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

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ABSTRACT

We use mutual fund flows as a measure of individual investor sentiment for different stocks, and find that high sentiment predicts low future returns. 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 related to the value effect: high sentiment stocks tend to be growth stocks. High sentiment also is associated with 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. 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, using our data we calculate that in 1999 investors sent $37 billion to Janus funds but only $16 billion to Fidelity funds, despite the fact that Fidelity had 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 $31 billion to Fidelity. In this instance, the reallocation caused wealth destruction to mutual fund investors as Janus and tech stocks performed horribly after 1999.

To systematically test the hypothesis that high sentiment predicts low future returns, we examine flows and stock returns over the period 1980-2003. 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, 18% of the shares outstanding of Cisco were owned by the mutual fund sector (using our sample of funds), of which 3% 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 15%. This 3% difference is our measure of investor sentiment. We then test whether this measure predicts differential returns on stocks.

Our main result is that on average, 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.

Our results contradict the "smart money" hypothesis of Gruber (1996) and Zheng (1999) that some fund managers have skill and some individual investors can detect that skill, and send their money to skilled managers. Gruber (1996) and Zheng (1999) show that the short term performance of funds that experience inflows is significantly better than those that experience outflows, suggesting that mutual fund investors have selection ability. We find that this smart money effect is confined to short horizons of about one quarter, but at longer horizons the dumb money effect dominates.

We show that the dumb money effect is related to the value effect. This relation reflects return-chasing 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)). As a consequence, money flows into mutual funds that own growth stocks, and flows out of mutual funds that own value stocks. The value effect explains some, but not all, of the dumb money effect. The fact that flows go into growth stocks 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.

In addition past returns of funds, decisions by individual investors also reflect their thinking about economic themes or investment styles, reinforced by marketing efforts by funds (see Jain and Wu (2000), Barber, Odean and Zheng (2004), and Cooper, Gulen, and Rau (2005)). 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. While Teo and Woo (2004) provide valuable evidence, our approach is more general. We do not have to define specific styles or categories. Instead, we impose no categorical structure on the data and just follow the flows.

More generally, one can imagine 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)). Our measure is different because it is based on trading by a specific set of investors, and thus allows us to perform an additional test confirming that sentiment-prone investors lose money from their trading. If sentiment affects 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. If some class of investors drives sentiment, 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. Individual retail investors are a good candidate for sentiment-prone investors because a variety of evidence indicates they make suboptimal investment decisions. 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 (see also Grinblatt and Keloharju (2000), Goetzmann and Massa (2002)).

If individuals are losing money via their mutual fund trades, who is making money? One candidate is institutional investors. A large literature explores whether institutions have better average performance than individuals (see Daniel, Grinblatt, Titman, and Wermers (1997) and Chen, Jegadeesh, and Wermers (2000)). Unfortunately, since individuals ultimately control fund managers, it can be difficult to infer the skill of the two groups. It is hard for a fund manager to be smarter than his clients. Mutual fund holdings and performance 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.

We find that demand by individuals and supply from firms are correlated. 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). One interpretation is that individual investors are dumb, and smart firms are opportunistically exploiting their demand for shares.

Although we find that sentiment affects stock prices, we do not attempt to analyze precisely the mechanism through which sentiment is propagated. Fund flows have positive contemporaneous correlations with stock returns (see, for example, Warther (1995) and Brown et al (2002)). Although it is difficult to infer causality from correlation, one interpretation is that inflows drive up stock prices. We do not attempt to test this hypothesis; instead, 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.

This paper is organized as follows. Section I discusses the basic measure of sentiment. Section II looks at the relation between flows and stock returns. Section III looks at a variety of robustness tests, including the relation to value, industry, and time period. Section IV looks at the relation between flows and mutual fund returns. Section V puts the results in economic context, showing the magnitude of wealth destruction caused by flows. Section VI looks at issuance by firms. Section VII presents conclusions.

I. 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, 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 that 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 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. 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 one cannot interpret the counterfactual world as an implementable alternative for the aggregate mutual fund sector. In section V, we discuss the effects of flows on investor wealth and 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 exist at any date between 1980 and 2003 for which quarterly total net assets (TNA) 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 returns and TNA as reported by CRSP. Let TNA_t^i be the total net asset 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

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

where *MGN* is the increase in total net assets due to mergers during quarter *t.* Note that (1) 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 TNA, while funds that die have outflows equal to their terminal TNA.

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 TNA as of quarter $t-k$. In order to compute the $FLOW$ at date t, we start by looking at the total net asset value of the fund at date $t-k$. Then, for every date s we track the evolution of the fund's counterfactual TNA using:

$$\hat{\mathrm{F}}_s^i = \frac{TNA_{t-k}^i}{TNA_{t-k}^{Agg}}\mathrm{F}_s^{\mathrm{Agg}} \qquad (2)$$

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

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

where $\hat{\mathrm{F}}^i$ and $\widetilde{TNA}^i$ are counterfactual flows and TNA. $\mathrm{F}^{\mathrm{Agg}}$ is the actual aggregate flows for the entire mutual fund sector, while $TNA_{t\text{-}k}^{\mathrm{Agg}}$ is the actual aggregate TNA 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, $\widetilde{TNA}^i$ is automatically zero – all new funds by definition represent new flows. The resulting counterfactual total net asset value $\widetilde{TNA}_t^i$ 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 other details on equations (2) and (3)). We obtain a quarterly time series of counterfactual total net asset values for every fund by repeating the counterfactual exercise every quarter t, and storing the resulting $\widetilde{TNA}_t^i$ 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 TNA's and aggregate flows. For this investor, $q\widetilde{\mathrm{TNA}}_t^i$ 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 (1997) 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 TNA. 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 use this simpler strategy.

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

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

The counterfactual under proportional flows is:

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

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 TNA of the funds. This difference reflects any deviation from value weighting by the TNA of the fund in marking new contributions.

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 the appendix for a few small exceptions). The holdings data in this study run from January 1980 to December 2003.

While the SEC requires mutual funds to disclose their holdings on a semi-annual basis, approximately 60% of funds additionally report quarterly holdings. 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. 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.

A particular data challenge, described further in the appendix, is matching the holdings data to the CRSP mutual fund database. This matching is more difficult in the earlier part of the sample period. Further, the holdings data are notably error-ridden, with obvious typographical errors. The appendix further describes issues of data errors and missing reports.

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

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

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

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

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 TNA for the last k periods, then mutual fund ownership in stock j would be lower by FLOW percent. Stocks with high FLOW are stocks that are owned by mutual funds that have experienced high inflows.

C. Describing the data

Table I shows summary statistics for the different types of data in our sample. Our sample starts in 1980. In Table I we describe statistics for FLOW resulting from funds flows over the past three years, thus the table describes data for flow starting in 1983.

Panel A shows the coverage of our sample as a fraction of the universe of CRSP equity funds and the universe of CRSP common stocks.[1] At the start of the sample, in 1983, we cover less than half of all stocks but 93% of the dollar value of the market (reflecting the fact that mutual funds avoid smaller securities). Our coverage rises over time as the relative size of the mutual fund sector grows substantially during the period. On average, over the entire period our sample contains 97% of the total market capitalization and 69% of the total number of common stocks in CRSP. Our sample of funds includes on average 99% of the total net asset of US equity funds and 92% of the total number of funds.

Panel C shows summary statistics for three year FLOW. FLOW 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.

In interpreting FLOW, 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 any notion of the absolute popularity of stock. For example, FLOW for Alcoa in December 1999 was -4.8%. The negative FLOW does not imply that Alcoa was unpopular with mutual funds, nor does it imply that mutual funds were 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.

D. Appropriate horizons

Table I shows the properties of three year flows. Throughout the paper, we use this three year horizon as our baseline specification, because we are interested in understanding the long-term effects of trading on individual investor wealth. Since we want to understand the net effect of trading, the relevant horizon should depend on the actual time series behavior of fund flows.

Figure 1 shows evidence on the appropriate chronological unit for fund flows. Every quarter, we sort mutual funds based on flows, defined as the dollar inflows/outflows divided by the total net assets at the end of the previous quarter. We assign funds to five quintile portfolios and track the subsequent average flows. We plot the subsequent cumulative difference in flows between high flow funds and low flow funds.[2] Figure 1 shows that mutual fund flows are persistent: funds experiencing high inflows this quarter tend to experience significant higher flows over the subsequent quarters. The total effect is complete approximately two to three years from portfolio formation. Thus, funds flows tend to cumulate over long horizons. Figure 1 shows similar results for sorting stocks based on one quarter FLOW and tracking the subsequent cumulative difference in FLOW between high flow stocks and low flow stocks.

Thus to understand the net effect of fund flows on investor wealth, it is not enough to relate short term flows to short term performance; one must also take into account how the effects of trading cumulate over time. If retail investors as a group were purchasing mutual funds in quarter t and redeem their shares in quarter $t+1$, then the appropriate measure would be one quarter FLOW. Since Figure 1 shows that retail investors as a group are not doing this, longer horizon FLOW is appropriate to study.

II. Flows and stock returns

To test for return predictability, we examine monthly returns in excess of Treasury bills on calendar time portfolios formed by sorting stocks on FLOW. At the beginning of every calendar month, we rank stocks in ascending order based on the latest available FLOW and assign them to one of five quintile portfolios. We compute FLOW over horizons stretching from three months (one quarter, the shortest interval we have for calculating flows) to five years. We rebalance the portfolios every calendar month using value weights.

In Panel A of Table II, we report time series averages of the sorting variable for each portfolio. The rightmost column shows the difference between the high flow stocks and the low flow stocks. The effect of flows on mutual fund ownership is fairly sizable. For the top quintile of three year flows, non-proportional flows raise the aggregate mutual fund ownership by more than 6 percent of the stock's total market capitalization. For the bottom quintile, flows lower ownership by 4 percent (although one cannot tell this from the table, the bottom quintile reflects stocks that are not just experiencing lower-than-average inflows, they are experiencing outflows). The difference between the top and bottom quintiles increases with the time horizon, indicating (consistent with Figure 1) that flows into individual stocks tend to cumulate over time.

Panel B of Table II shows the basic results of this paper. We report returns in month t of portfolios formed by sorting on FLOW in month $t-1$. The rightmost column shows the returns of a zero cost portfolio that holds the top 20 percent high flow stocks and sells short the bottom 20 percent low flow stocks. For every horizon but three months, high flow today predicts low subsequent stock returns. The relation is statistically significant for flow computed over horizon stretching from 6 months to 3 years. This dumb money effect is sizable: stocks with high FLOW as a result of the active reallocation across funds over the past six months to five years underperform low FLOW stocks by between 36 and 85 basis points per month or approximately between 4.3 percent and 10 percent per year, depending upon the horizon of the past flow.

Perhaps surprisingly, Table II shows no solid evidence for the smart money effect in stock returns, even at the shorter horizons where one might expect price momentum to dominate. Gruber (1996) and Zheng (1999) look at quarterly flows and find that high flows predict high mutual fund 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 in section IV; it turns out that one can find specifications with a significant smart money effect at short horizons.

Figure 2 gives an overview of how flow predicts returns at various horizons. We show the cumulative average returns in month $t+k$ on long/short portfolios formed on three month flow in month t. For $k<0$, the figure shows how lagged returns predict today's flows. The figure shows that flows into an individual stock are 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. For $k>0$, the figure shows the dumb money effect as the downward slope of cumulative returns becomes pronounced after six or twelve months. High FLOW stocks severely underperform low FLOW stocks over the course of about two years.

The results in Table II and Figure 2 show that stocks that are overweighted by retail investors due to fund flows tend to have lower subsequent returns. However, in term of measuring the actual returns experienced by mutual funds investors, this evidence doesn't conclusively prove that investors experience returns that are lower due to their active reallocation, 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 VII, we perform this exercise 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. From this perspective, then, individual investors in aggregate are unambiguously dumb.

III. Robustness Tests

A. Controlling for size, momentum, and value

Table III 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. This strategy might be a smart 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 III 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).[3] Here the dumb money effect is substantially reduced, with the coefficient falling from -0.85 to -0.42 for three year flows, still significant but approximately half as large. The right-hand side of Table III shows alphas and the corresponding factor loadings from a Fama and French (1993) three factor regression. Here the reduction of the three year dumb money effect is not as substantial, as the three-year differential return remains sizeable at -0.74. The high and negative coefficient on the HML, the Fama-French value factor, shows that high sentiment stocks tend to be stocks with high market-book.

In panel A of Table IV, 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 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 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.

Panel A of Table IV shows that, generally, neither effect dominates the other. As in Table III, the dumb money effect survives the correction for market-book. The dumb money effect is concentrated within growth stocks, while the value effect is concentrated among high flow stocks. High sentiment growth stocks actually underperform t-bills, while low sentiment growth stocks have very high returns.

Panel B 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). The results are similar to panel A: neither effect subsumes the other. However, the dumb money and value/reversal effect are clearly quite related, and perhaps reflect the same underlying phenomenon.

To summarize, the dumb money effect is not completely explained by the value effect. Up to half of the dumb money effect is explained by value and other characteristics, but a statistically significant portion remains. Neither the dumb money effect nor the value/reversal effect dominates the other. Thus investors hurt themselves by reallocating across mutual funds for two reasons. First, they hurt themselves by overweighting growth stocks. Second, controlling for market-book, they hurt themselves by overweighting stocks that underperform their category benchmarks, and in particular, they pick growth stocks that do especially poorly.

B. Controlling for industry

This section explores a different channel through which individual investor indirectly select stocks with low future returns: industry allocations.[4] We assign each stock to one of 48 industries, based on Fama and French (1997). We examine the extent to which the dumb money effect is an intra-industry vs. an inter-industry phenomenon.

Table V shows results for industries. The left-hand side shows intra-industry returns. We industry-adjust returns in a fashion similar to the DGTW returns on Table III, using the 48 matching industry portfolios. Industry adjusted returns are defined as raw returns minus the returns of the corresponding industry index. These portfolios test the hypothesis that individual investors overweight stocks that underperform their corresponding industry benchmarks. Table

V show that, within industries, there is a significant dumb money effect. By actively reallocating across their mutual funds investments, individual retail investors indirectly overweight stocks that underperform their industry benchmarks. Comparing the results to Table II, about half of the three year dumb money effect is explained by industry performance, with the other half reflecting industry-adjusted performance.

The right hand side of Table V looks at industry portfolios directly. We redo the analysis of Table II, except now we replace individual stocks with the corresponding industry portfolios. For each fund, we compute the portfolio weights in each of the 48 industries, and then we construct the counterfactual ownership as before. Hence, the FLOW for industry s is the actual percent of the industry owned by mutual funds minus the counterfactual percent. We report results for industry excess returns. Every month we sort the 48 industry portfolios using the last available industry FLOW and construct calendar time portfolios as before (with the top quintile containing the top 10 industries each month). This approach shows how individuals earn low returns by overweighting particular industries, showing directly that the dumb money effect is present across industries. Using three year flows, high flow industries underperform low flow industries by 70 basis points or approximately 8.4 percent per year.

To summarize, Table V shows that individual retail investors earn low returns through their mutual funds reallocation in two ways. First, investors tend to indirectly select stocks that underperform their industry benchmark. Second, investors tend to overweight industries with lower subsequent returns.

C. Further robustness tests

Table VI shows the results for different samples of stocks and different methods of calculating returns. First, it shows results for the sample of stocks which have market cap above and below the CRSP median. The dumb money effect tends to be larger for large cap securities, and larger for value weighted portfolios than for equally weighted portfolios. These results may reflect the fact that we use mutual fund holdings to construct the FLOW measure. FLOW is probably a better measure of individual sentiment for stocks mostly held by mutual funds, whose holdings tend to be skewed towards large cap securities.

One concern is that the return predictability in Table II may be driven by initial public offerings. To address this, in Table VI we defined new issues as stocks with less that 24 months of return data on the CRSP tape at the time of portfolio formation. We split the sample by separating out new issues and computing calendar time portfolio as before within the two sub-samples. Table VI shows that excluding new issues only slightly lowers the dumb money effect. Looking at return predictability within new issues, we find that there is a very large and significant dumb money effect. Thus the dumb money effect is much stronger among new issues, perhaps indicating the sentiment is particular relevant for this class of stocks. We further consider issuance in section VI.

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.[5] So the variables in Table II 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 web site 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 VI shows results with the flow variables lagged an additional 12 months. As one might expect given Figure 2, this lagging does not destroy the ability to construct a profitable trading strategy, just moving the effect into the higher rows of the table. Thus the dumb money effect is not primarily about short-term information contained in flows, it is about long-term mispricing.

In unreported results, we have also examined the dumb money effect in different categories of funds. First, we looked at the effect in load fund and no load funds. Second, we looked at the effect across different fund objective categories (aggressive growth, growth, growth & income, and balanced). In all cases the dumb money effect was present and about the same size.

D. Subsample stability

Table VII examines the performance of the strategy over time. Since we only have 23 years of returns for 3-year flows, inference will be naturally be tenuous as we look at subsamples. For each time period, the first row shows the baseline 3-year flow results, while the other rows show different versions of the dumb money effect. First, we split the sample into recessions (as defined by the NBER) and non-recessions. While the dumb money effect appears somewhat higher in recessions, with only 42 recession months, it is difficult to make any strong inference. One clear result is that the dumb money effect is certainly present in non-recession periods.

The next pair of columns split the sample in half, pre-1994 and post-1994. Looking at the baseline result, the dumb money effect is significantly negative in both halves of the sample, although it is much higher in the second half of the sample. It is not clear how to interpret this difference. Although the dumb money effect is more that three times as big in the second half of the sample, the difference between the two mean returns is not significant at conventional levels (we fail to reject the null hypothesis of equality of the two means with a t–statistic of 1.7) and as discussed previously, in the earlier part of the sample both our coverage of stocks and the relative size of the mutual fund industry are lower. Thus one might expect weaker results in the early years of the sample.

The last two pair of columns split the sample pre and post-1998. The dumb money effect is particularly large in the 1999-2003 period (although it is statistically significant excluding this period as well). One interpretation of the time pattern in Table VII is that the period around 2000 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.

Looking at results for the various robustness new issues and industry returns gives similar results. Every number is negative in every subsample, although not always significantly different from zero. Controlling for value (in the DGTW and Fama French rows), the effect is particularly weak in the earlier part of the sample. Looking at the results within or across industries, the effect is a bit more consistent over time. The effect within new issues is very large in all subperiods.

To summarize, the dumb money effect is reasonably robust across time periods, although point estimates are much higher in the second half of the sample. We further example subsample stability in section V, using a portfolio weighting scheme that is arguably less arbitrary and more economically relevant. There, the results for stock returns are much more constant across different time periods.

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 shows how our results relate to the previous work of Zheng (1999) and Gruber (1996). Table VIII 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 value weighted portfolios of funds (where the value weights reflect the TNA of the fund).

We first sort on actual flows minus counterfactual flows. Table VIII 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, the dumb money effect is still strong and we find evidence consistent with a significant smart money effect. 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 3-factor alpha results, where three month inflows predict a positive and significant differential of 35 basis points per month, while three year inflows predict a negative but 30 basis points. Suppose one believes that the Fama-French (1993) model is an appropriate risk adjustment. The fact that the differential is -0.30 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 0.35 percent differential in the first three months, this out-performance 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 funds. 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 aggregate 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 IX 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.

Table IX shows investor flows cause a significant reduction in both average returns and Sharpe ratios earned by mutual fund investors. Panel A shows the results using stock returns. A representative investor who is currently behaving like the aggregate mutual fund sector could increase his Sharpe ratio by 11% (from a monthly Sharpe ratio of 0.132 to 0.146) 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 II, 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 differential returns are 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.

In Panel B, 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. The results in Panel B are slightly stronger. Using mutual fund returns, the reduction in Sharpe ratio due to flows is 17%, and the magnitude of the dumb money effect (measured by R^{ACTUAL} - R^{NOFLOW}) is somewhat higher. 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.

Table IX 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 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 stock returns, this stock picking effect is 0.087 per month, with a t-statistic of 1.9. 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. Looking at fund returns, as usual costs and expenses eat up any stock picking ability managers have, so that the net benefit of stock picking in Table X is -0.03 per month.

B. Economic magnitude

The magnitude of the dumb money effect in on average 7.1 basis points (8.5 or 6.7 basis points depending upon whether one uses fund or stock return). Are 7 basis points per month a large effect? We argue that it is, for two reasons. First, it results in sizeable reductions in Sharpe ratios of 11-17 percent. Second, it is comparable in magnitude to the costs of active fund management. The average expense ratio for a typical mutual fund is around 1% per year, which translates into 8 basis points per month. In this sense, the dumb money effect costs as much as the entire mutual fund industry.

The results in Panel B 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 per year. Of this, almost 70 percent, -0.085, is explained by dumb money effect.[7] A large literature has documented that the mutual fund sector does poorly relative to passive benchmarks (see for example Malkiel, 1995). The results here show that fund flows appear to account for a large fraction of this poor performance. Thus the damage done by actively managed funds comes less from fees and expenses, and more from the wealth-destroying reallocation across funds.

C. Different measures of economic significance

In Table X we explore the robustness of the economic significance in two ways. First, we repeat the basic analysis for different horizons. It turns out that, at any horizon, individual retail investors are reducing their wealth by engaging in active reallocation across mutual funds. Even at the three month horizon, we find no evidence that trading helps investors earn higher returns. The results here are somewhat less sensitive to the choice of time horizon, particularly when calculated using mutual fund returns.

Second, we report the results for different subperiods. The effect is robust and large across all subperiods, indicating that the dumb money effect is not only concentrated in the latest part of the sample period. Again, the results are particularly consistent across time using mutual fund returns.

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 (see also Pontiff and Woodgate, 2005). 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.[8] 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 X 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 stocks when sentiment is high, and repurchase stocks 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 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. Lastly, because issuance is known to be correlated with valuation, we create characteristic-adjusted issuance in the same way we create characteristic-adjusted returns in Table III. The last row of Table XI shows the average deviations of issuance from a group of matching firms with similar size, valuation, and price momentum as of December. The results are about the same as with raw issuance, so that once again value does not subsume the effect of flows.

To understand the economic magnitudes shown in Table XI, it is useful to note from table II that the difference in the sorting variable (three year flow) is about 10 percent between the top and bottom quintile. That is, as a result of active reallocation across mutual funds in the past three years the top quintile has a mutual fund ownership that is on average 10 percent more as a percent of shares outstanding than the bottom quintile. This number is the same units as the numbers in Table XI since both flows and issuance are expressed as a fraction of current shares outstanding. Thus firms with flows that are 10 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 $10 billion in flows by issuing $3 billion in stock. Supply accommodates approximately one third 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 entirely 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 simply by refraining from destructive behavior.

Investors achieve low returns by a combination of different channels: they tend to overweight industries that subsequently perform poorly and overweight growth stocks always. Across industries or growth categories, individual investors indirectly select securities that on average underperform their relative benchmarks. Within new issues, they overweight stocks with especially low subsequent returns. All of the effects above generate poor performance of the stock portfolio investors indirectly hold via their mutual fund investments.

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 benefits from trading, but looking at the aggregate holdings of mutual funds by all individuals, we show that individuals as a whole are hurt by their reallocations.

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 stocks and repurchase stocks. 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.

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. It is clear that any satisfactory theory of the value effect will need to explain three facts. First, value stocks have higher 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

[1] We include delisting returns when available in CRSP. If a firm is delisted but the delisting return is missing, we investigate the reason for disappearance. If the delisting is performance-related, we follow Shumway (1997) and assume a -30 percent delisting return. This assumption does not affect any of the results.

[2] We compute averages in the spirit of Fama and MacBeth (1973): we calculate averages for each month and report time series means. This procedure gives equal weight to each monthly observation

[3] 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.

[4] We would like to thank the referee for suggesting this approach

[5] 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.

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

[7] Of course, this calculation may be misleading because the return earned by the CRSP value

weight portfolio is not a viable free alternative. We have redone the calculation, substituting the return on the Vanguard index fund for R^M (these returns includes fees and costs). In this case, the total wealth destruction is -0.16 instead of -0.12 (reflecting the fact the Vanguard fund outperformed the CRSP value weight portfolio during this period), while the dumb money effect remains of course at -0.085.

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

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Data Appendix

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.

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.

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

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.

The final match used is a union of this initial match file and the sample used by Cohen, Coval and Pastor (2005) (We would like to thank Randy Cohen, Josh Coval and Lubos Pastor for making their match file available. We also thank Antti Petajisto for combining the two matching files and providing us with the final matched sample). Every valid match was compared across the two samples. When the two matches produced different results or no match was found, the funds where checked by hand to determine the correct match using information on fund names, total net assets and holding company names. 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 fund by aggregating the corresponding total 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 fraction of total net assets of the matched funds invested in equities to the dollar value of the corresponding holdings. We multiply the total net assets of the fund to the fraction assets invested in equities as reported by CRSP, and we discard matches where the total asset value of the fund invested in equity differs from the sum of the dollar holdings by more than 30%.

Construction of the counterfactual flows

We assign a counterfactual total 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 $t-k \le s \le t$. Let $TNA_{\mathrm{t\text{-}k}}^{\mathrm{Agg}}$ be the lagged actual aggregate TNA 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:

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

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

For funds that die in quarter $s+1$ (so that their last TNA is quarter s), we set $\hat{\mathrm{F}}_{\mathrm{s+1}}^{\mathrm{i}}$ = $-\widehat{TNA}_{s}^{i}$ and $\widehat{TNA}_{s+h}^{i} = 0$ 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 TNA and set the counterfactual TNA 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 total 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 TNA using the recursion:

$$\tilde{TNA}^{i}_{t} = (1+R^{i}_{t})\tilde{TNA}^{i}_{t-1} + \hat{F}^{i}_{t} \qquad (3)$$

Between 1982 and 1993 fund # 2 dies, hence in the counterfactual world we assign an outflow in 1983 equal to the TNA in 1982 and set the counterfactual TNA to zero thereafter. Note that (2) does not guarantee that counterfactual total 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 $\tilde{TNA}^{i}_{t} = 0$ 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 TNAs occur for only 0.08% 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 TNA, we also merge the lagged TNA of the two funds when we compute the ratio $\frac{TNA^{i}_{t-k}}{TNA^{Agg}_{t-k}}$ used to determine the pro-rata share of the total flows.

Figure 1

This figure shows the average cumulative flows in quarter *t+k* for mutual funds (stocks) sorted on quarterly flows in quarter *t*. At the beginning of every quarter mutual funds (stocks) are ranked in ascending order based on their quarterly flows. Funds (stocks) are assigned to one of five quintile portfolios. We report the cumulative average difference in flows between the top 20% high flows funds (stocks) and the bottom 20% low flows funds (stocks). Funds flows are defined as dollar inflows/outflows divided by the total net assets of the fund at the end of the previous quarter. Stocks flows are defined as the actual percent of the stock owned by mutual funds minus the counterfactual percent.

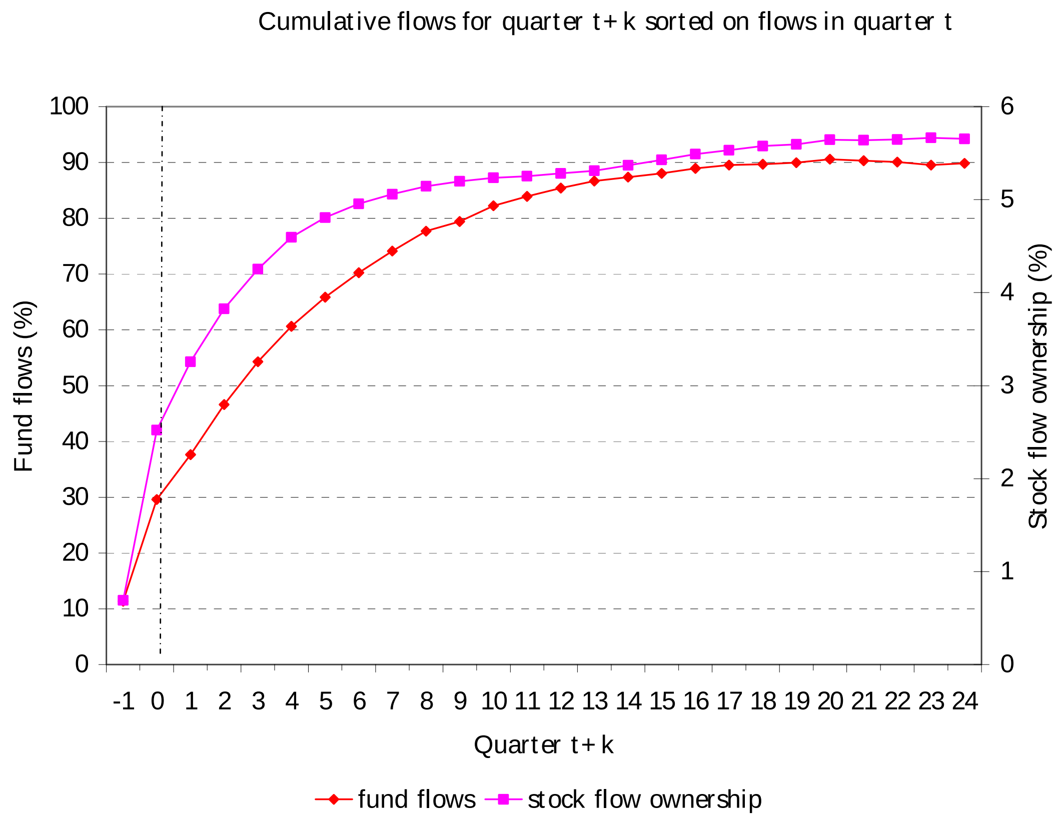

Figure 2

This figure shows the average cumulative returns in month *t+k* on a long/short portfolio formed on three month flow in month t. 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 quintile 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 value weights. The figure shows average cumulative returns over time of a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks.

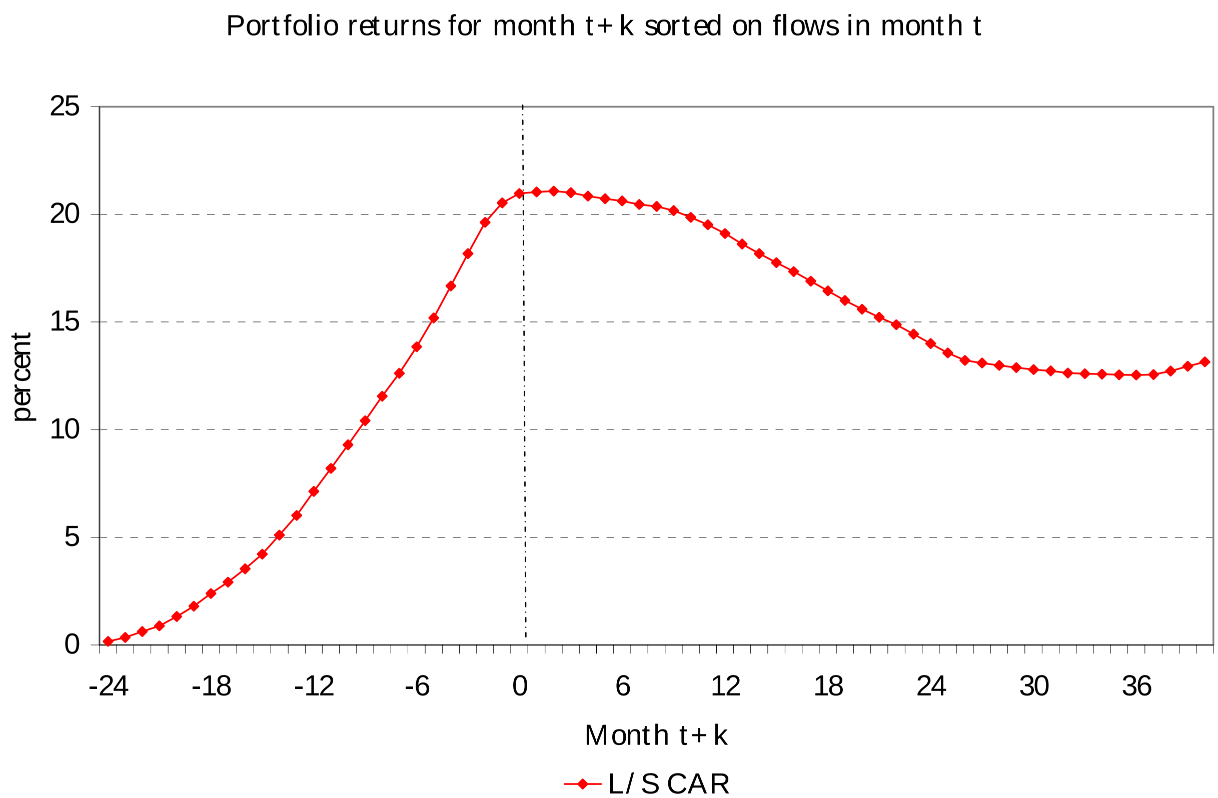

Table I: Summary statistics

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. TNA 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 percent of the stock held by mutual funds (the stock's actual total dollar value of mutual fund holdings divided by the stock's market capitalization). $\hat{z}$ is counterfactual z using a three year horizon, as defined in the text.

	Min	Max	Mean	Std Dev	Mean	
	Full sample, 1983-2003				1983	2003
Panel A: Time-series (annual observations, 1983-2003)						
Number of funds in the sample per year	285	9087	2159	2370	285	9087
Number of stocks in the sample per year	2710	6803	4690	1516	2710	4974
Percent coverage of stock universe (EW)	48.5	92.2	68.7	18.3	48.5	92.2
Percent coverage of stock universe (VW)	92.8	99.4	97.4	2.3	92.8	99.4
Percent coverage of fund universe (EW)	88.0	99.0	92.2	3.0	88.0	99.0
Percent coverage of fund universe (VW)	94.01	99.9	98.9	1.3	94.01	95.01
Panel B: Funds (Pooled year-fund observations, 1983-2003)						
TNA, millions of dollars	0.04	109,073	820	3331	245	746
Number of holdings per fund	1	4162	153	257	71	186
x (Percent of fund universe, actual)	0.00	7.86	0.13	0.41	0.49	0.05
$\hat{x}$ (Percent of fund universe, counterfactual)	0.00	11.4	0.17	0.52	0.66	0.06
Panel C: Stocks (Pooled stock-fund observations, 1983-2003)						
Number of funds per stock	1	1202	30	65	5	60
z (Percent owned by funds, actual)	0.00	99.35	9.10	10.13	6.09	10.56
$\hat{z}$ (Percent owned by funds, counterfactual)	0.00	234.32	9.21	4.56	5.02	8.23
FLOW = z - $\hat{z}$	-188	86.98	0.54	5.61	1.40	1.45

Table II: Calendar time portfolio excess returns and FLOW, 1980 – 2003

This table shows the average FLOW and excess returns for calendar time portfolios sorted on past 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. 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 quintile 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 value weights. In Panel A we report averages of the sorting variable for each cell. Flow is in percent. In Panel B we report average portfolio returns minus Treasury bill returns. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

Panel A: flow	Q1(low)	Q2	Q3	Q4	Q5(high)	Q5-Q1
3-month flow	-0.551	-0.156	-0.025	0.121	0.908	1.459
6-month flow	-0.993	-0.266	-0.025	0.248	1.653	2.646
1-year flow	-1.768	-0.437	-0.002	0.520	2.856	4.624
3-year flow	-4.088	-0.788	0.251	1.652	6.047	10.135
5-year flow	-6.319	-1.223	0.438	2.362	8.014	14.333

Panel A: flow	Q1(low)	Q2	Q3	Q4	Q5(high)	L/S
3-month flow	**0.628**	**0.648**	0.503	0.546	0.661	0.033
	[1.99]	[2.28]	[1.77]	[1.86]	[1.82]	[0.13]
6-month flow	**0.753**	**0.684**	**0.689**	0.544	0.390	**-0.363**
	[2.52]	[2.43]	[2.52]	[1.87]	[1.18]	[-2.08]
1-year flow	**0.909**	**0.848**	**0.760**	**0.590**	0.408	**-0.501**
	[3.02]	[3.03]	[2.79]	[1.97]	[1.18]	[-2.61]
3-year flow	**1.026**	**0.884**	**0.695**	0.450	0.180	**-0.846**
	[3.19]	[3.00]	[2.37]	[1.34]	[0.44]	[-3.30]
5-year flow	**0.880**	**0.748**	0.671	0.501	0.486	-0.394
	[2.67]	[2.38]	[1.85]	[1.36]	[1.11]	[-1.35]

Table III: Controlling for value, size, and momentum

This table shows calendar time portfolio abnormal returns. We report average characteristic adjusted returns and Fama and French (1993) alphas. DGTW 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. Fama French alpha is defined as the intercept in a regression of the monthly excess returns on the three factors of Fama and French (1993). Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

	DGTW			Fama French alpha			Loadings on L/S			
	Q1	Q5	L/S	Q1	Q5	L/S	MKT	SMB	HML	R2
3-month flow	-0.067	-0.016	0.051	-0.197	0.113	0.309	**-0.111**	**0.390**	**-0.498**	0.302
	[-1.08]	[-0.17]	[0.43]	[-1.55]	[0.85]	[1.37]	[-1.97]	[5.45]	[-5.84]	
6-month flow	-0.024	**-0.193**	**-0.169**	-0.030	-0.172	-0.143	-0.056	**0.136**	**-0.426**	0.291
	[-0.43]	[-2.75]	[-1.99]	[-0.30]	[-1.88]	[-0.92]	[-1.47]	[2.78]	[-7.30]	
1-year flow	0.027	**-0.238**	**-0.265**	0.092	**-0.238**	-0.331	-0.021	**0.139**	**-0.383**	0.226
	[0.42]	[-3.14]	[-2.68]	[0.93]	[-2.13]	[-1.86]	[-0.48]	[2.49]	[-5.74]	
3-year flow	0.093	**-0.329**	**-0.422**	**0.260**	**-0.474**	**-0.735**	0.074	**0.151**	**-0.426**	0.229
	[1.10]	[-3.33]	[-2.96]	[2.09]	[-3.14]	[-3.14]	[1.27]	[2.07]	[-4.90]	
5-year flow	0.013	-0.168	-0.181	0.083	-0.162	-0.245	0.007	**0.526**	**-0.525**	0.541
	[0.17]	[-1.46]	[-1.17]	[0.75]	[-1.15]	[-1.19]	[0.14]	[8.59]	[-6.99]	

Table IV: Flows vs. value and 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 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 value weights. We report average excess returns. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

Panel A: 3-year flow and value		Low flow				High flow	High flow minus low flow
		Q1	Q2	Q3	Q4	Q5	L/S
Value	Q1	**0.738**	**0.904**	**0.968**	**0.828**	**0.786**	0.048
		[2.10]	[2.50]	[2.66]	[2.18]	[2.15]	[0.17]
	Q2	**0.812**	**0.961**	**0.703**	**0.704**	0.500	-0.312
		[2.57]	[3.15]	[2.13]	[2.21]	[1.52]	[-1.28]
	Q3	**1.011**	**0.692**	0.573	0.536	**0.809**	-0.202
		[2.91]	[2.28]	[1.86]	[1.63]	[2.05]	[-0.84]
	Q4	**0.893**	**0.670**	0.517	0.697	0.472	**-0.421**
		[2.46]	[2.01]	[1.18]	[1.84]	[1.07]	[-2.51]
Growth	Q5	**1.322**	**0.792**	0.611	0.480	-0.179	**-1.501**
		[3.23]	[2.23]	[1.49]	[1.13]	[-0.33]	[-4.33]
Growth minus value	L/S	0.583	-0.112	-0.358	-0.347	**-0.966**	
		[1.75]	[-0.34]	[-0.85]	[-1.13]	[-2.34]	
Panel B: 3-year flow and reversals							
Loser	Q1	**1.117**	**1.408**	1.171	**1.163**	1.059	-0.059
		[2.25]	[2.39]	[1.90]	[2.13]	[1.90]	[-0.15]
	Q2	**1.415**	**1.044**	**1.158**	0.613	0.712	**-0.704**
		[3.66]	[2.60]	[2.94]	[1.52]	[1.61]	[-2.76]
	Q3	**1.162**	**1.179**	0.601	**0.712**	0.591	**-0.570**
		[3.57]	[3.62]	[1.84]	[2.28]	[1.56]	[-2.57]
	Q4	**0.770**	**0.853**	**1.094**	**0.680**	0.511	-0.259
		[2.47]	[2.96]	[3.60]	[2.41]	[1.53]	[-1.27]
Winner	Q5	**0.945**	**0.839**	0.644	0.471	0.109	**-0.836**
		[2.67]	[2.43]	[1.93]	[1.25]	[0.25]	[-2.98]
Winner minus loser	L/S	-0.172	-0.568	-0.527	-0.692	**-0.950**	
		[-0.45]	[-1.11]	[-0.99]	[-1.80]	[-2.39]	

Table V: Industry returns: calendar time portfolio, excess returns 1980 – 2003

This table shows calendar time stock returns and industry returns. We assign each CRSP stock to one of 48 industry portfolio at the end of June of each year. Industry adjusted returns are defined as raw monthly returns minus the returns of the corresponding industry portfolio. For industry returns, at the beginning of every calendar month industries are ranked in ascending order based on the last available 3-year flow. Industries are assigned to one of five quintile portfolios. L/S is a zero cost portfolio that holds the top 10 industries and sells short the bottom 10 industries. We report average excess returns. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	Q1	Q5	L/S	Q1	Q5	L/S
	Industry adjusted returns			Industry returns		
3 month flow	-0.187	-0.233	-0.046	**0.776**	**0.655**	-0.121
	[-1.01]	[-1.21]	[-0.30]	[2.41]	[2.03]	[-0.48]
6 month flow	-0.139	**-0.394**	**-0.255**	**0.828**	0.608	-0.220
	[-0.74]	[-2.02]	[-2.22]	[2.80]	[1.93]	[-1.04]
1 year flow	-0.121	**-0.420**	**-0.300**	**0.987**	0.594	-0.393
	[-0.63]	[-2.03]	[-2.16]	[3.20]	[1.83]	[-1.68]
3-year flow	-0.008	-0.411	**-0.403**	**1.113**	0.417	**-0.696**
	[-0.04]	[-1.89]	[-2.36]	[3.62]	[1.17]	[-2.39]
5-year flow	-0.132	-0.329	-0.197	**0.991**	0.267	**-0.724**
	[-0.58]	[-1.50]	[-0.98]	[3.11]	[0.68]	[-2.31]

Table VI: Robustness tests

This table shows calendar time returns of a zero cost portfolio that holds the top 20% high flow stocks and sells short the bottom 20% low flow stocks. Larger cap stocks are all stocks with market capitalization above the median of the CRSP universe that month, smaller cap are below median. New issues are defined as stocks with less than 24 months of return data on the CRSP tape at the time of portfolio formation. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

	Smaller cap	*Larger cap*	*Equal weight*	*Exclude new issues*	*Only new issues*	*Flow lagged 12 months*
3 month flow	-0.011	0.062	0.071	0.075	0.265	**-0.594**
	[-0.06]	[0.21]	[0.37]	[0.32]	[0.64]	[-2.70]
6 month flow	-0.048	**-0.394**	-0.204	**-0.333**	**-0.344**	**-0.678**
	[-0.34]	[-2.02]	[-1.95]	[-2.04]	[-1.24]	[-2.99]
1 year flow	-0.174	**-0.505**	**-0.304**	**-0.457**	**-0.626**	**-0.674**
	[-1.10]	[-2.44]	[-2.21]	[-2.49]	[-2.06]	[-3.00]
3-year flow	**-0.421**	**-0.824**	**-0.502**	**-0.755**	**-1.413**	-0.023
	[-2.09]	[-3.18]	[-3.26]	[-3.11]	[-3.99]	[-0.12]
5-year flow	**-0.507**	-0.475	-0.173	-0.317	**-1.185**	-0.031
	[-2.49]	[-1.58]	[-1.38]	[-1.17]	[-2.88]	[-0.14]

Table VII: Subsample stability

This table shows calendar time returns of a zero cost portfolio that holds the top 20% high flow stocks (industries) and sells short the bottom 20% low flow stocks (industries). Industry adjusted returns are defined as raw monthly returns minus the returns of the corresponding industry portfolio. DGTW 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. Fama French alpha is defined as the intercept in a regression of the monthly excess returns on the three factors of Fama and French (1993). New issues are defined as stocks with less than 24 months of return data on the CRSP tape at the time of portfolio formation. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

Panel A: time period	*Exclude NBER recessions*	*Only NBER recessions*	*83-93*	*94-03*	*83-98*	*99-03*
# of months	210	42	132	120	192	60
Stock returns	**-0.818**	-1.183	**-0.397**	**-1.294**	**-0.501**	**-1.879**
	[-3.34]	[-0.73]	[-2.06]	[-2.80]	[-2.79]	[-1.99]
DGTW	**-0.353**	-0.871	-0.101	**-0.731**	-0.145	**-0.796**
	[-2.52]	[-1.14]	[-0.62]	[-3.37]	[-1.08]	[-2.00]
Fama French alpha	**-0.690**	-1.074	-0.168	**-1.420**	-0.224	**-1.609**
	[-2.99]	[-1.06]	[-0.79]	[-3.81]	[-1.29]	[-2.39]
Industry adjusted returns	**-0.349**	-1.070	-0.225	**-0.582**	-0.259	-0.834
	[-2.09]	[-1.10]	[-1.43]	[-1.97]	[-1.92]	[-0.83]
Industry returns	**-0.700**	-0.641	**-0.580**	-0.811	**-0.584**	-1.031
	[-2.32]	[-0.55]	[-2.46]	[-1.52]	[-2.57]	[-1.03]
Exclude new issues	**-0.733**	-1.017	**-0.363**	**-1.146**	**-0.463**	-1.628
	[-3.16]	[-0.65]	[-1.98]	[-2.63]	[-2.64]	[-1.63]
Only new issues	**-1.260**	-3.297	**-0.865**	**-1.961**	**-0.843**	**-3.124**
	[-3.56]	[-1.85]	[-2.41]	[-3.23]	[-3.00]	[-3.12]

Table VIII: 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 value weights. Value weights are compute using total net assets. 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 excess returns and Fama and French (1993) alphas. Fama French alpha is defined as the intercept in a regression of the monthly excess returns on the three factors of Fama and French (1993). Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

	Sorted on $x-\hat{x}$ (actual vs counterfactual size of fund)						Sorted On raw flows	
	Excess returns			Fama-French alpha			Excess returns	Fama-French alpha
	Q1	Q5	L/S	Q1	Q5	L/S	L/S	L/S
3 month flow	0.414	**0.706**	0.292	**-0.196**	0.152	**0.348**	0.241	**0.352**
	[1.52]	[2.32]	[1.68]	[-2.76]	[1.79]	[2.93]	[1.69]	[3.00]
6 month flow	0.432	0.593	0.161	**-0.181**	0.087	**0.268**	0.132	**0.272**
	[1.62]	[1.93]	[0.87]	[-2.66]	[1.01]	[2.34]	[0.93]	[2.49]
1 year flow	**0.541**	0.432	-0.109	-0.097	-0.023	0.074	-0.171	0.002
	[2.01]	[1.42]	[-0.78]	[-1.37]	[-0.28]	[0.44]	[-1.19]	[0.02]
3-year flow	**0.677**	0.366	**-0.311**	0.049	**-0.211**	**-0.260**	**-0.292**	**-0.241**
	[2.35]	[1.20]	[-2.93]	[0.63]	[-3.26]	[-2.78]	[-2.70]	[-2.39]
5-year flow	**0.741**	0.491	**-0.250**	0.021	**-0.122**	-0.143	**-0.184**	-0.112
	[2.47]	[1.57]	[-2.51]	[0.28]	[-2.42]	[-1.91]	[-2.22]	[-1.55]

Table IX: Economic significance for the aggregate mutual fund investor

This table shows 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.

Panel A: using stock returns		*Mean*	*t-stat*	*SR*
Actual excess return on mutual fund holdings	$R^{ACTUAL} - R^F$	**0.657**	2.05	0.132
Counterfactual excess return on mutual fund holdings	$R^{NOFLOW} - R^F$	**0.727**	2.27	0.146
Market excess returns	$R^M - R^F$	**0.651**	2.26	0.143
Net benefit of mutual funds	$R^{ACTUAL} - R^M$	**0.018**	0.43	0.028
Dumb money effect	$R^{ACTUAL} - R^{NOFLOW}$	**-0.069**	-4.10	-0.269
Stock picking	$R^{NOFLOW} - R^M$	0.087	1.90	0.123
Panel B: Using mutual fund returns		*Mean*	*t-stat*	*SR*
Actual excess return on mutual funds	$R^{ACTUAL} - R^F$	0.502	1.75	0.113
Counterfactual excess returns on mutual funds	$R^{NOFLOW} - R^F$	**0.587**	2.08	0.133
Net benefit of mutual funds	$R^{ACTUAL} - R^M$	**-0.117**	-3.28	-0.210
Dumb money effect	$R^{ACTUAL} - R^{NOFLOW}$	**-0.085**	-4.09	-0.262
Stock picking	$R^{NOFLOW} - R^M$	-0.032	-0.92	-0.059

Table X: Robustness tests for economic significance of flows

This table shows calendar time portfolio returns for different horizons. 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.

$R^{ACTUAL} - R^{NOFLOW}$	*All sample*	*Exclude NBER recessions*	*Only NBER recessions*	*83-93*	*94-03*	*83-98*	*99-03*
Panel A: Using stock returns							
3 month flow	-0.015	-0.018	0.024	**-0.036**	0.007	**-0.036**	0.048
	[-1.23]	[-1.46]	[0.43]	[-2.16]	[0.38]	[-2.64]	[1.94]
6 month flow	-0.019	-0.024	0.038	**-0.038**	-0.000	**-0.039**	0.041
	[-1.54]	[-1.89]	[0.63]	[-2.27]	[-0.01]	[-2.95]	[1.39]
1 year flow	**-0.039**	**-0.040**	-0.015	**-0.050**	-0.028	**-0.050**	-0.003
	[-2.69]	[-2.80]	[-0.21]	[-2.92]	[-1.19]	[-3.75]	[-0.08]
3-year flow	**-0.069**	**-0.069**	-0.069	**-0.061**	**-0.077**	**-0.064**	**-0.084**
	[-4.17]	[-4.10]	[-0.89]	[-2.64]	[-3.24]	[-3.69]	[-2.03]
5-year flow	**-0.059**	**-0.058**	-0.069	**-0.061**	**-0.058**	**-0.071**	-0.024
	[-2.93]	[-2.85]	[-0.72]	[-2.18]	[-1.96]	[-3.43]	[-0.46]
Panel B: Using mutual fund returns							
3 month flow	**-0.042**	**-0.040**	-0.068	**-0.046**	**-0.037**	**-0.042**	-0.041
	[-2.89]	[-2.63]	[-1.38]	[-2.11]	[-1.98]	[-2.58]	[-1.31]
6 month flow	**-0.045**	**-0.042**	-0.079	**-0.050**	-0.039	**-0.044**	-0.047
	[-2.98]	[-2.66]	[-1.73]	[-2.25]	[-1.94]	[-2.65]	[-1.38]
1 year flow	**-0.055**	**-0.054**	-0.067	**-0.056**	**-0.055**	**-0.050**	-0.071
	[-3.23]	[-3.00]	[-1.54]	[-2.35]	[-2.21]	[-2.82]	[-1.63]
3-year flow	**-0.085**	**-0.081**	-0.147	**-0.063**	**-0.108**	**-0.057**	**-0.173**
	[-4.09]	[-3.79]	[-1.51]	[-2.49]	[-3.25]	[-3.00]	[-2.84]
5-year flow	**-0.074**	**-0.068**	-0.145	-0.050	**-0.094**	**-0.054**	-0.127
	[-2.97]	[-2.64]	[-1.43]	[-1.80]	[-2.39]	[-2.59]	[-1.75]

Table XI: 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 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. DGTW characteristic adjusted issuance is defined as raw issuance minus the average issuance on an equally weighted portfolio of all CRSP firms with non-missing flows in the same size, market-book, and one year momentum quintile.

	Low flow				*High flow*	*High flow Minus low flow*
	Q1	Q2	Q3	Q4	Q5	
Raw issuance	**1.828**	**0.823**	**0.896**	**1.607**	**3.162**	**1.334**
	[7.73]	[2.74]	[2.80]	[4.95]	[6.35]	[2.85]
Trimmed issuance	**1.959**	**1.017**	**0.974**	**1.647**	**3.248**	**1.289**
	[8.81]	[3.72]	[3.27]	[5.09]	[6.53]	[2.69]
Raw issuance 1981-1993	**1.394**	0.179	0.078	**0.922**	**2.387**	**0.992**
	[4.30]	[0.49]	[0.21]	[2.77]	[4.68]	[2.13]
Raw issuance 1994-2004	**2.262**	**1.466**	**1.715**	**2.293**	**3.937**	**1.675**
	[7.56]	[3.74]	[4.40]	[4.77]	[4.88]	[2.03]
DGTW adjusted issuance	**-0.654**	0.012	0.120	-0.110	0.239	**0.893**
	[-3.63]	[0.08]	[0.96]	[-1.03]	[1.68]	[3.99]

Table A.1: Hypothetic example showing counterfactual calculation

Actual data from individual funds	*Year*	*1980*	*1981*	*1982*	*1983*	*1985*
Returns	Fund 1	10%	10%	5%	10%	5%
	Fund 2	-5%	10%	-10%		
	Fund 3			10%	10%	5%
TNA	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						
TNA	Agg.	150	315	457	494	669
FLOW	Agg.	0	150	140	6	150
TNA, last year, of funds existing this year	Agg.		150	315	313	494
FLOW of non-dying funds	Agg.		150	140	150	150
Counterfactual data						
TNA	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