Where did the Smart Money go?

Evidence on fund-selection ability amongst UK investors

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Abstract

Studies have shown mixed results in testing fund-selection ability amongst investors as a possible explanation to the mutual fund puzzle proposed by Gruber (1996). While most studies focus on the US mutual fund market, Keswani & Stolin (2008) propose that the smart money effect is empirically evident in the UK market, using data on funds from 1991-2000. This study aims to evaluate their hypothesis on the latest dataset from 2000 – 2010. The motivation behind doing so lies in the tremendous growth facing the U.K. mutual fund industry in the last decade or so. Most of the growth in the industry's history has taken place during this time. Hence the argument of smart money as an explanation to the growth of the mutual fund industry dictates that fund-selection ability should be especially prominent during our sample period. However we find that this is not the case. Possible explanations for the failure to find the smart money effect include excessive risk-taking by fund managers and increased search costs for investors, amongst other reasons.

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Although existing academic literature has examined the demand side of the mutual fund industry from numerous dimensions, one critical question remains largely unanswered. Why has the mutual fund industry grown so phenomenally over the last few decades, especially when studies about the returns that investors earn are ambiguous at best? With no concrete evidence that investor returns are superior to cheaper alternatives like index funds, it is indeed a mystery that the assets under management for the industry keep growing at an impressive rate for most years.

The first study to attempt to face this puzzle was by Gruber (1996), who questioned the existence of actively managed funds despite the presence of index funds which provided higher returns for a minimal fund fee. Since previous studies had found insignificant or negative abnormal returns for the mutual fund industry over time, he concluded there must be an alternative strategy for investors to make money, one possibly based on genuine fund-selection ability. The argument stated that investor money was 'smart' enough to flow into mutual funds that would exhibit higher returns in the future. In other words, investors could identify superior fund managers and hence, predict a higher performance for their funds.

The smart money argument was further developed and tested by others; Zheng (1999) who found strong evidence in favor of smart money, Wermer (2003) who examined why funds with greater inflow are future outperformers, Sapp & Tiwari (2004) who claimed that the effect disappeared with the introduction of the momentum factor, and Keswani & Stolin (2008) who looked at the smart money effect in the U.K. market.

All studies are carried out on the U.S. mutual fund industry except one by Keswani & Stolin (2008). They look at the smart money effect in the U.K. context, which is the second largest asset management industry globally. Their study holds immense value for it provides strong evidence contrary to the claim that momentum explains away the smart money effect. They claim that monthly flows to funds make it easier to detect this effect, and hence use it to prove that investors in the U.K. industry exhibit fund-selection ability. However, their dataset is limited to the previous decade due to lack of data, and hence stops at the end of 1999.

While the Keswani & Stolin (2008) study is undoubtedly crucial in the limited literature on smart money, its findings are only valid for the previous decade and hence somewhat outdated. This study seeks resolve this issue by evaluating their hypothesis using the latest dataset available for the U.K. mutual fund industry, from the beginning of 2000 to the end of 2010. This study holds an objective beyond merely extending the Keswani & Stolin (2008) study; it aims to put the smart money argument through a rigorous test.

The primary motivation for carrying out this study can be attributed to a significant change that has occurred in the U.K fund industry over a decade or so. This phenomenon has occurred on the demand side; most of the growth in the local industry since it formed in 1930s has taken place in the last decade. This can be clearly seen in Table I, which provides basic statistics for the U.K. mutual fund industry. The spurt in growth translates into an increase in incentive for investors to participate in mutual funds since a decade. If one is to believe in the smart money argument, then the increased incentive through higher returns can mainly be credited to the fact that a more sophisticated class of investors have evolved over time, one that have better ability at identifying funds that will outperform their peers in the future. Hence, the rise in the popularity of mutual funds should signal a more statistically significant and perhaps, a more economically pronounced smart money effect over our period of study, which spans 11 years, as compared to that of Keswani & Stolin (2008). On the basis of this, the study forms a priori expectations of finding a strong smart money effect in its results.

[Table I]

A unique dataset is constructed, using data downloaded from Bloomberg and that manually extracted from previous issues of the Money Management magazine, which is a monthly professional magazine that lists data on all funds domiciled in the U.K. The latter is used to overcome the lack of a survivorship bias-free electronic database of U.K. mutual funds. The methodology is kept similar to that of Keswani & Stolin (2008), with both fund-level and portfolio-level regressions being run.

The results from this study contradict our prior expectations. All except one approach find no evidence of fund-selection ability amongst investors in the last 11 years. The one approach that does support the initial hypothesis is only significant at the 10% level. These findings are robust to different methodologies used. Hence, these findings greatly undermine the case for smart money as an answer to the mutual fund puzzle. If no substantial evidence exists in favor of it during the fastest growing phase the industry has witnessed, it is imperative that we question the link between smart money and the growth of the mutual fund industry. It may very well be the case that fund-selection ability exists amongst investors, but our study shows that this cannot possibly be an underlying explanation to why the industry attracts increasing amounts of investor money flows.

The paper finally discusses some of the possible reasons behind the decline in the smartness of money over time. Further analysis conducted shows that a majority of the influx of investors are chasers of past performance, and not the smart investors that can predict future returns. Secondly, some investors are found to base their investment decisions to some extent on exposure to factor loadings, such as the book-to-market factor and momentum factor, rather than seeking alpha in isolation. A third reason could potentially lie in the changing behavior of fund managers over the two study periods due to an introduction of a new legal structure of mutual funds in 1997 which reduced entry barriers and increased competition within the industry. Specifically, increased risk taking and overemphasis on short term profits means that it has become harder to predict fund returns. Together with an increase in search costs for investors to find superior funds, it comes as no surprise that investors find their fund-selection ability eroded.

The remainder of the paper is organized as follows. Section I discusses the previous literature on the topic in detail. Section II provides a brief background on the UK mutual fund industry and how a new legal form for funds impacts the industry. Section III discusses the data and presents descriptive statistics. Section IV presents the methodology used and results, whereas Section V undertakes a discussion on the results obtained and explores possible reasons behind them. Finally, Section VI wraps up the paper with a conclusion.

I. LITERATURE REVIEW

Although studies have long sought to evaluate the mutual fund industry in terms of its performance and risk characteristics, the first attempt to understand the demand side of the industry was made by Gruber (1996). He analyzed the returns of the entire industry relative to how investors would perceive them, rather than from a fund's perspective. He came up with a startling discovery that he aptly named the 'mutual fund puzzle'. Like those before him, he found that the industry underperformed as a whole but the benefits of diversification it offered were great enough to attract investors. However, with the advent of index funds in the mid 1980's it was possible for investors to achieve the same level of diversification, but without having to bear the high management expenses of actively managed mutual funds. Given the highly competitive capital markets, it would only be sensible to assume that these actively managed funds with high fees but a lower rate of return than simple indexes would be soon wiped out. However, it turned out that these mutual funds were only gaining more popularity over time.

Thus, Gruber (1996) put forward the puzzling question of why actively managed funds were in existence despite the presence of index funds which provided higher returns for a minimal fund fee. He suggested a possible explanation for this puzzle by resorting to the pricing method of such active mutual funds. Shares in open end mutual funds are by default sold and bought at their net asset value. They do not depend on the management's ability and therefore, this ability is not priced for in actively managed mutual funds. If it is assumed that some managerial ability exists in funds, then performance should be predictable to a certain extent since it is dependent on this ability. If this is true and some investors are able to identify such management ability, then cash flows into and out of funds should be predictable by the very same metrics that predict performance. Therefore, if these predictors hold and at least some investors can act on them when investing in mutual funds, then the return on new cash flows should be higher than that of the average return for all investors in these funds.

Gruber (1996) sought to test all hypotheses related to the above suggestions on monthly cash-flow-weighted alphas for 227 funds over the period of January 1985 to December 1994. He found overwhelming support for his argument. The study supported the notion that at least some of the investors in the market are sophisticated enough to pick on the predictors of future fund performance, meaning that these investors supplied new cash flows to benefit from this. This is proved in their results which show that new cash flows (both in and out of funds) over the ten years of the study earn risk-adjusted returns that are positive and above the returns earned by both the average actively managed funds, as well as index funds. This indicates that it is possible and in fact common, that these sophisticated investors take advantage of the fact that management ability is not priced. However, it is possible that this argument collapses if skilled fund managers are able to expropriate their abilities by increasing fund fees over time (i.e. price their ability), but evidence does not seem to support this theory. If anything, fund fees are found to be associated with inferior returns rather than being a predictor of future performance. A more appropriate predictor would be past performance, for a manager whose investment strategy has been continually successful in the past can claim to possess superior security selection skills.

This analysis was further developed by Zheng (1999). The objective of this study is two-fold; to test the 'smart money' effect and to observe whether investor's flows contain information that can be used to make abnormal returns. The latter is identified as the 'information effect'. Zheng (1999) expanded the data set to include all equity funds between 1970 and 1993. She chose to adopt Grinblatt and Titman's (1993) performance test to check for the smart money effect, and the conditional performance measure introduced by Shanken (1990) to capture the time variation in mutual fund risks and risk premia. According to this conditional measure, a portfolio should not be regarded as having superior performance if it can be replicated using publically available information. This conditional performance measure uses predetermined instruments for the time-varying expectations and controls common variation due to public information. This is useful because it helps to determine whether the smart money effect arises due to a rational response to macroeconomic variables (e.g. exchange rate fluctuation) or to style variables such as size, value and dividend yield.

The results by Zheng (1999) support the smart money effect. The study shows that investors demonstrate fund-selection ability by moving away from poor performing funds and into funds that outperform in the future. In other words, funds that enjoy positive net flows subsequently perform better on a raw as well as a risk-adjusted basis than funds that experience negative net flows. To assess the magnitude and implication of investor's fund selection ability, Zheng (1999) examines the returns on different strategies based on new money signals. The results confirm the smart money effect that investors are able to make buying and selling decisions based on good assessment of short-term future performance. The study then examines whether a trading strategy could be devised based on the predictive ability of net flows but finds that there is not enough evidence to support the notion that investors can beat the market by simply investing in funds with positive money flows. However, there is proof that positive money flows to small mutual funds can outperform the market. Amongst the sample of small funds, there is also evidence to support the information effect. Hence, the study finds that information on net flows into small funds can be used to make risk-adjusted profits. However, it is worth nothing that the smart money effect is often short-lived and that the performance ranking of the positive and negative portfolios reverses after 30 months.

Sapp and Tiwari (2004) look at the 'smart money' effect from a critical point of view. Their study accepts the fact that new money flows might be able to outperform the average mutual fund industry, but questions whether this should lead to an automatic acceptance of the belief that investors possess fund-selection ability. This doubt is fed by the fact that Gruber (1996) and Zheng (1999) fail to account for a well known phenomenon that was discovered by Jegadeesh and Titman (1993). This phenomenon is known as momentum in stocks and needs to be incorporated when benchmarking mutual fund performance, for it is an important common factor in explaining stock returns. This is because the momentum factor dictates that stocks that do well have a tendency to continue doing so in the future as well. Assuming that investors are mere chasers of past performance, they would invest more money into funds that already have disproportionate holdings of ex-post best performing stocks. Such good performing funds would no doubt benefit from momentum returns more than other funds would. Hence, it would seem that the new money investors put in give back higher rates of return as compared to old money, therefore leading to a find of the smart money effect. However, this term is misleading for investors have nothing to do with the ability to pick out superior fund managers in this case.

Sapp and Tiwari (2004) look at the complete universe of U.S. equity funds from 1970 to 2000 for their study. They follow a methodology similar to that of Gruber (1996) and Zheng (1999) for comparison purposes, but make an exception to allow for the momentum factor when examining the subsequent performance of the hypothetical portfolio fund using the Carhart (1997) benchmark model. They find that incorporating the momentum factor into their study results in a risk-adjusted excess return on the new money that is not significantly different from zero. Thus, they claim that the smart money effect is explained away by the momentum factor.

Wermer (2003) also contributes to this discussion by examining fund portfolio holdings to determine why funds that experience greater inflow outperform the average fund. His conclusions are in line with the findings of Sapp and Tiwari (2004) in the sense that investors do unknowingly benefit from momentum returns. However, it is observed that the magnitude of momentum earnings is much larger than previously thought. The reason behind this, as identified in the study, is that managers of winning funds that receive greater inflows that are then further invested in more momentum stocks so as to enable a continuous streak of good performance. By contrast managers of losing funds are reluctant to sell off their losing stock to finance purchases of new momentum stocks. This behavior may be attributed to the disposition effect, as mentioned by (Odean, 1998). Therefore, momentum continues to separate winning fund managers from losing ones for a much longer period of time than indicated by previous studies on the matter.

Keswani and Stolin (2008) challenge the results obtained by Wermer (2003) and Sapp and Tiwari (2004). Their study is unique in many ways. All previous studies examine only the U.S. mutual fund industry, and it is their paper that is the first to study the smart money effect in the UK context. Doing so is important because of two prominent differences in the UK market; mutual funds in UK compete within well-defined peer groups, and there is no tax overhang issue (i.e. investors do not have to realize their capital gains until they sell their fund shares) in the UK. Their dataset consists of UK mutual funds from 1991 to 2000.Another reason why their study is distinctive is that they employ a unique data set that uses monthly flows instead of quarterly, as well as actual flows instead of implied. Furthermore, they are able to distinguish between flows from institutional investors and those from individual investors. Because of their data set, they are able to formulate more hypotheses, mainly to study whether institutional or individual flows are smarter, as well as compare fund buys with sells.

Even with the introduction of a momentum factor in their benchmark portfolio, Keswani and Stolin (2008) discover that the smart money effect holds in the UK. To further check the robustness of their results, they use three different methodologies but obtain similar findings nevertheless. In order to determine why Sapp and Tiwari (2004) were unable to arrive at the same conclusion, they investigate U.S. mutual fund returns as well. They use a sample that is similar to that used by Sapp and Tiwari (2004), except that it contains monthly and actual flows to and out of funds. They find that the ability to pick up the smart money effect is dependent on data frequency, as well as the fact that the effect becomes more prominent over time. Hence they effectively respond to allegations that the smart money effect is explained away by the momentum factor.

Keswani and Stolin (2008) go on to contribute further to the smart money literature. Comparing institutional and individual flows, they find that both types exhibit smartness in their flows to funds (mutual fund buys) but not out of funds (mutual fund sells). This occurs due to the fact that fund buys are more related to fund performance rather than fund sells, which may take place due to other reasons such as liquidity needs of the investor or taxes. The authors put the smart money effect to further tests to see whether it is explained away by fund size or other fund characteristics, and find that it is not. They also examine the persistence of this smart money effect and conclude in line with previous studies that it is short-lived; 4 months with their sample of mutual funds.

Despite Keswani and Stolin's (2008) recent study that finds evidence in favor of the smart money effect, the literature on this matter is anything but conclusive. Most importantly, the initial puzzle raised by Gruber (1996) on the popularity of actively managed mutual funds remains largely unsolved. It is unclear whether the growth of the fund industry indicates the presence of a smart money effect. It is this link between the two that this study will attempt to examine.

II. UK MUTUAL FUND INDUSTRY BACKGROUND

The U.K mutual fund industry is one of the largest and most developed in the world. As of December 2010, it had a record GBP 577.6 billion in assets under management. The industry is highly competitive; there were 2,406 mutual funds that were being run by 101 fund families at the end of our study period[2]. In its existence of about 80 years, the predominant structure of mutual funds has been 'unit trusts'. The reason being that until the late 1990's, mutual funds were required to be organized as trusts, which differentiated them from other corporations which

[2] http://www.investmentuk.org/press/2010/stats/stats1110-00.pdf

were subject to regular corporate laws and regulations. Due to this differentiation, it was possible for the fund industry to be subject to relatively stricter regulations, which authorities deemed necessary given the sophisticated nature of the operations carried out by these funds. Though the severe fiduciary regulations were successful in curtailing opportunistic behavior amongst funds, they also served to suppress flexibility in undertaking investment activities.

It was only in May 1997 that this limitation was officially recognized and abolished. This was done by granting mutual funds the freedom to choose between two alternative legal structures; they could either be treated as a unit trust or as a corporation (known as Open Ended Investment Company). Since its introduction, the latter legal structure has gained popularity, with almost 70% of funds now classified as OEICs. Although most of the regulations imposed on both forms are similar, there is one considerable difference with respect to governance. Corporations are subject to less strict fiduciary laws, mainly in regard to legalities which essentially means that it is easier for fund managers to avoid being exposed to greater personal liability than they would be under trust laws. These stricter regulatory laws for unit trusts earlier served as an effective barrier to entry in the industry. The removal of these allowed funds the freedom to pursue investment opportunities that they might otherwise hesitate to take (Warburton, 2010).

In other regards, the framework of the UK mutual fund industry is relatively identical to that of the U.S., although it does differ on two important aspects. Firstly, unlike its counterpart, the UK industry has a single official fund classification system, managed by the Investment Management Association (IMA). The classification places funds in distinct sectors based on their asset allocation. This simplifies the decision-making process for most investors, for it provides a basis for comparison amongst similar funds, as well as clarifies a fund's investment goals. Although classification schemes do exist in the U.S. as well, they are mostly ambiguous. Due to the lack of an official system, numerous organizations use varying methods in assigning funds, which only complicates the investment decision.

The second difference lies in the treatment of capital gains tax. In the U.S., mutual funds have to distribute capital gains realized by the fund, and capital gains tax has to be paid when this is done. This leads to the tax overhang dilemma where the preference of existing investors to delay the capital gain realization would discourage new investors from buying into the fund. On the other hand, investors in the UK do not have to pay this tax until they sell their shares in the fund. Hence, the decision for UK investors is less complicated because they do not have to be concerned with any potential tax liabilities when investing.

III. DATA

The sample period for the study is chosen to be 11 years long, from January 2000 to December 2010. In line with the objectives of this study, the data used is restricted to just UK equity mutual funds. The reason for choosing only one asset class to focus on is because the study does not aim to examine the skills exhibited by investors in asset allocation. It is important to reiterate that the term ‘smart money’ is used only in relation to the ability of investors to identify superior future performers from a group of *comparable* funds. For the same reason, equity funds that invested in markets other than that of the UK were also dropped. Allowing them into the sample would risk the reliability of the findings on fund picking skills due to the interference with the ability to time markets. This is not unlike previous papers, all of which focus solely on funds investing in domestic equities.

Not all funds corresponding to this description were chosen though. Only funds that were allocated an official IMA classification were considered[3]. There were three IMA sectors that were related to domestic equity funds; UK All Companies, UK Smaller Companies, and UK Equity Income. This left 842 funds from the entire industry. Since the objective of the paper is to examine the ability of investors to pick out superior funds, all passively managed (i.e. index tracker) funds are dropped. Furthermore, only funds domiciled in the UK are considered, causing the offshore funds to be eliminated. The funds that remain after applying these filters are chosen. This meant that there were 720 unique fund classes that formed the dataset used in this study. It is to be noted that all share classes of a fund are combined in this study, in order to arrive at an accurate figure for a fund’s total net assets.

[3] The IMA covers more than 90% of the entire fund industry and hence is a good representation of the actual industry

The data on these selected funds was acquired from two databases; Bloomberg and Money Management magazine. Bloomberg was the primary source of data collection. However, complete and uninterrupted data on a significant number of funds was unavailable on Bloomberg. This was much more common for dead funds than surviving funds. Although the Bloomberg database claims to be free from survivorship bias, solely relying on it would have resulted in our study being biased from a lack of sufficient data on dead funds. This shortcoming was overcome by supplementing data, where it was not available, from Money Management, which is a monthly magazine published by the Financial Times for professionals in the industry. Since the online database for Money Management does not retain information about dead funds, the missing data required was manually extracted through published monthly issues of the magazine for the 11 years that constituted the study period.

The fields of interest for this study are a fund's asset flows and its performance. The actual amount of money put into or taken out of a fund is usually hard to obtain, which is why all previous studies use implied flows instead, with the exception of Keswani & Stolin (2008). However, even they find in their study that using implied flows in place of real flows does not influence results. Implied flows are an estimation of net money flows, derived from available data on fund assets and fund returns. More specifically, this is calculated as:

$$\text{Implied flows} = TNA_t - TNA_{t-1}\,(1 + r_t) - MGTNA_t$$

where TNA stands for a fund's Total Net Assets, the r stands for its returns and $MGTNA_t$ is the increase in the TNA of a fund due to a merger in period t. Fund flows that arise due to the merger of two or more funds do not reflect investor choice and hence have to subtracted to arrive at investor flows. It is worth noting that these implied flows are an estimation of the *net* money flows, and may indeed mask a greater movement of investment money in both directions. Despite its shortcoming, the findings on fund-selection ability are not affected by the use of this proxy, as discovered in a recent study by Keswani and Stolin (2008) which compared the use of both types of flows.

The second factor of concern is fund returns. These returns should be those that the investors in the fund acquire, not the returns of the fund's portfolio (although they both are linked). Thus, these returns are not only net of management fees and gross of taxes, but are estimated using the actual prices available to investors; the Net Asset Value in case of OEIC's, and the bid price for unit trusts. These values are logged to calculate the returns to investors. Dividends are incorporated into the calculated returns depending on the payout of the fund returns. If a fund pays dividends to its holders, these are included in the returns because their unit price fails to capture the payout. Dividend payments are accounted for at the ex-dividend date, giving the total return which in turn can be compared within the universe of funds in our data.

Fund returns cannot be used in isolation for they do not accommodate varying degrees of risk across different funds. To overcome this problem, risk-adjusted returns are used. From amongst the various approaches to capture risk-adjusted returns, the Carhart (1997) four-factor regression model is applied keeping in mind earlier studies. The four factors thus needed are the excess market premium, and the returns on the size, value and momentum factor mimicking portfolios. All these factors are taken from the work of Gregory, Tharyan and Huang (2009), who aim to provide accessible data on UK factor realizations from the beginning of 2000 to the end of 2008. The factor realizations were then extended up to the end of 2010 by adopting an approach similar to their work.

The frequency of the data studied is chosen to be monthly. This decision is important because Keswani and Stolin (2008) in the same paper compare the results using both monthly and quarterly data. They conclude that usually quarterly data makes it much more difficult to detect fund-selection ability relative to monthly data. Although most of the previous literature makes use of quarterly data, it should come as no surprise that this would obstruct the findings of any such study. Aside the obvious advantage of a greater number of observations and hence more reliable results, using monthly flows reduces the loss in accuracy that results from employing implied flows over longer periods of time.

The flow data has to be treated before it can be used further in the study. First of all, funds without any recorded TNA values are discarded, leaving 28,077 fund-months behind. This is lower than what one would expect because not all funds are in existence for the entire sample period. Second, 374 fund-months are dropped that had an abnormal value in any of the fields, whether it be the TNA, NAV/bid price or dividend. Next, the remaining data on money flows is 'cleaned' to avoid outlier observations influencing the results. This is done with respect to each month's flow rather than setting an absolute cutoff point for all our data, such that the 10% of the most extreme fund flows every month are excluded[4]. However, this cannot be done using the implied flows calculated earlier because ordinary flows to large funds will typically exceed any amount of unusual flows to smaller funds. Hence implied flows are normalized first, which means this flow figure is divided by the respective fund's asset base as of at the start of the month:

$$\text{Normalized Implied Flow} = \text{Implied Flow} / \text{TNA}_{t-1}$$

In this manner, only flows that are irregular to each individual fund are eliminated. The count for the number of these deductions is 170 fund-months, leaving behind a final dataset of 27,514 fund-months.

[Table II]

Table II presents the descriptive statistics on the normalized implied flows, averaged across the 132 months of the entire sample period. The mean is positive, meaning that the average monthly flow was an inflow of money. From an aggregate industry point of view, only 23 months experience an aggregate outflow from the industry as compared to 103 months of aggregate inflows. That means that in any month, the mutual fund sector is almost four times as likely to witness an increase in its asset base rather than a decrease.

IV. METHODOLOGY & DISCUSSION ON RESULTS

There are a number of possible ways to determine the existence of fund-selection ability amongst investors. One straightforward approach is to evaluate the performance of the money that flows into mutual funds. A benchmark is needed to judge this performance though. An expected point of comparison could be the performance of 'old money', which would comprise

[4] It is observed that setting the cutoff points to exclude either 1% or 5% of the extreme money flows instead of 10% does not change any of the final results.

of existing investments in funds. If indeed new investments can pick out future performers when compared to old money, the myth of investors simply following previous flows can be dismissed and they can be labeled smart. An equally likely alternative benchmark could be the performance of money that flows out of funds in the same period of time. In this case, if funds that witness significant inflows outperform funds that lose popularity, the investor can be said to exhibit some level of competent fund-selection ability.

Ideally, the approach to measuring the performance of new money against old money would through forming two hypothetical portfolios, one for each. In the case of the former, all remaining funds in the sample dataset will be weighted according to the amount of their money flow in the preceding month. The performance of this portfolio depicts how much an average pound invested in the mutual fund industry a month ago earns. Similarly, the hypothetical portfolio for old money will be weighted by the money already invested in the industry that is, on the basis of funds' total net assets before the addition of new flows in the last one month. This shows what one pound that is already invested in the industry will earn. Both the portfolios are rebalanced monthly. If investors are indeed smart, their investments should be able to earn a rate of return higher than this.

However, this method is not suitable if using implied flows. Since implied flows are an estimation of net flows only, every month some funds will experience negative net flows. If such funds are assigned a negative sign in the hypothetical portfolio above, it would mean that they are sold short. Since short selling is not possible amongst mutual funds, our study will be flawed with this method. Fortunately, a slight alteration in this approach will work even when using implied flows. All that needs to be done is to separate the sample of funds into those with positive net flows and those with negative net flow for every month. Now each fund is awarded a weight in proportion of the magnitude of their net flow, regardless of the direction, in their specific type of portfolio. Hence, a fund experiencing an outflow of money in a particular month, for example, will be assigned an absolute weight which corresponds to its outflow value divided by that month's total *negative* flows. This way, the performance of both types of funds is viewed separately. The most obvious comparison for fund-selection ability here is between the positive (comprising of funds with net inflows) and the negative (comprising of funds with net outflows) hypothetical portfolios. However, it is also possible to compare this performance against that of old money, by using the same two portfolios, but weighing them in proportion to their total net assets before the flows, rather than the net flows itself. This will help to determine whether new money beats old money amongst the positive or negative funds. It is to be noted that this comparison amongst either positive or negative funds should be viewed in isolation and cannot be jointly evaluated.

More specifically, the fund-level approach outlined by Zheng (1999) is adopted to carry out the study. This approach calls on individual risk-adjusted returns for each fund to be calculated before constructing the portfolios according to various weighing schemes. In order to determine these returns, a Carhart (1997) four-factor regression is run for each fund using the previous 24 months to obtain the estimated factor loadings on each of the four variables in the model below:

$$R_{it} - R_F = \alpha_i + \beta_i^{MKT}(MKT) + \beta_i^{SMB}(SMB) + \beta_i^{HML}(HML) + \beta_i^{UMD}(UMD) + e_{it}$$

where R_{it} is the rate of return of fund *i* in month *t*, R_F is the risk-free rate of return in month *t*, MKT is the market risk premium, and SMB, HML and UMD are returns on the size, value and momentum factor mimicking portfolios respectively. The next step in calculating the risk-adjusted returns (from now on referred to as the alpha), these estimated factor loadings are multiplied by the respective factor realizations for the current month under observation, and finally subtracted from that month's excess fund returns. The alpha is now ready to be used in the construction of different portfolios. It would also be interesting to observe the signs and significance of the factor betas for entire portfolios, so each fund's estimated factor loadings are also weighed by the appropriate proportions to give us that month's portfolio betas.

The resulting time series of the monthly figures calculated are used to obtain the overall performance of each individual hypothetical portfolio. These are then compared against each other to determine the presence and extent of the fund-selection ability amongst investors in the market. Table III shows the time-series averages of the alpha and the factors of the positive and the negative net flow portfolios. The last two rows show the difference in the average alpha of the portfolios, as well as the corresponding *p*-value for the hypothesis that the difference is zero. All tables also reports the results if the Fama-French (1993) three-factor model is used instead of the four-factor regression in Panel I. This is done for comparison purposes, keeping in mind that Sapp & Tiwari (2004) in their study claim that including the additional momentum factor explains away the smart money effect. Indeed we find that this is true for our results as well. Including the momentum factor makes most of our differences in alphas between two portfolios smaller in magnitude as well as insignificant. Having said this, our discussion will be centered on the results obtained using the Carhart (1997) four-factor model.

[Table III]

Before discussing the above results, it is important to point out that the positive and negative portfolios are not equivalent to comparing sales and repurchases of shares amongst funds. The portfolios are based simply on the *net* money flows in a particular month. In fact, it is very likely that each fund experiences a considerable amount of money flows in both directions each month. However, our methodology only considers the final change in a fund's asset base.

On comparison with each other in Panel II, it is found that the positive portfolio alpha is higher by almost 0.2 basis points. Despite the presence of a difference, it is insignificant as the *p*-value shows. This fails to prove that investors as a whole tend to be correct in identifying which funds to invest in, and where to take money out. This finding is contrary to that of Keswani and Stolin (2008) when looking at the 1990's. Turning to the values of the estimated factor loadings, the signs of all betas are in line with expectations, except for the momentum factor. The market premium beta is sufficiently high but below unity, as one would expect. The positive signs on the market premium and the size factors, as well as the value factor are similar to that found in previous studies of the UK market. The momentum factor for both the portfolios is slightly below zero, which essentially means that UK mutual funds sell momentum stocks, instead of herding into them. Although this is opposite of that in the US, previous studies (Quigley and Sinquefield (2000), Fletcher and Forbes (2002), Wylie (2005)) on the UK market confirm this phenomenon.

It would be interesting now to compare the two portfolios discussed above against the performance of old money. Two additional portfolios are formed that correspond to the ones above, where the funds in each portfolio remain the same, but are now weighed instead by the total net assets of each fund at the beginning of the month. As before, the difference in the alpha series of the relevant portfolios is presented, along with the *p*-values.

Table IV provides interesting insight about the investments flowing into the industry. As before, the signs and magnitude on the factor realizations are all in line with the expectations. However, amongst funds with positive implied flows, the difference between the alpha of the old money (the portfolio weighed by implied flows) and that of the new money (the portfolio weighed by total net assets at the start of the month) is positive, as would be expected according to the smart money argument. However, we find no support for it since it is insignificant. When the results are compared for funds with negative implied flows, a similar conclusion is reached against smart money. Although the alpha difference has a negligible positive sign, it essentially means that the funds which experience an outflow of money do not necessarily perform any worse than the average investments in those funds already. In other words, investors are not wise enough in deciding to disinvest since they are unable to predict which funds will perform poorly in the future. Hence, even with funds that experience a net outflow of funds, new money fails to beat old money, as shown by the high *p*-value.

[Table IV]

The discussion so far points towards the lack of fund-selection ability amongst investors. It would be interesting to study whether these findings hold if a different methodology is introduced. In order to check the robustness of our results, we will use two alternative evaluation methods; the portfolio-level regression and portfolios sorted by money flows.

The first of these two approaches is described in Zheng (1999) and is somewhat similar to the fund-level approach described above. There is however one notable difference: unlike before, this approach requires a portfolio of funds to be formed *first* on the basis of positive/negative flows. Using the weighted excess fund returns to calculate the portfolio returns, a regression is then run with the time series of factor realizations. The advantage of this approach is that more data can be used in the study, unlike the fund-level approach where only funds that existed for 24 months or more could be included. However, this approach does assume factor loadings to be constant throughout the 11 years, which is a drawback.

Table V reports the results using the portfolio-level approach. As can be seen the results are very similar to those attained while using the fund level approach. The difference in alpha between the positive and negative portfolio is positive, but insignificant. However, it is to be noted that the positive portfolio no longer has a positive alpha. Table VI compares the performance of new money against that of old money for both the positive and negative portfolios. Once again, the results are similar to that of the previous approach, showing that our results are robust.

[Table V]

The second alteration in the approach requires an altogether different basis to form the portfolios. For the new technique, instead of differentiating between funds with positive net flows and those with negative, an equally weighted portfolio of ‘popular’ funds is assessed against one consisting of ‘unpopular’ funds. The criterion for the popularity of funds is centered on the level of normalized flows a fund experiences. A fund with a normalized flow above the median for that month is labeled a popular fund; all others are put into the unpopular fund portfolio. All funds are equally weighted to avoid violating the short selling assumption (if there was no such assumption we could have simply assigned weights to all new flows to determine the magnitude, instead of differentiating between popular and unpopular funds). The results for these time series are presented below in Table VII.

[Table VI]

All the signs on the factor realizations are similar to earlier results, and in line with expectations. The risk-adjusted return on both portfolios is close to zero, with the popular portfolio alpha being slightly higher than zero. The difference is a minute 0.08 basis points but unlike previous results, is significant at the 10% level. This is the only result that shows slight support of the smart money argument, though nowhere near as significant as any of Keswani & Stolin’s (2008) results.

[Table VII]

Having analyzed all of these results, it seems that investors in the UK mutual fund industry could not have been said to exhibit any concrete fund-selection ability since 2000. Using the Fama-French (1993) three-factor model generates slight evidence of smart money but as shown, the inclusion of the momentum factor is responsible for this. Six of the seven results using the Carhart (1997) model point towards no such ability. The alpha difference between the popular and unpopular portfolio is significant statistically but not economically (only 0.08 basis points monthly). This is in contrast to highly significant alpha differences that Keswani & Stolin (2008) report in the 1990's despite the momentum factor. Their results remain consistent for all approaches used. Hence, we conclude that the smart money effect has disappeared for the current decade, directly in contrast to our a priori expectations that were in favor of a strong and significant smart money effect.

An important element to take into consideration when examining investor behavior is to understand how pervasive it may be. In context of fund-selection ability Zheng (1999) shows that the size of a fund may influence investor's decisions. Furthermore, previous literature (Chen et al., 2004) has shown that as a fund increases its total assets under management, it faces diseconomies of scale in returns. Hence a fund manager's ability to turn their skill into fund performance could be dependent on the fund size. If either of these is true, then we may witness a difference in the level of fund-selection ability amongst different fund size groups. Hence it is imperative that we repeat our analysis for large funds (those whose fund size is above the median in a given month) and for small funds (below the median) separately. We find that all of our results remain unchanged across fund size (results not shown). Hence we can state that controlling for fund size does not change our conclusions on the absence of fund-selection ability in the last decade.

V. DISCUSSION

The last decade witnessed the largest growth in the mutual fund industry and as per the smart money argument, an increase in the total assets under management should be proof of strong fund-selection ability. This formed the basis of our prior expectations. However, our results obtained contradict this statement by failing to prove any existence of smart money in all results except one, which too only shows a weak, economically insignificant presence. The essential issue that needs to be explored is the reason behind this erosion of smartness of investors.

There could be several possibilities that result in a decrease in smartness of money. A simple explanation could lie in the influx of ‘dumb’ investors in the industry over the last decade. These are unlike their smarter counterparts; they merely chase past performance (Chevalier and Ellison, 1997) and/or are attracted by the popularity of certain funds over others. We can put this argument to test by regressing monthly implied flows that have been normalized to the returns in the previous month and fund flows in the previous month. The results are shown in Panel I of Table VIII. The results show that current flows are influenced heavily by the returns in the previous month, but not by previous flows. Past returns remain significant even when other variables are added into the regression as shown in Panel III. The sign on the coefficient confirms that investors are indeed chasers of past performance and that past returns are a major determinant in investor’s decision to invest.

[Table VIII]

Perhaps it is wrong of us to assume that investors seek to maximize returns when it comes to investing in mutual funds. A second reason for the decline in fund-selection ability would then be based on the fact that investors do not try to search for managerial skill and base their decisions on fund alpha. This will explain why our results fail to detect superior future performance of popular funds. One alternative basis for picking funds then could depend on exposure to aggregate factors. Controlling exposure to aggregate risk factors could potentially supersede seeking alpha for investors. There are a variety of reasons why this might be so, ranging from managing risk to style investing (Barberis and Shleifer, 2003) in mutual funds. We can test this explanation by regressing fund flows to aggregate risk factors. Panel II of Table VIII shows these results.

The results uncover an interesting relationship between alpha and fund flows. The two are linked but the sign on the coefficient is opposite to what we would expect. It seems that investors are attracted towards funds that show inferior managerial skill! These findings do not change with the inclusion of additional variables from the previous regression (Panel III). All else being equal, a 1% decrease in alpha results in an increase of over 1.6% of a fund's monthly normalized net cash flow. Exposure to the market factor is significant only in Panel III and is slightly negative. The book-to-market factor is one that remains significant for both regressions in Panel II and III. The momentum factor is the other factor and negative sign on this factor means that investors do not follow a momentum strategy when investing in mutual funds, quite the opposite. This is in line with previous studies like Quigley and Sinquefield (2000).

A third possible reason for the decline in smartness may lie in a change in the framework of the fund industry, with the introduction of a new legal structure for mutual funds in the U.K. in May 1997. The passing of this law meant that mutual funds no longer had to be registered as trusts, but could now be registered under ordinary corporate laws as corporations (known as Open Ended Investment Corporations). Corporations are subject to less strict fiduciary laws, mainly in regard to legalities which essentially means that it is easier for fund managers to avoid being exposed to greater personal liability than they would be under trust laws. This law had a dramatic effect on the supply side of the industry; it eased regulations and hence lowered entry barriers for new entrants. As one would expect, there was a considerable subsequent rise in the number of funds operating, leading to fierce competition between (refer to Table I).

Under usual circumstances, smart investors might have eliminated the poor performing funds, reaching an equilibrium that resulted in more optimal number of funds in the industry. However, it seems that funds became too competitive and changed their tactics, which left investors confused about how to evaluate them. Possibly the most crucial change came in the form of a greater pressure on fund managers to perform. Warburton (2010) does show that over time, managers were successful in raising performance of the overall industry by a few basis points. However, in doing so, fund managers began to take on excessive risks. The incentive to beat the competition became so intense that they had to indulge in undue risk taking, often manipulating their risk limitations. This is not merely a speculation; studies have shown that the deregulation of the U.S. financial services industry over time has led to excessive competition and risk taking (Brown, Harlow and Starks, 1996; Chevalier and Ellison, 1997; and Goetzmann, Ingersoll, Spielgel and Welch, 2007). It is likely the same might have happened in the U.K. fund industry over the last 11 years. In fact, Warburton (2010) provides evidence for the increased risk taking that occurred after the 1997 legal amendment was made. He claims that the idiosyncratic risk from a four-factor model similar to the one used in this study, has increased following deregulation. This is likely to arise from fund managers seeking to actively add on greater idiosyncratic risk to their portfolios in order to beat the competition. For investors, this idiosyncratic risk is almost impossible to identify. If this argument is true, it would eventually mean that investors are left trying to pick out funds they think will be 'lucky' in the future. There is no longer any genuine stock-picking skill amongst fund managers, as was present in alpha earlier, to be identified.

An additional dimension on the increased pressure to perform comes from a shift in focus amongst fund managers on the short term profits, often at the expense of longer term profits. They exist because of the manner in which the compensation scheme is structured in funds, and is made more prominent when competition intensifies. For instance, Bernhardt & Davies (2009) show that fund managers have an incentive to direct new investments near the end of the quarter to existing stocks (known as portfolio pumping) to attain short term profits. But because the subsequent quarter starts with a larger deficit, there is only so long that a fund can keep doing this. Eventually, the deficit cannot be overcome, and the investor loses out on what seemed like a superior fund.

The adoption of different tactics by fund managers to survive may also distort signals that investors might use to pick superior funds. A case in point is fund fees. One would expect that in the face of increased competition, funds would lower their fund fees to attract investor money. Given then the tight profit margins, only funds that are genuinely superior would be able to charge higher fees. Thus, fund fees would have translated into a clear signal about the quality of a fund. However, Warburton (2010) found that fees for the overall industry increased after the deregulation, contrary to expectations. Other studies go on further to prove that fund fees are unrelated, or in some cases inversely related to future fund performance. This indicates that funds have tried to use fund fees as a method of projecting a superior image, regardless of how they might actually be doing.

Last but not the least, the search costs for investors has gone up as well. This is mostly attributable to the substantial increase in the number of funds to choose from, along with a greater variation in their fees, performance record, styles, etc. This has led to the much more complicated decision-making process when investing. On the other side, one may argue that the popularity of the industry has attracted greater media coverage as well as an increase in fund's marketing efforts, which should essentially reduce the search costs. However, previous research has shown quite the opposite effect. While increased media coverage does decrease search costs for investors and influences their decisions (Barber and Odean, 2008), it does so in a way that undermines fund-selection ability. Sirri and Tufano (1998) show that the media focuses on past performance of funds and hence greater media coverage leads to a more pronounced performance-flow sensitivity. This means that instead of being smart, investors become mere chasers of past performance.

In addition, Jain and Wu (2000) study the marketing efforts of funds to test whether advertising is used to signal the superior managerial ability of funds as opposed it being a strategy to simply seek attention and attract fund flows. Their results prove that funds who advertise actually underperform in the future when compared to a control group, allowing them to disown the signaling hypothesis. Instead they find that advertising attracts substantial flows to inferior funds. Hence marketing efforts by funds are likely to hinder the rational decision making process by investors, ultimately influencing them to invest in poor future performers. Both these reasons cause the erosion of the smart money effect found by Keswani & Stolin (2008).

VI. CONCLUSION

This study started out by examining the need for an empirical study on the smart money effect in the U.K. mutual fund industry for the last 11 years. The smart money argument had been put to test before in the U.K market but tremendous growth in the assets under management for the entire industry, the largest in any decade since its formation, presented the perfect opportunity to put the smart money hypothesis as suggested by Gruber (1997) to test. We established strong a priori expectation about the smart money effect based on this argument.

However, the findings in this study failed to find strong evidence for this effect. This contrasts with the findings in Keswani & Stolin (2008) for their period of study in the 1990's.

The contradictory results meant that there was more to than what the study had initially anticipated. We propose that the decline in smartness may be attributable to several reasons. An examination showed that the influx of investors were chasers of past performance, and not the smart investors that could predict future returns. Secondly, some investors were basing their investment decisions to some extent on exposure to factor loadings, such as the book-to-market factor and momentum factor, rather than seeking alpha in isolation. A third reason could potentially lie in the changing behavior of fund managers over the two study periods. Specifically, increased risk taking and overemphasis on short term profits means that it has become harder to predict fund returns. Together with an increase in search costs for investors to find superior funds, it comes as no surprise that investors find their fund-selection ability eroded.

In the light of these arguments and our results, it is imperative that we question the relationship between smart money and the growth of the mutual fund industry. It may be the case that fund-selection ability exists amongst investors, but this study shows that this cannot possibly be an underlying explanation to why the industry attracts increasing amounts of investor money flows, for it fails to find any evidence on this link. Hence this study concludes that substantial growth in the mutual fund industry can take place without the existence of fund-selection ability amongst its investors.

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Table I: Characteristics of the U.K. Mutual fund industry

This table provides a background on the basic features of the U.K. mutual fund industry, emphasizing the strong growth facing the industry in terms of assets under management and number of funds during the duration of our sample. OEIC refers to the new legal form introduced for mutual funds in May 1997, and stands for Open Ended Investment Company. Assets under management are in values of £ billions and rounded to the nearest billion. The last row shows the Assets under Management (AUM) for domestic equity funds only because it is this category of funds that make up our data for the study. All figures are those reported by fund companies to the Investment Management Association (IMA).

Year	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Assets (bn)	261	235	194	241	275	347	409	467	362	481	555
- Of which OEIC	72	82	104	152	172	216	256	286	224	304	354
No. of funds	1,749	1,787	1,692	1,710	1,970	2,007	2,034	2,178	2,366	2,409	2,406
- Of which OEIC	475	629	931	1927	1978	1250	1304	1442	1602	1669	1670
No. of fund families	155	142	130	129	121	118	113	110	110	108	101
- Of which OEIC	50	58	71	73	77	79	80	79	83	81	76
Equity AUM	164	187	145	179	202	252	294	315	225	293	350

Table II: Descriptive Statistics

The table shows the distribution of the main variables over the entire sample period, from 2003 to 2008. Implied flows are expressed as a percentage of the total net assets of the fund at the start of the month. Monthly net cash flows and fund size are in values of £1 million. The total number of fund-months considered for the study is 27,514.

	Mean	Std. Dev.	Minimum	25th Percentile	50th Percentile	75th Percentile	Maximum
Implied flows (%)	1.53	3.25	-31.73	-1.39	-0.05	1.85	40.28
Monthly Net cash flow (m)	28.82	218	-13372	-62	-0.13	34.52	6792
Fund size/ TNA (m)	2050	4865	7	240	430	1960	79982
Monthly Total Return (%)	0.08	0.05	-0.86	-0.02	0.01	0.03	0.53

Table III: Positive vs. Negative Portfolios

This table describes portfolios of U.K. equity mutual funds formed on the basis of the fund's money flows in the preceding month. The positive portfolio refers to the portfolio that consists of a net inflow of money based on the calculated implied flows. Similarly, the negative portfolio refers to those funds that have negative implied flows. Fund flow data is for 2002 to 2010. For each fund-month, we run a Carhart (1997) time-series regression over the preceding 24 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. 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 and the factor loadings as a money-weighted average of these measures for the funds comprising the portfolio. The table reports time-series averages of these quantities. The last two columns show the difference between the positive and the negative portfolio alpha and the p-value. The 3 factor model results are obtained exactly the same with one exception: the momentum factor (UMD) is excluded from the time-series regression.

	Positive	Negative	Difference	*p*-value
3 Factor model				
Alpha	0.001	-0.001	0.002	*0.075*
MKT	0.769	0.797		
SMB	0.165	0.179		
HML	0.005	0.013		
4 Factor model				
Alpha	0.001	-0.001	0.002	*0.143*
MKT	0.808	0.912		
SMB	0.200	0.163		
HML	0.056	0.073		
UMD	-0.009	-0.010		

Table IV: New vs. Old Money

This table describes portfolios of U.K. equity mutual funds formed on the basis of the fund's money flows in the preceding month. The positive portfolio refers to the portfolio that consists of funds with a net inflow of money based on the calculated implied flows. Similarly, the negative portfolio refers to those funds that have negative implied flows. There are two types of weights employed within both these portfolios; by implied flows (new money portfolio) and by total net assets (old money portfolio) existing at the start of the month. Fund flow data is for 2002 to 2010. For each fund-month, we run a Carhart (1997) time-series regression over the preceding 24 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. 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 and the factor loadings as a money-weighted average of these measures for the funds comprising the portfolio. The table reports time-series averages of these quantities. The last two columns show the difference between the new and the old portfolio alpha and the p-value. The 3 factor model results are obtained exactly the same with one exception: the momentum factor (UMD) is excluded from the time-series regression.

		Positive Portoflio			
		New	Old	Difference	*p*-value
3 Factor model					
	Alpha	0.001	0.000	0.001	*0.110*
	MKT	0.769	0.757		
	SMB	0.165	0.148		
	HML	0.005	0.003		
4 Factor model					
	Alpha	0.001	0.000	0.001	*0.255*
	MKT	0.808	0.865		
	SMB	0.200	0.178		
	HML	0.056	0.076		
	UMD	-0.009	-0.026		

Table IV: Continued

	Negative Portfolio			
	New	Old	Difference	*p*-value
3 Factor model				
Alpha	-0.001	-0.001	0.000	*0.081*
MKT	0.797	0.744		
SMB	0.179	0.146		
HML	0.013	0.101		
4 Factor model				
Alpha	-0.001	-0.001	0.000	*0.451*
MKT	0.912	0.892		
SMB	0.163	0.138		
HML	0.073	0.094		
UMD	-0.010	-0.020		

Table V: Portfolio Approach

This table compares the positive and negative portfolios formed using the Portfolio Approach. This approach requires a portfolio of funds to be formed first on the basis of positive/negative flows. Using the weighted excess fund returns to calculate the portfolio returns, a regression is then run with the time series of factor realizations. A Carhart (1997) time-series regression is run with 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. The last two columns show the difference between the positive and the negative portfolio alpha and the p-value. The 3 factor model results are obtained exactly the same with one exception: the momentum factor (UMD) is excluded from the time-series regression.

		Positive	Negative	Difference	*p*-value
3 Factor model					
	Alpha	0.001	-0.002	0.003	*0.249*
	MKT	0.815	0.812		
	SMB	0.183	0.197		
	HML	0.026	0.071		
4 Factor model					
	Alpha	-0.001	-0.003	0.002	*0.306*
	MKT	0.840	0.828		
	SMB	0.198	0.196		
	HML	0.033	0.063		
	UMD	-0.064	-0.041		

Table VI: New vs. Old money using Portfolio Approach

This table compares the new money (based on implied flows) and old money (based on Total Net Assets) portfolios formed using the Portfolio Approach. This approach requires a portfolio of funds to be formed first. Using the weighted excess fund returns to calculate the portfolio returns, a regression is then run with the time series of factor realizations. A Carhart (1997) time-series regression is run with 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. The last two columns show the difference between the new and the old portfolio alpha and the p-value. The 3 factor model results are obtained exactly the same with one exception: the momentum factor (UMD) is excluded from the time-series regression.

	Positive Portoflio			
	New	Old	Difference	*p*-value
3 Factor model				
Alpha	0.001	0.000	0.001	*0.128*
MKT	0.815	0.805		
SMB	0.183	0.150		
HML	0.026	0.032		
4 Factor model				
Alpha	-0.001	-0.001	0.000	*0.226*
MKT	0.840	0.823		
SMB	0.198	0.149		
HML	0.033	0.053		
UMD	-0.064	-0.045		

Table VI: Continued

	Negative	Portfolio		
	New	Old	Difference	*p*-value
3 Factor model				
Alpha	-0.002	-0.001	-0.001	*0.109*
MKT	0.812	0.773		
SMB	0.197	0.149		
HML	0.071	0.065		
4 Factor model				
Alpha	-0.003	-0.002	0.001	*0.180*
MKT	0.828	0.788		
SMB	0.196	0.148		
HML	0.063	0.083		
UMD	-0.041	-0.037		

Table VII: Popular vs. Unpopular Funds

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. The popular portfolio refers to the portfolio that consists of funds with normalized implied flows above the median value for a particular month. Likewise, the unpopular portfolio refers to all other funds that do not fit the previous criteria. For each fund-month, we run a Carhart (1997) time-series regression over the preceding 24 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. The last two columns show the difference between the new and the old portfolio alpha and the p-value. The 3 factor model results are obtained exactly the same with one exception: the momentum factor (UMD) is excluded from the time-series regression.

	Popular	Unpopular	Difference	*p*-value
3 Factor model				
Alpha	0.000	-0.001	0.001	*0.074*
MKT	0.781	0.847		
SMB	0.217	0.233		
HML	0.190	0.029		
4 Factor model				
Alpha	0.000	-0.001	0.001	*0.077*
MKT	0.751	0.866		
SMB	0.217	0.246		
HML	0.007	0.023		
UMD	0.000	-0.011		

Table VIII: Determinants of Implied Cash flows

This table shows cross-sectional regressions of normalized implied cash flows on explanatory variables. The sample period is from 2000 to 2010. The average of cross-sectional coefficients is used to obtain the estimates for the cross-sectional regression. Previous flows refer to previous cash flows in the preceding month. Previous returns refer to total returns in the preceding month. Both these values are at the fund-level. Panel I reports the regression with just these two variables and an intercept. Panel II includes exposures to risk factors: excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD). Panel III includes all variables in Panel I & II. The p-values are reported in italics.

	I	II	III
Intercept	0.001	0.004	0.007
	0.237	*0.395*	*0.182*
Previous Returns	0.849		0.736
	0.062		*0.000*
Previous Flows	0.031		0.000
	0.201		*0.516*
Alpha		-0.162	-0.142
		0.000	*0.000*
MKT loading		-0.007	-0.009
		0.147	*0.066*
SMB loading		0.001	0.001
		0.823	*0.799*
HML loading		-0.007	-0.005
		0.078	*0.089*
UMD loading		-0.007	-0.011
		0.054	*0.005*