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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.

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1. Introduction

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 three 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 to 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; 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, 2006; and Polk and Sapienza, 2008). 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 good candidates 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 to 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 skills 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 the company increases 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 by 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. Wermers (1999, 2004) presents evidence consistent with flow-related additions to existing positions pushing up stock prices. Coval and Stafford (2007) found evidence of price pressure in securities held in common by distressed funds when managers are forced to unwind their positions in response to large outflows, or expand existing positions in response to large inflows. We do not test this hypothesis nor draw a causal link between the price impact of individual funds and future stocks returns. Instead, the hypothesis we wish to test is that stocks owned by funds with big inflows are overpriced. We use fund flows to construct a measure of investors' demand for the underlying securities and test the hypothesis that stocks ranking high in popularity have low future returns. 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 2 discusses the basic measure of sentiment. Section 3 looks at the relation between flows and stock returns. Section 4 looks at a variety of robustness tests. Section 4 puts the results in economic context, showing the magnitude of wealth destruction caused by flows. Section 6 looks at issuance by firms. Section 7 presents conclusions.

2. 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 is 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 billion in assets and a value fund with \$80 billion. Suppose at quarter 1, the technology fund has an inflow of \$11 billion and has capital gains of \$9 billion (bringing its total assets to \$40 billion), while the value fund has an outflow of \$1 billion and capital gains of \$1 billion (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 billion in Cisco. If Cisco has \$16 billion 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 billion in assets and the total inflow is \$10 billion, 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 billion (giving it total assets of \$31 billion), while the value fund would receive (.80)*(10) = \$8 billion (giving it total assets of \$89 billion). In the counterfactual world the total investment in Cisco is given by (.1)*(31) = \$3.1 billion, 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 5, we discuss the effects of flows on investor wealth and consider an individual investor (who is too small to influence 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.

2.1 Flows

We calculate mutual fund flows using the CRSP 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.[1] 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:

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

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

$$t - k \leq s \leq t$$

where $\hat{\mathrm{F}}^{\mathrm{i}}$ and $\widehat{TNA}^{\mathrm{i}}$ are counterfactual flows and TNA. $\mathrm{F}^{\mathrm{Agg}}$ is the actual aggregate flows for the entire mutual fund sector, while $TNA_{\mathrm{t-k}}^{\mathrm{Agg}}$ is the actual aggregate TNA at date *t-k*. Eq. (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, $\widehat{TNA}^{\mathrm{i}}$ is automatically zero–all new funds by definition

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[1] We computed our measures under the alternative assumption of middle-of-period flows and found no effect on the main results.

represent new flows. The resulting counterfactual total net asset value $\widehat{TNA}_t^i$ 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 Eq. (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 $\widehat{TNA}_t^i$ 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 fund 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, $q\widehat{\mathrm{TNA}}_t^i$ 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 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 assets of fund i in month t as a percentage of total assets of the mutual fund sector:

$$x_{it} = \frac{TNA_t^i}{TNA_t^{Agg}} . \tag{4}$$

The counterfactual under proportional flows is:

$$\hat{x}_{it} = \frac{\widehat{TNA}_t^i}{\widehat{TNA}_t^{Agg}} . \tag{5}$$

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 making new contributions.

2.2 Holdings

Thomson Financial provides the CDA/Spectrum mutual funds database, which includes all registered domestic mutual funds filing with the SEC. 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 date. A typical fund-quarter-stock observation would be as follows: as of March 30, 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 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.[2]

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

$$z_{jt} = \left(\sum_i x_{it} \cdot w_{ijt} \cdot TNA_t^{Agg} \right) / MKTCAP_{jt} \tag{6}$$

where $MKTCAP_{jt}$ is the market capitalization of firm j at date t. The ownership that would have occurred with proportional flows into all funds and unchanged fund stock allocation and stock prices would be

$$\hat{z}_{jt} = \left(\sum_i \hat{x}_{it} \cdot w_{ijt} \cdot TNA_t^{Agg} \right) / MKTCAP_{jt} \,. \tag{7}$$

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

$$FLOW_{jt} = z_{jt} - \hat{z}_{jt} = \left\{ \sum_i \left[x_{it} - \hat{x}_{it} \right] \cdot w_{ijt} \cdot TNA_t^{Agg} \right\} / MKTCAP_{jt} \,. \tag{8}$$

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 flowed 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.

2.3 Describing the data

Table 1 shows summary statistics for the different types of data in our sample. Our

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[2] The Appendix of the NBER version of this paper, Frazzini and Lamont (2005), describes the matching process, issues of data errors, and missing reports.

sample starts in 1980. In Table 1 we describe statistics for FLOW resulting from fund flows over the past three years, thus the table describes data for flows 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. 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 U.S. 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.

2.4 Appropriate horizons

Table 1 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.

Fig. 1 shows evidence on the appropriate chronological unit for fund flows. Every quarter, we sort mutual funds based on flows, defined as net dollar inflows divided by TNA 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.[3] Fig. 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, fund flows tend to cumulate over long horizons. Fig. 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

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[3] 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.

quarter FLOW. Since Fig. 1 shows that retail investors as a group are not doing this, longer horizon FLOW is appropriate to study.

3. 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 2, 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% of the stock's total market capitalization. For the bottom quintile, flows lower ownership by 4% (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 Fig. 1) that flows into individual stocks tend to cumulate over time.

Panel B of Table 2 shows the basic results of this paper. We report returns in month *t* of portfolios formed by sorting on the last available FLOW as of month *t-1*. The rightmost column shows the returns of a zero cost portfolio that holds the top 20% high flow stocks and sells short the bottom 20% 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 horizons stretching from six months to three 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 to 10% per year, depending upon the horizon of the past flow.

Perhaps surprisingly, Table 2 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 4.5.

Fig. 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 2 and Fig. 2 show that stocks that are overweighted by retail investors due to fund flows tend to have lower subsequent returns. However, in terms of measuring the actual returns experienced by mutual funds investors, this evidence does not 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 5, 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.

4. Robustness Tests

4.1 Controlling for size, momentum, and value

Table 3 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 3 shows results where returns have been adjusted to control for value, size, and momentum. Following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW), 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).[4]

[4] 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 equally weighted and the quintiles are defined with respect to the entire universe in that month.

Using DGTW returns, the dumb money effect is substantially reduced, with the coefficient falling from -0.85% to -0.42% per month for three-year flows, still significant but approximately half as large. The right-hand side of Table 3 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% per month. 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 4, 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 4 shows that, generally, neither effect dominates the other. As in Table 3, 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.

4.2 Buy-and-hold long-term returns

The calendar time portfolios reported so far are rebalanced every month. In Fig. 3, we show a slightly different concept, buy-and-hold returns. For each stock, we calculate the k-month ahead total return (for example, the return over the next 36 months).[5] At the beginning of each quarter, we sort stocks based on past three-month flow and calculate the value weighted average of this long-term return for both the high FLOW and low FLOW stocks. We then take the difference between these two returns, and report the time-series average of this difference over the entire sample period.

In addition to reporting buy-and-hold (instead of calendar time portfolio) returns, we also use a slightly different risk adjustment procedure to address concerns that the raw portfolios and the matching portfolios are constructed using different information.[6] As with the flow-based

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[5] Both here and everywhere else, 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% delisting return. This assumption does not substantially affect any of the results. When calculating long-term returns, when a firm exits the database, we reinvest its weight into the remaining stocks in the portfolio.

[6] As noted in Footnote 4, in our previous results the DGTW portfolios are formed monthly.

portfolios, we calculate the buy-and-hold returns for the matching DGTW returns. We construct both the flow-based portfolios and the matching DGTW portfolios at the same frequency. Fund flows are available quarterly in our data, so we refresh both the dumb money portfolio and the matching DGTW portfolios quarterly. This procedure puts the dumb money and characteristic-matched portfolios on an equal footing.[7]

Given the fact that long-run abnormal returns can be very sensitive to the benchmarking technique used, we also report results for an alternative risk adjustment. Following Barber and Lyon (1997) we measure abnormal return comparing the return of a stock to the return of a single control stock. Every quarter, we first identify all firms with a market value of equity between 70% and 130% of the market value of equity of the sample firm; from this set of firms, we then rank potential matches according to book to market and return in the previous twelve months. We sum ranks across the different characteristics, and select the lowest rank as the matching stock. We maintain the match until the next portfolio rebalancing or the delisting date. If a match becomes unavailable at a given point because of delisting then from that point forward it is replaced by the second lowest rank stock. This procedure ensures that there is no look ahead bias.

Fig. 3 reports this difference in buy-and-hold returns in event-time in the 36 months subsequent to the formation date, using both raw, DGTW-adjusted and single match-adjusted long-term returns. Looking at raw returns, the results are similar to Fig. 2. Stocks with high inflows this quarter underperform stocks with low inflows this quarter by about 9% over the subsequent three years.

Looking at DGTW-adjusted buy-and-hold returns, the results are similar to Table 3.

[7] We also re-ran Table 3 where all portfolios including DGTW matching portfolios were refreshed quarterly. The results were virtually the same (for example, the three-year differential returns went from -0.422% per month in Table 3 to -0.414% per month).

Table 3 showed that DGTW adjustment reduces the total effect by about half. Fig. 3 shows DGTW adjustment reducing the effect by somewhat more than half, with high flow stocks underperforming by an adjusted 3% over the next three years. As in Table 3, this result reflects the fact that inflows tend to go to growth stocks, which have low average returns. Using a single control stock leads to very similar results.

4.3 Further robustness tests

Table 5 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 held mostly by mutual funds, whose holdings tend to be skewed towards large cap securities.

One concern is that the return predictability in Table 2 may be driven by initial public offerings. To address this, in Table 5 we define new issues as stocks with less than 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 5 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 particularly relevant for this class of stocks. We further consider issuance in Section 6.

One might ask whether the dumb money effect is an implementable strategy for outside investors using information available in real time. In constructing calendar time portfolios we use the end of quarter file date (FDATE) assigned by Thomson Financial. The mutual funds holdings data reflect both a "vintage" file date and a report date (RDATE). The report date is the calendar date when a snapshot of the portfolio is recorded. These holdings eventually become public information and the statutory maximum delay in filing after the report date is 60 days. Thomson Financial assigns file dates (FDATE) to the corresponding quarter ends of the filings and these dates do not correspond to the actual filing date with the SEC. As a result, if the lag between the report date and Thomson's file date is shorter than 60 days, these holdings are not public information on Thomson's file date.[8]

In our sample, only in 53.15% of fund-quarter observations is the Thomson's file date more than 60 days beyond the report date. Thus, although our methodology does involve some built-in staleness of flows, not all the variables in Table 2 are in the information set of any investor who has access to all the regulatory filings and reports from mutual funds, as they are filed with the SEC.

To address this issue, Table 5 shows results with the flow variables lagged an additional 12 months. As one might expect, given Fig. 2, this lagging does not destroy the ability to construct a profitable trading strategy. 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 funds and no load funds. Second, we looked at the effect across different fund objective categories (aggressive growth, growth, growth

[8] Furthermore, currently, holdings data appear on the SEC Edgar System on the business day following a filing, but information lags were probably longer at the beginning of the sample period.

& income, and balanced). In all cases the dumb money effect was present and about the same size.

In further unreported results, we also examined the extent to which the dumb money effect is an intra-industry vs. an inter-industry phenomenon. We found that about half of the three-year dumb money effect is explained by industry performance, with the other half reflecting industry-adjusted performance. Thus, investors tend to indirectly select stocks that underperform their industry benchmark, and they also tend to overweight industries with lower subsequent returns.

4.4 Subsample stability

Table 6 examines the performance of the strategy over time. Since we only have 23 years of returns for three-year flows, inference will naturally be tenuous as we look at subsamples. For each time period, the first row shows the baseline three-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 splits 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 than 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 pair of columns splits 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 6 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 specifications 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. 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 examine subsample stability in Section 5, 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.

4.5 Comparison to prior results

The prior literature has focused largely on how flows predict short-horizon returns. Warther (1995), for example, looks at aggregate flows and the aggregate stock market and found some evidence that high flows today predict high returns over the next four weeks. Similarly, Zheng (1999) and Gruber (1996) largely focus on how flows predict returns over the next few months. Looking at Fig. 3 and the first row of Tables 2 and 3, one can see a bit of evidence for this smart money effect at the three-month horizon, especially when adjusting for the value effect.

A previous version of this paper, Frazzini and Lamont (2005), examined mutual fund returns to show how our results relate to the previous work of Zheng (1999) and Gruber (1996).[9] Using mutual fund returns instead of stock returns, we found the dumb money effect is still strongly statistically significant at the three-year horizon. However, in contrast to the results using stock returns, the smart money effect comes in more strongly at the three-month horizon, and in some specifications it is statistically significant.

How should one reconcile these different results at different horizons? Whether behavior is "smart" or "dumb" depends on how it affects ultimate wealth. Despite the fact that individuals may earn positive returns in the first three months after reallocation, we argue this out-performance is wasted because the individuals as a group are not following a dynamic strategy of buying the best-performing funds, holding them for a quarter, and then selling them. As revealed in Fig. 1, they are instead 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. 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.

5. Economic significance to the aggregate investor

5.1 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

[9] Although Frazzini and Lamont (2005) had a less complete database than this paper, the basic results using mutual

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 fund 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:

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

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

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

We use three-year flows in these calculations. Table 7 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 7 shows investor flows cause a significant reduction in both average returns and Sharpe ratios (SR) 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.[10]

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 2, except that here all stocks owned by the mutual fund sector are

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fund returns were not substantially different.

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

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 Eqs. (9) and (10)). 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 7 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 have already 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 7 is -0.03% per month.

5.2 Economic magnitude

The magnitude of the dumb money effect in Table 7 is on average seven to nine basis points per month (depending upon whether one uses fund or stock returns). Is this number a large effect? We argue that it is, for two reasons. First, it results in sizeable reductions in Sharpe ratios of 11-17 %. Second, seven to nine basis points per month 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 eight 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% per month, or about 1.4% per year. Of this, almost 70%, -0.085%, is explained by the dumb money effect.[11] 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

[11] 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 500 Index Fund for R^{M} (these returns include 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%.

actively managed funds comes less from fees and expenses, and more from the wealth-destroying reallocation across funds.

In Table 8 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.

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. The results are particularly consistent across time using mutual fund returns.

6. 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 represent 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 (2006), 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.[12] 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 (2006) 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 9 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 three-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 1% 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 average issuance is around 3% (as a fraction of shares outstanding) per year in this sample, 1% 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

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

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 3. The last row of Table 9 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 9, it is useful to note from Table 2 that the difference in the sorting variable (three-year flow) is about 10% 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% more as a percent of shares outstanding than the bottom quintile. This number is in the same units as the numbers in Table 9 since both flows and issuance are expressed as a fraction of current shares outstanding. Thus, firms with flows that are 10% higher as a fraction of shares outstanding tend to increase shares by 1% of shares outstanding. Over three years, the firm would issue shares equivalent to 3% 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.

7. 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 few 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 the 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 both overweight growth stocks and select securities that on average underperform their growth 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 only weak evidence of 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 (2007), 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 useful 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.

Appendix

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 that 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 that were recently born, but excluding funds that die in month t), for $t-k \leq s \leq t$. 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 the total as follows:

$$\hat{\mathrm{F}}_{\mathrm{s}}^{\mathrm{i}} = \frac{TNA_{t-k}^{i}}{TNA_{t-k}^{Agg}} \mathrm{F}_{\mathrm{s}}^{\mathrm{Agg}} \tag{11}$$

$$t-k \leq s \leq t$$

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 two-thirds and one-third 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:

$$\widehat{TNA}_{\mathrm{t}}^{\mathrm{i}} = (1+R_t^i)\widehat{TNA}_{\mathrm{t-1}}^{\mathrm{i}} + \hat{\mathrm{F}}_{\mathrm{t}}^{\mathrm{i}} . \tag{12}$$

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 Eq. (12) does not guarantee that counterfactual total net asset values are always non-negative in quarters where we have aggregate outflows ($\mathrm{F}_{\mathrm{t}}^{\mathrm{Agg}} < 0$). In this case we override Eq. (12), set $\widehat{TNA}_{\mathrm{t}}^{\mathrm{i}} = 0$ 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 $TNA_{t-k}^{i} / TNA_{t-k}^{Agg}$ used to determine the pro-rata share of the total flows.

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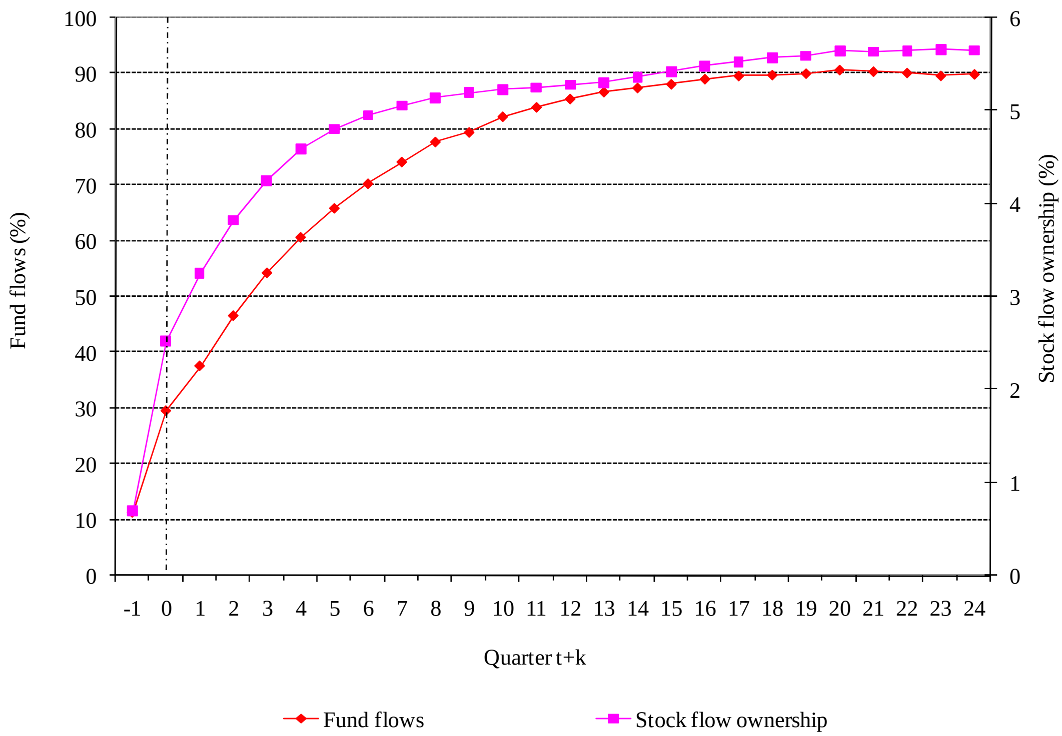

Fig. 1. Cumulative flows for quarter *t+k* sorted on flows in quarter *t*. This figure shows the average cumulative flows in quarter *t+k* for mutual funds (stocks) sorted on quarterly flows in quarter *t*. At the beginning of every quarter mutual funds (stocks) are ranked in ascending order based on 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 flow funds (stocks) and the bottom 20% low flow funds (stocks). Fund flows are defined as dollar inflows/outflows divided by the total net assets of the fund at the end of the previous quarter. Stock flows are defined as the actual percent of the stock owned by mutual funds minus the counterfactual percent.

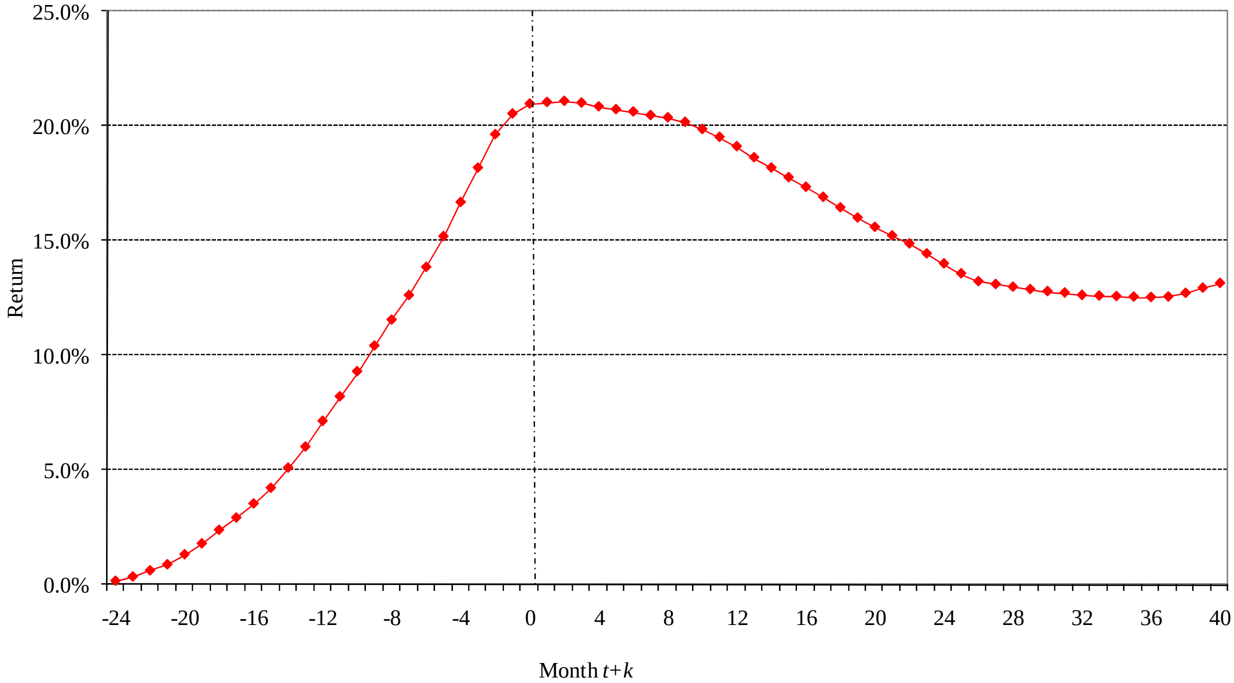

Fig. 2. Average cumulative return in month $t+k$ on a long/short portfolio formed on three-month flow in month t. At the beginning of every calendar month stocks are ranked in ascending order based on the last available flow. Stocks are assigned to one of five quintile portfolios. Portfolios are rebalanced monthly to maintain value weights. The figure shows average cumulative returns in event time of a zero cost portfolio that holds the top 20% stocks and sells short the bottom 20% stocks. The long/short portfolio used here, based on raw returns, corresponds to "3-month flow, L/S" in Table 2.

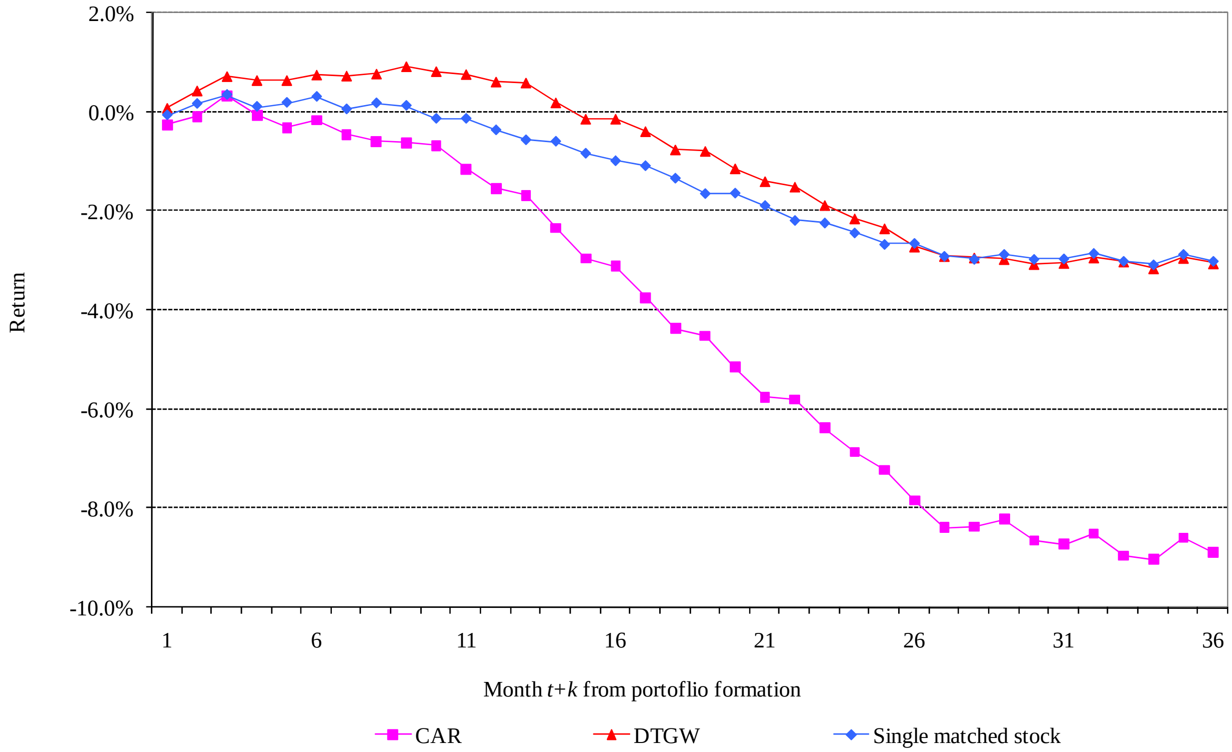

Fig. 3. Buy and hold return in month *t+k* on a long/short portfolio formed on three month flow in month *t*. This figure shows the event-time average buy and hold return in the 36 months subsequent to the formation date of a long/short portfolio formed on three-month flow. For each horizon k, we calculate for every stock the k-month ahead total return, DGTW-adjusted return, and single matched stock-adjusted return. DGTW-adjusted return is defined as total return minus the total return on an equally weighted portfolio of all CRSP firms in the same size, market-book, and one year momentum quintile. Single matched stock-adjusted return is defined as total return minus the total return of a stock to the return of a single control stock. We rank stocks with a market value of equity between 70% and 130% of the market value of equity of the sample stock according to book to market and one year momentum. We sum ranks and select the lowest rank as the matching stock. We maintain the match until the next portfolio rebalancing or the delisting date. If a match is delisted it is replaced by the second lowest rank stock. At the beginning of every calendar quarter, stocks are ranked in ascending order based on the last available three-month flow. We assign stocks to one of five quintile portfolios and calculate the value-weighted average of long-term return for both the high flow (top 20%) and low flow stocks (bottom 20%). This figure reports the time-series average of this difference over the entire sample period. The flow portfolio, the DGTW portfolio, and the matched stocks are refreshed quarterly and when calculating long-term returns; if a firm exits the database, we reinvest its weight into the remaining stocks in the portfolio.

Table 1
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	Level	
	Full sample, 1983-2003				1983	2003
Panel A: time-series (annual observations, 1983-2003)						
Number of funds in the sample per year	285	9,087	2,159	2,370	285	9,087
Number of stocks in the sample per year	2,710	6,803	4,690	1,516	2,710	4,974
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)	94.0	99.9	98.9	1.3	94.0	95.0
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	1,202	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 2
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 B: portfolio returns	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 3
Controlling for value, size, and momentum

This table shows calendar time portfolio abnormal returns. At the beginning of every calendar month stocks are ranked in ascending order based on the last available flow. Stocks are assigned to one of five 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. We report DGTW average characteristic adjusted returns and Fama and French (1993) alphas. DGTW characteristic adjusted returns are defined as raw monthly returns minus the average return of all CRSP firms in the same size, market-book, and one $\hat{z}$ year momentum quintile. The quintiles are defined with respect to the entire universe in that month and DGTW portfolios are refreshed every calendar month. 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 4
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 25 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.

	Low flow				*High flow*	*High flow minus low flow*
	Q1	Q2	Q3	Q4	Q5	L/S
Panel A: 3-year flow and value						
Q1(Value)	**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)
Q5 (Growth)	**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	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						
Q1 (Loser)	**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)
Q5 (Winner)	**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	-0.172	-0.568	-0.527	-0.692	**-0.950**	
	(-0.45)	(-1.11)	(-0.99)	(-1.80)	(-2.39)	

Table 5
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 6
Subsample stability

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. DGTW characteristic adjusted returns are defined as raw monthly returns minus the average return of all CRSP firms in the same size, market-book, and one year momentum quintile. The quintiles are defined with respect to the entire universe in that month and DGTW portfolios are refreshed every calendar month. 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.

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)
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 7
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 8
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 9
Issuance

This table shows issuance activity between January and December of year $t+1$, for portfolios of firms sorted on three-year flows as of December in year *t*. In December stocks are ranked in ascending order based on the last available three-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
Hypothetical 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