Dumb money: Mutual fund flows and the cross-section of stock returns

Andrea Frazzini
Department of Economics, Yale University

Owen A. Lamont
Yale School of Management and NBER

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ABSTRACT

We use mutual fund flows as a measure for individual investor sentiment for different stocks, and find that high sentiment predicts low future returns at long horizons. Fund flows are dumb money – by reallocating across different mutual funds, retail investors reduce their wealth in the long run. This dumb money effect is strongly positively related to the value effect. High sentiment also is associated high corporate issuance, interpretable as companies increasing the supply of shares in response to investor demand.

Individual retail investors actively reallocate their money across different mutual funds. Individuals tend to transfer money from low performing funds to high performing funds. In addition to looking at past returns of funds, individuals also may consider economic themes or investment styles in reallocating funds. Collectively, one can measure individual sentiment by looking at which funds have inflows and which have outflows, and can relate this sentiment to different stocks by examining the holdings of mutual funds. This paper tests whether sentiment affects stock prices, and specifically whether one can predict future stock returns using a flow-based measure of sentiment. If sentiment pushes stock prices above fundamental value, high sentiment stocks should have low future returns.

For example, in 1999 investors sent $36 billion to Janus funds but only $20 billion to Fidelity funds, despite the fact that Fidelity had more than three times the assets under management at the beginning of the year. Thus in 1999 retail investors as a group made an active allocation decision to give greater weight to Janus funds, and in doing so they increased their portfolio weight in tech stocks held by Janus. By 2001, investors had changed their minds about their allocations, and pulled about $12 billion out of Janus while adding $10 billion to Fidelity.[1] In this instance, the reallocation caused wealth destruction to mutual fund investors as Janus and tech stocks performed horribly after 1999.

According to the "smart money" hypothesis of Gruber (1996) and Zheng (1999), some fund managers have skill and some individual investors can detect that skill, and send their money to skilled managers. Thus (in contrast to the Janus example) flows should be positively correlated with future returns. Gruber (1996) and Zheng (1999) show that the short term performance of funds that experience inflows (in the last three months) is significantly better than those that experience outflows, suggesting that mutual fund investors have selection ability.

Our focus is on stocks, not on funds. We are interested in how investor sentiment affects stocks prices, and see fund flows as a convenient (and economically important) measure of sentiment. To test whether investor sentiment causes mispricing, one must test whether high sentiment today predicts low return in the future, and we focus on cross-sectional stock return predictability over periods of months and years. We ask the question of whether, over the long-term, investors are earning higher returns as a result of their reallocation across funds.

For each stock, we calculate the mutual fund ownership of the stock that is due to reallocation decisions reflected in fund flows. For example, in December 1999, 17% of the shares outstanding of Cisco were owned by the mutual fund sector (using our sample of funds), of which 2.5% was attributable to disproportionately high inflows over the previous 3 years. That is, under certain assumptions, if flows had occurred proportionately to asset value (instead of disproportionately to funds like Janus), the level of mutual fund ownership would have been only 14.5%. This 2.5% difference is our measure of investor sentiment. We then test whether this measure predicts differential returns on stocks.

Our main results are as follows. First, as suggested the example of Janus and Cisco in 1999, on average from 1980 to 2003, retail investors direct their money to funds which invest in stocks that have low future returns. To achieve high returns, it is best to do the opposite of these investors. We calculate that mutual fund investors experience total returns that are significantly lower due to their reallocations. Therefore, mutual fund investors are dumb in the sense that their reallocations reduce their wealth on average. We call this predictability the "dumb money" effect. This dumb money effect poses a challenge to rational theories of fund flows.

Second, the dumb money effect is highly related to the value effect. The returns on portfolios constructed using our flow-based measure of sentiment are quite positively correlated with the returns on portfolios constructed using market-book ratio. Money flows into mutual funds that own growth stocks, and flows out of mutual funds that own value stocks. This pattern poses a challenge to risk-based theories of the value effect, which would need to explain why one class of investors (individuals) is engaged in a complex dynamic trading strategy of selling "high risk" value stocks and buying "low risk" growth stocks.

Third, demand by individuals and supply from firms are highly related. When individuals indirectly buy more stock of a specific company (via mutual fund inflows), we also observe that company increasing the number of shares outstanding (for example, through seasoned equity offerings, stock-financed mergers, and other issuance mechanisms). This pattern is consistent with the interpretation that individual investors are dumb, and smart firms are opportunistically exploiting their demand for shares.

These results give a different perspective on the issue of individuals vs. institutions. A large literature explores whether institutions have better average performance than individuals. In the case of mutual funds, for example, Daniel, Grinblatt, Titman, and Wermers (1997) show that stocks held by mutual funds have higher returns, and Chen, Jegadeesh, and Wermers (2000) show that stocks bought by mutual funds outperform stocks sold by mutual funds. Both results suggest that mutual fund managers have stock-picking skill.

Unfortunately, since individuals ultimately control fund managers, it can be difficult to infer the views of fund managers by looking only at their holdings. For example, when the manager of tech fund experiences large inflows, his job is to buy more technology stocks, even if he thinks the tech sector is overvalued. So if we observe the mutual fund sector as a whole holding technology stocks, that does not imply that mutual managers as a whole believe tech stocks will outperform. It is hard for a fund manager to be smarter than his clients. Mutual fund holdings are driven by both managerial choices in picking stocks and retail investor choices in picking managers. We provide some estimates of the relative importance of these two effects.

This paper is organized as follows. Section I reviews the literature. Section II discusses the basic measure of sentiment, describes the data, and examines the relation of corporate issuance and flows. Section III looks at the relation between flows and stock returns. Section IV looks at the relation between flows and mutual fund returns. Section V uses calendar time portfolios to put the results in economic context, showing the magnitude of wealth destruction caused by flows and providing evidence on whether mutual fund managers have stock-picking skill. Section VI looks at issuance by firms. Section VII presents conclusions.

I. Background and literature review

A. Determinants of fund flows

A series of papers have documented a strong positive relation between mutual fund past performance and subsequent fund inflows (see, for example, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)). In addition, retail investors appear to allocate their wealth to funds that have caught their attention through marketing (see Jain and Wu (2000), and Barber, Odean and Zheng (2004)), or funds with names that reflect hot investment styles (Cooper, Gulen, and Rau (2005)). Benartzi and Thaler (2001) report evidence that retail investors employ simple rule-of–thumbs in allocating across different types of mutual funds.

For individual stocks, the picture looks different. Odean (1999), and Barber and Odean (2000, 2001, 2004) present extensive evidence that individual investors suffer from biased-self attribution, and tend be overconfident, thus engaging in (wealth-destroying) excessive trading. But in contrast to their return-chasing behavior in mutual funds, a variety of recent evidence suggests that individual investors act as contrarians when trading individual stocks (see Grinblatt and Keloharju (2000), Goetzmann and Massa (2002)).

While this apparent contradiction between return-chasing and contrarianism is interesting, the hypothesis we wish to test does not depend on resolving this issue. We are interested in testing whether individual investor sentiment predicts future returns, so our hypothesis is not contingent on measuring whether investors are ultimately return-chasing or not. If individual investor sentiment causes prices to be wrong and prices eventually revert to fundamental value, then sentiment should negatively predict future returns no matter what – whether individuals over-react or under-react, whether they return-chase or not. As it turns out, in the data we study, mutual fund flows are indeed return-chasing, and flows tend to go to stocks that have gone up recently.

B.   Causal effects of flows on prices

There is evidence that fund flows have positively contemporaneous correlations with stock returns (see, for example, Brown et al (2002)). Although it is difficult to infer causality from correlation, one interpretation of this fact is that inflows drive up stock prices. We do not attempt to test this hypothesis with our data, for three reasons. First, we are interested in whether sentiment causes long-term mispricing, not the short term dynamics of precisely how trading affects prices. Second, we observe flows and holdings and fairly low frequency (quarterly), so our data is not well suited to studying short-term price dynamics. Third, although the fund flows we consider are certainly economically large, we view them as an imperfect measure of sentiment since individual investor sentiment can be manifested in many other ways. While individuals were sending mutual fund money to tech funds in 1999, and thus indirectly purchasing tech stocks, they may have also been buying tech stocks directly in their brokerage accounts, or investing in hedge funds that bought tech stocks. In addition, flows can understate the effects of sentiment on the mutual fund sector itself. If Janus experiences inflows, then other funds experiencing outflows might seek to imitate Janus in order to appeal to whatever is in fashion. Thus flows are a way to measure sentiment, but are not the only channel for sentiment to work.

Thus the hypothesis we wish to test is that stocks owned by funds with big inflows are overpriced. These stocks could be overpriced because inflows force mutual funds to buy more shares and thus push stock prices higher, or they could be overpriced because overall demand (not just from mutual fund inflows) pushes stock prices higher. In either case, inflows reflect the types of stocks with high investor demand.

C. Styles and sentiment

A paper closely related to ours is Teo and Woo (2004), who also find evidence for a dumb money effect. Following Barberis and Shleifer (2003), Teo and Woo (2004) consider categorical thinking by mutual fund investors along the dimensions of large/small or value/growth. They show that when a particular category has large inflows, stocks in that category subsequently underperform. Like us, they relate mutual fund flows to stock returns, but unlike us they look only at style returns, not individual stock returns.

While Teo and Woo (2004) provide valuable evidence, our approach is more general. The benefit is that we do not have to define specific styles or categories, such as value/growth. While categorical thinking and style classification are undoubtedly important in determining fund flows, from a practical point of view it is difficult for the researcher to identify all relevant categories used by investors over time. For example, the growth/value category was not widely used in 1980. Instead, we impose no categorical structure on the data and just follow the flows. Most strikingly, we are able to document that the fund flow effect is highly related to the value effect, a finding that could not have been discovered using the method of Teo and Woo (2004).

More generally, one could devise many different measures of investor sentiment based on prices, returns, or characteristics of stocks (see for example Baker and Wurgler (2005) and Polk and Sapienza (2004)). If sentiment effects stocks prices and creates stock return predictability (as prices deviate from fundamentals and eventually return), as long as trading volume is not zero it must be that someone somewhere is buying overpriced stocks and selling underpriced stocks. To prove that some class of investors overweights high sentiment stocks, it is necessary to prove that these investors lose money on average from trading (before trading costs). Our measure of sentiment is based on the actions of one good candidate for sentiment-prone investors, namely individuals. Using their trades, we infer which stocks are high sentiment and which stocks are low sentiment. We show that this class of investors does indeed lose money on average from their mutual fund reallocations, confirming that they are the dumb money who buy high sentiment stocks.

II. Constructing the flow variable

Previous research has focused on different ownership levels, such as mutual fund ownership as a fraction of shares outstanding (for example, Chen, Jegadeesh, and Wermers, 2000). We want to devise a measure that is similar, but is based on flows. Specifically, we want to take mutual fund ownership and decompose it into the portion due to flows and the portion not due to flows. By "flows," we mean flows from one fund to another fund (not flows in and out of the entire mutual fund sector).

Our central variable is FLOW, the percent of the shares of a given stock owned by mutual funds that are attributable to fund flows. This variable is defined as the actual ownership by mutual funds minus the ownership that would have occurred if every fund had received identical proportional inflows (instead of experiencing different inflows and outflows), every fund manager chose the same portfolio weights in different stocks as he actually did, and stock prices were the same as they actually were. We define the precise formula later, but the following example shows the basic idea.

Suppose at quarter 0, the entire mutual fund sector consists of two funds: a technology fund with \$20 B in assets and a value fund with \$80 B. Suppose at quarter 1, the technology fund has an inflow of \$11 B and has capital gains of \$9 B (bringing its total assets to \$40 B), while the value fund has an outflow of \$1 B and capital gains of \$1 B (so that its assets remain constant). Suppose that in quarter 1 we observe the technology fund has 10% of its assets in Cisco, while the value fund has no shares of Cisco. Thus in quarter 1, the mutual fund sector as a whole owns \$4 B in Cisco. If Cisco has \$16 B in market capitalization in quarter 1, the entire mutual fund sector owns 25% of Cisco.

We now construct a world where investors simply allocate flows in proportion to initial fund asset value. Since in quarter 0 the total mutual fund sector has \$100 B in assets and the total inflow is \$10 B, the counterfactual assumption is that all funds get an inflow equal to 10% of their initial asset value. To simplify, we assume that the flows all occur at the end of the quarter (thus the capital gains earned by the funds are not affected by these inflows). Thus in the counterfactual world the technology fund would receive (.20)*(10) = \$2 B (giving it total assets of \$31 B), while the value fund would receive (.80)*(10) = \$8 B (giving it total assets of \$89). In the counterfactual world the total investment in CISCO is given by (.1)*(31) = \$3.1, which is 19.4% of its market capitalization. Hence, the FLOW for CISCO, the percent ownership of Cisco due to the non-proportional allocation of flows to mutual funds, is 25 – 19.4 = 5.6%.

FLOW is an indicator of what types of stocks are owned by funds experiencing big inflows. It is a number that can be positive, as in this example, or negative (if the stock is owned by funds experiencing outflows or lower-than-average inflows). It reflects the active reallocation decisions by investors. What FLOW does not measure is the amount of stock that is purchased with inflows; one cannot infer from this example that the technology fund necessarily used its inflows to buy Cisco. To the contrary, our assumption in constructing the counterfactual is that mutual fund managers choose their percent allocation to different stocks in a way that is independent of inflows and outflows.

Is it reasonable to assume that managers choose their portfolio weights across stocks without regard to inflows? Obviously, there are many frictions (for example, taxes and transaction costs) that would cause mutual funds to change their stock portfolio weights in different stocks in response to different inflows. Thus, we view FLOW as an imperfect measure of demand for stocks due to retail sentiment.

In equilibrium, of course, a world with different flows would also be a world with different stock prices, so once cannot interpret the counterfactual world as an implementable alternative for the aggregate mutual fund sector. Later, when we discuss the effects of flows on investor wealth, we consider an individual investor (who is too small to affect prices by himself) who behaves like the aggregate investor. We test whether this individual representative investor benefits from the active reallocation decision implicit in fund flows. For individual investors, refraining from active reallocation is an implementable strategy.

A. Flows

We calculate mutual fund flows using the CRSP US Mutual Fund Database. The universe of mutual funds we study includes all domestic equity funds that exists at any date between 1980 and 2003 for which quarterly net asset values (NAV) are available and for which we can match CRSP data with the common stock holdings data from Thomson Financial (described in the next subsection). Since we do not observe flows directly, we infer flows from fund return and NAV as reported by CRSP. Let N_t^i be the total NAV of a fund i and let R_t^i be its return between quarter $t-1$ and quarter t. Following the standard practice in the literature (e.g. Zheng (1999), Sapp and Tiwari (2004)), we compute flows for fund i in quarter t, F_t^i, as the dollar value of net new issues and redemptions using

$$F_t^i = N_t^i - (1 + R_t^i) \cdot N_{t-1}^i - MGN_t^i \qquad (1)$$

where MGN is the increase in total net assets due to mergers during quarter t. Note that (1) implicitly assumes that inflows and outflows occur at the end of the quarter, and that existing investors reinvest dividends and other distributions in the fund. We assume that investors in the merged funds place their money in the surviving fund. Funds that are born have inflows equal to their initial NAV, while funds that die have outflows equal to their terminal NAV.

Counterfactual flows are computed under the assumption that each fund receives a pro rata share of the total dollar flows to the mutual fund sector between date $t-k$ and date t, with the proportion depending on NAV as of quarter $t-k$. More precisely, in order to compute the FLOW at date t, we start by looking at the net asset value of the fund at date $t-k$. Then, for every date s we track the evolution of the fund's counterfactual NAV using:

$$\hat{\mathrm{F}}_{\mathrm{s}}^{\mathrm{i}} = \frac{N_{t-k}^i}{N_{t-k}^{Agg}} \mathrm{F}_{\mathrm{s}}^{\mathrm{Agg}} \qquad (2)$$

$$\hat{\mathrm{N}}_{\mathrm{s}}^{\mathrm{i}} = (1 + R_t^i)\hat{\mathrm{N}}_{\mathrm{s-1}}^{\mathrm{i}} + \hat{\mathrm{F}}_{\mathrm{s}}^{\mathrm{i}} \qquad (3)$$

$$t-k \le s \le t$$

where $\hat{\mathrm{F}}^{\mathrm{i}}$ and $\hat{\mathrm{N}}^{\mathrm{i}}$ are counterfactual flows and NAV's. $\mathrm{F}^{\mathrm{Agg}}$ is the actual aggregate flows for the entire mutual fund sector, while N^{Agg}_{t-k} is the actual aggregate NAV at date $t-k$. Equations (2) and (3) describe the dynamics of funds that exist both in quarter $t-k$ and in quarter *t*. For funds that were newly created in the past *k* quarters, $\hat{N}^i$ is automatically zero – all new funds by definition represent new flows. The resulting counterfactual net asset value $\hat{N}_t{}^i$ at date t represents the fund size in a world with proportional flows in the last k quarters.

For a detailed numerical example of our counterfactual calculations, see the appendix (which also discusses adjustments to equations (2) and (3) in the case of funds that die). We obtain a quarterly time series of counterfactual net asset values for every fund by repeating the counterfactual exercise every quarter t, and storing the resulting $\hat{N}^i{}_t$ at the end of each rolling window.

Consider a representative investor who represents a tiny fraction, call it q, of the mutual fund sector. Suppose that this investor behaves exactly like the aggregate of mutual investors, sending flows in and out of different funds at different times. The counterfactual strategy described above is an alternative strategy for this investor, and is implementable using the same information and approximately the same amount of trading by the investor. To implement this strategy, this investor only needs to know lagged fund NAV's and aggregate flows. For this investor, $q\hat{N}^i_t$ is his dollar holding in any particular fund.

In designing this strategy, our aim is to create a neutral alternative to active reallocation, which matches the total flows to the mutual fund sector. One could describe this strategy as a more passive, lower turnover, value-weighting alternative to the active reallocation strategy pursued by the aggregate investor. It is similar in spirit to the techniques of Daniel, Grinblatt, Titman, and Wermers (1999) and Odean (1999) in that it compares the alternative of active trading to a more passive strategy based on lagged asset holdings. A feature of our counterfactual calculations is that they do not mechanically depend on the actual performance of the funds. A simpler strategy would have been to simply hold funds in proportion to their lagged NAV. The problem with this strategy is that it mechanically tends to sell funds with high returns and buy funds with low returns. Since we wanted to devise a strategy that reflected only flow decisions by investors (not return patterns in stocks), we did not used this simpler strategy.

Let x_{it} be the net asset value of fund i in month t as a percentage of total asset of the mutual fund sector:

$$x_{it} = \frac{N_t^i}{N_t^{Agg}} \qquad (4)$$

The counterfactual under proportional flows is:

$$\hat{x}_{it} = \frac{\hat{N}_t^i}{N_t^{Agg}} \qquad (5)$$

The difference between x_{it} and $\hat{x}_{it}$ reflects the active decisions of investors to reallocate money from one manager to another over the past k quarters in a way that is not proportional to the NAV of the funds. This difference reflects any deviation from value weighting by the NAV of the fund in marking new contributions. In theory, this difference could reflect rebalancing away from high performing funds and into poorly performing funds, in order to maintain some fixed weights (instead of market weights). In practice, investors tend to unbalance (not rebalance), sending money from poorly performing funds to high performing funds.

B. Holdings

Thomson Financial provides the CDA/Spectrum mutual funds database, which includes all registered domestic mutual funds filing with the SEC. The data show holdings of individual funds collected via fund prospectuses and SEC N30D filings. The holdings constitute almost all the equity holdings of the fund (see Appendix for a few small exceptions). The holdings data in this study run from January 1980 to December 2003.

Most funds report their holdings quarterly, although the SEC requires mutual funds to disclose their holdings on a semi-annual basis. Approximately 60% of the funds report quarterly holdings, with the rest semiannual. Although reports may be made on any day, the last day of the quarter is most commonly the report day. A typical fund-quarter-stock observation would be as follows: as of March 30th, 1998, Fidelity Magellan owned 20,000 shares of IBM. The holdings data are notably error-ridden, with obvious typographical errors (sometimes involving transposed digits and misplaced decimal points). Furthermore, some reports are missing from the database.[2] We use a series of filters to eliminate data errors (see appendix).

In matching the holdings data to the CRSP mutual fund database, we utilized fund tickers, fund names and total net asset values. For each fund and each quarter, we calculate w_{ij} as the portfolio weight of fund *i* in stock *j* based on the latest available holdings data. Hence the portfolios weights w_{ij} reflect fluctuations of the market price of the security held.

Let *z* be the actual percent of the shares outstanding held by the mutual fund sector,

$$z_j = \left(\sum_i x_i \cdot w_{ij} \cdot N_t^{Agg} \right) / MKTCAP_j \tag{6}$$

where MKTCAP_j is the market capitalization of firm j. The ownership that would have occurred with proportional flows into all funds and unchanged fund stock allocation and stock prices would be

$$\hat{z}_j = \left(\sum_i \hat{x}_i \cdot w_{ij} \cdot N_t^{Agg} \right) / MKTCAP_j \tag{7}$$

For each stock, we calculate our central variable, FLOW, as the percent of the shares outstanding with mutual fund ownership attributable to flows. The flow of security j is given by

$$FLOW_{j,t} = z_{j,t} - \hat{z}_{j,t} = \left\{ \sum_i \left[x_{i,t} - \hat{x}_{i,t} \right] \cdot w_{ij} \cdot N_t^{Agg} \right\} / MKTCAP_{j,t} \qquad (8)$$

This flow has the following interpretation. If each portfolio manager had made exactly the same decisions in terms of percent allocation of his total assets to different stocks, and if stock prices were unchanged, but the dollars had flown to each portfolio manager in proportion to their NAV for the last k periods, then mutual fund ownership in stock j would be lower by FLOW. Stocks with high FLOW are stocks that are owned by mutual funds that have experienced high inflows.

C. Describing the data

We first describe the data for funds. Table I shows the top and bottom funds at year end for two years out of our sample, 1988 and 1999, ranked on the difference between actual fraction of the fund universe (x) and counterfactual fraction ($\hat{x}$). In 1999, the Magellan fund has assets that constituted 3.8% of our sample mutual fund universe, but had been receiving below average inflows over the past three years. Had Magellan received flows in proportion to its size over the previous three years, it would have been 5.4% of the universe instead of 3.8%. The table shows that in 1999, the funds receiving big inflows tended to be technology and growth funds.

Table II shows some results for individual firms for the years 1999 and 1988. The table shows the top and bottom firms ranked on total dollar flows over the past three years (in the analysis, we focus on flows as a percent of market value, but here we rank on dollar flows in order to generate familiar names). The effect of flows on mutual fund ownership can be fairly sizeable, with flows raising the total ownership of Sun Microsystems in 1999 from 16.6% to 20.5%. In 1999, stocks with the biggest inflows tend to be technology stocks, while stocks with the biggest outflows tend to be financial or manufacturing firms, closely correspond to our perceptions of investor sentiment in the three year period ending 1999. In contrast, in 1988, technology stocks such as DEC and IBM were experiencing outflows, while consumer goods companies like RJR and Pillsbury were experiencing inflows. Thus sentiment favors different types of stocks at different times.

In interpreting the flow variable, it is important to remember that flow is a relative concept driven only by differences in flows and holdings across different funds holding different stocks. Flow is not intended to capture is any notion of the absolute popularity of stock. For example, consider Alcoa in 1999. The fact the flow variable is large and negative in Table II does not mean that Alcoa was unpopular with mutual funds, nor does it mean that mutual funds are selling Alcoa. It could be that every mutual fund loved Alcoa, held a lot of it, and bought more of it in 1999. What the negative flow means is that the funds which overweighted Alcoa in 1999 received lower-than-average inflows (or perhaps outflows) in 1999. Individual investors favored funds which tilted toward stocks like Cisco more than funds which tilted towards stocks like Alcoa.

Table III shows summary statistics for the different types of data in our sample. Our sample starts in 1980. In table III we describe statistics for flows over the past three years, thus the table describes data for flows starting in 1983. One important feature of the sample is its changing nature over time. We have more information for the latter part of the sample, so our matching algorithm system works better in the latter part of the sample. As shown in Table III, we are only able to match 70% of the funds in the CRSP mutual fund database to the holdings data base in 1983; this number rises over time but is never 100%. In addition to this pure data problem, mutual funds as a whole grew larger as a fraction of the entire stock market. Thus our coverage of individual stocks rises over time for these two reasons.

As shown in the table, our coverage of large stocks is much more complete in the early part of the sample: in 1983, we have flow data for 92% of the universe of stocks on a value-weighted basis, but only 47% on an equal weighted basis. This difference partially reflects the fact that funds tend to own large stocks, but also the fact that we are failing to match some small funds in the early part of the sample period. One possible concern is survivorship bias, which we address in section IV by using a method that does not involve matching funds with stocks.

Table III shows summary statistics for three year flows. One way of describing FLOW is that it is the actual percent ownership by the mutual fund sector, minus the counterfactual percent ownership. Since the actual percent ownership is bounded above by 100%, FLOW is bounded above by 100%. In the counterfactual case, there is no accounting identity enforcing that the dollar value of fund holdings is less than the market capitalization of the stock. Thus FLOW is unbounded below. Values of FLOW less than -100% are very rare, occurring less than 0.01% of the time for three year flows.

III. Flows and stock returns

A. Excess returns

Table IV shows the basic results of this paper. We form calendar time portfolios and examine monthly excess returns on portfolios constructed using our flow measure. We show both equally weighted returns and value weighted returns in month t for five portfolios formed by sorting on the latest available flows as of month $t-1$. The table shows flows over horizons stretching from three months (one quarter, the shortest interval we have for calculating flows) to five years. The rightmost column shows the difference between the high flow stocks and the low flow stocks.

Quintile one is the bottom 20 percent of all stocks sorted on flows. It turns out that, for long-horizon flows, the bottom quintile reflects stocks that are not just experiencing lower-than-average inflows, they are experiencing outflows. That is, quintile one contains stocks that individual investors are selling (indirectly via mutual funds) and quintile five contains stocks that individuals are most heavily buying.

Looking at the difference between high flow and low flow stocks, it is striking that for every horizon but three months, high flows today predict low future stock returns. This relation is statistically significant at the three and five year horizon. This dumb money effect is sizeable: looking at three-year, equal weight results, the difference between high flow and low flow stocks is 61 basis points per month or approximately 8 percent per year. Remarkably, the dumb money effect is slightly larger using value weighting instead of equal weighting. This result stands in contrast to many other patterns in stock returns, which tend to be concentrated in small cap stocks.[3]

Perhaps surprisingly, in this table we find no solid evidence for the smart money effect in raw returns, even at the horizons of three to twelve months where one might expect price momentum to dominate. Gruber (1996) and Zheng (1999) look at quarterly flows and find that high flows predict high returns: one can see a hint of this in the three month flow results, although one cannot reject the null hypothesis. We return to this issue later; it turns out that this particular result is sensitive to alternative methods of measuring, and one can find specifications with a significant smart money effect at short horizons.

Figure 1 shows how flows predict returns at various different horizons. We show the average returns in month $t+k$ on long/short portfolios formed on three month flows in month t. The figure shows average returns over time with accompanying 95% confidence interval.

For $k<0$, the figure shows how lagged returns predict today's flows. The figure shows that flows into an individual stock are very strongly influenced by past returns on that stock.

This result is expected given the previous literature documenting high inflows to high performing funds. Flows tend to go to funds that have high past returns, and since funds returns are driven by the stocks that they own, flows tend to go to stocks that have high past returns. It appears that returns over the past twelve months are especially important, with the effect decreasing as one goes earlier than a year. For $k > 0$, the figure shows the (insignificant) smart money effect at one month horizon, becoming a significant dumb money effect after about a year has passed. The predictable negative returns persist for about a year after that, then fade away.

We focus on the three-year results in Table IV. Which horizon is it appropriate to focus on? Why do we focus on the three-year results (where inflows negatively forecast returns) instead of the three month results (where inflows positively forecast returns)? Isn't the horizon arbitrary? This is an important question. The answer is that the horizon one should use depends on what one is trying to measure. Since our goal is to understand the long-term effects on trading on individual investor wealth, the longer the horizon, the better. The results for longer horizons show that although mutual fund flows do seem to predict short term returns, this effect is swamped as we look longer horizons (which cumulate the returns over time).

To understand whether individuals are "smart" or "dumb", one needs to measure whether their trading is raising or lowering their total wealth (compared to some alternative involving refraining from trading) over their lifetime. To take an example, suppose Joe buys a stock from Sally for $10, and the next day the price rises to $11. Based on this evidence alone, one might conclude that Joe is smart (and Sally is dumb). However, if Joe continues to hold the stock, and it declines to $5 (at which point he sells it), Joe seems less smart. Joe could increase his wealth by refraining from trade. In this sense, longer horizons are better horizons for inferring the net effect of Joe's trading.

In terms of measuring investor experience, however, the evidence given in Table IV cannot resolve the question of smart or dumb, because this evidence does not correspond to the dollar holdings of any class of investors. One needs to look at all trades and all dollar allocations to different securities over time. In section V, we do this for the aggregate mutual fund investor, and show that trading does in fact decrease both average returns and the return/risk ratio for an individual who is behaving like the aggregate mutual fund investor. In turns out that when one looks at the whole portfolio, the answer no longer depends on the horizon: the dumb money effect exists at all horizons. From this perspective, then, individual investors in aggregate are unambiguously dumb.

B. Robustness tests

Table V shows robustness tests. We first split the sample approximately in half, 1981-1993 and 1994-2003. As discussed earlier, our data is noisier and sparser in the earlier part of the sample. The table shows that the dumb money effect is much stronger in the second half of the sample, perhaps reflecting better data in the second half, perhaps reflecting the extraordinary events of 1998-2000. Figure 2 shows further evidence on the dumb money effect over time. It shows cumulative returns on the long/short portfolio formed on three year equal weighted flows (we simply sum each monthly return over time). Figure 2 shows that the last few years of the sample are quite influential, with about 100 out of the total of 150 percent coming after 1998. But the dumb money effect is not due only to these years. The differential return is negative for 17 of the 21 calendar years available. Even discarding the post-1998 data, there is a clear dumb money effect in the data. Looking only at 1981-1998 data, the differential returns are significantly negative for both equally weighted and value weighted returns.

One interpretation of the time pattern is that the period around 1999-2001 was a time of particularly high irrationality, when irrational traders earned particularly low returns. Many anomalies grew larger in this period (see Ofek and Richardson (2003)). Indeed, one might propose that if a return pattern does not grow stronger in this period, then it is probably not attributable to irrational behavior.

Table V also shows results for the sample of stocks which have market cap above and below the CRSP median market cap. Again, the dumb money effect remains quite strong among large cap stocks.

One might ask whether the dumb money effect is an implementable strategy for outside investors using information available in real time. Our methodology involves substantial built-in staleness of flows, largely reflecting the way that Thomson Financial has structured the data.[4] So the variables in Table IV are certainly in the information set of any investor who has access to all the regulatory filings and reports from mutual funds, as they are filed. Currently, holdings data appear on the SEC EDGAR system on the next business days following a filing, but information lags were probably longer at the beginning of the sample period.

To address this issue, Table V shows results with the flow variables generously lagged an additional twelve months. Even lagged a full year, the three year flow variable remains a statistically significant predictor of equal weight returns and close to significant for value weight returns (the additional lagging decreases the number of available observations, making inference more difficult). As one might expect given Figure 1, the lagging produces a substantial and significant dumb money effect at the short horizons as well. Thus the dumb money effect is not primarily about short-term information contained in flows, it is about long-term mispricing.

In summary, three year mutual fund flows strongly negatively predict future stock returns, and there is no horizon at which flows reliable positively predict excess returns. The dumb money effect is present in both large and small cap stocks, and present in different time periods.

C. Controlling for size, momentum, and value

Table VI shows results for returns controlling for size, value, and price momentum. These variables are known to predict returns and likely to be correlated with flows. Sapp and Tiwari (2004), for example, argue that the short-horizon smart money effect merely reflects the price momentum effect of Jegadeesh and Titman (1993). If an individual follows a strategy of sending money to funds with past high returns in the last year and withdrawing money from funds with low returns, then he will end up with a portfolio that overweights high momentum stocks and underweights low momentum stocks. This strategy might be a smart (although high turnover) strategy to follow, as long as he keeps rebalancing the strategy. However, if the individual fails to rebalance promptly, eventually he will be holding a portfolio with a strong growth tilt. Thus over long horizons, stocks with high inflows are likely to be stocks with high past returns and are therefore likely to be growth stocks. So it is useful to know whether flows have incremental forecasting power for returns or just reflect known patterns of short horizon momentum and long horizon value/reversals in stock returns.

The left hand side of Table VI shows results where returns have been adjusted to control for value, size, and momentum. Following Daniel, Grinblatt, Titman, and Wermers (1997), it subtracts from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles (a total of 125 matching portfolios).[5] Here the dumb money effect is substantially reduced, with the coefficient falling from -0.61 to -0.22 for three year equal weighted flows, still significantly negative but less than half as large. This reduction largely reflects the fact that (as we shall see) high sentiment stocks tend to be stocks with high market-book.

The right-hand side of Table VI shows alphas from a Fama and French (1993) three factor regression. Here the reduction of the long-horizon dumb money effect is not as substantial, as the three-year equal weighted differential return falls from -0.61 to -0.45. Both methods cause the smart money effect to rise for equal weight returns, although it is still below conventional significance levels.

In Table VII, we take a closer look at the relation between the dumb money effect and the value effect by independently sorting all stocks into five flow categories and five market-book categories, with a resulting 25 portfolios. We sort on three year flows, and on market-book ratio following the definition of Fama and French (1993). The right-most column in each panel shows whether there is a flow effect within market-to-book quintiles. Thus if the value effect subsumes the dumb money effect, this column should be all zeros. The bottom row in each panel shows whether there is a value effect controlling for flows. If the dumb money effect subsumes the value effect, this row should be all zeros. If the two effects are statistically indistinguishable, then both the row and the column should be all zeros.

Table VII shows that, generally, neither effect dominates the other. Looking at equal weighted returns, the value effect appears to be much larger than the dumb money effect, with magnitudes of approximately one percent per month and high t-statistics. As before, the dumb money effect survives the correction for market-book. However, looking at value weighted returns, the dumb money effect looks stronger than value effect, with similar magnitudes and generally higher t-statistics.

Table VIII shows double sort portfolios for three year past stock returns instead of market-book, to explore the reversal effect of De Bondt and Thaler (1985). In order to make the reversal effect as powerful as possible, we sort on past returns lagged one year (in other words, we sort on stock returns from month t-48 to t-12). Here, looking at equal weighted returns, the results are similar to Table VII, with the dumb money effect looking slightly weaker. Looking at value weighted returns, the dumb money effect and the reversal effect have similar magnitudes and levels of significance.

To summarize, using standard adjustment techniques, the dumb money effect is not completely explained by the value effect. Neither the dumb money effect nor the value/reversal effect dominates the other. However, the dumb money and value/reversal effect are clearly quite related, and perhaps reflect the same underlying phenomenon.

IV. Flows and mutual fund returns

In this section, we set aside our main focus on stock returns, and examine the relation between mutual fund flows and mutual fund returns. This evidence is useful for two purposes. First, it shows how our results relate to the previous work of Zheng (1999) and Gruber (1996). Second, it shows whether our results are driven by problems in matching the CRSP mutual fund database with the holdings database. Table IX shows results using monthly mutual fund returns (instead of stock returns) and sorting on flows into funds instead of flows into stocks. The mutual fund returns reflect, in addition to the returns of the stocks held by the fund, the expenses and trading costs of each fund. The universe of funds includes all domestic equity funds in the CRSP mutual fund database. We show returns for both equally weighted and value weighted portfolios of funds (where the value weights reflect the NAV of the fund).

We first sort on actual flows minus counterfactual flows. Table IX shows first, using excess returns, that the dumb money effect comes in fairly strongly at the 3 year horizon, while the smart money effect comes in weakly at the 3 month horizon. Turning next to three-factor alphas, here the smart money effect comes in significant at the three-month and six-month horizon, while the dumb money effect is weaker for equal weighted results, while still strong for value weighted results. As a robustness check, we also sort on actual inflows (dollar inflows divided by assets under management) instead of actual inflows minus counterfactual inflows. This slightly different sorting most closely corresponds to the method of Zheng (1999) and Gruber (1996). The results are about the same using this sorting variable.

How should one interpret these results? Take for example the equal weighted 3-factor alpha results, where three month inflows predict a positive and significant differential of 19 basis points per month, while three year inflows predict a negative but insignificant 10 basis points. Suppose one believes that the Fama-French (1993) model is an appropriate risk adjustment. The fact that the differential is -0.10 percent for three year inflows means that the trading of individuals is not helping them achieve higher risk-adjusted average returns. Despite the fact that individuals earn significant and positive 0.19 percent differential in the first three months, this outperformance is wasted because the individuals are not following a dynamic strategy of buying the best-performing funds, holding them for a quarter, and them selling them. Instead, they are in aggregate following a strategy of buying the best-performing funds, and holding them for a long period of time. So the longer horizon return shows that investors are not actually benefiting from their trading.

To summarize, looking at mutual fund returns, there is a strong dumb money effect among large funds (when value weighting). Looking at smaller funds (equal weighting), the dumb money effect is smaller and insignificant, especially when correcting for value. Similar to previous results, we find a smart money effect at the quarterly horizon. However, this smart money effect is not enough to boost investor returns over the long term. For a more economically relevant measure of how these two effects balance out, in the next section we look at how the aggregate mutual fund investor is helped or hurt by his trading.

V. Economic significance to the aggregate investor

A. The magnitude of wealth destruction

So far, we have shown that stocks owned by funds with large inflows have poor subsequent returns. In this section, we measure the wealth consequences of active reallocation across funds, for the average investor. We assess the economic significance by measuring the average return earned by a representative investor, and comparing it to the return he could have earned by simply refraining from engaging in non-proportional flows. We examine both returns on stocks and returns on mutual funds.

Define R^{ACTUAL} as the return earned by a representative mutual investor who owns a tiny fraction of each existing mutual fund. The returns would reflect a portfolio of stocks where the portfolio weights reflect the portfolio weights of the aggregate mutual fund sector:

$$R_t^{ACTUAL} = \sum_i x_{i,t} \left[\sum_j w_{ij,t} R_t^j \right] \qquad (9)$$

where R^J is the return on stock j. The return from a strategy of refraining from non-proportional flows, R^{NOFLOW}, is

$$R_t^{NOFLOW} = \sum_i \hat{x}_{i,t} \left[\sum_j w_{ij,t} R_t^j \right] \qquad (10)$$

We use three year flows in these calculations. Table X shows excess returns on these two portfolios, and for comparison shows the value weighted market return as well. Since the two mutual fund portfolios use weights based on dollar holdings, they are of course quite similar to each other and to the market portfolio.

Although very similar, these portfolios are not identical. Table X shows investor flows cause a significant reduction in both average returns and Sharpe ratios earned by mutual fund investors. A representative investor who is currently behaving like the aggregate mutual fund sector could increase his Sharpe ratio 9% (from a monthly Sharpe ratio of 0.137 to 0.149) by refraining from active reallocation and just directing his flows proportionally.[6]

One can assess the significance of this difference in mean returns by looking at the returns on the long-short portfolio R^{ACTUAL} - R^{NOFLOW}. This return is similar to the long-short portfolio studied in Table IV, except that here all stocks owned by the mutual fund sector are included, and the weights are proportional to the dollar value of the holdings. The difference is negative and highly significant. Thus investor flows cause wealth destruction. This conclusion is, of course, a partial equilibrium statement. If all investors switched to proportional flows, presumably stock prices would change to reflect that. But for one individual investor, it appears that fund flows are harmful to wealth.

B. Better identification of mutual fund manager skill

Table X also helps disentangle the effect of flows from the effect of manager stock picking. We start by considering the average of $R^{ACTUAL} – R^{M}$, which measures the net return benefit of owning the aggregate fund holdings instead of holding the market (ignoring trading costs and expenses). R^{M} is the return on the CRSP value weighted market. The average of this difference, 0.03, consists of two components. The first, R^{ACTUAL} - R^{NOFLOW}, is the net benefit of reallocations. We already have seen that this dumb money effect is negative. The second, $R^{NOFLOW} – R^{M}$, measures the ability of the mutual fund managers to pick stocks which outperform the market (using value weights for managers). As shown in the table, using raw returns, this stock picking effect is 0.08 per month, with a t-statistic of 1.8. Thus there is some modest evidence that mutual fund managers do have the ability to pick stocks that outperform the market, once one controls for their clients' tendencies of switching money from one fund to another. As shown in the table, this modest skill is obscured (when looking only at actual holdings) by their clients anti-skill at picking funds.

C. Different measures of economic significance

We explore the robustness of the economic significance in two ways. First, in the bottom part of Table X, we repeat the basic analysis, again using three year flows but using funds instead of stocks. We define R^{ACTUAL} and R^{NOFLOW} using fund returns instead of stock returns (plugging in actual fund returns for the term in brackets in equations (9) and (10)). Again, as in section IV, using mutual fund returns allows us to avoid issues involving matching funds with holdings. On the other hand, the cost of this specification is that the results now also reflect issues such as fund expenses, fund turnover and trading costs, and fund cash holdings.

Looking at the dumb money effect, the results using mutual funds are nearly identical to the results using stocks. As with stocks, the dumb money effect is -0.05 percent per month with an almost identical t-statistic. So, measured using either mutual fund returns or stock returns, investors are lowering their wealth and their Sharpe ratios by engaging in disproportionate fund flows. A simple passive strategy would dominate the actual strategy of the aggregate mutual fund investors.

The results for mutual funds also give us some context for the economic magnitude of the wealth destruction due to fund flows. The total net benefit of mutual funds, $R^{ACTUAL} - R^{M}$, is -0.12 percent per month, or about 1.4 percent cost per year. Of course, this overstates the true cost of mutual funds since the return earned by the CRSP value weight portfolio is not a viable free alternative. Thus -0.12 percent is an overstatement of the wealth destruction caused by the high expenses and high turnover of the mutual fund industry. Of this -0.12, almost half, -0.05, is explained by dumb money effect. Thus fund flows appear to be a very significant contributor to the dismal performance earned by the average mutual fund investor: individual investors have only themselves to blame. Still, mutual managers do not emerge unscathed from Table X. As usual, costs and expenses eat up any stock picking ability managers have, so that the net effect is -0.07 per month.

In Table XI, we show the stock return measures of wealth destruction and stock picking for different horizon. It turns out that, although the short horizon smart money effect has showed up in some the specifications, it does not show up here. Even at the three month horizon, we find no evidence that trading helps investors earn higher returns. Thus from an economic perspective, the short term trading done by mutual fund investors does not seem smart.

VI. Issuance

If individual investors (acting through mutual funds) lose money on their trades, who is making money? Possible candidates include hedge funds, pension funds, other institutions, or individuals trading individual stocks. Here we focus on another class of traders: firms. In contrast to trading by individuals, reflecting uninformed and possibly irrational demand, the actions of firms represents informed and probably more rational supply. A substantial body of research studies whether firms opportunistically take advantage of mispricing by issuing equity when it is overpriced and buying it back when it is underpriced (for example Loughran and Ritter, 1995). Corporate managers certainly say they are trying to time the market (Graham and Harvey, 2001).

We measure firm behavior using the composite share issuance measure of Daniel and Titman (2004), which combines a variety of previously documented effects involving repurchases, mergers, and seasoned equity issues. Our version of their variable is 1 minus the firm's ratio of the number of shares outstanding one year ago to the number of shares outstanding today.[7] For example, if the company has 100 shares and has a seasoned equity issue of an additional 50 shares, the composite issuance measure is 33%, meaning that 33% of the existing shares today were issued in the last year. The measure can be negative (reflecting for example repurchases) or positive (reflecting for example executive stock options, seasoned equity offerings, or stock-financed mergers). Issuance and market-book ratios are strongly related: growth firms tend to issue stock, value firms tend to repurchase stock. Daniel and Titman (2004), show that when issuance is high, returns are low over the next year. This pattern suggests that firms issue and repurchase stock in response to mispricing.

Table XII shows the relation of annual issuance to past three-year flows, using the usual format but studying issuance instead of returns. The table shows issuance between January and December of year t, sorted on 3-year flows as of December in year t-1. The table uses the standard portfolio logic of forming groups, taking the average in each group for each of the 20 years available, and reporting the mean and t-statistic for the resulting 20 time series observations.

The first row shows that firms with the lowest three year inflows issue one percent less stock than firms with the highest inflows. Thus inflows are positively associated with issuance by firms. Firms tend to increase shares outstanding this year when previous year's flows are high. One interpretation of this pattern is that firms are seizing the opportunity to issue stock when sentiment is high, and repurchase stock when sentiment is low. Since the average issuance measure (which is as a fraction of shares outstanding) is around three percent per year in this sample, one percent is a large number.

The rest of the table shows robustness tests for this basic result. The next row shows value weighted results, which (as usual for flows) are somewhat stronger. The next row shows a truncated version of the issuance variable. Since the issuance variable as defined is unbounded below, we define trimmed issuance as max (-100, issuance). This change has little effect. We also look at the relation in the two different halves of the sample. As before, the relation is stronger in the second half of the sample, but significant always.

To understand the economic magnitudes shown in Table XII, it is useful to know that the difference in the sorting variable (three year flows) is about 12 percent between the top and bottom quintile. That is, the top quintile has had three year flows that are on average 12 percent more as a percent of shares outstanding than the bottom quintile. This number is the same units as the numbers in Table XII since both flows and issuance are expressed as a fraction of current shares outstanding. Thus firms with flows that are 12 percent higher as a fraction of shares outstanding tend to increase shares by 1 percent of shares outstanding. Over three years, the firm would issue shares equivalent to three percent of shares outstanding. Thus over time, one can loosely say that firms respond to $12 billion in flows by issuing $3 billion in stock. Supply accommodates approximately one quarter of the increase in demand.

VII. Conclusion

In this paper, we have shown that individual investors have a striking ability to do the wrong thing. They send their money to mutual funds which own stocks that do poorly over the subsequent years. Individual investors are dumb money, and one can use their mutual fund reallocation decisions to predict future stock returns. The dumb money effect is robust to a variety of different control variables, is not due to one particular time period, and is implementable using real-time information. By doing the opposite of individuals, one can construct a portfolio with high returns. Individuals hurt themselves by their decisions, and we calculate that aggregate mutual fund investor could raise his Sharpe ratio by 9% simply by refraining from destructive behavior. These facts pose a challenge to rational theories of fund flows. Of course, rational theories of mutual fund investor behavior already face many formidable challenges, such as explaining why investors consistently invest in active managers when lower cost, better forming index funds are available.

We have found mixed evidence on a smart money effect of short-term flows positively predicting short-term returns. One interpretation of this effect is that there is some short-term manager skill which is detected by investors. Another hypothesis, explored by Wermers (2004) and Coval and Stafford (2005), is that mutual fund inflows actually push prices higher. Another possibility, explored by Sapp and Tiwari (2004) is that by chasing past returns, investors are stumbling into a valuable momentum strategy. Whatever the explanation, it is clear that the higher returns earned at the short horizon are not effectively captured by individual investors. Of course, it could be that some subset of individuals benefit from trading, but looking at the aggregate holdings of mutual funds by all individuals, we show that individuals as a whole are hurt in the long run by their reallocations.

Although the dumb money effect is statistically distinct from the value/reversal effect, it is clear these two effects are highly related. It is remarkable that one is able to recover many features of the value effect without actually looking at prices or returns for individual stocks. In our sample, the value effect is generally bigger than the dumb money effect among small cap stocks, but the dumb money effect looks at least as big among large cap stocks.

The evidence on issuers and flows presents a somewhat nonstandard portrait of capital markets. Past papers have looked at institutions vs. individuals, and tried to test if institutions take advantage of individuals. Here, the story is different. Individuals do trade poorly, but these trades are executed through their dynamic allocation across mutual funds, that is, via financial institutions. As far as we can tell, it is not financial institutions that exploit the individuals, but rather the non-financial institutions that issue stock and repurchase stock. Stocks go in and out of favor with individual investors, and firms exploit this sentiment by trading in the opposite direction of individuals, selling stock when individuals want to buy it. We find some modest evidence that mutual fund managers have stock picking skill, but that any skill is swamped by other effects including the actions of retail investors in switching their money across funds. In our data, financial institutions seem more like passive intermediaries who facilitate trade between the dumb money, individuals, and the smart money, firms.

It is clear that any satisfactory theory of the value effect will need to explain three facts. First, value stocks have higher than average returns than growth stocks. Second, using various issuance mechanisms, the corporate sector tends to sell growth stocks and buy value stocks. Third, individuals, using mutual funds, tend to buy growth stocks and sell value stocks. One coherent explanation of these three facts is that individual investor sentiment causes some stocks to be misvalued relative to other stocks, and that firms exploit this mispricing.

ENDNOTES

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[1] See http://www.frcnet.com/graphics/pdf/Press%20Releases/Net%20Flows/FRC_December_01_%20Net_Flows_Release.pdf , http://www.thestreet.com/funds/funds/880027.html

[2] We handle missing reports as follows: whenever a fund has a missing report between two valid report dates, we assume that the fund did not change its holdings with respect to the previous report.

[3] Zheng (1999), for example, shows the smart money effect is concentrated in small cap stocks.

[4] The data shows holdings for points in time that reflect both a "vintage" file date (FDATE) and a report date. Neither of the two dates corresponds to the actual filing date with the SEC. The report date is the calendar day when a snapshot of the portfolio is recorded, while Thomson Financial always assigns file dates to the corresponding quarter ends of the filings. The report date coincides with the file date about 60% of the time, but in some cases dates back as much as 6 months prior to the file date, as fund manager have discretion about when to take a snapshot of their portfolio to be filed at a subsequent date. These holdings eventually become public information. For accuracy, we always use the end of quarter file date assigned by Thomson Financial. This quarterly interval introduces a source of staleness into the holdings data.

[5] These 125 portfolios are reformed every month based on the market equity, M/B ratio, and prior year return from the previous month. The portfolios are equal weighted and the quintiles are defined with respect to the entire universe in that month.

[6] Lamont (2002) finds similar results for the policy of refraining from buying new issues.

[7] We split-adjust the number of shares using CRSP "factor to adjust shares"

References

Baker, Malcom, and Jeffrey Wurgler, 2005, Investor sentiment and the cross-section of stock returns, *Journal of Finance*, forthcoming

Barber, B. and Odean T., 2000, Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors with Brad Barber, *Journal of Finance*, Vol. LV, No. 2, 773-806.

Barber, B. and Odean T., 2001, Boys will be Boys: Gender, Overconfidence, and Common Stock Investment, *Quarterly Journal of Economics*, February 2001, Vol. 116, No. 1, 261-292

Barber, B. and Odean T., 2004, All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, working paper

Barber, B., Odean T. and Zheng L. (2004) Out of Sight, Out of Mind: The Effects of Expenses on Mutual Fund Flows, *Journal of Business*, forthcoming

Barberis, N, and Shleifer, A., 2004, Style investing, *Journal of Financial Economics*, Volume 68, Issue 2, May 2003, Pages 161-199

Brown, Stephen J., Goetzmann, William N., Hiraki, Takato, Shiraishi, Noriyoshi and Watanabe, Masahiro, 2002, Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows (September 2002). Yale ICF Working Paper No. 02-09

Chen, H., Jegadeesh, N., Wermers, R., 2000. The value of active mutual fund management: an examination of the stockholdings and trades of fund managers. Journal of Financial and Quantitative Analysis 35, 343–368.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives*, Journal of Political Economy* 105, 1167-1200.

Cohen, Randolph B., Coval, Joshua and Pástor, Lubos, 2003 Judging fund managers by the company they keep; Working paper 04-023.; Boston: Division of Research Harvard Business School, 2003.

Cooper, Michael, Huseyin Gulen, and P. Raghavendra Rau, 2005, Changing Names With Style: Mutual Fund Name Changes And Their Effects On Fund Flows, Working Paper

Coval, Joshua and Stafford E., 2005, Asset Fire Sales in Equity Markets, Working paper

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52, 1035-1058.

Daniel, Kent, and Sheridan Titman, 2004, Market reaction to tangible and intangible information, working paper

De Bondt, W.F.M., and Thaler, R. (1985). Does the stock market overreact?, *Journal of Finance*, 40, 793-805.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3—56.

Goetzmann, W., and Massa, M., 2002. Daily momentum and contrarian behavior of index fund investors. *Journal of Financial and Quantitative Analysis* 37, 375-390.

Graham, John R., and Campbell Harvey, 2001, The Theory and Practice of Corporate Finance: Evidence from the Field, *Journal of Financial Economics* 60, 187-243.

Grinblatt, M., and S. Titman, and R. Wermers, 1995, Momentum Investment Strategies, Portfolio Performance and Herding, A Study of Mutual Fund Behavior, *American Economic Review*, 85, 1088-1105

Grinblatt, M., and Keloharju, M., 2000. The investment behavior and performance of various investor types: A study of Finland's unique data set. *Journal of Financial Economics* 55, 43-67.

Gruber, Martin, 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783-810

Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: evidence from the mutual fund industry, *Journal of Law and Economics* 35 (April 1992), 45-70.

Jain, Prem C., and Wu, Joanna Shuang, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937-958.

Jegadeesh, N. and S. Titman, 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency*, Journal of Finance*, 48, 65-91.

Kacperczyk E. , Marcin T., Clemens Sialm, and Lu Zheng (2005): On the Industry Concentration of Actively Managed Equity Mutual Funds, Forthcoming: *Journal of Finance*, 2005.

Lamont, Owen A., 2002, Evaluating value weighting: Corporate events and market timing, NBER Working Paper No. 9049.

Loughran, Tim, and Jay R. Ritter, 1995, The New Issues Puzzle, *Journal of Finance* 50, 23-51.

Odean T., 1999, Do Investors Trade Too Much?, *American Economic Review*, Vol. 89, 1279-1298.

Ofek, Eli and Matthew Richardson, 2003, DotCom mania: The rise and fall of Internet stock prices, *Journal of Finance* 58, 1113-1137.

Polk, Christopher and Paola Sapienza, 2004, The Real Effects of Investor Sentiment, NBER working paper 10563

Sirri, Erik R. and Peter Tufano, 1998, .Costly Search And Mutual Fund Flows,. *Journal of Finance*, 53, pp. 1589-1622

Teo, Melvyn and Sung-Jun Woo, 2004, Style effects in the cross-section of stock returns , *Journal of Financial Economics*,7, 367-398

Travis Sapp and Ashish Tiwari, 2004, Does Stock Return Momentum Explain the Smart Money Effect?, *Journal of Finance*, forthcoming

Wermers, R., 1999, Mutual Fund Trading and the Impact on Stock Prices, *Journal of Finance*, 54, 581-62

Wermers R., 2000, Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses, *Journal of Finance*, 55, 1655-1695

Wermers, Russell, 2004, Is Money Really Smart? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence, Working Paper

Zheng, Lu, 1999, Is money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance* 54, 901-933.

Data Appendix

A. Holdings data and error screens

We obtain data on stock holdings from the Thomson Financial CDA/Spectrum Mutual Funds database. Since our focus is on US equity funds, we remove all US-based international funds, fixed-income funds, real estate funds and precious metal funds.

Holdings are identified by CUSIPs, they constitute most of the equities, but are not necessarily the entire equity holdings of the manager or fund. The potential exclusions include: small holdings (typically under 10,000 shares or $200,000), cases where there may be confidentiality issues, reported holdings that could not be matched to a master security file, and cases where two or more managers share control (since the SEC requires only one manager in such a case to include the holdings information in their report).

Thomson identifies funds using a five-digit number (FUNDNO) but unfortunately numbered identifiers are reused in the data, hence we use a filter to identify new born-funds and generate a unique fund identifier. We start tracking funds as they appear in the database, a fund is then classified as a new-born fund and assigned a new unique identifier whenever there is a gap of more than 1 year between the current report and the last available report. A gap of more than one year between two consecutive reports typically reflects a different and unrelated manager or a major reorganization of the fund.

Holding are adjusted for stock splits, stock distributions, mergers and acquisitions and other corporate events that occur between the report date and the file date. This adjustment relies on the assumption by Thomson that funds report shares held on a pre-adjustment basis.

We merge the holdings with the CRSP/COMPUSTAT data and we use a series of filters to eliminate potential anomalies, probably due to misreporting, errors in data collecting or in computing adjustments. Holdings are set to missing whenever:

1. The report date is subsequent to the file date
2. The number of shares in a fund portfolio exceeds the total amount of shares outstanding at a particular date
3. The total amount of shares outstanding reported by CRSP is zero at a particular date

B. Merging Thomson and CRSP data

The CRSP mutual fund database utilizes a five character alpha-numeric identifier (ICDI). Both database report funds names but they use a different character string with different abbreviations. To match the two datasets we use a matching procedure base on TICKER symbols and fund names, similar in spirit to the technique proposed by Wermers (2000).

Thomson Financial reports fund tickers on a quarterly basis starting from the first quarter of 1999. For fund portfolios offering multiple share classes, multiple ticker symbols are provided. A combination of ticker-date typically uniquely identifies a mutual fund. First, we merge the two databases using a ticker-date match between the first quarter of 1999 and the last quarter of 2003. We generate a list of unique matches between the CRSP fund identifier and the unique identifier in the Thomson data computed above, and extrapolate backwards for the prior years.

After this initial merge, we use a "fuzzy" string matching algorithm to match the remaining funds. We use a "SOUNDEX" algorithm to match funds using their name and the corresponding date. The SOUNDEX algorithms were patented by Margaret I. Odell in 1918 and Robert C. Russell in 1922. They are based on an underlying principle of English and other Indo-

European languages. That is, most of the words can be reasonably represented by consonants alone. All the names are reduced to a phonetic equivalent character strings which can later be compared. We transform fund names into an alpha-numeric indicator by using the following steps:

1. Retain the first letter of the fund name and discard the letters A E H I O U W Y
2. Assign a numeric value to the following consonant: 1 $\rightarrow$ B F P V, 2 $\rightarrow$ C G J K Q S Z, 3 $\rightarrow$ D T, 4 $\rightarrow$L, 5 $\rightarrow$ M N, 6 $\rightarrow$ R
3. Discard all duplicate classification values if they are adjacent (that is BB will results in the single value 1)

We use the resulting strings to match the remaining funds at every quarterly date, and we discard every fund for which we could not find a corresponding match. Below we show a portion of the matched file:

date	CDA Fund ID	Thomson name	CRSP ICDI	CRSP name
12/31/2003	204	LORD ABBETT RES LG CAP S	13848	Lord Abbett Large Cap Research Fund/Y
03/31/1995	205	HERITAGE SER TR-VAL EQTY	13596	Heritage Series Trust:Value Equity Fund/A
06/30/1995	205	HERITAGE SER TR-VAL EQTY	13596	Heritage Series Trust:Value Equity Fund/A
06/30/1995	205	HERITAGE SER TR-VAL EQTY	13598	Heritage Series Trust:Value Equity Fund/C
09/30/1995	205	HERITAGE SER TR-VAL EQTY	13596	Heritage Series Trust:Value Equity Fund/A
09/30/1995	205	HERITAGE SER TR-VAL EQTY	13598	Heritage Series Trust:Value Equity Fund/C
12/31/1995	205	HERITAGE SER TR-VAL EQTY	13596	Heritage Series Trust:Value Equity Fund/A
12/31/1995	205	HERITAGE SER TR-VAL EQTY	13598	Heritage Series Trust:Value Equity Fund/C
09/30/2000	252	LIBERTY STRATEGIC BALANC	12722	Liberty Strategic Balanced Fund/B
09/30/2000	252	LIBERTY STRATEGIC BALANC	12724	Liberty Strategic Balanced Fund/C
01/31/1995	253	GOLDMAN S BALANCED FD	13706	Goldman Sachs Tr:Balanced Fund
07/31/1995	253	GOLDMAN S BALANCED FD	13706	Goldman Sachs Tr:Balanced Fund
01/31/1996	253	GOLDMAN S BALANCED FD	13706	Goldman Sachs Tr:Balanced Fund
07/31/1996	253	GOLDMAN S BALANCED FD	13706	Goldman Sachs Tr:Balanced Fund
01/31/1997	253	GOLDMAN S BALANCED FD	13706	Goldman Sachs Equity Port:Balanced Fund/A
07/31/1997	253	GOLDMAN S BALANCED FD	09039	Goldman Sachs Equity Port:Balanced Fund/C

In the CRSP database, if a fund has multiple share classes, each share class is classified as a separate entity. Different share classes have the same portfolio composition and are treated as a single fund in the Thomson database (for example fund # 205 in the table above). Therefore we combine multiple share classes in the CRSP data into a unique “super fund” by aggregating the corresponding net asset values, and computing the weighted average return of the fund using the total net asset value of the different share classes as weights.

As a final step, to ensure matching quality, we compare the net asset values of the matched funds reported by CRSP to the dollar value of their holdings, and discard matches where the total asset value of the fund reported by CRSP differs from the sum of the dollar holdings value by more than 100%.

The universe of mutual funds in our final sample tends to be larger than those in previous studies that use similar string matching algorithms. Wermers (2000) obtain a sample of 1,788 funds matched between 1975 and 1994. Kacperczyk, Sialm and Zheng (2005) use a sample of 1,917 unique equity funds between 1984 and 1999. Cohen, Coval and Pastor (2004) reported 235 funds matched at the end of 1980 and 1,526 matched funds in the second quarter of 2002. Our sample includes 3,221 unique funds between the first quarter of 1980 and the last quarter of 2003, with the number of funds starting from 200 funds in 1980 to 2,297 in 2003. Our matched sample covers on average about 81% of the dollar assets of the total universe of CRSP equity funds, with the level starting from 70% in 1980 and rising to 95% in 2003. As a final check of matching quality, we randomly extract 100 matched funds from the merged file and we hand-checked using both databases. In all 100 cases, we could not find errors in the matching process.

C. Construction of the counterfactual flows

We assign a counterfactual net asset value of zero to funds that were newly created in the past k quarters. New funds represent new flows, but in the counterfactual exercise they do not receive assets for the first k quarters. The universe of funds we consider when computing the counterfactual flows between date $t-k$ and date t is funds there were alive at both date $t-k$ and t.

More specifically, consider at generic date t and let $\mathrm{F}_{\mathrm{s}}^{\mathrm{Agg}}$ be the actual aggregate flows for all funds alive in quarter t (including funds who were recently born, but excluding funds that die in month t), for $t-k \leq s \leq t$. Let $\mathrm{N}_{\mathrm{t\text{-}k}}^{\mathrm{Agg}}$ be the lagged actual aggregate NAV aggregating only over those funds that exist in both month $t-k$ and in month t. We compute the counterfactual flows by assigning to each fund a share of total as follows:

$$\hat{\mathrm{F}}_{\mathrm{s}}^{\mathrm{i}} = \frac{N_{t-k}^{i}}{N_{t-k}^{Agg}} \mathrm{F}_{\mathrm{s}}^{\mathrm{Agg}} \qquad (1)$$

$$t-k \leq s \leq t \qquad (2)$$

For funds that die in quarter $s+1$ (so that their last NAV is quarter s), we set $\hat{\mathrm{F}}_{\mathrm{s+1}}^{\mathrm{i}} =$ $-\hat{N}_{s}^{i}$ and $\hat{N}_{s+h}^{i} = 0$ for all $h > 0$.

Table A shows a simplified example where we set k = 1 year. Fund # 3 is born in 1981, therefore in 1981 we register a net inflow equal to its initial NAV and set the counterfactual NAV to zero. In 1981 two funds are alive, fund # 1 and fund #2, and in 1980 they represented 2/3 and 1/3 of the total fund sector. Aggregate flows in 1981 were equal to $150, hence in the counterfactual exercise we assign a flow of $100 to fund # 1 (as opposed to the actual realized flow of $50) and a flow of $50 to fund # 2. Given the return of the two funds between 1980 and 1981, we can compute the counterfactual net asset value of fund # 1 and # 2 in 1981. Proceeding in the same manner whenever a fund is alive at date $t-k$ and t, we track the evolution of the fund's counterfactual NAV using the recursion:

$$\hat{N}^i_t = (1 + R^i_t)\hat{N}^i_{t-1} + \hat{F}^i_t \qquad (3)$$

Between 1982 and 1993 fund # 2 dies, hence in the counterfactual world we assign an outflow in 1983 equal to the NAV in 1982 and set the counterfactual NAV to zero thereafter. Note that (2) does not guarantee that counterfactual net asset values are always non-negative in quarters where we have aggregate outflows ($F^{Agg}_t < 0$). In this case we override (2) , set $\hat{N}^i_t = 0$ and redistribute the corresponding counterfactual flows to the remaining funds, to keep the total aggregate dollar outflow the same in both the counterfactual and actual case. Measuring FLOW over 12 quarters, negative counterfactual NAVs occur for only 0.12% of the sample.

Finally, we handle mergers as follows: we assume that investors keep earning returns on the existing assets of the surviving fund. For consistency, when constructing the counterfactual NAV, we also merge the lagged NAV of the two funds when we compute the ratio $\frac{N^i_{t-k}}{N^{Agg}_{t-k}}$ used to determine the pro-rata share of the total flows.

Figure 1

This figure shows the average returns in month t+k on a long/short portfolios formed on three month flows in month t. The figure shows average returns over time of a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks and the accompanying 95% confidence interval.

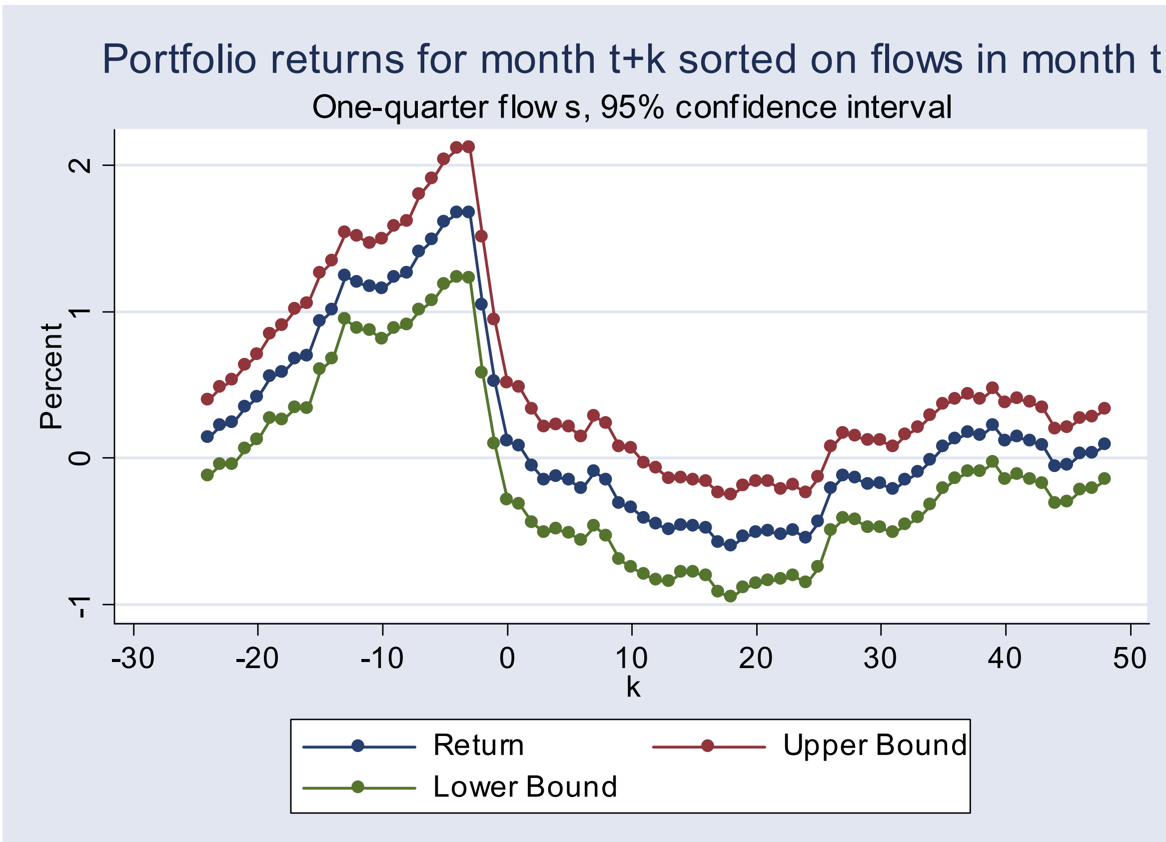

Figure 2

This figure shows cumulative returns on a long/short portfolios formed on three year flows in month t. At the beginning of every calendar month stocks are ranked in ascending order based on the last available flow. The figure shows the cumulative sum of monthly returns over time of a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks.

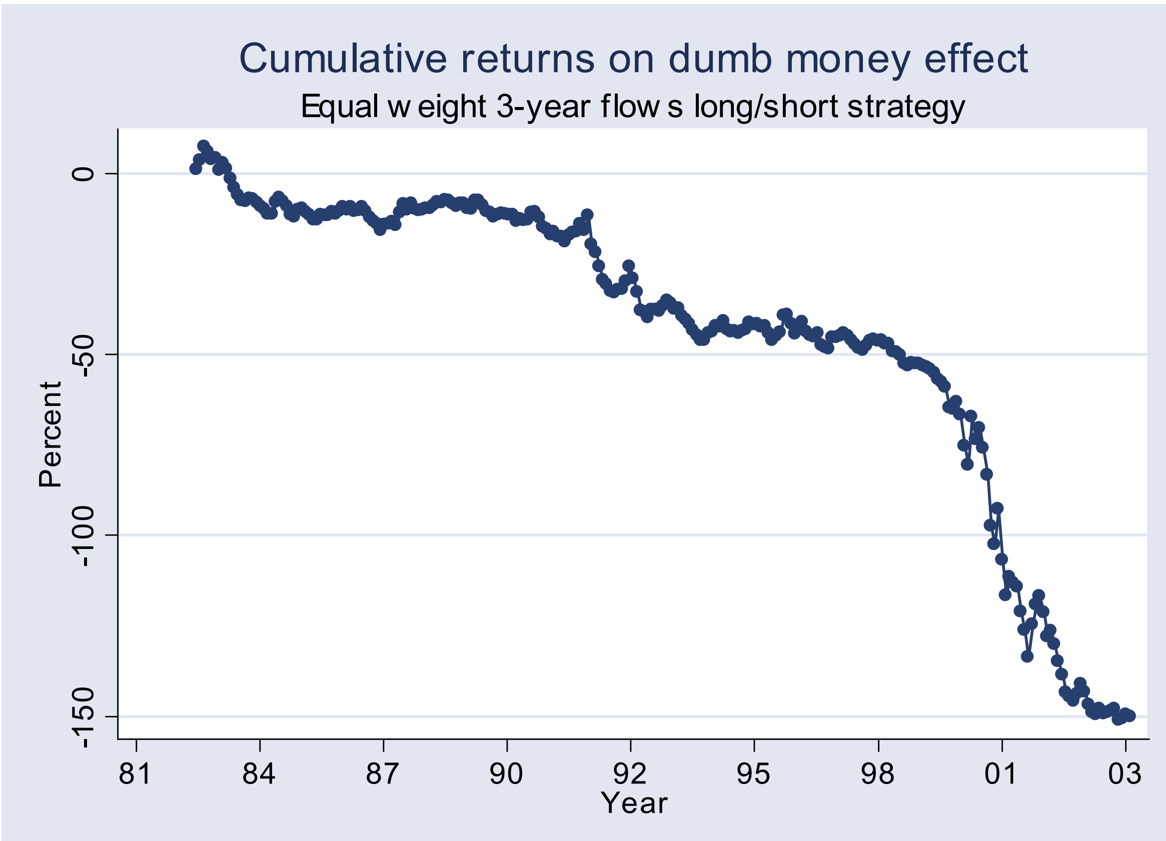

Table I: Flows by fund, selected dates

This table shows the top and bottom funds ranked on the difference between then actual and counterfactual weight in the aggregate mutual fund sector. x is the fund's actual percent of dollar value of the total mutual fund universe in the sample. $\hat{x}$ is counterfactual percent, using a horizon of three years.

	Percent of fund universe, actual	Percent of fund universe, counterfactual	Difference
	x	$\hat{x}$	
December 1999			
Bottom 5 funds			
FIDELITY MAGELLAN FUND	3.75	5.35	-1.60
INVEST. CO. OF AMERICA	1.99	2.73	-0.74
VANGUARD WINDSOR FUND	1.55	2.20	-0.65
FIDELITY CONTRAFUND	1.71	2.30	-0.59
TWENTIETH CENTURY ULTRA	1.55	2.04	-0.49
Top 5 funds			
VANGUARD INDEX - GROWTH	0.56	0.09	0.47
ALLIANCE PRMIER GROWTH	0.63	0.07	0.56
JANUS WORLDWIDE FUND	1.20	0.60	0.60
JANUS VALUE FUND	1.31	0.69	0.62
VANGUARD INDEX TRUST	3.71	2.96	0.75
December 1988			
Bottom 5 funds			
WINDSOR FUND	4.60	5.82	-1.22
DREYFUS FUND	1.78	2.71	-0.93
PRICE (ROWE) GROWTH STK.	1.02	1.91	-0.88
IDS STOCK FUND	0.96	1.79	-0.83
INVEST. CO. OF AMERICA	3.25	4.04	-0.78
Top 5 funds			
FIDELITY OTC PORTFOLIO	0.57	0.20	0.37
FRANKLIN UTILITIES	0.48	0.10	0.38
EVERGREEN TOTAL RETURN	1.02	0.27	0.75
WASH. MUTUAL INVESTORS	2.18	1.27	0.91
FIDELITY MAGELLAN FUND	7.08	5.66	1.42

Table II: Flows by stock, selected dates

This table shows the top and bottom stocks ranked on dollar FLOW, using three year flows. z is the stock's actual percent of the total dollar value of mutual fund holdings divided by the stock's market capitalization. $\hat{z}$ is counterfactual percent, using a horizon of three years. Flow is the three year FLOW, defined as the stock's actual percent of the total dollar value of mutual fund holdings divided by the stock's market capitalization minus the counterfactual percent, using a horizon of three years.

	Percent owned by mutual funds		
	Actual	Counterfactual	
	z	$\hat{z}$	FLOW
December 1999			
BOTTOM FIVE STOCKS			
CENDANT CORP	35.6	46.5	-10.9
VIACOM INC	42.8	48.3	-5.5
FEDERATED DEPT STORES INC DEL	34.2	45.0	-10.8
ALCOA INC	26.9	31.2	-4.3
ASSOCIATES FIRST CAPITAL CORP	37.5	43.6	-6.0
TOP FIVE STOCKS			
CISCO SYSTEMS INC	17.8	15.2	2.6
MICROSOFT CORP	12.6	11.6	1.0
SUN MICROSYSTEMS INC	20.5	16.6	3.9
DELL INC	12.3	9.0	3.2
INTEL CORP	11.4	10.2	1.2
December 1988			
BOTTOM FIVE STOCKS			
DIGITAL EQUIPMENT CORP	7.6	9.1	-1.6
CITICORP	16.7	18.9	-2.2
AMERICAN INTERNATIONAL GROUP INC	7.1	8.6	-1.5
FORD MOTOR CO DEL	10.4	11.0	-0.6
INTERNATIONAL BUSINESS MACHS COR	3.0	3.2	-0.2
TOP FIVE STOCKS			
REYNOLDS R J INDUSTRIES INC	2.7	1.7	1.0
PILLSBURY COMPANY	4.0	0.4	3.6
PLACER DOME INC	8.7	2.3	6.4
DISNEY WALT CO	5.4	3.4	2.0
BRISTOL MYERS SQUIBB CO	3.9	2.8	1.1

Table III: Summary statistics for three year flows, 1983-2003

This table shows summary statistics as of December of each year. Percent coverage of stock universe (EW) is the number of stocks with a valid three year FLOW, divided by total number of CRSP stocks. Percent coverage of stock universe (VW) is the total market capitalization of stocks with a valid three year FLOW, divided by the total market value of the CRSP stock universe. Percent coverage of fund universe (EW) is the total number of funds in the sample divided by the total number of equity funds in the CRSP mutual fund universe. Percent coverage of fund universe (VW) is the total net asset value of funds in the sample divided by the total net asset value of equity funds in the CRSP mutual fund universe. NAV is the total net asset value of a fund, in millions. x is the fund's actual percent of dollar value of the total mutual fund universe in the sample. $\hat{x}$ is counterfactual percent, using a horizon of three years. z is the stock's actual percent of the total dollar value of mutual fund holdings divided by the stock's market capitalization. $\hat{z}$ is counterfactual percent, using a horizon of three years. Flow is the three year FLOW, defined as the stock's actual percent of the total dollar value of mutual fund holdings divided by the stock's market capitalization minus the counterfactual percent, using a horizon of three years.

	Min	Max	Mean	Std Dev	Mean	
	Full sample, 1983-2003				1983	2003
Time-series (21 annual observations, 1983-2003)						
Number of funds in the sample per year	253	2439	1110	811	253	2297
Number of stocks in the sample per year	2875	6763	4822	1349	2875	4907
Percent coverage of stock universe (EW)	48.5	91.7	71.2	15.8	48.5	91.7
Percent coverage of stock universe (VW)	84.5	99.7	97.0	4.0	91.6	99.6
Percent coverage of fund universe (EW)	51.1	85.9	68.3	11.6	70.2	85.9
Percent coverage of fund universe (VW)	75.6	97.3	86.8	7.5	79.6	95.1
Funds (23 thousand pooled year-fund observations, 1983-2003)						
NAV, millions of dollars	0	109073	819	3355	210	811
Number of holdings per fund	1	4162	149	253	70	183
x (Percent of fund universe, actual)	0.00	7.97	0.13	0.38	0.49	0.05
$\hat{x}$ (Percent of fund universe, counterfactual)	0.00	9.69	0.15	0.47	0.67	0.06
Stocks (333 thousand pooled stock-fund observations, 1983-2003)						
Number of funds per stock	1	1001	26	54	5	50
z (Percent owned by funds, actual)	0.00	99.75	10.10	10.23	6.07	10.60
$\hat{z}$ (Percent owned by funds, counterfactual)	0.00	563.77	9.82	11.27	4.57	9.41
Flow	-497.01	84.35	0.36	5.93	1.21	2.16

Table IV : Calendar time portfolio, excess returns 1980 – 2003

This table shows calendar time portfolio returns. At the beginning of every calendar month stocks are ranked in ascending order based on the last available flow. Stocks are assigned to one of five portfolios. L/S is a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks. Portfolios are rebalanced monthly to maintain equal or value weights. We report average returns in excess of the Treasury bill rate. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

	Low flow				High flow	High flow minus low flow
	Q1	Q2	Q3	Q4	Q5	L/S
Equal weight						
Three month flow	0.73	0.80	0.80	0.71	0.84	0.11
	(2.05)	(2.34)	(2.13)	(1.91)	(2.15)	(0.57)
Six month flow	0.77	0.84	0.83	0.73	0.74	-0.03
	(2.16)	(2.43)	(2.20)	(1.95)	(1.87)	(0.15)
One year flow	0.79	0.95	0.83	0.67	0.67	-0.12
	(2.29)	(2.79)	(2.16)	(1.78)	(1.67)	(0.56)
Three year flow	1.03	1.07	0.83	0.66	0.42	-0.61
	(2.98)	(3.01)	(2.16)	(1.65)	(1.02)	(3.37)
Five year flow	0.99	0.99	0.97	0.79	0.67	-0.32
	(2.72)	(2.56)	(2.25)	(1.96)	(1.58)	(2.37)
Value weight						
Three month flow	0.67	0.69	0.34	0.58	0.71	0.04
	(2.10)	(2.40)	(1.12)	(1.96)	(1.91)	(0.17)
Six month flow	0.73	0.67	0.61	0.54	0.53	-0.19
	(2.29)	(2.31)	(2.17)	(1.77)	(1.44)	(0.73)
One year flow	0.74	0.87	0.59	0.45	0.46	-0.27
	(2.41)	(3.01)	(2.14)	(1.43)	(1.24)	(1.09)
Three year flow	0.96	0.93	0.79	0.52	0.29	-0.67
	(3.07)	(3.35)	(2.77)	(1.64)	(0.73)	(2.79)
Five year flow	0.95	0.76	0.69	0.54	0.45	-0.50
	(3.00)	(2.53)	(2.14)	(1.47)	(1.05)	(1.92)

Table V: Robustness tests

This table shows returns on high flow stocks minus returns on low flow stocks, using calendar time portfolio returns. "Larger cap stocks" are all stocks with market capitalization above the median of the CRSP universe that month, smaller stocks are below median. Returns are in monthly percent, t-statistics are shown below the coefficient estimates

	1981-1993	1994-2003	Larger cap	Smaller Cap	Flows Lagged 12 months
Equal weight					
Three month flow	0.01	0.24	0.18	0.20	-0.45
	(0.07)	(0.59)	(0.80)	(1.18)	(2.37)
Six month flow	-0.05	-0.00	-0.03	0.05	-0.49
	(0.39)	(0.00)	(0.13)	(0.28)	(2.62)
One year flow	0.07	-0.35	-0.07	-0.13	-0.59
	(0.47)	(0.80)	(0.28)	(0.69)	(3.01)
Three year flow	-0.29	-0.95	-0.52	-0.56	-0.38
	(1.90)	(2.83)	(2.66)	(2.57)	(2.59)
Five year flow	-0.31	-0.33	-0.23	-0.41	-0.24
	(2.20)	(1.48)	(1.50)	(2.14)	(2.08)
Value weight					
Three month flow	-0.03	0.13	0.03	0.44	-0.59
	(0.16)	(0.24)	(0.13)	(2.57)	(2.10)
Six month flow	-0.25	-0.13	-0.21	0.24	-0.62
	(1.34)	(0.23)	(0.77)	(1.39)	(2.17)
One year flow	-0.00	-0.61	-0.28	0.07	-0.66
	(0.00)	(1.18)	(1.10)	(0.34)	(2.54)
Three year flow	-0.19	-1.17	-0.66	-0.43	-0.42
	(0.94)	(2.67)	(2.76)	(2.09)	(1.85)
Five year flow	-0.14	-0.82	-0.50	-0.37	-0.26
	(0.62)	(1.83)	(1.88)	(1.97)	(1.02)

Table VI: Controlling for value, size, and momentum

This table shows calendar time portfolio abnormal returns. We report average characteristics adjusted returns and Fama and French (1993) alphas. Characteristic-adjusted returns are defined as raw monthly returns minus the returns on an equally weighted portfolio of all CRSP firms in the same size, market-book, and one year momentum quintile. Three factor alphas are defined as the intercept in a regression of the monthly excess return of the Treasury bill rate on the monthly returns from Fama and French (1993) mimicking portfolios. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

	Characteristic Adjusted returns			Fama-French 3 factor alpha		
	Q1	Q5	L/S	Q1	Q5	L/S
Equal weight						
Three month flow	0.02	0.17	0.15	-0.18	0.14	0.32
	(0.28)	(3.07)	(1.88)	(1.18)	(1.67)	(1.81)
Six month flow	0.05	0.08	0.03	-0.16	0.05	0.21
	(0.91)	(1.57)	(0.40)	(1.13)	(0.54)	(1.20)
One year flow	0.03	0.07	0.04	-0.13	0.00	0.14
	(0.54)	(1.20)	(0.45)	(1.01)	(0.01)	(0.79)
Three year flow	0.14	-0.08	-0.22	0.16	-0.29	-0.45
	(2.56)	(1.26)	(2.49)	(1.35)	(2.13)	(2.95)
Five year flow	0.12	-0.03	-0.15	0.10	-0.16	-0.26
	(2.15)	(0.49)	(1.88)	(0.90)	(1.25)	(2.31)
Value weight						
Three month flow	-0.02	-0.02	0.01	-0.20	0.15	0.35
	(0.33)	(0.20)	(0.08)	(1.64)	(1.20)	(1.61)
Six month flow	0.02	-0.14	-0.16	-0.16	0.01	0.17
	(0.24)	(1.82)	(1.31)	(1.25)	(0.09)	(0.77)
One year flow	-0.01	-0.13	-0.12	-0.10	-0.11	-0.01
	(0.10)	(1.47)	(0.89)	(0.82)	(0.80)	(0.05)
Three year flow	0.13	-0.26	-0.39	0.18	-0.35	-0.53
	(1.50)	(2.51)	(2.76)	(1.50)	(2.73)	(2.59)
Five year flow	0.12	-0.18	-0.30	0.14	-0.24	-0.38
	(1.34)	(1.99)	(2.06)	(1.31)	(1.79)	(1.97)

Table VII: 3 year flows vs. value

This table shows calendar time portfolio returns. At the beginning of every calendar month stocks are ranked in ascending order based on the last available flow and market-book ratio (M/B). M/B is market-book ratio (market value of equity divided by Compustat book value of equity). The timing of M/B follows Fama and French (1993) and is as of the previous December year-end. Stocks are assigned to one of twenty-five portfolios. L/S is a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks. Portfolios are rebalanced monthly to maintain equal or value weights. We report average returns in excess of the Treasury bill rate. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

		Low Flow				High Flow	High flow Minus Low flow
		Q1	Q2	Q3	Q4	Q5	L/S
				Equal weight			
Value	Q1	1.29	1.42	1.38	1.07	1.04	-0.25
		(3.80)	(3.84)	(3.57)	(2.97)	(2.99)	(1.46)
	Q2	1.17	1.17	1.20	1.05	0.85	-0.32
		(3.82)	(3.85)	(3.76)	(3.36)	(2.62)	(2.22)
	Q3	1.05	1.14	0.95	0.84	0.75	-0.30
		(3.11)	(3.54)	(2.87)	(2.45)	(2.00)	(2.07)
	Q4	0.77	0.84	0.57	0.61	0.47	-0.30
		(2.06)	(2.27)	(1.38)	(1.51)	(1.10)	(1.92)
Growth	Q5	0.55	0.59	0.08	0.07	0.01	-0.54
		(1.22)	(1.25)	(0.14)	(0.13)	(0.03)	(2.34)
Growth minus	L/S	-0.68	-0.76	-1.21	-0.91	-0.95	
Value		(2.55)	(2.70)	(4.16)	(2.77)	(3.08)	
				Value weight			
Value	Q1	0.92	1.14	0.98	0.67	0.96	0.04
		(2.77)	(3.59)	(2.98)	(2.13)	(2.86)	(0.16)
	Q2	0.79	0.79	0.85	0.81	0.59	-0.20
		(2.59)	(2.77)	(2.76)	(2.79)	(1.90)	(0.99)
	Q3	0.98	0.89	0.92	0.64	0.61	-0.37
		(3.00)	(3.18)	(3.15)	(1.98)	(1.72)	(1.88)
	Q4	0.78	0.85	0.84	0.59	0.24	-0.54
		(2.31)	(2.85)	(2.68)	(1.74)	(0.59)	(2.36)
Growth	Q5	0.91	0.87	0.58	0.23	0.16	-0.75
		(2.37)	(2.62)	(1.64)	(0.57)	(0.32)	(2.68)
Growth minus	L/S	-0.01	-0.25	-0.37	-0.41	-0.74	
Value		(0.02)	(0.89)	(1.20)	(1.44)	(2.26)	

Table VIII: 3 year flows vs. reversals

This table shows calendar time portfolio returns. At the beginning of every calendar month stocks are ranked in ascending order based on the last available flow and lagged three year returns. The returns have been lagged 12 months. Stocks are assigned to one of twenty-five portfolios. L/S is a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks. Portfolios are rebalanced monthly to maintain equal or value weights. We report average returns in excess of the Treasury bill rate. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

		Low Flow				High Flow	High flow minus Low flow
		Q1	Q2	Q3	Q4	Q5	L/S
				Equal weight			
Losers	Q1	1.64	1.46	1.47	1.52	1.17	-0.47
		(3.26)	(2.65)	(2.30)	(2.56)	(2.23)	(1.55)
	Q2	1.04	1.09	0.99	0.80	0.99	-0.05
		(2.98)	(2.99)	(2.48)	(2.05)	(2.60)	(0.29)
	Q3	0.99	1.07	0.94	0.95	0.72	-0.27
		(3.38)	(3.82)	(3.30)	(2.99)	(2.20)	(1.89)
	Q4	0.88	1.04	0.65	0.78	0.60	-0.28
		(2.93)	(3.72)	(2.39)	(2.72)	(1.85)	(2.07)
Winners	Q5	0.77	0.53	0.47	0.48	0.18	-0.59
		(2.04)	(1.52)	(1.23)	(1.29)	(0.43)	(3.23)
Losers minus	L/S	-0.80	-0.86	-0.93	-0.96	-0.91	
Winners		(2.46)	(2.29)	(2.04)	(2.52)	(2.94)	
				Value weight			
Losers	Q1	1.53	1.25	1.06	1.19	1.18	-0.34
		(3.52)	(2.47)	(1.88)	(2.26)	(2.23)	(0.85)
	Q2	1.15	1.18	0.96	0.89	1.12	-0.03
		(3.20)	(3.46)	(2.53)	(2.39)	(2.85)	(0.10)
	Q3	0.99	1.15	1.14	0.68	0.74	-0.26
		(3.22)	(4.04)	(3.55)	(2.20)	(2.22)	(1.30)
	Q4	0.85	0.76	0.83	0.71	0.59	-0.26
		(2.78)	(2.83)	(2.99)	(2.59)	(1.79)	(1.33)
Winners	Q5	0.81	0.80	0.66	0.53	0.23	-0.58
		(2.26)	(2.39)	(1.97)	(1.42)	(0.52)	(2.27)
Losers minus	L/S	-0.66	-0.41	-0.36	-0.61	-0.88	
Winners		(2.26)	(1.04)	(0.74)	(1.54)	(2.36)	

Table IX: Mutual fund returns

This table shows calendar time portfolio returns. At the beginning of every calendar month mutual funds are ranked in ascending order based on the last available difference between then actual x and counterfactual weight $\hat{x}$ in the aggregate mutual fund sector. x is the fund's actual percent of dollar value of the total mutual fund universe in the sample. $\hat{x}$ is counterfactual percent, using a horizon between three months and five years. Funds are assigned to one of five portfolios. Portfolios are rebalanced monthly to maintain equal or value weights. Value weights are compute using net asset values. When sorting funds on raw flows, we use the total dollar flow over different horizons divided by the net asset value of the fund at the beginning of the period. This table includes all available equity funds in the CRSP mutual fund database over the period 1980 – 2003. We report average returns in excess of the Treasury bill rate and Fama and French (1993) alphas. Alphas are defined as the intercept in a regression of the monthly excess return of the Treasury bill rate on the monthly returns from Fama and French (1993) mimicking portfolio. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

	Sorted on $x-\hat{x}$						Sorted On raw flows	
	Excess returns			Fama-French 3 factor α			Excess returns	3 factor α
	Q1	Q5	L/S	Q1	Q5	L/S	L/S	L/S
Equal weight								
Three month flow	0.49	0.62	0.13	-0.16	0.03	0.19	0.13	0.19
	(1.52)	(2.32)	(1.68)	(-2.54)	(0.65)	(2.74)	(1.69)	(2.85)
Six month flow	0.46	0.55	0.09	-0.17	-0.01	0.16	0.08	0.16
	(1.71)	(1.97)	(1.18)	(-2.71)	(-0.16)	(2.37)	(1.14)	(2.41)
One year flow	0.48	0.52	0.03	-0.15	-0.03	0.11	0.04	0.11
	(1.79)	(1.82)	(0.46)	(-2.48)	(-0.69)	(1.68)	(0.49)	(1.75)
Three year flow	0.55	0.40	-0.15	-0.09	-0.19	-0.10	-0.15	-0.10
	(1.94)	(1.39)	(-2.14)	(-1.67)	(-3.69)	(-1.43)	(-2.35)	(-1.62)
Five year flow	0.57	0.51	-0.06	-0.11	-0.14	-0.03	-0.07	-0.03
	(1.91)	(1.68)	(-1.16)	(-2.02)	(-2.81)	(-0.53)	(-1.31)	(-0.54)
Value weight								
Three month flow	0.41	0.71	0.25	-0.20	0.15	0.35	0.24	0.35
	(1.52)	(2.32)	(1.68)	(-2.76)	(1.79)	(2.93)	(1.69)	(3.00)
Six month flow	0.43	0.59	0.12	-0.18	0.09	0.26	0.13	0.27
	(1.62)	(1.93)	(0.87)	(-2.66)	(1.01)	(2.34)	(0.93)	(2.49)
One year flow	0.54	0.43	-0.11	-0.10	-0.02	0.05	-0.17	0.00
	(2.01)	(1.42)	(-0.78)	(-1.37)	(-0.28)	(0.44)	(-1.19)	(0.02)
Three year flow	0.68	0.37	-0.32	0.05	-0.21	-0.30	-0.29	-0.24
	(2.35)	(1.20)	(-2.93)	(0.63)	(-3.26)	(-2.78)	(-2.70)	(-2.39)
Five year flow	0.74	0.49	-0.19	0.02	-0.12	-0.14	-0.18	-0.11
	(2.47)	(1.57)	(-2.51)	(0.28)	(-2.42)	(-1.91)	(-2.22)	(-1.55)

Table X: Economic significance of three year flows for the aggregate mutual fund investor

This table shows the property of monthly calendar time portfolio returns. It uses three year flows. R^{ACTUAL} is returns on a mimicking portfolio for the entire mutual fund sector, with portfolio weights the same as the actual weights of the aggregate mutual fund sector. R^{NOFLOW} is returns on a mimicking portfolio for the counterfactual mutual fund sector, with portfolio weights the same as the counterfactual weights of the aggregate mutual fund sector. R^{M} is the CRSP value weighted market return.

		Mean	t-stat	SR
Using stock returns				
Actual excess return on mutual fund holdings	$R^{ACTUAL} - R^{F}$	0.68	2.16	0.137
Counterfactual excess return on mutual fund holdings	$R^{NOFLOW} - R^{F}$	0.73	2.35	0.149
Market excess returns	$R^{M} - R^{F}$	0.65	2.26	0.143
Net benefit of mutual funds	$R^{ACTUAL} - R^{M}$	0.03	0.68	0.043
Dumb money effect	$R^{ACTUAL} - R^{NOFLOW}$	-0.05	2.66	-0.169
Stock picking	$R^{NOFLOW} - R^{M}$	0.08	1.80	0.114
Using mutual fund returns				
Actual excess return on mutual funds	$R^{ACTUAL} - R^{F}$	0.51	1.83	0.116
Counterfactual excess returns on mutual funds	$R^{NOFLOW} - R^{F}$	0.56	2.03	0.129
Net benefit of mutual funds	$R^{ACTUAL} - R^{M}$	-0.12	3.34	-0.213
Dumb money effect	$R^{ACTUAL} - R^{NOFLOW}$	-0.05	2.64	-0.168
Stock picking	$R^{NOFLOW} - R^{M}$	-0.07	2.06	-0.132

Table XI: Robustness tests for economic significance of flows

This table shows the property of monthly calendar time portfolio returns for different horizons, using stock returns. R^{ACTUAL} is returns on a mimicking portfolio for the entire mutual fund sector, with portfolio weights the same as the actual weights of the aggregate mutual fund sector. R^{NOFLOW} is returns on a mimicking portfolio for the counterfactual mutual fund sector, with portfolio weights the same as the counterfactual weights of the aggregate mutual fund sector. R^{M} is the CRSP value weighted market return.

	Dumb money effect	Stock picking
	$R^{ACTUAL} - R^{NOFLOW}$	$R^{NOFLOW} - R^{M}$
Three month flow	-0.11	0.04
	(1.18)	(0.89)
Six month flow	-0.12	0.04
	(1.21)	(0.96)
One year flow	-0.13	0.06
	(1.34)	(1.28)
Three year flow	-0.05	0.08
	(2.66)	(1.80)
Five year flow	-0.05	0.10
	(2.21)	(2.23)

Table XII: Issuance

This table shows issuance activity between January and December of year $t+1$, for portfolios of firms sorted on 3-year flows as of December in year t. In December stocks are ranked in ascending order based on the last available 3 year flow. Stocks are assigned to one of five portfolios. Portfolios are rebalanced every year to maintain equal or value weights. Issuance is defined as 1 minus the firm's ratio of the number of shares outstanding one year ago to the number of shares outstanding today. Issuance is in percent, t-statistics are shown below the coefficient estimates.

	Low flow				High flow	High minus low
	Q1	Q2	Q3	Q4	Q5	
Equal weighted	2.66	2.95	3.15	2.83	3.64	0.98
	(11.21)	(6.85)	(8.08)	(8.89)	(9.88)	(3.55)
Value weighted	3.18	1.94	2.11	2.64	4.98	1.80
	(6.08)	(4.11)	(3.74)	(8.39)	(9.70)	(2.47)
Equal weighted, trimmed issuance	2.79	3.04	3.40	2.95	3.73	0.94
	(12.65)	(7.27)	(8.69)	(9.46)	(10.64)	(3.51)
Equal weighted, 1981-1993	2.38	1.55	1.87	2.07	2.85	0.47
	(7.24)	(3.26)	(4.82)	(4.22)	(5.83)	(2.29)
Equal weighted, 1994-2004	2.93	4.36	4.42	3.59	4.43	1.50
	(8.76)	(12.56)	(12.26)	(14.82)	(10.03)	(3.17)

Table A.1: Hypothetic example showing counterfactual calculation

	Year	1980	1981	1982	1983	1985
ACTUAL DATA FOR INDIVIDUAL FUNDS						
Returns	Fund 1	10%	10%	5%	10%	5%
	Fund 2	-5%	10%	-10%		
	Fund 3			10%	10%	5%
NAV	Fund 1	100	160	268	395	515
	Fund 2	50	105	144	0	0
	Fund 3		50	45	100	154
FLOWS	Fund 1		50	100	100	100
	Fund 2		50	50	-144	0
	Fund 3		50	-10	50	50
ACTUAL DATA FOR AGGREGATES						
NAV	Agg.	150	315	457	494	669
FLOW	Agg.	0	150	140	6	150
NAV, last year, of funds existing this year	Agg.		150	315	313	494
FLOW of non-dying funds	Agg.		150	140	150	150
COUNTERFACTUAL DATA						
NAV	Fund 1	100	210	292	449	591
	Fund 2	50	105	141	0	0
	Fund 3			22	46	79
FLOWS	Fund 1		100	71	128	120
	Fund 2		50	47	-141	0
	Fund 3			22	22	30