional purchases outperform value-weighted funds by 4.0 basis points, statistical significance is not reached. However, this may be due in part to the fact that only about one-half of our fund-months experience institutional investor activity.

Lastly, it is instructive to examine the patterns of factor loadings for our fund portfolios. Like in the U.S. (Carhart (1997), Sapp and Tiwari (2004)), money invested with the U.K.'s active managers has a market beta close to one and a positive exposure to the size factor. Contrary to the U.S., where value factor exposure tends to be negative and momentum exposure positive, in the U.K. these signs are reversed. These results are consistent with prior studies of U.K. mutual fund performance (Quigley and Sinquefield (2000), Fletcher and Forbes (2002)). The momentum result in particular has special significance because Sapp and Tiwari argue that momentum investing by U.S. funds alone accounts for the previously documented smart money effect. In the U.K., however, Wylie (2005) shows that mutual funds herd *out* of large stocks with high prior-year returns.

[Table V here]

In Table V, we look for evidence of smart money on the basis of net flows. In Panel A, for each net flow measure, we contrast flow-weighted performance of positive and negative net flow funds. The first row shows that positive implied net flows have an alpha of -0.1 basis points as compared to -16.4 basis points for negative implied flows, and that the difference is highly statistically significant. The performance spread between high and low flow funds is also significant on the basis of actual flows, 13.8 basis points. Recall that implied flows are a noisy estimate of actual fund flows, so that one might have expected the use of implied flows to hurt our ability to detect the smart money effect. This does not seem to be the case – at least when working with monthly money flows, as we do here.

Note also the quite similar UMD coefficient estimates for positive and negative money flow funds. This is in contrast with results reported for the U.S. by Sapp and Tiwari, where positive flow funds have markedly greater momentum exposure than do negative flow funds. However, this observation is consistent with the notion that U.K. fund managers are largely contrarians (at least with regard to the largest stocks), as suggested by Wylie's (2005) examination of portfolio holdings, as well as by the negative loadings on the UMD factor in our regressions. Thus, we would expect controlling for momentum to make little difference in looking for smart money in the U.K. – indeed three-factor model results (which we report in Section III.C of the paper) are close to those of the four-factor model.

The last two rows of Panel A examine flows from institutions and individuals separately. For both flow types, positive inflows beat negative ones by more than 10 basis points per month; however, the difference is only statistically significant for individuals. Taken together, the evidence thus far establishes that the average pound of new money outperforms the average pound of old money, and that money invested outperforms money disinvested. In short, new money is smarter than old money. But in view of the negative alphas earned by new money, can we say that new money is actually smart?

The papers that document the smart money effect in the U.S., namely, Gruber (1996) and Zheng (1999), also find a significant performance spread between new and old money. However, they additionally find that the alphas of new money are positive (although not always significantly different from zero), whereas in most of our tests new money in the U.K. has a negative (although small in magnitude) alpha.  This distinction makes it important to discuss what is the right performance benchmark for our tests, and why our evidence means that U.K. fund money flows are, in fact, smart in the Gruber-Zheng sense.

A natural point of departure for answering these questions is to compare alphas for actively managed mutual funds as a group in the U.K. and the U.S.  Recall from Table IV that the TNA-weighted four-factor alpha for actively managed UK funds during the 1992 to 2000 period is -9.6 basis points per month.  By contrast, Zheng's 1970 to 1993 TNA-weighted three-factor alpha for the U.S. is a positive 1.3 basis points.  To allow for a more direct comparison, we calculate the 1992 to 2000 U.S. TNA-weighted four-factor alpha to be -3.3 basis points (our handling of U.S. data is described in Section V).  Whence the 6.3 basis point difference?

We start with the caveat that no matter how much care is put into constructing a series of factor realizations in a pair of countries, the correspondence will never be perfect – and as a consequence, absolute alphas will never be exactly comparable.  Nonetheless, taking our estimates at face value, two reasons can explain a performance difference of this magnitude.  The first reason is the presence of a 0.5% "stamp duty" tax on share purchases in the U.K.  This means that a fund whose annual turnover in domestic equities is 80% of the fund's value (to take a typical turnover figure) will lose 40 basis points per year, or 3.3 basis points per month, to the stamp duty alone.  Since our factor realization series do not take the stamp duty into consideration, the result is a downward bias in the estimated alpha.  The second reason is that transaction costs on the London Stock Exchange have historically exceeded those of the main U.S. exchanges.  Once again, factor returns are gross of these costs.  Further, replicating the value, size, and momentum factors would involve trading some highly illiquid stocks and be even more costly than replicating the market factor. Therefore, even absent the stamp duty, a passive zero-alpha portfolio with factor loadings equal to those of a given actively managed fund is unattainable.

Thus, while the four-factor alpha is useful in comparing the performance of different U.K. funds, a negative alpha does not necessarily indicate value destruction by a fund. What, then, is the opportunity cost of investing money with a given active manager? A natural way to answer this question is to use the performance of the actively managed fund universe in this role – that is, our TNA-weighted alpha. By this criterion, U.K. money is smart. One can also argue that passively managed funds – and, in particular, low-cost passive funds – are the cheapest way of holding a diversified equity portfolio. A possible counterargument is that investors seeking a particular style and/or sector bet will not always find a suitable passive fund on offer. Nonetheless, our new money portfolios deliver higher alphas than even low-cost index funds. In other words, new money is, in fact, smart.

### *B. Portfolios of Funds Sorted by Money Flow*

In this section, in order to examine the pervasiveness of U.K. investors' ability to select superior funds, we compare equally weighted groups of popular and unpopular funds. This approach curtails the influence of funds with extreme flow observations. We start, in Panel B of Table V, with an equally weighted counterpart of the positive-versus-negative net money flow results shown in Panel A of the same table. Equal weighting shrinks the magnitude of the smart money effect from 13.8 to 6.5 basis points when sorting on actual net flows, but the difference continues to be highly significant. Moreover, there is now strong evidence that institutional money is smart as well (6.4 basis points, *p*-value < .01). The fact that positive flow funds perform better than negative flow ones is a direct counterpart of the U.S. analyses of Gruber (1996), Zheng (1999), and Sapp and Tiwari (2004), and it establishes the smart money effect for the U.K. mutual fund marketplace.

To understand which flow components drive this result, it is desirable to apply the same methodology to all the flow variables comprising net flows. However, the methodology above, which involves sorting funds into positive and negative flow groups, does not help us when studying sales and repurchases separately, since these flow components are nonnegative by definition. We therefore use a different approach and, for each flow component studied, partition funds into portfolios based on their normalized flow activity. Specifically, each month we sort funds using our measures of normalized money flows into high flow portfolios (consisting of funds where the normalized flow measure is above its median value for the month), and low flow portfolios (consisting of the remaining funds). We then compare the risk-adjusted performance of equally weighted high and low flow portfolios. Table VI contains the results.[17]

[Table VI here]

The sorting of funds into equal-sized groups appears to help in detecting the statistical significance of the smart money effect for the different flow components. At the 5% significance level, net aggregate flows (whether actual or estimated), as well as net institutional flows, are smart. In addition, all inflow measures – aggregate, individual only, or institutional only – are smart. Lastly, none of the outflow measures give rise to a significant performance difference between high and low outflow funds. In other words, the smart money effect in the U.K. is due to fund buys (but not sales) of both individual and institutional investors.

To verify that the smart money effect persists throughout the timespan we examine, we repeat our analysis separately for the first and last halves of our 1992 to 2000 study period (results not reported in a table). Indeed, the contributions of the two subperiods are of similar magnitude: In the earlier subperiod, high actual net flow funds outperform low flow funds by 5.8 basis points per month ($p$-value = 0.049), while in the later period this difference is 6.9 basis points per month ($p$-value = 0.075). In other words, the smart money effect manifests itself in the U.K. throughout the 1990s.

### *C. Results with Alternative Performance Evaluation Methods*

An alternative to the fund-level approach to appraising the smart money effect is what Zheng (1999) terms the portfolio-level approach. Under this method, a suitably weighted portfolio of funds is formed first, and then the resulting time series of excess portfolio returns is regressed on the time series of factor realizations. This overcomes the shortcoming of the fund-level method, whereby only funds with a sufficiently long return history (in our case, at least 30 months) are included. For this reason, and for comparability with portfolio-level results in Zheng (1999) and Sapp and Tiwari, we present the high-vs.-low fund money flow performance spread under the portfolio approach in Table VII.[18]

[Table VII here]

The results under the unconditional four-factor portfolio-level approach, summarized in the first two columns of Table VII, tell essentially the same story as our fund-level results. The smart money effect based on our net aggregate flow sorts is confirmed (high-minus-low difference = 8.6 basis points, *p*-value = 0.008). Rows 3 and 4 confirm that this effect is driven by investor purchases rather than withdrawals. Of the remaining rows, only one (individual inflow) shows results that are significant at the 5% level. This may be because aggregation across funds prior to risk adjustment renders the portfolio-level tests less powerful than the fund-level tests. (The reported *p*-values are based on the Kosowski et al. (2006) bootstrap procedure, but are very close to those based on the *t*-test.) We also note that point estimates of the smart money effect in individuals' and institutions' net flows are comparable (6.3 and 7.0 basis points, respectively).

Once again for comparability with Sapp and Tiwari, we test for smart money without taking the momentum factor into account. These estimates and their *p*-values are shown in the third and fourth columns of the table. The fact that these results are close to those of the four-factor model results again show that, in contrast to Sapp and Tiwari's findings for the U.S., stock return momentum has little to do with the U.K. smart money effect.

The next two columns of Table VII show portfolio-level results using Ferson and Schadt's (1996) conditional performance evaluation. Specifically, we follow Fletcher and Forbes (2002) in implementing the conditional version of the Carhart (1997) model for the U.K. with the lagged market dividend yield and risk-free rate representing the conditioning set of publicly available information.[19] The results are qualitatively similar to those under the unconditional portfolio approach: There is a smart money effect on the basis of net flows and inflows, but not outflows.

As a last methodological variation, we use the style adjustment approach, whereby each fund's abnormal return every month is obtained simply as the difference between that fund's investment return and the average investment return of the mutual fund sector to which the fund belongs. Abnormal returns for high flow and low flow funds are then averaged every month. The average monthly difference between the two groups and the associated *t*-test *p*-value are presented in the last two columns of Table VII. Although the style adjustment approach is a relatively crude method for detecting abnormal performance, the results once again confirm that inflows, and not outflows, give rise to the smart money effect in the U.K.

## IV. Further Evidence on the Smart Money Effect

### *A. Is the Smart Money Effect Concentrated in Small Funds?*

As we examine the smart money effect in the U.K. mutual fund marketplace, an important consideration is to document how pervasive this effect is across funds. In particular, Zheng (1999) draws attention to the role of fund size, which may both condition investor choice and influence the extent to which manager skill translates into fund performance. We therefore repeat our analyses separately for small funds (those below the median fund size in a given month) and large funds (the others). High and low money flow funds are defined with respect to the full fund universe, as before. Although the splitting of our sample into size groups hurts somewhat our ability to detect statistical significance, the point estimates of the smart money effect for actual net aggregate flows are of comparable magnitude for small and large funds (0.070 and 0.066, respectively; for brevity, full results are not shown in a table). In short, there is no evidence that either small or large funds are responsible for the bulk of the smart money effect.[20]

### *B. Is the Smart Money Effect Subsumed by Regularities in Mutual Fund Returns?*

The literature on mutual funds has long searched for predictors of mutual fund performance. Thus, extensive research has been dedicated to the issue of performance persistence (e.g., Carhart (1997) and Wermers (2003) for the U.S., Fletcher and Forbes (2002) for the U.K.). Carhart (1997) also shows that funds with higher fees underperform in the future. More recently, Chen et al. (2004) document a size effect for U.S. mutual funds, whereby larger funds exhibit poorer performance, presumably due to diseconomies of scale in investment management. If such regularities manifest themselves in our sample, then it is important to check whether they explain away investors' fund-picking ability. To do so, we conduct a multivariate analysis of fund performance. Specifically, we pool our data across funds and months, and regress the four-factor alpha on normalized flows and fund characteristics measured at the end of the preceding month.

[Table VIII here]

One of the main challenges in explaining fund performance is the highly nonnormal distribution of fund alphas. To address this problem we use least absolute deviation (LAD) regression analysis. In addition, to control for time fixed effects, we measure all variables as differences from their mean values for each month. The results are presented in Table VIII. The first regression confirms the smart money effect: Fund alpha is positively and significantly related to the previous month's net aggregate flow (coefficient = 2.110, *p*-value < 0.01). In the second regression, alongside net aggregate flow we include the logarithm of fund size and the four-factor fund alpha over the preceding 12 months. These variables' regression coefficients indicate that our sample is characterized by performance persistence but not by a fund size effect.[21] In any case, the coefficient for the money flow term, 1.573, remains highly significant

($p$-value < 0.01) indicating that neither performance persistence nor the fund size effect subsume the smart money effect.

In the third regression we conduct an additional check of the possibility that the smart money effect is unevenly distributed across fund sizes. To do so, we add an interaction term for the logarithm of fund size and money flow. Consistently with the evidence in the previous subsection, the interaction term is insignificant, while the money flow term continues to be highly significant.

Lastly, we consider the impact of annual management fees. If higher annual fees are not entirely recouped through higher returns, then the fee will have a negative impact on fund performance (since our fund returns, like those in the U.S. literature, are net of the annual fee), and smart money can be the result of simple avoidance of expensive funds. Indeed, the last regression in Table VIII shows the estimated coefficient for the annual fee variable to be negative and significant. More importantly for our purposes, the coefficient estimate for the money flow term continues to be positive and highly significant, suggesting that the smart money effect is not explained by the impact of annual fees on fund performance.

### *C. The Span of the Smart Money Effect*

While our analyses up to this point are based on fund performance in the month immediately following money flows, an interesting question is: How long does the smart money effect persist? Unfortunately, with only nine years of money flows, our data set is less than ideally suited for addressing this question. With this caveat, Table IX examines the performance of the smart money effect for up to one year ahead. Specifically, it uses the fund-regression approach to compare performance of high and low flow funds where flows are lagged from one to 12 months.

[Table IX here]

In the first two columns, funds are sorted based on their implied flows. We note that this is the only measure of flows that investors can actually observe. While the short sample period causes our point estimates to fluctuate considerably, both the signs and the *p*-values of the performance difference between high and low flow funds show the effect to be short lived: It is not detectable past the first month following the month in which the flow is measured.[22] Thus, even if mutual fund investments could be made without a front load (which in the U.K. typically can only be done by an investor transferring money within a fund family), and if (counterfactually) low flow funds could be sold short, an investor seeking to profit from the smart money effect would gain on average only a very modest return of no more than 20 basis points or so. Therefore, while investors tend to make good fund choices on average, this smart money effect does not give rise to what Zheng (1999) calls an "information effect."

The last two columns show results for actual flows. While the point estimates are rather imprecise as before, this time the signs and *p*-values of the performance differences between high and low flow funds suggest that the true smart money effect may last up to four months, that is, somewhat longer than the span observed using implied flows. This observation is consistent with investors making good mutual fund choices and implied flows being an approximation of actual investor behavior.

## V. Reconciling U.K. and U.S. results

The U.K. smart money effect we have documented holds over 1992 to 2000 using monthly fund flows.  This contrasts with the results of Sapp and Tiwari (2004), who, using quarterly fund flows over 1970 to 2000, conclude that there is no smart money effect in the U.S.  This leads one to ask: Is the smart money effect country specific, or can the difference in the results be explained by reliance on approximate flows, data frequency, and/or the period under study?  To answer these questions, we proceed as follows.  First, we examine the impact of data frequency and its interaction with reliance on implied flows using the fact that actual monthly flows are available for the U.K.  Next, we take advantage of the availability of monthly flow data for the U.S. since 1991 to analyze the role of data frequency and time period in that country.

The higher precision of our U.K. data stems from the fact that it is both at a higher frequency and that it uses exact money flows to funds.  The disadvantage inherent in using approximate money flows implied by fund TNA and investment returns has already been discussed.  Before proceeding, we note that there are at least three potential reasons why using data at the quarterly frequency would hamper a researcher's ability to detect the smart money effect.  First, the number of observations relative to the monthly frequency is reduced by a factor of three.  Second, implied flows lose accuracy as the span over which they are measured grows.  Lastly, when flows are quarterly, and consequently fund portfolios are rebalanced quarterly as well, flows are effectively used to predict returns between one and five months ahead, and three months ahead on average, as compared to one month ahead when monthly data are used.

To shed light on the impact of using implied flows when data are quarterly, we first turn to our U.K. data.  When we use actual net flows aggregated to the quarterly frequency, the performance spread between high flow and low flow funds under the fund-level approach is 5.9 basis points per month and significant (recall that the corresponding quantity using monthly flows is 6.3 basis points). If flows are inferred from quarterly TNA instead, as is the case in published U.S. work, the performance spread is virtually unchanged, at 6.0 basis points. This echoes Section III of our paper, where implied and actual flows produce similar results at the monthly frequency. In other words, the cost to the researcher of relying on implied rather than actual flows is low.[23] To understand better the cost of using quarterly rather than monthly implied flow data, we now turn to U.S. data.

In studying the role of data frequency for the U.S., we are aided by the fact that the CRSP Survivor-Bias-Free Mutual Fund Database provides monthly TNA from 1991 onwards. This enables us to calculate monthly implied money flows from that time (recall that quarterly TNA are available from 1970). Our U.S. data come from the 2005 version of the CRSP database. We retain only funds with diversified U.S. equities objectives.[24] For these funds, starting in 1970, we calculate quarterly absolute and normalized implied net money flows as

$TNA_t - TNA_{t-1}(1+r_t) - MGTNA_t$ and $\dfrac{TNA_t - TNA_{t-1}(1+r_t) - MGTNA_t}{TNA_t}$, respectively, where

$MGTNA_t$ is the increase in TNA due to mergers in quarter $t$. The same formulas are then used to calculate monthly money flows from 1991 onwards. Our sample consists of 9,488 distinct fund entities, which contribute 7,338 fund-years during 1970 to 1990 and 41,185 fund-years during 1991 to 2004.

[Table X here]

Table X shows the results of our analyses, where funds are sorted into those with above- and below-median flows and the fund-level approach is used (note that our conclusions are robust to sorting funds into those with positive and negative money flows, to weighting funds by signed flows, or to using the portfolio approach). In Panel A, results are separated according to the time period and whether monthly or quarterly flows are used. We start with quarterly flows over 1970 to 2000 (the sample period used by Sapp and Tiwari). Our results echo the central result of Sapp and Tiwari: There appears to be a significant smart money effect when using the three-factor model, but this is no longer the case when momentum is also controlled for. We next turn to the latter part of this time period, for which monthly flows can be extracted, namely, 1991 to 2000 (which almost coincides with our 1992 to 2000 U.K. sample period). Using monthly money flows, even after a full four-factor adjustment, there is a highly significant performance difference of 9.2 basis points per month between high and low money flow funds. Is this due to our use of monthly rather than quarterly periodicity, or to the more recent time period? The answer is both. When we use quarterly flows over 1991 to 2000, there is also a detectable smart money effect, but it is smaller in magnitude, at 6.6 basis point per month. By contrast, over 1970 to 1990 the corresponding number is 1.4 and insignificant.[25] It appears plausible that greater investor sophistication and data availability may be responsible for mutual fund investors' money becoming smart in the more recent years.

In brief, these results indicate that i) mutual fund investors' money has become "smarter" over time and ii) this "smartness" is easier to detect with monthly money flows. As an independent check on these conclusions, we turn to an out-of-sample 2001 to 2004 period, which, to our knowledge, has not previously been checked for smart money. Although this period is relatively short, it also reveals a significant smart money effect, at 9.6 basis points per month.

We note that a researcher working with quarterly flows over the same period would have found the corresponding number to be 3.9 and insignificant.

What, then, of the span of the smart money effect in the U.S.? Panel B examines the entire 1991 to 2004 period for which monthly money flows can be extracted. Using monthly flows and four-factor performance evaluation, there is a statistically significant effect up to 6 months following the assignment of funds to high or low money flow portfolios (both the time span and the magnitude of the effect are reduced if one works with quarterly flows). Overall, U.S. results are quite similar to those for the U.K. (the shorter statistically detectable time span in the U.K. may have to do with the smaller number of funds in that country).[26] Although in the U.S., like in the U.K., the high versus low money flow fund performance difference is too small and too short lived to be exploitable by investors, that is, to give rise to the "information effect," the results do suggest that the smart money effect is pervasive: At least since the early 1990s, it is present in both countries' mutual fund marketplaces.

We conclude that whether implied or actual flows are used to test for smart money matters little. The time period and use of monthly flows, however, are both very important. When monthly flows are available, U.S. funds and U.K. funds both exhibit a link between money flow and future performance that is robust to a number of methodological variations.

## VI. Discussion

Having established the existence of the smart money effect in the British mutual fund marketplace (and reestablished it for the U.S.), in this section we seek to put our findings in perspective. Specifically, we now discuss the interpretation of our results, their economic significance, and their implications.

We start with an important caveat. The term “smart money” in the mutual fund literature has come to be associated with investors’ ability (or lack thereof) to identify superior future performers from a group of comparable funds. Our paper follows this convention. There are, of course, other ways for mutual fund investors to be smart. For example, they can move their money among funds with different objectives so as to implement a dynamic asset allocation strategy. Indeed, the low net flows into domestic equity funds from institutional investors (as compared to those from individual investors) at the end of our sample period as shown in Table 1 may be an indication of institutional investor “smartness” in this sense. While this is an interesting and important topic, it falls outside the scope of our study. Although an investor who is good at sector picking may or may not be good at fund picking, it is the latter skill that is the focus of this paper and the literature that it extends.

Investor fund-picking ability originally attracted research interest as a possible explanation for the puzzling popularity of actively managed funds despite the availability of passive funds (Gruber (1996)). Like in the U.S., U.K. passive mutual funds are cheaper to own than active funds. Thus, in 1999, the median front-end load for the U.K.’s actively managed domestic equity funds was 5%, while the equivalent for passive funds was only 1% (U.K. funds do not have back-end loads); the median annual fee was 1.25% for active funds, and 1% for passive funds. The magnitude of the smart money effect we observe is not nearly enough to equate net-of-charges returns for new money invested in actively managed funds, taken in aggregate, with those for passively invested money over any investment horizon. We are therefore inclined to concur with Sapp and Tiwari’s (2004) assertion that Gruber’s (1996) puzzle is not explained by smart money

– or in any case, smart money can only be part of the answer. Our contribution, rather, is to demonstrate that in contrast to Sapp and Tiwari's findings, within the universe of actively managed funds investors consistently find funds that perform better than average in the future.

What lies behind this future outperformance? While a natural answer is manager skill, Wermers (2003) suggests another possibility. He argues that investor money flows are disproportionately used by funds to buy stocks they already own, exerting upward pressure on these stocks' prices, and thus contributing to funds' post-flow performance. Unfortunately, we do not have U.K. funds' portfolio holdings data to test this alternative explanation. However, price pressure is inherently a very short-term phenomenon, and as we work with monthly return data, one month is the relevant time horizon for distinguishing between genuine outperformance and the effect of price pressure. The fact that outperformance lasts well beyond the one-month mark suggests that mutual fund investors' money is, in fact, smart. We nonetheless check another testable implication of the price pressure story. We can expect an individual fund's influence on the price of stocks it buys or sells to be greater the less liquid these stocks are. Further, it is well known that generally liquidity is inversely related to market capitalization. Although we do not have the data to measure the market capitalization of stocks held by a given mutual fund, a crude measure of the "smallness" of a fund's holdings is its estimated coefficient on the SMB factor. We therefore implement regressions paralleling those of Table VIII, but including an interaction term between the SMB factor and net aggregate flow (results not reported in a table). This interaction term is insignificantly different from zero (whether we measure the net aggregate flow as proportion of fund value or as an absolute amount) while the separate normalized flow term continues to be significant. We regard this as inconsistent with the price pressure story being the explanation for our smart money effect.

Our interpretation of the smart money effect in the U.K. is that, indeed, mutual fund investors (both institutions and individuals) tend to buy into those actively managed funds that are able to deliver better-than-average returns for some time – at least until the market environment changes to one where the manager's skills become less valuable and/or until fund size increases to the point of hurting performance. At the same time, the fact that sales of mutual fund shares are not associated with poor subsequent performance is easy to reconcile with the notion of investors possessing fund-picking skill. Investors who are unhappy with their funds' performance prospects would need to weigh any potential performance gain by switching to another fund against the certainty of paying the initial charge on the money they transfer (unless they are transferring within the same fund family, in which case all or part of the initial charge may be waived). A complementary consideration is that, as Lynch and Musto (2003) argue, investors can rationally expect poor fund managers to be replaced.

It is important to note that although mutual fund investors are likely to hold on to their fund investments for a period of several years (Barber, Odean, and Zheng (2005), Ivkovic and Weisbenner (2006)), the outperformance we have been able to document lasts only a fraction of that duration. What might explain the short life span of the smart money effect? Recall that in order for a fund to attract high investor flows, a period of good prior performance is required. If, in addition, the abnormal returns on investor flows were to last (say) as long as the typical investment horizon, our results would contradict the many papers that find no evidence of long-term performance persistence. This absence of long-term persistence is of interest in and of itself, but beyond the scope of our paper. However, at least two contributing factors are plausible. One is the increasing difficulty in finding good investment opportunities as a successful fund grows in size due to investor inflows and its own investment performance.

Another is that a fund's success advertises its investment strategies and thereby attracts imitators, once again eroding the investment opportunities available to the fund.

The presence of smart money on both sides of the Atlantic poses an important question: What information do investors use to make good fund selection choices? A number of recent papers contain possible clues in this regard. Fund performance has been shown to be related to the characteristics of the fund itself (such as the industry concentration of its holdings, Kacperczyk, Sialm, and Zheng (2005)), of the investment manager (such as educational background, Chevalier and Ellison (1999)) and the manager's incentives (such as incentive fees, Elton, Gruber, and Blake (2003) or the manager's holdings of the investment portfolio, Khorana, Servaes, and Wedge (2007)), of the fund's corporate governance (Cremers et al. (2006)), and of the fund family (Nanda, Wang, and Zheng (2004)). Understanding whether, how, and to what extent such information is reflected in investors' fund buying choices is an important issue for future research.

## VII. Conclusion

Millions of investors around the world place their assets in mutual funds. Thousands of institutions do likewise. Their common goal, presumably, is to pick the best funds to invest in. Do they succeed?

If (at least some) investors can spot superior funds in advance, we should see a positive relationship between investors' money flows and subsequent abnormal fund performance. Using this insight, Gruber (1996) and Zheng (1999) document that indeed investors make good decisions, that is, money is "smart." However, after applying a more appropriate performance evaluation procedure that takes the stock return momentum effect into account, Sapp and Tiwari (2004), are unable to detect the smart money effect.

We revisit the smart money controversy with a unique British data set. Unlike previous studies, all of which are U.S.-based and use quarterly flows implied by fund sizes and investment returns, we have access to exact net flows for our funds. We also observe four key components of these net flows: Investments by individuals, investments by institutions, disinvestments by individuals, and disinvestments by institutions. These features of the data allow us to conduct a more powerful test of the smart money effect than previously possible.

We find conclusive evidence that smart money is alive and well in the U.K. The performance difference between new money and old money (or between high and low net flow funds, or between positive and negative net flow funds) although modest in magnitude, is highly statistically significant. The smart money effect is driven by fund purchases (but not withdrawals) of both individuals and institutions.

We also reexamine the U.S. evidence. We find that using monthly flows (which can be estimated from 1991 onwards), there is a smart money effect in the U.S. as well, even after controlling for the momentum factor. The U.S. smart money effect is comparable in magnitude to the one in the U.K. Sapp and Tiwari's failure to find a significant relation between money flows and subsequent fund returns in the U.S. can be attributed to their use of quarterly flows and to the influence of the pre-1991 period.

In recent years, legislators around the world have been considering whether investors should be protected, in various ways, from hurting themselves with poor mutual fund investment decisions. Underlying such initiatives appears to be the assumption that investors are unlikely to make good mutual fund choices on their own. Our empirical findings contradict this assumption. Much more needs to be done, however, to understand how different categories of investors arrive at their mutual fund buying and selling decisions. Gaining insight into mutual fund investor behavior continues to be an exciting area for future research.

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## Table I
## Characteristics of the Mutual Fund Sample

This table describes our sample of U.K. mutual funds investing in domestic equities. "Number of funds" and "total assets" counts eligible funds and their assets under management, respectively, at the start of the calendar year. Attrition rate is the proportion of funds in existence at the start of the year that cease to exist (through merger or liquidation) by the end of the year. Money inflow (outflow) is the exact amount of sales to (repurchases from) investors as reported by fund management companies to the Investment Management Association. Fund assets and money flow values are in £1 million.

Panel A: All U.K. equity funds

| | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | *average* |
|---|---|---|---|---|---|---|---|---|---|---|
| All funds | | | | | | | | | | |
| Number of funds | 425 | 447 | 438 | 436 | 466 | 491 | 480 | 469 | 496 | *461* |
| Total assets | 28,278 | 32,614 | 43,279 | 39,834 | 54,470 | 64,288 | 79,894 | 85,594 | 115,210 | *60,385* |
| Actively managed funds | | | | | | | | | | |
| Number of funds | 413 | 430 | 419 | 416 | 443 | 456 | 441 | 425 | 441 | *432* |
| Total assets | 27,686 | 31,422 | 41,676 | 38,264 | 52,181 | 60,985 | 74,117 | 77,551 | 103,263 | *56,349* |

Panel B: Funds with flow data

| | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | *average* |
|---|---|---|---|---|---|---|---|---|---|---|
| Number of funds | 265 | 293 | 315 | 311 | 323 | 331 | 339 | 319 | 306 | *311* |
| Total assets | 20,429 | 24,282 | 35,567 | 31,284 | 39,490 | 46,293 | 60,993 | 61,097 | 77,049 | *44,054* |
| Average fund size | 77 | 83 | 113 | 101 | 122 | 140 | 180 | 192 | 252 | *140* |
| Proportion of funds covered | 64.2% | 68.1% | 75.2% | 74.8% | 72.9% | 72.6% | 76.9% | 75.1% | 69.4% | *72.1%* |
| Proportion of assets covered | 73.8% | 77.3% | 85.3% | 81.8% | 75.7% | 75.9% | 82.3% | 78.8% | 74.6% | *78.4%* |
| Attrition rate | 3.4% | 4.4% | 6.0% | 4.8% | 3.7% | 7.9% | 10.6% | 12.5% | 3.6% | *6.3%* |
| Net aggregate flow | 253 | 3,073 | 3,248 | 1,883 | 2,003 | 2,491 | 1,264 | 2,101 | -73 | *1,805* |
| Aggregate inflow | 2,554 | 5,167 | 5,584 | 4,660 | 6,005 | 7,582 | 8,458 | 9,290 | 10,251 | *6,617* |
| Aggregate outflow | 2,301 | 2,094 | 2,336 | 2,777 | 4,002 | 5,092 | 7,195 | 7,189 | 10,324 | *4,812* |
| Net individual flow | 236 | 1,462 | 2,211 | 1,032 | 1,243 | 1,999 | 1,552 | 2,098 | 1,609 | *1,493* |
| Net institutional flow | 17 | 1,611 | 1,038 | 851 | 760 | 492 | -288 | 3 | -1,682 | *311* |
| Individual inflow | 1,161 | 2,593 | 3,514 | 2,693 | 3,447 | 4,630 | 5,423 | 5,991 | 6,251 | *3,967* |
| Individual outflow | 924 | 1,131 | 1,303 | 1,661 | 2,204 | 2,631 | 3,871 | 3,893 | 4,642 | *2,474* |
| Institutional inflow | 1,394 | 2,573 | 2,070 | 1,967 | 2,558 | 2,952 | 3,035 | 3,299 | 4,000 | *2,650* |
| Institutional outflow | 1,376 | 962 | 1,033 | 1,116 | 1,798 | 2,460 | 3,324 | 3,296 | 5,682 | *2,339* |

## Table II
## Distribution of Monthly Money Flows

This table shows the distribution of monthly money flows over the 1992 to 2000 period for 30,666 fund-months. Money flows are expressed as a percentage of start-of-month fund size. Moments and correlations in the tables are time-series averages of corresponding quantities calculated for each of the 108 monthly cross-sections.

Panel A: Moments of money flow measures

| | Mean | Standard Deviation | Minimum | Percentile 10th | 25th | Median | 75th | 90th | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| (1) Implied flow | 0.42 | 3.71 | -14.00 | -2.32 | -0.93 | -0.06 | 1.12 | 3.54 | 27.00 |
| (2) Net aggregate flow | 0.65 | 3.30 | -12.16 | -1.19 | -0.47 | 0.01 | 0.95 | 3.21 | 27.06 |
| (3) Aggregate inflow | 1.59 | 3.23 | 0.00 | 0.02 | 0.13 | 0.54 | 1.66 | 4.08 | 31.01 |
| (4) Aggregate outflow | 0.94 | 1.63 | 0.00 | 0.05 | 0.27 | 0.59 | 1.01 | 1.84 | 17.51 |
| (5) Net individual flow | 0.54 | 2.84 | -9.98 | -0.91 | -0.37 | -0.01 | 0.60 | 2.54 | 24.50 |
| (6) Net institutional flow | 0.26 | 2.18 | -8.71 | -0.74 | -0.16 | 0.01 | 0.37 | 1.42 | 15.23 |
| (7) Individual inflow | 1.26 | 2.76 | 0.00 | 0.01 | 0.07 | 0.35 | 1.24 | 3.30 | 26.44 |
| (8) Individual outflow | 0.73 | 1.20 | 0.00 | 0.03 | 0.20 | 0.47 | 0.82 | 1.43 | 13.12 |
| (9) Institutional inflow | 0.74 | 2.07 | 0.00 | 0.00 | 0.02 | 0.13 | 0.58 | 1.76 | 17.91 |
| (10) Institutional outflow | 0.48 | 1.35 | 0.00 | 0.00 | 0.01 | 0.11 | 0.37 | 1.13 | 11.76 |

Panel B: Correlations between money flows

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) Implied flow | 1 | 0.847 | 0.737 | -0.299 | 0.767 | 0.717 | 0.687 | -0.221 | 0.585 | -0.312 |
| (2) Net aggregate flow | 0.847 | 1 | 0.869 | -0.353 | 0.918 | 0.824 | 0.817 | -0.273 | 0.676 | -0.356 |
| (3) Aggregate inflow | 0.737 | 0.869 | 1 | 0.118 | 0.833 | 0.645 | 0.926 | 0.113 | 0.800 | 0.078 |
| (4) Aggregate outflow | -0.299 | -0.353 | 0.118 | 1 | -0.264 | -0.413 | 0.101 | 0.831 | 0.069 | 0.828 |
| (5) Net individual flow | 0.767 | 0.918 | 0.833 | -0.264 | 1 | 0.251 | 0.891 | -0.290 | 0.257 | -0.057 |
| (6) Net institutional flow | 0.717 | 0.824 | 0.645 | -0.413 | 0.251 | 1 | 0.231 | -0.081 | 0.791 | -0.461 |
| (7) Individual inflow | 0.687 | 0.817 | 0.926 | 0.101 | 0.891 | 0.231 | 1 | 0.141 | 0.273 | 0.008 |
| (8) Individual outflow | -0.221 | -0.273 | 0.113 | 0.831 | -0.290 | -0.081 | 0.141 | 1 | -0.011 | 0.137 |
| (9) Institutional inflow | 0.585 | 0.676 | 0.800 | 0.069 | 0.257 | 0.791 | 0.273 | -0.011 | 1 | 0.113 |
| (10) Institutional outflow | -0.312 | -0.356 | 0.078 | 0.828 | -0.057 | -0.461 | 0.008 | 0.137 | 0.113 | 1 |

## Table III
## Regression of Components of Money Flows on Lagged Flow and Performance

Each row of this table summarizes the results of 96 (January 1993 to December 2000) monthly cross-sectional regressions of different flow variables on their lagged values and past performance. All money flows variables are expressed as a proportion of start-of-month fund size. The columns labeled "Intercept," "Lagged flow," and "Performance" contain the average value of the coefficient estimates for that variable, followed by the *p*-value from a *t*-test based on the time-series standard deviation of the coefficient estimates. "Lagged flow" for each flow component is the value of the same flow component from 12 months earlier. "Performance" is the Carhart (1997) four-factor alpha (Panel B) averaged over the 12 months preceding the flow. "N" is the average number of funds in a cross-section, and "$R^2$" is the average of the cross-sectional regressions' R-squared values. Control variables not reported in the table are logarithms of fund TNA and fund age, as well as initial and annual fees.

| Dependent variable | Intercept | | Lagged flow | | Performance | | N | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| (1) Implied flow | 0.002 | *0.160* | 0.062 | *0.000* | 1.571 | *0.000* | 229 | 0.141 |
| (2) Net aggregate flow | 0.004 | *0.001* | 0.142 | *0.000* | 1.397 | *0.000* | 229 | 0.191 |
| (3) Aggregate inflow | 0.015 | *0.000* | 0.216 | *0.000* | 1.204 | *0.000* | 229 | 0.234 |
| (4) Aggregate outflow | 0.013 | *0.000* | 0.120 | *0.000* | -0.153 | *0.000* | 229 | 0.099 |
| (5) Net individual flow | 0.005 | *0.000* | 0.192 | *0.000* | 1.161 | *0.000* | 214 | 0.242 |
| (6) Net institutional flow | 0.003 | *0.133* | 0.121 | *0.000* | 0.465 | *0.000* | 109 | 0.151 |
| (7) Individual inflow | 0.011 | *0.000* | 0.285 | *0.000* | 0.994 | *0.000* | 214 | 0.285 |
| (8) Individual outflow | 0.007 | *0.000* | 0.189 | *0.000* | -0.137 | *0.000* | 214 | 0.156 |
| (9) Institutional inflow | 0.017 | *0.000* | 0.225 | *0.000* | 0.360 | *0.000* | 109 | 0.214 |
| (10) Institutional outflow | 0.015 | *0.000* | 0.207 | *0.000* | -0.095 | *0.028* | 109 | 0.158 |

## Table IV
## Comparison of New Money and Old Money Portfolios

This table describes portfolios of U.K. equity mutual funds formed on the basis of the funds' money flows in the preceding month. Fund flow data are for 1992 to 2000. Flows are classified by source as originating from individual investors or from institutional investors; we additionally calculate aggregate flows (individual and institutional flows combined). Flows are also classified by direction as inflows (sales to investors) or outflows (repurchases from investors). Only actively managed U.K. equity funds are used, with the exception of the last row, which describes an equally weighted portfolio of passive U.K. equity funds whose annual fees are below the median. Fund portfolios are characterized on the basis of fund-level regression results. Specifically, for each fund-month, we run a Carhart (1997) time-series regression over the preceding 36 months of excess fund returns on the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for the U.K. stock market. We require a minimum of 30 return observations for a fund to be included. The fund alpha is obtained as the fund excess return less the sum of the products of each of the four factor realizations and the corresponding factor loadings. For each month, we then calculate the portfolio alpha, the factor loadings, and the average $R^2$ as a money-weighted average of these measures for the funds comprising the portfolio (except for the last two rows, where the averages are equally weighted). The table reports time-series averages of these quantities. The average alpha value is followed by the *p*-value for its difference from zero, where the *p*-value is based on the time-series standard deviation. The last two columns show the difference between the average portfolio alpha and the alpha of the fund value-weighted portfolio, followed by the *p*-value for the hypothesis that the difference is zero.

| | | | Factor loading on | | | | | Alpha difference | |
|---|---|---|---|---|---|---|---|---|---|
| Portfolio description | Alpha | | MKT | SMB | HML | UMD | $R^2$ | from VW alpha | |
| (1) Weighted by aggregate inflow | -0.022 | *0.760* | 0.976 | 0.204 | 0.055 | -0.051 | 0.913 | 0.074 | *0.001* |
| (2) Weighted by aggregate outflow | -0.095 | *0.247* | 0.989 | 0.246 | 0.080 | -0.061 | 0.914 | 0.002 | *0.931* |
| (3) Weighted by individual inflow | -0.008 | *0.910* | 0.970 | 0.180 | 0.059 | -0.049 | 0.909 | 0.088 | *0.000* |
| (4) Weighted by individual outflow | -0.079 | *0.295* | 0.981 | 0.197 | 0.080 | -0.058 | 0.910 | 0.017 | *0.338* |
| (5) Weighted by institutional inflow | -0.057 | *0.472* | 0.986 | 0.243 | 0.051 | -0.054 | 0.920 | 0.040 | *0.243* |
| (6) Weighted by institutional outflow | -0.119 | *0.200* | 1.000 | 0.311 | 0.075 | -0.066 | 0.919 | -0.022 | *0.556* |
| (7) Weighted by fund value | -0.096 | *0.205* | 0.985 | 0.172 | 0.056 | -0.059 | 0.922 | --- | --- |
| (8) Equally-weighted | -0.072 | *0.369* | 0.983 | 0.257 | 0.049 | -0.037 | 0.894 | 0.024 | *0.356* |
| (9) Low cost index funds | -0.051 | *0.449* | 0.981 | -0.048 | -0.027 | -0.029 | 0.956 | 0.046 | *0.353* |

## Table V
## Performance of Positive vs. Negative Net Flow Funds

This table shows the performance of actively managed U.K. equity mutual funds classified on the basis of their net money flows from investors in the preceding month. Fund flow data are for 1992 to 2000. Flows are classified by source as originating from individual investors or from institutional investors; we additionally calculate aggregate flows (individual and institutional flows combined). "Implied flow" is obtained as fund TNA at the end of a month, less the product of the fund's TNA at the start of the month and its total return during the month. In Panel A, positive and negative money flow funds are weighted by the absolute value of their net flows. In Panel B, positive and negative net flow funds are equally weighted. Results in the table are based on fund-level regressions. Specifically, for each fund-month, we run a Carhart (1997) time-series regression over the preceding 36 months of excess fund returns on the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for the U.K. stock market. We require a minimum of 30 return observations for a fund to be included. The fund alpha is obtained as the fund excess return less the sum of the products of each of the four factor realizations and the corresponding factor loadings. For each month, we then calculate the portfolio alpha, the factor loadings, and the average $R^2$ as the simple average of these measures for the funds comprising the portfolio. The table reports time-series averages of these quantities. The last two rows show the difference between the average alphas of the positive and negative flow portfolios, followed by the *p*-value for the hypothesis that the difference is zero.

| | Positive money flow funds | | | | | | Negative money flow funds | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Flow variable | Alpha | MKT | SMB | HML | UMD | $R^2$ | Alpha | MKT | SMB | HML | UMD | $R^2$ | Alpha difference | |
| **Panel A: Funds are money flow weighted** | | | | | | | | | | | | | | |
| (1) Implied flow | -0.001 | 0.977 | 0.183 | 0.032 | -0.046 | 0.914 | -0.164 | 0.994 | 0.213 | 0.064 | -0.062 | 0.917 | 0.163 | *0.001* |
| (2) Net aggregate flow | 0.010 | 0.973 | 0.200 | 0.043 | -0.046 | 0.913 | -0.128 | 1.001 | 0.284 | 0.078 | -0.061 | 0.914 | 0.138 | *0.008* |
| (3) Net individual flow | 0.024 | 0.967 | 0.182 | 0.044 | -0.043 | 0.906 | -0.114 | 0.991 | 0.221 | 0.072 | -0.057 | 0.907 | 0.138 | *0.004* |
| (4) Net institutional flow | -0.036 | 0.983 | 0.227 | 0.047 | -0.049 | 0.921 | -0.139 | 1.005 | 0.321 | 0.077 | -0.064 | 0.920 | 0.104 | *0.123* |
| **Panel B: Funds are equally weighted** | | | | | | | | | | | | | | |
| (1) Implied flow | -0.025 | 0.978 | 0.256 | 0.034 | -0.033 | 0.896 | -0.111 | 0.988 | 0.257 | 0.061 | -0.041 | 0.894 | 0.086 | *0.000* |
| (2) Net aggregate flow | -0.038 | 0.976 | 0.250 | 0.037 | -0.032 | 0.897 | -0.103 | 0.990 | 0.260 | 0.059 | -0.041 | 0.892 | 0.065 | *0.007* |
| (3) Net individual flow | -0.047 | 0.975 | 0.241 | 0.033 | -0.030 | 0.896 | -0.094 | 0.990 | 0.267 | 0.060 | -0.042 | 0.893 | 0.047 | *0.063* |
| (4) Net institutional flow | -0.025 | 0.988 | 0.280 | 0.046 | -0.039 | 0.908 | -0.089 | 0.982 | 0.248 | 0.050 | -0.037 | 0.889 | 0.064 | *0.005* |

## Table VI
## Performance of Funds Sorted by Money Flows

This table shows the performance of actively managed U.K. equity mutual funds classified on the basis of their normalized money flows in the preceding month. Fund flow data are for 1992 to 2000. Flows are classified by source as originating from individual investors or from institutional investors; we additionally calculate aggregate flows (individual and institutional flows combined). Flows are also classified by direction as inflows (sales to investors) or outflows (repurchases from investors); we additionally calculate net flows (inflows less outflows). "Implied flow" is obtained as fund TNA at the end of a month, less the product of the fund's TNA at the start of the month and its total return during the month. We normalize each flow measure by dividing it by fund TNA at the start of the month. "High money flow funds" refers to an equally weighted portfolio of funds in the top 50% of all funds each month, according to the stated normalized flow measure. "Low money flow funds" refers to an equally weighted portfolio of the remaining funds. Fund portfolios are characterized on the basis of fund-level regression results. Specifically, for each fund-month, we run a Carhart (1997) time-series regression over the preceding 36 months of excess fund returns on the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for the U.K. stock market. We require a minimum of 30 return observations for a fund to be included. The fund alpha is obtained as the fund excess return less the sum of the products of each of the four factor realizations and the corresponding factor loadings. For each month, we then calculate the portfolio alpha, the factor loadings, and the average $R^2$ as the simple average of these measures for the funds comprising the portfolio. The table reports time-series averages of these quantities. The last two rows show the difference between the average alphas of the high and low flow portfolios, followed by the *p*-value for the hypothesis that the difference is zero.

| | High money flow funds | | | | | | Low money flow funds | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Flow variable | Alpha | MKT | SMB | HML | UMD | $R^2$ | Alpha | MKT | SMB | HML | UMD | $R^2$ | Alpha difference | |
| (1) Implied flow | -0.038 | 0.978 | 0.257 | 0.036 | -0.034 | 0.896 | -0.103 | 0.988 | 0.257 | 0.062 | -0.041 | 0.893 | 0.064 | *0.018* |
| (2) Net aggregate flow | -0.039 | 0.976 | 0.252 | 0.039 | -0.032 | 0.898 | -0.102 | 0.990 | 0.261 | 0.059 | -0.042 | 0.891 | 0.063 | *0.009* |
| (3) Aggregate inflow | -0.035 | 0.978 | 0.261 | 0.047 | -0.033 | 0.892 | -0.106 | 0.988 | 0.253 | 0.052 | -0.041 | 0.896 | 0.071 | *0.016* |
| (4) Aggregate outflow | -0.069 | 0.986 | 0.270 | 0.062 | -0.039 | 0.889 | -0.076 | 0.981 | 0.243 | 0.036 | -0.036 | 0.900 | 0.007 | *0.760* |
| (5) Net individual flow | -0.052 | 0.977 | 0.245 | 0.035 | -0.030 | 0.898 | -0.094 | 0.989 | 0.262 | 0.056 | -0.042 | 0.890 | 0.041 | *0.109* |
| (6) Net institutional flow | -0.026 | 0.988 | 0.280 | 0.045 | -0.038 | 0.908 | -0.099 | 0.993 | 0.257 | 0.075 | -0.047 | 0.907 | 0.073 | *0.007* |
| (7) Individual inflow | -0.032 | 0.976 | 0.254 | 0.049 | -0.032 | 0.889 | -0.114 | 0.989 | 0.253 | 0.043 | -0.041 | 0.897 | 0.082 | *0.009* |
| (8) Individual outflow | -0.064 | 0.982 | 0.258 | 0.058 | -0.037 | 0.885 | -0.085 | 0.984 | 0.249 | 0.034 | -0.036 | 0.902 | 0.021 | *0.395* |
| (9) Institutional inflow | -0.030 | 0.989 | 0.300 | 0.059 | -0.039 | 0.905 | -0.095 | 0.991 | 0.238 | 0.062 | -0.046 | 0.909 | 0.065 | *0.013* |
| (10) Institutional outflow | -0.054 | 0.994 | 0.292 | 0.073 | -0.043 | 0.905 | -0.073 | 0.986 | 0.243 | 0.048 | -0.043 | 0.910 | 0.018 | *0.441* |

## Table VII
## High vs. Low Money Flow Fund Performance Under Alternative Approaches

This table shows the difference in performance between funds receiving high and low normalized money flow from investors in the preceding month. The population of funds consists of actively managed U.K. equity mutual funds. Fund flow data are for 1992 to 2000. Flows are classified by source as originating from individual investors or from institutional investors; we additionally calculate aggregate flows (individual and institutional flows combined). Flows are also classified by direction as inflows (sales to investors) or outflows (repurchases from investors); we additionally calculate net flows (inflows less outflows). "Implied flow" is obtained as fund TNA at the end of a month, less the product of the fund's TNA at the start of the month and its total return during the month. We normalize each flow measure by dividing it by fund TNA at the start of the month. High money flow funds are those in the top 50% of all funds each month, according to the stated normalized flow measure; low money flow funds are the remaining funds. The first four columns of numbers reported in the table are the monthly performance difference and its *p*-value under the unconditional portfolio approach. The next two columns show the monthly performance difference and its *p*-value under the conditional portfolio approach. The last two columns show the monthly performance difference and its *p*-value under the style adjustment approach. Under the unconditional portfolio approach, the performance difference is obtained using either the three-factor or the four-factor performance evaluation model. In the four-factor case, the performance difference is the intercept of a Carhart (1997) regression, where the dependent variable is the difference between average return of high and low money flow funds, and independent variables are the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for the U.K. stock market. In the three-factor case, the momentum factor is omitted from the above specification. Under the conditional method, the four-factor specification is used, and the independent variables additionally include the products of the four factors and the demeaned FTA dividend yield, and the products of the four factors and the demeaned 90-day Treasury bill rate. The *p*-values for both the conditional and the unconditional methods are derived from the Kosowski et al. (2006) bootstrap procedure with 500 iterations. Under the style adjustment approach, the performance difference is the average of the sector-adjusted performance of high and low money flow funds. The *p*-value for the style adjustment approach is based on the *t*-test.

| | Unconditional portfolio approach | | | | Conditional portfolio approach, | | Style adjustment | |
|---|---|---|---|---|---|---|---|---|
| Flow variable | 4-factor model | | 3-factor model | | 4-factor model | | approach | |
| (1) Implied flow | 0.083 | *0.020* | 0.097 | *0.008* | 0.114 | *0.000* | 0.072 | *0.030* |
| (2) Net aggregate flow | 0.086 | *0.008* | 0.100 | *0.000* | 0.092 | *0.008* | 0.061 | *0.076* |
| (3) Aggregate inflow | 0.116 | *0.000* | 0.130 | *0.000* | 0.132 | *0.000* | 0.100 | *0.010* |
| (4) Aggregate outflow | 0.015 | *0.636* | 0.012 | *0.704* | 0.015 | *0.676* | 0.005 | *0.818* |
| (5) Net individual flow | 0.063 | *0.068* | 0.077 | *0.036* | 0.085 | *0.024* | 0.041 | *0.256* |
| (6) Net institutional flow | 0.070 | *0.076* | 0.086 | *0.036* | 0.043 | *0.296* | 0.036 | *0.295* |
| (7) Individual inflow | 0.107 | *0.000* | 0.122 | *0.000* | 0.131 | *0.000* | 0.104 | *0.007* |
| (8) Individual outflow | 0.027 | *0.384* | 0.024 | *0.432* | 0.025 | *0.460* | 0.029 | *0.227* |
| (9) Institutional inflow | 0.028 | *0.452* | 0.042 | *0.292* | 0.004 | *0.928* | 0.024 | *0.396* |
| (10) Institutional outflow | -0.015 | *0.576* | -0.007 | *0.788* | -0.005 | *0.888* | 0.026 | *0.268* |

**Table VIII**
**Regression of Fund Performance on Money Flows and Fund Attributes**

In this table, performance of actively managed U.K. equity mutual funds is regressed on previous month's money flows and other fund attributes. Data are pooled across funds and months. Fund performance for each month is measured using the Carhart (1997) model. Specifically, for each fund-month, we run a Carhart (1997) time-series regression over the preceding 36 months of excess fund returns on the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for the U.K. stock market. We require a minimum of 30 return observations. The fund alpha is obtained as the fund excess return less the sum of the products of each of the four factor realizations and the corresponding factor loadings. Net aggregate flows are expressed as proportion of fund TNA at the start of the month. Log(Size) is the logarithm of fund TNA, and prior year's average alpha is based on the Carhart (1997) four-factor model. Annual fee is the fund's annual management charge. All variables are measured as differences from each month's cross-sectional average. Results are based on least absolute deviation regressions. Standard errors are in parentheses. ** and * denote significance at the 0.01 and 0.05 level, respectively.

| Independent variable | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| Intercept | -0.029 ** | (0.009) | -0.020 ** | (0.010) | -0.020 * | (0.009) | -0.018 | (0.010) |
| Net aggregate flow | 2.110 ** | (0.345) | 1.573 ** | (0.397) | 1.941 ** | (0.399) | 1.588 ** | (0.391) |
| Log(Size) | | | -0.010 | (0.006) | -0.010 | (0.006) | -0.009 | (0.006) |
| Net aggregate flow * Log(Size) | | | | | 0.358 | (0.203) | | |
| Prior year's average alpha | | | 0.189 ** | (0.019) | 0.184 ** | (0.018) | 0.197 ** | (0.019) |
| Annual fee | | | | | | | -0.062 * | (0.032) |
| Number of observations | 27,698 | | 26,309 | | 26,309 | | 24,563 | |
| Pseudo R-squared | 0.001 | | 0.003 | | 0.003 | | 0.003 | |

## Table IX
## Performance of High vs. Low Money Flow Funds up to 12 Months Ahead

This table shows differences in performance up to 12 months ahead between funds receiving high and low normalized money flow from investors. The population of funds consists of actively managed U.K. equity mutual funds. Fund flow data are for 1992 to 2000. We normalize flows by dividing them by fund TNA at the start of the month. High money flow funds are those in the top 50% of all funds each month, according to the stated normalized flow measure; low money flow funds are the remaining funds. The first two columns of numbers reported in the table are the monthly performance difference and its *p*-value based on "implied" flows. The last two columns are the monthly performance difference and its *p*-value based on actual net aggregate flows. Implied flows are obtained as fund TNA at the end of a month, less the product of the fund's TNA at the start of the month and its total return during the month. Actual flows are obtained directly from our data set. Fund portfolios are characterized on the basis of fund-level regression results. Specifically, for each fund-month, we run a Carhart (1997) time-series regression over the preceding 36 months of excess fund returns on the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for the U.K. stock market. We require a minimum of 30 return observations. The fund alpha is obtained as the fund excess return less the sum of the products of each of the four factor realizations and the corresponding factor loadings. The performance difference is the difference between the time-series averages of average alphas for high and low money flow funds. The *p*-value is based on the *t*-test.

| Performance measure | Implied flows | | Actual flows | |
|---|---|---|---|---|
| 1 month ahead | 0.064 | *0.018* | 0.063 | *0.009* |
| 2 months ahead | 0.027 | *0.253* | 0.018 | *0.446* |
| 3 months ahead | 0.034 | *0.177* | 0.062 | *0.011* |
| 4 months ahead | 0.045 | *0.103* | 0.048 | *0.079* |
| 5 months ahead | -0.018 | *0.486* | 0.005 | *0.839* |
| 6 months ahead | -0.047 | *0.042* | 0.015 | *0.530* |
| 7 months ahead | -0.010 | *0.687* | 0.036 | *0.136* |
| 8 months ahead | 0.005 | *0.851* | -0.024 | *0.308* |
| 9 months ahead | -0.012 | *0.651* | 0.024 | *0.421* |
| 10 months ahead | -0.018 | *0.549* | -0.008 | *0.819* |
| 11 months ahead | 0.001 | *0.979* | 0.006 | *0.852* |
| 12 months ahead | -0.012 | *0.703* | 0.037 | *0.238* |

**Table X**
**Performance of High vs. Low Money Flow Funds in the U.S.**

This table shows difference in performance between U.S. equity funds receiving high and low normalized money flow from investors. Fund data are from the 2005 edition of the CRSP Survivor-Bias-Free U.S. Mutual Fund database. "High money flow funds" are those ranked in the top half of all funds each period, according to their monthly or quarterly normalized implied money flows; the remaining funds are "low money flow funds." Implied flow is obtained as fund TNA at the end of a period (one month or one quarter), less the product of the fund's TNA at the start of the period and its total return during the period. We normalize implied money flow by dividing it by fund TNA at the start of the period. Fund portfolios are characterized on the basis of fund-level regression results. Specifically, for each fund-month, we run a three-factor time-series regression over the preceding 36 months of excess fund returns on the excess market return (MKT), the size factor (SMB) and the value factor (HML), as well as a four-factor Carhart (1997) regression that additionally includes the momentum factor (UMD). The U.S. factor realizations are obtained from Kenneth French's website. We require a minimum of 30 return observations for a fund to be included. The fund alpha is obtained as the fund excess return less the sum of the products of each of the factor realizations and the corresponding factor loadings. Panel A displays results by calendar period. Panel B displays results for different time lags from the month in which funds are sorted on the basis of their money flows to the month in which performance is measured. For each money flow measurement frequency (monthly or quarterly) and for each performance evaluation model (three-factor or four-factor), the table shows the performance difference between high and low money flow funds, followed in italics by the associated *p*-value. The performance difference is the difference between the time-series averages of average alphas for high and low money flow funds. The *p*-value is based on the *t*-test.

Panel A: By time period

| | Money flow measured quarterly | | | | Money flow measured monthly | | | |
|---|---|---|---|---|---|---|---|---|
| | 3-factor model | | 4-factor model | | 3-factor model | | 4-factor model | |
| Time period | | | | | | | | |
| 1970-2000 | 0.047 | *0.047* | 0.031 | *0.168* | --- | --- | --- | --- |
| 1970-1990 | 0.009 | *0.758* | 0.014 | *0.623* | --- | --- | --- | --- |
| 1991-2000 | 0.128 | *0.004* | 0.066 | *0.054* | 0.154 | *0.000* | 0.092 | *0.003* |
| 2001-2004 | 0.064 | *0.167* | 0.039 | *0.343* | 0.083 | *0.027* | 0.096 | *0.030* |

**Table X (continued)**

| Panel B: 1991-2004 period, performance up to 12 months after the ranking | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Money flow measured quarterly | | | | Money flow measured monthly | | | |
| | 3-factor model | | 4-factor model | | 3-factor model | | 4-factor model | |
| Performance measure | | | | | | | | |
| 1 month ahead | 0.110 | *0.001* | 0.058 | *0.031* | 0.134 | *0.000* | 0.093 | *0.000* |
| 2 months ahead | 0.104 | *0.005* | 0.071 | *0.013* | 0.122 | *0.000* | 0.079 | *0.001* |
| 3 months ahead | 0.098 | *0.007* | 0.060 | *0.037* | 0.095 | *0.004* | 0.057 | *0.024* |
| 4 months ahead | 0.090 | *0.012* | 0.051 | *0.062* | 0.089 | *0.006* | 0.051 | *0.053* |
| 5 months ahead | 0.084 | *0.018* | 0.042 | *0.137* | 0.078 | *0.033* | 0.043 | *0.129* |
| 6 months ahead | 0.071 | *0.034* | 0.023 | *0.389* | 0.103 | *0.003* | 0.068 | *0.013* |
| 7 months ahead | 0.061 | *0.077* | 0.010 | *0.696* | 0.067 | *0.044* | 0.025 | *0.325* |
| 8 months ahead | 0.044 | *0.197* | 0.005 | *0.847* | 0.050 | *0.107* | 0.003 | *0.916* |
| 9 months ahead | 0.049 | *0.159* | 0.009 | *0.717* | 0.047 | *0.126* | 0.004 | *0.860* |
| 10 months ahead | 0.026 | *0.441* | -0.010 | *0.738* | 0.045 | *0.168* | 0.008 | *0.754* |
| 11 months ahead | 0.031 | *0.350* | -0.007 | *0.797* | 0.028 | *0.405* | -0.005 | *0.850* |
| 12 months ahead | 0.024 | *0.466* | -0.010 | *0.729* | 0.037 | *0.215* | -0.003 | *0.897* |

## NOTES

[1] We stress that the term "smart money" in this paper refers to investors' ability to select among comparable funds. It does not extend to ability to time the market or investment styles. We discuss this important point further in Section VI.

[2] The late 1990s saw the introduction of a new legal structure for the U.K.'s open-ended mutual funds, called open-ended investment company, or OEIC. For our purposes, however, differences between unit trusts and OEICs are unimportant and we refer to both types of funds as mutual funds.

[3] From http://www.investmentuk.org/press/2002/stats/stats0102.asp.

[4] The IMA enforces its sector definitions, and if the asset allocation of a fund contravenes the allocation rules of its current sector, the IMA will warn the fund to change its allocation if it does not wish to change sectors. If the fund does not comply, the IMA will move the fund to a new sector reflecting its new asset allocation. The sectors are well defined and relatively stable over time (although the IMA occasionally revises its sector definitions to reflect the industry's and investors' needs). For example, throughout much of the 1990s, U.K. equity funds were subdivided into Income, Growth and Income, Growth, and Smaller Companies categories. Such diverse information providers as Standard & Poor's, Hemscott, Money Management, and Allenbridge all use the official classification system. By contrast, in the U.S. there is a proliferation of methods for assigning funds to a peer group (e.g., Morningstar, Wiesenberger, Strategic Insight, and ICDI each have their own classification).

[5] The IMA started collecting these data in January 1992. The data available to us stop in 2000 for confidentiality reasons.

[6] Management groups who did not report their data to the IMA are relatively small (such as Acuma or Elcon) and typically run only a few funds. To check that eligible funds omitted from our sample do not cause a severe selection bias, we calculate their sector-adjusted annual returns using data from the *Unit Trust Year Book*. While classic survivorship bias would cause poor performers to be dropped, the average sector-adjusted return of our excluded funds is 0.12% per year and not significantly different from zero. With regard to fund size, the mean ratio of excluded fund-years' assets under management to their sector averages is 0.85, confirming that excluded funds tend to be smaller than funds retained in our sample.

[7] However, we check that our conclusions do not change if instead we simply exclude the 1%, 5%, or 10% of the funds with extreme flows every month.

[8] Ideally, institutional (retail) flows would be scaled by the amount of institutional (retail) holdings of each fund. Unfortunately, these data are unavailable.

[9] Both the average and the standard deviation are estimated excluding the fund-month under consideration. In other words, we regress the net aggregate normalized flows for each fund on unity, and drop fund-months for which the value of the externally studentized residual exceeds five in magnitude.

[10] Thus, the advantages of our data set compared to U.S. data come at a price: For example, Sapp and Tiwari's final sample has 29,981 fund-*years*.

[11] The literature additionally applies an adjustment for TNA increase due to fund mergers. To avoid problems due to the quality of our data about fund mergers, we do not include fund months in which mergers take place.

[12] Gross of tax returns could not be collected for approximately 10% of the fund-months in our data set. When a gross return is missing, we estimate it as the corresponding net return plus the average gross-net difference for that calendar month. This gross-up procedure is applied to 3,439 of our 30,666 fund-months. An earlier version of this paper used net-of-tax returns to obtain very similar results. We note that during our sample period, using net-of-tax returns reduces performance by about 5 basis points per month on average.

[13] The only deviation from Carhart's method is that our averages are value-weighted, to avoid spurious results due to "micro-cap" companies. Monthly returns and market capitalizations are taken from London Business School's London Share Price Database. For evidence on the pervasiveness of the momentum effect internationally, including in the U.K., see Rouwenhorst (1998) and Nagel (2001).

[14] We require a minimum of 30 monthly returns to estimate the regression coefficients.

[15] To reflect this interpretation, the exact weight we use is the start-of-month TNA cumulated to the end of the month at the fund's rate of investment return.

[16] Specifically, each month we include only index funds whose annual fee is below the median annual fee for U.K.'s domestic equity index funds.

[17] To guard against the possibility that our results are influenced by a relatively small number of extreme fund returns, we also weight funds by the inverse of their estimation-period residual return variance (results not reported in a table). This leaves the tenor of our results unchanged.

[18] In spite of this shortcoming, our preference is for using the fund-level approach, for several reasons. First, under the portfolio approach, the factor loadings (or their functional form, if conditional methods are used) are unvaried over the full period of the study. Second, unlike fund-level alphas, portfolio-level alphas for a given period need not be a time-weighted average of portfolio-level subperiod alphas, which complicates interpretation. Third, the portfolio approach has lower power than the fund-level approach, which is particularly relevant to our study since our U.K. sample is both smaller in size and shorter in duration than previously examined U.S. samples. Lastly, unlike the fund-level approach, the portfolio-level approach does not correspond to a feasible investment strategy since the factor loadings are estimated over the full study period and hence not known in real time.

[19] These variables are obtained from the London Share Price Database as the dividend yield for the FTA index and the 90-day Treasury bill rate, respectively.

[20] The fact that the average U.K. fund is much smaller than the average U.S. fund may explain the insignificant size effect (we thank the referee for pointing this out).

[21] In the U.S., persistence in mutual fund performance has been linked to the momentum effect in stock returns (Carhart (1997)). In the U.K., the momentum effect has also been documented (Rouwenhorst (1998), Nagel (2001)). Despite this fact, U.K. mutual funds, unlike their U.S. counterparts, are not momentum investors (Wylie (2005)). Evidence on performance persistence among U.K. managed funds has been the subject of considerable debate and reported results vary depending on the population of funds studied, the time period, and the methodology used (see references cited in Keswani and Stolin (2006)). Our sample exhibits statistically significant performance persistence whether or not we control for the momentum factor, and this holds both in the first and second halves of our sample period.

[22] The significant negative performance in month 6 is spurious, as suggested by the pattern of performance differences for implied flows, the result for month 6 based on actual flows, and the fact that the significance disappears if we partition flows into positive and negative rather than high and low.

[23] As before, this conclusion is robust to using three-factor rather than four-factor performance evaluation, and to using the portfolio-level rather than the fund-level approach.

[24] To identify these funds, we use ICDI, Strategic Insight, Wiesenberger, and CRSP objective codes according to the algorithm in Kacperczyk, Sialm, and Zheng (2006), Appendix A.

[25] It is also interesting to note that during 1970 to 1990 the performance spread between high flow and low flow funds *decreases* if the momentum factor is omitted from the performance evaluation model.

[26] We also note that the impact of switching from quarterly to monthly data is greater for the U.S. than for the U.K. This is largely attributable to a combination of two facts. First, with quarterly data, the average time lag between money flows and one-period-ahead performance under our smart money test is longer than when monthly data are used. Second, the difference between the one-month-ahead smart money effect and the smart money effects at longer lags is more pronounced in the U.S. than it is in the U.K. Taken together, these mean that the increase in the smart money effect as data frequency is increased from quarterly to monthly is greater in the U.S. than in the U.K.