ISSN 0956-8549-643

A Flow-Based Explanation for Return Predictability

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THE PAUL WOOLLEY CENTRE
WORKING PAPER SERIES NO 7
DISCUSSION PAPER NO 643

DISCUSSION PAPER SERIES

November 2009

Dong Lou has been teaching at the London School of Economics since July 2009. He earned a Ph.D. in Finance from Yale University and a B.S. in Computer Science from Columbia University. Lou's research mostly focuses on understanding market inefficiencies, and their distortionary effects on resource allocation (such as capital and managerial effort) in the real economy. In his Ph.D. dissertation, Lou shows that mutual fund investment-flow induced trading can have a long-lasting return effect in the stock market. In some follow-up projects, Lou further studies the potential effects of such temporary price pressure on firms' debt financing and investment decisions, and firms' interactions with non-equity stakeholders, such as suppliers and customers.

A Flow-Based Explanation for Return Predictability *

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First Draft: April 2008

This Draft: November 2009

Abstract

This paper proposes and tests an investment-flow based explanation for three empirical findings on return predictability – the persistence of mutual fund performance, the "smart money" effect, and stock price momentum. Since mutual fund managers generally scale up or down their existing positions in response to investment flows, and the portfolios of funds receiving capital generally differ from those that lose capital, investment flows to mutual funds can cause significant demand shocks in individual stocks. Moreover, given that mutual fund flows are largely predictable from past fund performance and past flows, this paper further establishes that flow-induced price pressure is predictable. Finally, this paper shows that such flow-based return predictability can fully account for mutual fund performance persistence and the "smart money" effect, and can partially explain stock price momentum.

*This paper is based on a chapter of my doctoral dissertation at Yale University. I am indebted to my advisors Nick Barberis and Will Goetzmann for encouragement and discussions. I also thank Zhiwu Chen, James Choi, Lauren Cohen, Josh Coval, Kai Du, Pengjie Gao, Pingyang Gao, Stefan Lewellen, Andrew Metrick, Antti Petajisto, Christopher Polk, Geert Rouwenhorst, Paul Tetlock, Sheridan Titman, Chuck Trzcinka, Peter Tufano, Dimitri Vayanos, Paul Woolley, Jinghua Yan, and seminar participants at Boston College, Columbia University, Cornell University, Dartmouth College, Harvard Business School, University of Illinois at Urbana Champaign, Indiana University, London Business School, London School of Economics, University of Notre Dame, Ohio State University, University of Texas at Austin, University of Toronto, Yale School of Management, and Tykhe Capital for helpful comments. All remaining errors are my own.

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1 Introduction

Past research has documented that a) mutual fund performance is persistent, b) money flows disproportionately to mutual funds that outperform in the future (i.e., the "smart money" effect), and c) individual stocks exhibit price momentum. This paper argues that all three empirical regularities are importantly driven by a single mechanism: the price pressure generated by capital flows from individual investors to mutual funds, and then from mutual funds to individual stocks.

The flow-based mechanism is sustained by two empirical facts. First, the amount of capital flows *across* mutual funds are enormous, typically in the magnitude of trillions of dollars each year.[1] Second, mutual funds receiving capital generally hold different stocks from those that lose capital, as capital flows have been shown to chase certain portfolio characteristics (e.g. past performance).[2] If investment flows do not contain useful information about individual stock returns, managers are expected to (roughly) scale up or down their existing holdings in response to capital flows, so as to maintain their optimal portfolio weights. Given the magnitude and the directional nature of mutual fund flows, such flow-induced trading can cause significant price pressure in individual stocks – an effect I label *flow-induced price pressure*. Moreover, since mutual fund flows can be largely forecasted from past fund performance and past fund flows, flow-induced trading and the resulting price pressure are also predictable.

This mechanism of return predictability can give rise to mutual fund performance persistence. Since capital flows strongly chase past fund performance, stocks that are held by past winning funds are likely to experience flow-induced purchases in the subsequent period, while stocks held by past losing funds experience flow-induced sales. This can lead the former to outperform the latter subsequently; as a result, past winning funds continue outperforming past losing funds.

Similarly, the flow-based mechanism can lead to the "smart money" effect. Given that mutual fund flows are highly persistent, stocks that are widely held by funds with capital inflows in the *current* period are expected to experience additional flow-induced purchases in the *next* period, and the reverse is true for stocks held by funds with current outflows. Consequently, funds with inflows outperform those with outflows subsequently.

[1] According to the Investment Company Institute, the *gross* capital flows (purchases plus redemptions) to all equity mutual funds exceeded \$1.4 trillion in the first eight months of 2009.

[2] See, for example, Ippolito (1992); Gruber (1996); Chevalier and Ellison (1997); Sirri and Tufano (1998).

Finally, flow-based return predictability can also cause the stock price momentum effect. Winning funds attract inflows from investors, and in turn scale up their existing holdings, which are (by definition) concentrated in winning stocks. In other words, investors in mutual funds are indirectly buying the winning stocks of the previous period by purchasing the shares of winning funds. Similarly, investors are indirectly selling losing stocks by redeeming shares in losing funds. As a result, performance-chasing mutual fund flows drive past winning stocks to outperform past losing stocks in the subsequent period.

The mechanism of flow-induced return predictability offers a unified explanation for mutual fund performance persistence, the smart money effect, and stock price momentum, which in the literature are attributed to distinct mechanisms – heterogeneity in managerial skills, investors' ability to identify superior skills, and investors' underreaction to news, respectively. The key feature of the flow-based explanation, that differentiates it from alternative models, is the *interplay* between mutual fund performance and stock returns. Rather than suggesting a direct link between a stock's (fund's) past performance and its own future performance, this mechanism maintains that the expected stock return is partially determined by the past performance of mutual funds that are holding the stock; and similarly, the expected fund performance is partially driven by the past performance of all other mutual funds that are holding overlapping positions with the fund.

To formally test the flow-induced price pressure hypothesis and the resulting return predictability, I construct a variable that captures the price impact of mutual fund flow-induced trading in two steps. In the first step, I estimate the part of mutual fund trading that is motivated by investment flows and find that, while managers on average scale down their positions dollar-for-dollar with redemptions, they partially scale up their existing positions, by sixty-two cents for every dollar of inflow. Based on the partial-scaling results, I then compute a flow-induced price pressure ($FIPP$) variable for each stock in each quarter by aggregating flow-induced trading across all mutual funds.

The data yield strong support for the flow-induced price pressure hypothesis. The return spread between the top and bottom deciles sorted by $FIPP$ is 5.19% in the portfolio-formation quarter, insignificant in the following year, and -7.20% in years two and three. Expected flow-induced price pressure ($E[FIPP]$), constructed from *expected* mutual fund flows, delivers similar results. The difference in stock returns between the top and bottom deciles ranked by $E[FIPP]$ is 5.28% in the year after portfolio formation and -5.67% in quarters six to twelve. I also construct an expected flow-induced price pressure measure for each mutual fund, defined as the portfolio-weighted average expected $FIPP$ (denoted $E[FIPP^*]$). Consistent with the stock return results, the spread between fund returns of the top and bottom deciles sorted by $E[FIPP^*]$ is 4.80% in the year following portfolio formation, and a total of -4.62% in quarters six to twelve. The return patterns, both at the stock level and the mutual fund level, are consistent with the hypothesis that mutual fund flow-induced trading can cause temporary demand shocks and that the demand shocks are predictable.

I then examine the degree to which the flow-based mechanism is responsible for the three aforementioned empirical regularities about return predictability. The results suggest that this mechanism can fully account for mutual fund performance persistence and the smart money effect, and can partially explain stock price momentum. Specifically, I find that, in a conditional sort of mutual funds first by $E[FIPP^*]$ and then by fund alpha, fund alpha no longer predicts future abnormal fund returns; but in the conditional sort of the *reverse* order (i.e., first by alpha and then by $E[FIPP^*]$), $E[FIPP^*]$ remains significant in predicting future fund performance. This implies that fund alpha contains little information about future fund performance beyond its correlation with $E[FIPP^*]$. Similarly, I show that fund flows are also completely subsumed by $E[FIPP^*]$ in predicting abnormal fund performance. These results contrast with existing theories, and indicate that the evidence of mutual fund performance persistence and the smart money effect is more consistent with the flow-driven price pressure hypothesis.

To answer the question of what drives the individual stock price momentum effect, I conduct a regression analysis that includes both past stock returns and $E[FIPP]$ on the right hand side of the equation. The results indicate that after controlling for $E[FIPP]$, the magnitude of price momentum declines by 25–50%, depending on the data sample and the way the variables are constructed. In particular, $E[FIPP]$ accounts for a larger part of the price momentum effect in the latter half of the sample and among large-cap stocks, consistent with the observation that mutual fund holdings are more important in more recent years and among large-cap stocks.

The results in this paper complement a number of recent studies on the potential price impact of mutual fund flows. Warther (1995), Edelen and Warner (2001), Gompers and Metrick (2001), Goetzmann and Massa (2003), Teo and Woo (2004), and Braverman, Kandel, and Wohl (2007) find that aggregate capital flows to mutual funds in a particular sector (e.g., equity vs. fixed income) or a particular investment style (e.g., value vs. growth) negatively predict subsequent sector or style returns. The closest work to mine is Coval and Stafford (2007), who examine the price impact of *extreme* mutual fund flows on individual stocks.[3] This paper differs from Coval and Stafford (2007) in two important aspects. First, this paper adopts a more general method for the identification of flow-induced trading. While Coval and Stafford focus exclusively on mutual funds with extreme investment flows (which usually are smaller funds) and assume that all trades under extreme-flow scenarios are non-discretionary or flow-driven, this study estimates flow-induced trading for all mutual funds by scaling up or down each of their positions based on the partial-scaling mechanism. In doing so, I am able to construct a much more comprehensive sample of mutual funds and stocks, which affords me the possibility to study the implications of flow-induced price pressure for prior findings in the asset pricing literature. Second and more importantly, the two papers have different goals and implications. While Coval and Stafford focus on the price effect of fire sales in the equity market, this paper tests the return predictability resulting from mutual fund flow-induced trading and its relation to some previously documented empirical regularities.

This paper is also related to the extensive literature on mutual fund herding and momentum trading. For example, Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), Wermers (1999), and Sias (2004) find strong evidence of institutional investors' tendencies to trade in the same direction, and to chase past stock returns. Most prior studies attribute herding to correlated information, social learning, reputation concerns, and fads. This paper offers an additional explanation for herding and momentum trading; in the context of this study, the persistence and the performance-chasing nature of investment flows from retail investors drive institutional investors to trade together and to follow momentum strategies.

This paper proceeds as follows. Section 2 describes the datasets and the screening procedures. Section 3 formally defines flow-induced price pressure and analyzes its impact on stock returns and fund performance. Section 4 and 5 study the implications of the flow-based mechanism for mutual fund performance predictability and stock price momentum, respectively. Section 6 examines an alternative explanation and performs robustness tests. Section 7 discusses potential interpretations of the results in this paper. Finally, section 8 concludes.

[3]Frazzini and Lamont (2008) also look at the effect of mutual fund flows on individual stock returns, but the measure used in their paper is a combination of mutual fund discretionary trading and flow-induced trading.

2 Data

2.1 Mutual Fund Data

Mutual fund holdings data are obtained from the CDA/Spectrum database provided by Thompson Financial for the period 1980 – 2006. The database is compiled from mandatory SEC filings, as well as voluntary disclosures by mutual funds. Most mutual funds in the database report their holdings on a quarterly basis, even though for a large part of the sample period they are only required to report semi-annually. Although every fund files its report at the end of a quarter, the date on which the holdings are valid (report date) is often different from the filing date; sometimes the filing date can be a few quarters after the report date. To calculate the number of shares held by each mutual fund at the end of a quarter, I assume the manager does not trade between the report date and the quarter end (adjusted for stock splits).

Total net assets, monthly returns, expense ratios, and 12(b)1 fees are obtained from the CRSP mutual fund database. I use the pre-expense fund returns in the study (i.e., monthly net returns plus 1/12 of annual expenses and fees).[4] For funds with multiple share classes reported in CRSP, I sum up the total net assets (TNA) in each share class to derive the TNA of the fund. For net returns and expense ratios, I compute the TNA-weighted average across all share classes. For other fund characteristics, I use the value from the share class with the largest total net assets. Moreover, I calculate the fund alpha using a 12-month rolling window. Specifically, at the end of each quarter, I run a time-series regression of monthly fund returns in the previous twelve months on the Carhart four factors and take the intercept as the fund alpha of the prior year.[5]

To merge CDA/Spectrum data with CRSP data, I rely on the Mutual Fund Links dataset provided by Russ Wermers on Wharton Research Data Services (WRDS). According to the WRDS manual, MFLinks maps over 90% of domestic equity funds between the two data sources with high accuracy.

Since this study focuses on the price impact of aggregate flow-induced trading in the equity market, I include all domestic equity mutual funds in the sample. Specifically, I require the investment objective code reported by CDA/Spectrum to be aggressive growth, growth, growth and

[4] Monthly returns reported by CRSP are net returns (i.e., after fees, expenses, and brokerage commissions but before any front-end or back-end loads).

[5] I also compute fund alpha based on monthly returns in the prior two and three years and obtain similar results.

income, balanced, unclassified, or missing. This restriction effectively excludes all fixed-income funds, international funds, and precious metal funds. However, due to limited coverage of sector funds and balanced funds in the Mutual Fund Links, a significant number of funds are lost in the merging process. As a robustness check, I further restrict the sample to only diversified equity funds by removing balanced and sector funds from the sample, and the results are by and large unchanged.

Moreover, since some mutual funds misreport their investment objective codes, I also require the ratio of equity holdings to total net assets to be between 0.75 and 1.2. The lower bound is to make sure that the return from the equity portfolio accounts for a significant portion of the total fund return while the upper bound is to get rid of some apparent data errors. To further ensure data quality, I require a minimum fund size of $1M and that the TNAs reported by CDA and CRSP do not differ by more than a factor of two (i.e., $0.5 < TNA^{CDA}/TNA^{CRSP} < 2$).

With the aforementioned screening procedures, I obtain a sample of 77,983 fund-quarter observations and 2,989 distinct mutual funds. Table I shows the number of funds in each year along with the summary statistics on fund size and fund equity holdings. There is a significant rising trend in both the number of funds and the average fund size. Moreover, the distribution of fund size is heavily right skewed; in most years, the median fund size is less than a quarter of the average fund size. Finally, the fraction of the equity market value held by mutual funds in the sample rises steadily from less than 2.3% in 1980 to about 14% in 2006.

2.2 Fund Flows

Following prior studies (e.g., Chevalier and Ellison (1997); Sirri and Tufano (1998)), I compute the investment flows of fund i in quarter t as:

$$FLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1} * (1 + ret_{i,t}) - MGN_{i,t}, \tag{1}$$

where $MGN_{i,t}$ is the increase in TNA due to a fund merger in quarter t. Neither CRSP nor CDA/Spectrum reports the exact date on which a merge takes place. Following the literature, I use the last NAV report date of the acquiree to proxy for the merge date. Since this simple method produces many obvious mismatches, I employ the following smoothing procedure. I match an acquiree to its acquirer from t-1 to t+5, where t is the last report date, I then pick the month that gives me the smallest absolute percentage flow as the event month. Implicitly, I assume that inflows and outflows occur at the end of a quarter, and that investors reinvest their dividends and capital appreciation distributions in the same fund. I further assume that after a merger, investors place all their money in the surviving fund. Funds that are initiated have inflows equal to their initial TNA, while funds that are liquidated have outflows equal to their terminal TNA.

2.3 Other Data

Stock returns, trading volume, and the number of shares outstanding are obtained from the CRSP monthly stock file. In order to avoid microstructure issues, I exclude all stocks whose prices are below five dollars a share and whose market capitalizations are in the bottom decile of NYSE stocks at the beginning of the holding period.

Stock liquidity data are obtained from Joel Hasbrouck's website. Among the various measures provided in the dataset, three are used in the current study: the Gibbs estimate of effective bid-ask spreads computed from the Basic Market-Adjusted model (c^{BMA}), and the Gibbs estimates of γ_0 and γ_1 from the Latent Common Factor model. Since the results are qualitatively the same with all three measures, only those derived with c^{BMA} are reported. For a more detailed discussion of various measures of stock liquidity, see Hasbrouck (2006).

3 Flow-Induced Price Pressure

Flow-induced trading can cause demand shocks in individual stocks. If the market for liquidity provision is not perfect (e.g., due to market frictions), such demand shocks can affect stock returns. Prior studies on the price impact of mutual fund flows have focused on the effect of *aggregate* investment flows to the equity market or a particular investment style. Warther (1995) documents a positive relation between aggregate flows to equity mutual funds and *contemporaneous* market returns. Using a more refined dataset on daily investment flows, Edelen and Warner (2001) and Goetzmann and Massa (2003) show that mutual fund flows lead intra-day index returns. Two recent papers, Teo and Woo (2004) and Braverman, Kandel, and Wohl (2007) find that aggregate flows to a sector or an investment style *negatively* predict future sector or style returns, providing some evidence of the price pressure hypothesis. More recently, Coval and Stafford (2007) study the price effect of fire sales (i.e., extreme fund flows) in the stock market. In this section, I test the temporary price pressure effect of mutual fund flow-induced trading (defined in a general way) on *individual* stocks.[6]

3.1 Partial Scaling

How should mutual fund managers respond to investment flows? In a simplified model without liquidity constraints, nor wealth effect (i.e., managers have CARA utility functions), managers' portfolio choices are independent of fund size. Put it different, if investment flows to mutual funds are uninformative about individual stock returns, fund managers should *proportionally* scale up or down their existing holdings based on their inflows or outflows. Clearly, in the actual financial market with significant liquidity costs, holdings are not infinitely scalable.[7] As a result, managers may deviate from this perfect scaling scheme in some situations.

There are three things that managers can do to mitigate the liquidity costs associated with capital flows. First, they can use a cash buffer to reduce the impact of flows in the short run, but this is not a long-term solution as keeping a large cash reserve is very costly.[8] Second, managers can choose to expand their current positions only by a fraction of their inflows and use the remainder to initiate new positions. In other words, managers can *partially* scale up their current holdings if the costs of scaling up outweight the potential benefits. The portfolio-level partial scaling, however, is not feasible for outflows; managers have to scale down dollar-for-dollar to meet redemptions. Finally, managers can scale up or down each of their holdings differently based on each stock's scaling costs; for example, they can let their more liquid and smaller positions absorb more of the capital flows.

I gauge the effect of trading costs on the degree of partial scaling with the following panel regression, which is equivalent to a decomposition of fund trading into a flow-induced component

[6] This is essentially a joint test of a) whether capital flows to mutual funds are informative about individual stock returns and b) whether demand shocks can affect stock returns.

[7] For example, Chen, Hong, Huang, and Kubik (2004) and Pollet and Wilson (2008) find that fund size is negatively related to expected fund returns.

[8] Coval and Stafford (2007) find that actively managed mutual funds maintain about 4-5% of their total net assets in cash, and this ratio stays steady over time.

and an information-driven component (the residual term).

$$
\begin{aligned}
\Delta shares_{i,j,t} =& \beta_0 + \beta_1\ percflow_{i,t} + \beta_2\ own_{i,j,t-1} + \beta_3\ percflow_{i,t} * own_{i,j,t-1} + \\
& \beta_4\ liqcost_{j,t-1} + \beta_5\ percflow_{i,t} * liqcost_{j,t-1} + \beta_6\ own_{i,t-1} + \\
& \beta_7\ percflow_{i,t} * own_{i,t-1} + \beta_8\ liqcost_{i,t-1} + \beta_9\ percflow_{i,t} * liqcost_{i,t-1},
\end{aligned} \tag{2}
$$

where $shares_{i,j,t}$ is the number of shares held by fund i in stock j at the end of quarter t, and $shares^{split\_adj}_{i,j,t-1}$ is the number of shares held at the end of quarter t-1 adjusted for stock splits in quarter t; $\Delta shares_{i,j,t} = \frac{shares_{i,j,t}}{shares^{split\_adj}_{i,j,t-1}} - 1$ is the percentage change in shares held from quarter t-1 to t; $percflow_{i,t} = \frac{FLOW_{i,t}}{TNA_{i,t-1}}$ is the investment flow in quarter t, as a percentage of the TNA at the end of the previous quarter; $\omega_{i,j,t-1}$ is the portfolio weight in stock j at the end of quarter t-1; $own_{i,j,t-1} = \frac{shares_{i,j,t-1}}{shrout_{j,t-1}}$ is the ownership share held by mutual fund i in stock j (i.e., the fraction of stock j that is owned by fund i), and $own_{i,t-1} = \sum_j(\omega_{i,j,t-1} * own_{i,j,t-1})$ is the portfolio weighted average ownership share; $liqcost_{j,t-1} = c^{BMA}_{j,t-1}$ is the effective bid-ask spread for stock j, and $liqcost_{i,t-1} = \sum_j(\omega_{i,j,t-1} * liqcost_{j,t-1})$ is the portfolio weighted average bid-ask spread.[9]

I use two variables, $own_{i,j,t-1}$ and $liqcost_{j,t-1}$, to capture the total cost of scaling in the analysis; the former measures the size of flow-induced trading and the latter the marginal liquidity cost. Besides the size of scaling, $own_{i,j,t-1}$ also captures the effect of other size-related constraints; for example, mutual funds are usually reluctant to hold more than 5% of the shares outstanding in a stock, in order to avoid mandatory filings with the SEC. I also include $own_{i,t-1}$ and $liqcost_{i,t-1}$, the portfolio-weighted average ownership share and liquidity costs respectively, in the regression to measure the degree of partial scaling at the portfolio level. Since such portfolio-level partial scaling is only possible for mutual funds getting new investment but not for those losing investment, I conduct two separate regressions on the sub-samples with positive and negative quarterly flows.

Moreover, to deal with the heteroscedasticity issue, I conduct a weighted OLS regression. The problem stems from the fact that the residual term in the regression (i.e., information-motivated trading) varies in magnitude across funds and over time. Imagine that a manager that receives a signal s about a stock updates his position in the stock by x% of the fund's TNA. For the purpose

[9] I also try a number of alternative specifications; for example, the portfolio weights adjusted for returns in quarter t, the gross trading volume in the preceding year instead of shares outstanding in the denominator of $own_{i,j,t-1}$. The results are by and large unchanged.

of illustration, let's make the following simplifying assumptions: a) $x_i = f_i(s)$ for each manager differs only by a constant multiplier λ_i (i.e., $f_i(\cdot) = \lambda_i * g(\cdot)$) and b) managers roughly keep the number of holdings in their portfolios constant over time. In this case, the standard error of the residual term, or the magnitude of information-driven trading, is proportional to the reciprocal of the number of holdings in a manager's portfolio. Hence the weight for each observation in the regression is set to $\#holdings_{i,t-1} * w_{i,j,t-1}$.[10]

If managers on average *perfectly* scale their existing positions in response to capital flows, as we would expect in a frictionless market, β_1 should be equal to one and all other coefficients be zero. This benchmark case is certainly an over-simplification. In the real equity market, we expect the estimate of β_1 to be smaller than one and the estimates of β_3, β_5, β_7, and β_9 to be negative to reflect managers' increasing tendencies to deviate from perfect scaling as trading costs rise.

The empirical results, presented in Table II (Panel A), are consistent with our predictions. Columns 1 to 5 correspond to the sample with outflows. On average, managers nearly perfectly scale down their holdings in response to outflows; for every 1% of redemptions, managers shrink their existing positions by 0.97%, while absorbing the remaining 0.03% with their cash reserves and/or non-equity holdings. Between the two measures of scaling costs, the ownership share (i.e., $\frac{shares_{i,j,t-1}}{shrout_{j,t-1}}$) has no effect on the degree of partial scaling down both at the holding level and the portfolio level.[11] The marginal liquidity cost measured by the effective bid-ask spread c^{BMA}, has a significant and negative effect on partial scaling, but only with marginal statistical significance. I also include the squared terms of the flow and the ownership share in the analysis to capture potential nonlinear effects in the regression, but neither shows up significantly.

The results for the inflow sample, presented in Columns 6 to 10, exhibit two notable differences from the outflow sample. First, managers on average invest only 62% of their new capital in the existing holdings, and leave the remaining 38% either for new positions or as cash. Second, both the portfolio-average ownership share and the portfolio-average liquidity cost are significantly and negatively related to the degree of partial scaling up.

[10] $w_{i,j,t-1}$ is used to adjust information-driven trading to the the same numeraire as the dependent variable, $\Delta shares$, which is calculated as a percentage of the shares held as of the last quarter.

[11] When both the position-level and the portfolio-average ownership share are included in the regression (Column 5), β_3 is significantly negative and β_7 is significantly positive. This is likely due to the multi-collinearity problem; the correlation between the two variables is 0.83 in the outflow sample.

For the purpose of robustness checks, I conduct a similar regression at the fund-quarter level:

$$\Delta shares_{i,t} = \gamma_0 + \gamma_1\ percflow_{i,t} + \gamma_2\ own_{i,t-1} + \gamma_3\ percflow_{i,t} * own_{i,t-1} + \gamma_4\ liqcost_{i,t-1} + \gamma_5\ percflow_{i,t} * liqcost_{i,t-1}, \tag{3}$$

where $\Delta shares_{i,t} = \sum_j (\Delta shares_{i,j,t} * \omega_{i,j,t-1})$. The results, presented in Panel B, are largely consistent with those reported in Panel A. Managers perfectly scale down their positions in response to redemptions, and partially scale up with new investment; moreover, the degree of partial scaling up is determined by the portfolio-average ownership share and marginal liquidity cost.

3.2 $FIPP$

Based on the partial scaling results from the prior section, I define flow-induced trading in each stock by each mutual fund as:

$$FIT_{i,j,t} = shares_{i,j,t-1} * (percflow_{i,t} * PSF_{i,t-1}), \tag{4}$$

where $PSF_{i,t-1}$ is the partial scaling factor of fund i at the end of quarter t-1, defined as $PSF^{inflow}_{i,t-1} = 0.86 - 21.34 * own_{i,t-1} - 51.08 * liqcost_{i,t-1}$, and $PSF^{outflow}_{i,t-1} = 0.97$.[12]

For each stock, I then compute its flow-induced price pressure ($FIPP$) in each quarter as the cumulative flow-induced trading by all mutual funds, divided by the aggregate number of shares held by mutual funds at the end of the previous quarter. Ideally, the denominator in $FIPP$ should capture the amount of *active* liquidity provision in the market, so that the ratio reflects the resulting short-term price impact. However, there is so far no clear evidence as to which variable best captures liquidity provision. The choice of total shares held by mutual funds is motivated by the empirical observations that mutual fund managers have a strong preference for liquidity stocks (e.g., Gompers and Metrick (2001)) and that they act as active liquidity providers (e.g., Da, Gao,

[12] This definitions is based on the regression coefficients in Columns 1 and 8 of Table II. I also use the estimates from Column 4 and 9 to calculate PSF. The results are qualitatively the same. For robustness, I also implement a rolling-window regression using observations up to t-1 to estimate PSF for the period t, the results are again similar.

and Jagannathan (2007)). Formally, I define:

$$FIPP_{j,t} = \frac{\sum_i FIT_{i,j,t}}{\sum_i shares_{i,j,t-1}}. \tag{5}$$

One way to think about this measure is that, if we think of the entire mutual fund industry as one mutual fund, $FIPP$ captures the magnitude of flow-induced trading of this aggregate fund in each quarter.[13]

Table III presents the monthly returns of the calendar-time portfolios constructed from $FIPP$. At the end of each quarter, I sort all stocks based on $FIPP$ into deciles and hold the decile portfolios for the following twelve quarters. Panel A reports the magnitude of $FIPP$ in each decile from one year before the portfolio ranking to one year after. In the ranking quarter (i.e., quarter 0), the stocks in the top decile experience significant flow-induced purchases; mutual funds in aggregate increase their holdings in these stocks by 17% due to investment inflows. Stocks in the bottom decile experience substantial flow-induced sales; the difference in $FIPP$ between the top and bottom deciles is about 22%. $FIPP$ also exhibits significant persistence. The measure is monotonically increasing from decile 1 to 10 in each of the eight quarters surrounding the ranking quarter, and the difference in $FIPP$ between deciles 10 and 1 is statistically significant in all eight quarters. The strong persistence in $FIPP$ is consistent with the finding that investment flows to mutual funds are highly persistent for more than four quarters. It is also worth noting that due to the large amount of aggregate capital inflows to the mutual fund industry in the sample period, the average $FIPP$ (across all deciles) in each quarter is positive.

The portfolio return results (equal-weighted returns in Panel B and value-weighted returns in Panel C) provide strong support for the flow-induced price pressure hypothesis. The equal-weighted return difference between the top and bottom deciles ranked by $FIPP$ is 5.19% in the ranking quarter (5.73% three-factor adjusted, 4.50% four-factor). While the spread is indistinguishable from zero in the year following portfolio formation, it is significantly negative thereafter, reaching a total of -7.20% (-5.52% on a three-factor adjusted basis) in years two and three.[14] Consistent with the empirical regularity that mutual funds are more likely to invest in large-cap stocks, the value-

[13] I also use alternative definitions of $FIPP$ based on, for example, the number of shares outstanding and the total trading volume in the previous year. The results are qualitatively the same.

[14] As shown later in the paper, the flow-induced return effect is closely related to stock price momentum; therefore the Carhart four-factor model is an inappropriate adjustment to detect a return reversal pattern.

weighted results are stronger than the equal-weighted ones. The value-weighted return difference between the top and bottom deciles ranked by $FIPP$ is 6.36% in the ranking quarter (6.93% three-factor adjusted, 5.28% four-factor), and is -11.04% (-10.08% on a three-factor adjusted basis) in years two and three. These results indicate that the positive returns obtain by the hedge portfolio in the formation quarter are completely reversed at the end of year three, in support of the price pressure hypothesis.

A puzzling observation in Table III is that the reversal caused by flow-induced price pressure emerges one year after portfolio formation. This result seems to be at odds with Coval and Stafford (2007) which documents a significant reversal pattern immediately after the ranking quarter. The difference is mainly caused by the relative strength of two countervailing forces associated with $FIPP$. On the one hand, flow-induced trading in a quarter drives stock prices away from their fundamental values, demanding an immediate reversal in the subsequent quarters. On the other hand, since $FIPP$ is highly persistent (Panel A), stocks that undergo flow-induced purchases (sales) in the current quarter are likely to experience more flow-induced purchases (sales) subsequently. Taken together, the two forces work against each other and the net effect is insignificant in my sample. In contrast, the reversal effect dominates in the extreme-flow sample analyzed in Coval and Stafford (2007), for two reasons. First, extreme investment flows cause larger demand shocks in individual stocks, and hence lead to a stronger reversal. Second, extreme capital flows are less likely to repeat themselves, and therefore current extreme-flow-induced trading is a poor predictor of future flow-induced trading. As a result, Coval and Stafford (2007) find a reversal pattern immediately following portfolio ranking in their analysis.

3.3 Expected $FIPP$

Given that mutual fund flow-induced trading can generate significant price pressure in individual stocks and that investment flows to mutual funds are largely predictable, one may wonder whether this flow-based mechanism can lead to stock return predictability. The seemingly apparent link between predictable demand shocks and predictable stock returns is not theoretically obvious. The standard arbitrage argument maintains that arbitrageurs, anticipating that mutual funds will have to buy or sell due to capital inflows or outflows in the next period, would buy or sell in the current period to front run mutual funds. In doing so, arbitrageurs effectively eliminate stock return predictability by incorporating the predictable part of future demand shocks into stock returns today. However, due to the risk involved in this arbitrage strategy – specifically, realized flows and thereby flow-induced trading are uncertain – arbitrageurs pursue this strategy to a less extent than it is required to completely eliminate return predictability. This way, a part of the stock return predictability remains in the data, and arbitrageurs are (fairly) compensated for bearing the risk involved in their arbitrage activities.

3.3.1 Expected Mutual Fund Flows

To test the possibility that the flow-based mechanism can cause predictable stock returns, I first replicate the flow-performance relation that has been extensively studied in the prior literature (e.g., Ippolito (1992); Gruber (1996); Chevalier and Ellison (1997); Sirri and Tufano (1998)):

$$\begin{aligned} percflow_{i,t} =& \beta_0 + \beta_1 \ alpha_{i,t-4:t-1} + \beta_2 \ adjret_{i,t-4:t-1} + \beta_3 \ \log(TNA_{i,t-1}) + \\ & \beta_4 \ alpha_{i,t-4:t-1} * \log(TNA_{i,t-1}) + \beta_5 \ percflow_{i,t-1} + \\ & \beta_6 \ percflow_{i,t-2} + \beta_7 \ percflow_{i,t-3} + \beta_8 \ percflow_{i,t-4}, \end{aligned} \tag{6}$$

where $alpha_{i,t-4:t-1}$ and $adjret_{i,t-4:t-1}$ are the four-factor fund alpha and the market-adjusted fund return in the prior year, respectively. I also include four lags of quarterly flows in the regression to control for the persistence in investment flows.

The first four columns of Table IV report the coefficient estimates using the Fama and MacBeth (1973) approach and the next four columns the estimates from pooled OLS regressions. Consistent with prior findings, all coefficients appear statistically and economically significant. Most notably, fund alpha, in excess of the Carhart (1997) four-factor model, appears to be an important determinant of future investment flows; this is true even after controlling for market-adjusted fund returns in the analysis. In a univariate regression, a 1% increase in the four-factor fund alpha leads to a more than 4.8% increase in investment flows in the subsequent quarter. This may seem surprising at first as retail investors unlikely use factor models to evaluate mutual fund performance, but as suggested by anecdotal evidence, many retail investors rely on benchmark-adjusted returns to guide their investment decisions, which in essence is a way to control for systematic risk.

3.3.2 Scaling in Response to Anticipated Flow

If flows can be forecasted by an econometrician, flows can also be forecasted by mutual fund managers, perhaps with a greater precision. If mutual fund managers in anticipation of future flows adjust their holdings in advance, expected investment flows may *not* lead to demand shocks in the future as they are already incorporated in today's holdings. This preemptive mechanism, however, is unlikely to be the case. First, as most mutual funds do not buy stocks on margin, managers cannot invest with anticipated inflows. Second, with moderate expected outflows, managers may have little incentive to engage in preemptive selling as they probably want to preserve cash for extreme outflow scenarios, when the costs of liquidity are the dearest. Finally, in anticipation of extreme future outflows, even if managers are eager to dump their holdings in order to build a cash buffer, there is probably not much they can do, as the funds are likely already facing large outflows.

I conduct a formal test of the preemptive mechanism by including expected flows computed from lagged fund alpha (in place of actual flows) in the partial scaling regression (3). If managers on average anticipate future flows and take preemptive actions, we expect the coefficient of expected flows to be significantly smaller than that of realized flows. The results, shown in Columns 4 and 8 in Panel B of Table II, indicate otherwise; the coefficient estimates for anticipated outflows and inflows are almost identical to those in Columns 1 and 5, suggesting that managers do *not* scale their portfolios in anticipation of flows.

3.3.3 The Return Pattern of Expected $FIPP$

Expected flow-induced price pressure (or $E[FIPP]$) is defined almost identically as $FIPP$, except that expected investment flows are now used in place of actual flows. Specifically, $E[FIPP]$ for stock j in quarter t is defined as:

$$E[FIPP_{j,t}] = \frac{\sum_i E[FIT_{i,j,t}]}{\sum_i shares_{i,j,t-1}}, \tag{7}$$

where $E[FIT_{i,j,t}] = shares_{i,j,t-1} * (E[percflow_{i,t}|alpha_{i,t-1}] * PSF_{i,t-1})$. I further define a measure of the expected flow-induced price pressure for each mutual fund i in quarter t as the portfolio weighted average $E[FIPP]$ across its holdings.

$$E[FIPP^*_{i,t}] = \sum_j (E[FIPP_{j,t}] * \omega_{i,j,t-1}). \quad (8)$$

Note that past fund flows are excluded in the estimation of expected future flows. This is because, as shown in Table III, past flow-induced price pressure does not predict stock returns in the following quarter/year, due to the two countervailing effects discussed before.

To test the return predictability of expected $FIPP$, at the end of each quarter, I sort all stocks into deciles based on $E[FIPP]$ and hold the equal-weighted portfolios for twelve quarters.[15] As shown in Panel A of Table V, the return difference between the top and the bottom deciles is 2.52% (2.79% three-factor adjusted, 1.59% four-factor adjusted) in the quarter following portfolio formation and 5.28% (6.96% three-factor adjusted, 4.44% four-factor adjusted) in the following year. While the return spread is indistinguishable from zero in quarter five, it becomes significantly negative after quarter six, reaching a total of -5.67% (-5.67% on a three-factor adjusted basis) from quarters six to twelve. In other words, the initial gains in the first year are (almost) completely revered in the subsequent two years, consistent with a story of predictable price pressure.[16]

I also conduct a similar sort on mutual funds by $E[FIPP^*]$. As shown in Panel B of Table V, the difference in fund returns between the top and bottom deciles ranked by $E[FIPP^*]$ is 1.65% (2.13 three-factor adjusted, 1.23% four-factor adjusted) and 4.80% (6.60% three-factor adjusted, 4.44% four-factor adjusted) in the quarter and year following portfolio formation, respectively. The return spread turns significantly negative in quarters six through twelve, reaching -4.62% (-5.25% on a three-factor adjusted basis) in total over this period. One potential implication of the return pattern is that mutual fund managers are unable to foresee the return reversal and to unload their positions before the reversal starts. In addition, the return reversal in the third year is weaker than that in the second year, in terms of magnitude. This is consistent with the fact that on average mutual funds turn over their positions once every one and a half years; in other words, managers have already unloaded most of the holdings they accumulated at the beginning of the holding period

[15] The value-weighted returns are similar.

[16] The expected price pressure effect documented here is distinct from the style effect identified in the previous literature (e.g., Teo and Woo (2004)). The fund performance measure used in here is the abnormal fund return after controlling for the size and value factors.

by the end of the second year.

To sum up, the results presented in this section suggest that mutual fund flow-induced trading can have significant return effects both at the stock level and at the fund level. In addition, since investment flows to mutual funds are predictable, the flow-driven return effect is also predictable. In the remainder of this paper, I will explore the implications of the flow-based mechanism for prior studies on mutual fund performance predictability and stock return predictability.

4 Mutual Fund Performance Predictability

At the end of 2006, equity mutual funds owned over 30% of the US equity market and collected over $20 billion in annual fees and expenses.[17] It is therefore of enormous importance both for investors and researchers to understand whether professional portfolio management adds value and if so, how to identify managers with superior skills. While the existing literature finds little support for overall superior performance by mutual funds in terms of net returns, there is ample evidence of *heterogeneity* in managerial ability.[18] Most notably, the prior literature documents that mutual fund performance is persistent – i.e., funds with stronger prior performance continue outperforming their peers in the subsequent periods, and that money is smart – i.e., money flows mutual funds that underperform subsequently to those that outperform. The conventional interpretations of these findings are that some managers are more skilled than others and that retail investors are able to identify managers with superior skills.

4.1 Mutual Fund Performance Persistence

A large body of research has been dedicated to detecting the persistence in mutual fund performance. Grinblatt and Titman (1992), Goetzmann and Ibbotson (1994), and Brown and Goetzmann (1995) are among the first to document significant persistence in the (abnormal) performance rankings among mutual funds. Using a calendar-time portfolio approach, Hendricks, Patel, and Zeckhauser (1993) report that mutual funds in the top return octile outperform those in the bottom octile by about 8% (risk adjusted) in the following year. Carhart (1997) reduces the return spread

[17]See, for example, French (2008). Fees and expenses are computed from the CRSP mutual fund dataset.

[18]For example, Coval and Moskowitz (2001), Kacperczyk, Sialm, and Zheng (2005), and Cremers and Petajisto (2007) find that mutual funds with a stronger local bias, a higher industry concentration, and larger Active Share tend to have better performance.

to about 4% a year (still statistically significant) after controlling for stock price momentum as an additional risk factor.[19] More recently, Bollen and Busse (2005) and Cohen, Coval, and Pastor (2005) report stronger performance predictability by using daily mutual fund performance data and a refined measure of fund alpha, respectively.

Table VI (Panel A) replicates prior studies on mutual fund performance persistence.[20] At the end of each quarter, I sort all mutual funds into deciles based on the Carhart four-factor alpha computed from monthly fund returns in the previous year, and hold the equal-weighted portfolios for the next twelve quarters.[21] The spread between the four-factor alpha of the top and bottom deciles is 1.17% in the subsequent quarter and 4.44% in the subsequent year. This is then followed by an insignificant reversal in years two and three. Consistent with Cohen, Coval, and Pastor (2005), I find that more than half of the alpha spread in the post-formation year is due to continued outperformance by past winning funds.

At the face value, the evidence presented here and in prior studies is consistent with the idea that there is considerable heterogeneity in manager ability and that realized risk-adjusted fund performance (reasonably well) captures such heterogeneity. In this section, I offer a new way to think about the evidence. Specifically, I argue that past winning funds, by *collectively* scaling up their existing holdings with investment inflows, effectively drive up their own performance in the subsequent period; similarly, past losing funds, *collectively* scaling down their holdings due to capital outflows, push down their performance.

The key word here is *collectively*; the price pressure is unlikely caused by a single mutual fund, but rather the collective purchases or sales by all mutual funds with similar past performance. Put it differently, the mutual funds with the best past performance are not necessarily going to experience the largest upward flow-induced price pressure subsequently; rather, it is the mutual funds whose stocks are also widely held by other winning funds that will enjoy the largest upward price pressure from investment flows. This unique feature of the flow-based mechanism enables me

[19] It is worth pointing out that there are two sets of results in Carhart (1997), although the author focuses on one of them. When the unadjusted fund returns are used to rank mutual funds, the return spread between the top and bottom deciles in the post-formation period is insignificant after controlling for stock price momentum; however, if the four-factor adjusted fund alpha is used in the ranking procedure, the resulting return spread in the post-formation period is about 4% (statistically significant) even with the control of price momentum.

[20] The procedure used here is very similar to the one used in Carhart (1997), except that Carhart rebalances the portfolios once a year only at the end of December.

[21] I also compute fund alpha based on the returns in the prior three years and the results are qualitatively the same.

to differentiate the price pressure hypothesis from the ability story, because the latter predicts that a mutual fund's past performance is a good predictor of its own future performance.

To empirically distinguish between the two hypotheses, I conduct two *sequential* sorts.[22] In the first sequential sort, I rank mutual funds first by $E[FIPP^*]$ and then by fund alpha, and hold the resulting portfolios for one quarter. If fund alpha indeed captures ex-ante manager ability, it is expected to remain a significant predictor of future fund performance after controlling for $E[FIPP^*]$. On the other hand, if fund alpha predicts future fund performance only because it predicts future flow-induced price pressure, it should be subsumed by $E[FIPP^*]$, as the latter more accurately captures such price pressure. Panel B of Table VI reports the equal-weighted returns of the 25 portfolios. After controlling for $E[FIPP^*]$, the return spread between the top and bottom quintiles ranked by alpha ranges from -0.42% to 0.63% and is insignificant in four out of the five $E[FIPP^*]$ quintiles. The average spread is also insignificant: 0.15% on a three-factor adjusted basis and 0.21% on a four-factor adjusted basis.

To test whether $E[FIPP^*]$ contains information about future fund performance that is not included in alpha, I conduct a second sequential sort in the reverse order, first by fund alpha and then by $E[FIPP^*]$. As shown in Panel C, $E[FIPP^*]$ remains significant in predicting future fund performance after controlling for fund alpha. The spread between the abnormal returns of the top and bottom quintiles ranked by $E[FIPP^*]$ ranges from 0.42% to 1.80% and is significant in most of the fund alpha quintiles. The average spreads, 1.23% (on a three-factor adjusted basis) and 0.78% (on a four-factor adjusted basis), are both economically and statistically significant. Taken together, the results of the two conditional sorts suggest that the evidence of mutual fund performance persistence is largely driven by predictable flow-induced price pressure.

4.2 The Smart Money Effect

If there is heterogeneity in ability among mutual fund managers, a related question is whether retail investors are able to identify managers with superior skills. This is an important question given the enormous amount of capital flows across mutual funds. If capital is not directed from less skilled to more skilled fund managers, it raises some serious doubt about investor rationality and market

[22] Instead of performing an independent sort by $E[FIPP^*]$ and fund alpha, I conduct two sequential sorts. This is due to the high correlation (≈ 0.55) between the two variables.

efficiency. Gruber (1996) proposes an intuitive test to settle this debate: if retail investors are smart, or put it differently, if money is smart (hence the name the "smart money" effect), then past investment flows should positively predict future fund performance. A number of follow-up studies (see, e.g., Zheng (1999); Frazzini and Lamont (2008); Keswani and Stolin (2008)) find supportive evidence for this prediction, yet with the qualification that such performance predictability is confined to the first quarter after portfolio ranking.

I replicate the prior studies on the smart money effect and report the results in Table VII (Panel A). At the end of each quarter, I sort all mutual funds into deciles based on their quarterly flows and hold the equal-weighted portfolios for the next twelve quarters. Consistent with prior studies, the return difference between the top and bottom deciles ranked by flows is 0.51% (0.84% on a three-factor adjusted basis) in the following quarter, statistically significant at the 10% (1%) level. The total spread at the end of the first year, however, is indistinguishable from zero, indicating some reversal in quarters two to four. The spread then becomes significantly negative in years two and three, reaching a total of -3.12% (-3.12% on a three-factor adjusted basis). This fund return pattern suggests that on average retail investors are losing money over the long run by flipping their mutual fund investment – inconsistent with the predictions of the smart money effect.

Nevertheless, the initial positive spread we see in the first quarter after portfolio formation is largely consistent with the idea that retail investors are able to identify superior manager skills – perhaps only in the very short run. In this section, I provide an alternative explanation for this evidence. Specifically, mutual funds with current inflows receive more investment subsequently, collectively scale up their existing holdings, and effectively drive up their subsequent performance, and the opposite is true for funds that are currently losing capital.

To test whether the mutual fund flow-based mechanism is responsible for the smart money effect, I *independently* sort mutual funds by both $E[FIPP^*]$ and fund flows, and hold the resulting portfolios for one quarter (Panel B). If past flows predict future fund performance only because they predict future flow-induced price pressure, past flows should be subsumed by $E[FIPP^*]$ in the horse race, since the latter is a more accurate measure of such price pressure. After controlling for $E[FIPP^*]$, lagged flows no long predict future fund performance. The return spread between the top and bottom quintiles ranked by quarterly flows ranges from -0.03% to 0.48% in the following quarter and is insignificant in four out of the five $E[FIPP^*]$ quintiles; the average spread is 0.09%

(0.21% on a three-factor adjusted basis), statistically insignificant at any conventional level. On the other hand, $E[FIPP^*]$ remains statistically significant in predicting future fund performance. In sum, the portfolio return results in the double sort, and the long-term reversal pattern in the uni-variate sort by quarterly flows alone, suggest that the evidence of the smart money effect is more consistent with the flow-induced price pressure hypothesis.

What may seem puzzling at first is that while the aggregate capital flows to a stock in quarter t do *not* predict the stock return in quarter t+1 (Table III Panel B and C), the investment flows to a mutual fund in quarter t strongly predict the fund return in quarter t+1. The key to solve this puzzle is to understand an important difference between the investment flows to a mutual fund and the flows to a stock: the amount of flow-induced trading in a stock is determined by the investment flows to all the mutual funds that are holding the stock. Put it differently, the mutual funds with the largest investment inflows (outflows) are not necessarily holding the stocks with the largest flow-induced purchases (sales).

4.3 A Regression Analysis

As a complement to the calendar-time portfolio approach, I conduct a multivariate regression analysis on the predictability of mutual fund performance. In doing so, I can better isolate the effect of each of the three variables ($E[FIPP]$, fund alpha, and fund flows), while controlling for other fund characteristics that are known to predict future fund performance. Formally, I conduct the following regression analysis with quarterly mutual fund observations:

$$\begin{aligned} ret_{i,t+1} =& \beta_0 + \beta_1\ E[FIPP^*_{i,t}] + \beta_2\ alpha_{i,t} + \beta_3\ \log(flow_{i,t}) + \beta_4\ expenses_{i,t} + \\ & \beta_5\ log(age_{i,t}) + \beta_6\ log(no\_stocks_{i,t}) + \beta_7\ log(TNA_{i,t}) + \beta_8\ log(turnover_{i,t}), \end{aligned} \tag{9}$$

where the dependent variable is the mutual fund return in quarter t+1; $E[FIPP^*]$ is the portfolio weighted average expected flow-induced price pressure for fund i computed based on fund returns in the previous year, and *alpha* is the Carhart four-factor alpha computed based on monthly fund returns in the previous year; $flow$ is the percentage investment flow in quarter t; *expenses* is the expense ratio, *age* is the number of years since fund inception, and *no_stocks* is the number of stocks held in the portfolio at the end of quarter t; and finally, *turnover* is the portfolio turnover in quarter t. The coefficients are estimated using the Fama and MacBeth (1973) approach and the standard errors are Newey-West corrected with four lags.

The results, shown in Table VIII, are consistent with the calendar-time portfolio analysis. $E[FIPP^*]$ is a significant predictor of subsequent fund performance in all regression specifications. Past fund alpha and past fund flows significantly and positively predict future fund performance when included in the regression alone, but their predictive power is completely subsumed by $E[FIPP^*]$, once $E[FIPP^*]$ is added to the regression. The coefficients on other fund characteristics are in line with the findings in the prior literature: smaller funds, funds that hold a larger number of stocks and turn over their portfolios faster tend to have better subsequent performance. In sum, the results from the multivariate regression analysis lend further support to the hypothesis that both mutual fund performance persistence and the smart money effect are manifestations of the predictable price pressure induced by mutual fund flows.

5 Stock Price Momentum

Stock price momentum is one of the most robust and puzzling anomalies in the asset pricing literature. It has been replicated and confirmed in almost all asset classes, all countries, and all time periods.[23] What makes the price momentum effect particularly interesting to academic research is that a) unlike most other anomalies, the price momentum effect is also significant among large-cap stocks, and b) the momentum strategies have stayed profitable for more than two decades (e.g., Fama and French (2008)). Given the robustness and persistence of the anomaly, it is important to understand its causes; yet despite a large body of theoretical works on price momentum, there is little empirical evidence as to its underlying drivers.[24] This section tests an additional mechanism that can potentially contribute to our understanding of the stock price momentum effect. In particular, I argue that winning funds, by scaling up their existing holdings that are concentrated in past winning stocks, drive up the returns of past winning stocks; and similarly, losing funds, by scaling down their existing holdings, drive down the returns of past losing stocks.[25]

[23] See, for example, Jegadeesh and Titman (1993); Rouwenhorst (1998); Moskowitz and Grinblatt (1999); Jegadeesh and Titman (2001).

[24] See, for example, Barberis, Shleifer, and Vishny (1998); Daniel, Hirshleifer, and Subrahmanyam (1998); Hong and Stein (1999); Grinblatt and Han (2005).

[25] In an independent work, Vayanos and Woolley (2008) formalize this intuition in a rational framework.

To examine the extent to which the flow-based mechanism is responsible for the price momentum effect, I conduct a Fama and MacBeth (1973) return regression with both cumulative past stock returns and $E[FIPP]$ on the right hand side. Since the prior literature on stock price momentum focuses on *gross* stock returns, I use a slightly different definition of expected flow-induced price pressure, in which expected investment flows are estimated from the market-adjusted fund returns rather than the four-factor fund alpha. In addition, as mutual funds report their holdings once every quarter, I conduct the cross-sectional regression on a quarterly basis. Since the price momentum effect is stronger with a holding period of three months than one month (e.g., Jegadeesh and Titman (1993)), using quarterly stock returns as the dependent variable does not bias against the momentum effect. Finally, I require a stock to be held by at least three mutual funds at the end of the previous quarter to be included in the sample. The cross-sectional regression is specified as follows:

$$\begin{aligned} ret_{j,t+1:t+3} =& \beta_0 + \beta_1\ E[FIPP_{j,t-k+1:t}] + \beta_2\ ret_{j,t} + \beta_3\ ret_{j,t-k:t-1} + \beta_4\ ret_{j,t-36:t-k-1} + \\ & \beta_5\ bm_{j,t} + \beta_6\ log(mktcap_{j,t}) + \beta_7\ turnover_{j,t-11:t}. \end{aligned} \tag{10}$$

The dependent variable is the cumulative stock return in the next quarter. The right-hand side variables include the expected flow-induced price pressure $E[FIPP]$ calculated from the market-adjusted fund returns in the prior k months, cumulative past stock returns measured at various horizons, and control variables that have been shown to predict future stock returns. $ret_{t-k:t-1}$, the cumulative stock return in months t-k to t-1, captures the price momentum effect.[26] *bm* and *mktcap* are the book-to-market ratio and the market capitalization at the end of month t, respectively. *turnover* is the average monthly share turnover in the previous year. If mutual fund flow-induced trading is partially responsible for the stock price momentum effect, we expect the coefficient of $ret_{t-k:t-1}$ to drop significantly after controlling for $E[FIPP]$ in the regression.

The results, presented in Table IX (Panel A), indicate that while the flow-based mechanism is distinct from the price momentum effect, it is an important source of the momentum profits. In the period of 1980-2006, after controlling for $E[FIPP]$, the predictive power of $ret_{t-k:t-1}$ on future stock returns drops by 25%, 31%, and 42% when k is equal to 12, 6, and 3, respectively.

[26] I skip a month between the formation and holding periods to address the short-term stock return reversal effect.

The drops in coefficients for both k equal to 6 and 3 are statistically significant at the 5% level (t=2.34 and 2.18, respectively).[27] It is evident from the regression results that $E[FIPP]$ accounts for a larger portion of the momentum effect when both $E[FIPP]$ and $ret_{t-k:t-1}$ are measured at a shorter horizon. One possibility for this pattern is that, since mutual funds are continuously updating their positions, the shorter the formation period is, the more representative the end-of-period holdings are of the average holdings in the formation period, the latter of which determine the fund performance in the ranking period.

Moreover, as suggested by prior literature (e.g., Jegadeesh and Titman (1993, 2001)), the price momentum effect exhibits a strong seasonal pattern – momentum returns are significantly positive from February to December but are significantly negative in January. To address the seasonality in price momentum, I conduct the same regression analysis on a monthly frequency (with k=6) and report two sets of coefficient estimates (Columns 9 to 12 of Panel A), one for the month of January and the other for the remainder of the year. Interestingly, the January reversal effect of the momentum strategy is quite weak in my sample, potentially due to the fact that mutual funds tend to hold larger stocks. The momentum effect in February – December is partially explained by $E[FIPP]$. The coefficient on $ret_{t-k:t-1}$ decreases by about 35% (t=2.02) after controlling for $E[FIPP]$.

Panel B reports additional tests that exploit time-series and cross-sectional variations in mutual fund ownership in stocks. Given the substantial increase in the presence of mutual funds in the stock market (see Table I) over the past three decades, we expect the flow-based mechanism to account for a larger part of the momentum effect in the second half of the sample than in the first half. Similarly, since mutual fund holdings are more concentrated in large-cap stocks, and in addition other explanations for stock price momentum (e.g., underreaction to information and implementation costs) are less suited for large-cap stocks, flow-induced price pressure should explain more of the momentum effect among large-cap than among small-cap stocks. Both predictions are corroborated by the data. The first four columns report the coefficient estimates for the first and the second half of the sample period. $E[FIPP]$ accounts for more than 39% (t=2.12) of stock price momentum in the post-1993 period, compared to only 16% in the pre-1993 period. The

[27] The standard errors are estimated from the time-series of coefficients.

next four columns present the coefficient estimates for small-cap and large-cap stocks.[28] While the flow-based mechanism accounts for close to 50% (t=2.46) of the momentum effect and renders past stock returns insignificant in the regression among large-cap stocks, it explains less than 20% of the effect among small-cap stocks.

The key takeaways from table IX are threefold. First, while the flow-based mechanism is an important driver of the stock price momentum effect, it is by no means the only one; therefore the mechanism should be viewed as a complement to rather than a substitute of the existing theories. Second, this mechanism is substantially more powerful to explain stock price momentum in more recent years and among large-cap stock; in a way, this mechanism explains the main puzzle of the price momentum effect – its persistence and robustness. Finally, although the analysis in table IX focuses exclusively on the investment flows to mutual funds, the same mechanism can be easily generalized to other types of institutional money managers, such as investment clubs, hedge funds, and pension funds, and it is reasonable to think that the generalized flow-based mechanism can account for an even larger portion of the stock price momentum effect.

6 Robustness Checks

6.1 An Alternative Hypothesis

In a recent paper, Cohen, Coval, and Pastor (2005) propose a two-step measure of manager ability that aggregates past fund alpha across managers with similar holdings. Specifically, the authors first calculate a measure of stock "quality," defined as the average past four-factor fund alpha across all mutual funds holding the stock.[29] Formally, the stock quality (Γ) for stock j in quarter t is defined as:

$$\Gamma_{j,t} = \frac{\sum_i alpha_{i,t-1} * \omega_{i,j,t-1}}{\sum_i \omega_{i,j,t-1}}. \tag{11}$$

[28] In each quarter, a stock is classified as a large-cap stock if its market-cap is above the medium market-cap of NYSE stocks at the end of the prior quarter, and a small-cap stock otherwise.

[29] Wermers, Yao, and Zhao (2007) construct a similar stock quality measure.

In the second step, the authors construct a measure of manager ability by aggregating the expected "quality" of all stocks in his portfolio, or formally:

$$\Gamma^*_{i,t} = \sum_j \Gamma_{j,t} * \omega_{i,j,t-1}. \tag{12}$$

The intuition is that stocks held primarily by skilled managers, as measured by past four-factor alpha, should have higher "quality" or expected returns than those held primarily by unskilled managers; by the same token, managers that are holding stocks with higher "quality" must be more skilled than those holding stocks with lower "quality." The authors argue that this refined measure of manager ability is superior to the traditional measure of fund alpha, because, if the alpha is a noisy measure of a manager's true ability, then "pooling information across managers adds precision." This reduced-error hypothesis seems to bear out in the data; Γ^* subsumes past four-factor fund alpha in predicting future fund performance.

Some simple algebra shows that the stock quality measure Γ is closely related to the expected flow-induce price pressure variable introduced in this paper:

$$\begin{aligned} E[FIPP_{j,t}] &= \frac{\sum_i shares_{i,j,t-1} * E[percflow_{i,t}] * PSF_{i,t-1}}{\sum_i shares_{i,j,t-1}} \\ &= \frac{\sum_i E[percflow_{i,t}] * \omega_{i,j,t-1} * TNA_{i,t-1} * PSF_{i,t-1}}{\sum_i \omega_{i,j,t-1} * TNA_{i,t-1}}. \end{aligned} \tag{13}$$

A comparison of Equation (13) to Equation (11) reveals that the only difference between Γ and $E[FIPP]$ is whether to include the fund size and the partial scaling factor in the formula. Empirically, the two variables have a positive correlation close to 0.85. Therefore, we can not distinguish between the reduced-error and the flow-induced price pressure hypotheses simply by running a horse race between Γ and $E[FIPP]$, due to the potentially severe multi-collinearity problem.

6.1.1 A Return Reversal Pattern

The key distinction between the reduced-error and price pressure hypotheses lies in their different predictions about long-term stock and fund returns. While the former maintains that the abnormal stock/fund returns of the hedging portfolio are a permanent price effect, the latter predicts a complete return reversal over the long run. In untabulated results, I show that the stock return pattern associated with Γ is almost identical to the one in Table III (Panel B): the positive return earned by the hedging portfolio in the first year is completely reversed at the end of year three. Similarly, sorting mutual funds into deciles based on Γ^*, I find that the positive return spread in the first year between "skilled" and "unskilled" managers are almost completely reversed in years two and three.

6.1.2 Comovement

The two hypotheses also differ importantly in their predictions about stock return comovement. The reduced-error hypothesis predicts that stocks held by "skilled" ("unskilled") managers have high (low) expected future returns, but says nothing about the stock return comovement pattern. On the other hand, the price pressure story predicts that stocks held by mutual funds expected to get inflows (or outflows) are going to exhibit comovement in returns, as the daily fluctuations in investment flows can introduce a common variation in stock returns. Moreover, if investors withdraw from some mutual funds in order to invest in others (e.g., Barberis and Shleifer (2003)), we should see a negative return correlation between stocks with expected inflow-induced purchases and those with expected outflow-induced sales.

To test the comovement pattern in stock returns, at the end of each quarter, I sort all stocks into quintiles based on Γ and conduct the following time-series regression using daily or weekly returns in the following year:

$$r_{j,t} = \beta_0 + \beta_1 \; r_{grp,t} + \beta_2 \; r_{opp,t} + \beta_3 \; r_{ffind,t} + \beta_4 \; r_{mktrf,t} + \beta_5 \; r_{smb,t} + \beta_6 \; r_{hml,t} + \beta_7 \; r_{umd,t}, \quad (14)$$

where $r_{grp,t}$ is the return of the quintile portfolio to which stock j belongs, $r_{ffind,t}$ is the return of the industry portfolio based on the Fama and French (1997) 48-industry definition, $r_{mktrf,t}$, $r_{smb,t}$, $r_{hml,t}$, and $r_{umd,t}$ are the market, size, value, and momentum factors, respectively. For stocks in the top and bottom quintiles, I also include $r_{opp,t}$ in the regression, which is the return of the opposite quintile portfolio. All portfolio returns are computed on a value-weighted basis, and for $r_{grp,t}$ and $r_{ffind,t}$, I exclude the stock being analyzed from the calculation. After obtaining one set of regression coefficients for each stock at the end of each quarter, I take the cross-sectional averages of the coefficients in each quarter. I then report the time-series averages of the coefficient estimates and their t-statistics based on standard errors with Newey-West corrections of up to four lags. If Γ indeed captures some unobserved manager ability, we expect an insignificant return comovement pattern among stocks within each quintile beyond what is captured by common risk factors, or in other words, β_1 to be indistinguishable from zero.

The regression results, shown in Table X, are consistent with the price pressure hypothesis. Panel A reports the coefficient estimates computed based on weekly stock returns. β_1 is significantly positive in all five Γ quintiles, suggesting considerable comovement within each of the five quintiles on top of the common risk factors. In addition, the comovement is significantly stronger in the extreme Γ quintiles than in the middle quintile, consistent with the fact that the flow-induced return effect is greater in the extreme quintiles. Finally, stock returns in quintiles one and five appear to be negatively correlated (significant at the 10% level), again in support of the price pressure hypothesis. Panel B conducts the same analysis based on daily stock returns and the results are qualitatively the same.

In sum, the results presented in this section – both the return reversal and comovement patterns – are more consistent with the flow-induced price pressure hypothesis, and less so with an ability story.

6.2 More Robustness Tests

6.2.1 Pre-1993 vs. Post-1993

As shown in Table I, the aggregate mutual fund ownership in the first half of the sample is less than one third of that in the second half (3.67% vs. 12.02%). Since the time-series differences in mutual fund ownership are unlikely to be driven by some endogenous choices made by mutual funds, we expect $E[FIPP]$ to have a significantly stronger return predictive power in the second half than in the first half of the sample. The calendar-time portfolio return results, shown in the first four columns of Table XI, support this prediction; the spread in the four-factor alpha between the top and bottom deciles ranked by $E[FIPP]$ is substantially higher in the post-1993 period than in the pre-1993 period (2.13% vs. 1.44%), and the difference of 0.70% is statistically significant at the 5% level (t=2.43).

6.2.2 First Calendar Quarter vs. the Remaining Quarters

Prior research on mutual fund flows finds that, because a large fraction of retail investors only rebalance their portfolios at the beginning of a year (e.g., Chevalier and Ellison (1997)), the magnitude of capital flows across mutual funds is much larger in the first calendar quarter than the other three quarters. Since this difference is unrelated to any confounding factors, such as manager ability, it provides us with a clean means of identification. If aggregate mutual fund flow-induced trading affects stock prices, we expect the return predictability of $E[FIPP]$ to be significantly stronger in the first calendar quarter. On the other hand, if managerial ability is driving flow-based return predictability (as argued by Cohen, Coval, and Pastor (2005)), we expect no significant difference in return predictability in different calendar quarters. The results shown in Columns 4-8 of Table XI support the price pressure hypothesis. The return predictability of $E[FIPP]$ in the first calendar quarter is more than twice as large as that in other quarters (3.24% vs. 1.26%), and the difference of 1.99% is statistically significant at the 5% level (t=2.27). In sum, the subsample analyses based on time periods and calendar quarters lend further support to the flow-based price pressure hypothesis.

7 Managerial Ability and Retail Investor Rationality

How do we interpret the findings of this paper that neither mutual fund performance persistence nor the "smart money" effect survives after we control for the flow-based mechanism of return predictability? In particular, how do we reconcile the lack of performance persistence with the findings in prior literature that some managers are able to earn positive abnormal returns?[30] There are two potential explanations for the evidence presented in this study, and the main difference between them lies in whether retail investors *rationally* respond to past mutual fund performance.

The first explanation is motivated by the model in Berk and Green (2004), which has the following two key ingredients. First, investors correctly infer manager ability from past fund performance and reward good managers with more investment capital. Second, there are decreasing returns for managers to deploying capital. In equilibrium, the model predicts that the abnormal returns

[30] See, for example, Coval and Moskowitz (2001); Kacperczyk, Sialm, and Zheng (2005); Cremers and Petajisto (2007); Cohen, Frazzini, and Malloy (2008).

expected to be earned by skilled managers are immediately eliminated by competitive capital provision, and hence there is no performance predictability either in the short-run or in the long-run. The model's predictions also rely on two implicit assumptions: a) mutual fund trading does not have price implications and b) investors can move capital across mutual funds without any constraints or costs. In the real market, both assumptions are unlikely to hold perfectly. The mutual fund herding literature documents significant price impact resulting from mutual funds' trading in the same direction; studies on mutual fund flows also find significant persistence in the investment flows to mutual funds, suggesting that capital movement is constrained at least in the short-run. Loosening the no price impact and the perfect capital mobility assumptions, we can reconcile the predictions in Berk and Green (2004) with the stock and mutual fund return patterns observed in this paper. To be specific, investment capital *gradually* moves to managers with superior skills, and eventually eliminates abnormal returns earned by these managers. But in the process, managers receiving new capital have to scale up their portfolios while managers losing investment have to scale down; such flow-induced trading drives stock prices temporarily away from the fundamental values, and gives rise to return patterns that look like performance-persistence and the "smart money" effect in the short-term.

An alternative interpretation of my findings is that past fund performance is a poor measure of manager ability, but retail investors, limited by their access to other information sources, rely excessively on fund past performance to guide their investment decisions. The reason that short-term fund performance, such as the four-factor fund alpha measured in a year, is a poor measure of manager ability is twofold. First, short-term mutual fund performance is noisy, and on top of that the estimation of risk-adjusted fund performance introduces even more noise. Second, fund alpha may capture factors other than manager ability. Intuitively, if we think about a mutual fund portfolio as a combination of a passive portfolio that tracks the benchmark index and an active portfolio that represents the manager's private information (in the spirit of Berk and Green (2004)), the total alpha is determined by both the performance and the size of the active portfolio. While the former arguably reflects manager ability, the latter is partially determined by the manager's risk aversion and his self-perception; a less risk-averse or more (over)confident manager tends to have a larger active portfolio and hence, *ceteris paribus*, larger alpha. Since both risk aversion and self-perception can vary over time, one must sort out these confounding factors in order to back out manager ability, a difficult task if at all possible.

In addition to performance persistence and the "smart money" effect, the flow-based mechanism introduced in this paper has broad implications for mutual fund performance evaluation. Specifically, any variable that can predict future mutual fund flows and flow-induced trading may appear as an ex-ante measure of manager ability. There are a number of tests we can do to distinguish the ability story from the price pressure hypothesis. The first and most straightforward test is to conduct a horse race between the variable that is supposed to capture manager ability and expected flow-induced price pressure. Second, we can test for a reversal pattern over the long run. Third, we can analyze the return comovement pattern within each group of stocks sorted by the ability variable. If the variable really captures some unobserved manager ability, we expect a) that it remains significant in predicting future fund performance after controlling for $E[FIPP]$, b) a permanent return effect (i.e., no reversal in the subsequent periods), and c) little return comovement beyond what is explained by common risk factors.

8 Conclusion

This paper proposes and tests a mechanism through which mutual fund flows can affect *individual* stock returns and mutual fund performance. This paper further demonstrates that such a mechanism is responsible for mutual fund performance persistence and the smart money effect, and partially explains stock price momentum. These findings have implications for both asset pricing theories and mutual fund performance evaluation.

A potential direction for future research is to systematically examine both flow-induced trading and information-driven trading (i.e., the decomposition in equation (2)). A number of authors have looked at aggregate mutual fund holding and trading decisions, but have at best found mixed evidence regarding manager ability (e.g., Chen, Jegadeesh, and Wermers (2000); Wermers (1999, 2000)). Separating flow-induced trading, which has little to do with stock-picking ability but can cause significant price pressure, from total trading may help us better understand how managers collect and exploit private information. Earlier studies on this topic include Edelen (1999), who decomposes total fund *turnover* into a flow-driven component and an information-driven one. Interestingly, Edelen reports that both flow-induced and information-driven trading destroys value.

More surprisingly, the negative returns associated with flow-induced turnover are entirely driven by inflows and not by outflows. A decomposition of trading in individual stocks, rather than of fund turnover, may shed more light on the mutual fund performance analysis.

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Table I: Summary Statistics of the Mutual Fund Sample (1980-2006)

This table reports the summary statistics of the mutual fund sample as of December in each year. I exclude international, fixed income, and precious metal funds from the sample. The CRSP mutual fund database and the CDA/Spectrum database are merged using MFLinks. *Num Funds* is the number of actively managed equity mutual funds at the end of each year. *TNA* is the total net assets under management reported by CRSP. *Total Equity Holdings* is the total dollar value of equities held by a mutual fund obtained from CDA/Spectrum. *% of Market Held* is the percentage of the U.S. equity market that is held by the mutual funds in this sample.

Year	Num Funds	TNA ($M)		Total Equity Holdings ($M)		% of Market Held	
		Medium	Mean	Medium	Mean	Num Stocks	Mean
1980	228	53.45	146.74	45.61	122.24	3646	2.27%
1981	226	53.66	137.71	42.11	109.31	3543	2.21%
1982	232	70.64	170.95	50.90	132.00	3393	2.21%
1983	255	97.41	222.14	79.74	182.20	4173	2.74%
1984	270	86.23	221.24	71.98	176.03	3985	2.95%
1985	297	114.12	275.98	89.48	222.04	3845	3.08%
1986	341	106.42	298.47	88.59	241.28	4134	3.46%
1987	376	87.00	286.30	74.03	238.41	4544	3.89%
1988	405	82.47	285.34	69.56	232.77	3906	3.84%
1989	440	95.08	340.49	77.91	265.36	3798	3.92%
1990	480	83.85	306.07	61.95	240.20	3175	4.15%
1991	579	100.23	379.32	79.85	309.56	3548	4.78%
1992	685	115.22	426.04	93.25	346.45	3913	5.39%
1993	925	105.56	442.40	90.00	350.65	4663	6.54%
1994	1044	105.43	450.12	85.19	352.88	4951	6.88%
1995	1168	134.35	610.98	112.60	488.36	5338	9.02%
1996	1314	145.88	750.48	123.31	605.90	5724	10.04%
1997	1480	163.42	933.60	135.21	774.02	5858	11.07%
1998	1570	167.00	1071.47	144.55	927.39	5028	11.81%
1999	1686	187.52	1307.48	164.05	1139.49	4958	12.95%
2000	1890	186.27	1283.93	159.08	1089.54	4698	12.54%
2001	1915	155.22	1018.79	133.73	882.57	3670	13.36%
2002	1970	111.80	771.11	96.53	672.64	3282	13.46%
2003	2001	146.05	976.25	128.51	852.98	3760	13.54%
2004	1961	165.93	1128.54	144.58	978.38	3820	13.82%
2005	1918	196.90	1251.72	169.84	1067.81	3884	14.02%
2006	1789	221.75	1400.29	193.07	1187.58	3858	13.71%

Table II: Determinants of Partial Scaling (1980-2006)

This table reports the regressions of *delta shares* on *percflow* and a number of variables that may affect the cost of partial scaling. Panel A reports the regression with fund-holding observations, and Panel B reports the regression with portfolio-average observations. *Delta shares(i,j,t)* is the percentage change of shares in stock *j* held by fund *i* from quarter *t*-1 to quarter *t* with split-adjustment. *Delta shares(i, t)* is the portfolio weighted average change in shares held. *percflow(i, t)* is the net capital flow received by fund *i* in quarter *t* scaled by the fund's total net assets at the end of quarter *t*-1. *% held(i,j,t-1)* is the percentage of shares outstanding held by fund *i* at the end of quarter *t*- 1. *liq_cost(j,t-1)* is the effective half spread estimated from the Basic Market-Adjusted model described in Hasbrouck (2006). *%held (fund)* and *liq_cost (fund)* are the portfolio-weighted average ownership share, and the portfolio-weighted average effective spread, respectively. *high_TNA* is an indicator variable, equal to one if the fund's TNA is above the medium TNA of the mutual fund sample in a quarter. *exp_flow* is the expected flow computed from the four-factor fund alpha of the prior year. Quarter fixed effects are included in every regression specification. T-statistics, shown in parentheses below the coefficient estimates, are computed based on standard errors clustered at the fund level. Estimates significant at the 5% level are in bold font.

Panel A: DepVar = delta shares (Holding Level Regression)

	Outflow					Inflow				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Intercept	**-0.059**	-0.029	-0.022	-0.022	-0.022	**-0.032**	0.000	0.020	0.020	0.020
	(-6.62)	(-1.32)	(-0.85)	(-0.88)	(-0.88)	(-3.42)	(0.02)	(1.22)	(1.21)	(1.21)
percflow	**0.970**	**1.028**	**1.107**	**1.107**	**1.112**	**0.618**	**0.737**	**0.858**	**0.855**	**0.852**
	(16.82)	(17.64)	(10.97)	(11.27)	(11.32)	(15.78)	(14.64)	(10.57)	(10.57)	(10.33)
own		0.429		**-1.196**	**-1.107**		-0.766		-0.471	-0.640
		(1.35)		(-2.35)	(-1.98)		(-1.50)		(-0.65)	(-0.83)
flow * own		-2.355		**-20.588**	-10.539		**-12.431**		-1.669	-3.384
		(-0.58)		(-3.25)	(-0.87)		(-3.74)		(-0.51)	(-0.50)
liqcost		**-7.455**		**-5.755**	**-5.735**		**-7.529**		**-3.416**	**-3.438**
		(-2.97)		(-5.38)	(-5.38)		(-3.95)		(-4.77)	(-4.71)
flow * liqcost		**-28.559**		**-13.999**	**-14.105**		**-25.748**		**-8.433**	**-7.820**
		(-2.48)		(-2.18)	(-2.23)		(-3.71)		(-2.39)	(-2.24)
own (fund)			**2.171**	**3.924**	**3.905**			-0.364	0.212	0.278
			(3.58)	(4.06)	(3.95)			(-0.44)	(0.18)	(0.24)
flow * own (fund)			11.265	**41.242**	**37.171**			**-21.337**	**-19.235**	**-17.741**
			(1.32)	(3.10)	(2.60)			(-3.20)	(-2.58)	(-2.34)
liqcost (fund)			-11.127	-6.084	-6.018			**-18.461**	**-15.505**	**-15.480**
			(-1.89)	(-1.24)	(-1.24)			(-3.08)	(-2.79)	(-2.75)
flow * liqcost (fund)			-57.295	-44.609	-45.767			**-51.076**	**-42.332**	**-41.681**
			(-1.90)	(-1.43)	(-1.47)			(-3.01)	(-2.49)	(-2.40)
$flow^2$ * own					19.315					-2.606
					(1.08)					(-0.39)
flow * $(own)^2$					-70.042					53.280
					(-1.00)					(1.30)
R^2	4.68%	6.31%	6.21%	6.43%	6.43%	9.53%	10.07%	11.36%	11.46%	11.47%
No Obs	1044863	1044863	1044863	1044863	1044863	2215027	2215027	2215027	2215027	2215027

Table II (Continued)

Panel B: DepVar = delta shares (Fund Level Regression)								
	Outflow				Inflow			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	**-0.099**	**-0.106**	**-0.071**	**-0.205**	**-0.062**	**-0.071**	**-0.051**	**-0.097**
	(-15.38)	(-16.20)	(-7.82)	(-6.78)	(-7.42)	(-8.39)	(-4.97)	(-12.95)
percflow	**0.915**	**0.902**	**0.874**		**0.570**	**0.617**	**0.787**	
	(34.17)	(31.39)	(15.45)		(26.23)	(26.25)	(18.06)	
own (fund)		**1.806**	**3.554**			**2.689**	**3.175**	
		(4.91)	(6.24)			(5.83)	(5.22)	
flow * own (fund)		3.936	-1.455			**-17.702**	**-8.934**	
		(0.97)	(-0.28)			(-4.19)	(-2.24)	
liq_cost (fund)			**-21.139**				**-18.436**	
			(-7.31)				(-6.83)	
flow * liqcost (fund)			-1.018				**-35.563**	
			(-0.07)				(-4.19)	
high_tna			0.001				**0.012**	
			(0.23)				(2.02)	
flow * high_tna			-0.011				0.061	
			(-0.19)				(1.65)	
exp_flow				**0.972**				**0.537**
				(5.50)				(6.20)
R^2	15.90%	16.29%	19.76%	6.67%	28.26%	29.05%	33.27%	2.44%
No Obs	16765	16765	16765	16406	21671	21671	21671	23129

Table III: Flow-Induced Price Pressure (1980-2006)

This table reports the calendar-time returns of stock portfolios sorted by flow-induced price pressure (*FIPP*). *FIPP* is defined as the aggregate flow-induced trading (*FIT*) in a quarter scaled by the total shares held by mutual funds at the end of the prior quarter. The portfolios are rebalanced every quarter and held for three years. Quarter 0 is the formation quarter. Panel A reports the magnitude of *FIPP* in each quarter from four quarters before the ranking period to four quarter after. Panel B and C report the equal-weighted and value-weighted monthly portfolio returns, respectively. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Three different monthly returns are reported: the return in excess of the risk-free rate, the Fama-French three-factor alpha, and the Carhart four-factor alpha. T-statistics, shown in parentheses, are computed based on White's standard errors. Estimates significant at the 5% level are in bold font.

Panel A: The Magnitude of FIPP from t-4 to t+4

Decile	Qtr -4	Qtr -3	Qtr -2	Qtr -1	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4
1	1.27%	0.81%	0.48%	-0.24%	-5.50%	0.20%	0.59%	0.61%	1.21%
	(3.83)	(2.45)	(1.56)	(-0.76)	(-19.31)	(0.52)	(1.84)	(2.42)	(4.60)
2	1.24%	0.88%	0.57%	-0.01%	-2.00%	-0.10%	0.39%	0.70%	1.03%
	(4.80)	(3.21)	(2.32)	(-0.06)	(-10.39)	(-0.47)	(1.78)	(3.34)	(4.56)
3	1.35%	1.09%	0.94%	0.50%	-0.81%	0.38%	0.75%	1.07%	1.17%
	(5.69)	(4.56)	(4.17)	(2.51)	(-4.32)	(1.94)	(3.47)	(5.33)	(5.46)
4	1.68%	1.47%	1.32%	1.02%	0.09%	0.84%	1.17%	1.28%	1.39%
	(7.06)	(6.23)	(5.86)	(4.72)	(0.48)	(4.13)	(5.66)	(6.42)	(6.69)
5	1.83%	1.83%	1.76%	1.50%	0.92%	1.33%	1.57%	1.65%	1.72%
	(7.28)	(7.58)	(7.10)	(6.60)	(4.65)	(6.16)	(7.43)	(7.52)	(8.16)
6	2.29%	2.31%	2.26%	2.08%	1.81%	1.90%	1.92%	1.96%	1.94%
	(8.60)	(8.99)	(8.82)	(8.22)	(8.35)	(8.05)	(8.41)	(8.74)	(8.74)
7	2.77%	2.69%	2.80%	2.83%	2.82%	2.50%	2.44%	2.32%	2.38%
	(9.83)	(9.78)	(9.72)	(9.99)	(11.41)	(9.72)	(9.70)	(9.20)	(9.73)
8	2.99%	3.26%	3.34%	3.59%	4.18%	3.28%	3.03%	2.76%	2.64%
	(10.03)	(10.78)	(10.19)	(10.15)	(13.87)	(11.10)	(10.87)	(9.47)	(9.97)
9	3.62%	4.05%	4.36%	4.95%	6.46%	4.50%	3.88%	3.51%	3.05%
	(11.16)	(11.39)	(11.41)	(11.72)	(15.37)	(11.68)	(11.72)	(10.68)	(10.28)
10	5.00%	5.88%	6.69%	8.62%	16.76%	8.06%	6.10%	5.25%	4.23%
	(13.17)	(13.74)	(14.37)	(13.20)	(17.52)	(13.39)	(13.10)	(11.95)	(10.65)
10 - 1	**3.73%**	**5.07%**	**6.21%**	**8.86%**	**22.27%**	**7.86%**	**5.51%**	**4.65%**	**3.02%**
	(11.00)	(13.20)	(15.98)	(14.37)	(22.94)	(12.54)	(14.91)	(15.25)	(12.61)

Table III (Continued)

Panel B: Equal-Weighted Portfolio Returns Sorted by FIPP										
	Qtr 0 (Formation Qtr)			Qtr 1-4			Qtr 5-8		Qtr 5-12	
Decile	excess	alpha_3f	alpha_4f	excess	alpha_3f	alpha_4f	excess	alpha_3f	excess	alpha_3f
1	0.09%	-0.83%	-0.64%	0.68%	-0.22%	0.06%	0.90%	-0.06%	0.92%	0.05%
	(0.27)	(-6.01)	(-5.43)	(2.05)	(-1.90)	(0.63)	(2.57)	(-0.54)	(2.90)	(0.67)
2	0.13%	-0.79%	-0.53%	0.71%	-0.23%	0.05%	0.89%	-0.06%	0.91%	0.03%
	(0.38)	(-5.90)	(-4.59)	(2.19)	(-2.06)	(0.53)	(2.75)	(-0.69)	(3.00)	(0.35)
3	0.37%	-0.57%	-0.35%	0.73%	-0.20%	0.04%	0.92%	0.00%	0.93%	0.04%
	(1.10)	(-4.72)	(-3.31)	(2.30)	(-1.94)	(0.55)	(3.01)	(0.03)	(3.10)	(0.54)
4	0.57%	-0.38%	-0.24%	0.74%	-0.16%	0.08%	0.90%	0.00%	0.85%	-0.04%
	(1.73)	(-3.62)	(-2.67)	(2.36)	(-1.62)	(1.08)	(3.01)	(0.02)	(2.86)	(-0.56)
5	0.66%	-0.26%	-0.17%	0.74%	-0.12%	0.08%	0.88%	0.01%	0.87%	-0.03%
	(2.10)	(-3.03)	(-2.24)	(2.42)	(-1.29)	(1.09)	(3.04)	(0.12)	(2.94)	(-0.38)
6	0.86%	-0.04%	0.01%	0.72%	-0.12%	0.10%	0.88%	0.03%	0.81%	-0.08%
	(2.66)	(-0.50)	(0.20)	(2.31)	(-1.29)	(1.03)	(3.08)	(0.41)	(2.76)	(-1.01)
7	1.00%	0.13%	0.09%	0.76%	-0.07%	0.14%	0.80%	-0.06%	0.83%	-0.07%
	(3.15)	(1.93)	(1.30)	(2.42)	(-0.69)	(1.33)	(2.76)	(-0.68)	(2.81)	(-0.70)
8	1.23%	0.37%	0.30%	0.70%	-0.07%	0.10%	0.73%	-0.11%	0.74%	-0.15%
	(3.73)	(4.98)	(3.85)	(2.23)	(-0.77)	(0.93)	(2.46)	(-1.00)	(2.47)	(-1.46)
9	1.42%	0.62%	0.52%	0.66%	-0.09%	0.05%	0.66%	-0.17%	0.74%	-0.10%
	(4.35)	(6.82)	(5.12)	(2.07)	(-0.86)	(0.33)	(2.11)	(-1.30)	(2.56)	(-0.99)
10	1.82%	1.08%	0.86%	0.66%	-0.02%	0.04%	0.49%	-0.33%	0.63%	-0.17%
	(5.21)	(8.08)	(6.80)	(1.94)	(-0.16)	(0.22)	(1.40)	(-1.81)	(2.10)	(-1.36)
10 - 1	**1.73%**	**1.91%**	**1.50%**	-0.03%	0.20%	-0.02%	**-0.40%**	-0.27%	**-0.30%**	**-0.23%**
	(7.77)	(8.31)	(7.38)	(-0.17)	(1.36)	(-0.10)	(-2.46)	(-1.46)	(-2.70)	(-2.10)

Table III (Continued)

Panel C: Value-Weighted Portfolio Returns Sorted by FIPP										
	Qtr 0 (Formation Qtr)			Qtr 1-4			Qtr 5-8		Qtr 5-12	
Decile	excess	alpha_3f	alpha_4f	excess	alpha_3f	alpha_4f	excess	alpha_3f	excess	alpha_3f
1	-0.22%	-1.05%	-0.82%	0.73%	-0.09%	-0.02%	0.87%	0.19%	0.82%	0.19%
	(-0.67)	(-5.80)	(-4.50)	(2.52)	(-0.88)	(-0.16)	(3.04)	(1.83)	(2.91)	(1.99)
2	0.01%	-0.80%	-0.57%	0.76%	-0.06%	0.02%	0.89%	0.22%	0.83%	0.19%
	(0.04)	(-5.60)	(-3.82)	(2.72)	(-0.52)	(0.20)	(3.25)	(1.95)	(3.13)	(2.14)
3	0.26%	-0.57%	-0.45%	0.79%	0.02%	0.06%	0.84%	0.18%	0.76%	0.10%
	(0.90)	(-4.23)	(-3.43)	(2.96)	(0.17)	(0.56)	(3.23)	(2.12)	(3.02)	(1.60)
4	0.47%	-0.29%	-0.19%	0.72%	-0.01%	0.02%	0.81%	0.14%	0.76%	0.11%
	(1.69)	(-2.63)	(-1.86)	(2.75)	(-0.06)	(0.22)	(3.16)	(1.92)	(3.08)	(1.27)
5	0.58%	-0.18%	-0.15%	0.71%	0.03%	0.10%	0.82%	0.18%	0.78%	0.16%
	(2.00)	(-1.75)	(-1.55)	(2.60)	(0.38)	(1.55)	(3.09)	(2.10)	(3.03)	(1.96)
6	0.88%	0.15%	0.04%	0.60%	-0.08%	-0.01%	0.67%	-0.01%	0.66%	-0.02%
	(2.99)	(1.33)	(0.42)	(2.08)	(-0.95)	(-0.17)	(2.55)	(-0.11)	(2.57)	(-0.46)
7	1.04%	0.32%	0.06%	0.61%	-0.04%	0.01%	0.66%	-0.02%	0.63%	-0.04%
	(3.32)	(2.47)	(0.46)	(2.05)	(-0.36)	(0.07)	(2.35)	(-0.21)	(2.35)	(-0.62)
8	1.41%	0.74%	0.49%	0.60%	0.00%	-0.09%	0.51%	-0.13%	0.53%	-0.13%
	(4.25)	(4.99)	(3.25)	(1.88)	(-0.02)	(-0.74)	(1.75)	(-1.11)	(1.90)	(-1.42)
9	1.71%	1.04%	0.68%	0.52%	-0.09%	-0.27%	0.33%	-0.29%	0.40%	-0.26%
	(4.60)	(5.70)	(4.10)	(1.54)	(-0.68)	(-1.85)	(1.02)	(-2.04)	(1.36)	(-2.31)
10	1.90%	1.26%	0.93%	0.64%	0.05%	-0.22%	0.21%	-0.35%	0.36%	-0.23%
	(4.81)	(6.16)	(4.65)	(1.75)	(0.36)	(-1.46)	(0.61)	(-2.12)	(1.16)	(-1.89)
10 - 1	**2.12%**	**2.31%**	**1.76%**	-0.08%	0.15%	-0.21%	**-0.66%**	**-0.54%**	**-0.46%**	**-0.42%**
	(5.96)	(6.78)	(5.11)	(-0.35)	(0.68)	(-0.93)	(-3.04)	(-2.85)	(-2.80)	(-2.61)

Table VI: Determinants of Expected Flows (1980-2006)

This table reports the regression of *percflow(t)* on *alpha(t-4,t-1)* , *adjret(t-4,t-1),* and lagged *percflow*. *percflow(t)* is the dollar flow to a mutual fund in quarter *t* scaled by the fund's *TNA* at the end of quarter *t* -1. *alpha(t-4,t-1)* is the Carhart four-factor alpha computed from the fund's monthly returns in the prior year. *adjret(t-4,t-1)* is the cumulative market-adjusted fund return in the prior year. The coefficients are estimated both with the Fama-MacBeth approach and with a pooled OLS regression. Standard errors for the Fama-MacBeth estimates are computed with the Newey-West correction of four lags. For the pooled OLS, quarter fixed effects are included in every regression specification and standard errors are clustered at the fund level. T-statistics are shown in parentheses. Estimates significant at the 5% level are in bold font.

Dependent Variable = percflow(t)								
	Fama-MacBeth				Pooled OLS			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	**0.028**	**0.028**	**0.312**	**0.010**	**0.016**	**0.014**	**0.375**	**0.007**
	(5.38)	(5.77)	(13.39)	(3.65)	(25.89)	(18.77)	(20.12)	(7.72)
alpha(t-4,t-1)	**4.827**	**1.766**	**15.242**	**0.953**	**4.232**	**2.453**	**10.069**	**1.330**
	(9.67)	(4.38)	(4.29)	(4.47)	(9.02)	(9.15)	(4.17)	(5.43)
adjret(t-4,t-1)		**0.396**		**0.229**		**0.202**		**0.089**
		(7.34)		(6.72)		(5.17)		(2.74)
log_tna			**-0.015**				**-0.019**	
			(-14.63)				(-19.11)	
alpha_tna			**-0.562**				**-0.311**	
			(-3.14)				(-2.59)	
percflow(t-1)				**0.194**				**0.228**
				(8.78)				(17.21)
percflow(t-2)				**0.102**				**0.109**
				(5.28)				(7.55)
percflow(t-3)				**0.122**				**0.090**
				(6.29)				(6.03)
percflow(t-4)				**0.033**				**0.029**
				(5.47)				(3.67)
R^2	4.53%	7.70%	7.15%	24.79%	5.25%	7.14%	7.79%	19.83%
No Obs	93629	93629	93629	93629	93629	93629	93629	93629

Table V: Expected Flow-Induced Price Pressure (1980-2006)

Panel A reports the equal-weighted calendar-time returns of stock portfolios sorted by expected flow-induced price pressure (*E[FIPP]*). *E[FIPP]* is computed as the aggregate expected flow-induced trading (*E[FIT]*) in a quarter scaled by the total shares held by mutual funds at the end of the quarter. The expected capital flow in a quarter is estimated from the four-factor fund alpha in the prior year. Panel B reports the calendar-time returns of mutual fund portfolios sorted by portfolio-weighted average expected flow-induced price pressure (*E[FIPP*]*). The portfolios are rebalanced every quarter and held for three years. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Three different monthly returns are reported: the return in excess of the risk-free rate, the Fama-French three-factor alpha, and the Carhart four-factor alpha. T-statistics, shown in parentheses, are computed based on White's standard errors. Estimates significant at the 5% level are in bold font.

Panel A: Sort Stocks by E[FIPP]

	Qtr 1			Qtr 1-4			Qtr 5		Qtr 6-8		Qtr 6-12	
decile	excess	alpha_3f	alpha_4f	excess	alpha_3f	alpha_4f	excess	alpha_3f	excess	alpha_3f	excess	alpha_3f
1	0.38%	-0.50%	-0.25%	0.53%	-0.40%	-0.13%	0.52%	-0.24%	0.84%	-0.01%	0.94%	0.13%
	(1.08)	(-3.37)	(-1.88)	(1.56)	(-3.02)	(-1.04)	(1.53)	(-2.41)	(2.54)	(-0.08)	(2.98)	(1.40)
2	0.55%	-0.37%	-0.21%	0.67%	-0.29%	-0.07%	0.67%	-0.22%	0.94%	0.07%	0.91%	0.06%
	(1.68)	(-3.26)	(-2.00)	(2.10)	(-2.58)	(-0.69)	(2.07)	(-1.80)	(2.96)	(0.69)	(2.97)	(0.80)
3	0.68%	-0.25%	-0.12%	0.74%	-0.21%	-0.02%	0.73%	-0.14%	0.86%	-0.01%	0.88%	0.01%
	(2.11)	(-2.47)	(-1.34)	(2.37)	(-2.16)	(-0.18)	(2.34)	(-1.34)	(2.81)	(-0.13)	(3.00)	(0.18)
4	0.84%	-0.09%	0.00%	0.80%	-0.14%	0.02%	0.77%	-0.07%	0.83%	-0.03%	0.88%	0.01%
	(2.66)	(-0.94)	(0.02)	(2.59)	(-1.69)	(0.28)	(2.44)	(-0.66)	(2.76)	(-0.34)	(3.02)	(0.18)
5	0.85%	-0.08%	-0.01%	0.82%	-0.11%	0.06%	0.76%	-0.09%	0.79%	-0.08%	0.85%	-0.04%
	(2.69)	(-1.08)	(-0.14)	(2.69)	(-1.35)	(0.82)	(2.47)	(-0.96)	(2.63)	(-1.00)	(2.95)	(-0.50)
6	0.83%	-0.07%	-0.01%	0.85%	-0.06%	0.08%	0.68%	-0.14%	0.74%	-0.13%	0.81%	-0.09%
	(2.68)	(-0.94)	(-0.16)	(2.83)	(-0.83)	(1.31)	(2.18)	(-1.17)	(2.45)	(-1.39)	(2.81)	(-1.04)
7	0.82%	-0.05%	-0.02%	0.81%	-0.08%	0.06%	0.61%	-0.18%	0.74%	-0.13%	0.77%	-0.14%
	(2.63)	(-0.72)	(-0.31)	(2.66)	(-1.04)	(0.93)	(1.96)	(-1.48)	(2.42)	(-1.20)	(2.66)	(-1.40)
8	0.90%	0.04%	0.05%	0.87%	-0.01%	0.10%	0.60%	-0.17%	0.71%	-0.16%	0.76%	-0.16%
	(2.80)	(0.59)	(0.71)	(2.80)	(-0.08)	(1.50)	(1.89)	(-1.44)	(2.28)	(-1.37)	(2.55)	(-1.46)
9	1.10%	0.27%	0.19%	0.87%	0.03%	0.10%	0.63%	-0.15%	0.71%	-0.15%	0.76%	-0.15%
	(3.33)	(3.15)	(2.23)	(2.75)	(0.39)	(1.22)	(1.87)	(-1.06)	(2.23)	(-1.22)	(2.52)	(-1.38)
10	1.21%	0.43%	0.27%	0.97%	0.18%	0.24%	0.63%	-0.01%	0.54%	-0.23%	0.67%	-0.14%
	(3.33)	(3.64)	(2.20)	(2.76)	(1.66)	(1.76)	(1.67)	(-0.03)	(1.58)	(-1.56)	(2.12)	(-1.06)
10 - 1	**0.84%**	**0.93%**	**0.53%**	**0.44%**	**0.58%**	**0.37%**	0.10%	0.23%	**-0.29%**	-0.22%	**-0.27%**	**-0.27%**
	(3.96)	(4.15)	(3.51)	(2.63)	(3.30)	(2.26)	(0.49)	(0.81)	(-2.06)	(-1.32)	(-2.17)	(-2.04)

Table V (Continued)

Panel B: Sort Funds by E[FIPP]*

	Qtr 1			Qtr 1-4			Qtr 5		Qtr 6-8		Qtr 6-12	
decile	excess	alpha_3f	alpha_4f	excess	alpha_3f	alpha_4f	excess	alpha_3f	excess	alpha_3f	excess	alpha_3f
1	0.58%	-0.17%	-0.03%	0.62%	-0.15%	-0.11%	0.71%	0.07%	0.87%	0.25%	0.79%	0.18%
	(1.90)	(-1.36)	(-0.15)	(2.11)	(-1.62)	(-0.91)	(2.38)	(0.64)	(2.90)	(2.71)	(2.67)	(2.44)
2	0.62%	-0.11%	-0.03%	0.69%	-0.05%	-0.03%	0.62%	-0.01%	0.76%	0.16%	0.74%	0.15%
	(2.15)	(-1.09)	(-0.27)	(2.47)	(-0.65)	(-0.32)	(2.18)	(-0.14)	(2.69)	(2.17)	(2.66)	(2.35)
3	0.68%	-0.03%	0.01%	0.70%	-0.01%	0.00%	0.62%	0.02%	0.68%	0.07%	0.69%	0.09%
	(2.43)	(-0.40)	(0.08)	(2.61)	(-0.08)	(0.04)	(2.27)	(0.28)	(2.49)	(1.27)	(2.64)	(1.89)
4	0.69%	-0.01%	0.01%	0.71%	0.02%	0.02%	0.59%	-0.03%	0.69%	0.07%	0.69%	0.07%
	(2.57)	(-0.16)	(0.21)	(2.70)	(0.33)	(0.38)	(2.19)	(-0.59)	(2.59)	(1.59)	(2.71)	(1.93)
5	0.68%	-0.02%	-0.02%	0.71%	0.01%	0.02%	0.63%	0.04%	0.67%	0.03%	0.68%	0.04%
	(2.52)	(-0.42)	(-0.45)	(2.71)	(0.33)	(0.46)	(2.42)	(0.71)	(2.58)	(0.83)	(2.74)	(1.00)
6	0.68%	0.01%	0.02%	0.72%	0.05%	0.07%	0.63%	0.01%	0.63%	-0.01%	0.64%	-0.01%
	(2.54)	(0.28)	(0.34)	(2.80)	(1.22)	(1.45)	(2.37)	(0.16)	(2.44)	(-0.14)	(2.54)	(-0.28)
7	0.72%	0.06%	0.05%	0.73%	0.06%	0.07%	0.65%	0.04%	0.67%	0.04%	0.67%	0.01%
	(2.64)	(1.13)	(0.74)	(2.77)	(1.45)	(1.44)	(2.47)	(0.70)	(2.60)	(0.93)	(2.67)	(0.33)
8	0.73%	0.10%	0.05%	0.76%	0.11%	0.09%	0.64%	0.06%	0.63%	0.00%	0.64%	-0.01%
	(2.57)	(1.67)	(0.75)	(2.77)	(2.31)	(1.84)	(2.33)	(0.82)	(2.36)	(-0.06)	(2.52)	(-0.11)
9	0.87%	0.27%	0.18%	0.83%	0.19%	0.15%	0.70%	0.11%	0.64%	0.01%	0.65%	0.01%
	(2.85)	(3.04)	(1.99)	(2.89)	(3.07)	(2.20)	(2.41)	(1.30)	(2.32)	(0.15)	(2.47)	(0.14)
10	1.14%	0.54%	0.37%	1.02%	0.40%	0.26%	0.70%	0.11%	0.56%	-0.05%	0.57%	-0.07%
	(3.42)	(4.09)	(3.01)	(3.29)	(4.24)	(2.92)	(2.20)	(0.99)	(1.87)	(-0.53)	(2.03)	(-0.77)
10 - 1	**0.55%**	**0.71%**	**0.41%**	**0.40%**	**0.55%**	**0.37%**	-0.01%	0.04%	**-0.31%**	**-0.30%**	-0.22%	-0.25%
	(2.66)	(3.14)	(2.58)	(2.65)	(3.44)	(2.34)	(-0.06)	(0.22)	(-2.23)	(-2.07)	(-1.70)	(-1.87)

Table VI: Mutual Fund Performance Persistence (1980-2006)

Panel A reports the calendar-time returns of mutual fund portfolios sorted by the four-factor fund alpha in the prior year. Panel B reports the calendar-time portfolio returns first sorted by *E[FIPP*]* and then by the four-factor fund alpha, and Panel C reports the calendar-time portfolio returns first sorted by the four-factor fund alpha and then by *E[FIPP*]* . *E[FIPP*]* is the portfolio-weighted average expected flow-induced price pressure. The portfolios are rebalanced every quarter and held for up to three years. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Three different monthly returns are reported: the return in excess of the risk-free rate, the Fama-French three-factor alpha, and the Carhart four-factor alpha. T-statistics, shown in parentheses, are computed based on White's standard errors. Estimates significant at the 5% level are in bold font.

Panel A: Mutual Fund Performance Persistence (Sort by the Four-Factor Fund Alpha)

	Qtr 1			Qtr 1-4			Qtr 5-8		Qtr 5-12	
decile	excess	alpha_3f	alpha_4f	excess	alpha_3f	alpha_4f	excess	alpha_3f	excess	alpha_3f
1	0.58%	-0.13%	-0.09%	0.63%	-0.09%	-0.10%	0.75%	0.15%	0.72%	0.13%
	(1.96)	(-1.48)	(-0.95)	(2.20)	(-1.38)	(-1.37)	(2.61)	(2.41)	(2.57)	(2.41)
2	0.65%	-0.05%	-0.03%	0.67%	-0.03%	-0.05%	0.67%	0.07%	0.66%	0.06%
	(2.35)	(-0.81)	(-0.54)	(2.48)	(-0.66)	(-0.89)	(2.48)	(1.41)	(2.51)	(1.32)
3	0.66%	-0.04%	-0.02%	0.69%	-0.01%	-0.02%	0.61%	0.01%	0.62%	0.01%
	(2.44)	(-0.69)	(-0.39)	(2.64)	(-0.12)	(-0.35)	(2.35)	(0.27)	(2.46)	(0.21)
4	0.69%	0.01%	0.02%	0.70%	0.01%	0.00%	0.63%	0.02%	0.63%	0.02%
	(2.60)	(0.28)	(0.34)	(2.70)	(0.14)	(-0.01)	(2.43)	(0.65)	(2.55)	(0.60)
5	0.71%	0.04%	0.04%	0.70%	0.02%	0.02%	0.63%	0.02%	0.63%	0.02%
	(2.71)	(0.83)	(0.80)	(2.74)	(0.45)	(0.38)	(2.47)	(0.66)	(2.58)	(0.49)
6	0.70%	0.02%	0.01%	0.73%	0.05%	0.04%	0.64%	0.03%	0.62%	0.01%
	(2.64)	(0.55)	(0.30)	(2.82)	(1.42)	(1.07)	(2.50)	(0.90)	(2.53)	(0.24)
7	0.73%	0.06%	0.05%	0.76%	0.07%	0.07%	0.66%	0.05%	0.65%	0.03%
	(2.74)	(1.39)	(1.16)	(2.92)	(1.86)	(1.71)	(2.58)	(1.52)	(2.63)	(0.83)
8	0.78%	0.12%	0.09%	0.78%	0.11%	0.10%	0.65%	0.03%	0.66%	0.04%
	(2.81)	(2.57)	(1.96)	(2.94)	(2.55)	(2.28)	(2.46)	(0.73)	(2.62)	(0.92)
9	0.83%	0.17%	0.14%	0.82%	0.15%	0.13%	0.68%	0.08%	0.66%	0.04%
	(2.87)	(3.35)	(2.52)	(2.94)	(3.17)	(2.65)	(2.50)	(1.58)	(2.52)	(0.83)
10	1.04%	0.40%	0.30%	0.98%	0.33%	0.27%	0.66%	0.09%	0.67%	0.07%
	(2.98)	(4.28)	(3.05)	(2.95)	(4.47)	(3.39)	(2.08)	(1.16)	(2.23)	(0.97)
10 - 1	**0.46%**	**0.52%**	**0.39%**	**0.35%**	**0.42%**	**0.37%**	-0.08%	-0.06%	-0.05%	-0.07%
	(3.36)	(4.00)	(3.19)	(3.32)	(4.51)	(3.89)	(-0.95)	(-0.68)	(-0.74)	(-0.76)

Table VI (Continued)

Panel B: First Sort by E[FIPP] and Then by Fund Alpha*

Quintiles of Fund Alpha	Quintiles of *E[FIPP*]* 1	2	3	4	5	5 - 1	average	Quintiles of *E[FIPP*]* 1	2	3	4	5	5 - 1	average
	Qtr 1 (alpha_3f)							Qtr 1 (alpha_4f)						
1	-0.17%	-0.06%	-0.06%	0.18%	0.36%	**0.53%**	0.05%	-0.09%	-0.07%	-0.08%	0.12%	0.27%	**0.36%**	0.03%
	(-1.33)	(-0.90)	(-1.03)	(2.35)	(3.33)	(2.81)	(1.08)	(-0.64)	(-1.16)	(-1.37)	(1.55)	(2.26)	(2.01)	(0.51)
2	-0.20%	-0.03%	0.01%	0.09%	0.37%	**0.57%**	0.05%	-0.11%	-0.02%	0.00%	0.06%	0.25%	**0.36%**	0.03%
	(-1.85)	(-0.49)	(0.13)	(1.50)	(3.74)	(3.27)	(1.29)	(-0.94)	(-0.40)	(-0.07)	(1.05)	(2.44)	(2.15)	(0.83)
3	-0.19%	-0.05%	-0.02%	0.09%	0.30%	**0.49%**	0.03%	-0.12%	-0.04%	-0.03%	0.08%	0.22%	**0.34%**	0.02%
	(-1.83)	(-0.88)	(-0.37)	(1.64)	(3.04)	(2.80)	(0.85)	(-1.17)	(-0.76)	(-0.54)	(1.53)	(2.12)	(1.96)	(0.55)
4	-0.09%	-0.04%	-0.03%	0.07%	0.34%	**0.42%**	0.05%	-0.03%	-0.03%	-0.03%	0.06%	0.23%	0.25%	0.04%
	(-0.86)	(-0.71)	(-0.46)	(1.27)	(3.40)	(2.43)	(1.32)	(-0.25)	(-0.45)	(-0.47)	(1.18)	(2.36)	(1.50)	(1.02)
5	-0.11%	0.01%	-0.01%	0.04%	0.57%	**0.69%**	**0.10%**	-0.05%	0.03%	0.00%	0.04%	0.48%	**0.52%**	0.10%
	(-1.02)	(0.17)	(-0.09)	(0.69)	(4.50)	(3.41)	(2.24)	(-0.41)	(0.56)	(0.01)	(0.62)	(3.44)	(2.58)	(1.95)
5 - 1	0.06%	0.07%	0.05%	-0.14%	**0.21%**		0.05%	0.04%	0.10%	0.08%	-0.08%	**0.20%**		0.07%
	(0.56)	(1.15)	(0.71)	(-1.71)	(2.67)		(1.05)	(0.35)	(1.28)	(1.07)	(-0.96)	(2.59)		(1.21)

Panel C: First Sort by Fund Alpha and Then by E[FIPP]*

Quintiles of *E[FIPP*]*	Quintiles of Fund Alpha 1	2	3	4	5	5 - 1	average	Quintiles of Fund Alpha 1	2	3	4	5	5 - 1	average
	Qtr 1 (alpha_3f)							Qtr 1 (alpha_4f)						
1	-0.31%	-0.10%	-0.05%	0.01%	0.02%	**0.32%**	-0.09%	-0.15%	-0.04%	0.00%	0.05%	0.03%	0.18%	-0.03%
	(-2.02)	(-0.96)	(-0.61)	(0.07)	(0.20)	(2.31)	(-1.01)	(-0.94)	(-0.33)	(-0.01)	(0.54)	(0.32)	(1.21)	(-0.26)
2	-0.13%	-0.08%	-0.05%	-0.03%	0.08%	0.21%	-0.04%	-0.09%	-0.05%	-0.05%	-0.01%	0.07%	0.16%	-0.03%
	(-1.26)	(-1.08)	(-0.99)	(-0.48)	(1.24)	(1.80)	(-0.79)	(-0.85)	(-0.74)	(-0.85)	(-0.20)	(1.07)	(1.36)	(-0.50)
3	-0.12%	0.00%	-0.02%	-0.06%	0.26%	**0.38%**	0.01%	-0.10%	0.00%	-0.03%	-0.04%	0.19%	**0.28%**	0.00%
	(-1.60)	(-0.03)	(-0.50)	(-1.03)	(2.75)	(2.90)	(0.29)	(-1.21)	(-0.05)	(-0.53)	(-0.76)	(1.97)	(2.31)	(0.09)
4	-0.06%	-0.04%	0.03%	0.16%	0.41%	**0.47%**	**0.10%**	-0.10%	-0.04%	0.02%	0.13%	0.30%	**0.40%**	0.06%
	(-1.05)	(-0.84)	(0.50)	(2.67)	(3.68)	(3.55)	(2.28)	(-1.72)	(-0.86)	(0.38)	(2.09)	(2.78)	(3.13)	(1.40)
5	0.13%	0.15%	0.29%	0.35%	0.61%	**0.48%**	**0.31%**	0.05%	0.10%	0.22%	0.25%	0.50%	**0.45%**	**0.23%**
	(1.53)	(1.87)	(3.55)	(3.46)	(4.73)	(4.50)	(3.70)	(0.51)	(1.23)	(2.64)	(2.24)	(3.61)	(4.21)	(2.49)
5 - 1	**0.44%**	0.26%	**0.34%**	**0.35%**	**0.60%**		**0.41%**	0.21%	0.14%	**0.23%**	0.20%	**0.47%**		**0.26%**
	(2.45)	(1.69)	(2.34)	(2.14)	(3.35)		(2.67)	(1.83)	(0.86)	(1.98)	(1.24)	(2.62)		(2.08)

Table VII: The Smart Money Effect (1980-2006)

Panel A reports the calendar-time returns of mutual fund portfolios sorted by the fund flow in each quarter. Panel B reports the calendar-time portfolio returns independently sorted by *E[FIPP*]* and fund flows in each quarter. *E[FIPP*]* is the portfolio-weighted average expected flow-induced price pressure. The portfolios are rebalanced every quarter and held for up to three years. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Three different monthly returns are reported: the return in excess of the risk-free rate, the Fama-French three-factor alpha, and the Carhart four-factor alpha. T-statistics, shown in parentheses, are computed based on White's standard errors. Estimates significant at the 5% level are in bold font.

Panel A: The Smart Money Effect (Sort by Fund Flow)

	Qtr 1			Qtr 1-4			Qtr 5-8		Qtr 5-12	
decile	excess	alpha_3f	alpha_4f	excess	alpha_3f	alpha_4f	excess	alpha_3f	excess	alpha_3f
1	0.69%	-0.06%	-0.05%	0.79%	0.05%	0.02%	0.75%	0.14%	0.73%	0.12%
	(2.40)	(-0.82)	(-0.67)	(2.84)	(0.82)	(0.27)	(2.69)	(2.79)	(2.70)	(2.66)
2	0.69%	-0.01%	0.02%	0.73%	0.02%	0.00%	0.73%	0.12%	0.70%	0.09%
	(2.52)	(-0.20)	(0.33)	(2.73)	(0.40)	(0.07)	(2.70)	(2.71)	(2.66)	(2.16)
3	0.71%	0.01%	0.03%	0.72%	0.02%	0.01%	0.67%	0.05%	0.66%	0.04%
	(2.61)	(0.21)	(0.48)	(2.75)	(0.41)	(0.10)	(2.55)	(1.36)	(2.60)	(1.14)
4	0.72%	0.04%	0.06%	0.72%	0.04%	0.04%	0.62%	0.01%	0.63%	0.01%
	(2.67)	(0.97)	(1.22)	(2.76)	(0.97)	(0.99)	(2.40)	(0.24)	(2.50)	(0.17)
5	0.72%	0.04%	0.05%	0.72%	0.04%	0.04%	0.64%	0.03%	0.63%	0.02%
	(2.65)	(1.02)	(1.16)	(2.73)	(0.91)	(0.85)	(2.45)	(0.92)	(2.52)	(0.52)
6	0.70%	0.04%	0.02%	0.72%	0.04%	0.03%	0.62%	0.02%	0.61%	0.01%
	(2.54)	(0.81)	(0.49)	(2.70)	(1.08)	(0.76)	(2.36)	(0.49)	(2.44)	(0.17)
7	0.71%	0.03%	0.01%	0.72%	0.03%	0.02%	0.65%	0.04%	0.63%	0.02%
	(2.56)	(0.73)	(0.12)	(2.68)	(0.80)	(0.54)	(2.47)	(1.11)	(2.47)	(0.40)
8	0.73%	0.07%	0.03%	0.74%	0.06%	0.04%	0.64%	0.02%	0.65%	0.02%
	(2.61)	(1.51)	(0.60)	(2.70)	(1.49)	(0.88)	(2.38)	(0.51)	(2.51)	(0.60)
9	0.78%	0.11%	0.06%	0.75%	0.06%	0.03%	0.61%	0.00%	0.63%	0.00%
	(2.70)	(2.34)	(0.82)	(2.68)	(1.39)	(0.66)	(2.24)	(0.03)	(2.42)	(0.08)
10	0.86%	0.22%	0.10%	0.78%	0.12%	0.06%	0.60%	-0.01%	0.61%	-0.01%
	(2.85)	(3.29)	(1.25)	(2.71)	(2.39)	(0.97)	(2.12)	(-0.19)	(2.27)	(-0.18)
10 - 1	0.17%	**0.28%**	0.15%	-0.01%	0.08%	0.04%	**-0.15%**	**-0.15%**	**-0.13%**	**-0.13%**
	(1.72)	(2.74)	(1.58)	(-0.08)	(1.27)	(0.61)	(-3.05)	(-2.63)	(-3.26)	(-2.68)

Table VII (Continued)

Panel B: Independent Sort by E[FIPP] and Fund Flow*														
Quintiles of Fund Flow	Quintiles of *E[FIPP*]*							Quintiles of *E[FIPP*]*						
	1	2	3	4	5	5 - 1	average	1	2	3	4	5	5 - 1	average
	Qtr 1 (excess)							Qtr 1 (alpha_3f)						
1	0.57%	0.71%	0.68%	0.79%	1.01%	**0.45%**	**0.75%**	-0.23%	-0.04%	-0.03%	0.12%	0.36%	**0.59%**	0.03%
	(1.98)	(2.73)	(2.68)	(3.08)	(3.51)	(2.89)	(2.87)	(-2.13)	(-0.49)	(-0.54)	(1.84)	(3.67)	(3.51)	(0.68)
2	0.59%	0.69%	0.70%	0.74%	0.90%	0.30%	**0.72%**	-0.17%	-0.01%	0.00%	0.07%	0.25%	**0.43%**	0.03%
	(2.10)	(2.71)	(2.78)	(2.91)	(3.02)	(1.91)	(2.78)	(-1.65)	(-0.16)	(-0.03)	(1.33)	(2.35)	(2.54)	(0.68)
3	0.65%	0.65%	0.62%	0.69%	0.93%	0.29%	**0.71%**	-0.10%	-0.06%	-0.06%	0.04%	0.32%	**0.42%**	0.03%
	(2.30)	(2.54)	(2.51)	(2.60)	(3.21)	(1.78)	(2.73)	(-0.89)	(-0.84)	(-1.18)	(0.68)	(3.54)	(2.49)	(0.75)
4	0.66%	0.66%	0.70%	0.71%	0.91%	0.25%	**0.73%**	-0.09%	-0.05%	0.00%	0.08%	0.32%	**0.41%**	0.05%
	(2.33)	(2.54)	(2.73)	(2.69)	(3.07)	(1.60)	(2.77)	(-0.88)	(-0.66)	(0.01)	(1.48)	(3.00)	(2.21)	(1.31)
5	0.64%	0.71%	0.67%	0.80%	1.12%	**0.49%**	**0.79%**	-0.08%	-0.01%	-0.02%	0.14%	0.52%	**0.60%**	**0.10%**
	(2.19)	(2.69)	(2.53)	(2.95)	(3.66)	(2.68)	(2.92)	(-0.65)	(-0.06)	(-0.39)	(2.42)	(4.67)	(3.03)	(2.64)
5 - 1	0.07%	-0.01%	-0.01%	0.00%	0.11%		0.03%	0.14%	0.03%	0.01%	0.03%	**0.16%**		0.07%
	(0.83)	(-0.12)	(-0.19)	(0.06)	(1.25)		(0.61)	(1.56)	(0.44)	(0.18)	(0.40)	(2.02)		(1.33)

Table VIII: Mutual Fund Performance Predictability (1980-2006)

This table reports the regression of quarterly mutual fund returns on *E[FIPP*], alpha, flow, expenses, log(age), log(no_stocks), log(TNA), and log(turnover). E[FIPP*]* is the portfolio-weighted average expected flow-induced price pressure (*E[FIPP]*) computed from the four-factor fund alpha in the previous year. *alpha* is the Carhart four-factor fund alpha in the previous year. *flow* is the log percentage flow in the previous quarter. *expenses* is the expense ratio in the previous quarter. *age* is the number of years since fund inception. *no_stocks* is the number of stocks in the portfolio. *TNA* is the total net assets of the fund. Finally, *turnover* is the turnover ratio in the previous quarter. The regression coefficients are estimated using the Fama-MacBeth approach. T-statistics, shown in parentheses, are computed based on standard errors with the Newey-West correction of up to four lags. Estimates significant at the 5% level are in bold font.

	Dependent Variable = ret(t+1)					
	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	**0.050**	**0.053**	**0.053**	**0.049**	**0.051**	**0.051**
	(5.47)	(5.85)	(5.69)	(5.20)	(5.48)	(5.30)
E[FIPP*]	**3.081**			**2.602**	**2.952**	**2.687**
	(3.06)			(2.35)	(2.93)	(2.43)
alpha		**0.581**		0.042		0.005
		(3.82)		(0.24)		(0.03)
flow			**0.012**		0.004	0.004
			(2.28)		(0.82)	(0.93)
epxenses	-0.351	-0.830	-0.765	-0.319	-0.657	-0.653
	(-0.27)	(-0.55)	(-0.48)	(-0.26)	(-0.51)	(-0.52)
log(age)	0.000	0.000	0.001	0.000	0.000	0.001
	(0.17)	(0.47)	(0.63)	(0.37)	(0.65)	(0.84)
log(no_stocks)	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**
	(3.58)	(3.95)	(3.72)	(3.27)	(3.44)	(3.02)
log(TNA)	-0.001	**-0.001**	**-0.001**	-0.001	**-0.001**	**-0.001**
	(-1.91)	(-2.18)	(-2.18)	(-1.82)	(-2.08)	(-2.00)
log(turnover)	**0.002**	0.002	0.002	**0.001**	**0.002**	**0.001**
	(2.05)	(1.76)	(1.56)	(1.96)	(2.06)	(1.96)
R^2	15.77%	11.03%	8.06%	17.46%	16.53%	18.24%
No Obs	80182	80182	80182	80182	80182	80182

Table IX: Momentum (1980-2006)

This table reports the regression of the quarterly or monthly stock return on *E[FIPP(t-k+1,t)], ret(t), ret(t-k, t-1), ret(-36, t-k-1), bm, log(mktcap),* and *turnover. ret(m,n)* is the cumulative stock return from month *m* to *n* . *E[FIPP]* is the aggregate expected flow-induced trading (*E[FIT]*) in a quarter scaled by the total shares held by mutual funds at the end of the quarter. The expected capital flow in a quarter is estimated from the market-adjusted fund return in the previous *k* months. *bm* and *mktcap* are the book-to-market ratio and the market capitalization at the end of the quarter, respectively. *turnover* is the average monthly turnover in the previous year. Columns 1-6 in Panel A and the entire Panel B report the regression results with quarterly stock returns, while Columns 7-10 in Panel A report the same regression with monthly stock returns. Panel B divides the full sample into two halves based on either time periods or market capitalizations. Small and large stocks are classified based on the medium market capitalization of NYSE stocks in the prior quarter. The coefficients are estimated using the Fama-MacBeth approach. T-statistics, shown in parentheses, are computed based on White's standard errors. Estimates significant at the 5% level are in bold font.

Panel A: Full Sample										
	Dependent Variable = ret(t+1, t+3)						*Dependent Variable = ret(t+1)*			
	k=12 (80-06)		k=6 (80-06)		k=3 (80-06)		k=6 (Jan)		k=6 (Feb-Dec)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Intercept	**0.103**	**0.092**	**0.096**	**0.077**	**0.094**	**0.084**	**0.133**	**0.124**	**0.047**	**0.042**
	(2.81)	(2.36)	(2.63)	(2.01)	(2.58)	(2.34)	(2.91)	(2.65)	(4.07)	(3.54)
E[FIPP(t-k+1, t)]		**0.085**		**0.145**		**0.250**		0.084		**0.044**
		(3.07)		(2.93)		(3.32)		(1.60)		(2.91)
ret(t)	-0.024	**-0.029**	-0.024	**-0.030**	-0.020	**-0.029**	**-0.091**	**-0.095**	**-0.038**	**-0.040**
	(-1.67)	(-2.16)	(-1.63)	(-2.26)	(-1.35)	(-2.18)	(-5.31)	(-5.76)	(-6.80)	(-7.58)
ret(t-k, t-1)	**0.020**	**0.015**	**0.027**	**0.020**	**0.024**	0.014	-0.011	-0.013	**0.008**	0.005
	(4.06)	(3.31)	(3.59)	(2.82)	(2.29)	(1.40)	(-0.94)	(-1.17)	(2.47)	(1.93)
ret(t-36, t-k-1)	**-0.005**	**-0.004**	**-0.004**	**-0.004**	**-0.004**	**-0.004**	**-0.005**	**-0.005**	**-0.001**	**-0.001**
	(-3.19)	(-3.05)	(-2.64)	(-2.56)	(-2.54)	(-2.54)	(-3.25)	(-3.61)	(-2.11)	(-2.00)
bm	0.005	0.005	0.005	0.005	0.006	0.006	0.001	0.004	0.001	0.002
	(1.33)	(1.37)	(1.25)	(1.42)	(1.40)	(1.78)	(0.31)	(1.10)	(1.16)	(1.46)
log(mktcap)	**-0.003**	-0.003	**-0.003**	-0.002	-0.003	-0.002	**-0.005**	**-0.005**	**-0.002**	**-0.001**
	(-2.16)	(-1.73)	(-1.96)	(-1.33)	(-1.88)	(-1.59)	(-2.75)	(-2.42)	(-3.43)	(-2.91)
turnover	**-0.004**	**-0.005**	-0.004	**-0.004**	-0.004	**-0.004**	0.003	0.002	-0.001	-0.001
	(-2.02)	(-2.26)	(-1.87)	(-2.06)	(-1.63)	(-2.05)	(0.93)	(0.83)	(-1.24)	(-1.66)
R^2	7.08%	7.85%	6.75%	7.85%	6.38%	7.88%	8.32%	9.02%	6.46%	7.36%
No Obs	223268	223268	223268	223268	223268	223268	54383	54383	606112	606112

Please note that the unit of *t* is a month in this table.

Table IX: Momentum (Continued)

Panel B: Subsamples Based on Time Periods and Firm Size

	Dependent Variable = ret(t+1, t+3)							
	k=6 (80-93)		k=6 (94-06)		k=6 (Small Cap)		k=6 (Large Cap)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.072	0.065	**0.119**	0.090	**0.653**	**0.631**	**0.223**	**0.190**
	(1.37)	(1.29)	(2.54)	(1.65)	(5.53)	(5.16)	(5.84)	(4.28)
E[FIPP(t-k+1, t)]		0.106		**0.203**		**0.158**		**0.175**
		(1.80)		(3.44)		(3.50)		(3.35)
ret(t)	-0.022	-0.027	-0.022	-0.029	-0.012	-0.018	-0.031	**-0.041**
	(-1.10)	(-1.43)	(-1.07)	(-1.60)	(-0.85)	(-1.39)	(-1.55)	(-2.36)
ret(t-k, t-1)	**0.032**	**0.027**	**0.023**	0.014	**0.035**	**0.028**	**0.021**	0.011
	(2.77)	(2.75)	(2.44)	(1.92)	(4.82)	(4.62)	(3.10)	(1.57)
ret(t-36, t-k-1)	-0.003	-0.003	**-0.006**	**-0.006**	**-0.005**	**-0.004**	-0.003	-0.003
	(-1.83)	(-1.83)	(-4.13)	(-4.11)	(-2.41)	(-2.27)	(-1.68)	(-1.62)
bm	0.004	0.003	0.007	0.008	0.006	0.006	0.002	0.003
	(0.78)	(0.77)	(1.12)	(1.36)	(1.45)	(1.47)	(0.43)	(0.86)
log(mktcap)	-0.002	-0.001	**-0.004**	-0.003	**-0.033**	**-0.032**	**-0.008**	**-0.007**
	(-0.76)	(-0.60)	(-2.21)	(-1.35)	(-6.47)	(-6.12)	(-5.57)	(-3.93)
turnover	**-0.007**	**-0.007**	-0.001	-0.001	**-0.006**	**-0.006**	-0.001	-0.002
	(-2.23)	(-2.31)	(-0.29)	(-0.41)	(-2.49)	(-2.73)	(-0.44)	(-0.84)
R^2	7.76%	8.44%	5.69%	6.99%	6.78%	7.55%	8.81%	9.96%
No Obs	72946	72946	150322	150322	104970	104970	118298	118298

Please note that the unit of *t* is a month in this table.

Table X: Comovement (1980-2006)

This table reports the regression of *ret(j, t)* on (contemporaneous) *ret(grp, t)* , *ret(opp, t)* , *ret(ffind, t)* , *ret(mktrf, t)* , *ret(smb, t)* , *ret(hml, t),* and *ret(umd, t).* In each quarter, I sort all stocks into quintiles based on the stock quality measure (*Gamma*) proposed in Cohen, Coval, and Pastor (2005) and Wermers, Yao, and Zhao (2007). *ret(grp, t)* is the return of the quintile portfolio to which stock *j* belongs*; ret(ffind, t)* is the return of the industry portfolio (based on the Fama-French 48 industry definition) to which stock *j* belongs, *ret(mktrf, t), ret(smb, t),* and *ret(hml, t)* are Fama-French market, size, and value factor returns, and *ret(umd, t)* is the momentum factor return. For stocks in quintiles 1 and 5, I also include *ret(opp,t)* in the regression, which is the return of the opposite quintile portfolio. All portfolio returns are computed on a value-weighted basis, and for *ret(grp, t)* and *ret(ffind, t)* , I exclude the stock being analyzed from the calculation. The regression is conducted for each stock at the end of each quarter using weekly (Panel A) or daily (Panel B) returns in the subsequent year. I then take the cross-sectional averages of the regression coefficients at the end of each quarter. Finally, I report the time series averages of these estimates and their t-statistics (shown in parentheses) based on standard errors with the Newey-West correction of four lags. Estimates significant at the 5% level are in bold font.

Panel A: Weekly Returns

	Quintiles of *Gamma*								
	1	2	3	4	5	1 - 3	5 - 3	1	5
ret_grp	**0.183**	**0.103**	**0.096**	**0.129**	**0.207**	**0.087**	**0.111**	**0.178**	**0.202**
	(6.99)	(4.71)	(6.50)	(8.69)	(8.28)	(2.48)	(4.54)	(6.74)	(7.88)
ret_opp								-0.045	-0.032
								(-1.72)	(-1.74)
ret_ffind	**0.346**	**0.420**	**0.445**	**0.418**	**0.332**	**-0.099**	**-0.112**	**0.348**	**0.330**
	(12.45)	(27.04)	(44.59)	(32.74)	(18.50)	(-4.09)	(-5.43)	(12.93)	(18.47)
mktrf	**0.402**	**0.399**	**0.395**	**0.398**	**0.389**	0.008	-0.006	**0.453**	**0.434**
	(13.14)	(16.28)	(17.15)	(13.99)	(9.71)	(0.27)	(-0.21)	(9.65)	(9.99)
smb	**0.665**	**0.582**	**0.537**	**0.597**	**0.664**	**0.128**	**0.127**	**0.697**	**0.685**
	(27.21)	(37.73)	(47.82)	(27.98)	(15.97)	(5.91)	(3.39)	(22.52)	(16.12)
hml	**0.159**	**0.146**	**0.162**	**0.156**	**0.148**	-0.003	-0.015	**0.150**	**0.149**
	(7.93)	(7.79)	(8.08)	(5.91)	(4.73)	(-0.17)	(-0.70)	(7.67)	(5.05)
umd	**-0.100**	**-0.071**	**-0.059**	**-0.046**	**-0.029**	**-0.041**	**0.030**	**-0.105**	**-0.030**
	(-8.51)	(-7.22)	(-5.44)	(-3.65)	(-2.56)	(-2.80)	(2.92)	(-8.82)	(-3.34)

Panel B: Daily Returns

	Quintiles of *Gamma*						
	1	2	3	4	5	1 - 3	5 - 3
ret_grp	**0.164**	**0.112**	**0.120**	**0.127**	**0.197**	0.044	**0.077**
	(7.08)	(7.31)	(13.05)	(12.89)	(9.66)	(1.87)	(3.74)
ret_ffind	**0.310**	**0.382**	**0.401**	**0.373**	**0.274**	**-0.092**	**-0.127**
	(10.43)	(20.58)	(30.57)	(27.93)	(16.92)	(-4.07)	(-6.58)
mktrf	**0.437**	**0.422**	**0.402**	**0.426**	**0.431**	0.035	0.030
	(12.53)	(17.96)	(18.13)	(13.41)	(11.15)	(1.55)	(1.16)
smb	**0.612**	**0.539**	**0.506**	**0.561**	**0.602**	**0.107**	**0.096**
	(32.13)	(42.30)	(46.44)	(25.07)	(16.79)	(5.25)	(3.28)
hml	**0.163**	**0.159**	**0.167**	**0.155**	**0.160**	-0.004	-0.007
	(6.92)	(8.72)	(8.84)	(6.78)	(5.16)	(-0.24)	(-0.39)
umd	**-0.059**	**-0.062**	**-0.047**	**-0.034**	**-0.024**	-0.013	**0.023**
	(-4.90)	(-8.83)	(-8.31)	(-4.39)	(-3.15)	(-1.07)	(3.03)

Table XI: Subsample Robustness of E[FIPP] (1980-2006)

This table reports the equal-weighted calendar-time returns of stock portfolios sorted by expected flow-induced price pressure (*E[FIPP]*). *E[FIPP]* is computed as the aggregate expected flow-induced trading (*E[FIT]*) in a quarter scaled by the total shares held by all mutual funds at the end of the quarter. The expected capital flow in a quarter is estimated from the four-factor fund alpha in the prior year. I divide the full sample into two halves based on time periods (1980-1993 vs. 1994-2006) or calendar quarters (first calendar quarter vs. the remaining three quarters). The portfolios are rebalanced every quarter and are held for one quarter. Both the Fama-French three-factor alpha and the Carhart four-factor alpha are reported. T-statistics, shown in parentheses, are computed based on White's standard errors. Estimates significant at the 5% level are in bold font.

Subsamples Based on Time Periods and Calendar Quarters

	1980 - 1993		1994 - 2006		1st Calendar Qtr		Other Calendar Qtrs	
decile	alpha_3f	alpha_4f	alpha_3f	alpha_4f	alpha_3f	alpha_4f	alpha_3f	alpha_4f
1	-0.17%	-0.08%	-0.67%	-0.36%	-0.49%	-0.39%	-0.37%	-0.13%
	(-1.38)	(-0.63)	(-2.69)	(-1.57)	(-1.44)	(-1.44)	(-2.26)	(-0.85)
2	-0.12%	-0.07%	-0.50%	-0.29%	-0.35%	-0.29%	-0.31%	-0.16%
	(-1.34)	(-0.69)	(-2.93)	(-2.00)	(-1.24)	(-1.19)	(-2.70)	(-1.55)
3	-0.16%	-0.10%	-0.39%	-0.23%	-0.27%	-0.21%	-0.28%	-0.17%
	(-1.94)	(-1.13)	(-2.48)	(-1.64)	(-1.26)	(-1.24)	(-2.69)	(-1.76)
4	-0.07%	-0.03%	-0.19%	-0.08%	-0.03%	0.01%	-0.15%	-0.09%
	(-1.05)	(-0.46)	(-1.41)	(-0.61)	(-0.19)	(0.10)	(-1.76)	(-1.17)
5	-0.03%	0.01%	-0.08%	0.00%	-0.08%	-0.03%	-0.05%	-0.04%
	(-0.39)	(0.13)	(-0.65)	(-0.01)	(-0.48)	(-0.21)	(-0.63)	(-0.47)
6	-0.15%	-0.12%	-0.12%	0.01%	-0.16%	-0.09%	-0.12%	-0.09%
	(-2.28)	(-1.60)	(-0.92)	(0.11)	(-0.71)	(-0.52)	(-1.78)	(-1.28)
7	-0.01%	0.08%	0.08%	0.10%	0.16%	0.20%	0.01%	0.01%
	(-0.07)	(1.05)	(0.68)	(0.90)	(1.05)	(1.33)	(0.19)	(0.11)
8	0.15%	0.20%	0.25%	0.24%	0.27%	0.27%	0.17%	0.14%
	(2.01)	(2.76)	(2.09)	(2.01)	(1.56)	(1.56)	(2.04)	(1.66)
9	0.11%	0.10%	0.28%	0.25%	0.30%	0.32%	0.15%	0.05%
	(1.42)	(1.26)	(1.90)	(1.68)	(1.25)	(1.30)	(1.49)	(0.48)
10	0.46%	0.40%	0.52%	0.36%	0.74%	0.69%	0.39%	0.29%
	(3.78)	(3.65)	(3.13)	(2.27)	(2.89)	(2.89)	(3.45)	(2.48)
10 - 1	**0.63%**	**0.48%**	**1.19%**	**0.71%**	**1.23%**	**1.08%**	**0.75%**	**0.42%**
	(3.48)	(2.92)	(3.37)	(3.32)	(2.45)	(2.77)	(3.39)	(1.97)