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Costly Search and Mutual Fund Flows

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ABSTRACT

This paper studies the flows of funds into and out of equity mutual funds. Consumers base their fund purchase decisions on prior performance information, but do so asymmetrically, investing disproportionately more in funds that performed very well the prior period. Search costs seem to be an important determinant of fund flows. High performance appears to be most salient for funds that exert higher marketing effort, as measured by higher fees. Flows are directly related to the size of the fund's complex as well as the current media attention received by the fund, which lower consumers' search costs.

ALTHOUGH MUCH ACADEMIC RESEARCH on mutual funds addresses issues of performance measurement and attribution, we can learn more from this industry than whether fund managers can consistently earn risk-adjusted excess returns. Researchers studying funds have shed light on how incentives affect fund managers' behavior,[1] how board structure affects oversight activities,[2] and how scale and scope economies affect mutual fund costs and fees.[3] More generally, the fund industry is a laboratory in which to study the actions of individual investors who buy fund shares. In this paper, we study the flows of funds into and out of individual U.S. equity mutual funds to better understand the behavior of households that buy funds and the fund complexes and marketers that sell them.

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[1] See Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1995).

[2] See Tufano and Sevick (1997).

[3] See Baumol et al. (1990) and Dermine and Röller (1992).

In the first half of this paper, we analyze nearly two decades of data on equity mutual funds and demonstrate a striking performance-flow relationship: Mutual fund consumers chase returns, flocking to funds with the highest recent returns, though failing to flee from poor performers. Consumers are fee-sensitive in that lower-fee funds and funds that reduce their fees grow faster. There is mixed evidence that consumers are sensitive to the ex post riskiness of fund investments.

Recently, some researchers have analyzed the performance-flow relationship to test whether *individual investors* can earn risk-adjusted excess returns by actively selecting mutual funds.[4] These papers treat households as if they were professional portfolio managers: Fund managers pick stocks, and households pick funds. Yet, selecting funds is not a full-time job for most households. Most retail investors are not formally trained in portfolio analysis and few have up-to-date information on the universe of potential fund investments. It might be more appropriate to compare a household's fund purchase with its decision to buy a large durable good, like an automobile.

The average mutual fund account size is approximately of the same magnitude as the price of new cars purchased by U.S. consumers.[5] In both cases, consumers must choose from a large number of alternatives, with the "brand" selected being the combination of a firm (General Motors or Fidelity) and a specific model (Cadillac Catera or Magellan Fund.) The consumer is bombarded with advertising and columnists offering advice, as well as direct solicitations by salespeople. One cannot merely use price/horsepower ratios to determine the "value" of a particular car, nor is it easy to measure or predict risk-adjusted performance of a mutual fund. Were we to try to explain car sales solely on the basis of engineering considerations without recognizing the important role of brand name, advertising, and distribution ability, we would be left with a partial answer.

Economists acknowledge that consumers' purchasing decisions—whether for cars or funds—are complicated by the phenomenon of costly search. As a result, in the fund industry, rating services and periodicals provide advice for consumers, and fund vendors spend more than half their expenses in marketing.[6] The second half of the paper analyzes the implications of costly search for mutual fund flows. Using different measures of search costs, we find that funds that receive greater media attention and that belong to larger complexes grow more rapidly than other funds. Also, the performance-flow relationship is most pronounced among funds with higher marketing effort (reflected in higher fees), which in turn lowers the consumers' search costs. We interpret these data to suggest that mechanisms or conditions that reduce search costs have a ma-

[4] See Gruber (1996) and Zheng (1998).

[5] In 1994, the average mutual fund account was approximately \$17,325 (Investment Company Institute, *Mutual Fund Fact Book*, 1996). In that year, the average new car bought in the United States cost \$18,657 (Paul Linert, "Family income needed to buy cars is rising again," *The Detroit News*, August 21, 1996).

[6] See Sirri and Tufano (1993) for estimates of breakdowns of security selection, marketing, and administrative costs for funds.

terial impact on consumer fund choices. Thus, to the extent that it is optimal for individual investors to chase past performance, as Gruber's (1996) results suggest, then we must credit marketers and the financial press for directing money in this manner. In their absence, investors might be much less performance-sensitive in allocating their monies to funds.

In Section I, we briefly describe the data studied and report on consumers' apparent sensitivity to fund performance and expenses, ignoring considerations of costly search. Section II describes how costly search might affect the relative growth of different funds and tests these predictions. We conclude with a brief discussion of the managerial implications of this research in Section III.

I. Historical Performance and Mutual Fund Flows

A. Predictions from a Costless-Search Model of Mutual Fund Buying Behavior

As a starting point, we consider mutual fund purchases in a world in which consumers can obtain and process information about mutual funds at zero cost. Further, we ignore differences in the quantity or quality of other services provided by mutual funds.

If consumers were prescient, they would select funds that would subsequently generate the highest risk-adjusted returns. However, they only have information about *past* net performance, reflecting the return, risk, and fees charged. Academics study whether this historical information can be used to predict future returns, and reach contradictory conclusions. Though the answer to this question is still the subject of much controversy, the academic literature suggests the following:

- Persistence in fund returns is observable among the lowest performing funds, i.e., poor performers repeat (Hendricks, Patel, and Zeckhauser (1993)). Carhart (1997) concludes that fund expenses have a significant impact on fund returns in general; Brown and Goetzmann (1995) find that high fees cannot explain the persistence of the poorest performing funds.
- There is mixed support for persistence among high performers (Hendricks et al. (1993), Malkiel (1995)), although these results are attributed to survivorship biases (Brown and Goetzmann (1995), Brown et al. (1992)). Grinblatt and Titman (1992) find evidence of repeated winners, and Ibbotson and Goetzmann (1994) find positive performance persistence as well.
- Though some studies find that funds with higher expenses have performance high enough to offset these higher fees (Ippolito (1989)), more recent studies find that higher-fee funds do not perform as well as lower-fee funds (Elton et al. (1993), Carhart (1997)).

If consumers can collect and process mutual fund information at zero cost, and if they act in accordance with these academic findings, we might expect to find:

- a performance-flow relationship among the worst-performing funds, as consumers realize the likelihood that these funds may continue to perform poorly;
- an observable, but possibly weaker, performance-flow relationship among the best-performing funds, as consumers may believe that excellent performance may repeat;
- a negative relationship between risk borne and flows (holding constant performance and fees), as consumers would always prefer less risk to more, and
- a negative relationship between fees charged and flows, ceteris paribus, reflecting consumers' elasticity of demand with respect to the price of investment management services.

B. Data

To test the above-mentioned hypotheses, we purchase data from the Investment Company Data Institute (ICDI), a private data vendor. These data include information on open-end equity funds offered to the public from December 1971 through December 1990. For each fund, the database contains:

1. net asset values (NAVs) or the *per share* value of a funds' portfolio, reported monthly throughout the period
2. the date and amount of all capital gains and income distributions for each fund throughout the period
3. total net assets (TNAs), or the *total* dollar value of each fund's portfolio, reported quarterly
4. classification variables, such as fund age, fund category (aggressive growth, long-term growth, etc.), method of distribution, fund-family identifier, and other cross-sectional parameters, as of December 1990.

Our sample consists of the three main objective categories of equity mutual funds: aggressive growth, growth and income, and long-term growth funds.[7] In total, our sample includes 690 funds offered by 288 different mutual fund families. Table I describes the funds in our sample at three points in time: 1971, 1980, and 1990.

The ICDI data were spot-checked by hand against the *Wiesenberger Investment Reports* and *Morningstar Mutual Fund Values*. A series of tests were used to check for coding and data entry errors. Any questionable data points were reported to ICDI, which either confirmed or corrected the data. The database was supplemented by hand-collected material taken from a variety of print data sources. The "Mutual Fund Panorama" section of the *Wiesenberger Investment Reports* was used to collect information on mutual fund fees including expense ratios, front-end loads, and 12b-1 charges. These

[7] The sample excludes specialty equity mutual funds such as sector funds and international funds.

Table I

Cross-Sectional Characteristics of the Equity Mutual Fund Sample in 1971, 1980, and 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. "Number of funds" reflects the number of equity funds in our sample still in existence as of the end of the year. The total number of different funds in our sample is 690, but by the end of 1990, 58 of these funds ceased to exist. "Fund complexes" are separate families of mutual funds which must sell at least one equity fund to be included in our sample. "Total fee" is estimated as expense ratio plus amortized load, where the load is amortized without discounting over seven years, which is the average holding period for an equity fund in these data. For complex and individual fund data, the mean and standard deviation (S.D.) are reported for each characteristic.

		1971	1980	1990
Equity fund sector characteristics				
Number of funds		228	264	632
Total fund assets ($billions)		$35.5	$36.7	$171.7
Fund complex characteristics				
Assets managed ($millions)	Mean	$329.4	$315.6	$ 588.2
	S.D.	$669.2	$593.0	$2269.7
Number of funds sold by complex	Mean	2.53	3.39	8.28
	S.D.	1.96	3.03	12.89
Individual equity fund characteristics				
Fund assets ($millions)	Mean	$185	$176	$272
	S.D.	$383	$306	$785
Charging load		74%	53%	52%
Load charged (for load funds)	Mean	8.29%	7.80%	5.25%
	S.D.	1.07%	1.34%	1.51%
Annual expense ratios	Mean	0.96%	1.05%	1.44%
	S.D.	0.67%	0.56%	0.82%
Total fee (annual)	Mean	1.66%	1.47%	1.37%
	S.D.	6.37%	7.40%	9.51%

data are available only on an annual basis. *Barron's* and *Morningstar Mutual Fund Values* were also used as supplementary sources for cross-sectional data.

The ICDI data are a reasonably complete sample of U.S. equity funds in existence at the end of 1990. The completeness of the database can be checked by comparing the dollar value of assets covered in our sample against the universe of mutual funds in existence that year, as tabulated by the Investment Company Institute, the national industry association for mutual funds (Investment Company Institute (1991)). Over the twenty-year period, our main sample includes 87 percent of the total assets invested in these equity categories, and 71 percent of the number of funds. Thus, our sample represents the vast majority of the equity mutual fund sector, weighted toward larger funds.

The ICDI data suffer from survivorship bias. At the time we purchased the data, ICDI only maintained data on "live" funds still being offered to the public. When a fund ceased to exist, ICDI dropped the entire history of the fund from its database. The bulk of our data consists of 632 funds still offered as of the end of 1990. As a result, this portion of the database becomes more complete over time, accounting for 80 percent of equity fund dollars in 1971, but 90 percent by 1990. Fortunately, we obtained from ICDI information on funds that no longer existed as of December 1990—those that had "died" sometime during the period 1987 through 1990. Thus, for the period 1987 through 1990, we have an unbiased sample that includes virtually all equity funds in the three investment objective categories we study, regardless of their status as of the end of 1990. The "dead fund" subsample includes 58 funds, so that in the period 1987 through 1990, the total sample includes 690 funds. We use the unbiased 1987 through 1990 sample to test whether any survivorship bias affects our results, but for the bulk of the paper we report results for the full sample.

C. Definitions of Flows, Performance, and Fees

Net flows (FLOW) is defined as the net growth in fund assets beyond reinvested dividends. Formally, it is calculated as:

$$\mathrm{FLOW}_{i,t} = \frac{\mathrm{TNA}_{i,t} - \mathrm{TNA}_{i,t-1} * (1 + \mathrm{R}_{i,t})}{\mathrm{TNA}_{i,t-1}}, \tag{1}$$

where $\mathrm{TNA}_{i,t}$ is fund i's total net assets or the dollar value of all shares outstanding at time t, and $\mathrm{R}_{i,t}$ is the fund's return over the prior year.[8] FLOW reflects the percentage growth of a fund in excess of the growth that would have occurred had no new funds flowed in and had all dividends been reinvested.

Fund performance can be measured in many ways. In selecting which performance measure to use, we focus on the type of annual information available to consumers in the period 1970 to 1990 through leading purveyors of mutual fund data: *Wiesenberger, Lipper, Barron's, Money Magazine, U.S. News and World Report,* and *Morningstar*. Throughout most of this period, consumers had ready access only to rudimentary performance measures such as historical returns, return rankings relative to other funds with a similar objective, and market-adjusted returns. Similarly, funds' relative riskiness was reported in terms of their total risk (the standard deviation of historical returns), rather than by the portfolio beta, which captures the systemic portion of portfolio exposures. For the bulk of our tests, we use these crude consumer return and risk measures, supplementing them with more formal portfolio performance measures (Jensen's one-factor alphas and excess returns) for some of our results.

[8] This measure assumes that the flow occurs at the end of the period. None of the results in the paper are affected by recalculating this measure for flows occurring at the beginning, halfway through, or continuously throughout the year.

Investors pay many different types of fees to buy and hold mutual funds, including up-front fees (loads or sales commissions) and ongoing fees (reflected in the fund's expense ratio). We are interested in the total fees charged to consumers, rather than the individual components of fees, and we calculate these total fees as the expense ratio plus the up-front load amortized over a seven-year holding period (which is the average holding period for equity mutual funds), annualizing the total fees that a new investor would face.[9]

D. Initial Analysis of Return, Risk, Fees, and Flows

The relationship between relative returns and flows is shown in Figure 1. For each year and objective category, funds are ranked into one of twenty bins on the basis of their realized returns net of expenses. The graph plots the average flow for the next year for the funds that comprise each of the twenty performance groupings. The results are striking. For funds in the bottom 80th percentile, there is a positive but relatively shallow relationship between realized return and subsequent flows, but no pronounced penalty for extremely poor relative performance. However, there is a marked bonus for high realized returns; the performance-flow relationship is very strong for funds whose historic performances place them in the top 20th percentile in the prior year.

A general positive relationship between performance and flows has been demonstrated previously. A number of early papers report a positive *linear* relationship between asset growth and performance of individual funds.[10] Later papers call attention to the *nonlinear* performance-flow relationship identified in Figure 1. Ippolito (1992) finds that the coefficient of performance on fund growth is greater for funds with positive rather than negative market-model excess returns. Other papers that study the nonlinearity in more detail include Carhart (1994), Goetzmann and Peles (1997), Chevalier and Ellison (1995), and Gruber (1996).

[9] To calculate the *total fees* paid by a consumer, we express loads and annual expenses on a common annualized basis. To annualize loads, we estimate the period over which the consumer will hold the investment and amortize the load over this period. In 1990, the TNA-weighted redemption rate for the equity funds we study (aggressive growth, long-term growth, and growth/income) was 14 percent, which implies an average holding period of approximately seven years (Investment Company Institute (1991, p. 88)). Therefore, to roughly estimate the *total fees* paid by investors, expressed on an annualized basis, we add to the expense ratio one-seventh of the load charged to a new investor.

[10] Early studies include Spitz (1970) and Smith (1978). Patel, Zeckhauser, and Hendricks (1991), studying 96 no-load open end equity funds for the period 1975 to 1987, report a positive linear relationship between a fund's annual dollar growth and both its size and its ranked raw returns. Kane, Santini, and Aber (1991), studying 131 open-end equity funds with at least six years of history in 1973 through 1985, detect a similar linear relationship between quarterly percentage growth and fund performance measured using excess returns, Sharpe ratios, and Jensen's alphas. Lakonishok, Shleifer, and Vishny (1992) study approximately 250 institutional money managers and find a positive association between the number of new accounts gained and three-year industry-adjusted returns. Ippolito (1992), studying 143 open-end equity funds for the period from 1965 to 1984, finds a positive linear relationship between the annual growth rate of a fund and a fund's excess returns. Warther (1995) primarily studies the behavior of aggregate (vs. fund-by-fund) flows.

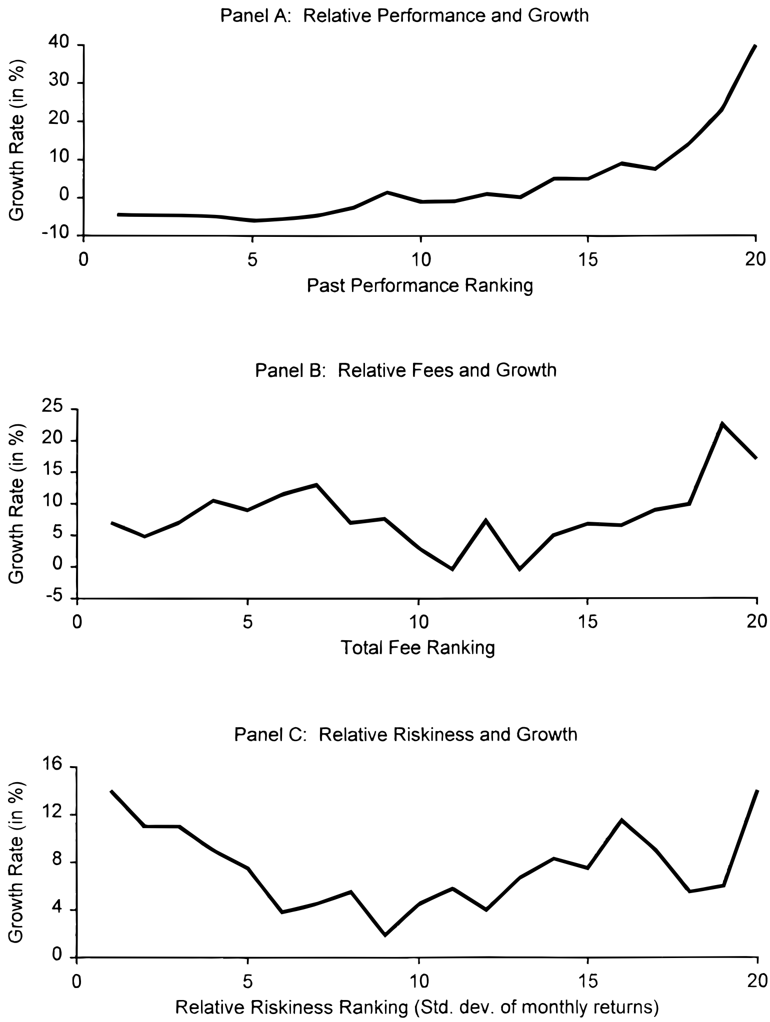

Figure 1. The mean growth rate of 690 open-end U.S. equity mutual funds as a function of their relative performance, fee levels, and return volatility, 1970 through 1990. For each year from 1971 to 1990, funds are ordered within one of three objective categories (aggressive growth, growth and income, and long-term growth), and divided into 20 equal groups based on their total return, level of fees, and portfolio return volatility, respectively. For each of these 20 groups, the mean growth rate of the funds in that group is calculated. The growth rate is defined as $(\text{TNA}_t - \text{TNA}_{t-1}) * (1 + \text{R}_t)/\ \text{TNA}_{t-1}$, where TNA_t is the total net assets of the fund at time t and R_t is the return of the fund in period t. The top panel divides the samples into groups based on the prior years' total return. The middle panel divides the sample into groups based on the prior years' level of total fees (which equals the expense ratio plus one-seventh of the load). The bottom panel divides the sample into groups based on the prior year's standard deviation of monthly returns, a measure of return volatility.

Just as Panel A in Figure 1 graphs the relationship between historical returns and inflows, the remaining panels plot flows against fund fees and risk. For each objective category and year, funds are ranked into one of 20 equal bins according to their total fees (as defined above) and the total risk borne by the fund (as measured by the standard deviation of monthly fund returns over the prior 12 months.) These graphs do not convey simple monotonic relationships with investors preferring less risk and lower fees. Interpreting these univariate plots is difficult, however, as realized returns, fees, and risks are not likely to be independent. For instance, funds that take on the greatest risk might populate the tails of the returns distribution, and high fee funds could either be high performers that capture rents of skill or poor performers. The fee/flow relationship in particular suggests that consumers do not simply view their mutual fund purchase decisions as a choice among identical commodity products in which price is the primary consideration. These concerns naturally lead us to use multivariate analysis to disentangle these effects.

We analyze the link between returns, risk, fees, and flows more formally, using a linear regression framework applied to twenty years of fund-level data. In these analyses, we fit the following general model to the data:

$$\begin{aligned} FLOW_{i,t} = (&Return_{i,t-1}, Riskiness_{i,t-1}, \\ &Expenses_{i,t-1}, OBJFLOW_t, LogTNA_{i,t-1}), \end{aligned} \tag{2}$$

where $FLOW_{i,t}$ represents the net percentage growth in fund i in period t. $OBJFLOW_t$ represents the growth of the fund objective category in period t, which we use as a control for sectoral-level flows, as we are attempting to explain fund-level flows. We include the size of the fund in the previous period ($LogTNA_{i,t-1}$, or the log of the total net assets of fund i in period $t-1$) again as a control, reflecting the fact that an equal dollar flow will have a larger percentage impact on smaller funds.

Even if performance and riskiness affect fund flows, it is unclear what particular measures and levels of performance (or risk) are most salient to consumers, or over what time period this measure should be calculated. Therefore, we consider alternative measures of performance and risk, calculated over various time horizons. These specifications explore the robustness of the results to alternative specifications, and are not meant to prove which measure is the “best” predictor of consumer behavior.

The models can be estimated on the entire dataset as a pool, in which each firm-year observation is considered an independent observation. This technique may inappropriately underestimate standard errors and overstate t-statistics if each fund-year is not an independent observation. Therefore, we analyze each year’s observations separately, reporting the means and t-statistics on the mean of this time series of coefficient estimates as in Fama and MacBeth (1973). This method incorporates the potential nonindependence of the annual observations, and produces more conservative estimates of the significance levels of our coefficient estimates. Throughout the paper, we report Fama-MacBeth regression coefficients and significance levels.

D.1. The Base Specification.

As a starting point, we report a base specification in Table II, column (A). As a measure of return, we use each fund's raw return ranking relative to other funds within the same investment objective, which is commonly reported in consumer periodicals. Using Net Asset Values (NAVs) and fund distributions, we calculate a raw monthly return series for each mutual fund, assuming that distributions are reinvested in the fund on the distribution date at the prevailing NAV for that day. Returns for fund i, $R_{i,t}$, are then calculated over a one-year horizon (t). For each investment objective and year, these returns are ordered, and each fund is assigned a rank ranging from 0 (poorest performance) to 1 (best performance.) In this first table, we use a one-year performance horizon, as this is commonly reported and requires us to discard the smallest number of funds. As we are interested in asymmetric responses to high and low performance, we structure the analysis using piecewise linear regression, which allows us to separately calculate the sensitivity of growth to performance in each of five performance quintiles. As a measure of risk, we use the historical standard deviation of monthly returns over the past year, which was commonly reported to consumers over this period.

Most, but not all, of the conjectures asserted above are confirmed by the data. As predicted, consumers seem to prefer funds with lower fees and less risk. Based on our results, fee differences of 100 basis points between funds are associated with 2.9 percent differences in fund flows. The control variables seem to capture significant impacts; individual fund flows are strongly related to sectoral flows and smaller funds enjoy larger percentage flows than do larger funds. There is some evidence that consumers are averse to risk, given the negative coefficient on the standard deviation of lagged monthly returns, though the coefficient is only marginally significant. The mean standard deviation of monthly returns in the sample is 0.05; for each 0.01 increase in a funds' standard deviation, flows decline by about 1 percent.[11]

The results in column (A) confirm that equity mutual fund inflows are sensitive to historical performance, but this sensitivity is not linear. For top performers—those in the top quintile of funds in their objective category—performance is associated with economically and statistically significant inflows. For other funds, performance is positively associated with flows, but this relationship is statistically weak. In the lowest quintile (the poorest performers), there is virtually no relationship between historical performance and flows. This can be seen graphically in these data by referring back to the top panel of Figure 1 and noting the absence of a slope in the leftmost portion of the flow/performance graph. We can reject the hypothesis that the performance sensitivity of the top quintile differs significantly from that of each of the four remaining quintiles (p-values of 0.0001), but we

[11] We also test if investors exhibit any sensitivity to skewness of a fund's return distribution by including a measure of the skewness of lagged monthly returns in the regression. The skewness coefficient is not significant in any specifications.

Table II

The Effect of Relative Performance, Return Volatility, and Fee Levels on the Growth of 690 Equity Mutual Funds, 1971 through 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. The table reports OLS coefficient estimates using the growth rate of net new money as the dependent variable, which is defined as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1}) * (1 + R_{i,t})/(\text{TNA}_{i,t-1})$, where $\text{TNA}_{i,t}$ is fund i's total net assets at time t, and $\text{R}_{i,t}$ is the raw return of fund i in period t. The independent variables include the log of fund i's total net assets in the prior period (Log lag $\text{TNA}_{i,t-1}$), the growth rate of net new money for all funds in the same investment category as fund i (Flows to fund category), the volatility of the prior year's monthly returns, the level of total fees (expense ratio plus amortized load) charged by the fund for an investor with a seven-year holding period, and measures of the fractional performance rank of fund i in the preceding years. A fund's fractional rank (RANK_t) represents its percentile performance relative to other funds with the same investment objective in the same period, and ranges from 0 to 1. In this table, fractional ranks are defined on the basis of a funds' one-year raw return. The coefficients on fractional ranks are estimated using a piecewise linear regression framework over five quintiles in column (A). For example, the 5th or bottom performance quintile (LOWPERF) is defined as $\text{Min}(\text{RANK}_{t-1}, 0.2)$, the 4th performance quintile is defined as $\text{Min}(0.2, \text{RANK}_{t-1} - \text{LOWPERF}_{t-1})$, and so forth, up to the highest performance quintile (HIGHPERF). In column (B), the middle three performance quintiles are combined into one grouping labeled as the 2nd–4th performance quintile (MIDPERF), defined as Min (0.6, RANK − LOWPERF). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the performance-growth relationship over their range of sensitivity. These regressions are run year-by-year, and standard errors and t-statistics are calculated from the vector of annual results, as in Fama and MacBeth (1973). p-values are given in parentheses below the coefficient estimates.

Independent Variable	(A)	(B)
Intercept	0.245	0.252
	(0.002)	(0.001)
Log lag TNA	−0.048	−0.048
	(0.000)	(0.000)
Flows to fund category	0.949	0.965
	(0.004)	(0.003)
Std. dev. of monthly returns	−1.043	−1.068
	(0.105)	(0.101)
Total fees	−0.029	−0.029
	(0.061)	(0.057)
Breakdown of RANK		
Bottom performance quintile (LOWPERF)	−0.007	−0.035
	(0.971)	(0.843)
4th performance quintile	0.104	—
	(0.355)	
3rd performance quintile	0.283	—
	(0.009)	
2nd–4th performance quintiles (MIDPERF)	—	0.170
		(0.000)
2nd performance quintile	0.061	—
	(0.694)	
Top performance quintile (HIGHPERF)	1.693	1.633
	(0.000)	(0.000)
Adjusted R^2	14.2%	14.3%
Number of observations	4098	4098

cannot reject the hypothesis that the other four quintiles are equal to one another in pairwise tests (p-values range from 0.39 to 0.97). Moving five percentiles in the highest performance category (say from the 85th to the 90th percentile) is associated with a significantly greater inflow than a similar move in any other performance range (8.4 percent versus 0 to 1.4 percent). For parsimony, in the remainder of the paper, we use a specification that isolates the top and bottom quintiles from the middle 60 percent of funds, as shown in column (B) of Table II.

The performance-flow relationship documented here, in conjunction with the prevailing compensation structure of the mutual fund industry in which management fees are a function of fund size, gives fund complexes a payout that resembles a call option. If returns are high, funds gain assets and total fee revenue rises, but if relative returns are very low, losses of assets and fees are more modest. This suggests that funds can exploit the option-like nature of their payoff by increasing variance of returns, and hoping for an extraordinary return. Brown et al. (1996) and Chevalier and Ellison (1995) explicitly test whether managers are motivated to increase volatility to maximize the value of this call. Chevalier and Ellison find some evidence of this behavior in the later part of the calendar year. The marginally significant negative coefficient on the volatility of fund returns suggests that this call option may not be entirely free, in that increases in risk reduce flows somewhat.

D.2. Alternative Performance Specifications.

Table III repeats the test given in Table II using alternative performance and risk measures. As mentioned above, the purpose of these analyses is to show the robustness of the base specification result, not to prove that a particular risk or return metric is more closely associated with consumers' purchase decisions. Columns (A) and (B) use rankings based on three- and five-year raw returns; for both, we observe the same asymmetric performance-flow relationship. We do not observe that the reaction to performance is markedly stronger for extreme performance measured after five years than after one year, which may be consistent with consumers responding most strongly to the most recent fund history. We observe this propensity in column (C), where we separately include performance rankings from years -1, -2, and -3. Though performance from two and three years ago has a lingering affect on current flows, recent performance seems to be much more strongly associated with fund flows, especially for top quintile funds.[12]

These specifications in columns (D) through (G) use somewhat more sophisticated performance measures to measure risk and return. (As discussed earlier, recall that the financial press did not report these types of measures

[12] Though not reported here, we also test whether the relationship between performance (in year -1) and flows is stronger when the most recent performance is either a major reversal or a continuation of prior performance. There is no statistical difference between the coefficient on year -1 performance when we condition on earlier performance.

for much of this period.) Column (D) ranks funds on the basis of their market-model excess returns within an objective category.[13] Column (E) ranks funds based on their one-factor Jensen's alpha, calculated for each fund for each year using the technique in Jensen (1968). The alphas and betas for year t are estimated using monthly return data taken from the prior five years, and are only calculated for funds with at least 60 months of prior return history. Columns (F) and (G) include fund rankings calculated using both one-year raw returns and rolling five-year alphas. Flows are also related to these performance measures, especially the Jensen's alpha measure; however, using this measure forces us to discard 35 percent of the sample in order to have five years of prior data. The crude performance rankings in columns (F) and (G) continue to have a material relationship with flows, even after including the alpha measures, which suggests that raw performance rankings may have a separate impact on fund flows beyond that of more precise performance measures.[14]

The results in Table III produce a consistent result. Regardless of the specific performance measure selected, or the time period over which performance is measured, historical performance and the growth in new assets are positively related for some funds. Furthermore, whatever performance measure we use, we find that consumers respond differently to high and low performance.

D.3. Survivorship Bias

If poor performing funds shrink and cease to be sold, and if our data only include funds that survive, we might fail to detect a positive performance-flow relationship among the worst performing funds.[15] Fortunately, for the period 1987 to 1990 we have a sample of virtually all equity mutual funds, including

[13] Excess returns are calculated by estimating a single beta coefficient, B_i, for each fund against the Center for Research in Security Prices (CRSP) equally weighted index using all available monthly data:

$$(R_{i,t} - R_{f,t}) = a + B_i(R_{m,t} - R_{f,t}) + e_{i,t},$$

where $R_{m,t}$ is the CRSP equally weighted return and $R_{f,t}$ is the 90-day treasury bill rate. This beta, in conjunction with the risk-free rate and the market return, is used to produce the expected return of the fund:

$$E(R_{i,t}) = R_{f,t} + B_i(R_{m,t} - R_{f,t}).$$

The difference between the fund's realized return, $R_{i,t}$, and $E(R_{i,t})$ is the excess return.

[14] Gruber (1996) finds similar results. He uses four-index alphas to measure performance and finds that flows are positively and nonlinearly related to performance, and he gets similar results using single index alphas or excess returns (p. 800). When he includes both four-index alphas and raw returns to estimate cash flows, he finds that both have some explanatory power. Gruber's specification differs from ours in that he estimates a *linear* relationship between performance and flows, treats the entire dataset as a single pool, and does not use performance rankings.

[15] Brown et al. (1992) develop a detailed analysis of the importance of survivorship bias in performance studies. Additionally, Goetzmann, Greenwald, and Huberman (1992) investigate the effect of survivorship bias on estimates of fund inflows.

Table III

The Effect of Alternative Performance and Risk Measures on the Growth of Equity Mutual Funds, 1971 through 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. The table reports OLS coefficient estimates for seven separate regressions using the growth rate of net new money as the dependent variable, which is defined as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1}) * (1 + \text{R}_{i,t}) / (\text{TNA}_{i,t-1})$, where $\text{TNA}_{i,t}$ is fund i's total net assets at time t, and $\text{R}_{i,t}$ is the raw return of fund i in period t. The independent variables used in all seven regressions include the log of fund i's total net assets in the prior period (Log lag $\text{TNA}_{i,t-1}$) and the growth rate of net new money for all funds in the same investment category as fund i (Flows to fund category). The regressions also include various measures of the fractional performance rank (RANK_t) of fund i in the preceding years. The performance ranks are divided into three unequal groupings. For example, the bottom performance grouping (LOWPERF) is the lowest quintile of performance, defined as $\text{Min}(\text{RANK}_{t-1}, 0.2)$. The middle three performance quintiles are combined into one grouping (MIDPERF) defined as Min (0.6, RANK − LOWPERF), and the highest performance quintile (HIGHPERF) is defined as RANK − (LOWPERF + MIDPERF). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the performance-growth relationship over their range of sensitivity. These fractional ranks are defined using the prior three-year raw returns (column A), the prior five-year raw returns (column B), and each of the prior three-years' raw returns separately (column C). Column D uses a measure of RANK based on market-model excess returns, defined as $\text{R}_{i,t} - \text{E}(\text{R}_{i,t})$, where $\text{E}(\text{R}_{i,t})$ is defined using an estimate of beta from past monthly returns. Columns E and F report regressions using a measure of RANK based on estimates of Jensen's alpha over the preceding five years. Column G uses the fractional ranks from the prior one-year raw return and the level of the five-year Jensen's alpha. Because the raw return measures in columns A through C do not incorporate any risk adjustment, we also include the volatility of monthly returns over the same period in which the performance is measured. These regressions are run year-by-year, and standard errors and t-statistics are calculated from the vector of annual results, as in Fama and MacBeth (1973). p-values are given in parentheses below the coefficient estimates.

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Intercept	0.241	0.211	0.165	0.191	0.143	0.092	0.204
	(0.025)	(0.107)	(0.103)	(0.002)	(0.041)	(0.134)	(0.006)
Log lag of TNA	−0.043	−0.033	−0.042	−0.049	−0.033	−0.031	−0.027
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Flows to fund category	0.758	0.831	0.737	0.898	0.971	0.988	0.883
	(0.049)	(0.051)	(0.049)	(0.014)	(0.013)	(0.011)	(0.008)
Standard deviation of monthly returns							
Over months −1 to −36	−1.007	—	—	—	—	—	—
	(0.343)						
Over months −1 to −60	—	−0.792	—	—	—	—	—
		(0.511)					

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Standard deviation of monthly returns							
Over months −1 to −12	—	—	−0.053	—	—	—	—
			(0.950)				
Over months −13 to −24	—	—	−0.955	—	—	—	—
			(0.243)				
Over months −25 to −36	—	—	−1.047	—	—	—	—
			(0.150)				
Percentile ranking based on raw returns							
Bottom quintile, year −1 (LOWPERF)	—	—	0.030	—	—	0.136	−0.204
			(0.902)			(0.547)	(0.121)
Middle three quintiles, year −1 (MIDPERF)	—	—	0.183	—	—	0.107	0.092
			(0.001)			(0.041)	(0.054)
Top quintile, year −1 (HIGHPERF)	—	—	1.027	—	—	0.899	1.164
			(0.012)			(0.045)	(0.016)
Bottom quintile, year −2 (LOWPERF)	—	—	0.055	—	—	—	—
			(0.781)				
Middle three quintiles, year −2(MIDPERF)	—	—	0.124	—	—	—	—
			(0.027)				
Top quintile, year −2 (HIGHPERF)	—	—	0.313	—	—	—	—
			(0.108)				
Bottom quintile, year −3(LOWPERF)	—	—	−0.097	—	—	—	—
			(0.679)				
Middle three quintiles, year −3 (MIDPERF)	—	—	0.083	—	—	—	—
			(0.156)				
Top quintile, year −3 (HIGHPERF)	—	—	0.401	—	—	—	—
			(0.015)				
Bottom quintile, years −1 to −3 (LOWPERF)	−0.047	—	—	—	—	—	—
	(0.769)						
Middle three quintiles, years −1 to −3 (MIDPERF)	0.215	—	—	—	—	—	—
	(0.006)						

Table III—*Continued*

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Percentile ranking based on raw returns							
Top quintile, years −1 to −3 (HIGHPERF)	0.998 (0.000)	—	—	—	—	—	—
Bottom quintile, years −1 to −5 (LOWPERF)	—	−0.176 (0.435)	—	—	—	—	—
Middle three quintiles, years −1 to −5 (MIDPERF)	—	0.174 (0.003)	—	—	—	—	—
Top quintile, years −1 to −5 (HIGHPERF)	—	1.545 (0.000)	—	—	—	—	—
Percentile ranking based on excess returns							
Bottom quintile, year −1 (LOWPERF)	—	—	—	0.189 (0.128)	—	—	—
Middle three quintiles, year −1 (MIDPERF)	—	—	—	0.145 (0.002)	—	—	—
Top quintile, year −1 (HIGHPERF)	—	—	—	1.465 (0.001)	—	—	—
Jensen's alpha (5 years)	—	—	—	—	—	—	19.851 (0.000)
Percentile ranking based on Jensen's alpha							
Bottom quintile, years −1 to −5 (LOWPERF)	—	—	—	—	−0.157 (0.275)	−0.212 (0.200)	—
Middle three quintiles, years −1 to −5 (MIDPERF)	—	—	—	—	0.285 (0.003)	0.194 (0.011)	—
Top quintile, years −1 to −5 (HIGHPERF)	—	—	—	—	2.165 (0.000)	1.842 (0.000)	—
Adjusted R^2	14.0%	16.6%	12.9%	12.9%	16.9%	20.6%	10.5%
Number of observations	3286	2675	3286	4098	2675	2675	2675

those that die during this period. This short but complete sample permits us to directly test whether our failure to observe a performance-flow link among poor performers is due to survivorship bias. We reestimate the base specification over the period 1987 to 1990 for the entire sample that includes 632 survivors and 58 funds that went out of existence during this period. Following Goetzmann and Peles (1997), we assign a flow of −100 percent to a fund in the year that it died. The results, which are not reported separately, mirror those found in Table III: We continue to find strong performance sensitivity among high performers and a much weaker relationship among the poorest performers. The absence of a strong link between performance and flows for the poorest performers in our sample is not attributable to survivorship bias.[16] Gruber's database is specially constructed to address issues of survivorship, and it yields the same result, suggesting that survivorship cannot explain the asymmetry of the performance-flow relationship.

D.4. Fee Changes.

The specification in Tables II and III shows that funds with higher fees tend to grow more slowly than funds with lower fees. Alternatively, one can ask how flows are affected when funds *alter* their fees. Because other characteristics of funds (such as service levels and possibly long-run performance) are presumably stable, we would expect that *ceteris paribus*, investors would react strongly to fee changes. Table IV, column (A), adds fee changes to our analysis of fund flows, and shows that flows are inversely related to fee changes, as predicted. Specifically, these data imply that for funds that increase total fees one standard deviation from the mean (from 1.74 percent to 2.41 percent), flows would drop from the mean of 11.4 percent per year to 3.0 percent. This analysis assumes that the investors' response to fee increases and decreases is symmetric, but it does not need to be so. Column (B) separately analyzes fee increases and fee decreases and shows that fee increases are not associated with fund flows, but decreases are. As fees are lowered (the variable "decrease in fees" is negative), the flows increase (holding constant total return). For a 20 basis point decrease in fees, flows would be 4.2 percent higher (-0.2×-0.213). In Section II, we discuss possible reasons why fee increases may not lead to decreases in flows when there are substantial search costs, and we also discuss the results shown in columns (C) and (D).

II. Costly Search, Marketing, and Mutual Fund Flows

A. Costly Search and Consumer Decision Making

Up to this point, we have disregarded search costs and assumed that consumers can collect and process information about performance, fees, and other fund characteristics at zero costs. Unfortunately, as discussed in the

[16] We also estimate the survivorship bias test using other specifications and find that the asymmetry of fund flows to performance is not attributable to fund survival.

Table IV

The Effect of Fee Changes on the Growth of Equity Mutual Funds, 1971 through 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. The table reports OLS coefficient estimates for four separate regressions using the growth rate of net new money as the dependent variable, which is defined as $(\mathrm{TNA}_{i,t} - \mathrm{TNA}_{i,t-1}) * (1 + \mathrm{R}_{i,t})/(\mathrm{TNA}_{i,t-1})$, where $\mathrm{TNA}_{i,t}$ is fund i's total net assets at time t, and $\mathrm{R}_{i,t}$ is the raw return of fund i in period t. The independent variables used in all four regressions include the log of fund i's total net assets in the prior period (Log lag $\mathrm{TNA}_{i,t-1}$), the log of the total net assets of all funds in fund i's complex in the prior period (Log lag complex $\mathrm{TNA}_{i,t-1}$), the growth rate of net new money for all funds in the same investment category as fund i (Flows to fund category), and the standard deviation of monthly returns. The new independent variables in this table are the change in total fees (column A), which is broken down into fee increases and decreases (column B), and changes in expense ratios and loads (column C), broken down into expense and load increases and decreases (column D). The regressions also include measures of the fractional performance rank (RANK_t) of fund i based on raw returns in the preceding year. The performance ranks are divided into three unequal groupings. The bottom performance grouping (LOWPERF) is the lowest quintile of performance, defined as $\mathrm{Min}(\mathrm{RANK}_{t-1}, 0.2)$. The middle three performance quintiles are combined into one grouping (MIDPERF) defined as Min (0.6, RANK − LOWPERF), and the highest performance quintile (HIGHPERF) is defined as RANK − (LOWPERF + MIDPERF). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the performance-growth relationship over their range of sensitivity. These regressions are run year-by-year, and standard errors and t-statistics are calculated from the vector of annual results, as in Fama and MacBeth (1973). p-values are given in parentheses below the coefficient estimates.

	(A)	(B)	(C)	(D)
Intercept	0.124	0.121	0.114	0.104
	(0.020)	(0.035)	(0.039)	(0.080)
Log lag TNA	−0.079	−0.077	−0.080	−0.075
	(0.000)	(0.000)	(0.000)	(0.000)
Log lag complex TNA	0.035	0.035	0.036	0.037
	(0.002)	(0.002)	(0.001)	(0.001)
Flows to fund category	1.172	1.161	1.156	1.108
	(0.002)	(0.003)	(0.004)	(0.008)
Std. dev. of monthly returns	−0.820	−0.947	−0.688	−0.988
	(0.213)	(0.181)	(0.279)	(0.191)
Total fees	−0.026	−0.034	−0.026	−0.050
	(0.126)	(0.056)	(0.089)	(0.008)
Change in total fees	−0.119	—	—	—
	(0.015)			
Increase in total fees	—	0.042	—	—
		(0.529)		
Decrease in total fees	—	−0.213	—	—
		(0.012)		
Change in expenses	—	—	−0.253	—
			(0.001)	
Increase in expenses	—	—		0.070
				(0.126)
Decrease in expenses	—	—	—	−0.689
				(0.000)

Table IV—*Continued*

	(A)	(B)	(C)	(D)
Change in load	—	—	0.004	—
			(0.442)	
Increase in load	—	—	—	0.022
				(0.614)
Decrease in load	—	—	—	0.011
				(0.106)
Bottom performance quintile (LOWPERF)	0.109	0.105	0.111	0.173
	(0.430)	(0.454)	(0.404)	(0.240)
Middle three performance quintiles (MIDPERF)	0.161	0.159	0.155	0.151
	(0.001)	(0.001)	(0.001)	(0.000)
Top performance quintile (HIGHPERF)	1.697	1.692	1.638	1.530
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	19%	20%	20%	19%
Number of observations	3721	3721	3721	3721

introductory remarks, this stylized model fails to capture important aspects of consumers' buying process. Once we acknowledge that collecting and processing information are costly activities, we predict that *consumers would purchase those funds that are easier or less costly for them to identify*. These may be offerings from larger, more well-known fund families, those with more extensive marketing efforts, and those receiving greater media attention. In marketer's terms, these traits enhance brand awareness and recall and they place a product in a "consideration set" from which consumers select products.[17]

Marketers speak of a product attribute as "salient" if consumers consider it to be important, react to it almost automatically, recall it easily, and assign it disproportionate amounts of attention. From the findings in the previous section, we can define historical performance as a salient product characteristic. This definition would be consistent with marketing research, which has found that characteristics may acquire salience externally, through advertising, repeated reference, and vividness. Mutual fund advertising, marketing, and journalism all use historical performance as the basis for attracting attention, and marketers would find it quite natural that performance would thus become salient.

Combining the notion of costly search and salience, we expect that performance would be most salient—that is, it would exert the greatest influence on consumer decision making—in the presence of low search costs, or alternatively for those funds whose management companies engage in significant

[17] For a brief summary of the relevant marketing literature, see Alba, Hutchison, and Lynch (1991).

marketing efforts to lower search costs.[18] Though strong performance per se may attract new investments, the combination of strong performance and low search costs should be even more potent. Capon, Fitzsimons, and Prince (1996) look at the related problem of how investors gather information and make choices about mutual funds. Using survey methods, they find that most investors have little knowledge of the products they are buying. They identify subgroups of investors by their purchasing behavior, and classify the groups based on the salience of the information they use. They find that past fund performance is the most important source of information for all groups of investors, and fund advertising is one of the top three factors for virtually all investors. Thus, we predict that strong performance should produce more inflows for funds that are within consumers' consideration sets, which in this case includes funds in well-known fund complexes and those conducting more extensive marketing.

B. Three Measures of Search Costs

In order to test whether search costs have a material impact on fund flows, either unconditionally or conditional on performance, we must construct meaningful measures of search costs and marketing efforts. Marketers estimate search costs with a diverse set of measures, including indicators of aided and unaided brand recall, advertising levels, or geographic metrics such as the distance to the nearest store carrying the product. For mutual funds, our goal is to capture the spirit of these measures within the practical limitations of our data. Therefore, we use three related measures as proxies for the costs of identifying fund products: mutual fund complex size, marketing and distribution expenditures, and media coverage.

By using fund complex size, measured by the log of total net assets under management in the fund complex, as a measure of search costs, we assume that larger complexes are more visible and have greater brand awareness than smaller complexes. We test whether funds in larger complexes, which consumers find easier to identify, grow faster and can better capitalize on high performance, holding attributes such as performance and fees constant.

Funds attempt to increase recognition and awareness through a variety of marketing and selling activities. Marketing includes print, television, and radio advertising and direct mail, and selling activities include the efforts of brokers, financial planners, or other intermediaries. Both marketing and selling are costly activities that consumers support through a combination of front-end loads, annual 12b-1 fees, and back-end loads (or contingent deferred sales charges). We assume that higher total fees are related to higher marketing/selling expenditures, and use total fees charged to consumers as a measure of marketing/selling efforts. Higher fees, including marketing expenses, have at least two contrary effects on the attractiveness of a fund:

[18] Klibanoff, Lamont, and Wizman (1998) find that the values of closed-end funds seem to respond to fundamental changes more strongly when media coverage is greater.

They increase the *price* of the fund, but if spent on marketing, they decrease search costs borne by the consumer.[19] In Section I, we observed a negative relationship between fees and flows, consistent with the notion that the former effect dominates the latter. In this section, we additionally test the conditional impact of fee levels (or marketing/selling efforts) on the performance-flow relationship, in which we predict that high-fee (high-marketing) complexes will have a stronger performance response than low-fee complexes, by virtue of their ability to market this salient characteristic.

Not all expenses are used for the same purpose. Increases in expenses that are earmarked for marketing will tend to reduce search costs. Though the unconditional increase in fees may slow down the flow of new investment, the counterbalancing force of greater marketing should mitigate this effect, at least in part. Therefore, we can test whether consumer flow reaction to fee changes differs for changes in marketing fees (and thus marketing effort) versus other fees.

Neither complex size nor fee levels are direct measures of brand recognition. Therefore, as a measure of brand awareness, we collect data on the extent to which the funds in our sample receive media attention. We posit that funds more frequently mentioned in newspapers and magazines are more likely to be well-recognized by consumers. We construct a database of media citations of individual funds in major newspapers and periodicals and construct a measure of media coverage. Though complex size and marketing expenditures are under the control of the fund complex (at least in part), the amount of media attention a fund receives is determined by the tastes of financial journalists. We posit that funds receiving greater media attention will grow faster, and may have a stronger performance-flow relationship.

Finally, we examine the proposition that a fund may benefit from strong performance by another fund within its complex—that is, a spillover effect. We hypothesize that strong performance by one fund in the complex may make the complex more visible to investors, and somehow enable other funds to grow faster.

C. Complex Size and Flows

Table V, column (A), adds complex size information to the base specification. Complex size is measured by the log of assets under management in the complex in the prior year. We also construct a dummy variable, LARGE, that equals one if in that year the fund belongs to a complex that is larger than the median complex size for that year, and zero otherwise. This dummy variable is interacted with the piecewise performance measures. We posit that funds that are part of larger complexes (and hence more recognizable brands) will receive greater inflows and that the performance-flow relationship will be stronger for larger complexes.

[19] If price is a signal of quality, then higher fees could signal higher future performance. Research by Carhart (1997) and others suggests that higher fees do not signal higher ex post performance.

Table V

The Impact on the Growth of Equity Mutual Funds of Variables that Capture the Extent to Which Consumers Face Search Costs in Identifying Fund Investments, 1971 through 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. The table reports OLS coefficient estimates for separate regressions using the growth rate of net new money as the dependent variable, which is defined as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1}) * (1 + \text{R}_{i,t})/(\text{TNA}_{i,t-1})$, where $\text{TNA}_{i,t}$ is fund i's total net assets at time t, and $\text{R}_{i,t}$ is the raw return of fund i in period t. The independent variables used in the regressions include the log of fund i's total net assets in the prior period (Log lag $\text{TNA}_{i,t-1}$), the log of the total net assets of all funds in fund i's complex in the prior period (Log lag complex $\text{TNA}_{i,t-1}$), the growth rate of net new money for all funds in the same investment category as fund i (Flows to fund category), the standard deviation of monthly returns, the total fees charged (expense ratio plus amortized load), and changes in total fees. The regressions include measures of the fractional performance rank (RANK_t) of fund i based on raw returns in the preceding year. The performance ranks are divided into three unequal groupings. The bottom performance grouping (LOWPERF) is the lowest quintile of performance, defined as $\text{Min}(\text{RANK}_{t-1}, 0.2)$. The middle three performance quintiles are combined into one grouping (MIDPERF) defined as Min (0.6, RANK − LOWPERF), and the highest performance quintile (HIGHPERF) is defined as RANK − (LOWPERF + MIDPERF). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the performance-growth relationship over their range of sensitivity. The regression in Column A includes an interaction term that is the product of a dummy that equals one only for complexes whose assets under management are larger than the median complex for year $t - 1$ (LARGE) times the fund's performance ranking. The regression in Column B includes an interaction term that is the product of a dummy that equals one only for funds whose fees are above the median for their objective category for year $t - 1$ (HIGHFEE) times the fund's performance ranking. Column C includes both sets of these interaction terms. These regressions are run year-by-year, and standard errors and t-statistics are calculated from the vector of annual results, as in Fama and MacBeth (1973). p-values are given in parentheses below the coefficient estimates.

	(A)	(B)	(C)
Intercept	0.167	0.121	0.138
	(0.010)	(0.053)	(0.040)
Log lag TNA	−0.077	−0.077	−0.077
	(0.000)	(0.000)	(0.000)
Flows to fund category	1.142	1.074	1.092
	(0.002)	(0.005)	(0.004)
Std. dev. of monthly returns	−0.954	−1.187	−1.172
	(0.123)	(0.082)	(0.072)
Total fees	−0.027	−0.012	−0.015
	(0.099)	(0.530)	(0.474)
Change in total fees	−0.098	−0.112	−0.100
	(0.028)	(0.011)	(0.015)
Log lag complex TNA	0.029	0.034	0.031
	(0.029)	(0.001)	(0.024)
Bottom performance quintile (LOWPERF)	0.054	0.081	0.085
	(0.731)	(0.669)	(0.635)
Middle three performance quintiles (MIDPERF)	0.128	0.215	0.205
	(0.011)	(0.004)	(0.005)
Top performance quintile (HIGHPERF)	1.646	1.123	1.007
	(0.005)	(0.003)	(0.066)

Table V—*Continued*

	(A)	(B)	(C)
Interaction terms:			
Large-complex dummy times...			
Bottom performance quintile	0.040	—	0.009
(LOWPERF * LARGE)	(0.834)		(0.964)
Middle three performance quintiles	0.041	—	0.033
(MIDPERF * LARGE)	(0.577)		(0.666)
Top performance quintile	0.046	—	0.212
(HIGHPERF * LARGE)	(0.939)		(0.761)
Interaction terms:			
High-total-fee dummy times...			
Bottom performance quintile	—	−0.069	−0.034
(LOWPERF * HIGHLFEE)		(0.579)	(0.788)
Middle three performance quintiles	—	−0.117	−0.132
(MIDPERF * HIGHFEE)		(0.143)	(0.089)
Top performance quintile	—	1.127	1.230
(HIGHPERF * HIGHFEE)		(0.029)	(0.048)
Adjusted R^2	18.8%	18.7%	20.1%
Number of observations	3858	3858	3858

The results provide mixed support for the notion that funds within larger complexes enjoy the benefits of lower search costs. We observe that funds in larger complexes grow more quickly. The mean complex in 1980 had \$316 million in assets; for each additional \$100 million under management, its flows in the subsequent year are predicted to be slightly less than 1 percentage point higher $((\ln(416) - \ln(316)) * 0.029)$. Though these results are consistent with the hypothesis that larger complexes are more visible, and hence investors are more likely to know about the complex and its funds, the results could also be consistent with the hypothesis that larger complexes offer greater services to investors. For example, larger complexes may give investors more fund choices within the complex, allowing them to easily switch their investments from fund to fund, and this externality may make their funds preferred by consumers.

However, we do not observe that funds in larger complexes enjoy a stronger performance-flow relationship in any of the performance ranges. Neither the level of the coefficients on the interaction terms nor their statistical significance are consistent with the notion that funds in larger complexes are any more performance-sensitive than funds in smaller complexes. Thus, although being in a large complex may lead to certain across-the-board flow benefits, these do not manifest themselves in the form of getting a bigger boost for higher performance.

D. Fees and Flows

We have already shown that funds charging higher fees grow more slowly and that decreases in fees tend to be associated with faster fund growth. In our earlier discussion of Table IV, we ignored columns (C) and (D), which look at the differences in flows due to changes in loads (which are used to compensate salespersons) and expenses (which combine compensations for the investment manager, administrator, and custodian with some marketing expenses). The results in columns (C) and (D) demonstrate the impact of marketing effort on flows. Changes in expenses are inversely related to flows, but not changes in loads. Increasing loads increases fees, which makes the fund less attractive to consumers, but it does so by increasing marketing effort and thereby decreasing search costs, presumably because the higher load motivates sales representatives to sell more aggressively. It appears that these two effects cancel each other out, such that changes in loads do not increase or decrease flows. (The marginally significant coefficient on decreases in loads in column (D) suggests that decreasing loads might reduce flows, as the incentives for salespeople are weakened.) However, changes in expense ratios are less related to fund marketing efforts because they cover management fees, administrative charges, and other costs, and so the former effect (the elasticity of demand with respect to price) seems to dominate, leading to lower flows. From column (D), we see that it is the reduction in expense ratios that is most strongly related to fund flows, with reductions in annual fees having a strong positive effect on flows.

We hypothesize that greater marketing effort could affect performance sensitivity, as brokers and advertisements often promote the most recent high performing fund.[20] In Table V, columns (B) and (C), we examine whether high-fee (high-marketing) funds exhibit greater performance-flow sensitivity. We construct a dummy, HIGHFEE, that equals one if the total fees are above the median level in the fund category, and we interact this dummy variable with the piecewise performance measures. We see a strong relationship between fees and performance sensitivity in the data. Complexes that charge higher fees enjoy flows from high performance that are twice as large as those of their rivals. For example, the coefficient in column (B) on the top performance quintile in the piecewise framework is 1.12 for funds charging fees below the median for their objective, but is 2.25 for funds charging fees above the median for their objective. Since a large fraction of fees is used to support marketing activities, this is consistent with high marketing being the vehicle used to deliver a strong performance-

[20] This issue has recently gained attention due to the practice of fund complexes "incubating" funds. Management companies either start a large number of very small funds which are not marketed or selectively convert other types of managed pools of money such as separate accounts or variable annuities, allowing each to generate a track record. The fund is then "rolled out" and the highest performers among the group are advertised.

flow relationship.[21] Low-cost funds, which have lower costs often by virtue of the fact that they expend fewer resources on marketing, benefit less from high performance. The significant negative coefficient on the interaction term for medium performance in column (C) suggests that higher-fee funds may be less performance-sensitive than other funds for the bulk of the performance range.[22] Further, the differential performance/flow effect for high-fee funds persists even after allowing for interaction of performance with complex size, suggesting that the relationship is not due to any spurious correlation between fee levels and the size of the fund complex.

Though we cannot be sure that all of the high-fee funds are high-marketing funds, the results suggest that stronger levels of marketing may be used in two ways. First, by heavy promotion, funds may be able to accentuate the consumer response to attractive historical performance. However, the marginally significant, negative coefficients on the interaction term of high-total fees times middle performance suggest that the same marketing muscle may be able to make consumers less sensitive to moderate levels of current performance, perhaps by focusing attention away from the current performance and onto ancillary services, convenient intrafund transfers, a low risk, long-horizon performance record, etc. To the extent that marketing makes performance salient, it does so selectively. Were we able to obtain detailed data on fund marketing activities (such as advertising spending by fund and complex, commission schedules for brokers, advertising copy), it might be possible to test how the micromanagement of the marketing activity affects fund flows.

We recognize the possibility that the strong performance sensitivity of high-fee funds could be the result of star performance being aggressively promoted by salespersons of load funds, which tend to have higher total expenses. Other research concludes that load-fund customers are less informed about their funds than investors who purchase direct distributed funds (Capon et al. (1996), Securities and Exchange Commission (1996)).

[21] Ideally, one would like to separately identify all marketing expenditures and condition this test solely on the level of marketing efforts. While it is possible to identify the costs of personal selling that are reimbursed through load fees, with our data we are not able to break out those marketing expenses are not part of a load. For example, though we can identify whether a fund's board approved the levying of 12b-1 fees to support distribution, we cannot tell the magnitude of these fees for most of our sample. Furthermore, marketing efforts by the fund complex, such as advertisements, cannot be reliably collected for this period. If we restrict our attention to the later years of our sample, we can identify the level of 12b-1 spending. In results not reported here, we find that funds with higher 12b-1 fees enjoy higher performance-flow sensitivity in the highest performance quintile.

[22] We also estimate a specification where we test if the performance-flow relationship differs between load and no-load funds. We find no significant coefficient on the interaction term that is a product of performance and a load dummy for either high or low performance quartiles, and a modestly less significant performance-flow relationship for middle-range performance. This is inconsistent with the proposition that only brokered sales have a unique advantage in promoting performance over direct marketed funds.

Load fund investors may heed their broker's advice and not pull money out of funds with poor performance, whereas no-load or directly distributed fund investors may be sensitive to poor investment performance and pull their monies out of bad funds. If this is the case, funds' pricing structures proxy for an adverse selection problem among investors types. To examine this, we estimate the models of Table III separately for load and no-load funds. The results, not reported here, are the same for both groups; that is, high-performing funds garner large inflows and poor-performing funds do not suffer comparable outflows. We conclude that adverse selection, though perhaps contributing to the result, is not driving the findings.

E. Media Attention

We posit that funds that receive more media attention should grow faster, and should also enjoy a stronger response to good performance. To measure media attention, we search Lexis/Nexis for references to each fund (under its current and prior names) for each year from 1971 to 1990, in nine major periodicals and eleven major newspapers, weighing each story by the circulation of the publication in which the story ran.[23] In total, the funds in our sample are mentioned in these publications more than 33,000 times in the period 1970 to 1990. We are unable to classify the 33,000 stories as positive, negative, or neutral news about the fund; thus they indicate the sheer information flow about a fund. Media attention to mutual funds, as registered by citations in Lexis/Nexis, has increased over time. Recognizing this, we calculate media share measures that reflect the annual share of the media cites attributable to each fund within each fund category.

We do not expect media attention to be a random event, so we first attempt to ascertain the factors that make a fund more likely to receive news attention. We posit that larger funds, those from larger complexes, those with extreme (high or low) performance, and those with more volatile returns are more likely to be covered, and we examine these relationships in Table VI. The dependent variable is the fund's annual share of circulation-weighted cites relative to other funds in the same objective category. As expected, sheer media coverage is higher for larger funds, funds with higher fees, and funds with more volatile returns. The media seem to treat good and bad performers almost equally. The negative sign on the bottom quintile suggests a U-shaped relationship between performance and media attention. Extreme performance—whether high or low—gets media attention, and at almost the same rate. One cannot therefore attribute consumers' differential reaction to the top and bottom performers to media coverage biases.

[23] The nine financial periodicals include *Business Week, Changing Times, Consumer Reports, Financial World, Forbes, Fortune, Money, The Economist, and U.S. News and World Report*. The eleven newspapers include the *Chicago Tribune, Financial Times, Los Angeles Times, Newsday, St. Louis Post-Dispatch, St. Petersburg Times, The Boston Globe, The New York Times, The Washington Post, USA Today,* and *The Wall Street Journal*. The list of financial periodicals and newspapers was selected on the basis of their circulation figures and availability on Lexis/Nexis.

Table VI

The Determinants of the Share of Circulation-Weighted Media Citations Received by Equity Mutual Funds, 1971 through 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. The dependent variable in this OLS analysis is each fund's media share, defined as the share of circulation-weighted media citations received by each fund as a percentage of the total circulation-weighted media citations received by other funds with the same objective in each year. This measure is constructed from the number of stories about each fund appearing in Lexis-Nexis over the period 1971 to 1990 in twenty leading financial periodicals and newspapers, weighting each cite by that periodical's circulation. The independent variables used in the regressions include the log of fund i's total net assets in the prior period (Log lag $\text{TNA}_{i,t-1}$), the log of the total net assets of all funds in fund i's complex in the prior period (Log lag complex $\text{TNA}_{i,t-1}$), the standard deviation of monthly returns, and the total fees charged (expense ratio plus amortized load). The regression includes the fractional performance rank (RANK_t) of fund i based on raw returns in the preceding year. The performance ranks are divided into three unequal groupings. The bottom performance grouping (LOWPERF) is the lowest quintile of performance, defined as $\text{Min}(\text{RANK}_{t-1}, 0.2)$. The middle three performance quintiles are combined into one grouping (MIDPERF) defined as Min (0.6, RANK − LOWPERF), and the highest performance quintile (HIGHPERF) is defined as RANK − (LOWPERF + MIDPERF). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the performance-growth relationship over their range of sensitivity. p-values are given in parentheses below the coefficient estimates.

Independent Variable	Coefficient (p-value)
Intercept	0.001
	(0.534)
Log lag TNA	0.003
	(0.000)
Total fees	0.001
	(0.061)
Std. dev. of monthly returns	0.027
	(0.066)
Log lag complex TNA	−0.001
	(0.000)
Bottom performance quintile (LOWPERF)	−0.019
	(0.044)
Middle three performance quintiles (MIDPERF)	0.002
	(0.327)
Top performance quintile (HIGHPERF)	0.028
	(0.000)
Adjusted R^2	4.39%
Number of observations	3305

Table VII shows the impact of media attention on fund flows, using contemporaneous media coverage, prior media coverage, and residual prior media coverage. Residual prior media coverage is the residuals from the regression shown in Table VI, which therefore captures the portion of media coverage that is unrelated to performance, fund size, and fund riskiness. We use prior year media coverage as well as the residual of prior year media coverage to address the fact that current period media coverage may be endogenous. As before, we include not only the level of coverage, but also a set of interaction terms that combine media dummy variables with fund performance. To capture the impact of being in the spotlight, the media dummy equals one if the fund is above the median in terms of share of media coverage. (We also try specifications where the media dummy equals 1 if media coverage is in the top decile or top quartile of all funds in that objective.)

Table VII provides mixed support for the notion that media attention is an important determinant of search costs and funds flows. In column (A), we see a very strong relationship between the level of current media attention and the growth of funds. However, this contemporaneous relationship cannot be interpreted as a causal one. Although media attention may lead to higher fund flows, higher flows could also lead to more media attention. However, even using current year media attention, there is no differential performance-flow response between funds receiving more and less media attention.

To try to control for this simultaneity problem, we include a dummy variable for prior year media coverage, LAGMED, in column (B), and in column (C) the residual of prior year media coverage, RESMED, as calculated by the regression in Table VI. In neither case do we find a significant relationship between flows and past levels of media attention. We also fail to find any significant difference in the performance-flow relationship between funds receiving more and less media attention. (Though not reported here, these results do not change when we use the top quartile or decile of media attention to define the interaction terms.)

One possible interpretation of these results is that media attention has a very short half-life, in that current media may matter, but being last years' media darling may be unimportant to consumers with short memories. Alternatively, our media variable may be too weak in that it fails to discriminate between stories that are positive, negative, or neutral about funds. A third conjecture is that media coverage of the mutual fund industry has increased over the years, and it is inappropriate to average across the nearly two decades of results as we do with the Fama–MacBeth procedure. Therefore, we also run the regressions in Table VII year by year. We do not observe any systematic pattern in the by-year analyses, except that in the 1980s the coefficient on the interaction term representing the dummy for the top quartile media times the top quintile performance is significantly positive for over half of the years. However, with the annual data we do not observe a strong relation for other media breakdowns (e.g., above median), nor do we find a consistent relationship between flows and lagged media or residual media share. Therefore, we are reluctant to overinterpret this finding.

F. Spillover effects

As a final exploration of the costly search problem, we consider whether a fund family is able to lower search costs for a particular fund by enjoying "halo effects" from other funds in the complex that perform well. This

Table VII

The Impact of the Amount of Media Attention Received by Funds on Their Growth, 1971 through 1990

The sample includes open-end U.S. funds that have an investment objective of aggressive growth, growth and income, or long-term growth, as classified by the Investment Company Data Institute. The table reports OLS coefficient estimates for separate regressions using the growth rate of net new money as the dependent variable, which is defined as $(TNA_{i,t} - TNA_{i,t-1}) * (1 + R_{i,t})/(TNA_{i,t-1})$, where $TNA_{i,t}$ is fund i's total net assets at time t, and $R_{i,t}$ is the raw return of fund i in period t. The independent variables used in the regressions include the log of fund i's total net assets in the prior period (Log lag $TNA_{i,t-1}$), the log of the total net assets of all funds in fund i's complex in the prior period (Log lag complex $TNA_{i,t-1}$), the growth rate of net new money for all funds in the same investment category as fund i (Flows to fund category), the standard deviation of monthly returns, the total fees charged (expense ratio plus amortized load), and changes in total fees. The regressions include measures of the fractional performance rank ($RANK_t$) of fund i based on raw returns in the preceding year. The performance ranks are divided into three unequal groupings. The bottom performance grouping (LOWPERF) is the lowest quintile of performance, defined as $\mathrm{Min}(RANK_{t-1}, 0.2)$. The middle three performance quintiles are combined into one grouping (MIDPERF) defined as Min (0.6, RANK − LOWPERF), and the highest performance quintile (HIGHPERF) is defined as RANK − (LOWPERF + MIDPERF). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the performance-growth relationship over their range of sensitivity. The additional independent variables in this table attempt to capture the extent of search costs faced by consumers. In column A, we add each fund's media share (Share of media by objective), defined as the share of circulation-weighted media citations received by each fund as a percentage of the total circulation-weighted media citations received by other funds with the same objective in each year, and interaction terms equal to the product of the three performance groupings with an indicator variable (CURMED) that equals one only if the fund is in the 90th percentile of media attention that year for its objective category. In column B, we add each fund's lagged media share (Lagged share of media by objective) and interaction terms equal to the product of the three performance groupings with an indicator variable (LAGMED) that equals one only if the fund is in the 90th percentile of media attention for the previous year for its objective category. In column C, we add an independent variable defined using the regression specified in Table VI as the residual of the regression of media attention on a group of independent variables (Lagged residual share of media), and interaction terms equal to the product of the performance groupings with an indicator variable (RESMED) that equals one only if the fund has a media regression residual in the 90th percentile of all media residuals for the previous year for its objective category. These regressions are run year-by-year, and standard errors and t-statistics are calculated from the vector of annual results, as in Fama and MacBeth (1973). p-values are given in parentheses below the coefficient estimates.

	(A)	(B)	(C)
Intercept	0.104	0.257	0.041
	(0.196)	(0.228)	(0.507)
Log lag TNA	−0.102	−0.080	−0.053
	(0.000)	(0.000)	(0.000)
Log lag complex TNA	0.044	0.069	0.027
	(0.004)	(0.065)	(0.000)
Flows to fund category	0.383	4.943	0.979
	(0.632)	(0.214)	(0.011)
Std. dev. of returns	−0.599	−1.058	−0.476
	(0.321)	(0.223)	(0.419)
Total fees	−0.007	−0.146	−0.017
	(0.722)	(0.267)	(0.253)
Change in total fees	0.048	0.056	−0.049
	(0.725)	(0.665)	(0.152)

Table VII—*Continued*

	(A)	(B)	(C)
Bottom performance quintile (LOWPERF)	−0.038	5.101	0.202
	(0.919)	(0.333)	(0.108)
Middle three performance quintiles (MIDPERF)	0.136	−1.771	0.116
	(0.144)	(0.365)	(0.027)
Top performance quintile (HIGHPERF)	1.509	1.314	0.951
	(0.009)	(0.117)	(0.002)
Level of media attention			
Share of media by objective	3.055	—	—
	(0.001)		
Lagged share of media by objective	—	0.997	—
		(0.262)	
Lagged residual of share of media	—	—	1.360
			(0.262)
Interaction terms: Media times performance			
Current media above median times			
Bottom quartile performance	0.143	—	—
(LOWPERF ∗ CURMED)	(0.634)		
Middle three quartiles performance	0.008	—	—
(MIDPERF ∗ CURMED)	(0.952)		
Top quartile performance	0.341	—	—
(HIGHPERF ∗ CURMED)	(0.738)		
Prior year media above median times			
Bottom quartile performance	—	−4.850	—
(LOWPERF ∗ LAGMED)		(0.352)	
Middle three quartiles performance	—	1.977	—
(MIDPERF ∗ LAGMED)		(0.332)	
Top quartile performance	—	0.165	—
(HIGHPERF ∗ LAGMED)		(0.882)	
Prior year residual media above median times			
Bottom quartile performance	—	—	−0.087
(LOWPERF ∗ RESMED)			(0.375)
Middle three quartiles performance	—	—	0.092
(MIDPERF ∗ RESMED)			(0.211)
Top quartile performance	—	—	0.479
(HIGHPERF ∗ RESMED)			(0.300)
Adjusted R^2	18.2%	24.1%	20.0%
Number of observations	3129	2993	2825

is related to the media effects described above. If a fund performs well, investors learn not just about the fund itself but also about the fund family. Thus, if the T. Rowe Price New Horizons fund performs extremely well in period $t-1$, this may benefit not only the New Horizons fund in period t but also other funds in the T. Rowe Price family because the fund family name appears in the media alongside the actual fund name. We conjecture that such media results may lead to increased flows for other equity funds in the complex, and term this effect a "performance spillover."

To search empirically for such an effect, in each year we identify those funds that are in the top 2.5 percent, top 5 percent, or top 10 percent of all funds in their investment category, depending on the specification. We then form dummy variables that take on the value of 1 if *another* fund in its family is in this performance group, and a value of 0 otherwise. We then reestimate the model from Table II, column (B), including the spillover variable. The interpretation of the coefficient on the new variable is the additional flow going to a fund that has a related fund in the top performance group of our sample.

The results are mixed and are not reported here. There is some weak evidence that performance spillovers exist because in some specifications the coefficient on the spillover variable is positive and significant, with values around 0.04. This suggests that, other things equal, a 4 percent additional flow would go to a mutual fund that was a member of a fund family that had a stellar-performing offering in another objective category. However, this coefficient is not robust across specifications, depending on the performance level we use to define the "star" fund that might cause spillovers. We suspect that, in part, the spillover variable is serving as a proxy for fund complex size. Though we explicitly control for complex size in our regressions, this may not be a perfect control. Other things equal, a large complex with many funds is more likely to have a fund fall into the top grouping than would a small complex. This is not an artifact: It may be one of the real benefits of selling funds through a large complex and established brand name. We conclude that though our data are suggestive of the presence of spillover effects, the results are not strong enough to make a definitive statement about their impact.

III. Summary and Implications for Future Research

This study of the determinants of flows into equity mutual funds over two decades suggests a number of intriguing findings. We find that consumers of equity funds disproportionately flock to high performing funds while failing to flee lower performing funds at the same rate. Flows are fee-sensitive, but consumers' response to fees is also asymmetric in that they respond differently to high and low fees, as well as to fee increases and decreases. Finally, there is some evidence that consumers respond to the risk of their portfolios, which may offset—but may not eliminate—managers' incentives to increase fund volatility.

Gruber (1996) finds evidence that the aggregate pattern of consumer investing behavior is rational. He finds that were investors to invest in funds receiving inflows, and to disinvest from those experiencing outflows, they would earn a risk-adjusted return that beats passive index funds, even after fees.[24] To the extent that mutual fund investors succeed as

[24] Also see Zheng (1998), whose results on small funds are consistent with Gruber's findings. Shefrin and Statman's (1985) disposition effect, i.e., the propensity of investors to fail to recognize poor performers quickly enough, would produce a similar performance-flow relationship.

active managers, part of the credit must go to marketing, which seems related to the pronounced performance-flow sensitivity of consumers. Though we can assume away search costs and posit that consumers are highly informed about their current and potential investments, empirical evidence such as that of Capon et al. (1996) and others suggests that this is a heroic assumption.[25] We provide evidence consistent with the hypothesis that mutual fund flows are affected by factors related to the search costs that consumers must bear. We find that high-fee funds, which presumably spend much more on marketing than their rivals, enjoy a much stronger performance-flow relationship than do their rivals. Because percentage fees tend to decline as funds grow, this is not an effect driven by fund size. We believe this suggests that aiming a marketing spotlight on fund performance may explain why consumers flock to winners. It is also plausible that because marketing rarely illuminates poorer performers, those funds are relatively less performance-sensitive.

We study the media coverage of mutual funds and find some evidence that garnering a larger share of current media cites is related to faster current growth. Though we cannot easily disentangle within a single year the direction of causality, these results are suggestive of some relationship between media coverage and fund flows, which could be the basis for future research. We begin this analysis by analyzing the determinants of media attention, finding that the financial press's coverage of funds is weighted toward larger funds, funds from larger complexes, and more volatile funds. Yet, we find that media coverage is fairly evenhanded about covering performance. Funds whose performance is either very strong or very weak seem to be equally newsworthy (in terms of cites), though those in between receive less attention. If the media are important determinants of consumer decisions, they probably deserve much more attention in the finance literature than our simple count of the thousands of stories over twenty years.

Finally, though most studies of mutual funds treat funds as separate business entities, our research recognizes that funds are typically part of a large fund complex, such as Fidelity Investments, Vanguard Group, or Merrill Lynch Asset Management. We find that membership in a large complex is an important determinant of fund flows in the pre-1990 period, and one interpretation of this result is that the larger complexes reduce consumers' search costs for funds. An equally plausible interpretation of these results would be that the services complexes provide are an important determinant of consumer financial decisions. In either event, we believe that future research must recognize that the structure and organization of the industry may have a large impact on the decisions that individual investors make.

[25] See Goetzmann and Peles (1997) for a study of the information that consumers have about their mutual fund investments.

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