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Investor flows and the assessed performance of open-end mutual funds☆

Roger M. Edelen*

The Wharton School, University of Pennsylvania, Philadelphia, PA 19104, USA

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Abstract

Open-end equity funds provide a diversified equity positions with little direct cost to investors for liquidity. This study documents a statistically significant indirect cost in the form of a negative relation between a fund's abnormal return and investor flows. Controlling for this indirect cost of liquidity changes the average fund's abnormal return (net of expenses) from a statistically significant −1.6% per year to a statistically insignificant −0.2% and also fully explains the negative market-timing performance found in this and other studies of mutual fund returns. Thus, the common finding of negative return performance at open-end mutual funds is attributable to the costs of liquidity-motivated trading.

JEL classification: G23; G29

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* Tel.: + 1-215-898-6298; fax: + 1-2156-898-6200.

E-mail address: edelen@wharton.upenn.edu (R.M. Edelen)

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1. Introduction

It is often taken for granted that the return performance of open-end mutual funds can be used to assess fund managers' ability to identify mispriced securities and generate abnormal returns. The logic is that fees and expenses can simply be added back to net returns to arrive at a summary measure of ability. Given this logic and the widespread empirical evidence of negative average abnormal net return (α) performance, a conventional belief has developed in the academic community that mutual fund managers as a group have no special ability to identify and profit from mispriced securities.[1] The negative average abnormal return typically found in performance studies is interpreted as being the zero abnormal return of a randomly selected portfolio less the fees and expenses deducted from the fund. This unfavorable view of fund managers' contribution to portfolio returns is not improved upon with market-timing performance studies, many of which document a perverse tendency of fund managers to negatively time the market.[2] This result is particularly odd, as it is not easily explained with expenses.

The conventional analysis gives no consideration to the fact that fund managers provide a great deal of liquidity to investors and thus engage in a material volume of uninformed, liquidity-motivated trading. When consideration is given to this fact within a rational expectations framework as developed in Grossman (1976), Hellwig (1980), and Verrecchia (1982), it becomes apparent that the fund managers liquidity-motivated trading likely has an adverse effect on fund returns. The gist of these and related theoretical models, particularly Grossman and Stiglitz (1980), is that in an asymmetrically informed market with costly information production, equilibrium is attained only when liquidity-motivated traders sustain losses to informed traders. These losses offset the informed traders' costs of information production, allowing for the possibility that a choice to become informed is rational. Thus, any trader forced to engage in a material volume of liquidity-motivated trading in a financial market that is in informational equilibrium will be unable to avoid below-average performance, ceteris paribus.

Consider the performance of an open-end fund manager who occasionally has private information that leads to positive risk-adjusted returns, but who also satisfies investors' liquidity demands. A well-functioning performance measure should identify this manager as being informed. Yet fund flows force the

[1] Jensen (1968), Friend et al. (1970), Lehmann and Modest (1987), Elton et al. (1993), Malkiel (1995), and Carhart (1997) all use a CAPM or multiple-factor benchmark and conclude that the average risk-adjusted net return (α) is on the order of -150 to -300 basis points per year.

[2] See, e.g., Treynor and Mazuy (1966), Kon and Jen (1979), Kon (1983), Chang and Lewellen (1984), Henriksson (1984), Jagannathan and Korajczyk (1986), and Ferson and Schadt (1996).

manager to engage in liquidity-motivated trading. Depending on the timing and relative magnitude of information arrival and investor flows, the fund's average risk-adjusted return could very well be negative even though the manager is informed. Thus, the very act of providing a liquid equity position to investors at low cost, arguably the primary service of an open-end mutual fund, can cause an informed fund manager to have negative abnormal returns.

Performance metrics that do not account for a fund's flow-induced trading activity can yield negatively biased inferences regarding fund managers' ability to identify mispriced securities. In fact, virtually all performance studies to date show only that the net effect of providing liquidity and making discretionary investment decisions is zero. This study disentangles these two components to sharpen inferences about fund managers' information-processing skills and finds a statistically and economically significant relation between a fund's risk-adjusted return and its measured volume of liquidity-motivated trading. A unit of liquidity-motivated trading, defined as an annual rate of trading equal to 100% of fund assets, is associated with an estimated 1.5–2% decline in abnormal returns (depending on the estimation procedure). This calls into question the common finding in previous performance studies that fund managers underperform.

Indeed, when consideration is given to the liquidity service that fund managers provide, the conclusion as to performance changes. Specifically, the unconditional average net abnormal return in the sample of 166 equity funds considered here is -1.63% per year, which is in line with most other studies and is significant at about the 6% level. However, after controlling for the detrimental effects of liquidity-motivated trading, the average conditional net annual abnormal return is -0.20%, less than 0.25 standard errors from zero. The abnormal return at the median fund is positive. Thus, when the costs associated with providing liquidity to investors are controlled for, α performance net of fees and expenses (which average 1.72% per year in this sample) is essentially zero. This implies that fund managers' portfolio-choice decisions add about one and one-half percent per year to the value of the fund, an entirely different picture of the effectiveness of fund managers' portfolio choice decisions than that implied by the unadjusted sample average abnormal return of -1.63%. In particular, fund managers appear to fit the profile of informed traders in a market in Grossman–Stiglitz informational equilibrium, once it is recognized that their liquidity services cause them to also act as uninformed liquidity traders.

Previous findings regarding market-timing performance are equally faulty. Under certain conditions, investor flows will be associated with negative market timing in fund returns. Thus, assessing fund managers' market-timing ability without considering flow can again result in negatively biased inferences. The average fund in the sample considered here exhibits statistically significant negative market timing. However, when a second market-timing regressor – interacted with the fund's realized flow – is included, all of the negative market-timing relation falls on the interactive regressor. That is, funds exhibit negative market timing when and only when they experience flow. Absent flow, the inferred market-timing ability of the fund manager is positive. Again, the conclusion about fund manager performance changes when liquidity services are addressed.

This market-timing result highlights and reinforces the insights in Ferson and Schadt (1996), who argue that, because flow affects the funds' beta at the wrong time (expected returns move with aggregate flow), it is important to have a conditional benchmark that takes into account the induced time-variation in the fund's expected returns. Ferson and Schadt (1996) use a conditional benchmark that is shown in Ferson and Warther (1996) to control for a relation between aggregate fund flows and time varying expected returns. The effect of liquidity-motivated trading is also implicitly addressed by Grinblatt and Titman (1989a,1993) and Grinblatt et al. (1995), who directly examine the performance of a fund's portfolio holdings, rather than the actual portfolio performance (with its imbedded costs associated with liquidity-motivated trading and perhaps other factors). Both sets of studies find relatively favorable evidence for fund managers when compared to standard performance tests. This paper extends their finding by showing the effectiveness of using the fund's realized flow as a conditioning variable.

Costs associated with liquidity-motivated trading are an important premise to a theoretical study of load fees by Chordia (1996). Chordia argues that a load fee can induce a separating equilibrium in which flow-causing investors cluster at no-load funds, and long-term investors willingly invest in a load fund to avoid the costs that flow imposes. This paper complements Chordia's paper by empirically documenting the costs (i.e., negative performance) attributable to flow.

The organization of the paper is as follows. Section 2 develops the preceding arguments more fully. Section 3 outlines the data used in the study. Section 4 analyzes the empirical relation between flow and a fund's trading activity. Section 5 examines the relation between flow and α performance measures, and Section 6 examines the relation between flow and market-timing performance measures. Section 7 concludes the study.

2. The argument

This section briefly outlines the application of the standard rational expectations model of trade to fund performance. The objective is to motivate the empirical analysis and outline the assumptions necessary for flow to have an effect on performance.

2.1. Theoretical background

Consider a fund manager who initially holds some target efficient portfolio. Suppose that the manager experiences a cash flow shock (a random number of redemptions and new sales) and also receives a collection of signals as to certain stocks' value. Suppose that after these events occur there is a single round of trade, and then the payoffs to the stocks are revealed. This simplified setting captures the essence of the two services a fund manager provides yet fits into the standard rational expectations model of trade.

The flow shock that the fund experiences moves the fund away from the target portfolio. Getting back to an efficient portfolio requires trade in some or all stocks. Whether or not this liquidity-motivated trading is warranted depends on the magnitude of the flow shock. Small deviations from an optimal portfolio are perhaps not worth acting upon (e.g., Long et al., 1977). However, if the typical flow shock is large, then choosing not to trade leads to large, random fluctuations in the cash position of the fund. This is undesirable to both investors and the fund manager. On the one hand, investors would like to know what they are getting when they invest so that they can make accurate risk-return choices. On the other hand, fund managers' compensation relates to their ability to track and beat a benchmark portfolio (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998). A high standard deviation in the funds' cash position compromises that objective. Thus, fund managers probably trade to counteract flow shocks, but the extent to which they do so is an empirical issue.

This liquidity component of the fund managers' trading plays the role of the exogenous supply-noise trading in standard rational expectations models of trade. Since 'noise' traders face expected losses, an open-end fund manager should experience negative return performance in proportion to the realized volume of flow. The theoretical models outlining this effect (e.g., Grossman and Stiglitz, 1980; Hellwig, 1980; Verrecchia, 1982) all employ a simplified setting with a single risky security. In practice, the setting of mutual fund performance evaluation is one of many risky securities with correlated returns. Performance can then be defined with respect to the systematic component of returns (market-timing performance) or with respect to the idiosyncratic component of returns (α performance). The intuition of the single-risky-security model provides insight into the effects of flow on either performance measure.

2.2. α performance

Consider an α performance metric. When the fund manager allocates a portion of the cash flow shock's liquidation to stock i, the single-risky-security model predicts a loss (on average) in proportion to the volume of flow allocated to that trade. To the extent that the flow shock is uncorrelated with the market return at the time of trade, that loss is idiosyncratic in nature. The total effect of the liquidation of the cash flow shock is then just the sum of the individual effects, with a collection of uninformed trades each making a marginal negative contribution to the fund's α. In aggregate, the fund's α is reduced by an amount proportional to the liquidity-motivated trading of the fund. For such an effect to occur, the volume of liquidity-motivated trading must be material and such trading must materially distort the prices of the stocks traded.

The empirical analysis of a liquidity-trading effect on α performance is straightforward. A fund's α should be composed of two terms, a positive term relating to the fund manager's information trading and a negative term proportional to the fund's realized flow. The empirical analysis is therefore framed around a regression of abnormal returns on the corresponding fund's realized flow. This regression identifies an adverse performance effect from liquidity-motivated trading by documenting a negative coefficient on flow. The fund manager's information-trading skill is then measured as the average abnormal return after controlling for this relation to flow.

Out-of-pocket costs such as brokerage commissions and other operational costs of trading are almost certainly material in comparison to the asymmetric information costs outlined above. These additional costs associated with liquidity-motivated trading can only exaggerate the negative α performance associated with liquidity-motivated trading. Thus, a more complete test, using fund returns net of fees, expenses, and brokerage commissions, should indicate stronger effects than a test using gross returns.

Using data on the funds' trading activity, there is an alternate test of fund managers' information-trading skill that does not require an explicit control for the effects of flow. In the standard model of informed trade, the position acquired in an information-motivated trade is proportional to the precision of that information. The same holds true for the subsequent abnormal return on that position (e.g., Admati and Pfliederer, 1990; or Verrecchia, 1982). Thus, a more informed manager (higher average signal precision) engages in a greater volume of information-motivated trading and obtains a more positive α. Under the premise that the discretionary trading at the fund (the total trading less that attributable to flow) represents rational information-motivated trading, the volume of discretionary trading is positively correlated with the fund's α. One can therefore test the degree to which managers are informed by examining this correlation.

The issue of gross versus net returns is also relevant to the analysis of discretionary trading. The predicted positive relation between abnormal returns and the volume of discretionary trading arises in the absence of out-of-pocket costs associated with information production or trading. However, in an equilibrium with costly information production, the portfolio gains associated with information-motivated trading should be partially (or fully) offset by the costs of information acquisition (Grossman and Stiglitz, 1980; Verrecchia, 1982). Hence the relation between discretionary trading and abnormal returns should be more easily detected using gross returns than using net returns. A positive relation with net returns is predicted only if fund managers pass on to investors the gains associated with superior information production.

2.3. Market-timing performance

Under certain conditions, the single-risky-security model also predicts a market-timing performance effect. Recall the standard simplified setting of this model. There are two relevant time intervals: the time between the flow and signal realizations and trade, and the time between trade and the payoff to the risky security. The return over the first interval is affected by aggregate liquidity-motivated trading and by aggregate information as to the final payoff, as these two factors determine the equilibrium price at the time of trade. Consider a market basket of all stocks as the single risky security. Flow induces a negative market-timing effect if it is positively correlated either with the aggregate liquidity-motivated trading in the market or with the aggregate information regarding the final payoff on the market in the subsequent round of trading. If the fund manager regains a fully invested position at the time of trade, then the fund experiences zero market timing in the second time interval.

Warther (1995) demonstrates a strong positive correlation between aggregate fund flow and market returns at a monthly frequency. The correlation potentially arises because aggregate flow is correlated with the aggregate liquidity-motivated demands in the market in the subsequent round of trading (i.e., the next opportunity to invest or disinvest that flow shock). If aggregate liquidity-motivated demands affect the market price, then aggregate fund flow is positively correlated with subsequent market returns, leading to a positive concurrent monthly correlation. Since a fund manager who realizes a flow shock cannot regain a fully invested position until *after* trading, flow induces negative market timing in the first period.

However, Warther also points out that the correlation between aggregate flow and monthly market returns can arise because high-frequency (e.g., daily) returns are correlated with subsequent high-frequency flow. In that case, flow might not be correlated with subsequent aggregate liquidity-motivated demands, or those demands might have no effect on the market price. Nevertheless, a market-timing effect could still arise. Market returns exhibit positive one-day autocorrelation due to factors like nonsynchronous trading. For example, the one-lag autocorrelation of the return on the Center for Research in Security Prices (CRSP) value-weighted index over the sample period for this study is $+0.11$ with a t-statistic over 4.0). If flow is positively correlated with same-day and/or previous-day returns, then flow is potentially positively correlated with subsequent market returns, giving rise to negative market timing.

Evidence in this regard is presented in a working paper by Edelen and Warner (1998), who demonstrate a very strong correlation between flow on day t and returns on day t and $t-1$, but essentially no correlation at any other lags. There is no significant correlation between the return on day t and flow on preceding days. Given this evidence, negative market timing resulting from flow is conceivable for either of the two aforementioned reasons.

3. Data

Data on mutual funds' flow and trading activity are taken from semiannual filings of the N-SAR report at the Securities and Exchange Commission. The N-SAR reports the total inflow and total outflow from investors each month (item 28) and the total security trading (both purchases and sales) over six-month intervals (item 71). Because of the limitation of the trading data, the basic interval length in the analysis of liquidity-motivated trading (Section 4) is six months.

The advantage of these data is the fact that both sides of flow (inflow and outflow) and trading (purchases and sales) are present. This makes for a more complete analysis of liquidity-motivated trading and its effect on performance. One disadvantage is the fact that these data are hand-collected from microfiche, and thus subject to processing error. Furthermore, idiosyncratic events such as mergers or asset transfers within fund families can lead to extreme measured flow when in fact no cash flow occurs. For these reasons, the largest 2% of observations (values that are over ten times the mean) and the smallest 2% of observations (for symmetry) are removed from the sample.[3]

Return data for most of the sample are taken from the Morningstar, Inc. CD-ROM. The remainder is hand-collected from concurrent issues of *Barron's*.

3.1. The sample

The sample consists of 166 open-end mutual funds selected randomly from the Summer 1987 edition of Morningstar's Sourcebook; each fund has an

[3] The general approach of a truncated regression to curb the influence of outliers is discussed in detail in Chan and Lakonishok (1992), who show that such a procedure makes for more robust beta estimation, as well as in Kothari and Zimmerman (1995), who argue that such a procedure improves estimates of the relation between prices and earnings. As in these papers, the strength of the relation is diminished when outliers are kept in the sample.

investment emphasis at least partly on equity securities. On average, the sample contains about five years of data for each fund, with most of the data coming from the years 1985 through 1990. The sample consists of a range of management styles: approximately 21% are small-capitalization or aggressive-growth funds, 37% are growth funds, 24% are growth and income funds, and 18% are income, balanced, or mixed funds (classification by Morningstar).

When a sample of mutual funds is selected from a rating agency publication such as Morningstar's Sourcebook, survival bias is potentially a concern (e.g., Brown et al., 1992). However, survival bias is not likely to affect the results in this paper for several reasons. First, over 70% of the return data used in this study come from periods subsequent to the fund-selection date and are hand-collected where necessary. Since subsequent returns cannot affect sample selection, there is no bias in these returns. Second, even if a survival bias exists in the sample, it does not necessarily affect the central test in this paper, as that test relates the cross-section of funds' abnormal returns to the cross-section of flow volume. The focus is not on the level of α per se. Survival bias is a concern only if higher flow volume is associated with less survival bias. The opposite is more likely: Brown et al. (1992) show that the extent of positive survival bias is proportional to the return volatility of the funds. Since extreme positive (negative) abnormal returns are typically associated with extreme net inflow (e.g., Ippolito, 1992), volatile returns should be associated with high flow volume. Thus, to the extent that there is a positive survival bias in the sample, it is probably greatest at funds with high flow volume, biasing against our prediction of a negative effect.

Table 1 provides descriptive characteristics of the sample of funds. Unless otherwise noted, figures in this and all subsequent tables are scaled by the average fund size over the six-month N-SAR reporting period (item 71C) and presented in annual terms. The sample is representative of the mutual fund universe in terms of size, fees, and returns (see, for example, Morningstar's Sourcebook), and exhibits substantial cross-sectional variation on all descriptive dimensions. Note that the -1.63% average annual net abnormal return, calculated from a single-factor market model using the CRSP value-weighted index, is negative and significant with a *t*-statistic equal to -1.87 (the *t*-statistic is calculated from a time-series regression of the equal-weighted portfolio of all funds). This indicates *prima facie* poor performance. When expenses are added back, the average fund's return is very close to zero, indicating *prima facie* that fund managers do little besides collect fees.

3.2. Flow

Table 2 shows that the average open-end fund experiences a significant volume of both inflow and outflow over the course of a year. Approximately one-half (one-third) of the average (median) fund's assets are redeemed in the

Table 1
Characteristics of the sample of 166 open-end funds

The data are taken from each fund's N-SAR filing with the Securities and Exchange Commission. The beginning and ending dates of the sample vary across funds, with a mean beginning date of May 1985 and a mean ending date of July 1989. The market model regressions use the CRSP value-weighted index. The indicated variable is first averaged across alll observations for a particular fund. Statistics are then presented on these 166 mean values. Total expenses exclude brokerage commissions. Brokerage commissions represent the total payment and the brokerage commission rate represents brokerage commissions divided by the volume of trading.

	Mean	Std. deviation	Median	Time-series std. deviation
First year of operations	1967	16yrs.	1969	
Assets managed ($millions)	273	433	98	28.2%
Number of monthly obs.	54	12	54	
Total expenses	1.72%	1.60%	1.41%	0.55%
Brokerage commissions	0.44%	0.47	0.32	
Brokerage commission rate	0.21%	0.15	0.17	
Market-model intercept	− 1.63%	4.50%	− 0.68%	3.00%
Market-model beta	0.90	0.24	0.92	

course of a year, and over two-thirds (38%) of the average (median) fund's assets arrived as new inflow in the previous year. In the average (median) one-year period, 33% (22%) of the dollars invested in the fund enter and leave within the year. Thus, the typical fund experiences a material volume of both inflow and outflow. Further, there is substantial time-series volatility in that the time-series standard deviation of the annual rate of net inflow is 70%. Note also that there is substantial variation across funds in the average rate of net inflow (the standard deviation across funds is 48%). Both inflow and outflow are autocorrelated, with inflow being the more persistent process (monthly autocorrelation = 0.71 versus 0.47, respectively). There is a market-wide component to flow, but most of the time-series variation in flow is idiosyncratic in nature (the average correlation between an individual-fund's flow volume and aggregate flows is about 35%).

3.3. Trading activity

The average annual volume of security purchases and security sales are both over 100% of assets managed (Table 2). The average annualized rate of turnover (calculated as twice the minimum of purchases or sales over a six-month period) is 90% of fund assets. These figures are consistent with population averages (see Morningstar's Sourcebook). In spite of this high volume of trading activity, the

Table 2
Characteristics of flow and trading activity

All variables are scaled by the average assets managed over the six-month N-SAR filing period. Flow is observed monthly and annualized (multiplied by 12). Trading activity is observed every six months and annualized (multiplied by two). Cash (or trading) turnover is the minimum of the inflow (purchases) over the six-month filing period and the outflow (sales) over that period, annualized (multiplied by two). Net flow is the month's inflow minus outflow, annualized (multiplied by 12). Net purchases are determined at each six-month observation, then annualized (multiplied by two).

Panel A. Sample statistics

The indicated variable is first averaged across all observations for a particular fund. Statistics are then presented on these mean values. Ratios are at the individual fund six-month level, then averaged.

	Mean	Std. deviation	Median	Time-series std. deviation
Flow				
Inflow	65%	72%	38%	67%
Outflow	48	51	34	35
Cash turnover	33	43	22	25
Net inflow	16	48	01	70
Trading activity				
Purchases	113	78	89	54
Sales	103	75	82	42
Turnover	90	65	73	38
Net purchases	10	35	01	46
Ratios				
Inflow/Purchases	61	46	47	
Outflow/Sales	66	53	52	
Turnover: cash/trading	62	57	40	

Panel B. Autocorrelations

Observations are monthly for flow and semiannual for trading activity. The panel presents the coefficient estimate from an AR(1) model.

Flow		*Trading*	
Inflow	0.71	Purchases	0.21
Outflow	0.47	Sales	0.15
Cash turnover	0.67	Turnover	0.17
Net inflow	0.49	Net purchases	0.13

Panel C. Marketwide components

The panel presents the average regression statistics across funds. Per-fund inflow (outflow) is regressed on concurrent aggregate inflow (outflow) (source of aggregate data: Investment Company Institute).

	Coefficient	R^2
Inflow	0.54	0.12
Outflow	0.53	0.13

flow/trading activity ratios indicate that a material fraction of overall trading activity is plausibly motivated by a need for liquidity. An observation-by-observation calculation of the ratio of flow volume to trading activity shows that flow volume is equal to about half of the respective trading volume at the median fund.

The data show that the volume of flow at the typical open-end fund is quite material, whether flow is scaled by fund assets or by trading activity. This suggests that there is indeed a lot of liquidity-motivated trading at the typical open-end fund, and that an adjustment in the performance metric to account for realized flow is likely to be an important consideration in an unbiased assessment of performance.

4. The empirical relation between flow and trading activity

The adverse effect of flow on α performance depends on the degree to which flow is associated with a marginal increase in trading activity. In and of itself, flow should not affect idiosyncratic returns. This section analyzes the empirical relation between flow and trading activity with two objectives: to investigate the efficacy of flow as a proxy for liquidity-motivated trading and to estimate the volume and relevance of mutual funds' liquidity-motivated trading in aggregate. Both objectives are addressed with a regression analysis of trading activity on flow. The best specification of that regression is a matter worth discussing.

4.1. Empirical specification

Most fund managers probably employ some form of cash accumulation policy in responding to flow, in which case flow shocks that reverse themselves within the implicit accumulation period do not lead to trading. Thus, liquidity-motivated trading relates to the net cash inflow over some undefined accumulation period. If that accumulation period is short, then the overall volume of purchase (sales) activity will approach the total inflow (outflow). Conversely, if the accumulation period is long, then a material fraction of the inflow occurring within the period will be offset by concurrent outflow. In that case, the overall volume of liquidity-motivated purchases (sales) will be only a fraction of total inflow (outflow). Thus, the actual correspondence between flow and trading activity is an empirical question, as it depends on the unobservable accumulation period. A regression analysis using gross flow and trading activity provides a natural calibration of the correspondence between flow and liquidity-motivated trading: the regression coefficient will adapt to the actual accumulation period and the resulting liquidity-motivated trading/flow ratio that obtains, whatever that might be.

An alternative approach would be to use a regression analysis of net flow/net trading activity, which seemingly corresponds more closely to the intuition that it is net flow (over some accumulation period) that leads to liquidity-motivated trading. In spite of this intuition, this approach yields a useful model of liquidity-motivated trading under the premise that the typical mutual fund's cash accumulation period is on the order of six months, as that is the minimum observation length of trading in the data. This premise seems unlikely given the volatility of monthly net cash flows observed in the sample. For example, Table 2 shows that if the cash accumulation period were on the order of six months the fund's cash balance would fluctuate randomly with a standard deviation equal to 24% of assets managed every six months. Further, under this premise, there would be little association between six-month trading turnover and flow turnover. As will be seen below, the regression evidence shows a strong association. Thus, the regression analysis using net flow probably leads to a less accurate proxy than the gross flow approach.

Further, a gross flow analysis allows a separate regression for both inflow and outflow, thus using twice the data and controlling for omitted factors that can cause a different flow-trading response coefficient for inflow versus outflow. I estimate

$$\tilde{\tau}^{\mathrm{P}}_{jt} = a^{\mathrm{I}} + c^{\mathrm{I}}\tilde{f}^{\mathrm{I}}_{jt} + \tilde{\varepsilon}^{\mathrm{P}}_{jt}, \tag{1a}$$

$$\tilde{\tau}^{\mathrm{S}}_{jt} = a^{\mathrm{O}} + c^{\mathrm{O}}\tilde{f}^{\mathrm{O}}_{jt} + \tilde{\varepsilon}^{\mathrm{S}}_{jt}, \tag{1b}$$

where $\tilde{\tau}^{\mathrm{P}}_{jt}$ ($\tilde{\tau}^{\mathrm{S}}_{jt}$) denotes fund j's purchases (sales) volume during data interval t and $\tilde{f}^{\mathrm{I}}_{jt}$ ($\tilde{f}^{\mathrm{O}}_{jt}$) denotes fund j's inflow (outflow) during data interval t. Using these regressions, I construct a proxy for liquidity-motivated trading as $\hat{f}_{jt} = \hat{c}^{\mathrm{I}}\tilde{f}^{\mathrm{I}}_{jt} + \hat{c}^{\mathrm{O}}\tilde{f}^{\mathrm{O}}_{jt}$. The flow-trade response coefficient estimates $\hat{c}^{\mathrm{I}}$ and $\hat{c}^{\mathrm{O}}$ are expected to be less than one to the extent that inflow crosses with outflow within a cash accumulation period or the fund manager simply does not respond to the change in cash position. (Coefficient estimates less than one are also consistent with flow shocks being partially incorporated into information-motivated trading and thus not triggering marginal trading activity.)

4.2. *Regression results: Trading activity on flow*

Eqs. (1a) and (1b) can be estimated using either time-series or cross-sectional regressions. With a time-series approach the estimates of the flow-trade response coefficients are allowed to differ across funds, but the individual fund time-series estimates are very noisy. (The time-series regressions have on average just 7.9 degrees of freedom – recall that the shortest observation length available for trade data is six months.) With a cross-sectional approach, only the average flow-trade response coefficient is estimated but the regressions have many more degrees of freedom and yield a much more precise estimate of the average response coefficient. Estimates from both procedures are provided.

4.2.1. Time-series regressions

Panel A of Table 3 provides the time-series regression estimates. In addition to the purchases and sales regressions outlined in Eqs. (1a) and (1b), a turnover-on-turnover and net-on-net specification is presented. The regressions suggest that for every dollar of inflow (outflow), approximately \$0.63 (\$0.76) goes to a marginal increase in security transaction volume. Note that there is no statistically meaningful difference in these two estimates. Assuming $\hat{c}^{\mathrm{I}} = \hat{c}^{\mathrm{O}}$, liquidity-trade proxy implied from these regressions is 0.70* $(f^{\mathrm{I}}_{jt} + f^{\mathrm{O}}_{jt})$.

Approximately 30% of all flow never shows up as incremental trading activity – it either crosses with flow of the opposite sign, or is incorporated into discretionary trades that would have occurred anyhow. Further evidence on the use of a cash accumulation period is provided with the net-on-net regressions. On average, only 75% of the net cash inflow in a six-month period ends up as contemporaneous net purchases. The remaining net inflow must be carried across six-month periods. This confirms the intuition that, to some degree, a cash inventory policy is relevant. The cash accumulation period is, however, much less than six months. This is indicated by the turnover-on-turnover regression. Even though cash turnover refers to redemptions that cancel new sales within a six-month period, there is an increase in security turnover equal to 75% of the flow turnover. Clearly, the typical delay in responding to cash flow shocks is much less than six months.

The estimated average volume of liquidity-motivated purchases (sales), calculated as the regression coefficient times the average of the corresponding flow measure at that fund, is 24% (28%) of assets managed per year. Alternatively, approximately 28% of total trading activity can be characterized as liquidity-motivated. Note also that cash turnover (cash that comes and goes within six months) induces annual security turnover of approximately 15% of assets managed. Thus, flow-induced trading is not simply a phenomenon of net growth or decline in assets managed. It is material at funds of relatively stable size as well. The time-series evidence therefore suggests that a material volume of liquidity-motivated trading occurs at the average mutual fund, and that liquidity-motivated trading makes up a material fraction of the fund's overall trading activity.

4.2.2. Cross-sectional regressions

Panel B of Table 3 presents the cross-sectional regression estimates. The coefficient estimates are 67% and 68% for inflow and outflow respectively, matching the time-series estimates. These estimates are significantly less than one, confirming the hypothesis that a cash inventory is relevant. The results for turnover and net flow also confirm the time-series estimates, although the

Table 3
Regressions of trading activity on flow

Four groups of regressions are presented, corresponding to (1) purchases τ^{P} on inflow f^{I} (2) sales τ^{S} on outflow f^{O} (3) trading turnover τ^{T} on cash turnover f^{T} (4) and net purchases τ^{N} on net inflow f^{N}. The observation length is six months. All variables are scaled by the average fund size over the six-month N-SAR filing period and annualized. The estimated volume of liquidity-motivated trading at the fund is calculated as the regression coefficient times the average of the corresponding flow measure at that fund, scaled by either the fund's average size or average trading volume.

Panel A presents the mean of the indicated statistic averaged over a separate regression for each of 128 funds for which at least eight time-series observations are available (the mean regression degrees of funds for which at least eight time-series observations are available (the mean regression degrees of freedom is 7.9). Standard error estimates are the sample standard errors (across funds) of the relevant statistic. Panel B presents the mean of the indicated statistic averaged over a separate regression for each of 12 semi-annual periods (the mean regression degrees of freedom is 122). Standard error estimates are the sample standard errors (across dates) of the relevant statistic. Standard errors are in parentheses.

	Intercept	Coefficient	R^2	Adjusted R^2	Estimated liquidity-motivated trading volume, scaled by	
					Fund size (%)	Trad. volume (%)
Panel A. Time-series regressions						
τ^{P} on f^{I}	0.84	0.63	0.31	0.22	24	29
	(0.08)	(0.15)	(3.0)	(3.0)	(0.04)	(0.04)
τ^{S} on f^{O}	0.71	0.76	0.22	0.11	28	27
	(0.06)	(0.17)	(2.0)	(2.0)	(0.06)	(0.05)
τ^{T} on f^{T}	0.73	0.74	0.18	0.07	15	18
	(0.06)	(0.22)	(2.0)	(2.0)	(0.04)	(0.04)
τ^{N} on f^{N}	0.02	0.75	0.48	0.42		
	(0.10)	(0.06)	(3.0)	(3.0)		
Panel B. Cross-sectional regressions						
τ^{P} on f^{I}	0.81	0.67	0.30	0.29	36	33
	(0.04)	(0.04)	(3.0)	(4.0)	(0.04)	(0.04)
τ^{S} on f^{O}	0.74	0.68	0.16	0.14	30	30
	(0.07)	(0.08)	(2.0)	(3.0)	(0.04)	(0.03)
τ^{T} on f^{T}	0.77	0.55	0.13	0.10	18	21
	(0.06)	(0.07)	(2.0)	(3.0)	(0.03)	(0.03)
τ^{N} on f^{N}	0.75	0.75	0.55	0.55		
	(0.10)	(0.10)	(3.0)	(4.0)		

turnover coefficient estimate (0.55) is somewhat less than the corresponding time-series estimate. Lastly, the estimated overall volume of liquidity-motivated trading from the cross-sectional regressions is generally higher than the corresponding estimates found in the time-series regressions, but the differences are within one standard error. The inferences from cross-sectional regressions are therefore similar to those of the time-series regressions.

5. α measures of performance

Before analyzing the relation between trading activity and α performance, several implementation and specification issues must be addressed. The first issue is reverse causality. This paper argues that flow adversely affects a fund's measured α performance because the position acquired in a liquidity-motivated trade has a negative impact on the fund's abnormal return. Testing this assertion is problematic given the ample empirical evidence demonstrating that fund's abnormal returns affect flow.[4] This reverse causality potentially obscures the relation being tested.

Section 2 argues that a fund's α can be decomposed into two terms: a positive component due to information-motivated trading and a negative component due to liquidity-motivated trading. This suggests a regression of the form

$$AR_{jt} = \lambda \hat{f}_{jt} + \delta \hat{d}_{jt} + \tilde{e}_{jt}, \tag{2}$$

where AR_{jt} is the abnormal return, $\hat{f}_{jt} = \hat{c}(\tilde{f}^{\mathrm{I}}_{jt} + \tilde{f}^{\mathrm{O}}_{jt})$ is the estimated liquidity-motivated trading, and $\hat{d}_{jt} = \tilde{\tau}^{\mathrm{P}}_{jt} + \tilde{\tau}^{\mathrm{S}}_{jt} - \hat{f}_{jt}$ is the estimated information-motivated (discretionary) trading. Given the results in Section 4, I assign a value of 0.70 to $\hat{c}$.

Persistence in mutual fund abnormal returns implies that lagged abnormal returns constitute an omitted regressor to Eq. (2).[5] Were lagged abnormal returns included, their coefficients would presumably be positive. Since they are not included, there is a positive bias on any included regressor that covaries with lagged abnormal returns. While, as noted earlier, a positive relation between net flow and lagged abnormal returns has been documented elsewhere, a positive correlation between gross flows (the proxy used in this paper) and lagged abnormal returns does not necessarily follow.

[4] See, e.g., Friend et al. (1970), Smith (1978), Ippolito (1992), Sirri and Tufano (1998), and Chevalier and Ellison (1997).

[5] Grinblatt and Titman (1992), Grinblatt et al. (1995), Hendricks et al. (1993), Brown and Goetzmann (1994), Malkiel (1995), Elton et al. (1996), Gruber (1996), and Carhart (1997) all demonstrate persistence in mutual fund returns.

Table 4 shows that both inflows and outflows are positively related to lagged abnormal returns (outflows insignificantly so). Thus, gross flow at time t is positively related to lagged abnormal returns. Given the known persistence in fund returns, this implies that $E(\hat{f}_{jt}, \tilde{\varepsilon}_{jt}) > 0$, in which case Eq. (2) yields a biased estimate of λ.

Much of this bias can be removed by simply adding lagged abnormal return regressors to Eq. (2). However, it is likely that some bias remains no matter how many lags are included. Since observations are monthly, lagged abnormal return regressors cannot control for a 'contemporaneous' positive covariance between AR_{jt} and $\hat{f}_{jt}$ wherein the fund's return in the early part of the month affects the fund's flow in the latter part of the month. Edelen and Warner (1998) document that aggregate flow responds to past market returns quite strongly in a matter of days. Thus, an intramonth reverse causality, introducing a positive bias in the λ estimate even with all relevant lagged abnormal return controls included, is almost surely a factor in estimating Eq. (2).

This intramonth reverse-causality bias can be addressed by exploiting the autocorrelation in flow (see Table 2) and using $\hat{f}_{jt-1} = \hat{c}(f^{\mathrm{I}}_{jt-1} + f^{\mathrm{O}}_{jt-1})$ as an instrument. Provided that lagged flow is uncorrelated with the innovation to the time-series of abnormal returns (that is, gross flow does not anticipate the nonpersistent component of abnormal returns), this instrument, coupled with the lagged abnormal return controls, provides an unbiased estimate of λ.

Gruber's (1996) analysis is particularly relevant here. Gruber argues that 'smart money' chases past mutual fund returns knowing that returns persist, and he shows that there is indeed a component to net inflow that is positively correlated with subsequent abnormal returns. If the source of Gruber's findings is smart money chasing the persistent component of returns, then reverse causality is indeed a source of bias in this study. The relevant lag length in the abnormal return controls suggested by Gruber's study is 12 months or more. However, including more lags in Eq. (2) constricts the usable data. To reflect this tradeoff I present an analysis with six and twelve monthly lags of abnormal returns.

Another potential problem has to do with cross correlation. Risk-adjusted mutual fund returns are likely to have cross-correlated errors owing to, for example, industry effects. This cross-correlation biases the standard errors of the coefficient estimates from the instrumental-variable estimation of Eq. (2). Further, the estimation uses generated regressors (since the instruments for liquidity-motivated trading and information-motivated trading both depend on the estimated coefficient $\hat{c}$ in the flow-on-trade regressions), which also biases the coefficient standard error. To address these issues, a variation on the procedure developed in Fama and Macbeth (1973) is employed. The λ and δ coefficients are estimated in a cross-sectional regression at each date, and then

Table 4
Flow regressed on 12 lags of abnormal returns

A cross-sectional regression is run each month for which sufficient data are available (66 months). Two sets of regressions are presented, with a dependent variable equal to the individual fund monthly cash inflow and outflow scaled by the average assets managed over the corresponding six-month N-SAR filing period. The regressors are the fund's abnormal return for month $t-1$ through $t-12$ from a time series regression of fund returns on the CRSP value-weighted index. All variable are annualized. The table presents the average of the coefficient estimates across the 66 regressions (t-statistics in parentheses).

AR:	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$	$t-9$	$t-10$	$t-11$	$t-12$
Inflow	0.25	0.25	0.25	0.16	0.25	0.15	0.17	0.12	0.15	0.04	0.15	0.21
	(3.0)	(2.8)	(3.0)	(2.2)	(3.4)	(2.0)	(2.5)	(1.6)	(2.1)	(0.5)	(2.3)	(3.0)
Outflow	0.01	0.08	0.08	0.01	−0.01	0.01	0.00	−0.01	0.00	0.01	0.02	0.14
	(0.2)	(1.1)	(1.1)	(0.1)	(−0.1)	(−0.1)	(0.0)	(0.1)	(0.0)	(0.1)	(0.4)	(2.3)

sample statistics (mean and standard error) are calculated from the time-series of coefficient estimates.[6]

The lagged-flow instrument for $\hat{f}_{jt}$ is constructed by first separately estimating

$$\hat{f}_{jt} = a_t + b_t \hat{f}_{jt-1} + \tilde{e}_{jt} \tag{3}$$

by month (recall that $\hat{f}_{jt}$ is the realized flow volume times the estimated flow-trading response coefficient in Table 3). The instrument for $\hat{f}_{jt}$ is $\hat{b}\hat{f}_{jt-1}$ where $\hat{b}$ denotes the average $\hat{b}_t$ estimate across 66 months.

5.1. The abnormal return effects of providing liquidity

Liquidity-motivated trading should be associated with negative abnormal returns whether the trade is a sale or a purchase. The strongest signal of a liquidity-trading effect should be seen when sales and purchases are combined, as in Table 5. However, Table 6 examines the two components of trading separately. Table 6 also includes an analysis using the absolute value of net inflow as the measure of flow. While this is not likely to provide as precise a measure of liquidity-motivated trading as gross flow, as argued in Section 4.1, it is included for completeness. In Table 5, regressions are presented with four abnormal return measures, based on net fund returns and a variety of gross returns formed by adding back the fund's expenses and brokerage commissions. Abnormal returns, flow, and trading activity are all presented in annualized terms. The observation length is monthly. While returns and flow are observed monthly, trading activity is observed every six months. The annualized figure over that six-month period is used for each of the six corresponding monthly observations.

In Table 5 the estimated coefficient on liquidity-motivated trading using net abnormal returns indicates that a dollar of liquidity-motivated trading is associated with a statistically significant \$0.017 (\$0.022) decline in fund assets with six (12) lags of abnormal returns. The estimated cost of providing liquidity declines as out-of-pocket costs are added back to net abnormal returns, suggesting that the cost is partly attributable to an increase in brokerage commissions or the costs of administering the fund. In particular, both expenses and brokerage commissions seem to contribute about 30 basis points each to the liquidity-trading effect. The coefficient on liquidity-motivated trading retains marginal significance using most measures of gross abnormal returns and six lags of abnormal returns, but is quite significant using 12 lags of abnormal returns. This

[6] Serial correlation could be induced in these parameter estimates from the fact that trading data are only available at a six-month frequency, whereas the cross-sectional regressions are monthly. To correct for any bias this might induce, an MA[5] time-series model is fit to the time series of parameter estimates. The correction has no effect on the estimated standard errors.

Table 5

Abnormal return regressed on flow and discretionary trading

The following cross-sectional regression is estimated for each of the 66 months in the sample:

$$AR_{jt} = a + \lambda(\hat{F}_{jt}) + \delta\hat{d}_{jt} + \sum_{c=1}^{K} \eta_c AR_{jt-c} + e_{jt},$$

where

- $\hat{F}_{jt}$ is the proxy for liquidity-motivated trading equal to $\hat{f}_{jt-1}\sum_{t=1}^{66}\hat{b}_t$, where $\hat{b}_t$ is the estimated coefficient in a cross-sectional regression of flow ($\hat{f}_{jt} = \hat{c}(f^{\mathrm{I}}_{jt} + f^{\mathrm{O}}_{jt})$) on lagged flow, $\hat{c}$ is the average flow-trading response coefficient from Table 3, and $f^{\mathrm{I}}_{jt}(f^{\mathrm{O}}_{jt})$ is the gross inflow (outflow).
- $\hat{d}_{jt}$ is the estimated discretionary trading, equal to the total trading (fund j, period t) less $\hat{F}_{jt}$.
- AR_{jt} is the abnormal return of the fund. Four measures of abnormal returns are considered, corresponding to *net* (fund returns net of all expenses except sales charges); *net + expenses* (net plus adding back the reported total expenses charged to the fund); *net + brok*Volume* (net plus the brokerage commission rate times the trading volume of the fund); and *net + expense*Volume*.
- The abnormal return is calculated from a regression of the indicated return measure on the CRSP value-weighted index (Panel A) or on the index excess return and its square (Panel B).

The table presents the average (t-statistic) of the coefficient estimates across the 66 cross-sectional regressions. The intercept and coefficient estimates on the lagged-abnormal return control variables are not presented. (The intercept is always insignificant. The average coefficient is 0.02 and they are individually significant out to nine lags.) Results are presented with $K = 6$ and $K = 12$ (t-statistics in parentheses).

	Six lags of abnormal returns		Twelve lags of abnormal returns	
	λ	δ	λ	δ
Panel A. Abnormal returns from a univariate market model				
Net	− 1.74	− 0.18	− 2.23	− 0.16
	(− 2.4)	(− 0.9)	(− 3.1)	(− 0.8)
+ expenses	− 1.37	0.11	− 1.77	0.07
	(− 1.9)	(0.5)	(− 2.4)	(0.4)
*+ brok*Volume*	− 1.43	0.03	− 1.92	0.10
	(− 2.2)	(0.1)	(− 2.7)	(0.5)
+ expenses	− 1.11	0.26	− 1.27	0.30
*+ brok*Volume*	(− 1.5)	(1.2)	(− 1.8)	(1.4)
Panel B. Abnormal returns from a quadratic market model				
Net	− 1.90	− 0.16	− 2.11	− 0.13
	(− 2.7)	(− 0.8)	(− 2.9)	(− 0.7)
+ expenses	− 1.37	0.11	− 1.40	0.08
	(− 2.1)	(0.6)	(− 2.1)	(0.4)
*+ brok*Volume*	− 1.55	0.04	− 1.54	0.07
	(− 2.1)	(0.2)	(− 2.4)	(0.3)
+ expenses	− 1.01	0.27	− 0.95	0.27
*+ brok*Volume*	(− 1.3)	(1.4)	(− 1.5)	(1.4)

Table 6
Abnormal return regressed on separate components of flow and discretionary trading

This table is similar to Table 5, Panel A (abnormal returns from a univariate market model) except that the regressions use a different measure of flow and discretionary trading. Gross inflow is used in Panel A ($\hat{f}_{jt} = \hat{c}f^{\mathrm{I}}_{jt}$), gross outflow is used in Panel B ($\hat{f}_{jt} = f^{\mathrm{O}}_{jt}$), and net inflow is used in Panel C. Discretionary trading is purchases, sales, and net trading, respectively, less the corresponding flow measure. (t-statistics in parentheses).

	Six lags of abnormal returns		Twelve lags of abnormal returns	
	λ	δ	λ	δ
Panel A. Inflow				
Net	− 3.10	− 0.18	− 3.67	− 0.11
	(− 2.5)	(− 0.5)	(− 3.1)	(− 0.3)
+ *expenses*	− 2.22	0.44	− 2.67	0.43
	(− 1.9)	(1.0)	(− 2.5)	(1.1)
+ *brok∗Volume*	− 2.77	0.26	− 2.84	0.40
	(− 2.2)	(0.6)	(− 2.8)	(1.0)
+ *expenses*	− 1.55	0.73	− 1.73	0.83
+ *brok∗Volume*	(− 1.3)	(1.8)	(− 1.66)	(2.0)
Panel B. Outflow				
Net	− 2.15	− 0.76	− 3.60	− 0.64
	(− 0.9)	(− 1.7)	(− 1.8)	(− 1.5)
+ *expenses*	− 1.00	− 0.20	− 2.99	− 0.25
	(− 1.0)	(− 0.5)	(− 1.5)	(− 0.6)
+ *brok∗Volume*	− 2.29	− 0.42	− 3.17	− 0.3
	(− 1.0)	(− 0.8)	(− 1.6)	(− 0.7)
+ *expenses*	− 1.69	0.03	− 2.21	0.11
+ *brok*Volume*	(− 0.7)	(0.1)	(− 1.1)	(0.2)
Panel C. Net flow				
Net	− 2.29	− 0.15	− 3.57	− 0.10
	(− 1.2)	(− 0.8)	(− 1.9)	(− 0.5)
+ *expenses*	− 1.80	0.17	− 3.25	0.13
	(− 0.9)	(0.9)	(− 1.6)	(0.7)
+ *brok∗Volume*	− 2.96	0.11	− 4.22	0.12
	(− 1.4)	(0.5)	(− 2.1)	(0.6)
+ *expenses*	− 1.17	0.32	− 2.52	0.32
+ *brok∗Volume*	(− 0.6)	(1.6)	(− 1.3)	(1.6)

suggests that out-of-pocket costs are relevant, but that the adverse-selection cost is probably the most important source of poor performance.

Jensen (1972) points out that the α performance measure can be biased for a fund that engages in market-timing activity as well. This is further analyzed in Grinblatt and Titman (1989b). Given the relation between flow and market-timing performance outlined in Section 2 (and investigated later), the relation documented in Panel A of Table 5 could reflect a market-timing bias in α. Panel B presents the analysis using abnormal returns from a regression of fund returns on $\tilde{R}_{Mt}$ and $\tilde{R}^2_{Mt}$. The relation between flow and abnormal returns in this panel is directly attributable to a relation between flow and the fund's idiosyncratic returns. The results are not materially changed. The analysis using 12 lags suggests that about 30 basis points of the liquidity-trading effect can be attributed to market timing. The analysis using six lags does not indicate any contribution from a market-timing bias.

Table 6 shows that the separate estimates for inflow-related trading and outflow-related trading (and net flow) are negative as predicted. This suggests that the costs associated with providing liquidity are a function of uninformed trading activity in general, and not related somehow to the specific trade direction. However, these separated estimates are noisier than the total trading estimates and only the inflow/purchase evidence is statistically significant. The lack of significance in the outflow/sales regressions is probably due to the much lower variability of outflow relative to inflow (see Table 2) which implies lower explained variation.

5.2. *The conditional expectation of α given zero flow*

It is useful to investigate the average fund's α performance in the absence of liquidity demands. The regression line relating liquidity-motivated trading to abnormal returns gives the conditional expected abnormal return in the event of zero flow. This is calculated as the average abnormal return using the CRSP value-weighted index (see Table 2) less the estimated cost associated with the fund's realized liquidity demands (the Table 5 coefficient times the average flow volume). Using six (12) abnormal return lags, the estimate is -0.26% ($+0.11$) per year. For the median fund the average adjusted net abnormal return is $+0.20\%$ ($+0.43$) per year. Neither the average nor the median figure is more than a fraction of one standard error different from zero.

Thus, while the average fund in the sample underperforms by -1.63% per year (t-statistic $= -1.87$) measured following the usual approach to performance evaluation, there is no underperformance when a liquidity-adjusted benchmark is applied. Taking the liquidity-trading effect into account, the typical fund's performance after deducting fees and expenses is zero. Thus, the typical fund manager enhances portfolio returns to a degree about equal to the expenses charged to the fund. This is the result that Grossman and Stiglitz (1980) predict in a competitive world where information is costly to produce.

Under the assumption that the volume of discretionary trading (trading that is unrelated to flow) is a proxy for the fund manager's information precision, there should be a positive correlation between abnormal returns and discretionary trading activity. Tables 5 and 6 include the regression results for discretionary trading. The coefficient estimate for discretionary trading is always insignificantly different from zero.

There are several plausible explanations for this result, besides the obvious explanation that fund managers' attempts at informed trading are unsuccessful. First, the discretionary trading proxy uses six-month observations compared to monthly observations for the liquidity-trading proxy. Thus, the discretionary trading proxy is noisier and may have insufficient covariance with the fund manager's true month-by-month information-motivated trading. Second, there are many other reasons to trade included in the discretionary trading proxy, such as portfolio rebalancing and tax-related trading. Even if the volume of information-motivated trading is positively associated with abnormal returns, these contaminants in the discretionary trading proxy are negatively associated with abnormal returns (they are just another form of uninformed trading). Thus, the contaminated proxy might not reveal an underlying true positive correlation between discretionary trading and abnormal returns. Third, the premise that more precise information leads to higher trading volume depends on the specific assumption about fund managers' preferences and about the nature of information. Under different preference assumptions, or with cross-sectional variation in the nature of information (specifically, short-lived versus long-lived), the predicted positive correlation in cross-section between discretionary trading activity and abnormal returns might not arise.

Finally, several studies find that mutual fund performance is sensitive to the return benchmark (see, e.g., Lehmann and Modest, 1987; Grinblatt and Titman, 1989b,1994; Elton et al., 1993; Carhart, 1997). The analysis in Table 5 is repeated in Table 7 with a multivariate benchmark that includes the CRSP value-weighted index plus size, dividend-yield, and lagged-return factors. The inferences are similar to those obtained using a single-factor benchmark.

6. Market-timing measures of performance

A link between flow and fund managers' perverse tendency towards negative market timing has been the subject of two other papers: Ferson and Schadt (1996) and Ferson and Warther (1996). Both studies operate at an aggregate, rather than individual, fund level but the arguments are similar to those presented here. Ferson and Schadt demonstrate that the negative market timing that is typically found in fund returns can be removed using a conditional

Table 7
Abnormal return regressed on flow and discretionary trading with a multifactor return model

Table 7 differs from Panel A of Table 5 only in that abnormal returns are calculated using a multifactor benchmark. In addition to the CRSP value-weighted index, the factors are:

- The return differential on a portfolio of the smallest size-decile stocks over the largest size-decile stocks
- The return differential on a portfolio of the highest dividend-yield stocks
- The return differential on a portfolio of the previous best-performing stocks over the previous worst performing stocks

(t-statistics in parantheses).

	Six lags of abnormal returns		12 lags of abnormal returns	
	λ	δ	λ	δ
Net	− 1.48	− 0.31	− 1.93	− 0.26
	(− 2.3)	(− 1.8)	(− 2.8)	(− 0.8)
+ *expenses*	− 1.05	− 0.11	− 1.41	− 0.03
	(− 1.5)	(− 0.5)	(− 2.0)	(− 0.1)
+ *brok∗Volume*	− 1.26	− 0.17	− 1.73	0.07
	(− 1.8)	(− 0.9)	(− 2.3)	(0.2)
+ *expenses*	− 0.90	0.06	− 1.00	0.11
+ *brok∗Volume*	(− 1.2)	(0.4)	(− 1.6)	(0.5)

benchmark that controls for time-varying expected market returns. They do not identify why that might be the case, but speculate that it is linked to fund flows. Preliminary work in that paper and more fully developed in Ferson and Warther documents a positive correlation between aggregate fund flows and lagged instruments for time-varying expected returns, suggesting that flow is indeed the source of negative market timing. This section directly examines the relation between a fund's market-timing performance and its flow. The results demonstrate that a fund experiences negative market timing when and only when that fund experiences flow. This clearly establishes that the source of mutual funds' negative market timing is the realized flow at that fund.

The market-timing test is essentially the procedure described in Treynor and Mazuy (1966). This involves the time-series regression

$$\tilde{R}_{jt} = \alpha + \gamma_1 \tilde{R}_{Mt} + \gamma_2 \tilde{R}_M^2 + \tilde{u}_{jt}, \tag{4}$$

where $\tilde{R}_{jt}$ is the excess return on the fund and $\tilde{R}_{Mt}$ is the excess return on the CRSP value-weighted index. The change in fund returns with respect to market returns is $\gamma_1 + 2\gamma_2 \tilde{R}_{Mt}$. Thus, γ_2 indicates the degree to which the fund's β 'times'

Table 8
Flow and market-timing measures of performance

Regressions are run separately for each fund using the 135 funds with at least thirty monthly observations. The table presents averages of the statistics from these individual-fund regressions (the t-statistics in parantheses are calculated using the sample standard error of the 135 individual-fund estimates). The regressions are

$$\tilde{R}_{jt} = a + \gamma_1 \tilde{R}_{Mt} + \gamma_2 \tilde{X}_{Mt} + \varepsilon_{jt}$$

$$\tilde{R}_{jt} = a + \gamma_1 \tilde{R}_{Mt} + \gamma_2 \tilde{X}_{Mt} + \gamma_3 (\hat{c}(f^{\mathrm{I}} + f^{\mathrm{O}}))\tilde{X}_{Mt} + \varepsilon_{jt}$$

$\tilde{R}_{jt}$ ($\tilde{R}_{Mt}$) denotes the fund (CRSP value-weighted) return. The market-timing regressor $\tilde{X}_{Mt}$ is either $\tilde{R}^2_{Mt}$ or $|\tilde{R}_{Mt}| \cdot \hat{c}$ is the estimated flow-trading response coefficient taken from Table 3 and $f^{\mathrm{I}}(f^{\mathrm{O}})$ is the gross inflow (outflow). Flow is either concurrent with returns or lagged one month. All returns are at an annual rate (t-statistics in parentheses).

Market-timing regressor	Squared excess returns				Absolute value excess returns			
	a	γ_1	γ_2	γ_3	a	γ_1	γ_2	γ_3
	− 0.08	0.89	− 0.24		− 0.56	0.90	− 0.033	
	(− 0.2)	(44)	(− 2.9)		(1.0)	(44)	(− 4.2)	
concurrent flow	− 0.21	0.89	0.23	− 0.59	0.21	0.90	0.041	− 0.037
	(− 0.4)	(44)	(1.1)	(− 2.4)	(0.4)	(44)	(0.2)	(− 2.0)
Lagged flow	− 0.31	0.89	0.45	− 0.82	0.15	0.90	0.018	− 0.057
	(0.3)	(44)	(2.1)	(− 3.4)	(0.3)	(44)	(1.1)	(− 3.4)

the market. A similar test is provided using $|R_{Mt}|$ as the market-timing regressor, as developed in Henriksson and Merton (1981). When the excess market return is positive (negative), $\gamma_1 + \gamma_2$ ($\gamma_1 - \gamma_2$) is the beta of the fund. Thus, $2\gamma_2$ is the reduction in the fund's beta in a down market.

The sample considered in this study exhibits statistically significant negative market timing, as seen in Table 8. In the squared-returns regression, the estimated γ_2 is -0.24 with a t-statistic of -2.9. A similar result obtains with the absolute-value regression, where γ_2 is -0.03 with a t-statistic of -4.4. This evidence is consistent with previous studies and indicates a perverse tendency of fund managers to negatively time the market.

A link between the fund's market-timing performance and the volume of flow at the fund is provided by adding a third regressor, $(\tilde{f}^{\mathrm{I}}_{jt} + \tilde{f}^{\mathrm{O}}_{jt})\tilde{T}_{Mt}$, where $\tilde{T}_{Mt}$ denotes the market-timing regressor, either $\tilde{R}^2_{Mt}$ or $|\tilde{R}_{Mt}|$. This interactive regressor controls for the effect of flow on market timing, so that the coefficient on $\tilde{R}^2_{Mt}$ or $|\tilde{R}_{Mt}|$ provides an unbiased representation of the fund managers' timing information. The reverse-causality problem described in the α analysis (Section 5.1) is an issue with this interactive term when flow and market returns are observed concurrently. Therefore, I also use an interactive term with flow lagged one month, $(f^{\mathrm{I}}_{jt-1} + f^{\mathrm{O}}_{jt-1})\tilde{T}_{Mt}$.

The negative market timing found using (4) can be completely attributed to the realized flow at the fund. With the flow interactive term present, γ_2 is now positive (though generally insignificant) while the coefficient on the interactive term is significantly negative. Thus, a fund's β covaries negatively with market returns only to the extent that *that fund* experiences flow. As expected, the results are stronger using lagged flow, which avoids a spurious positive covariance between flow and market returns due to reverse causality within the month. Similar to the α analysis, the appearance of poor market-timing performance is completely due to the perverse effects of the fund managers' liquidity service.

7. Conclusions

Open-end mutual funds' tendency toward underperformance has little to do with a lack of ability on the fund manager's part. It results from the liquidity service that fund managers provide investors. In a sample that, consistent with the literature, exhibits an average annual α equal to -1.63% and a significant negative correlation between the fund's β and market returns, there is no evidence of either α or market-timing underperformance after controlling for the effects of flow-related liquidity trading.

The implicit assumption behind most performance studies is that the zero abnormal return of a passive portfolio is the appropriate benchmark for evaluating fund managers. This benchmark offers no consideration to the fact that fund managers provide a valuable liquidity service to investors. The appropriate benchmark to assess open-end fund managers should reflect the indirect costs of providing liquidity. In an α performance metric, this benchmark is a negative abnormal return equal to the fund's realized flow volume times a multiplier on the order of 1.5%. In a market-timing test, the fund's time series of realized flow must be incorporated into the analysis for a fair assessment of the fund manager's ability.

One can compare the analysis and conclusions of this paper with those applied to other investment vehicles. Both closed-end funds and hedge funds have explicit restrictions on the liquidity of investors. Ceteris paribus, both might be expected to outperform as a result of this restriction. Closed-end funds tend to perform poorly. However, they might face abnormally high agency costs. Important evidence in this regard is provided in Barclay et al. (1993), who show that the lack of monitoring at closed-end funds can lead to serious agency costs and underperformance.[7] In the case of an open-end fund, with investors able to

[7] Chevalier and Ellison (1997), Brown et al. (1996), and Dow and Gorton (1994) also discuss these issues.

exit at will if they detect misbehavior, agency problems are not onerous. On the other hand, the restrictions placed on flow appear to be an important factor in the success of hedge funds. Ackermann et al. (1999) examines the determinants of the performance of hedge funds and finds that the existence of a lock-out provision (a period in which the investor is contractually prohibited from removing funds) is associated with a statistically and economically significant increase in returns.

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