A Flow-Based Explanation for Return Predictability

Dong Lou
London School of Economics

I propose and test a capital-flow-based explanation for some well-known empirical regularities concerning return predictability—the persistence of mutual fund performance, the "smart money" effect, and stock price momentum. First, I construct a measure of demand shocks to individual stocks by aggregating flow-induced trading across all mutual funds, and document a significant, temporary price impact of such uninformed trading. Next, given that mutual fund flows are highly predictable, I show that the expected part of flow-induced trading positively forecasts stock and mutual fund returns in the following year, which are then reversed in subsequent years. The main findings of the paper are that the flow-driven return effect can fully account for mutual fund performance persistence and the smart money effect, and can partially explain stock price momentum. (*JEL* G12, G14, G23)

Past research has documented that (1) mutual fund performance is persistent over a one-year horizon, (2) capital flows positively predict fund performance in the following quarter (i.e., the "smart money" effect), and (3) individual stocks exhibit medium-term price momentum. I argue that all three empirical patterns of stock and fund return predictability are, at least partially, driven by a single mechanism: predictable price pressure caused by capital flows from retail investors to mutual funds, and in turn from mutual funds to individual stocks.

This flow-based explanation of return predictability rests on two empirical results from prior research. First, recent studies find that institutional flows can affect contemporaneous stock returns, which are reversed subsequently. For example, Coval and Stafford (2007) show that mutual fund managers tend to

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expand their existing holdings with capital inflows and liquidate their positions to pay for redemptions; such flow-induced trading, across mutual funds, can have a significant impact on individual stock returns and drive stock prices temporarily away from their information-efficient benchmarks.

Second, a large body of literature shows that mutual fund flows are predictable from past fund performance and past flows (e.g., Ippolito 1992; Chevalier and Ellison 1997; Sirri and Tufano 1998). Given that realized capital flows, and the associated flow-induced trading, can affect contemporaneous stock returns, it is natural to ask whether expected capital flows can forecast future returns. In particular, I hypothesize that the expected flows to all mutual funds holding a stock should positively predict the stock's future return, and the expected flows to all mutual funds holding overlapping positions with a fund should positively predict the fund's future performance. Such flow-driven return effect should then reverse subsequently as flow-induced price pressure dissipates.

The goal of the paper is to relate this flow-based mechanism to a number of well-known empirical findings on return predictability. First, the flow-based mechanism can generate the pattern of mutual fund performance persistence. Past winning funds attract capital inflows and collectively invest the new capital in their existing holdings, while past losing funds face capital outflows and collectively liquidate their holdings. These flow-induced purchases and sales can drive past winning funds to continue outperforming past losing funds, an empirical pattern that has long been viewed as evidence of heterogeneous managerial ability.

The flow-based mechanism can also give rise to the smart money effect. Because flows are highly persistent, mutual funds with past inflows are expected to receive additional capital, expand their existing holdings, and drive up their own performance in the subsequent period; in contrast, funds with past outflows are expected to experience additional redemptions, further liquidate their positions, and drive down their future performance. Consequently, mutual funds with past inflows should outperform their peers with past outflows, an empirical pattern that has been traditionally interpreted as evidence of retail investors' ability to identify skilled managers.

Moreover, the flow-based mechanism can potentially cause stock price momentum. Past winning funds receive capital inflows and expand their existing holdings, which are disproportionately invested in past winning stocks; at the same time, past losing funds lose capital and have to liquidate their holdings, which are concentrated in past losing stocks. As a result, performance-chasing mutual fund flows can lead past winning stocks to keep outperforming past losing stocks, an empirical pattern that is dubbed stock price momentum.

To examine the extent to which mutual fund flow-induced trading is responsible for these patterns of stock and fund return predictability, I construct a measure of expected flow-induced trading in three steps. First, I estimate the part of mutual fund trading that is associated with capital flows. The results suggest that fund managers sell their holdings dollar-for-dollar to meet redemptions, while investing around sixty-two cents for every dollar of inflow in their existing positions. Next, I compute an aggregate measure of flow-induced trading across all mutual funds, denoted *FIT*, for each stock in every quarter. Finally, I compute expected flow-induced trading, or $E[FIT]$, by replacing realized capital flows with expected flows.

The return results provide strong support for a predictable flow-induced price pressure effect. Consistent with Coval and Stafford (2007), I find that stocks that are heavily bought by mutual funds with capital inflows significantly outperform stocks that are heavily sold by mutual funds with outflows in the ranking period, and that this return differential is completely reversed in subsequent years. In addition, using past abnormal fund performance to forecast future fund flows, I show that expected flow-induced trading positively predicts stock returns in the short run, but negatively over the long run. Specifically, the return spread between the top and bottom deciles ranked by $E[FIT]$ is 5.28% ($t = 2.63$) in the year following portfolio formation and is -5.67% ($t = -2.17$) in the subsequent two years. Moreover, stocks that are expected to receive inflow-induced purchases tend to comove with one another, after controlling for common risk factors, in the subsequent year; the same is also true for stocks that are expected to experience outflow-induced sales. This suggests that capital flows may also play a role in causing excess stock return comovement.

Building on the stock return result, I further analyze the effect of expected flow-induced trading on fund performance, as mutual funds turn over the holdings gradually. Specifically, I define a measure of expected flow-induced trading for each mutual fund, denoted $E[FIT^*]$, as the portfolio-weighted average $E[FIT]$ across all holdings in the portfolio. Similar to the stock return pattern, mutual funds whose holdings are expected to experience flow-induced purchases significantly outperform funds whose holdings are expected to experience flow-induced sales in the following year; this effect is then reversed in years two and three.

The main findings of the paper are that the flow-based mechanism of return predictability can fully account for mutual fund performance persistence and the smart money effect and can partially explain stock price momentum. Specifically, I show that while past abnormal fund returns and fund flows are significant predictors of future fund performance when included in the analysis alone, both are subsumed by $E[FIT^*]$ in a horse race. These results hold in both a calendar-time portfolio approach and a Fama-MacBeth regression analysis. Together, they suggest that the observed patterns of mutual fund performance persistence and the smart money effect are likely to be manifestations of predictable flow-induced price impacts.

Next, to analyze the role of flow-induced trading in causing stock price momentum, I conduct a horse race between past cumulative stock returns and $E[FIT]$ to forecast future stock returns. After controlling for $E[FIT]$, the coefficient on lagged stock returns drops by 25% to 50%, depending on the sample used. For example, $E[FIT]$ accounts for about half of the price momentum effect in the second half of the sample and among large-cap stocks, consistent with mutual funds playing a more central role in these subsamples. In addition, once I control for $E[FIT]$, stock price momentum is no longer statistically significant in these two subsamples. In a way, the flow-based mechanism explains the most puzzling aspects of the price momentum effect: its persistence over time and robustness across all stocks.

My results complement the fast-growing body of literature on the price impact of institutional flows.The closest work to mine is Coval and Stafford (2007) and Frazzini and Lamont (2008). This paper differs from the two earlier studies in terms of the focus and objective. While Coval and Stafford (2007) and Frazzini and Lamont (2008) both analyze the return reversal pattern subsequent to mutual fund flow-induced trading, in an effort to establish the price pressure effect, this paper focuses on the return continuation pattern that arises from the flow-performance relation and, more importantly, the role of such return continuation in driving some well-known empirical regularities.

This paper is also related to the extensive literature on mutual fund herding and momentum trading. While prior studies often attribute institutional herding to correlated information, social learning, reputation concerns, and fads, my results suggest that performance-chasing investment flows from retail investors can cause institutional investors to herd and follow momentum strategies, and that such flow-induced herding can have important asset pricing implications.

1. Data

1.1 Mutual fund data

Quarterly mutual fund holdings data are obtained from the CDA/Spectrum database for the period of 1980–2006. The database is compiled from both mandatory SEC filings and voluntary disclosures. While mutual funds almost always file their reports at the end of a quarter, the date on which the holdings are valid (report date) is often different from the filing date. To calculate the number of shares held by each mutual fund at the end of the quarter, I assume that the manager does not trade between the report date and the quarter-end (adjusting for stock splits).

Mutual funds' total net assets, net monthly returns, expense ratios, and other fund characteristics are obtained from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund database. Because the focus of the study is on gross returns, monthly fund returns are calculated as net returns plus 1/12 of annual fees and expenses. For mutual funds with multiple share classes reported by CRSP, I sum the total net assets (TNA) across all share classes 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, such as the investment objective code, I use the value from the share class with the largest total net assets. To estimate monthly fund alpha, I conduct rolling-window regressions using monthly fund returns from the previous twelve months.[1] Finally, I use the MFLinks file to merge between CDA/Spectrum and the CRSP mutual fund database.

Since this paper 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 income, balanced, unclassified, or missing. This restriction effectively excludes all fixed-income funds, international funds, and precious metal funds. However, because of limited coverage of sector and balanced funds in MFLinks, I lose a fraction of the mutual fund sample when merging CDA/Spectrum with CRSP. As a robustness check, I further restrict my sample to diversified equity funds by excluding balanced and sector funds; the results are by and large unchanged.

Moreover, because some mutual funds misreport their investment objective codes, I require the ratio of the equity holdings to total net assets to be between 0.75 and 1.2. The lower bound is set to exclude funds that are misclassified as equity funds, while the upper bound is used to eliminate apparent data errors. To further ensure data quality, I require a minimum fund size of $1 million and that the TNAs reported by CDA/Spectrum and CRSP do not differ by more than a factor of two (i.e., $0.5 < TNA^{CDA}/TNA^{CRSP} < 2$).

After applying all these screening procedures, I end up with a sample of 77,983 fund-quarter observations with 2,989 distinct mutual funds. Table 1 shows the number of domestic equity mutual funds in each year along with summary statistics of some fund characteristics. There is a significant rising trend in both the number of funds and average fund size. The fraction of the U.S. equity market held by mutual funds in my sample steadily increases from less than 2.3% in 1980 to about 14% in 2006, comparable to the figures reported in prior literature.

1.2 Fund flows

Following prior literature (e.g., Chevalier and Ellison 1997; Sirri and Tufano 1998), I compute the investment flow to fund i in quarter t as

$$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}}{TNA_{i,t-1}}, \tag{1}$$

where $MGN_{i,t}$ is the increase in TNA due to fund mergers in quarter t. Neither CRSP nor CDA/Spectrum reports the exact date on which a merger takes place. Following prior studies, I use the last net asset value (NAV) report date of the target fund as an estimate of the merger date. Because this simple method produces many obvious mismatches, I employ the following smoothing procedure. Specifically, I match a target fund to its acquirer from one month

[1] The results are similar if I use two years or three years of monthly returns to compute fund alpha.

Table 1
Summary statistics

Year	No. Funds	TNA ($ Million)		Total Equity Holdings ($ Million)		% Market Held	
		Median	Mean	Median	Mean	No. Stocks	% Held
1980	228	53.45	146.74	45.61	122.24	3,646	2.27
1981	226	53.66	137.71	42.11	109.31	3,543	2.21
1982	232	70.64	170.95	50.90	132.00	3,393	2.21
1983	255	97.41	222.14	79.74	182.20	4,173	2.74
1984	270	86.23	221.24	71.98	176.03	3,985	2.95
1985	297	114.12	275.98	89.48	222.04	3,845	3.08
1986	341	106.42	298.47	88.59	241.28	4,134	3.46
1987	376	87.00	286.30	74.03	238.41	4,544	3.89
1988	405	82.47	285.34	69.56	232.77	3,906	3.84
1989	440	95.08	340.49	77.91	265.36	3,798	3.92
1990	480	83.85	306.07	61.95	240.20	3,175	4.15
1991	579	100.23	379.32	79.85	309.56	3,548	4.78
1992	685	115.22	426.04	93.25	346.45	3,913	5.39
1993	925	105.56	442.40	90.00	350.65	4,663	6.54
1994	1,044	105.43	450.12	85.19	352.88	4,951	6.88
1995	1,168	134.35	610.98	112.60	488.36	5,338	9.02
1996	1,314	145.88	750.48	123.31	605.90	5,724	10.04
1997	1,480	163.42	933.60	135.21	774.02	5,858	11.07
1998	1,570	167.00	1,071.47	144.55	927.39	5,028	11.81
1999	1,686	187.52	1,307.48	164.05	1,139.49	4,958	12.95
2000	1,890	186.27	1,283.93	159.08	1,089.54	4,698	12.54
2001	1,915	155.22	1,018.79	133.73	882.57	3,670	13.36
2002	1,970	111.80	771.11	96.53	672.64	3,282	13.46
2003	2,001	146.05	976.25	128.51	852.98	3,760	13.54
2004	1,961	165.93	1,128.54	144.58	978.38	3,820	13.82
2005	1,918	196.90	1,251.72	169.84	1,067.81	3,884	14.02
2006	1,789	221.75	1,400.29	193.07	1,187.58	3,858	13.71

This table reports summary statistics of the mutual fund sample as of December in each year. The sample period is from 1980 to 2006. Because the focus of the paper is on the U.S. equity market, international, fixed income, and precious metal funds are excluded from the sample. Information regarding fund size, monthly returns, and capital flows is obtained from the CRSP survivorship-bias-free mutual fund database, and fund holdings data are obtained from the Thompson Financial's CDA/Spectrum database. The two data sets are then merged using the MFLinks file provided on WRDS. The table reports the following summary statistics: *No. 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 (in millions of dollars); *Total equity holdings* is the total dollar value of equity held by a mutual fund reported by CDA/Spectrum (in millions of dollars); and *% Market held* is the percentage of the U.S. equity market that is held by all mutual funds in the sample.

before its last NAV report date to five months after; I then designate the month in which the acquirer has the smallest absolute percentage flow, after accounting for the merger, as the event month. I further assume that inflows and outflows occur at the end of each quarter, and that investors reinvest their dividends and capital appreciation distributions in the same fund. Finally, mutual funds that are initiated have inflows equal to their initial *TNA*, while funds that are liquidated have outflows equal to their terminal *TNA*.

1.3 Other data

Stock return and trading information is obtained from the CRSP monthly stock file. To address potential microstructure issues, I exclude all stocks whose price is below five dollars a share and whose market capitalization is in the bottom NYSE size decile (similar to Jegadeesh and Titman 2001). Stock liquidity data are obtained from Joel Hasbrouck's Web site. Among the various measures provided in the data set, I use three in this paper: 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. Because the results are qualitatively the same with all three measures, I report only those based on c^{BMA}. For a more detailed description of various measures of stock liquidity, see Hasbrouck (2009).

2. Flow-Induced Price Pressure

There is an extensive body of literature on the price impact of institutional flows. Warther (1995) documents a positive relation between aggregate flows to equity mutual funds and contemporaneous stock market returns. Edelen and Warner (2001) and Goetzmann and Massa (2003), using daily mutual fund flow data, show that mutual fund flows lead intraday market returns. More recently, Teo and Woo (2004) and Braverman, Kandel, and Wohl (2008) find that aggregate flows to an investment style or investment sector negatively predict future style or sector returns, lending further support to a price pressure story. Coval and Stafford (2007) and Frazzini and Lamont (2008), instead of focusing on aggregate institutional flows, examine the impact of mutual fund flow-induced trading on *individual* stock returns. In this section, I extend the analysis in Coval and Stafford (2007) in two ways: (1) to study the price pressure effect of flow-induced trading on individual stocks in a more general setting, and (2) to test whether the *expected* component of flow-induced trading forecasts future stock and fund returns.

2.1 Trading in response to capital flows

How should mutual funds adjust their holdings in response to capital flows? In a simple framework without liquidity constraints or wealth effects, portfolio choices are unaffected by capital flows. In other words, fund managers should *proportionally* expand or liquidate their existing holdings in response to inflows or outflows, as long as capital flows from retail investors are uninformative about future stock returns. In actual financial markets, where liquidity and other constraints are nonnegligible, stock holdings are not infinitely scalable.[2] Consequently, fund managers may optimally choose to deviate from the perfect-scaling benchmark in some situations.

There are three types of deviations that can help mitigate the liquidity costs of capital flows. First, managers can use their cash reserve to absorb capital flows. This is unlikely to be a long-term solution, as maintaining a large cash buffer can be very costly. Second, in response to capital inflows, managers can invest part of the new capital in their existing holdings and use the remaining inflow to initiate new positions. Managers with outflow, however, would have to

[2] For example, Chen et al. (2004) and Pollet and Wilson (2008) show that fund size is negatively related to expected fund returns, consistent with decreasing returns to deploying capital.

sell their holdings dollar-for-dollar to pay for redemptions (aside from tapping into their cash reserve). Finally, managers can expand or liquidate individual positions to different degrees depending on the liquidity costs; for example, managers can use their more liquid and smaller positions to disproportionately absorb capital flows.

I gauge the effect of trading costs and other constraints on the degree of partial scaling with the following panel regression:

$$trade_{i,j,t} = \beta_0 + \beta_1\ flow_{i,t} + \gamma_2\ X + \gamma_3\ flow_{i,t}\ X + \varepsilon_{i,t}. \tag{2}$$

The dependent variable, $trade_{i,j,t} = \frac{shares_{i,j,t}}{shares_{i,j,t-1}^{split\_adj}} - 1$, is the percentage trading in stock j by fund i in quarter t, with split adjustments. The main independent variable of interest is $flow_{i,t}$, which is the capital flow to fund i in quarter t as a fraction of the fund's total net assets at the end of the previous quarter. X is a set of variables that reflect trading costs: (1) the ownership share of mutual fund i in stock j (defined as $\frac{shares_{i,j,t-1}}{shrout_{j,t-1}}$), and (2) the effective bid-ask spread of stock j derived from the Basic Market-Adjusted model. The former captures the size of flow-induced trading for each individual position, while the latter measures the marginal trading cost.[3] I also include the portfolio-weighted average ownership share and liquidity cost in the X vector. This is to examine the effect of portfolio-level constraints on managers' decisions to invest capital inflows in their existing positions versus to initiate new positions. One way to think about this regression is that it effectively decomposes fund trading into two parts: a flow-dependent component (the fitted part) and a residual term, which can be potentially attributed to information.[4]

If managers on average proportionally expand or liquidate their holdings in response to capital flows, as in the benchmark case, we expect β_1 to be equal to one and γ_3 to be a zero vector. In the actual financial market, where liquidity and other constraints may be binding, we expect β_1 to be less than one and all components of γ_3 to be negative to reflect deviations from the perfect scaling benchmark. Moreover, since mutual funds are likely to respond to capital inflows and outflows in different ways, I conduct separate regressions for the inflow and outflow subsamples.

The results, shown in Table 2, suggest that mutual funds indeed face liquidity constraints when dealing with capital flows. Columns 1 to 4 report regression results of the outflow sample. As shown in Column 1, the coefficient on $flow$ in a univariate regression is 0.97 (t = 16.82), which is not statistically different from one. This suggests that fund managers on average liquidate their

[3] Ownership share also reflects other size-related constraints. For example, mutual funds are usually self-restrained from holding more than 5% of the shares outstanding of a firm, to avoid mandatory SEC filings.

[4] The magnitude of information-driven trading may vary across mutual funds, which creates a heteroscedasticity issue in the regression. To address this issue, I conduct a weighted OLS regression, with the weight being $\#holdings_{i,t-1}$.

Table 2
Fund responses to capital flows

	The Outflow Sample				The Inflow Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**−0.059**	−0.029	−0.022	−0.022	**−0.032**	0.000	0.020	0.020
	(−6.62)	(−1.32)	(−0.85)	(−0.88)	(−3.42)	(0.02)	(1.22)	(1.21)
$flow_{i,t}$	**0.970**	**1.028**	**1.107**	**1.107**	**0.618**	**0.737**	**0.858**	**0.855**
	(16.82)	(17.64)	(10.97)	(11.27)	(15.78)	(14.64)	(10.57)	(10.57)
$own_{i,j,t-1}$		0.429		**−1.196**		−0.766		−0.471
		(1.35)		(−2.35)		(−1.50)		(−0.65)
$flow_{i,t} \times own_{i,j,t-1}$		−2.355		**−20.588**		**−12.431**		−1.669
		(−0.58)		(−3.25)		(−3.74)		(−0.51)
$liqcost_{j,t-1}$		**−7.455**		**−5.755**		**−7.529**		**−3.416**
		(−2.97)		(−5.38)		(−3.95)		(−4.77)
$flow_{i,t} \times liqcost_{j,t-1}$		**−28.559**		**−13.999**		**−25.748**		**−8.433**
		(−2.48)		(−2.18)		(−3.71)		(−2.39)
$own_{i,t-1}$			**2.171**	**3.924**			−0.364	0.212
			(3.58)	(4.06)			(−0.44)	(0.18)
$flow_{i,t} \times own_{i,t-1}$			11.265	**41.242**			**−21.337**	**−19.235**
			(1.32)	(3.10)			(−3.20)	(−2.58)
$liqcost_{i,t-1}$			−11.127	−6.084			**−18.461**	**−15.505**
			(−1.89)	(−1.24)			(−3.08)	(−2.79)
$flow_{i,t} \times liqcost_{i,t-1}$			−57.295	−44.609			**−51.076**	**−42.332**
			(−1.90)	(−1.43)			(−3.01)	(−2.49)
Adjusted R^2	4.68%	6.31%	6.21%	6.43%	9.53%	10.07%	11.36%	11.46%
No. observations	1,207,060	1,044,623	1,207,060	1,044,623	2,462,355	2,215,898	2,462,355	2,215,898

This table reports regression analyses of mutual fund trading in response to capital flows. The dependent variable in all specifications is the percentage change in shares held by fund i in stock j from quarters $t-1$ to t with split adjustments. The main independent variable of interest is $flow_{i,t}$, which is the net capital flow to fund i in quarter t divided by the fund's total net assets at the end of the previous quarter. Other control variables include $own_{i,j,t-1}$, the percentage of all shares outstanding of stock j that is held by fund i at the end of quarter $t-1$; and $liqcost_{j,t-1}$, the effective half bid-ask spread estimated from the Basic Market-Adjusted model as described in Hasbrouck (2006, 2009). $own_{i,t-1}$ and $liqcost_{i,t-1}$ are the portfolio-weighted average ownership share and effective bid-ask spread, respectively. The coefficients are estimated using a panel OLS approach with quarter fixed effects. t-statistics, shown in parentheses, are computed based on standard errors clustered at the fund level. Coefficient estimates significant at the 5% level are indicated in bold.

holdings dollar-for-dollar in response to capital outflows and that cash plays a limited role in absorbing capital outflows at the quarterly horizon. Columns 2 through 4 show that ownership share has no significant impact on the extent to which managers liquidate their individual positions.[5] In contrast, the marginal liquidity cost is a significant determinant of managers' liquidation decisions; the coefficient on the interaction term between $flow$ and the effective bid-ask spread is -13.99 ($t = -2.18$). Together, these results suggest that fund managers sell their holdings, in particular, their liquid holdings, to meet redemption requests.

The results of the inflow sample, shown in Columns 5 to 8, exhibit a few distinct patterns. First, managers invest only 62 (t = 15.78) cents out of each dollar of inflow in their existing holdings, reflecting a significant deviation from the perfect scaling benchmark. Second, the larger the portfolio-average holding

5 Column 4 includes both the position-level and portfolio-average ownership share in the regression. Because the correlation between the two variables is 0.83 in the outflow sample, the coefficient estimates are likely to be affected by a multicollinearity problem.

size (measured by ownership share) and portfolio-average marginal trading cost, the less the manager invests his capital inflow in the existing holdings: The coefficients on the interaction terms between $flow$ and the portfolio-average ownership share and portfolio-average marginal liquidity cost are -19.24 ($t = -2.58$) and -42.33 ($t = -2.49$), respectively. Third, the coefficients on the interaction terms between $flow$ and stock-specific holding size and marginal liquidity costs are also statistically significant, but they are substantially smaller than their portfolio-average counterparts in terms of the economic magnitude. Together, these results suggest that managers on average invest *part* of their inflows in their existing holdings, and that they use more of their new capital to initiate new positions if the portfolio-average holding size or liquidity cost is larger.

2.2 The return pattern

Building on the result from the previous section, I define flow-induced trading (*FIT*) for each stock in each quarter as

$$FIT_{j,t} = \frac{\sum_i shares_{i,j,t-1} * flow_{i,t} * PSF_{i,t-1}}{\sum_i shares_{i,j,t-1}}, \tag{3}$$

where $flow_{i,t}$ is the dollar flow to fund i in quarter t scaled by the fund's lagged total net assets, and $shares_{i,j,t-1}$ is the number of shares held by mutual fund i at the end of the previous quarter.[6] $PSF_{i,t-1}$ is the partial scaling factor, computed based on the regression specifications shown in Columns 1 and 7 of Table 2.[7] An intuitive way to interpret this measure is that if we think of the entire mutual fund industry as one giant fund, *FIT* then captures the magnitude of flow-induced trading by this aggregate fund.

I then examine the return pattern associated with mutual funds' flow-induced trading. At the end of each quarter, stocks are sorted into deciles based on *FIT* in ascending order and are held for twelve quarters. Panel A of Table 3 reports the magnitude of *FIT* in each decile from one year before the ranking quarter to one year after. In quarter zero (i.e., the ranking quarter), stocks in the top decile experience significant flow-induced purchases, while those in the bottom decile experience significant flow-induced sales; the difference in *FIT* between the

[6] I also use lagged shares outstanding and total trading volume as the denominator, and obtain similar return patterns. Conceptually, the denominator in *FIT* should capture the amount of active liquidity provision in the market, so that the ratio reflects the resulting short-term price impact from uninformed trading. However, there is no clear evidence as to which variable best captures liquidity provision. The choice to use total shares held by mutual funds as the scaler is motivated by prior findings that mutual funds tilt their holdings toward liquid stocks (e.g., Gompers and Metrick 2001) and that they also act as active liquidity providers (e.g., Da, Gao, and Jagannathan 2011). In untabulated analyses, I show that *FIT* scaled by total shares held by mutual funds has more explanatory power for both contemporaneous and future stock returns than does *FIT* scaled by shares outstanding.

[7] The main results of the paper are not sensitive to the particular choice of PSF. Using specifications in other columns of Table 2 yields similar return patterns. To ensure robustness, I also conduct a rolling-window regression to estimate PSF using observations up to $t-1$, and obtain virtually identical results.

top and bottom deciles is about 22% (t = 22.94). *FIT* also exhibits significant persistence over time: It is monotonically increasing from deciles one to ten in each of the eight quarters surrounding the ranking period, and the difference in *FIT* between the top and bottom deciles is statistically significant in all eight quarters. The strong positive autocorrelation in *FIT* is consistent with prior results that mutual fund flows are persistent and that mutual funds turn over their positions gradually.

Panels B and C of Table 3 report the monthly returns to these decile portfolios ranked by *FIT*. As shown in Panel B, the difference in equal-weighted returns between the top and bottom deciles ranked by *FIT* is 5.19% (t = 7.77) in the ranking quarter. While the return spread is indistinguishable from zero in the following year, it is −7.20% (t = −2.70) in years two and three combined. Moreover, since mutual funds significantly tilt their portfolios toward large-cap stocks (e.g., Gompers and Metrick 2001), the value-weighted portfolios exhibit a more pronounced return pattern. The difference in value-weighted portfolio returns between the top and bottom deciles is 6.36% (t = 5.96) in the ranking quarter, and is −11.04% (t = −2.80) in years two and three combined. Controlling for known risk factors has little impact on my results. Figure 1 shows the cumulative return to the hedge portfolio that goes long in the top decile and short in the bottom decile. The curve with triangles shows the return pattern of equal-weighted portfolios, while the curve with squares shows the return pattern of value-weighted portfolios. It is clear that the positive return to the long-short portfolio accumulated in the formation quarter is completely reversed by the end of year three.

An interesting observation from Figure 1 is that the return reversal pattern of flow-induced trading does not occur immediately; rather, it starts about one year after portfolio formation and takes another two years to finish. Such a gradual reversal pattern seems inconsistent with a simple price pressure story; it is also different from the finding in Coval and Stafford (2007) that extreme mutual fund outflows are followed immediately by higher stock returns. The difference in our return patterns is likely to be driven by two countervailing effects associated with flow-induced trading. On the one hand, flow-induced trading drives stock prices away from their fundamental value, calling for an immediate reversal. On the other hand, because mutual fund flows are highly persistent, stocks that experience flow-induced purchases (sales) in the current quarter are expected to experience more flow-induced purchases (sales) in subsequent quarters, sending their prices further away from their fundamental value. The timing and magnitude of the reversal pattern is thus determined by the net effect of these two countervailing forces.

It seems, in my sample, that the two forces counteract each other in year one, rendering the net return effect insignificant. In years two and three, as the persistence in fund flows dies out, the reversal effect dominates. In contrast, in the extreme-flow sample analyzed by Coval and Stafford (2007), as extreme flows tend to cause a larger price impact in the formation period (hence a

Table 3
The flow-induced price effect

Panel A: The magnitude of *FIT* from quarters −4 to +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%
10	5.00%	5.88%	6.69%	8.62%	16.76%	8.06%	6.10%	5.25%	4.23%
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)

Panel B: Equal-weighted returns to portfolios ranked by *FIT*

Decile	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	Excess Return	3-Factor Alpha
	Qtr. 0 (Formation Qtr.)			Qtr. 1–4			Qtr. 5–8		Qtr. 5–12	
1	0.09%	−0.83%	−0.64%	0.68%	−0.22%	0.06%	0.90%	−0.06%	0.92%	0.05%
10	1.82%	1.08%	0.86%	0.66%	−0.02%	0.04%	0.49%	−0.33%	0.63%	−0.17%
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)

Panel C: Value-weighted returns to portfolios ranked by *FIT*

Decile	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	Excess Return	3-Factor Alpha
	Qtr 0 (Formation Qtr.)			Qtr. 1–4			Qtr. 5–8		Qtr. 5–12	
1	−0.22%	−1.05%	−0.82%	0.73%	−0.09%	−0.02%	0.87%	0.19%	0.82%	0.19%
10	1.90%	1.26%	0.93%	0.64%	0.05%	−0.22%	0.21%	−0.35%	0.36%	−0.23%
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)

This table reports calendar-time returns to portfolios ranked by flow-induced trading (*FIT*). *FIT* is defined as the aggregate mutual fund flow-induced trading in a quarter divided by the total shares held by all mutual funds at the end of the previous quarter. The portfolios are rebalanced every quarter and are held for three years. Quarter 0 is the formation quarter. Panel A reports the magnitude of *FIT* in each of the nine quarters from one year before to one year after the ranking period. Panels B and C report the equal-weighted and value-weighted monthly portfolio returns in the following three years, 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. Monthly returns with different risk adjustments 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 standard errors with Newey-West corrections of twelve lags. Estimates significant at the 5% level are indicated in bold.

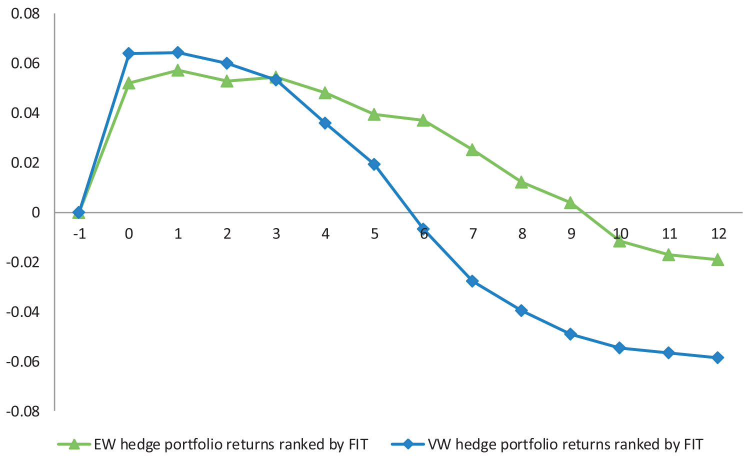

Figure 1
Equal- and value-weighted stock return patterns of *FIT*
This figure shows cumulative returns to the hedge portfolio ranked by *FIT*, which is defined as the aggregate mutual fund flow-induced trading in a quarter divided by the total shares held by all mutual funds at the end of the previous quarter. At the end of each quarter, all stocks are sorted into deciles based on *FIT*. These decile portfolios are then rebalanced every quarter and are held for three years. The hedge portfolio is a long-short portfolio that goes long in decile 10 and goes short in decile 1. Quarter 0 is the formation quarter. The curve with triangles shows cumulative returns to the equal-weighted hedge portfolio, and the curve with squares shows cumulative returns to the value-weighted hedge portfolio.

stronger reversal) and are less likely to repeat themselves (hence weaker return continuation), the reversal effect dominates immediately.

2.3 Expected flows and future returns

2.3.1 Expected fund flows. If mutual fund flow-induced trading can affect contemporaneous stock returns and given that fund flows are highly predictable, a natural question is, can forecastable flows to mutual funds help predict *future* stock and fund returns? To test this possibility, I first examine the flow-performance relation as suggested in prior literature, with an additional forecasting variable—the Carhart four-factor fund alpha. While retail investors are unlikely to use factor models to evaluate fund performance, many of them rely on benchmark-adjusted returns to make investment decisions, which, in essence, is a way to adjust for systemic risks. Specifically, I conduct the following regression analysis:

$$flow_{i,t+1} = \beta_0 + \beta_1\, alpha_{i,t} + \beta_2\, adjret_{i,t} + \beta_3\, flow_{i,t} + \beta_4\, flow_{i,t-1} + \beta_5\, flow_{i,t-2} + \beta_6\, flow_{i,t-3} + \varepsilon_{i,t+1}, \quad (4)$$

where the dependent variable is the percentage flow to a mutual fund in the following quarter. The independent variables include the monthly four-factor fund alpha, market-adjusted fund returns, and quarterly fund flows, all measured in the previous year.

Table 4
Predicting future flows

	Fama-MacBeth			Pooled OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**0.028**	**0.028**	**0.010**	**0.016**	**0.014**	**0.007**
	(5.38)	(5.77)	(3.65)	(25.89)	(18.77)	(7.72)
$alpha_{i,t}$	**4.827**	**1.766**	**0.953**	**4.232**	**2.453**	**1.330**
	(9.67)	(4.38)	(4.47)	(9.02)	(9.15)	(5.43)
$adjret_{i,t}$		**0.396**	**0.229**		**0.202**	**0.089**
		(7.34)	(6.72)		(5.17)	(2.74)
$flow_{i,t}$			**0.194**			**0.228**
			(8.78)			(17.21)
$flow_{i,t-1}$			**0.102**			**0.109**
			(5.28)			(7.55)
$flow_{i,t-2}$			**0.122**			**0.090**
			(6.29)			(6.03)
$flow_{i,t-3}$			**0.033**			**0.029**
			(5.47)			(3.67)
Adjusted R^2	4.53%	7.70%	24.79%	5.25%	7.14%	19.83%
No. observations	98,264	98,264	95,285	98,264	98,264	95,285

This table reports forecasting regressions of future mutual fund flows. The dependent variable in all regression specifications is the capital flow to mutual fund i in quarter $t+1$ scaled by the fund's total net assets at the end of the previous quarter. The main independent variables include $alpha_{i,t}$, the monthly Carhart four-factor alpha computed from the fund's returns in the previous year, and $adjret_{i,t}$, the cumulative market-adjusted fund return in the previous year. $flow_{i,t}$, $flow_{i,t-1}$, $flow_{i,t-2}$, and $flow_{i,t-3}$ are lagged capital flows in the previous four quarters. The coefficients are estimated using both the Fama-MacBeth and pooled OLS approaches. Standard errors of the Fama-MacBeth estimates are computed with Newey-West corrections of four lags. For the pooled OLS approach, quarter fixed effects are included in all regression specifications, and standard errors are clustered at the fund level. t-statistics are shown in parentheses. Coefficient estimates significant at the 5% level are indicated in bold.

The first three columns of Table 4 report the regression coefficients based on the Fama and MacBeth (1973) approach, and the next three columns report coefficient estimates using a pooled OLS approach. Consistent with prior research, the coefficients on lagged fund returns and fund flows are statistically and economically significant in all regression specifications. What is new is that the Carhart four-factor fund alpha also significantly predicts future fund flows. For example, in a univariate regression, a 1% increase in monthly four-factor fund alpha in the previous year is associated with a 4.8% ($t=9.67$) increase in capital flows in the subsequent quarter. This coefficient remains economically and statistically significant after controlling for lagged fund returns and fund flows.

It is worth noting that forecastable flows to mutual funds do not necessarily imply forecastable returns. If mutual fund managers fully adjust their holdings in *anticipation* of future flows, the predictable part of mutual fund flows then only affects fund trading today, not trading in the future. Such anticipatory trading, however, is unlikely to play a significant role in practice. For one thing, mutual funds usually cannot invest with anticipated inflows, as a vast majority of them cannot buy securities on margin. In addition, mutual funds with anticipated outflows are likely to be experiencing redemptions already, thus having limited capacity to create additional cash buffer for future outflows. In untabulated analyses, I show that mutual funds respond to expected capital flows in a similar way to unexpected flows.

2.3.2 The expected return pattern. To examine the return predictive pattern of forecastable flows to mutual funds, I construct a measure of expected flow-induced trading, denoted $E[FIT]$, by replacing actual flows with expected flows. Specifically, $E[FIT]$ for stock j at time t is defined as

$$E_t[FIT_j] = \frac{\sum_i shares_{i,j,t} * E_t[flow_i] * PSF_{i,t}}{\sum_i shares_{i,j,t}}, \tag{5}$$

where $E_t[flow_i]$ is the expected capital flow to mutual fund i conditional on fund performance measured at the end of period t.[8] For most of the paper, expected flows are constructed from lagged four-factor fund alpha. I exclude raw fund returns in the construction of $E[FIT]$ because the flow-based mechanism is also an important driver of the price momentum effect (see discussion in Section 5). Thus, including raw fund returns in the definition of $E[FIT]$, and at the same time adjusting the resulting portfolio returns by the momentum factor, would bias the result against finding any return predictive power of $E[FIT]$.[9]

At the end of each quarter, I then sort all stocks into deciles based on $E[FIT]$ and hold these decile portfolios for twelve quarters. Consistent with my prediction, the expected part of mutual fund flow-induced trading positively forecasts stock returns in the short run, and negatively over the long run. As shown in Panel A of Table 5, the return difference between the top and bottom deciles ranked by $E[FIT]$ is 2.52% ($t = 3.96$) in the quarter following portfolio formation and 5.28% ($t = 2.63$) in the following year. The return spread then becomes negative, reaching a total of -5.67% ($t = -2.17$) in quarters six to twelve. Controlling for known risk factors has little impact on the return pattern.

Given that expected flow-induced trading strongly forecasts future stock returns, we expect a similar return predictive pattern at the fund level, as mutual funds turn over their holdings gradually. To test this possibility, I define an expected flow-induced trading measure for each mutual fund as the portfolio-weighted average $E[FIT]$ across its holdings. Specifically, we have

$$E_t[FIT_i^*] = \sum_j (E_t[FIT_j] * \omega_{i,j,t}), \tag{6}$$

where $\omega_{i,j,t}$ is the weight of stock j in fund i's portfolio. At the end of each quarter, I then sort all mutual funds into deciles based on $E[FIT^*]$ and hold these decile portfolios for twelve quarters. Consistent with the stock return

8 I exclude lagged fund flows to forecast future flows in Equation (5), because lagged flow-induced trading has no predictive power for stock returns in the subsequent year. As discussed in Section 3.2, there are two countervailing forces associated with flow-induced trading, and the net effect of the two forces is close to zero in the year following portfolio formation in my sample.

9 The only exception to this rule is in Section 5, where I examine the extent to which flow-induced trading drives the price momentum effect. Because stock price momentum usually refers to the autocorrelation patterns in raw, rather than risk-adjusted, stocks returns, $E[FIT]$ in Section 5 is computed based on lagged fund returns instead of fund alpha.

Table 5
The expected flow-induced price effect

Panel A: Stocks ranked by $E[FIT]$

Decile	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	Excess Return	3-Factor Alpha	Excess Return	3-Factor Alpha
	Qtr. 1			Qtr. 1–4			Qtr. 5		Qtr. 6–8		Qtr. 6–12	
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%
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%
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)

Panel B: Mutual funds ranked by $E[FIT^*]$

Decile	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	4-Factor Alpha	Excess Return	3-Factor Alpha	Excess Return	3-Factor Alpha	Excess Return	3-Factor Alpha
	Qtr. 1			Qtr. 1–4			Qtr. 5		Qtr. 6–8		Qtr. 6–12	
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%
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%
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)

This table reports the association between expected capital flows to mutual funds and future stock and fund returns. Panel A reports calendar-time returns to portfolios sorted by expected flow-induced trading ($E[FIT]$). Specifically, at the end of each quarter, all stocks are ranked into deciles based on $E[FIT]$, the aggregate expected mutual fund flow-induced trading divided by the total shares held by all mutual funds at the end of the quarter, where the expected capital flow to a mutual fund is estimated using the monthly four-factor fund alpha in the previous year. Panel B reports calendar-time returns to various mutual fund portfolios. At the end of each quarter, all mutual funds are sorted into deciles based on $E[FIT^*]$, the portfolio-weighted average expected flow-induced trading. The portfolios in both Panels A and B are rebalanced every quarter and are 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. Monthly returns with different risk adjustments 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 standard errors with Newey-West corrections of twelve lags. Estimates significant at the 5% level are indicated in bold.

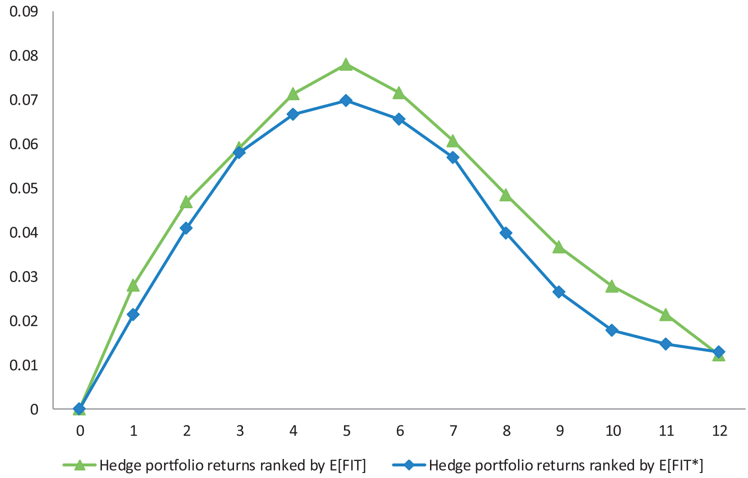

Figure 2
Return patterns of $E[FIT]$ and $E[FIT^*]$
This figure shows cumulative returns to the hedge portfolios ranked by $E[FIT]$ and $E[FIT^*]$. $E[FIT]$ is the aggregate expected mutual fund flow-induced trading divided by the total shares held by all mutual funds at the end of the quarter, where the expected capital flow to a mutual fund is estimated using the monthly four-factor fund alpha in the previous year; $E[FIT^*]$ is the portfolio-weighted average expected flow-induced trading. At the end of each quarter, all stocks are sorted into deciles based on $E[FIT]$. These decile portfolios are then rebalanced every quarter and are held for three years. The curve with triangles shows cumulative returns to the hedge portfolio that goes long in stocks in decile 10 and goes short in stocks in decile 1. Similarly, at the end of each quarter, all mutual funds are sorted into deciles based on $E[FIT^*]$. The curve with squares shows cumulative returns to the hedge portfolio that goes long in mutual funds in decile 10 and goes short in mutual funds in decile 1.

result, $E[FIT^*]$ significantly and positively predicts fund performance in the following year, and negatively in years two and three. As can be seen in Panel B of Table 5, the spread in fund returns between the top and bottom deciles ranked by $E[FIT^*]$ is 1.65% (t = 2.66) in the following quarter and 4.80% (t = 2.65) in the following year. The return spread then becomes −4.62% (t = −1.70) in quarters six to twelve after portfolio formation. Adjusting for known risk factors has, again, little impact on these returns. Figure 2 shows the return patterns associated with expected mutual fund flow-induced trading at both the stock and fund levels. It is clear that the positive return to the long-short portfolio in the first year, ranked by either $E[FIT]$ or $E[FIT^*]$, is completely reversed in the subsequent two years.

A potential concern with these return results is that since lagged fund alpha explains less than 5% of the variation in future fund flows in the first-stage regression (Column 1 of Table 4), $E[FIT]$, which is constructed from lagged fund alpha, may have little power to predict future flow-induced trading, and the documented return effect may be spurious. To directly address this concern, I conduct a regression of $E[FIT]$ to forecast FIT. In a univariate setting, $E[FIT]$ explains close to 15% of the variation in future FIT (untabulated for brevity), almost three times as large as the R^2 in the first-stage regression. This is because a large part of the noise in mutual fund flows—that is, the residual term in the flow-forecasting regression—is washed out when we aggregate flow-induced trading across mutual funds, as funds with similar holdings are equally likely to receive residual inflows and residual outflows.

In sum, the results in this section support the prediction that expected capital flows and flow-induced trading positively forecast stock and fund returns in the short run, which are then reversed over the long run. The hump-shaped return pattern at the fund level also suggests that mutual fund managers are unable to foresee the reversal in stock returns and to unwind their positions before the reversal starts. In the remainder of the paper, I explore the implications of forecastable flow-induced trading for some well-known return anomalies.

3. Mutual Fund Performance Predictability

Prior studies find that mutual funds with good past performance continue outperforming their peers with poor past performance, and that money flows disproportionately to mutual funds that outperform subsequently. The conventional interpretations of these findings are that some mutual fund managers are more skilled than others and that retail investors are able to identify managers with superior skills. In this section, I offer an alternative way to think about these return patterns based on a single mechanism—predictable price pressure caused by mutual fund flow-induced trading.

3.1 Mutual fund performance persistence

Whether mutual fund performance is persistent has long been of interest to asset pricing research. Grinblatt and Titman (1992), Goetzmann and Ibbotson (1994), and Brown and Goetzmann (1995) find considerable persistence in mutual fund rankings based on abnormal performance. Hendricks, Patel, and Zeckhauser (1993), using a calendar-time portfolio approach, show 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) cuts that return spread by half after including stock price momentum as an additional source of risk in both the ranking and holding periods. More recently, Bollen and Busse (2005) and Cohen, Coval, and Pastor (2005) report stronger performance persistence by using daily mutual fund return data and a more refined measure of fund alpha, respectively.

I start my analysis by replicating prior studies on mutual fund performance persistence (untabulated for brevity). At the end of each quarter, I sort all mutual funds into deciles based on their Carhart four-factor fund alpha in the previous year, and hold the resulting decile portfolios for the next twelve quarters. There is significant continuation in abnormal mutual fund performance in the short run. The spread in four-factor fund alpha between the top and bottom deciles is 1.17% (t = 3.19) in the subsequent quarter and 4.44% (t = 3.89) in the subsequent year. Similar to Cohen, Coval, and Pastor (2005), I find that more than half of the return spread in the postformation year is due to continued outperformance by past winning funds. Moreover, there is no significant reversal in mutual fund returns in the long run.

While this return pattern, taken at face value, is consistent with a model of heterogeneous manager ability, there is an alternative way to think about the evidence. In particular, past winning funds receive capital inflows and use the new capital to expand their existing holdings; such inflow-induced purchases then drive up their subsequent performance. In contrast, past losing funds lose capital and collectively sell their existing holdings to meet redemption requests, driving down their future performance. As a result, the flow-performance relation combined with flow-induced price pressure can generate persistence in mutual fund performance.

To distinguish between the flow-based explanation and the heterogeneous managerial ability story, I conduct a horse race between $E[FIT^{*}]$ and the four-factor fund alpha in a calendar-time portfolio approach to forecast future fund performance. But, instead of conducting an independent portfolio sort, I perform two sequential sorts, as the correlation between $E[FIT^{*}]$ and the four-factor fund alpha is about 0.55. More specifically, in the first portfolio test, I rank mutual funds into quintiles first by $E[FIT^{*}]$, and then within each $E[FIT^{*}]$ group, I further sort funds into five groups by fund alpha. I then hold the resulting twenty-five portfolios for one quarter. If fund alpha indeed captures ex ante manager ability, it should remain a significant predictor of future fund performance after controlling for $E[FIT^{*}]$. In contrast, if fund alpha predicts future fund performance because it predicts flow-induced trading, it should be subsumed by $E[FIT^{*}]$, as the latter more accurately reflects such flow-induced price impacts. Panel A of Table 6 reports the returns to these twenty-five portfolios. After controlling for $E[FIT^{*}]$, the return spread between the top and bottom quintiles ranked by fund alpha ranges from -0.42% to 0.63% and is insignificant in four out of the five $E[FIT^{*}]$ quintiles. The average spread across all $E[FIT^{*}]$ quintiles is also insignificant: 0.15% (t = 1.05) on a three-factor adjusted basis and 0.21% (t = 1.21) on a four-factor adjusted basis.

In the second portfolio test, I first rank mutual funds into quintiles by fund alpha and then within each fund alpha quintile, I further sort funds into five groups by $E[FIT^{*}]$. As shown in Panel B of Table 6, $E[FIT^{*}]$ remains a significant predictor of future fund performance after controlling for fund alpha. The spread in abnormal fund returns between the top and bottom quintiles ranked by $E[FIT^{*}]$ ranges from 0.42% to 1.80% and is statistically significant in four out of the five fund alpha quintiles. The average spread across all fund alpha quintiles is both economically and statistically significant: 1.23% (t = 2.67) on a three-factor adjusted basis and 0.78% (t = 2.08) on a four-factor adjusted basis. Together, these results suggest that the well-known pattern of mutual fund performance persistence is likely to be a manifestation of forecastable flow-induced trading.

Table 6
Mutual fund performance persistence

Panel A: Mutual funds first ranked by $E[FIT^*]$ then by *alpha*

Quintiles of *alpha*	Quintiles of $E[FIT^*]$							Quintiles of $E[FIT^*]$						
	1	2	3	4	5	5 - 1	Average	1	2	3	4	5	5 - 1	Average
	Qtr. 1 (3-Factor Alpha)							Qtr. 1 (4-Factor Alpha)						
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 B: Mutual funds first ranked by *alpha* then by $E[FIT^*]$

Quintiles of $E[FIT^*]$	Quintiles of *alpha*							Quintiles of *alpha*						
	1	2	3	4	5	5 - 1	Average	1	2	3	4	5	5 - 1	Average
	Qtr. 1 (3-Factor Alpha)							Qtr. 1 (4-Factor Alpha)						
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)

This table reports the horse race between four-factor fund alpha and expected flow-induced trading to predict future fund performance. In Panel A, mutual funds are sorted into a five-by-five matrix first by $E[FIT^*]$ and then by the Carhart four-factor fund alpha. Panel B reports the same sequential sort in the reverse order; mutual funds are sorted into a five-by-five matrix first by the four-factor fund alpha and then by $E[FIT^*]$. $E[FIT^*]$ is the portfolio-weighted average expected flow-induced trading, where expected mutual fund flows are computed from the four-factor fund alpha in the previous year. The portfolios are rebalanced every quarter and are held for one quarter. 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. Monthly returns with different risk adjustments are reported: the Fama-French three-factor alpha and the Carhart four-factor alpha. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags. Estimates significant at the 5% level are indicated in bold.

3.2 The "smart money" effect

If mutual fund managers have heterogeneous ability, an important and related question is, can retail investors identify managers with superior skills? In particular, given the enormous amount of capital that is delegated to the fund industry and the large capital flows across mutual funds in each year, if capital is not directed from less-skilled to more-skilled managers, it raises serious questions about market efficiency and the notion that the market is getting more efficient over time. Gruber (1996) proposes a simple test for this "smart money" hypothesis: If investors are able to distinguish good managers from bad ones, capital flows to mutual funds should positively forecast future fund performance, assuming that the additional capital does not instantaneously crowd out superior performance. A number of follow-up studies (e.g., Zheng 1999; Keswani and Stolin 2008) find supportive evidence for the smart money hypothesis: There indeed is a positive relation between quarterly fund flows and the subsequent quarter fund performance.

I first replicate prior studies on the smart money effect using a longer sample period (untabulated for brevity). At the end of each quarter, I sort mutual funds into deciles based on their lagged quarterly flows and hold the resulting portfolios for the next twelve quarters. Consistent with the smart money hypothesis, mutual funds with past inflows significantly outperform those with past outflows in the immediate future; the spread in three-factor fund alpha between the top and bottom flow deciles is 0.84% (t = 2.74) in the subsequent quarter.[10] While the spread is indistinguishable from zero in quarters two through four, it becomes significantly negative in years two and three, reaching a total of −3.12% (t = −2.68). This reversal pattern implies that investors actually lose money in the long run by churning their mutual fund investments, potentially contradicting the smart money hypothesis.

Drawing on the return pattern of flow-induced trading, I offer an alternative explanation for the correlation between fund flows and future fund performance. In particular, because capital flows are persistent, mutual funds with past inflows tend to receive more capital inflows subsequently and invest the new capital in their existing holdings; such flow-induced purchases then drive up their subsequent performance. In contrast, funds with past outflows tend to experience further redemptions, and collectively sell their existing holdings, driving down their own performance. Consequently, the mechanism of flow-induced trading can generate a return pattern that is consistent with the smart money effect in the short run but reverses over the long run.

To examine whether mutual fund flow-induced trading can account for the short-term smart money effect, I conduct a horse race between $E[FIT^*]$ and

[10] It may seem puzzling that capital flows to mutual funds positively predict subsequent fund performance, but flow-induced trading does not predict subsequent stock returns (see Table 3). The key to resolve this puzzle is that flow-induced trading in an individual stock is determined by the capital flows to *all* mutual funds holding the stock; in other words, mutual funds experiencing the largest inflows (outflows) are not necessarily holding stocks with the largest inflow-induced purchases (outflow-induced sales).

quarterly fund flows to predict future abnormal fund performance. Specifically, at the end of each quarter, I sort all mutual funds into a five-by-five matrix independently by $E[FIT^{*}]$ and fund flows, and hold these twenty-five portfolios for one quarter. If past flows predict future fund performance because flows reflect heterogeneous manager ability, past flows should remain a significant predictor of future fund performance after controlling for $E[FIT^{*}]$. As can be seen in Table 7, while $E[FIT^{*}]$ remains statistically significant in the horse race, lagged fund flows no longer predict future fund performance. The return spread between the top and bottom flow quintiles ranges from −0.03% to 0.48% and is insignificant in four out of the five $E[FIT^{*}]$ quintiles; the average spread across all $E[FIT^{*}]$ quintiles of 0.09% (t = 0.61) is also statistically insignificant. In sum, the results suggest that the empirical pattern previously thought to be consistent with the smart money effect is more likely to be driven by the mechanism of mutual fund flow-induced trading.[11]

3.3 A regression approach

To better isolate the marginal predictive power of $E[FIT^{*}]$, fund alpha, and fund flows for future fund performance, and to control for other fund characteristics that are known to be related to fund performance, I conduct the following Fama-MacBeth return predictive regression:

$$RET_{i,t+1}=\beta_0+\beta_1\ E_t[FIT_i^{*}]+\beta_2\ alpha_{i,t}+\beta_3\ flow_{i,t}+\gamma\ Control_t+\varepsilon_{i,t+1}, \tag{7}$$

where the dependent variable is the fund return in quarter $t+1$. The main independent variables include lagged $E[FIT^{*}]$, fund alpha, and fund flows, all of which are measured at the end of quarter t. The list of control variables includes the expense ratio, fund age, number of stocks in the portfolio, fund size, and portfolio turnover.

The results, shown in Table 8, are consistent with those from the calendar-time portfolio analysis. $E[FIT^{*}]$ is a significant predictor of subsequent fund performance in all regression specifications. Past four-factor fund alpha and past quarterly flows both significantly and positively predict future fund performance when included in the regressions alone, but their predictive power is subsumed by $E[FIT^{*}]$ in the full specification. For example, after controlling for $E[FIT^{*}]$, the coefficient on fund alpha drops from 0.581 (t = 3.82) to 0.005 (t = 0.03), and that on quarterly fund flows drops from 0.012 (t = 2.28) to 0.004 (t = 0.93). The coefficients on other fund characteristics are similar to those reported in prior literature: For example, smaller funds, funds holding a

[11] Relatedly, Sapp and Tiwari (2004) find that the smart money effect becomes insignificant or marginally significant once we control for the price momentum factor. This section contributes to prior literature by providing an explanation for the smart money effect based on a specific, flow-based mechanism of return predictability, rather than on an empirical regularity of which we have limited understanding. In fact, one way to think about the evidence shown in this paper is that the mechanism of flow-induced trading drives both stock price momentum (see Section 5) and the smart money effect.

Table 7
The smart money effect

Mutual funds independently sorted by $E[FIT^*]$ and *flow*

Quintiles of *flow*	Quintiles of $E[FIT^*]$							Quintiles of $E[FIT^*]$						
	1	2	3	4	5	5 - 1	Average	1	2	3	4	5	5 - 1	Average
	Qtr. 1 (Excess Return)							Qtr. 1 (3-Factor Alpha)						
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)

This table reports the horse race between lagged capital flows to mutual funds and expected flow-induced trading to predict future fund performance. At the end of each quarter, all mutual funds are sorted into a five-by-five matrix *independently* by $E[FIT^*]$ and lagged fund flows. $E[FIT^*]$ is the portfolio-weighted average expected flow-induced trading, where expected mutual fund flows are computed from the four-factor fund alpha in the previous year. The portfolios are rebalanced every quarter and held for one quarter. 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. Monthly returns with different risk adjustments are reported: the return in excess of the risk-free rate and the Fama-French three-factor alpha. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags. Estimates significant at the 5% level are indicated in bold.

Table 8
Mutual fund performance regressions

	Fama-MacBeth Regressions of Quarterly Fund Returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	**0.050**	**0.053**	**0.053**	**0.054**	**0.049**	**0.051**	**0.051**
	(5.47)	(5.85)	(5.69)	(5.82)	(5.20)	(5.48)	(5.30)
$E[FIT^*]$	**3.081**				**2.602**	**2.952**	**2.687**
	(3.06)				(2.35)	(2.93)	(2.43)
$aplha_{i,t}$		**0.581**		**0.548**	0.042		0.005
		(3.82)		(3.64)	(0.24)		(0.03)
$flow_{i,t}$			**0.012**	**0.010**		0.004	0.004
			(2.28)	(2.08)		(0.82)	(0.93)
$expenses_{i,t}$	−0.351	−0.830	−0.765	−1.138	−0.319	−0.657	−0.653
	(−0.27)	(−0.55)	(−0.48)	(−0.75)	(−0.26)	(−0.51)	(−0.52)
$\log(age_{i,t})$	0.000	0.000	0.001	0.001	0.000	0.000	0.001
	(0.17)	(0.47)	(0.63)	(0.90)	(0.37)	(0.65)	(0.84)
$\log(numStocks_{i,t})$	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**
	(3.58)	(3.95)	(3.72)	(3.78)	(3.27)	(3.44)	(3.02)
$\log(TNA_{i,t})$	−0.001	**−0.001**	**−0.001**	**−0.001**	−0.001	**−0.001**	**−0.001**
	(−1.91)	(−2.18)	(−2.18)	(−2.30)	(−1.82)	(−2.08)	(−2.00)
$turnover_{i,t}$	**0.002**	0.002	0.002	0.002	**0.001**	**0.002**	**0.001**
	(2.05)	(1.76)	(1.56)	(1.74)	(1.96)	(2.06)	(1.96)
Adjusted R^2	15.77%	11.03%	8.06%	11.91%	17.46%	16.53%	18.24%
No. observations	93,805	93,805	93,805	93,805	93,805	93,805	93,805

This table reports Fama-MacBeth forecasting regressions of future fund returns. The dependent variable in all specifications is the return of mutual fund i in quarter $t+1$. The main independent variables of interest include $E[FIT^*]$, the portfolio-weighted average expected flow-induced trading, where expected fund flows are computed from the four-factor fund alpha in the previous year; *alpha*, the Carhart four-factor fund alpha in the previous year; and *flow*, the capital flow to the mutual fund in the previous quarter. Other control variables include the expense ratio in the previous year, the fund age since inception, the number of stocks the fund is holding in its portfolio, the logarithm of the fund's total net assets of the fund at the end of the previous quarter, and the fund's turnover ratio in the previous quarter. Regression coefficients are estimated using the Fama-MacBeth approach. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of four lags. Estimates significant at the 5% level are indicated in bold.

larger number of stocks, and those with higher turnover tend to have higher expected returns. In sum, the results of the Fama-MacBeth regressions lend further support to the view that the mechanism of flow-induced trading drives both mutual fund performance persistence and the smart money effect.

4. Stock Price Momentum

I next analyze the potential role of mutual fund flow-induced trading in causing stock price momentum, which is perhaps the most robust and puzzling return anomaly.[12] What makes the price momentum effect particularly interesting to academic research is that (1) the strategy has been profitable for decades even after it was made publicly known by academic research, and (2) the return pattern is also robust to large-cap stocks (e.g., Fama and French 2008). The price momentum effect has traditionally been attributed to (1) investors' underreaction to information, and relatedly, the slow diffusion of information

12 See, for example, Jegadeesh and Titman (1993, 2001) and Rouwenhorst (1998). Jegadeesh and Titman (2005) provide an excellent survey of existing literature on the price momentum effect.

across investors (e.g., Barberis, Shleifer, and Vishny 1998; Hong and Stein 1999), (2) the disposition effect—i.e., the tendency to sell winners and hold on to losers (e.g., Grinblatt and Han 2005), and (3) the self-serving attribution bias (e.g., Daniel, Hirshleifer, and Subrahmanyam 1998).[13]

In this section, I propose a new flow-based explanation for the price momentum effect, in particular, for the persistence and robustness of momentum profits. Specifically, I hypothesize that winning mutual funds, by investing capital inflows in their existing holdings that are concentrated in past winning stocks, drive up the subsequent returns of past winning stocks. In contrast, past losing funds, by liquidating their existing holdings that are concentrated in past losing stocks, drive down the subsequent returns of these losing stocks. As a result, performance-chasing fund flows can lead past winning stocks to continue outperforming past losing stocks in the subsequent period. The flow-based explanation further predicts a reversal to the momentum strategy in the long run, as the price pressure effect dissipates. This is consistent with the prior result that part of the momentum effect indeed reverses in years two to five after portfolio formation (e.g., Lee and Swaminathan 2000; Jegadeesh and Titman 2001).[14]

To examine the extent to which the mechanism of flow-induced trading is driving the price momentum effect, I run a horse race between expected flow-induced trading and lagged stock returns to forecast future returns. Because the price momentum effect concerns raw, rather than risk-adjusted, returns, I define $E[FIT]$ based on lagged fund returns instead of four-factor fund alpha. I also 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. With these qualifications, I conduct the following Fama-MacBeth regression:

$$ret_{j,t+1:t+3} = \beta_0 + \beta_1\ E_t[FIT_j^k] + \beta_2\ ret_{j,t-k:t-1} + \gamma\ Control_t + \varepsilon_{j,t+1:t+3}. \quad (8)$$

The dependent variable is the stock return in the next quarter. The main independent variables of interest are the expected flow-induced trading, $E[FIT]$, conditioned on market-adjusted fund returns in the previous k months and the cumulative stock return measured in the same period.[15] Other control variables include the lagged one-month stock return, long-run past return, the book-to-market ratio, firm size, and average monthly turnover in the previous year. If mutual fund flow-induced trading is partially driving stock price momentum, we expect the coefficient on $ret_{t-k:t-1}$ to drop significantly after controlling for $E[FIT]$.

The baseline results are reported in Panel A of Table 9. Consistent with the portfolio test shown in Table 5, expected flow-induced trading is a

[13] There are also risk-based explanations for stock price momentum. For a partial list, see Berk, Green, and Naik (1999), Johnson (2002), and Liu and Zhang (2008).

[14] Vayanos and Woolley (2010) formalize this intuition in a continuous-time model with fully rational agents.

[15] I skip a month in computing lagged cumulative stock returns to avoid the short-term reversal effect.

Table 9
Stock price momentum

Panel A: The full sample

	$k=12$		$k=6$		$k=3$	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**0.103**	**0.092**	**0.096**	**0.077**	**0.094**	**0.084**
	(2.81)	(2.36)	(2.63)	(2.01)	(2.58)	(2.34)
$E_t[FIT_j^k]$		**0.085**		**0.145**		**0.250**
		(3.07)		(2.93)		(3.32)
$ret_{j,t-k:t-1}$	**0.020**	**0.015**	**0.027**	**0.020**	**0.024**	0.014
	(4.06)	(3.31)	(3.59)	(2.82)	(2.29)	(1.40)
$ret_{j,t}$	−0.024	**−0.029**	−0.024	**−0.030**	−0.020	**−0.029**
	(−1.67)	(−2.16)	(−1.63)	(−2.26)	(−1.35)	(−2.18)
$ret_{j,t-36,t-k-1}$	**−0.005**	**−0.004**	**−0.004**	**−0.004**	**−0.004**	**−0.004**
	(−3.19)	(−3.05)	(−2.64)	(−2.56)	(−2.54)	(−2.54)
$bm_{j,t}$	0.005	0.005	0.005	0.005	0.006	0.006
	(1.33)	(1.37)	(1.25)	(1.42)	(1.40)	(1.78)
$\log(mktcap_{j,t})$	**−0.003**	−0.003	**−0.003**	−0.002	−0.003	−0.002
	(−2.16)	(−1.73)	(−1.96)	(−1.33)	(−1.88)	(−1.59)
$turnover_{j,t}$	**−0.004**	**−0.005**	−0.004	**−0.004**	−0.004	**−0.004**
	(−2.02)	(−2.26)	(−1.87)	(−2.06)	(−1.63)	(−2.05)
Adjusted R^2	7.08%	7.85%	6.75%	7.85%	6.38%	7.88%
No. observations	198,692	198,692	198,692	198,692	198,692	198,692

Panel B: Subsample analyses ($k=6$)

	1980–1993		1994–2006		Small-Cap Stocks		Large-Cap Stocks	
	(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)
$E_t[FIT_j^k]$		0.106		**0.203**		**0.158**		**0.175**
		(1.80)		(3.44)		(3.50)		(3.35)
$ret_{j,t-k:t-1}$	**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)
$ret_{j,t}$	−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)
$ret_{j,t-36,t-k-1}$	−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)
$bm_{j,t}$	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)
$\log(mktcap_{j,t})$	−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)
$turnover_{j,t}$	**−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)
Adjusted R^2	7.76%	8.44%	5.69%	6.99%	6.78%	7.55%	8.81%	9.96%
No. observations	65,047	65,047	133,645	133,645	89,255	89,255	109,437	109,437

This table reports Fama-MacBeth forecasting regressions of future stock returns. The dependent variable in all specifications is the quarterly stock return (i.e., the cumulative stock return in months $t+1$ to $t+3$). The main independent variables of interest include $E[FIT]$, the aggregate expected flow-induced trading divided by the total shares held by all mutual funds at the end of quarter t, where expected capital flows are computed from the market-adjusted fund return in the previous k months, and $ret_{j,t-k:t-1}$, the cumulative stock return in the previous k months. Other control variables include the lagged one-month stock return, lagged long-run returns, book-to-market ratio, logarithm of firm size, and average monthly turnover. Panel A reports regression coefficients for the full sample, which spans 1980–2006. Panel B reports the coefficient estimates for various subsamples. Small- and large-cap stocks are classified based on the median market capitalization of NYSE stocks at the end of the previous quarter. Regression coefficients are estimated using the Fama-MacBeth approach. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of four lags. Estimates significant at the 5% level are indicated in bold.

strong predictor of future stock returns in all specifications. Moreover, flow-induced trading appears to be an important source of momentum profits. After controlling for $E[FIT]$, the coefficient on $ret_{t-k:t-1}$ is reduced by 25% ($t = 1.85$), 31% ($t = 2.34$), and 42% ($t = 2.18$) for k equal to 12, 6, and 3, respectively.[16] It is clear from these coefficients that the flow-based explanation accounts for a larger fraction of momentum profits with a shorter formation period. This is because mutual funds constantly turn over their positions; so, the longer the ranking period, the more changes mutual funds make to their holdings and the more likely winning (losing) funds end up holding stocks that have performed poorly (well) by the end of the ranking period.

Panel B reports regression results for various subsamples. Given the substantial growth in the mutual fund industry over the past few decades, we expect $E[FIT]$ to be a stronger predictor of future stock returns and to explain a larger fraction of the price momentum effect in more recent years than in the earlier sample. Similarly, since mutual funds heavily tilt their holdings toward large-cap stocks, the flow-based explanation should account for a larger fraction of the price momentum effect among larger stocks. Both predictions are borne out in the data. The first four columns of Panel B report regression coefficients for the first and second halves of the sample. $E[FIT]$ accounts for about 40% ($t = 2.12$) of stock price momentum in the post-1993 period, compared to less than 16% (statistically insignificant) in the pre-1993 period. The next four columns report regression coefficients for small- versus large-cap stocks, classified based on the median market capitalization of the NYSE sample. While the flow-based mechanism explains less than 20% (statistically insignificant) of stock price momentum among small-cap stocks, it accounts for close to 50% ($t = 2.46$) of the price momentum effect among large-cap stocks. Moreover, after controlling for $E[FIT]$, the price momentum effect is no longer statistically significant in the more recent period and among large-cap stocks.

There are three main takeaways from Table 9. First, mutual fund flow-induced trading is an important driver of the price momentum effect, but perhaps not the only one. Second, the flow-based mechanism is substantially more powerful for explaining momentum profits in more recent years and among large-cap stocks. In a way, this mechanism explains the most puzzling aspects of the price momentum effect—its persistence and robustness. Finally, while this paper focuses exclusively on capital flows to mutual funds, the same set of analyses can be readily applied to other types of institutional money managers, such as investment clubs, hedge funds, pension funds, etc. It is conceivable that the more generalized measure of flow-induced trading can account for an even larger part of the price momentum effect.

[16] To deal with the seasonal pattern in momentum profits, I conduct a similar Fama-MacBeth regression for the month of January and the rest of the year. The price momentum effect in February to December is again partially explained by $E[FIT]$ (untabulated for brevity).

5. Flow-Induced Stock Return Comovement

The mechanism of flow-induced trading has implications not only for expected stock returns, but also for stock return comovement. To illustrate, imagine a mutual fund that receives \$20 million of capital inflows in a month, or over twenty trading days.[17] Further assume that the mutual fund receives \$1.5 million on even days and \$0.5 million on odd days and immediately invests the new capital in its existing holdings. To the extent that flow-induced trading can temporarily affect stock returns, fluctuations in capital flows to the mutual fund on a day-to-day basis can cause nonfundamental comovement among its holdings in this simple example. Drawing on this intuition, I hypothesize that stocks held by mutual funds with similar flows tend to experience correlated flow-induced trading, and thus comove with one another, if one of the following two conditions holds: (1) mutual funds with similar flows also have similar holdings or (2) mutual funds receive correlated inflows or face correlated outflows.[18]

To test this prediction, I rank stocks into quintiles based on $E[FIT]$ at the end of each quarter, and examine the return comovement pattern within each of these quintiles in the following year. In the first-stage analysis, I verify that stocks in the same $E[FIT]$ quintile indeed experience correlated flow-induced trading subsequently. To this end, I conduct the following time-series regression for each stock using monthly mutual fund flow data in the following year:

$$FIT_{j,t} = \beta_0 + \beta_1\ FIT_{grp,t} + \beta_2\ FIT_{ffind,t} + \varepsilon_{j,t}, \tag{9}$$

where $FIT_{j,t}$ is the flow-induced trading in stock j in month t, $FIT_{grp,t}$ is the average flow-induced trading in the $E[FIT]$ quintile to which stock j belongs, and $FIT_{ffind,t}$ is the average FIT of the Fama and French (1997) 48-industry to which stock j belongs.[19] Stock j is excluded from the calculation of both $FIT_{grp,t}$ and $FIT_{ffind,t}$. For each quarter, I then compute the average regression coefficients across all stocks in each $E[FIT]$ quintile. Finally, I report the time-series averages of these quarterly coefficients and the associated standard errors that are adjusted for serial correlations.

The results, shown in Panel A of Table 10, provide strong support for the prediction that stocks in the same $E[FIT]$ quintile subsequently experience correlated flow-induced trading. The β_1 coefficient is positive in all $E[FIT]$ quintiles and is statistically significant in four out of the five. Moreover, consistent with the notion that stocks in the extreme $E[FIT]$ quintiles are most

17 Alternatively, one can imagine a set of mutual funds with perfectly correlated inflows that sum to \$20 million.

18 Two recent studies, Anton and Polk (2010) and Greenwood and Thesmar (2011), also examine the implications of mutual fund flow-induced trading for stock return comovement. In particular, Anton and Polk (2010) focus on common institutional ownership across stocks, while Greenwood and Thesmar (2011) center on the covariance structure of investment flows across mutual funds.

19 Monthly flows are available in the CRSP mutual fund database for the post-1991 period. I do not use daily flows, because the daily flow data are available only for a subset of mutual funds for less than ten years in my sample.

Table 10
Stock return comovement

Panel A: Comovement in monthly *FIT*

Rank by $E[FIT]$	1	2	3	4	5
$FIT_{grp,t}$	**0.626**	**0.413**	0.169	**0.573**	**0.751**
	(2.69)	(2.54)	(0.91)	(3.16)	(2.84)
$FIT_{ffind,t}$	**1.072**	**0.993**	**0.978**	**0.907**	**0.962**
	(4.63)	(6.42)	(10.13)	(7.34)	(4.11)
Adjusted R^2	53.82%	52.69%	51.70%	53.17%	54.98%
No. observations	31,329	31,329	31,329	31,329	31,329

Panel B: Comovement in weekly stock returns

Rank by $E[FIT]$	1	2	3	4	5
$ret_{grp,t}$	**0.199**	**0.128**	**0.116**	**0.152**	**0.230**
	(6.84)	(6.00)	(7.60)	(8.30)	(8.78)
$ret_{ffind,t}$	**0.419**	**0.487**	**0.507**	**0.483**	**0.402**
	(18.10)	(26.85)	(29.84)	(27.46)	(24.32)
$ret_{mkt,t}$	**0.369**	**0.370**	**0.368**	**0.372**	**0.368**
	(13.50)	(17.02)	(17.13)	(14.66)	(9.45)
$ret_{smb,t}$	**0.658**	**0.562**	**0.521**	**0.589**	**0.668**
	(25.14)	(35.46)	(33.36)	(31.65)	(17.26)
$ret_{hml,t}$	**0.149**	**0.127**	**0.143**	**0.134**	**0.129**
	(7.07)	(6.75)	(6.72)	(5.02)	(4.28)
$ret_{umd,t}$	**−0.100**	**−0.068**	**−0.055**	**−0.045**	**−0.027**
	(−8.78)	(−6.72)	(−4.62)	(−3.24)	(−2.36)
Adjusted R^2	27.22%	30.65%	31.73%	30.34%	26.74%
No. observations	39,170	39,170	39,170	39,170	39,170

This table shows correlation patterns in monthly flow-induced trading and weekly stock returns. At the end of each quarter, all stocks are sorted into quintiles based on $E[FIT]$, where expected fund flows are computed based on lagged four-factor fund alpha. I then conduct a time-series regression for each stock in each quarter using monthly fund flows or weekly stock returns in the following year. In Panel A, the dependent variable is the flow-induced trading in stock j in month t, and the independent variables are $FIT_{grp,t}$, the average *FIT* of the quintile portfolio to which stock j belongs, and $FIT_{ffind,t}$, the average *FIT* of the Fama and French (1997) 48-industry to which j belongs. In Panel B, the dependent variable is the return of stock j in week t, and the main independent variable is $ret_{grp,t}$, the value-weighted return of the quintile portfolio to which stock j belongs. Other control variables include the value-weighted return of the industry portfolio to which j belongs, as well as the market, size, value, and momentum factors. For $FIT_{grp,t}$, $FIT_{ffind,t}$, $ret_{grp,t}$ and $ret_{ffind,t}$, I exclude stock j from the calculation. I then take the cross-sectional averages of these regression coefficients for each quintile in each quarter. Finally, I report the time-series averages of these coefficient estimates and corresponding T-statistics, shown in parentheses, based on standard errors with Newey-West corrections of four lags. Estimates significant at the 5% level are indicated in bold.

strongly affected by flow-induced trading, β_1 monotonically decreases as we move toward the center quintile. Specifically, the difference in β_1 between quintiles 1 and 3 is 0.457 ($t = 2.25$) and that between quintiles 5 and 3 is 0.581 ($t = 2.05$).

Next, to examine the return comovement patterns, I repeat the analysis of Equation (9) by replacing monthly flow-induced trading with weekly stock returns in the following year:

$$ret_{j,t} = \beta_0 + \beta_1\, ret_{grp,t} + \beta_2\, ret_{ffind,t} + \gamma\, CommonRiskFactors_t + \varepsilon_{j,t}, \quad (10)$$

where $ret_{j,t}$ is the return of stock j in week t, $ret_{grp,t}$ is the value-weighted return of the quintile portfolio to which stock j belongs, and $ret_{ffind,t}$ is the value-weighted return of the Fama and French (1997) 48-industry to which stock j belongs.[20] Stock j is again excluded from the calculation of both $ret_{grp,t}$ and $ret_{ffind,t}$. I also include contemporaneous market, size, value, and momentum factors in the regression. If flow-induced trading can indeed cause excess comovement among stocks over and beyond the Carhart four-factor model, we expect β_1 to be positive.

The regression results, shown in Panel B of Table 10, confirm this prediction. β_1 is positive and statistically significant in all $E[FIT]$ quintiles. Moreover, the comovement pattern is significantly stronger in the two extreme $E[FIT]$ quintiles than in other quintiles; the difference in β_1 between quintiles 1 and 3 is 0.084 (t = 3.25), and that between quintiles 5 and 3 is 0.115 (t = 4.44).[21] Taken together, the results shown in this paper suggest that the mechanism of flow-induced trading is an important driver of asset prices, affecting both the first and second moments of asset returns.

6. Conclusion

In this paper, I provide a simple flow-based explanation for some well-known empirical patterns of return predictability. Specifically, I show that expected flow-induced trading by mutual funds positively forecasts future stock and fund returns in the short run, but negatively over the long run. This return pattern is consistent with the notion that arbitrageurs have limited capacity to absorb temporary demand shocks in the financial market, even if these shocks are fully anticipated. The main findings of the paper are that this flow-based explanation drives mutual fund performance persistence, the smart money effect, and partially stock price momentum.

While I focus on two specific patterns of mutual fund performance predictability in this paper, the mechanism of flow-induced trading has broader implications for mutual fund performance evaluation: Any variable that predicts future fund flows, and thus flow-induced trading, may be erroneously identified as a measure of manager ability. A number of simple tests outlined in this paper can help us determine the exact mechanism at work. For example, one can try (1) to examine the long-run return pattern associated with the proposed ability measure, (2) to conduct a horse race between the ability measure and expected flow-induced trading to forecast future stock/fund returns, and (3) to analyze the return comovement patterns within various groups of stocks ranked by the ability measure.

A potentially interesting direction for future research is to systemically examine both flow-induced and information-motivated trading (i.e., to follow

[20] The results are unchanged if I use daily stock returns.

[21] In untabulated analyses, I find a marginally significant negative correlation between stocks in quintile 1 and those in quintile 5 ($t = -1.93$). This is potentially consistent with the style-investing view that investors withdraw capital from some mutual funds while at the same time putting money into some other mutual funds (see, e.g., Barberis and Shleifer 2003).

the trade decomposition in Equation (2)). A number of studies have looked at aggregate mutual fund holding and trading decisions but have found at best mixed evidence regarding manager ability (e.g., Chen, Jegadeesh, and Wermers 2000; Wermers 2000). Isolating flow-induced trading, which has little to do with investment skills, from total trading can help us better understand how fund managers collect, process, and trade on value-relevant information.

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