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Investor risk evaluation in the determination of management incentives in the mutual fund industry

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Abstract

This paper examines the way in which investors evaluate risk in deciding which mutual funds to invest. New fund investment is found to be positively related to a distributed lag of past fund performance with a strong degree of inertia. The relationship is mostly linear with significant nonlinearities at the upper (and possibly the lower) end of the performance spectrum. Investors appear to use publicly available data in a way that is consistent with the theory, giving equal weight in their decisions to the return and market risk components of the performance measure, while ignoring diversifiable risk. Finally, it is shown that improved performance in any year has a significant impact on the earnings of the management company. Because managers are rewarded on the basis of risk adjusted returns, risk neutral managers have no incentive to manipulate risk, except at very high performance levels. © 2000 Published by Elsevier Science B.V. All rights reserved.

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1. Introduction

Driven by the boom in retirement savings, mutual funds now hold record assets of more than $5.5 trillion, exceeding bank deposits in the U.S. as well as the gross domestic products of Britain and Canada. Of this sum, about $2.98 trillion represents investment in the rapidly growing equity fund segment of the mutual fund market.[1] As the baby boomer generation ages and their disposable income continues to rise, the size of their investment in mutual funds is also expected to grow.

The way in which these investors evaluate risk in deciding which mutual funds to invest is important since, if investors discount risk either more or less than would be expected when making their investment decisions, fund managers will adjust the composition of their portfolios accordingly to improve their own well being. To address this problem, we estimate in this paper the flow of new capital into individual funds in response to different measures of performance. Using these results, we can then examine the incentives associated with the widely adopted asset-based compensation mechanisms.

A number of previous papers have looked at the relationship between the inflow of new investment into mutual funds and their past performance. Table 1 provides a summary of the methodologies used in these studies. In general, the dependent variable has been defined as the growth of new investment, measured as the net growth in fund assets beyond reinvested dividends.[2] We adopt the same measure in our paper for ease of comparison.

Generally, previous studies have used annual panel data but, except for Ippolito (1992), do not employ econometric panel procedures to disentangle the time series and cross-section effects. In particular, the studies by Berkowitz and Kotowitz (1993), Chevalier and Ellison (1997) and Goetzmann and Peles (1997) combine the time series and cross section effects, while Gruber (1996) and Sirri and Tufano (1998) use only the cross sectional information. The latter two papers, in particular, employ the Fama and MacBeth (1973) methodology by estimating the annual cross-sectional performance–flow relationship and then reporting the mean of the time series of the coefficient estimates.

Further, with the exception of Sirri and Tufano and Berkowitz and Kotowitz, other studies employ a single measure of performance, varying in sophistication from raw returns (Chevalier and Ellison and Goetzmann and Peles) to 4-index

[1] Refer to Investment Company Institute, *Mutual Fund Fact* Book, 1999 Edition, Washington, D.C.

[2] In a recent paper, Fant (1999) uses vector autoregressions to examine the relationship between the components of mutual fund flows and stock market returns. The author shows that the flow–return relationship exists exclusively between market returns and exchanges-in and -out, not for new sales and fund redemptions.

Table 1
Recent studies relating flow of new investment and past performance of funds

Column headings defined as follows:
Fixed Effects – Does the study use a fixed effects model?
Time Dummies – Does the study use time dummy variables?
Fama-MacBeth – Does the study employ the Fama-MacBeth methodology?
Perf. Measures – Which performance measures are used in the study?
Ranked/Abs. Performance – Does the study use ranked performance or absolute performance measures?
Time Varying Risk – Does the study incorporate time varying measures of risk?
Unit of Time – What unit of time is the data measured?

Study	Fixed effects	Time dummies	Fama-MacBeth	Perf. measure	Ranked/abs. perf	Time varying risk	Unit of time
Ippolito (1992)	Yes	Yes	No	Excess returns	Abs.	No	Annual
Berkowitz and Kotowitz (1993)	No	Yes	No	Jensen, Sharpe and Treynor	Abs	No	Annual
Gruber (1996)	No	No	Yes	4-Index alphas	Abs.	Yes	Annual
Chevalier and Ellison (1997)	No	No	No	Excess returns(no risk)	Abs.	No	Annual
Goetzmann and Peles (1997)	No	Yes	No	Raw returns	Ranked	No	Annual
Sirri and Tufano (1998)	No	Yes	Yes	Raw returns, mkt. excess returns, alpha	Ranked	Yes	Annual

alpha (Gruber), but none compare alternative performance measures or evaluate separately the effects of risk, with the exception of Berkowitz and Kotowitz, who were unable to distinguish among different performance measures due to high collinearity.

Regardless of the methodology and performance measure used, prior studies have found a significant effect of recent past performance on fund growth, though Goetzmann and Peles and Sirri and Tufano find that such effects are restricted to the top segments of the performance spectrum.

Our study differs from others in several important respects. By taking advantage of the panel properties of our database to run a fixed effects specification with quarterly data, we are able to examine the time series features of the performance–flow relationship. This allows us to account for the performance residuals possibly being correlated within funds over time and across funds within years, causing the standard errors on the coefficients to be understated. Throughout the paper, we estimate standard errors that are heteroskedastic-consistent to overcome potential heteroskedacity within the panel.[3] The fixed effects model takes account of the cross-sectional variation across funds and the addition of quarterly time dummy variables accounts for the variation over time which is common to all, or to subgroups of funds.[4] To account for the differential responsiveness to the time effects across funds with different investment objectives, the quarterly time dummy variables are crossed with each of the fund objective dummy variables.[5] This distinction proves important because the panel approach is less susceptible to problems of survivorship and omitted variables bias in the data.

We also explicitly evaluate the effects of risk on investment behavior by examining a number of alternative performance measures, each of which relies only upon readily accessible inputs, in order to determine which measure best predicts the future flow of funds. In analyzing the different performance measures, we differentiate between the return and risk components of each measure in order to see if consumers react to the risk–return relationship as the theory suggests they should.

Among the alternative performance measures examined in this paper, we show that, even when we separate the return and risk components, the Jensen alpha is the best predictor of future investment flows. Investors appear to use the publicly available data in a way that is consistent with the theory, giving equal weight in their decisions to the return and market risk components of the

[3] Refer to White (1980).

[4] We also tested the random coefficients model and found the fixed effects model to be superior according to the Hausman (1978) specification test.

[5] To allow for differential responsiveness of funds to time effects, Blake et al. (1999) measured the extent to which their time dummies were uncorrelated with fund specific dummies using a variance ratio statistic.

performance measure. We show, moreover, that improved performance in any year has a significant impact on the earnings of the management company.

The paper is organized as follows. Section 2 describes the determinants of mutual fund flows while Section 3 evaluates alternative performance criteria. Section 4 describes the data used in the study while Section 5 presents the empirical model. Section 6 presents the empirical results. Section 7 examines the specific incentive properties of asset-based mechanisms. Finally, Section 8 is by way of summary.

2. The determinants of mutual fund flows

Because most mutual fund companies use asset-based fee structures in which the aggregate fee collected is a fixed percentage of the net asset value of the fund, an understanding of those factors which determine the flow of investment into a fund is essential to an understanding of the incentives facing fund managers. We begin our investigation into the factors affecting fund choice with the premise that each investor attempts to forecast the future performance of the funds being considered and then allocates investable wealth accordingly.

Formally, investors are assumed to form their expectations of future performance on the basis of the performance information which they have available to them, namely past performance. In particular, we assume that expectations of future performance are based upon a simple distributed lag model in which the expected performance for fund i in period t ($\hat{x}_{it}$) is positively related to past performance:

$$\hat{x}_{it} = a_i + \sum_{j=1}^{p} b_j x_{it-j}, \tag{1}$$

where a_i is a fund specific time invariant factor, or vector of factors, that affects the fund's performance and x_{it-j} represents the actual performance of fund i in $t-j$.

Net percentage growth in fund i's assets (CF) is defined as the net growth in assets less reinvested earnings, i.e.,

$$\mathrm{CF}_{it} = \frac{\mathrm{NAV}_{it} - \mathrm{NAV}_{it-1}(1 + r_{it})}{\mathrm{NAV}_{it-1}}, \tag{2}$$

where NAV_{it} is fund i's net asset value at time t and r_{it} is the fund's net return over the previous period. Empirically, we analyze the relationship between the net percentage growth in fund i in period t and a number of alternative measures of expected performance measured relative to market or submarket benchmarks, controlling for other possible factors which might also influence consumers' investment behavior. In particular, the general model is

$$\begin{aligned}\mathrm{CF}_{it} &= (\hat{x}_{it}, z_{it-1}, z_i, z_{t-1})\\ &= (x_{it-1}, \dots, x_{it-p}, z_{it-1}, z_i, z_{t-1}),\end{aligned} \tag{3}$$

where z_{it-1} is a vector of fund i's attributes in $t-1$ used by individuals to make their investment decision (e.g., size of fund); z_i is a vector of fund attributes that are constant over time (e.g., load status of fund); and z_{t-1} is a vector of time related factors that affect all funds (e.g., overall new money flowing into the industry and market swings) or subsets of funds (e.g., flows to subgroups of funds such as technology, value, etc.).

In estimating Eq. (3), we are constrained by the availability of information on individual fund characteristics and the determinants of aggregate capital flows. As our focus is on the evaluation of risk, we chose to utilize the fixed effects model, which eliminates all fund specific fixed factors (z_i). Similarly, we use time dummies, which take the value of one for each quarter and zero otherwise, as opposed to separately modeling aggregate or group varying time effects (z_t) such as flows into all or subgroups of equity funds.

While this procedure is efficient in removing common time varying effects, it eliminates potential distinctions among performance measures based on different benchmarks, so that we cannot distinguish between raw returns and returns relative to a common benchmark (market index, risk-free rate, etc.). However, by introducing separate time dummies for different fund objectives, we are able to test for the possibility that investors use subgroup benchmarks in addition to average market benchmarks.

Two time varying attributes of individual funds (z_{it-1}) are used in the study. First, the logarithm of the size of the fund (measured by total net asset value) in the previous period is added as an explanatory variable in order to control for equal dollar flows having a larger percentage impact on smaller funds.[6]

Second, the variance of lagged returns is used as an instrument for the magnitude of estimation error in the right-hand-side parameter estimates and to mitigate some of the potential problems due to survivorship bias in our data.[7]

The resulting basic linear model is:

$$\begin{aligned}\mathrm{CF}_{it} = a_{0i} &+ \sum_{j=1}^{p} a_j x_{it-j} + a_{r+1}\mathrm{LNAV}_{it-1} + a_{r+2}\mathrm{VAR}_{it-1}\\ &+ \sum_{T=14}^{q} b_{1T} D_T + \sum_{k=1}^{r}\sum_{T=14}^{q} c_{kT} d_k D_T + \tilde{\varepsilon}_{it},\end{aligned} \tag{4}$$

[6] Sirri and Tufano (1998), among others, included the log of total net assets in period $t-1$ as a control reflecting the fact that an equal dollar flow will have a larger percentage impact on smaller funds. Their results support this hypothesis.

[7] Survivorship bias issues are discussed in Section 4.

where $E(\tilde{\varepsilon}_{it}/x_{it}, x_{it-1}) = 0$ and all other explanatory variables are assumed uncorrelated with $\tilde{\varepsilon}_{it}$. Further, x_{it-j} represents performance of fund i in period $t-j$; LNAV_{it-1} is the logarithm of the quarterly net asset value of fund i in $t-1$; and VAR_{it-1} is the variance of the fund's quarterly return evaluated at $t-1$. The parameter p represents the optimal number of lags in performance; q is the last quarter; and r is the number of alternative fund types. D_t represents quarterly time dummy variables equal to 1 if $t = T$ and zero otherwise. Dummy variable d_k equals 1 when the fund has the specific objective (aggressive growth, growth & income and small company) and is equal to zero otherwise.

3. The evaluation of performance

The issue of the "correct" measure of performance bedevils much of the theoretical and empirical literature. The first problem involves the nature of the valuation and the relevant components of risk which are appropriate for discounting raw returns. The correct relationship between risk and return remains unresolved as do questions regarding the correct measure of risk to use and how to account for shifting parameters of the performance measure when portfolios are actively managed. While various studies have analyzed the components of investment performance, we believe that most investors in mutual funds lack the required information to determine the components of these measures and therefore do not use this information to determine their allocation of resources to alternative funds.[8] In the choice of measures, we have concentrated on relatively simple metrics based upon information that is generally available to investors.

Second, the relationship between *ex ante* and *ex post* measures of risk is problematic. In contrast to most empirical studies which evaluate *ex post* performance using a measure of variance, or beta, calculated over the entire *ex post* period, we focus on the *ex ante* evaluation of risk based upon the information available at the time. To do this, we use a time varying measure of beta (or standard deviation) for each fund estimated over the prior 36 month period. As can be seen from Fig. 1, these beta estimates vary considerably over the period, from an average fund high within the sample of 1.14 in 92 : 4 to an average fund low of 0.95 in 89:1. This introduces variation over time into the individual fund risk measures in addition to the variation across funds

[8] As of year end 1997, U.S. households owned 78.4% of the mutual fund industry's assets. According to the Investment Company Institute, *1998 Mutual Fund Fact Book*, a study conducted by them in 1995 found that the average mutual fund investor is middle class, 44 years old, has typically purchased the funds through a salesperson, and has a long term investment horizon primarily with a retirement objective.

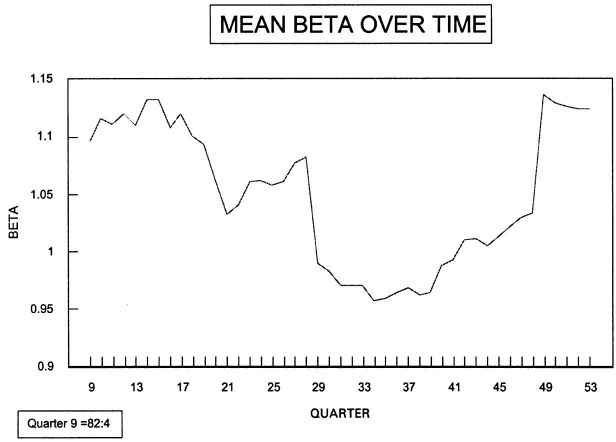

Fig. 1.

and should help in identifying the effects of risk even in the presence of group time dummies.

We examine four commonly used performance measures that require inputs that are readily available to investors: raw returns, Jensen's alpha, the Sharpe measure, and the Treynor-Black measure.[9] It is important to note here that the coefficients on the raw returns variables are net of the time dummy effects and thus measure the effects of returns relative to market or group benchmarks. We then separate the risk and return components of the Jensen, Sharpe, and Treynor-Black measures to see if investors behave as the theory predicts, i.e., that the coefficients on return and risk are equal and opposite in sign. If our hypothesis about investor behavior is correct, the results of this study should provide some insight into the way mutual fund investors evaluate risk, regardless of the theoretical justification for such evaluation.

4. Description of data

The sample of mutual funds used in this study was derived from two sources. The Morningstar (June 1994) OnDisk provided monthly return (r_i) data on 1174 U.S. equity funds over the period January 1976–December 1993. Quarterly net asset values (NAV) were obtained from Lipper Analytical Securities for equity funds over the period 1980:4 to 1993:4. We limited the study to general U.S.

[9] Jobson and Korkie (1981) have shown that the Treynor measure has poor sampling properties so it was excluded from our analysis.

equity funds so that we constructed a merged data base consisting of aggressive growth, growth, growth and income, small company growth and equity-income funds common to both the Morningstar and Lipper data bases.[10] This resulted in an unbalanced panel consisting of 860 funds that survived to December 1993. We further restricted the available sample because of both the number of lags used in the estimation procedure and the calculation of rolling betas and standard deviations over the prior 36 months.

As a result, our sample consists of 348 funds with 9234 fund-quarters of data which is described in Table 2. Our sub-sample is quite similar to the overall sample of U.S. equity firms in the Morningstar database with respect to load and fund objective. However, the need for sufficient data to calculate the time varying risk measures used to estimate our model resulted in a somewhat underweighting of small and young funds.

Since our sample consists of only those funds that survived to December 1993, our results may suffer from survivorship bias because good performers tend to survive while poor performers do not. There are two sources of this potential survivorship bias. The first may arise if investors' fund allocations in response to the performance on non survivors (during their existence) is different than the response to the performance of survivors. The second is concerned with the pattern of censorship in the data for the surviving funds which may induce a J-shaped relationship between performance in one period and that in another period.[11] Given our data, we cannot offer any evidence on the first problem. However, both Goetzmann and Peles (1997) and Sirri and Tufano (1998) found no significant survivor bias for the fund growth equations in their studies.

The censorship problem was identified by Hendricks et al. (1997) who describe how a pattern of censorship can induce a J-shaped response relating performance in one period to that in another and consequently affect the relationship between past performance and fund growth. Brown et al. (1997) show that this nonlinearity in response is specifically related to the second moment of the distribution of performance measures.[12] To mitigate this problem, we used the variance of lagged returns as an explanatory variable in the model.

[10] Sectoral and other specialty funds are excluded from the sample.

[11] The J-shape was first pointed out by Hendricks et al. (1997).

[12] In an earlier study, Brown et al. (1992) demonstrate that, if fund volatility is constant over time but varies cross-sectionally, and if funds disappear each period on the basis of whether their performance that period falls into the bottom fraction of funds, then survivorship induces spurious persistence. Conditional on survival, the best funds tend to have high volatility. Thus, in a sample of surviving funds, those that tend to win in the first period tend to have higher volatility and subsequently also win in the second period.

Table 2
Comparison by alternative fund characteristics of the 348 fund sub-sample used in estimation with the overall sample of 1174 equity funds on the June 1994 Morningstar OnDisk.

	Morningstar	%	Sub-sample	%
Size ($MM)				
5000 +	15	1.2	11	3.2
1000–4999	93	8	60	17.2
500–999	91	7.9	56	16.1
100–499	346	29.6	113	32.5
50–99	200	17.1	53	15.2
10–49	273	23.4	40	11.5
10-	150	12.8	15	4.3
Objective				
Aggressive growth	70	6	53	15.2
Growth	542	46.2	141	40.5
Growth & income	297	25.3	111	31.9
Small company	186	15.8	43	12.4
Equity income	79	6.7	0	0
Load				
Front-end	444	37.8	155	44.5
Deferred	138	11.8	31	8.9
No-load	592	50.4	162	46.6
Age of Fund (Years)				
50 +	40	3.4	34	9.8
30–49	78	6.6	65	18.7
10–29	251	21.4	210	60.3
5–9	292	24.9	39	11.2
3–4	193	16.4	0	0
2	203	17.3	0	0
1	117	10	0	0

5. Empirical model

We first estimate the linear version of the model (Eq. (4)), to test for the significance of the group time dummies and the time pattern of response. We then expand the model to allow for the presence of nonlinearities in the performance variables as well as for the possibility that the performance coefficients may vary across funds. The existence of nonlinear responses has been documented by previous studies (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Goetzmann and Peles, 1997) which have suggested that investment tends to flow into past winners (top decile) and out of past losers (bottom decile). In addition, the strength of response to past performance may vary among different fund types. For example, investors in load funds, which are frequently purchased on the advice of brokers and financial advisers, may respond to past performance differently than those which invest in no load funds.

We use the following equation to empirically estimate the general model in (3):

$$\mathrm{CF}_{it} = a_{0i} + \sum_{j=1}^{12} a_j x_{it-j}\left[1 + \sum_{k=1}^{4} c_k d_k + c_5 H_{it-j} + c_6 L_{it-j}\right] + \sum_{T=1}^{53} b_{1T} D_T + \sum_{k=1}^{3}\sum_{T=1}^{53} c_{kT} d_k D_T + a_{13}\mathrm{LNAV}_{it-1} + a_{14}\mathrm{VAR}_{it-1} + \tilde{\varepsilon}_{it}, \tag{5}$$

where $E(\tilde{\varepsilon}_{it}/x_{it}, x_{it-1}) = 0$ and all other explanatory variables are assumed uncorrelated with $\tilde{\varepsilon}_{it}$. Each of the variables above is defined as in the basic linear model with the addition of d_4 being a dummy variable equal to one for load funds and zero otherwise. The H and L terms will be defined shortly.

We examine the hypothesis that the a_j coefficients are functions of specific attributes by crossing them with 4 alternative fund characteristics (d_k), e.g., load and fund objective. This introduces a nonlinearity in the coefficients so that OLS can no longer be used. Instead, we adopt a nonlinear estimation technique to jointly estimate the coefficients of the lagged performance variables (*aj*'s) and the coefficient of each attribute, d_k.

Furthermore, investors may respond to past performance in a nonlinear fashion, giving greater weight to extreme performance, possibly because of increased publicity. For example, funds are more likely to heavily advertize superior performance and avoid advertizing poor performance. In addition, the financial press tends to highlight extreme performances at either end of the spectrum. Consequently, the nature of the nonlinearity may be different for positive and negative performance.[13] We test for this possibility by separating the performance distribution into piecewise linear segments where H and L represent dummy variables equal to one if the corresponding value of performance is above some critical value or below some critical value, respectively, and zero otherwise.

6. Empirical results

This section is organized as follows: We use a linear approximation of the base Eq. (4) to establish the appropriate lag structure and to determine the best of the suggested measures of performance. Using the chosen lag structure and

[13] Ippolito (1992) and Chevalier and Ellison (1997) have shown that the flow–performance relationship appears to be nonlinear.

performance measure, we estimate different variants of Eq. (4) and look for nonlinearities in the functional relationship, and analyze investors' risk discounts.

6.1. Lag structure

We examined alternative lag structures for past performance measures using the fixed coefficient model with group time dummy variables to denote the quarter. Twelve quarters of lagged performance variables appear to be relevant to investors' decisions with higher weights given to more recent performance levels. The lagged coefficients are highly significant at conventional levels and this lag structure is insensitive to the inclusion of group time dummies and to the use of alternative performance measures.

We also estimated the equations using the average performance over the prior three years in place of the quarterly performance variables. The hypothesis that the quarterly coefficients are equal is rejected in all cases. For example, the hypothesis is rejected at the 1% level ($F_{12,8895} = 11.488$) with the Jensen performance measure. Thus, use of an average one (or three) year performance measure which is common in other studies, might be misleading in this application.

6.2. Performance evaluation

We next examine the question of investors' evaluation of performance. We first tested the significance of the group time dummies in order to allow for the possibility that investors use different benchmarks for different types of funds. Regardless of the performance measure used, we cannot reject the hypothesis that the coefficients of the individual group time dummies are similar to each other, with the exception of the aggressive growth funds.[14] We also note that other coefficients are insensitive to the inclusion of the individual group dummies. We therefore present the results with separate time dummies for aggressive growth funds and for all other funds in aggregate.

Tables 3 and 4 compare and contrast the roles of the four performance measures in the linear version of Eq. (4).[15] By the usual criteria, the results are

[14] F-tests were performed for the inclusion of the group time dummy variables with each of the four performance measures. The results suggest that, irrespective of the performance measure used, only the Aggressive Growth fund type-time dummies were significantly different from zero as a group. For the Jensen measure, $F_{40,8789} = 3.879$ which is significant at the 1% level.

[15] For ease of comparison of the coefficients across performance measures, the Sharpe and Treynor-Black performance coefficients are neutrally scaled. This is done by dividing each of the lagged raw coefficients by the average standard deviation of the return over the 12 lag periods for the Sharpe measure, or the average standard deviation of the residual for the Treynor-Black measure.

Table 3
Tests of the percentage change in cash flows due to historical quarterly performance of funds

This table presents the results from estimating the regression given by

$$\mathrm{CF}_{it} = a_{0i} + \sum_{j=1}^{12} a_j x_{it-j} + b_{13}\mathrm{LNAV}_{it-1} + b_{14}\mathrm{VAR}_{it-1} + \sum_{t=14}^{53} c_{1t} D_t + \sum_{t=14}^{53} c_{2t} D_{it} + \tilde{\varepsilon}_{it}$$

where $E(\varepsilon_{it}/x_{it}, x_{it-1}) = 0$ and all other explanatory variables are assumed uncorrelated with $\tilde{\varepsilon}_{it}$. The dependent variable, CF_{it}, is measured as $(\mathrm{NAV}_{it}/\mathrm{NAV}_{i,t-1}) - (1 + R_{it})$. Alternative performance measures used include: Raw Returns $= R_{it}$; Jensen $= R_{it} - \beta_{it}(R_{Mt} - R_{ft}) - R_{ft}$; Sharpe $= (R_{it} - R_{ft})/\sigma(R_{it})$; and Treynor-Black $= [R_{it} - \beta_{it}(R_{Mt} - R_{ft}) - R_{ft}]/\sigma(\varepsilon_{it})$. LNAV_{t-1} is the logarithm of the quarterly net asset value of the fund in $t-1$; VAR_{t-1} is the variance of the fund's quarterly return evaluated at $t-1$. D_t represent quarterly time dummy variables and D_{it} are dummy variables representing the Aggregate Growth objective dummy variable times the quarterly time dummy variable in t. T-statistics in parentheses.

	Performance measure			
	Raw Ret.	Jensen	Sharpe	Treynor-Black
X_{t-1}	0.343 (8.650)	0.428 (9.296)	0.381 (9.100)	0.315 (8.523)
X_{t-2}	0.295 (5.908)	0.363 (6.696)	0.355 (7.581)	0.333 (8.521)
X_{t-3}	0.299 (7.454)	0.338 (6.958)	0.324 (6.996)	0.313 (6.978)
X_{t-4}	0.385 (4.191)	0.408 (3.671)	0.377 (5.624)	0.338 (7.332)
X_{t-5}	0.227 (5.344)	0.187 (4.229)	0.204 (4.711)	0.195 (5.098)
X_{t-6}	0.170 (4.820)	0.161 (3.544)	0.166 (3.955)	0.156 (3.869)
X_{t-7}	0.197 (5.322)	0.176 (4.469)	0.162 (4.318)	0.153 (4.732)
X_{t-8}	0.194 (5.907)	0.175 (4.611)	0.196 (4.697)	0.186 (5.157)
X_{t-9}	0.110 (3.094)	0.095 (2.222)	0.083 (2.253)	0.087 (2.602)
X_{t-10}	0.098 (2.454)	0.074 (1.939)	0.058 (1.367)	0.068 (2.038)
X_{t-11}	0.076 (2.702)	0.102 (2.818)	0.094 (2.758)	0.107 (3.434)
X_{t-12}	0.049 (1.369)	0.101 (2.733)	0.099 (2.743)	0.100 (2.973)
LNAV_{t-1}	− 0.018 (− 2.723)	− 0.019 (− 2.723)	− 0.016 (− 2.337)	− 0.016 (− 2.251)
VAR_{t-1}	0.00004 (0.426)	0.0003 (2.244)	0.0002 (1.862)	0.0002 (1.995)
Adj. R^2	0.1980	0.2046	0.1997	0.1900

Table 4
J-tests for alternative composite performance measures. Null hypothesis: Alternative measure adds no explanatory power. T-statistics in parentheses.

	Alternative composite performance measures			
Performance measures	Jensen	Raw returns	Treynor-black	Sharpe
Jensen		– 0.159 (– 1.192)	– 0.347 (– 1.313)	0.143 (0.457)
Raw returns	1.181 (7.716)			
Treynor-black	1.304 (4.574)			
Sharpe ratio	1.048 (2.850)			

highly significant and support the model. Table 4 reports on the J-test for non-nested alternative specifications to see if one specification is superior to the others.[16] The results suggest that the Jensen measure dominates the alternative specifications. The addition of either of the three alternative performance measures provides no additional explanatory power relative to the model based on the Jensen measure alone. Similarly, the Jensen measure provides significant explanatory power when added to each of the alternative. These results suggest that systematic risk indeed matters to investors in determining the performance of their investment portfolios.

To examine further how investors evaluate risk, the Jensen measure was separated into its risk and return components. The coefficients on the risk measure are all negative and most are significantly different than zero, supporting the hypothesis that investors discount market risk. Moreover, an F-test comparing the results of the separated Jensen measure with the simple composite Jensen measure yields a value of $F_{12,8963} = 1.116$, thus failing to reject the hypothesis that all the coefficients on return and risk are equal and opposite in sign for all quarters. It appears that the implicit model of choice for consumers is the composite Jensen measure. The superiority of the Jensen measure suggests that investors ignore diversifiable risk and discount market risk in accordance with theory.

This implies an unexpected degree of sophistication on the part of investors. One possible reason for this finding is that even naive investors in mutual funds rely upon published performance ratings (e.g., Morningstar's ratings) which are

[16] Davidson and MacKinnon (1981).

based upon the same inputs that are used to construct the Jensen measure. Since we do not have a time series for such ratings, we were unable to test this proposition directly. However, for cross-sectional data as of December 1993, we found a correlation of 0.74 between the Morningstar rating and the relevant 3-year alpha, which lends weak support to this hypothesis.

The inclusion of the variance of return term in the model has two effects. It controls for possible differential risk associated with survivorship bias in the data and it also provides an indication of the consumers' discount of overall risk, even in the raw returns model. As can be seen in the Jensen model, the coefficient of VAR_{t-1} is positive, which perhaps represents the expected effect resulting from survivorship bias in the data since this measure already discounts market risk. In contrast, the coefficient is just about zero for the raw return results, perhaps suggesting that the risk discount just about offsets the survivorship bias.

In each model, the coefficient of the logarithm of the size variable is significant and negative, implying that larger funds grow more slowly. However, as the dependent variable approximates the change in the logarithm of size (less the current quarterly return), the coefficient on the logarithm of size measures the departure from unit root, so cannot be evaluated by standard t-tests. Unfortunately, there are apparently no appropriate tests available for panel procedures. However, treating the observations as if they were a consecutive time series enables us to use the Dickey-Fuller statistic to test for significance. Using this test suggests that the size coefficients are only marginally significant.[17] In addition, the magnitude of the effect is quite small, less than 2% per quarter, suggesting that persistence in fund assets is the dominant effect. Given the superiority of the Jensen measure in Table 3, we restricted further testing of nonlinearity and fund attribute effects to the Jensen measure.

6.3. Other fund attributes

The basic model in (5) allows us to control for other fund attributes which might also affect the flow of new investment into funds. Table 5 presents the results controlling for the load characteristics of the fund and the fund objective.[18] We find a significant difference in the responses of investors to the past

[17] The Dickey-Fuller critical values are -2.86 at the 5% significance level and -2.57 at the 10% level. Once performance is differentiated for aggressive growth funds, the coefficients of LNAV_{t-1} in Table 5 are clearly not unit root. Because of the possible statistical problems with this variable, we also estimated all the equations without it and the results are not substantially different from those presented.

[18] Other fund attributes (e.g., tenure of manager as of December 1993, age of fund, and management company) were also examined with none of these variables exhibiting significant additional explanatory power. We also examined the effect of excluding funds with minimum initial investments of at least $25,000 as did Chevalier and Ellison (1997), but unlike these authors, we found our results robust to the inclusion of these funds.

Table 5
Tests of the percentage change in cash flows due to historical values of performance as measured by the Jensen alpha and alternative fund characteristics.

$$\mathrm{CF}_{it} = a_{0i} + \sum_{j=1}^{12} b_j \mathrm{ALPHA}_{it-j} + b_{13}\mathrm{LNAV}_{it-1} + b_{14}\mathrm{VAR}_{it-1} + b_{15}\sum_{j=1}^{12} \mathrm{DALPHA}_{it-j} + b_{16}\sum_{j=1}^{12} \mathrm{NALPHA}_{it-j}$$
$$+ b_{17}\mathrm{LOAD}*\sum_{j=1}^{12} \mathrm{ALPHA}_{it-j} + b_{18}\mathrm{AGGRTH}*\sum_{j=1}^{12} \mathrm{ALPHA}_{it-j} + \sum_{t=14}^{53} c_{1t}D_t + \sum_{t=14}^{53} c_{2t}D_{it} + \tilde{\varepsilon}_{it}$$

The dependent variable, CF_{it}, is measured as $(\mathrm{NAV}_{it}/\mathrm{NAV}_{i,t-1}) - (1 + R_{it})$. The Jensen alpha is defined as $R_{it} - \beta_{it}(R_{Mt} - R_{ft}) - R_{ft}$. LOAD is the dummy variable for those funds which charge either front-end or rear-end load fees. AGGRTH is the dummy variable referring to Aggressive Growth funds where $E(\tilde{\varepsilon}_{it}/x_{it}, x_{it-1}) = 0$ and all other explanatory variables are assumed uncorrelated with $\tilde{\varepsilon}_{it}$. LNAV_{t-1} is the logarithm of the quarterly net asset value of the fund in $t-1$. VAR_{t-1} is the variance of the quarterly return for fund evaluated at $t-1$. D_t represent quarterly time dummy variables and D_{it} are dummy variables representing the Aggregate Growth objective dummy variable times the quarterly time dummy variable in t. DALPHA is the excess return for those funds with values of alpha $\geqslant 0.15$ and NALPHA is the excess return for those funds with values of alpha $\leqslant -0.10$. T-statistics in parentheses.

	1	2	3	4	5	6	7	8
ALPHA_{t-1}	0.428	0.320	0.479	0.356	0.414	0.375	0.283	0.335
	(9.296)	(9.629)	(10.225)	(9.804)	(9.743)	(9.290)	(8.996)	(8.686)
ALPHA_{t-2}	0.363	0.272	0.429	0.330	0.387	0.323	0.249	0.297
	(6.696)	(8.768)	(9.372)	(9.368)	(9.054)	(8.550)	(8.434)	(8.170)
ALPHA_{t-3}	0.338	0.285	0.429	0.284	0.343	0.342	0.239	0.290
	(6.958)	(8.892)	(9.249)	(8.015)	(8.082)	(8.800)	(7.982)	(7.926)
ALPHA_{t-4}	0.408	0.434	0.482	0.381	0.453	0.518	0.392	0.472
	(3.671)	(12.580)	(10.488)	(10.637)	(10.269)	(11.801)	(11.241)	(10.595)
ALPHA_{t-5}	0.187	0.142	0.202	0.152	0.161	0.151	0.115	0.124
	(4.229)	(4.676)	(4.462)	(4.551)	(4.109)	(4.222)	(4.286)	(3.898)
ALPHA_{t-6}	0.161	0.093	0.160	0.122	0.119	0.085	0.070	0.064
	(3.544)	(3.190)	(3.553)	(3.693)	(3.090)	(2.475)	(2.718)	(2.106)

$ALPHA_{t-7}$	0.176	0.100	0.203	0.132	0.159	0.116	0.078	0.093
	(4.469)	(3.448)	(4.510)	(4.047)	(4.095)	(3.384)	(30.91)	(3.058)
$ALPHA_{t-8}$	0.175	0.103	0.202	0.140	0.166	0.123	0.087	0.105
	(4.611)	(3.209)	(4.344)	(4.114)	(4.122)	(3.234)	(3.128)	(3.145)
$ALPHA_{t-9}$	0.095	0.141	0.132	0.078	0.102	0.174	0.110	0.139
	(2.222)	(4.432)	(2.840)	(2.319)	(2.562)	(4.557)	(3.957)	(4.102)
$ALPHA_{t-10}$	0.074	0.078	0.102	0.050	0.065	0.096	0.050	0.064
	(1.939)	(2.503)	(2.196)	(1.486)	(1.635)	(2.583)	(1.855)	(1.979)
$ALPHA_{t-11}$	0.102	0.062	0.130	0.109	0.128	0.071	0.061	0.071
	(2.818)	(1.936)	(2.825)	(3.288)	(3.259)	(1.877)	(2.241)	(2.177)
$ALPHA_{t-12}$	0.101	0.042	0.117	0.072	0.086	0.048	0.026	0.030
	(2.733)	(1.219)	(2.466)	(2.115)	(2.130)	(1.168)	(0.876)	(0.847)
$LNAV_{t-1}$	− 0.019	− 0.019	− 0.018	− 0.019	− 0.019	− 0.019	− 0.019	− 0.020
	(− 2.723)	(− 6.502)	(− 6.089)	(− 6.409)	(− 6.595)	(− 6.667)	(− 6.831)	(− 6.959)
VAR_{t-1}	0.0003	0.0001	0.0002	0.0002	0.0002	0.0001	0.0001	0.0001
	(2.244)	(1.338)	(3.769)	(3.731)	(3.521)	(1.106)	(1.131)	(0.934)
ALPHA-LOAD			− 0.280		− 0.280	− 0.299		− 0.306
			(− 4.687)		(− 4.087)	(− 4.318)		(− 3.948)
ALPHA-AGGRTH				0.715	0.564		0.717	0.564
				(4.535)	(4.188)		(3.894)	(3.664)
DALPHA		2.301				1.903	2.442	2.013
		(7.771)				(7.410)	(7.119)	(6.846)
NALPHA		− 0.158				− 0.174	− 0.307	− 0.288
		(− 1.156)				(− 1.511)	(− 1.961)	(− 2.200)
Adj R^2	0.2046	0.2283	0.2215	0.2224	0.2234	0.2294	0.2299	0.2308

performance of load and no-load funds. Load funds are significantly less sensitive to past performance. This is probably because investors in load funds are more likely to rely on the advice of financial planners and brokers, who tend to benefit from directing investors to load funds. Such investors are likely to be less informed and possibly more risk averse than better informed investors. As a consequence, they are less responsive to past performance in their fund choice.[19]

An alternative argument suggests that load charges are likely to increase investor inertia, i.e., increases in transaction costs lead investors in load funds to invest for a longer time horizon than those investing in no-load funds. To examine this proposition we tested for differences between the persistence coefficients for load and no-load funds. While the results are consistent with this hypothesis, they are largely insignificant. There are no significant differences in persistence between the two types of investments.[20] All investor types appear to invest for the long haul.

Using growth funds as the benchmark, we find no significant variation among fund objectives in investors' response to past performance except for aggressive growth funds, the performance of which has a greater impact on new investment than does past performance for all other funds. Because the variance of the Jensen alphas is greatest for aggressive growth funds among all fund objectives examined, it may be that investors in aggressive growth funds are the least risk averse investors in the sample and aggressively react to changes in portfolio performance to realize the highest risk-adjusted return possible.

It should be noted that these effects are both highly significant and relatively large. Thus, the managerial incentives of load funds are weakened by over 25% relative to no-load funds. Similarly, the effects of performance on the flow of investment into aggressive growth funds is about 50% higher than for other funds.

6.4. Nonlinearity

To examine the nonlinearity hypotheses specified in Eq. (5) we estimated a series of piecewise linear regressions varying the cutoff values in the positive

[19] There is an argument that financial advisers may cause excessive movement between funds in order to benefit from new sales commissions. However, the existence of trailer fees and long-term client relationships reduce this incentive. Our evidence clearly does not support this argument.

[20] We examined the load structure across fund types. All fund types had approximately 50/50 load/no-load split except for growth funds which were 62% load. It is also the case that of the load funds, at least 90% are front-end. The exception are the small company group where about 50% are front-end and 50% deferred. However, the small company funds are not significantly different than the others.

and negative regions of alpha to search for nonlinearities in the extreme parts of the performance distribution. The results shown in column 2 of Table 5 suggest a strong nonlinear effect in the positive region for performance measures exceeding 15% per quarter and a weaker nonlinear effect in the extreme negative region of the distribution for alphas below -10% per quarter.[21] This result is particularly interesting in that our sample includes only those funds with a history of six or more years. In contrast, Chevalier and Ellison found a strong nonlinearity for poor performance levels only in the younger funds within their sample. It may be that the nonlinearity found in our sample of poor performing funds would be stronger if younger funds were also included. Our results also contrast with those of Sirri and Tufano (1998) and Goetzmann and Peles (1997) who found that the strong performance–flow relationship was restricted to the top performing funds in their respective samples.

7. Incentive properties of asset-based fees

The incentive properties of asset-based fees are closely linked to the market's response to past fund performance. All other things equal, a one-time increase in fund return produces a temporary increase in investment flows to the fund, which leads to a long term increase in the fund's assets. Hence, there is a strong incentive with the asset-based fee structure for managers to improve their performance.

To begin, we define the asset-based fee per dollar of net asset value as f and let A_t be the net asset value of the fund in period t. It follows that the product of these two variables, fA_t, represents the compensation to the manager, π_t, i.e.,

$$\pi_t = f\mathrm{e}^{[a + r_{ft} + \sum_{i=1}^{12} b_i x_{t-i}]}(1 - \lambda^t)/(1 - \lambda)A_0^{\lambda^t}, \tag{6}$$

where λ is the period-to-period persistence and a is the growth rate of the fund which is unrelated to the fund's performance. Starting from a steady state in which assets in each period are equal, i.e., $A_t = A_{t-1} = \cdots = A_0$, the effect of a one-time-only change in return in $t = 0$ is

$$\frac{\mathrm{d}\pi_t}{\mathrm{d}r_0}\frac{1}{A_0} = \frac{fA_t}{A_0}\frac{\mathrm{dLn}A_t}{\mathrm{d}r_0} = fB\lambda^t, \tag{7}$$

[21] A quadratic (in alpha) approximation for positive and negative alphas yielded very similar results to the piecewise linear regressions, suggesting a positive significant nonlinearity at the upper performance range and a weak insignificant effect at the lowest performance range.

where $B = \lambda^{-1} + \sum_{j=1}^{12} b_j \lambda^{j-11}$. It follows that the change in the present value of the net compensation benefits (Π) to the fund is

$$\frac{\mathrm{d}\Pi}{\mathrm{d}r_0}\frac{1}{A_0} = \int_0^\infty fB\lambda^t \mathrm{e}^{-\delta t}\,\mathrm{d}t \simeq \frac{fB}{\delta + (1-\lambda)}, \tag{8}$$

where δ is the quarterly discount rate.

We can now look at the empirical estimates of our model in order to understand the incentive implications for the manager. From Table 3 (column 2), $\lambda \approx 0.981$ and together with the respective b_j values yields $B = 4.02$. Based upon a risk-free quarterly discount rate over the period of 0.0162 and an average value of $f = 0.25\%$ per quarter, it follows that the change in lifetime compensation to the manager for a one-time quarterly increase in performance is approximately 30% of the increase in fund profits.[22] This constitutes a large relative effect on fund income. The elasticity of the present value of fund income with respect to quarterly performance is approximately 2. This implies that a one percentage point improvement in performance during a single quarter increases the present value of fund manager's income by about 2%.

It is clear that the incentives are sensitive to the manager's discount rate. If the manager is risk averse and unable to diversify, a higher discount rate will be used. For example, a discount rate of 0.0429, which is the average quarterly return on the S&P 500 over the period, would reduce the effect of lifetime earnings to 17% of the change in performance. However, the elasticity of the present value of fund manager's income with respect to performance actually increases to about 2.8.

It should be noted that the increase in the manager's compensation is not at the expense of fund shareholders, the value of whose shares fully reflects the increased fund profits. Instead, it is at the expense of other fund managers who lose market share to the better performing fund. This reward to successful managers (punishment to unsuccessful ones) constitutes a powerful incentive for managers. Moreover, because managers are rewarded on the basis of returns adjusted for market risk, there is little incentive for risk neutral managers to manipulate risk for the average fund, which has an alpha close to zero.

However, the existence of significant nonlinearities in management rewards at the upper performance levels are likely to induce risk neutral fund managers to increase effort for performance improvement whenever they find themselves at extreme positive performance levels. In contrast, for poor performers, the

[22] We assume an annual management fee of 1% and use the quarterly average of the one-month T-bill rate over the sample period as the discount rate.

marginal reward to better performance is somewhat lower than the average, reducing their incentives.[23]

Moreover, the nonlinearities at both ends of the performance spectrum generate significant incentives for managers to manipulate risk. Managers who find themselves near the inflection points in their performance (i.e., $\alpha = -0.10$ and $+0.15$) have an incentive to increase risk as the marginal rewards to the managers are asymmetric at these points, particularly at the high levels of performance. Note that this incentive applies to the fund's acquisition of both systematic and idiosyncratic risk. These results are consistent with the risk taking pattern found by both Chevalier and Ellison (1997) and Brown et al. (1996).

Our discussion of the incentives associated with the nonlinearities in the flow/performance relationship has assumed risk neutral managers. Clearly, risk aversion of managers will modify these results. As pointed out in the extensive theoretical literature, the precise results depend on the managers' utility function and the nature of the exclusive information of the manager.[24] In any case, the correspondence between managers' and investors' interests will be seriously weakened even in the linear range of the reward function. For example, managers will attempt to reduce idiosyncratic risk, even though investors who diversify among funds do not discount it. Moreover, managers may trade off market risk against idiosyncratic risk by becoming 'closet indexers' even when operating in the linear range of the reward function.

8. Summary and conclusions

This paper has examined the mutual fund market as a market for the sale of management services using quarterly data for an unbalanced panel of 348 U.S. equity funds over the 1980:4 to 1993:4 period. Using heteroskedastic-consistent fixed effects estimation procedures, we found that net new fund investment is positively related to a distributed lag of past fund performance with a strong degree of inertia and a significant nonlinear effect at the extreme levels of performance. This nonlinearity is particularly strong for extremely good performances, suggesting that investors direct new funds towards stellar recent performers.

Some market segmentation also appears to exist. Investors in load funds are less responsive to past performance than are investors in no-load funds,

[23] However, as shown by Brown and Goetzmann (1995), it is likely that the primary disciplinary effect at this end of the performance spectrum is the decreased probability of survival with continued poor performance.

[24] Refer to Stoughton (1993) and Admati and Pfleiderer (1997), among others.

suggesting that investors in load funds are less informed, so that management performance incentives are significantly weakened for load funds. We do show, however, that irrespective of whether they pay a load or not, investors in mutual funds are in for the long haul.

The high degree of inertia that we find in new investment is probably due to very slow revisions of expectations by consumers as well as to significant transaction, tax and decision costs.[25] The effects of improved performance, therefore, have a large cumulative long term effect on fund assets and creates strong incentives for managers to improve their performance in order to increase their compensation under the common asset based remuneration mechanism.

Our main concern in this paper has been with the way in which consumers evaluate risk in deciding upon which funds to invest and the effect of such risk evaluation on manager incentives. Among the alternative performance measures examined in this paper, we show that even when we separate the return and risk components, the Jensen alpha best predicts future investment flows. Investors appear to use the publicly available data in a way that is consistent with the theory, giving equal weight in their decisions to the return and market risk components of the performance measure.

The fact that, for the majority of funds, significant managerial rewards are linearly related to *risk adjusted* performance, suggests that risk neutral managers have strong incentives to exert effort on behalf of their shareholders and little or no incentive to manipulate risk. However, managers who have performed particularly well (or poorly) have an incentive to take on additional risk due to the asymmetric marginal risk return tradeoff in the neighborhood of the inflection points.

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[25] Goetzmann and Peles (1997) suggest that cognitive dissonance may contribute to the high degree of inertia exhibited among investors.

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