Where Are the Smart Investors? New Evidence of the Smart Money Effect

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Abstract

Prior research debates focus on whether investors are smart enough to invest in funds that subsequently outperform. This paper documents a robust smart money effect among small fund investors who invest in the top performing funds, even after controlling for the momentum factor argued by Sapp and Tiwari (2004). I further explore the reason for the smart money effect and find that such outperformance comes from the market timing ability of smart investors. Market timing ability distinguishes smart investors from investors who naïvely chase the winners.

JEL classification: G11; G20

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I. Introduction

If there are smart investors, would they put money in poorly performing funds? Recent studies debate whether investors are smart enough to invest in funds that will outperform in the future, the so-called 'smart money effect' (Gruber, 1996; Zheng, 1999; Sapp and Tiwari, 2004; Keswani and Stolin, 2008). To provide evidence for the smart money effect, most studies pay attention to the fund flow of all equity fund investors in aggregate. However, if investors are really smart, i.e. they can learn from prior investments, they will pick top performing funds as their final destination and stay with them. That is, the top performing fund group should be the best place to identify smart investors. This paper provides evidence for the above argument. Furthermore, I also find that smart investors possess the market timing ability to earn risk-adjusted returns which cannot be explained by the momentum effect. In other words, the smartest investors not only perceive which fund to invest in but also detect when to invest.

Research concerning the smart money effect in the mutual fund context was initiated by Gruber (1996), confirmed by Zheng (1999), challenged by Sapp and Tiwari (2004), and finally re-examined by Keswani and Stolin (2008). Gruber (1996) and Zheng (1999) coined the term ‘smart money effect’ and find evidence that a group of sophisticated investors seem to identify the superior funds and invest accordingly to outperform the market. However, after controlling for the momentum effect, Sapp and Tiwari (2004) demonstrate that the smart money effect is no longer significant. They conclude that the outperformance is due to the momentum effect rather than the intelligence of investors. Subsequently, Keswani and Stolin (2008) attribute the insignificant smart money effect exhibited by Sapp and Tiwari (2004) to the use of quarterly data and the weight they put on the pre-1991 period. Keswani and Stolin (2008) use monthly data of U.K. funds and find a robust smart money effect in the U.K.

It is interesting to note that previous studies, whether they support or reject the smart money effect, focus on all fund investors in the market, of course including naïve investors who may simply chase the star funds (Guercio and Tkac, 2008), to investigate the smart money effect. In other words, the smart money effect may be diluted by using all fund investors in the market as observations. In addition, according to the samples used in previous studies, prior researchers implicitly assume that smart investors can be found in poorly performing funds. However, if smart investors are really “smart”, they should be able to avoid poorly performing funds and invest in top performing funds.

Therefore, unlike pervious studies, I investigate the smart money effect by examining the risk-adjusted returns of investors in different fund groups ranked by fund excess returns. If investors who invest in top performers can make significant risk-adjusted returns even after the momentum effect is controlled for, it suggests that these investors are really smart and have undiscovered skills to earn abnormal returns.

The test uses the complete universe of 9,607 diversified U.S. equity mutual funds for the period from January 1993 to September 2008 in the CRSP Survivor-Bias Free U.S. Mutual Fund Database. Similar to Zheng (1999), this paper starts with an examination of GT measure (Grinblatt and Titman, 1993). This measure examines whether investors can profit by tilting their portfolio weights over time in favor of assets with higher expected returns and away from assets with lower expected returns. The result indicates that investors who put money into funds whose total net assets (TNA) are in the lowest 20% can switch their money to funds with higher expected returns.

However, the GT measure is not implementable in practice, because most funds forbid short selling of their shares. Hence, I follow the methods of Zheng (1999) to construct eight trading strategies weighted by unexpected money flows (Coval and Stafford, 2007) and another two trading strategies based on the GT measure to observe whether risk-adjusted returns can be earned by following the trading strategies. Since the GT measure is significant only for funds whose TNA are in the lowest 20%, i.e. the smallest fund group, I focus on this group to further investigate the practical implications of investor buying and selling decisions.

The results of trading strategies suggest that the smart investors can be found in the top performing funds. After I rank the smallest funds to quintiles by excess returns, only the fund group with the top performance exhibits the significantly positive risk-adjusted return, and such outperformance cannot be eliminated by the inclusion of the momentum factor. That is, the risk-adjusted returns earned by investors who invest in the winners cannot be explained by the momentum effect argued by Sapp and Tiwari (2004). However, the trading strategies of the entire smallest fund group before grouping to quintiles do not exhibit the significant risk-adjusted returns over the market. This shows that the smart money effect would be diluted by using unclassified observations, as I argue above. In addition, when using the accumulative unexpected flows as weights, I find that the information of unexpected flows is less informative as time goes by, which means that the smart money effect is short-lived.

The significant risk-adjusted returns and the short-lived phenomenon inspire a question: Why is this intelligence of smart investors short-lived? Since the behavior of flocking to the top performing funds itself is momentum, it is surprising to find that the risk-adjusted returns of the top performing fund group cannot be explained by the momentum effect. Therefore, the smart investors must possess undiscovered skills to distinguish themselves from the momentum-style investors who simply chase funds that were recent winners.

If both smart investors and momentum-style investors can identify superior funds and flock to them, the potential difference between smart investors and momentum-style investors is knowing when to buy or sell these superior funds, i.e. timing ability. When fund performance reverses, smart investors can make a correct and immediate response while the momentum-style investors cannot. For example, if there is a fund which performs very well from $t+1$ to $t+12$, the smart investors who are able to recognize this will buy it at the beginning of $t+1$ and sell it at the end of $t+12$. On the other hand, for the momentum-style investors who chase the winners based on the past three-month returns, they can still identify this fund due to the momentum investing strategy. However, their momentum investing strategy would lead them to buy this fund at the beginning of $t+4$

and sell it at the end of *t+15*. Under such a situation, both smart investors and momentum-style investors would invest in this fund from *t+4* to *t+12*, but the smart investors would obtain higher returns than momentum-style investors due to better timing ability. However, owing to the overlap of investment periods, it is possible that smart investors are misidentified as momentum-style investors when using all fund investors in the market as the sample.

The significant risk-adjusted returns earned by smart investors documented above provide us with a good opportunity to examine whether timing ability is the determinant of earning abnormal returns for smart investors. Therefore, I use the smart investors who are in the top performing fund group as the sample and follow the methods of Chen, Adams and Taffler (2009) to observe whether they have timing ability. If the risk-adjusted returns earned by the smart investors can be fully explained by timing factors, I can conclude that the undiscovered skills possessed by smart investors are timing skills.

The result provides evidence that the short-lived smart money effect comes from the market timing skill of smart investors. After the influence of timing activities is considered in the performance evaluation model, the risk-adjusted returns in the top performing fund group are no longer significant. The coefficient significance suggests that smart investors possess market timing ability. This finding is also complemented by the short-lived smart money effect presented above. The short-lived phenomenon implies that the skill owned by smart investors might be a skill that appears only at some special point in time but does not last, or a skill that can only be practiced within a short time period. Market timing ability possesses these characteristics.

In summary, the evidence in this paper demonstrates that smart investors appear in the top performing fund group. Moreover, in addition to unwittingly benefitting from the momentum effect, smart investors also possess market timing ability to distinguish themselves from those ones who naïvely chase the winners. Since a group of smart investors can time the market to invest accordingly and thereby earn significant risk-adjusted returns, the question posed by Gruber (1996) – why do investors buy actively managed mutual funds? – could be partially answered. The findings provide a rationale for the growth in actively managed mutual funds.

The paper is organized as follows. I describe the related literature briefly in Section II and introduce the methodology in Section III. Section IV describes the data. Section V provides evidence on the performance of 10 portfolios. Section VI examines the abilities possessed by the smart investors identified in Section IV. Section VII presents further evidence to make the findings more robust. The conclusion is presented in Section VIII.

II. Literature Review

The four key studies concerning the smart money effect are those of Gruber (1996), Zheng (1999), Sapp and Tiwari (2004), and Keswani and Stolin (2008). Gruber's aim is to understand the continued expansion of the actively managed mutual fund sector despite widespread evidence that, on average, active fund managers do not add value. To test whether investors are more sophisticated than simple chasers of past performance, he examines whether investor money tends to flow to the funds that subsequently outperform. He finds evidence that a group of sophisticated investors seems to identify the superior funds, as evidenced by the flow of new money into and out of mutual funds that predict future performance. Thus, money appears to be smart.

Expanding the dataset to cover the universe of all equity funds between 1970 and 1993, a subsequent study by Zheng (1999) claims that the short-term performance of funds that experience positive new money flow is significantly better than that of those that experience negative new money flow. Interestingly, Zheng (1999) also examines whether a trading strategy could be devised based on the predictive ability of net flows and finds evidence that information about net flows into small rather than large funds could be used to make risk-adjusted profits.

However, Sapp and Tiwari (2004) question the smart money effect because they find that it is explained by the stock return momentum phenomenon documented by Jegadeesh and Titman (1993). They also demonstrate that investors naïvely chase recent winners and are incidentally benefiting from the momentum effect. Since 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. Due to the disproportionate holdings of ex post best performing stocks by these funds, investors benefit from the momentum returns on winning stocks by buying into winning funds. Their viewpoint is also strengthened by the work of Wermers (2003), which suggests that fund managers will perpetuate good fund performance by investing a large proportion of the new inflow money in stocks that have recently done well.

The smart money debate was raised again by the recent work of Keswani and Stolin (2008). Differing from the above studies, which all use U.S. data, Keswani and Stolin re-examine the smart money issue with the U.K. data for the period 1992–2000. Although the U.K. mutual fund industry is much smaller than that in the U.S.[1], the mutual funds data in the U.K. allow researchers to conduct a stronger test for the smart money effect by using monthly flow data, and to gain greater insight into investor decisions by considering the sales and purchases of individual and institutional investors separately. They find that the portfolios of new money weighted by inflow all perform better than those weighted by outflow. Their results provide evidence that the smart money effect in the U.K. is due to the fund buying (but not sales) of both individual and institutional investors. Keswani and Stolin (2008) also test the U.S. data from 1991 to 2000 and document a statistically significant smart money effect in the U.S. They attribute the insignificance of the smart money effect found by Sapp and Tiwari (2004) to the use of quarterly data and the weight

[1] Keswani and Stolin (2008) indicate that at the end of 2000, 155 fund families ran 1,937 mutual funds managing £261 billion (US$390 billion) in assets, making the U.K. mutual fund industry one of the largest outside the United States (Khorana *et al*. (2005)). According to the 2008 *Investment Company Fact Book* published by the Investment Company Institute (ICI), at the end of 2007 there were 8,029 funds operated by 683 fund sponsors. These funds managed $13 trillion in assets for 90 million U.S. investors.

they put on the pre-1991 period.

Regarding investor ability, Fama (1972) suggests that the returns of mutual fund managers can be subdivided into two parts: return from stock selection and return from timing activity. Similarly, fund investor return can also be attributed to fund selection and timing ability. Research by Frazzini and Lamont (2008) suggests that poor fund selection decisions end up costing longer-term investors about 0.84% per year, a result they dub the 'dumb money' effect. Meanwhile, at the individual fund level, Friesen and Sapp (2007) examine the timing ability of mutual fund investors using cash flow data. While numerous studies have examined the timing ability of mutual fund managers (e.g. Bollen and Busse, 2001), the work of Friesen and Sapp (2007) is the first comprehensive study to examine the timing ability of mutual fund investors. They compute monthly dollar-weighted returns over the period 1991–2004 for 7,125 equity mutual funds and find that the geometric average monthly return is 0.62%, while the average monthly dollar-weighted return is 0.49%. This finding indicates that investors underperform by about 0.13% per month, or 1.56% annually, relative to a buy-and-hold strategy.

In summary, prior studies do not exploit the possibility for smart investors to invest in top performing funds is higher than that for other investors. Therefore, this paper focuses on the returns of investors in top performing funds to observe whether these investors possess timing ability to earn significant risk-adjusted returns.

III. Methodology

A. The GT Measure of Performance

To estimate the abilities of investors in aggregate in selecting mutual funds and switching between them, I employ the measure of portfolio performance introduced by Grinblatt and Titman (1993) – the GT measure. Although the GT measure evaluates the performance earned by switching between funds, it also implicitly considers the time of the switch. In other words, the GT measure is a measurement that jointly considers fund selection ability and timing ability. The GT performance measure for a given month is calculated by multiplying the monthly change in each fund portfolio weight by the return of that fund during the following month. The month *t* component for a given fund is

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

where $w_{i,t}$ is the portfolio weight for fund *i* at time *t*, which is equal to the TNA for fund *i* divided by the total TNA for all domestic equity funds. The change of portfolio weight for fund *i*, i.e. $(w_{i,t} - w_{i,t-1})$, is called the GT weight, which will be utilized to construct portfolios in a later section. $R_{i,t+1}$ is the return of fund *i* between time *t* and *t+1*.

The GT measure in expression (1), which illustrates the return of a zero-cost portfolio, uses its own portfolio holdings in the preceding period as a benchmark. If the null hypothesis that investors have no skill is true, then the weight change, i.e. $(w_{i,t} - w_{i,t-1})$, should be uncorrelated with current returns, and thus, expression (1) converges to zero for large samples. On the other hand, if the alternative hypothesis that the investor has specific skills is true, then expression (1) should be positive, under the assumption that the expected return of each stock does not change systematically from period to period.

However, the zero-cost portfolio assumption implicitly assumes that the investor can short sell some assets to finance the purchase of others. When investors are generally not allowed to short sell funds, the GT measure is not implementable and the abnormal returns earned by the short-long strategy are unlikely to be realized by individual investors in practice. That is, although the result of GT measure is a good indicator of the smart money effect, it cannot be implemented by investors to earn abnormal returns. Similar to the work of Zheng (1999), I employ several trading strategies to explore the practical implications of investor abilities.

B. Measurement of Unexpected Flows

Unlike the work of Zheng (1999) and Sapp and Tiwari (2004), this paper constructs portfolios weighted by the unexpected flows rather than new money signals. Unexpected flows are the differences between the actual flows and expected flows, which are estimated by lagged fund returns and new cash flows from the previous year (Coval and Stafford, 2007). Since capital flows to and from mutual funds are strongly related to past performance (e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998), most new cash flows are attributed to the phenomenon of flocking to recent winners and cannot present the behavior of smart investors. That is, the information of new cash flows is very noisy. To exclude the behavior of chasing the winners by unsophisticated investors, I forecast fund flows based on past performance and lagged flows from the previous year to purge the purchases and redemptions that are not merely related to prior performance.

Before computing unexpected flows, I first calculate new cash flows. New cash flows in this paper are defined as the dollar change in total net assets (TNA) minus the appreciation in the fund assets and the increase in total assets due to mergers. I employ the Gruber (1996) "follow the money" approach that assumes that investors in merged funds place their money in the surviving fund and continue to earn a return from the surviving fund. Since defunct funds are not excluded from the sample before they disappear, this mitigates survivorship bias. I assume that new cash flow is invested at the end of each month:

$$FLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t}) - MGTNA_{i,t} \tag{2}$$

where $TNA_{i,t}$ refers to the TNA at the end of quarter t, $R_{i,t}$ is the fund's raw return for month t, and $MGTNA_{i,t}$ is the increase in the TNA due to mergers during month t. Asset appreciation includes capital appreciation, income, and capital gains distributions.

Based on the new cash flows, I can compute the unexpected flows with a procedure similar to that used by Coval and Stafford (2007). To reduce the possible skewness induced by large funds, $FLOW_{i,t}$ in expression (2) is normalized by dividing by the corresponding TNA at time *t-1*.

(3) $$flow_{i,t} = \frac{FLOW_{i,t}}{TNA_{i,t-1}}$$

Similar to Sirri and Tufano (1998) and Coval and Stafford (2007), I use a simple Fama and MacBeth (1973) style regression model to forecast fund flows based on past returns and lagged flows.

(4) $$flow_{i,t} = a + \sum_{k=1}^{12} b_k \cdot flow_{i,t-k} + \sum_{h=1}^{12} c_h \cdot R_{i,t-h} + \varepsilon_{i,t}$$

where the residual, $\varepsilon_{i,t}$, is the unexpected flow, $flow_{i,t-k}$ is the lagged normalized new cash flow in expression (3), and $R_{i,t-h}$ is the past raw return. For each month *t*, I estimate a cross-sectional regression, as in (4), by including lagged flows and fund returns from the previous year. I then calculate the time-series average of the coefficients. Unexpected flows are calculated as the $flow_{i,t}$ in expression (3) minus the fitted values in (4) using the time-series average of the coefficients. In particular, in order to obtain the most reliable data, I limit the changes in TNA so that they cannot be too extreme:

$-3.0 \leq \frac{FLOW_{i,t}}{TNA_{i,t-1}} \leq 3.0$[2]. In total, I have 189 cross-sectional regressions throughout the 16-year observation period. Alternatively, I also use a pooled regression. As the overall results remain the same, I do not report these results.

C. Trading Strategies

To examine whether investor flows indicate information that can be used to earn abnormal returns, similar to the work of Zheng (1999), I construct several hypothetical trading strategies. In the following analysis, I will use these trading strategies in funds with differing performance to observe whether they can earn abnormal returns.

Portfolio 1: Equally weighted portfolio of all available funds.

Portfolio 2: In all available funds and weighted by current total net assets of the fund.

Portfolio 3: Equally weighted portfolio of all available funds with positive unexpected flows.

[2] For some mutual funds, the new cash flows are hundreds of times the TNA, which is not possible or can happen only in very special situations. For funds which cannot conform to the data requirements, I delete the observation for fund *i* at time *t*. Alternatively, I also run regressions without the data requirement and the major results are unchanged.

Portfolio 4: Equally weighted portfolio of all available funds with negative unexpected flows.

Portfolio 5: In all available funds with positive unexpected flows and weighted in proportion to the unexpected flow of the fund.

Portfolio 6: In all available funds with negative unexpected flows and weighted in proportion to the unexpected flow of the fund.

Portfolio 7: Equally in all available funds with above-median unexpected flows.

Portfolio 8: Equally in all available funds with below-median unexpected flows.

Portfolio 9: In all available funds with positive GT weights and weighted in proportion to GT weights of the funds.

Portfolio 10: In all available funds with negative GT weights and weighted in proportion to GT weights of the funds.

Portfolios 3 through 8 are constructed from strategies based on unexpected flows. I refer to portfolios 3 and 5 as positive portfolios and portfolios 4 and 6 as negative portfolios. Portfolios 7 and 8 classify all observations into two groups according to the median of unexpected flows, and thus control for the fact that there might be a disproportionate number of funds with positive and negative unexpected flows in some periods. I also construct portfolios 9 and 10 using the GT weight, i.e. $(w_{i,t} - w_{i,t-1})$, calculated in the GT measure, to take the spirit of the GT measure into consideration.

All trading portfolios are constructed at the beginning of each month, based on the relevant information of the immediately preceding month. These portfolios are held for one month, and then re-constructed according to the same criteria at the beginning of the next month. For example, to construct the returns for portfolio 5 in May 2000, I first select funds with positive unexpected flows at the end of April 2000. The monthly returns of the selected funds in May are then weighted by their corresponding unexpected flows. To calculate the monthly returns for the portfolio for June 2000, I reselect funds according to the new money data at the end of May 2000 and repeat the previous procedure to get the weighted average return for June 2000.

I calculate a time series of raw returns for each of the 10 portfolios and perform OLS regressions to estimate their portfolio factor loadings and the abnormal returns.[3] The

[3] To control for idiosyncratic variations in mutual fund returns, Kosowski, Timmermann, Wermers, and White (2006) use the bootstrap method to analyze the significance of alphas. I also apply the bootstrap method of Kosowski et al. (2006) to reconstruct the distribution of the model coefficients, and then use this distribution to test for statistical significance instead of employing the standard *t*-test. The results of using

abnormal returns of portfolios are evaluated by the three-factor model by Fama and French (1993) and the four-factor model by Carhart (1997). The approach below is referred to as the "portfolio regression approach" by Zheng (1999). The model is given by:

(5) $$r_{p,t} = \alpha_p + \beta_p^{RMRF} RMRF_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + e_{p,t}$$

(6) $$r_{p,t} = \alpha_p + \beta_p^{RMRF} RMRF_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \beta_p^{PR1YR} PR1YR + e_{p,t}$$

where $r_{p,t}$ is the monthly return on a portfolio of funds in excess of the one-month T-bill return; α_p is the risk-adjusted return of portfolio i, $RMRF_t$ is the return on the market portfolio in excess of the risk-free rate, and SMB_t, HML_t and $PR1YR_t$ are value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns respectively. These factor data are collected from the website of Kenneth R. French.

D. Timing Ability

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the bootstrap method are similar to those when using the standard t-test.

Treynor and Mazuy (1966) and Henriksson and Merton (1981) demonstrate two methods of measuring market timing ability based on the CAPM-based model.

TM – Treynor and Mazuy (1966) model:

(7) $$r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + \gamma_{1,i} \cdot RMRF_t^2 + \varepsilon_{i,t}$$

HM – Henriksson and Merton (1981) model:

(8) $$r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + \gamma_{1,i} \cdot RMRF_t^* + \varepsilon_{i,t}$$

$$RMRF_t^* = I\{RMRF_t > 0\} \cdot RMRF_t$$

where $r_{i,t}$ is the month *t* excess return of the mutual fund *i* (net return minus T-bill return); α_i is the abnormal return that cannot be explained by the model; $RMRF_t$ is month t excess return on a value-weighted aggregate market proxy portfolio. $I\{condition\}$ is an indicator function that equals one if the condition is true, and zero otherwise.

Volkman (1999), Bollen and Busse (2001), and Chen, Adams, and Taffler (2009) apply the two methods to Carhart's (1997) four-factor model, which means that the methods of

Treynor and Mazuy (1966) and Henriksson and Merton (1981) can be applied, not only to the excess market return $RMRF_t$, i.e. market timing ability, but also to other factors, i.e. SMB_t, HML_t, and $PR1YR_t$. Applying the two methods to SMB_t measures the size timing ability – the ability to choose between small and big capitalization companies. Similarly, HML_t captures the book-to-market timing ability – the ability to choose between value and growth stock – and $PR1YR_t$ reveals the momentum-strategy timing ability – the ability to choose between momentum and contrarian strategies (Chen *et al*., 2009). Like fund managers, these four timing abilities, i.e. market timing, size timing, book-to-market timing, and momentum-strategy timing, are the abilities that investors who earn abnormal returns may possess. I include all four timing measures to observe what kind of timing ability is possessed by smart investors. The following are the two timing ability models:

CTM – Carhart's (1997) four-factor Treynor and Mazuy (1966) model:

(9)
$$\begin{aligned} r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + p_i \cdot PR1YR_t + \\ \gamma_{1,i} \cdot RMRF_t^2 + \gamma_{2,i} \cdot SMB_t^2 + \gamma_{3,i} \cdot HML_t^2 + \gamma_{4,i} \cdot PR1YR_t^2 + \varepsilon_{i,t} \end{aligned}$$

CHM – Carhart's (1997) four-factor Henriksson and Merton (1981) model:

$$r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + p_i \cdot PR1YR_t + \gamma_{1,i} \cdot RMRF_t^* + \gamma_{2,i} \cdot SMB_t^* + \gamma_{3,i} \cdot HML_t^* + \gamma_{4,i} \cdot PR1YR_t^* + \varepsilon_{i,t} \tag{10}$$

$$RMRF_t^* = I\{RMRF_t > 0\} \cdot RMRF_t$$
$$SMB_t^* = I\{SMB_t > 0\} \cdot SMB_t$$
$$HML_t^* = I\{HML_t > 0\} \cdot HML_t$$
$$PR1YR_t^* = I\{MOM_t > 0\} \cdot PR1YR_t$$

where $r_{i,t}$, α_i and $RMRF_t$ use the same calculations in equation (7) and (8); SMB_t, HML_t, and $PR1YR_t$ are returns on value-weighted, zero-investment factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns respectively. $I\{condition\}$ is an indicator function that equals one if the condition is true, and zero otherwise. $\{\gamma_{1,i}, \gamma_{2,i}, \gamma_{3,i}, \gamma_{4,i}\}$ are measures of market timing, size timing, book-to-market timing, and momentum-strategy timing respectively.

IV. Data and Samples

The data were collected from the Center for Research in Security Prices (CRSP) mutual fund database. The CRSP database provides survivor-bias-free data on net returns for each share class of every US open-end mutual fund since 1 January 1962. The sample includes all domestic equity funds that exist during the period from January 1993 to

September 2008. I exclude international funds, sector funds, specialized funds, and balanced funds, because these funds may have risk characteristics that are not spanned by the factors driving the returns of most other mutual funds. I base the selection criteria on two objective codes: the Strategic Insights Objective Code and the Lipper Objective Code. Since the Strategic Insights Objective Code generally provides fund objective codes from 1993 to 1998, while the Lipper Objective Code does so from 1998 to 2008, I selected the observations based on a union of the two codes. The sample includes both load and no-load funds, which enables us to compare the performance of load funds to that of no-load funds. In summary, the sample has a total of 9,607 fund-entities and 868,190 fund-years.

Table 1 presents descriptive statistics for the mutual fund sample. The average (median) fund size measured by TNA is $466.28 ($37.8) million. From the difference between the mean and median, we can observe that the fund size in the sample is very extreme. I therefore classify the funds into quintiles, ranking by TNA. In the unreported results, the average (median) fund size of the top quintile ranking by TNA is $2131.46 ($744.9) million, whereas the average (median) fund size of the bottom quintile is $1.29 ($0.8) million. It is obvious that the variation of fund size is large enough to produce different results concerning the abnormal returns of small and big funds in the study by Zheng (1999). The average monthly net cash flow is a positive $1.77 million. However, a negative unexpected flow of about -0.19% can be observed.

[INSERT TABLE 1 HERE]

V. The Smart Money Effect

Assessing the significance of the smart money effect is complicated by the possibility of misspecification of trading strategies or the location of such an effect. For example, if the smart money effect can only be found in funds with specific characteristics but we try to discover it by using the entire sample, then the significance level is likely to be diluted. Following this, it is possible to come to the conclusion that investors are not smart due to the insignificant risk-adjusted returns. Some studies use the long-short strategies to obtain significant risk-adjusted returns; however, these strategies are not practically implementable. To test whether smart investors gather in top performing funds, I classify the entire sample to quintiles based on excess returns to locate smart investors. Moreover, to exclude the inflows which come from investors who naïvely chase the recent winners, I use the concept of unexpected flows to be the weights of trading strategies. In brief, the empirical results demonstrate that some trading strategies can earn significant risk-adjusted returns after including the momentum factor.

A. GT Measure

By constructing eight trading strategies, Zheng (1999) finds that small funds display a very strong smart money effect but large funds display almost no such effect. However, for the GT measure, she only shows that equity funds in aggregate demonstrate a positive GT measure, but does not examine whether the GT measure also has such different results in small and large funds. This section first investigates whether investor ability in switching between funds is also significant in the small fund group.

I start by ranking funds by their total net assets (TNA) into quintiles. Table 2 presents the GT measure estimates for the aggregate portfolios in different quintiles. The time-series means of the GT measures and the significance statistics from the *p* value are documented. The average GT measure for the whole sample is 0.54 basis points per month, or approximately 6.50 basis points per year. Unfortunately, unlike the findings of Zheng

(1999), the GT measure for the entire sample is not significant. However, after ranking the entire sample into quintiles by TNA, I observe that the time-series mean of the GT measure for the bottom quintile is significant, while it is insignificant for the other four quintiles. For the bottom quintile, the average GT measure is 2.36 basis points per month, or approximately 28.69 basis points annually. This number is much smaller than that found in the work of Zheng (1999).

[INSERT TABLE 2 HERE]

This finding provides evidence that only investors in small funds, whose TNA are in the lowest 20% among all equity funds, show significant ability. Other investors, i.e. those who invest in other quintiles do not significantly switch their money to assets with increasing expected returns. In other words, the smart money effect is not an overall phenomenon, but can only be observed in the bottom TNA quintile ranking. This phenomenon can be attributed to two possibilities. First, unless their performance is impressive, small funds have less media coverage (Jain and Wu, 2000). Due to the attention-grabbing effect (Barber and Odean, 2008), investors would notice and invest their money in the small funds only when these small funds achieve good performance. In other words, the ex post performance of these small funds would be better because they have performed well and investors would unwittingly benefit from this. Under such an argument, the returns earned by investing in small funds with good performance would be explained by the momentum effect (Sapp and Tiwari, 2004).

On the other hand, the alternative interpretation is that fund size may affect investor strategy. Investors might be more cautious when investing in small funds than in larger funds (Zheng, 1999). In addition, funds with different sizes may attract different investors. Small funds generally have less media coverage, so investors who put money into small funds are more likely to buy funds based on some sophisticated reasons rather than on newspaper recommendations. If this argument is true, the risk-adjusted returns earned by investors in small funds would be significant, even with the inclusion of the momentum factor. Based on the significant GT measure of the bottom quintile funds, ranked by TNA, in the following I construct portfolios for the bottom quintile funds to distinguish between these two interpretations, and examine whether the significant GT measure can be converted to significant abnormal returns.

B. The Performance of Trading Strategies

In this section I focus on the small funds which exhibited significant ability in the previous section, i.e. the funds whose TNA are in the lowest 20% among all equity funds in the sample. As mentioned above, this section intends to investigate whether the risk-adjusted returns earned by investors cannot be explained by the momentum effect. In addition to the entire sample of small funds, I also examine the five performance quintiles of the small funds classified by their excess returns.

Table 3 reports the positive and negative signs and the significance of raw and risk-adjusted returns. Unlike Zheng (1999), I do not observe any significantly positive risk-adjusted returns when using the entire sample. Interestingly, funds whose performances are grouped into the first, second, and third performance quintiles, i.e. they have performance generally below the median, have negative Fama-French and Carhart risk-adjusted returns in almost all portfolios. Conversely, in the groups that perform well, i.e. the fourth and fifth performance quintiles, I obtain significantly positive Fama-French risk-adjusted returns in portfolios 1, 2, 5, and 9. However, these positive Fama-French risk-adjusted returns disappear after including the momentum factor. The results are similar in spirit to those reported by Sapp and Tiwari (2004), which indicates that including a stock return momentum benchmark eliminates abnormal returns.

[INSERT TABLE 3 HERE]

However, the Carhart four-factor risk-adjusted returns of the top performance quintiles in portfolios 5 and 9 are positive at the 1% and 5% significance levels, even when the momentum factor is considered. In most cases, the smart money effect is explained by exposure to stock return momentum. However, the abnormal returns of the positive portfolio weighted by unexpected flow cannot be eliminated by the momentum factor. This finding also provides evidence for the argument in Section 4.1 that fund size may affect investor strategy.

Note that when I examine the entire small fund sample, i.e. the funds whose TNA are in the lowest 20%, the Carhart four-factor risk-adjusted returns in portfolios 5 and 9 are no longer significant. I also investigate the sample which includes all equity funds and divide them into quintiles ranked by excess returns. The Carhart four-factor risk-adjusted returns of the group with top performance are not significant in 10 portfolios. Therefore, the results indicate that the four-factor risk-adjusted returns found in the positive portfolios

(portfolios 5 and 9) weighted by unexpected flow would be diluted when including other observations.

Panel A of Table 4 shows the returns and risk-adjusted returns of all portfolios in the top performance quintile of the small funds over the period from 1993 to 2008. The monthly four-factor risk-adjusted returns for portfolio 5 in the top performance quintile is 54.59 basis points per month, or approximately 6.55% per year. The similar portfolio examined by Zheng (1999), which includes all available funds in the market with positive new money cash flow and weighted by the funds' new money, can earn an insignificant 0.3 basis points per month, or approximately 3.6 basis points annually. The similar portfolio examined by Sapp and Tiwari (2004)[4] obtains an insignificant alpha – about -0.3 basis points per month. Note that alphas in the studies by both Zheng (1999) and Sapp and Tiwari (2004) are not statistically significant and very small compared to the alpha shown in Table 4. These comparisons demonstrate the extent to which aggregate mutual fund unexpected flows in the top performance quintile can predict future performance. But this outperformance cannot be obtained by following the strategies of investors placing

[4] The portfolios in the work of Zheng (1999) and Sapp and Tiwari (2004), and portfolio 5 in this paper are similar. The difference is that portfolio 5 in this paper is grouped and weighted by the funds' unexpected flows, but by new money cash flow in the work of Zheng (1999) and Sapp and Tiwari (2004).

money in the bottom performance quintile.

[INSERT TABLE 4 HERE]

Panel B of Table 4 reports the returns earned by the long-short strategy, where one buys the positive portfolios and sells the corresponding negative portfolios. In Carhart's four-factor model, portfolio 5 significantly outperforms portfolio 6 by 45.07 basis points per month, or 5.54% annually, which is significant at the 1% level. The risk-adjusted returns of the long-short strategies do not correspond to implementable strategies, because investors are normally not allowed to short sell funds in practice. The significantly positive difference, however, still provides evidence for the argument that small fund investors who invest in the top performing funds are smart.

The findings of this section have two implications. First, strategies based on the unexpected flow of investors in the top performance quintile contain information about making abnormal returns by exploiting unexpected flow information. Secondly, the abnormal returns of small fund investors who invest in the top performing funds, ranked by excess returns, cannot be explained by the momentum factor. If these investors naïvely chase the winners, their performance can be explained by the momentum factor; that is to say, they do not have any special skills to earn abnormal returns. However, the result indicates that small fund investors in the top performing fund group have undiscovered skills, not only by chasing winners. Previous studies, which include all equity funds as samples, tend to ignore these smart investors.

C. The Span and Accumulation of Effective Information

The above analyses are based on a one-month holding period, and this raises two interesting questions: How long is the information of unexpected flows (or GT weights) effective? Do accumulative unexpected flows (or GT weights) carry more information than those of a single period? To answer these questions, I use the portfolio regression approach, and compare performance using accumulative unexpected flows and GT weights as weights.

Table 5 examines the performance of portfolios 5 and 9 for up to six months ahead. Rows *TS1~TS6* describe the length of the accumulation period; columns *t-1~t-6* indicate the starting point of the accumulation period. For example, the element *(t-3, TS4)* in Panel A of Table 5 measures the performance of a portfolio with a positive sum of unexpected flows into the fund from *t-3* to *t-6* and is weighted in proportion to the sum of the unexpected flows. Similarly, the element *(t-2, TS3)* in Panel B of Table 5 measures the performance of the portfolio with a positive sum of the GT weight change from *t-2* to *t-4* and weighted by the sum of the GT weight change from *t-2* to *t-4*. The results in *(t-1, TS1)* are identical with the results of portfolios 5 and 9 in Table 4.

[INSERT TABLE 5 HERE]

The abnormal return of *(t-1, TS1)* is the most significant in Panel A of Table 5. As the time spans increase, the significance of abnormal returns reduces. For example, the abnormal returns of *(t-1, TS2)* and *(t-1, TS3)* are no longer significant. Similar results can also be observed in Panel B of Table 5. The performance of *(t-1, TS1)* is the largest and the most significant. Using the accumulative unexpected flows and the accumulative GT weights does not create larger abnormal returns. The performance in the month immediately following unexpected flows is the most significant.

These results indicate that abnormal returns earned by small fund investors in the top performance quintile are short-lived. This finding is consistent with that of Keswani and Stolin (2008). In terms of the short-lived smart money effect, I further ask: Why is it that these investors are smart but their intelligence lasts for only a short period? Similar to fund manager returns, fund investor returns can also be classified as fund selection and timing abilities. If both smart investors and momentum-style investors who naïvely chase the winners flock to superior funds, the major difference between smart investors and momentum-style investors is the time point of buying superior funds and selling the funds owned by them. That is to say, unlike momentum-style investors, smart investors can decide when to invest and redeem their money, i.e. time the market, to enhance their returns. To examine whether smart investors possess timing ability, I utilize Carhart's (1997) four-factor Treynor and Mazuy (1966) model and Carhart's (1997) four-factor Henriksson and Merton (1981) model in the following section.

VI. The Skills of Smart Investors

This section tests whether small fund investors in the top performance quintile have timing ability. The basic idea of timing activity relates to the ability to forecast future market states and weight equity exposure accordingly, while fund selection ability is defined as the difference between the return on a managed fund portfolio and the return on a naïvely selected fund portfolio with the same level of market risk. Table 6 shows the test results based on four models – the traditional Treynor and Mazuy (1966) model (TM), the traditional Henriksson and Merton (1981) model (HM), the Carhart (1997) four-factor Treynor and Mazuy (1966) model (CTM) and the Carhart (1997) four-factor Henriksson and Merton (1981) model (CHM). After including the timing skill coefficients, the alphas in Column 2 of Table 6 are no longer significant – the abnormal returns are fully explained by the timing coefficients in all four timing models. This result implies that the superior performance obtained by following the strategies of small fund investors in the top performance quintile, ranked by excess returns, is attributable to timing skills. To put it practically, small fund investors in the top performance quintile can choose superior funds from among all funds and purchase them at a good time point.

[INSERT TABLE 6 HERE]

If small fund investors in the top performance quintile have timing ability, what kind of timing ability do they have? Concerning portfolio 5, the TM and HM models in Panel A and B show that these smart investors possess market timing ability. The market timing coefficients of portfolio 5 are 1.717 and 1.318 at the 5% level of significance. The market timing coefficients of portfolio 9 in Panel A and B are also significant at the 5% level. After including the other three timing factors in Panel C and D, the market timing coefficients of portfolio 5 are 1.520 and 0.302 at the 5% and 10% levels of significance. However, compared to portfolio 5, the market timing coefficients of portfolio 9 are not significant. In unreported results, which adopt the bootstrapping methods used by Kosowski *et al*. (2006), the coefficient of market timing becomes significant in portfolio 9. Except for this significant coefficient of market timing for portfolio 9, the other results using the bootstrapping methods of Kosowski *et al*. (2006) are similar to those using standard *t*-statistics.

In brief, the test results reveal that smart investors who put money in the small and top 20% performing funds appear to mainly possess market timing skills. Since the abnormal returns earned by small fund investors in the top performance quintile fund group are attributable to market timing skills, the fact that the smart money effect is short-lived is not surprising. Market timing ability itself is mainly based on an outlook of aggregate market or economic conditions at a point in time, but is less likely to be observed over a long time interval. Therefore, the short-lived smart money effect and the argument that small fund investors in the top performance quintile have market timing ability mutually reinforce each other. Furthermore, by using the four timing models, the results implicitly distinguish between timing ability with respect to individual funds and the market. The former indicates that smart investors realize when to invest in a specific fund, whereas the latter shows that smart investors can forecast whether the market is in a boom and invest in corresponding funds. CTM and CHM are designed to identify market timing rather than fund-specific timing activity. Since the abnormal returns can be fully explained by the timing factors in the four timing models, this implies that instead of timing the funds, smart investors time the market to make risk-adjusted returns.

The finding concerning market timing ability is not contrary to that of Friesen and Sapp (2007), who conclude that equity fund investors' timing decisions lead to underperformance. While Friesen and Sapp (2007) focus on the timing ability of all investors at the individual fund level, I examine only the timing ability of the investor group that can earn abnormal returns at the entire fund market level. Although the timing ability of investors in aggregate reduces their fund returns, there are some smart investors who know when to invest in the fund industry to make significant abnormal returns.

VII. Further Evidence of the Smart Money Effect

A. Are Investors in No-Load Funds Smarter?

Investors in load funds are commonly regarded as uninformed investors, because the higher cost of trading in load funds may prevent informed investors from investing (Zheng, 1999). Hence, I investigate whether the different investment behavior of investors in load and no-load funds influences portfolio performance. I still have funds in the lowest 20% ranked by TNA as the sample, and rank these funds by their excess returns. The portfolios are formed according to the same strategies for load and no-load funds separately.

The empirical evidence in this paper does not support the view that investors in load funds are not as well informed as investors in no-load funds. Both portfolios 5 and 9 have significantly positive risk-adjusted returns in load and no-load funds. Intuitively, investors are reluctant to buy load funds unless they believe that they will be compensated by a return premium. The positive four-factor risk-adjusted returns in both load and no-load funds implies that for the investors in the top performance quintile, as long as the return premium compensates for the load fees, load fees are not their major determinate for buying or not buying the funds. Alternatively, it indicates that small fund investors in the top performance quintile are not influenced by load fees when they purchase funds.

B. Do Investors Become Smarter Over Time?

Are investors smarter now? To observe whether the results obtained above change over time, the testing period is separated into two sub-periods, 1993/01–2000/12 and 2001/01–2008/09, and we find that the results are not influenced by the observation period. Portfolios 5 and 9 are still significantly positive for the top performance quintile by using the four-factor model in both 1993/01–2000/12 and 2001/01–2008/09. I further divide the entire testing period into three sub-periods, such that each sub-period covers five years. Portfolios 5 and 9 for the top performance quintile still produce a significantly positive Carhart's alpha. Therefore, the finding that small fund investors in the top performance quintile can make abnormal returns by exploiting unexpected flow information is not influenced by time, i.e. it is robust.

C. Robustness Test

I examine the distribution of the time-series performance measures to make sure that the positive abnormal return is not caused by several outliers. To test the effect of these outliers on the abnormal return, I eliminate observations for which the absolute value of the monthly return measure is more than 95% and less than 5% of the total sample. The results are similar to those above. Portfolios 5 and 9 still demonstrate significant abnormal returns. Furthermore, because the flows of newly established funds are often larger within the first few months than the subsequent average level, I recalculate portfolio returns by excluding the flow information for the first three months for all funds after they were established within the sample period. Again, the results remain virtually the same. In brief, all earlier results are virtually unchanged, even when I delete outliers and exclude the initial flow information of newly established funds.

To sum up, all major conclusions remain unchanged under the classification of load and no-load funds, different time periods, and the exclusion of outliers and unstable flow information, which means that the results in this paper are robust.

VIII. Conclusion

The term *smart money* in mutual fund literature has come to be associated with the ability of investors to identify future superior performers from a group of comparable funds. Four important studies by Gruber (1996), Zheng (1999), Sapp and Tiwari (2004), and Keswani and Stolin (2008) examine whether mutual fund investors have the ability to predict fund performance and invest smartly. Gruber (1996) and Zheng (1999) provide evidence of a "smart money" effect – investors appear to invest in funds that subsequently outperform the market. Sapp and Tiwari (2004) attribute this outperformance to the momentum effect and conclude that the smart money effect is an artifact of stock return momentum. However, Keswani and Stolin (2008) find that positive cash flow portfolios outperform negative cash flow portfolios when using monthly, rather than quarterly, UK data. Unfortunately, although Keswani and Stolin (2008) find a significant smart money effect by using the long-short strategy, they do not deal with the smart money effect by using single portfolios, like those in the work of Zheng (1999). In this paper, I examine the risk-adjusted returns of every single portfolio to address this omission and ask two questions: Where are the smart investors? Why are they smart?

Using the GT measure introduced by Grinblatt and Titman (1993), I find that the smallest fund investors in aggregate reduce the amount of money invested in funds with decreasing expected returns but increase the amount of money invested in funds with increasing expected returns, while big fund investors do not. To investigate the magnitude and practical implications of investor specific skills, I construct 10 trading strategies weighted by unexpected flows, TNA and GT weights respectively. When I classify the small funds, whose TNA are in the lowest 20% of all equity funds, by ranking their excess returns, investors of the top performing funds exhibit abnormal risk-adjusted returns which cannot be eliminated by the inclusion of the momentum effect. In other words, smart investors locate this group and have some undiscovered skills, rather than simply chasing the winner, to earn significant abnormal returns.

I find that the undiscovered skill possessed by smart investors is market timing ability. The risk-adjusted returns earned by investing in the top performing funds become insignificant after including the timing factors. This ability can distinguish smart investors from momentum-style investors, who naïvely chase recent winners and benefit incidentally from the momentum effect.

The findings have two important implications. First, I locate the smart investors and identify their ability. Although smart investors identify and flock to the winners, the outperformance of smart investors is attributable to their market timing ability. Hence, the abnormal returns earned by smart investors cannot be explained by the momentum effect. Secondly, it answers the puzzle posed by Gruber (1996): Why do investors buy actively managed mutual funds when actively managed funds do not offer superior performance but charge management fees? Gruber refers this phenomenon to sophisticated investors being able to identify skilled fund managers and invest accordingly. This paper confirms the answer in a more detailed way.

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Table 1 Descriptive Statistics

Table 1 presents a summary of the descriptive statistics of the mutual fund sample obtained from the CRSP Survivor-Bias Free U.S. Mutual Fund Database. The sample includes all U.S. equity mutual funds that existed at any time from January 1993 to September 2008. I exclude sector funds, international funds, specialized funds, and balanced funds. The final sample consists of 9,607 fund-entities comprising 868,190 fund-years. The monthly net cash flow for fund i during month t is measured as $FLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t}) - MGTNA_{i,t}$, where $TNA_{i,t}$ refers to the total net assets at the end of month, t, $R_{i,t}$ is the fund's raw return for month t, and $MGTNA_{i,t}$ is the increase in the TNA due to mergers during month t. The monthly raw return is the original return without risk adjustment. The monthly excess return is the monthly raw return in excess of the risk-free rate. The unexpected flow is defined as the residuals of the simple Fama-MacBeth regression model: $flow_{i,t} = a + \sum_{k=1}^{12} b_k \cdot flow_{i,t-k} + \sum_{h=1}^{12} c_h \cdot R_{i,t-h}$, where $flow_{i,t}$ is computed as the monthly net cash flow (FLOW) for fund i divided by the corresponding TNA, and $R_{i,t-h}$ is the monthly raw return. For each item, the cross-sectional average in each year from January 1993 to September 2008 is calculated. The reported statistics are computed from the time series of the 16 annual cross-sectional average figures for each item.

	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
TNAs ($ millions)	466.28	37.80	6.20	187.20	2,643.00
Monthly Net Cash Flow (FLOW) ($ millions)	1.77	0.04	-1.19	2.24	167.65
Monthly Raw Return (basis point)	61.72	93.70	-202.47	348.78	522.45
Monthly Excess Return (basis point)	32.92	65.47	-229.48	318.75	522.27
Unexpected Flow (%)	-0.19	-0.95	-2.96	1.70	11.35

Table 2 GT Performance: January 1993 to September 2008

This table presents the numbers and significance of the GT measures in different fund groups. All equity funds are ranked into quintiles by their total net assets (TNA). The GT Performance measure = $\sum R_{i,t+1}(w_{i,t} - w_{i,t-1})$, where $w_{i,t}$ is the portfolio weight for fund *i* at time *t*, and $R_{i,t+1}$ is the return of fund *i* between time *t* and *t+1*. I calculate monthly portfolio weights as the TNA of each fund divided by the sum of the TNA of all funds for each month from January 1993 to September 2008. The differenced weights (weights for month *t* minus weights for month *t-1*) are multiplied by the corresponding future monthly fund returns. According to Grinblatt and Titman (1993), under the null hypothesis that investors have no specific skill, the GT measures are serially uncorrelated with a mean of zero. The *t*-statistics in parentheses test whether the GT measures are significantly different from mean zero. The *p*-values are in brackets. Performance measures are in basis points per month.

Quintiles	1 (bottom)	2	3	4	5 (top)	All Funds
	2.36*	1.26	0.93	0.72	0.51	0.54
GT Measure	(1.72)	(1.63)	(1.32)	(1.01)	(1.02)	(1.03)
	[0.09]	[0.10]	[0.19]	[0.31]	[0.31]	[0.30]

Table 3 The Sign and Significance of Portfolio Performance for Small Funds Estimated by Simple Excess Returns and Risk-Adjusted Returns: January 1993 to September 2008

This table presents the sign and significance of risk-adjusted returns for the 10 portfolios. The corresponding numbers of the risk-adjusted returns are in Table 4. The sample in this table covers the funds whose TNA are in the lowest 20% of all equity funds during January 1993 to September 2008. Each month from January 1993 to September 2008, mutual funds are grouped into five quintiles according to excess returns, where one is the worst performing fund group and five is the best performing fund group. Portfolio 1 to Portfolio 10 are portfolios constructed on different criteria. Portfolio 1 is an equally weighted portfolio of all available funds. Portfolio 2 is a portfolio weighted by current total net assets of the fund. Portfolios 3 (4) is also an equally weighted portfolio but only cover funds with positive (negative) unexpected flows. Portfolio 5 (6) is constructed by using funds with positive (negative) unexpected flows and weighted in proportion to unexpected flow in the fund. The construction of Portfolio 7 (8) is similar to that of Portfolio 3 (4) but only covers funds with above 0 median (below-median) unexpected flows. Portfolio 9 (10) is constructed by using all available funds with positive (negative) GT weights and weighted in proportion to GT weights of the funds. GT weight, i.e., $(w_{i,t} - w_{i,t-1})$, is calculated in the GT measure. Unexpected flows are residuals of the equation: $flow_{i,t} = a + \sum_{k=1}^{K} b_k \cdot flow_{i,t-k} + \sum_{h=1}^{H} c_h \cdot R_{i,t-h}$, where $flow_{i,t-k}$ is the lagged normalized new cash flows and $R_{i,t-h}$ is past performance. The excess returns are calculated as $R_{it} - R_{mt}$. The CAPM is estimated by the single factor model: $r_{p,t} = \alpha_p + \beta_p^{RMRF} RMRF_t + e_{p,t}$, where α_p is the risk-adjusted return of the model and RMRF is the excess market return, $R_{mt} - R_{ft}$. The Fama-French three-factor portfolio alpha is calculated as the intercept from the monthly time series regression of portfolio excess returns on the market excess return (RMRF) and mimicking portfolios for size (SMB) and book-to-market (HML) factor: $r_{p,t} = \alpha_p + \beta_p^{RMRF} RMRF_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + e_{p,t}$. RMRF, SMB, and HML are constructed according to the descriptions in Fama and French (1993). Carhart's four-factor portfolio shares the same calculation by including the above three factors and the extra momentum (UMD) factor. +++, ++, and + denote positive returns with significance levels of 1%, 5%, and 10% respectively, based on *t*-statistics. Conversely, ---, --, and – present negative returns with the significance levels of 1%, 5%, and 10% respectively, based on *t*-statistics.

Portfolio 1	Raw Ret	E. Ret	CAPM	Fama French	Carhart	Portfolio 2	Raw Ret	E. Ret	CAPM	Fama French	Carhart
1 (worst)			---	---	---	1			---	---	---
2	+		--	---	---	2	++		--	---	---
3	++			---	---	3	++			---	---
4	++					4	+++				
5 (best)	+++	++	+	+		5	+++	++	+	+	
All	++			--	--	All	++			--	--
Portfolio 3	Raw Ret	E. Ret	CAPM	Fama French	Carhart	Portfolio 4	Raw Ret	E. Ret	CAPM	Fama French	Carhart
1			---	---	---	1			--	---	---
2			---	---	---	2	+		-	---	---
3	++			---	---	3	++			---	---
4	++					4	++				
5	+++	+				5	+++	++			
All	++			---	--	All	++			--	---
Portfolio 5	Raw Ret	E. Ret	CAPM	Fama French	Carhart	Portfolio 6	Raw Ret	E. Ret	CAPM	Fama French	Carhart
1			---	---	---	1			--	---	--
2	+			--	-	2	+		-	---	---
3	++					3	++			---	---
4	++					4	+++				
5	+++	+++	+++	+++	+++	5	+++	+			
All	++					All	++			--	---
Portfolio 7	Raw Ret	E. Ret	CAPM	Fama French	Carhart	Portfolio 8	Raw Ret	E. Ret	CAPM	Fama French	Carhart
1			---	---	---	1			--	---	---
2			---	---	---	2	+			---	---
3	++		--	---	---	3	++			-	--
4	++					4	++				
5	+++	+				5	+++	++			
All	+		-	---	---	All	++			-	---
Portfolio 9	Raw Ret	E. Ret	CAPM	Fama French	Carhart	Portfolio 10	Raw Ret	E. Ret	CAPM	Fama French	Carhart
1			-	--	--	1			-	-	
2	++			--	--	2	+		--	---	---
3	+++					3	++			---	--
4	+++	+				4	++				
5	+++	+++	++	+++	++	5	+++	++			
All	+++	+				All	++			--	-

Table 4 Portfolio Performance for the Top Performing Small Funds Estimated by Simple Excess Returns and Risk-Adjusted Returns: January 1993 to September 2008

This table presents the simple excess returns and risk-adjusted returns for 10 portfolios. The sample in this table covers funds whose TNA are in the lowest 20% of all equity funds and whose performance ranking by excess returns are in the top 20% between January 1993 and September 2008. Panel A evaluates the performance of each portfolio. Portfolio 1 to Portfolio 10 are portfolios constructed by different criteria, where portfolios 3 and 5 are positive unexpected flow portfolios and portfolios 4 and 6 are negative unexpected flow portfolios, based on the sign of the unexpected flow experienced by each fund during the previous month. Portfolio 9 (10) is constructed by using all available funds with positive (negative) GT weights and weighted in proportion to GT weights of the funds. GT weight, i.e., $(w_{i,t} - w_{i,t-1})$, is calculated in the GT measure. Unexpected flows are residuals of the equation: $flow_{i,t} = a + \sum_{k=1}^{K} b_k \cdot flow_{i,t-k} + \sum_{h=1}^{H} c_h \cdot R_{i,t-h}$, where $flow_{i,t-k}$ is the lagged normalized new cash flows and $R_{i,t-h}$ is past performance. The excess returns are calculated as $R_{it} - R_{mt}$. The CAPM is estimated by the single factor model: $r_{p,t} = \alpha_p + \beta_p^{RMRF} RMRF_t + e_{p,t}$, where α_p is the risk-adjusted return of the model and RMRF is the excess market return, $R_{mt} - R_{ft}$. The Fama-French three-factor portfolio alpha is calculated as the intercept from the monthly time series regression of portfolio excess returns on the market excess return (RMRF) and mimicking portfolios for size (SMB), and book-to-market (HML) factor: $r_{p,t} = \alpha_p + \beta_p^{RMRF} RMRF_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + e_{p,t}$. Carhart's four-factor portfolio shares the same calculation by including the above three factors and the extra momentum (UMD) factor. Panel B demonstrates the results by using the long-short strategy to test whether the performance difference between the positive and negative portfolios is significantly different from zero. The *t*-statistics are in parentheses and the *p* values are in brackets. Performance measures are in basis points per month.

Portfolio	Raw Ret	Excess Ret	CAPM	Fama-French	Carhart
			Panel A: Portfolio Performance		
Portfolio 1	104.24	73.13	29.53	25.58	19.35
	(3.20)	(2.25)	(1.81)	(1.74)	(1.29)
	[0.00]	[0.03]	[0.07]	[0.08]	[0.20]
Portfolio 2	104.95	73.85	30.39	26.68	20.03
	(3.23)	(2.28)	(1.85)	(1.81)	(1.34)
	[0.00]	[0.02]	[0.07]	[0.07]	[0.18]
Portfolio 3	96.83	65.18	23.01	21.42	17.91
	(2.83)	(1.91)	(1.33)	(1.35)	(1.10)
	[0.01]	[0.06]	[0.18]	[0.18]	[0.27]
Portfolio 4	96.88	65.23	24.55	18.71	10.61
	(2.94)	(1.99)	(1.50)	(1.25)	(0.71)
	[0.00]	[0.05]	[0.14]	[0.21]	[0.48]
Portfolio 5	131.82	100.17	57.36	61.12	54.59
	(3.57)	(2.72)	(2.67)	(3.12)	(2.73)
	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]
Portfolio 6	95.25	63.59	22.72	17.80	9.52
	(2.81)	(1.88)	(1.26)	(1.09)	(0.58)
	[0.01]	[0.06]	[0.21]	[0.28]	[0.56]
Portfolio 7	95.26	63.61	22.47	19.74	16.69
	(2.87)	(1.92)	(1.37)	(1.30)	(1.07)
	[0.00]	[0.06]	[0.17]	[0.20]	[0.29]
Portfolio 8	98.61	66.96	25.56	20.67	12.37
	(2.93)	(2.00)	(1.50)	(1.34)	(0.80)
	[0.00]	[0.05]	[0.13]	[0.18]	[0.43]
Portfolio 9	127.02	95.86	50.55	47.48	38.08
	(3.60)	(2.72)	(2.58)	(2.67)	(2.12)
	[0.00]	[0.01]	[0.01]	[0.01]	[0.04]
Portfolio 10	104.75	73.60	30.70	25.93	20.94
	(3.03)	(2.13)	(1.49)	(1.40)	(1.10)
	[0.00]	[0.03]	[0.14]	[0.16]	[0.27]
			Panel B: Performance Difference		
P3 – P4	-0.05	-31.70	-1.54	2.71	7.30
	(-0.01)	(-5.60)	(-0.28)	(0.50)	(1.36)
	[0.99]	[0.00]	[0.78]	[0.62]	[0.17]
P5 – P6	36.57	4.92	34.65	43.32	45.07
	(3.74)	(0.50)	(3.54)	(4.54)	(4.61)
	[0.00]	[0.61]	[0.00]	[0.00]	[0.00]
P7 – P8	-3.35	-35.00	-3.09	-0.93	4.33
	(-0.66)	(-6.65)	(-0.60)	(-0.18)	(0.87)
	[0.51]	[0.00]	[0.55]	[0.86]	[0.39]
P9 – P10	22.27	-8.89	19.84	21.55	17.13
	(1.74)	(-0.70)	(1.55)	(1.63)	(1.27)
	[0.08]	[0.49]	[0.12]	[0.10]	[0.21]

Table 5 The Span of the Smart Money Effect and the Accumulation of Effective Information

This table presents the Carhart's four-factor risk-adjusted returns for portfolios 5 (Panel A) and 9 (Panel B) for up to six months, using accumulative unexpected flow information. Unexpected flows are residuals of the equation: $flow_{i,t} = a + \sum_{k=1}^{K} b_k \cdot flow_{i,t-k} + \sum_{h=1}^{H} c_h \cdot R_{i,t-h}$, where $flow_{i,t-k}$ is the lagged normalized new cash flows and $R_{i,t-h}$ is past performance. The population of funds in this table consists of funds whose TNA are in the lowest 20% of all equity funds and whose performance ranking by excess returns are among the top 20% between January 1993 and September 2008. Row *TS1~TS6* describes the length of the accumulation period and column *t-1~t-6* indicates its starting point. For example, the element (*t-3*, *TS4*) in Panel A measures the performance of the portfolio with positive unexpected flows and is weighted in proportion to the sum of unexpected flows (Portfolio 5) from *t-3* to *t-6*. The element (*t-2*, *TS3*) in Panel B measures the performance of the portfolio with positive GT weights and is weighted by the sum of the GT weight change from *t-2* to *t-4*. The *t*-statistics are in parentheses and the *p* values are in brackets. Performance measures are in basis points per month.

	TS1	*TS2*	*TS3*	*TS4*	*TS5*	*TS6*
			Panel A: Portfolio 5			
t-1	54.59	39.66	40.69	32.98	31.36	33.84
	(2.728)	(2.031)	(1.819)	(1.594)	(1.531)	(1.631)
	[0.007]	[0.043]	[0.070]	[0.112]	[0.127]	[0.104]
t-2	9.02	22.23	17.81	17.77	20.51	21.88
	(0.470)	(0.989)	(0.879)	(0.882)	(0.999)	(1.066)
	[0.638]	[0.323]	[0.380]	[0.378]	[0.318]	[0.287]
t-3	25.86	17.78	19.05	23.69	22.50	23.08
	(1.131)	(0.866)	(0.937)	(1.123)	(1.091)	(1.127)
	[0.259]	[0.387]	[0.349]	[0.262]	[0.276]	[0.261]
t-4	8.23	8.04	18.31	16.28	17.52	14.60
	(0.45)	(0.465)	(1.014)	(0.905)	(0.973)	(0.813)
	[0.652]	[0.642]	[0.311]	[0.366]	[0.331]	[0.417]
t-5	4.68	20.71	20.47	22.71	14.03	13.08
	(0.276)	(1.188)	(1.092)	(1.249)	(0.795)	(0.732)
	[0.782]	[0.236]	[0.276]	[0.213]	[0.427]	[0.465]
t-6	39.67	32.04	28.54	18.07	21.56	15.68
	(1.976)	(1.625)	(1.497)	(0.97)	(1.142)	(0.838)
	[0.049]	[0.105]	[0.136]	[0.333]	[0.255]	[0.402]
			Panel B: Portfolio 9			
t-1	38.08	35.28	36.70	29.98	27.22	26.24
	(2.122)	(1.958)	(2.071)	(1.668)	(1.53)	(1.464)
	[0.035]	[0.051]	[0.039]	[0.097]	[0.127]	[0.144]
t-2	29.89	31.05	23.49	20.90	21.79	21.74
	(1.694)	(1.753)	(1.313)	(1.186)	(1.222)	(1.239)
	[0.091]	[0.081]	[0.190]	[0.237]	[0.223]	[0.216]
t-3	21.93	15.41	15.61	18.52	18.75	19.14
	(1.292)	(0.891)	(0.897)	(1.053)	(1.103)	(1.156)
	[0.197]	[0.373]	[0.370]	[0.293]	[0.271]	[0.248]
t-4	11.81	13.51	18.02	20.72	20.53	20.29
	(0.678)	(0.792)	(1.025)	(1.235)	(1.265)	(1.267)

	[0.498]	[0.429]	[0.306]	[0.218]	[0.207]	[0.206]
t-5	18.28	19.50	23.82	23.56	23.55	21.17
	(1.054)	(1.133)	(1.425)	(1.433)	(1.422)	(1.293)
	[0.292]	[0.258]	[0.155]	[0.153]	[0.156]	[0.197]
t-6	23.21	24.45	23.02	23.61	24.33	25.89
	(1.308)	(1.398)	(1.333)	(1.365)	(1.443)	(1.509)
	[0.192]	[0.163]	[0.184]	[0.173]	[0.150]	[0.133]

Table 6 The Timing Ability of Smart Investors

This table reports the results of the timing abilities of smart investors found in Tables 3 and 4, based on monthly return data of US equity mutual funds from January 1993 to September 2008. Panel A refers to the traditional Treynor and Mazuy (1966) model (TM) and Panel B refers to the traditional Henriksson and Merton (1981) model (HM). Panel C refers to the Carhart (1997) four-factor Treynor and Mazuy (1966) model (CTM) and Panel D refers to the Carhart (1997) four-factor Henriksson and Merton (1981) model (CHM). Both CTM and CHM models contain Carhart's (1997) four factors, which include market excess return (RMRF), Fama and French's (1993) factor-mimicking portfolios for size (SMB) and book-to-market equity (HML), and Carhart's (1997) factor-mimicking portfolio for one-year return momentum (MOM). The four CTM timing parameters are the squares of Carhart's four factors: $r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + p_i \cdot PR1YR_t + \gamma_{1,i} \cdot RMRF_t^{\,2} + \gamma_{2,i} \cdot SMB_t^2 + \gamma_{3,i} \cdot HML_t^2 + \gamma_{4,i} \cdot PR1YR_t^2 + \varepsilon_{i,t}$.

The four CHM timing parameters are equal to the respective Carhart factor when the factor ≥ 0, and 0 otherwise: $r_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + p_i \cdot PR1YR_t + \gamma_{1,i} \cdot RMRF_t^* + \gamma_{2,i} \cdot SMB_t^* + \gamma_{3,i} \cdot HML_t^* +$ $\gamma_{4,i} \cdot PR1YR_t^* + \varepsilon_{i,t}$ where $RMRF_t^* = I\{RMRF_t > 0\} \cdot RMRF_t$, $SMB_t^* = I\{SMB_t > 0\} \cdot SMB_t$, $HML_t^* = I\{HML_t > 0\} \cdot HML_t$, $PR1YR_t^* = I\{MOM_t > 0\} \cdot PR1YR_t$. In each model, the alphas and four timing ability coefficients are presented for portfolios 5 and 9. The *t*-statistics are in parentheses and the *p* values are in brackets.

Portfolio	alpha	RMRF timing	SMB timing	HML timing	MOM timing	Adj-R^2
Panel A: Treynor and Mazuy (1966) model (TM)						
Portfolio 5	0.002	1.717				0.743
	(0.887)	(2.490)				
	[0.377]	[0.014]				
Portfolio 9	0.001	1.318				0.772
	(0.631)	(2.068)				
	[0.529]	[0.040]				
Panel B: Henriksson and Merton (1981) model (HM)						
Portfolio 5	0.000	0.331				0.741
	(-0.113)	(2.185)				
	[0.910]	[0.030]				
Portfolio 9	-0.001	0.287				0.772
	(-0.377)	(2.076)				
	[0.707]	[0.039]				
Panel C: Carhart (1997) four-factor Treynor and Mazuy (1966) model (CTM)						
Portfolio 5	0.002	1.520	0.309	1.521	-0.528	0.745
	(0.848)	(2.040)	(0.558)	(1.488)	(-1.413)	

	[0.398]	[0.043]	[0.578]	[0.139]	[0.160]	
Portfolio 9	0.001	1.115	0.359	1.182	-0.363	0.773
	(0.514)	(1.610)	(0.695)	(1.243)	(-1.046)	
	[0.608]	[0.109]	[0.488]	[0.216]	[0.297]	
Panel D: Carhart (1997) four-factor Henriksson and Merton (1981) model (CHM)						
Portfolio 5	-0.002	0.302	0.048	0.361	-0.163	0.743
	(-0.525)	(1.786)	(0.284)	(1.784)	(-1.279)	
	[0.601]	[0.076]	[0.777]	[0.076]	[0.203]	
Portfolio 9	-0.003	0.210	0.014	0.215	0.005	0.771
	(-0.777)	(1.354)	(0.087)	(1.153)	(0.042)	
	[0.438]	[0.178]	[0.931]	[0.250]	[0.967]	