NBER WORKING PAPER SERIES

RISK TAKING BY MUTUAL FUNDS AS A RESPONSE TO INCENTIVES

Judith A. Chevalier
Glenn D. Ellison

Working Paper No. 5234

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 1995

Both authors wish to thank the National Science Foundation (SBR 94-14141, SBR 93-10009). Chevalier acknowledges research support from the Centel Foundation/Robert P. Reuss Faculty Research Fund at the Graduate School of Business, the University of Chicago, and Ellison acknowledges support from the Harvard Clark Fund. Andrea Densham, Judy Lubin, Matthew Sevick, and Ramin Toloui provided excellent research assistance. We thank Yacine Ait-Sahalia, John Cochrane, Sara Fisher Ellison, Paul Joskow, Jack Porter, Rob Porter, Andrei Shleifer, and seminar participants at Chicago, Harvard, MIT, Northwestern, the US Department of Justice and the NBER 1995 winter meetings in Industrial Organization for their comments. This paper is part of NBER's research programs in Corporate Finance and Industrial Organization. Any opinions expressed are those of the authors and not those of the National Bureau of Economic Research.

NBER Working Paper #5234
August 1995

RISK TAKING BY MUTUAL FUNDS AS A RESPONSE TO INCENTIVES

ABSTRACT

This paper examines the agency conflict between mutual fund investors and mutual fund companies. Investors would like the fund company to use its judgement to maximize risk-adjusted fund returns. A fund company, however, in its desire to maximize its value as a concern has an incentive to take actions which increase the inflow of investment. We use a semiparametric model to estimate the shape of the flow-performance relationship for a sample of growth and growth and income funds observed over the 1982-1992 period. The shape of the flow-performance relationship creates incentives for fund managers to increase or decrease the riskiness of the fund which are dependent on the fund's year-to-date return. Using a new dataset of mutual fund portfolios which includes equity portfolio holdings for September and December of the same year, we show that mutual funds do alter their portfolio riskiness between September and December in a manner consistent with these risk incentives.

Judith A. Chevalier
Graduate School of Business
University of Chicago
1101 East 58th Street
Chicago, IL 60637
and NBER

Glenn D. Ellison
Department of Economics
MIT
E52-373
Cambridge, MA 02139
and NBER

"If I have to leave money on the table, I'd rather do that than have shareholders leave the fund." — Robert Beckwitt, fund manager of Fidelity Asset Manager, *Boston Globe*, January 22, 1995.

1 Introduction

The potential conflict between mutual fund companies and the people who invest in them is a classic example of an agency problem. Consumers would like the fund in which they invest to use its judgment to maximize risk-adjusted expected returns. Mutual fund companies, however, are motivated by their own profits, and the information that they possess and how they use it are not directly observable. As a result, if actions which maximize fund company profits differ somewhat from the actions which maximize risk-adjusted expected returns, we would expect some inefficiencies to arise.[1]

The mutual fund industry provides a rare opportunity to explore agency problems because we are able to observe empirically the nature of the incentives provided to mutual funds and how the funds react.[2] The compensation scheme used by most mutual funds gives the fund company an incentive to maximize the total assets under management. We can thus explore the incentives which consumers provide to funds by empirically investigating the relationship between fund performance and inflows of investments. We are able to observe funds' reactions to these incentives in a new detailed dataset on the equity holdings of a large number of mutual funds. The particular aspect of fund behavior on which we focus is risk-taking.

Our analysis proceeds in two main steps, each of which should be of independent in-

[1] Holmstrom (1982) provides the classic discussion of the distortion of effort which arises when (as we imagine here) the market is trying to learn the ability of managers. Scharfstein and Stein (1990) and Zwiebel (1995) discuss herding as such an inefficiency. See Borland (1992) for a survey of this literature.

[2] Borenstein and Zimmerman (1988) is an example of other research which posits that the possibility of demand loss provides behavioral incentives to firms. Previous research on responses by individuals or teams to incentives generated by performance evaluation and compensation schemes has been limited. Other contexts in which responses to incentive schemes have been explored include golf tournaments (Bronars (1987), Ehrenberg and Bognanno (1990a and 1990b), auto racing (Becker and Huselid (1992), and laboratory experiments (Bull, et. al. (1987)). The only other work of which we are aware which examines risk-taking as response to a performance evaluation scheme is Knoeber and Thurman's (1994) study of broiler chicken producers. Both Asch (1990) and Healy (1985) discuss other distortions in behavior which result from nonlinearities in rewards.

terest. First, we examine of the relationship between fund performance and subsequent investment flows in order to determine whether the relationship generates incentives for fund management to alter the riskiness of their portfolios. To do so we extend previous work in exploring the shape of the flow-performance relationship using a semiparametric model, and then discuss what incentives for risk-taking may exist toward the end of the year considering how portfolio changes affect expected inflows. Second, we exploit a new dataset on mutual fund holdings to examine how mutual funds portfolios are actually altered toward the end of the year, trying to determine whether any systematic changes in riskiness are consistent with the previously identified incentives. The analysis of how funds alter their portfolios toward the end of the year provides new insight into an aspect of behavior which has received little academic attention – whether funds appear toward the end of the year to to try to "lock-in" gains or to "gamble" in hopes of wiping out earlier losses. That we are able to tie the behavior of mutual funds to their incentives illustrates the applicability of agency models and also suggests that a similar empirical approach may be useful for other problems.

The starting point for our analysis of incentives in the mutual fund industry is the observation that because mutual fund companies usually receive a fixed percentage of assets under management as compensation, mutual funds will have an incentive to take whatever actions increase the total assets of the fund. Several authors have previously documented a strong relationship between the inflow of new investment into a mutual fund and the fund's past performance.[3] We view the flow-performance relationship as an implicit incentive contract whose existence is a good thing – it provides funds with some incentive to perform well. The first main empirical goal of this paper is to explore the shape of the flow-performance relationship in order to better understand precisely what kinds of incentives this relationship creates.

Our primary empirical strategy for investigating the relationship further is to apply a semiparametric model to a dataset containing flow and performance data for a sample of

[3]See, for example Spitz (1970), Smith (1978), Patel, Zeckhauser, and Hendricks (1990), Ippolito (1992), Sirri and Tufano (1993), and Goetzmann and Peles (1993). This link has also been explored by Berkowitz and Kotowitz (1993), who argue, as we do, that the link between flow and performance functions as a performance contract for fund management.

growth and growth and income funds containing 3036 fund-years observed over the 1982-1992 period. To understand why we do this, it is instructive to contrast our goal with that of the previous flow-performance literature. The previous papers have generally used simple linear (or occasionally piecewise linear) models to verify that the flow-performance relationship has some feature which is compatible with a hypothesized model of consumer behavior.[4] In this paper, we are explicitly not concerned with testing any particular hypothesis about how investors behave. To the contrary, we believe that what makes the agency problem in the mutual fund industry so interesting is that the flow-performance relationship which results from consumer behavior (and which provides incentives to mutual funds) is empirically estimable. We thus wish to obtain the most detailed view of the flow-performance relationship, and to put as few a priori restrictions on the shape as is feasible. We show that specification testing indicates that given the data available we can reject all of the linear and piecewise linear specifications imposed by the previous literature. We therefore feel that by estimating a semiparametric model where the shape of the relationship between flow and the previous year's return is unrestricted we can obtain useful new information about the nature of flows and incentives. We find significant nonlinearities in the relationship, with the overall sensitivity of the relationship and its shape being highly dependent on the age of the fund in question.

While we hope our work may improve understanding of consumer behavior in the mutual fund industry, our primary interest derives from a desire to understand what incentives for fund risk taking the consumer behavior engenders. In particular, we use our analysis of the flow-performance relationship to derive estimates of how the market implicitly compensates funds for increasing or decreasing the riskiness of their portfolios toward the end of the year as a function of the funds' January-September year-to-date performance, age, and other characteristics. To see how such implicit incentives might be created, suppose that because of limited information availability or otherwise many consumers of mutual fund services react to year-end performance results, and that given a particular fund's characteristics and year-to-date performance at the end of September it knows that its future inflows of

[4] In doing so, several authors have previously noted that the relationship between flow and performance may be nonlinear. (See e.g. Ippolito (1992), Sirri and Tufano (1993) and Goetzmann and Peles (1993).)

investments will (in some range) be a convex function of its fourth quarter performance. In such a case, the fund would be able to increase its expected growth by increasing the variance of its fourth quarter return.

The second main goal of the paper is to examine empirically how funds alter the riskiness of their portfolios toward the end of the year (and in particular, whether they appear to respond to the incentives which we identify in looking at the flow-performance relationship.) In this task, our paper is related to a few other papers which have tested for distortions in behavior by investment managers, including Lakonishok, Shleifer, Thaler and Vishny's (1991) study of "window dressing" by pension fund managers and Lakonishok, Shleifer and Vishny's (1992) and Grinblatt, Titman and Wermers' (1993b) study of herding. The one other paper we are aware of on risk-taking is the recent working paper of Brown, Harlow and Starks (1994), which looks at whether mutual funds whose performance is behind the market in the first part of the year have more variable returns during the remainder of the year than do mutual funds who were ahead of the market. Because they do not have any data on holdings, however, Brown, Harlow and Starks can provide only a very limited description of risk taking, and can not say whether differences are due to changes made to portfolios or whether the results simply stem from leading and trailing funds having different types of portfolios to begin with. We hope in this paper to provide a far more detailed view of risk-taking, and most importantly see whether observed risk-taking is compatible with the incentives we have identified.[5]

We begin our analysis of actual risk-taking behavior by using a newly constructed dataset which contains the complete equity portfolios of a large number of mutual funds both at the end of September and at the end of December of a given year to analyze the changes which funds make to their portfolios between September and December. We find that the changes appear to be related to the incentives we have previously identified, with the pattern of actual changes corresponding to the estimated incentives in some detail. To verify that these changes appear to be reflected in measures of riskiness based on the

[5] Brown, Harlow and Starks (1994) do informally discuss why tournaments may create incentives to take risks, although the only evidence on flow on which they rely (that of Sirri and Tufano (1993)) is incompatible both with their predictions and results and with the incentives we identify.

complete portfolios of mutual funds as well, we explore also changes in fund composition and time series data on fund returns.

The outline of the paper is as follows. In Section 2, we describe the data prepared for the estimation. In Section 3, we empirically estimate the flow-performance relationship. In Section 4, we estimate each fund's incentives to increase or decrease its level of risk. Finally, in Section 5, we examine the portfolio changes undertaken by firms between September and December in order to test whether these portfolio changes reflect the incentives to take risks estimated in Section 4. Section 6 concludes.

2 Data

Virtually all of the data used in this paper are obtained from Morningstar Inc. The primary data source is Morningstar's January 1994 *Mutual Funds OnDisc*. From the CD-ROM, we obtain data on mutual fund returns, assets under management, minimum initial purchase requirements, and expense ratios as well as information on whether the fund had ever been involved in a merger. While the *Mutual Funds OnDisc* data include only mutual funds which were still in operation as of January 1994, Morningstar has maintained a list of funds deleted from the database since the beginning of 1989. Using this list, we reconstructed the returns and other information back to 1989 for funds which were not still in existence using the *Mutual Fund Sourcebook*, a Morningstar publication.

A large dataset containing the complete equity portfolios of a large number of mutual funds was obtained directly from Morningstar. Portfolio reporting to Morningstar is voluntary and we have portfolio data for only a minority of the fund-years in this database. In addition, the frequencies with which portfolios are available to us varies with the fund: some portfolios are available quarterly or more frequently, some only at the end of the year, and some at sporadic intervals. Much of our analysis focuses on 839 cases (involving 398 different funds) where we have the portfolios of a fund at both the end of September and the end of December of the same year.

In order to construct measures of the riskiness and the beta of each mutual fund at each point in time at which a portfolio was available, we matched the portfolio holdings to the Center for Research in Security Prices database. For each fund-date for which portfolio data were available, the Morningstar database generally contained the name of the security, the number of shares of the security and the value of the holding. Unfortunately, the database does not contain CUSIPs and frequently does not contain ticker symbols – the tickers are missing for 80435 of the 121895 security records in the 1678 ($=2\times839$) portfolios mentioned above. For each holding in the database, we attempted to generate (possibly more than one) potentially correct tickers by (a) trying to match the holding name electronically to the name of a security in the CRSP data, (b) trying to match the holding name to the name of another holding in the Morningstar data for which Morningstar provided a ticker, and (c) trying to match manually the holding name to the complete listing of CRSP securities. Morningstar holdings were matched to CRSP security records which matched both the tentatively assigned ticker and the per share price in the Morningstar data.[6] At the end of this process, we were able to find matches for 92.5% of the security records. A variety of things appear in the lists of unmatched securities: foreign securities, holdings of shares in other mutual funds, securities where the prices in the Morningstar data may be incorrect, and securities which may be in CRSP, but for which we simply could not find the match. When we use the CRSP data on returns in the previous year to estimate betas and standard deviations of portfolios, additional securities must be dropped because they are new or otherwise lack sufficient historical return data. On average, we are able to use about 89% of the records for this purpose. In our analysis, we will generally restrict ourselves to looking at funds for which estimates are based on matches to at least 85% of the portfolio by value.

Clearly there are several potential areas for concern with the data. Because Morningstar did not keep records on funds which were dropped from its database prior to 1989, collecting data on such funds was decided to be prohibitively difficult, and our dataset is survivorship biased for the period prior to 1989.

[6] Prices were required only to be within $1 per share. For 71 of the 41603 ticker-date-price combinations this resulted in multiple CRSP matches being found and the match with the smaller price difference was selected.

Another concern about the database is that the return and other information from *Mutual Funds OnDisc* may have a back-filling problem. At the time Morningstar began to provide information about a fund, Morningstar may have filled in back data for the fund. However, we have been told by Morningstar that they considered it inefficient to backfill portfolio data, since only current portfolio data are presented in Morningstar publications. Thus, the post-1989 portfolio data should have neither back-filling nor survivorship bias contamination. We will use the post-1989 subsample of the data for which we have portfolio information to reconstruct some of our major results and assure that the results are not due to survivorship bias or backfilling. For all periods, the portfolio data does have the problem that reporting to Morningstar is voluntary. We cannot speculate what biases this may induce.

Despite the difficulties with the database that we have noted, the database we constructed from the Morningstar data is a unique resource for mutual fund portfolio data. The difficulty of the task of matching data from Morningstar or other sources to CRSP has prevented researchers from doing much analysis of mutual fund portfolios. The only other database of mutual fund holdings of which we are aware is the data on 274 mutual funds over the 1975-1984 period used in Grinblatt and Titman (1989a, 1989b, 1992, and 1993), Grinblatt, Titman and Wermers (1993), and Wermers (1993a and 1993b).

3 The Flow-Performance Relationship

When consumers are faced with the decision of choosing a mutual fund, they must form beliefs about the suitability of each fund to their objectives and about the ability of each fund to generate excess returns. Previous research on the relationship between investment flows and past performance has demonstrated that consumers do react strongly to historical returns. Our primary interest is in understanding what types of incentives this creates for funds to manipulate their portfolios, and how these incentives vary both over time as returns are realized and cross-sectionally with fund attributes. As the first step toward this goal, we find it necessary to develop a more detailed description of the flow-performance relationship.

In particular we extend previous analyses in two directions — using a semiparametric model to discuss the shape of the flow-performance relationship, and looking at how the strength and shape of the relationship varies with the age of the fund. The basic outline of this section is that we begin with a simple linear model which provides a review of some of the basic facts and a first look at age effects, use specification tests to discuss the inadequacy of linear and piecewise linear specifications, and finally introduce the semiparametric model from which we derive our most important conclusions.

3.1 A linear model with fund age effects

A number of the most salient features of the flow-performance relationship are easily captured in a simple linear model. Our basic regression model relates the flow of investments into a fund in year $t+1$ to past performance and other characteristics, with the primary focus being on the effect of the year t return:

$$\begin{aligned} Flow_{it+1} &= \sum_k \gamma_k Age\_k_{it}(r_{it} - rm_t) + \sum_k \delta_k Age\_k_{it} \\ &\quad + \alpha_1(r_{it-1} - rm_{t-1}) + \alpha_2(r_{it-2} - rm_{t-2}) + \alpha_3(r_{it+1} - rm_{t+1}) \\ &\quad + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 log(Assets_{it}) + \epsilon_{it+1}. \end{aligned}$$

The flow measure $Flow_{it+1}$ is the proportional growth in total assets under management for the fund between the start and end of year $t+1$ *net* of internal growth in year t (assuming reinvestment of dividends and distributions), *i.e.*

$$Flow_{it+1} = (Assets_{it+1} - Assets_{it})/Assets_{it} - r_{it+1}.$$

We examine the relationship between investment flows in year $t+1$ and market-adjusted excess returns in year t. In our base model, our measurement of excess returns in year t is simply the return relative to the market return, $r_{it} - rm_t$.[7]. In recognition of the fact that consumers updating their beliefs about the quality of a mutual fund from noisy observations may treat young and old funds quite differently, the primary addition we have

[7] Note that we also examine later specifications based on $r_{it} - \beta rm_t$

made to previous specifications is to allow return relative to the market, $r_{it} - rm_t$, to enter with a coefficient which varies with the age category, Age_k, to which the fund belongs.[8] If consumers are attempting to infer the quality of a fund from historical data, we would expect flows into and out of younger funds to be more sensitive to recent performance. We allow also for separate intercepts for age each category so that average growth rates may also differ by age.

We include also as explanatory variables the market adjusted return of the fund in years $t-1$ and $t-2$ (with this latter variable set to zero for two year old funds). The market adjusted return in year $t+1$ is included to reflect both flows in response to intra-year returns and the fact that funds with high returns in year $t+1$ exhibit additional growth due to the internal growth of investments which are made before the end of year $t+1$. Additional variables included as controls are the growth in total assets under management by the equity mutual fund industry (taken from the 1994 *Mutual Fund Factbook*), and the natural logarithm of the total assets under management by the fund in question at the end of year t.

The dataset on which we estimate our flow regressions contains information on flows into 449 growth and growth and income mutual funds during all years between 1983 and 1993 for which they were active. Our basic regression is run on a sample of 3036 fund-years which consists of all observations meeting certain criteria. First, because we thought the nature of their flows might be quite different, we removed funds which were closed to new investors, funds which are primarily institutional (which we defined as having a minimum initial purchase of at least $25000), and funds which have very high expense ratios (in excess of 4%). We also eliminated funds which merged with other funds in year $t+1$ (and hence have misleading growth rates) and two groups of funds for which the flow data are exceptionally noisy: funds less than two years of age at the end of year t and funds with less than $10 million dollars in assets at the end of year t.[9] Table 1 contains summary

[8] Sirri and Tufano (1993) do show one specification allowing the flow-performance relationship to be different for funds less than three years old and funds greater than three years old.

[9] When discussing the flow into a fund in year $t+1$, we will refer to a fund as being of age k if it is k years old at the start of year $t+1$, *i.e.* if its inception date falls within year $t-k$. Our feeling is also that for funds of age less than two and for very small funds our growth rate specification is probably inappropriate.

statistics for all of the variables.

Table 1: Summary Statistics for Flow-Performance Regressions

	Full Sample		Young Funds		Old Funds	
Variable	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
$Flow_{t+1}$	0.122	0.646	0.251	0.700	0.079	0.620
$r_t - rm_t$	-0.005	0.084	-0.006	0.085	-0.005	0.083
$r_{t-1} - rm_{t-1}$	-0.002	0.087	0.0002	0.091	-0.003	0.086
$r_{t-2} - rm_{t-2}$	-0.001	0.080	0.001	0.073	-0.002	0.083
$r_{t+1} - rm_{t+1}$	-0.008	0.077	-0.006	0.084	-0.009	0.075
$IndustryGrowth_{t+1}$	0.283	0.173	0.272	0.181	0.286	0.169
$\log(Assets)$	4.936	1.427	4.254	1.173	5.172	1.431

Age Category	2	3	4	5	6-7	8-10	11+
Number of Fund-Years	221	199	189	171	238	168	1850

The first column of Table 2 presents parameter estimates for the basic regression. Note first that as in previous studies there is a large and clearly identified relationship between investment flows and returns. For example, the point estimate of 3.33 on the age-return interaction for two year old funds implies that a two year old fund with characteristics such that it would have zero expected growth were its return to be five points below the market would instead be expected to grow by one-third of its initial size if it achieved a return five points ahead of the market. Separate intercepts and flow-return sensitivities are allowed for funds in seven age categories: 2, 3, 4, 5, 6-7, 8-10, and 11 or greater. Younger funds have higher flows on average than older funds and have flows which are more sensitive to period t returns. The additive *Age_2* dummy is significantly larger (at the 5% level) than the coefficient on the dummy for all funds of age eight or greater; the coefficient on the *Age_2*-return interaction is also significantly larger than the interactions for funds of age five or greater.

The other coefficients of the model are generally consistent with those reported in pre-

For young funds particularly one would probably want to use end of year $t+1$ size as the dependent variable and include a number of additional explanatory variables such as fund family size. We therefore believe that it would be appropriate to conduct a completely separate study of small and young funds.

Table 2: Linear Flow-Performance Model

Independent Variables	Dependent Variable: $Flow_{t+1}$ (1)	(2)	(3)	(4)	(5)	(6)
excess $return_t \cdot Age\_2$	3.33	3.32	—	3.40	3.09	2.38
	(0.50)	(0.51)		(1.41)	(1.37)	(1.14)
excess $return_t \cdot Age\_3$	2.16	2.15	—	1.41	1.31	1.29
	(0.57)	(0.59)		(1.78)	(2.51)	(1.12)
excess $return_t \cdot Age\_4$	3.62	3.47	—	3.16	3.02	3.75
	(0.46)	(0.47)		(1.03)	(0.94)	(0.76)
excess $return_t \cdot Age\_5$	1.93	1.89	—	3.80	2.96	2.68
	(0.49)	(0.50)		(1.43)	(1.18)	(0.87)
excess $return_t \cdot Age\_6\text{-}7$	1.97	—	1.96	3.15	2.73	1.99
	(0.44)		(0.44)	(0.89)	(0.76)	(0.68)
excess $return_t \cdot Age\_8\text{-}10$	1.40	—	1.43	0.66	1.23	1.23
	(0.50)		(0.50)	(1.03)	(1.11)	(0.74)
excess $return_t \cdot Age\_11+$	1.56	—	1.58	1.58	1.58	1.64
	(0.17)		(0.17)	(0.40)	(0.40)	(0.37)
Age_2	0.38	0.44	—	0.34	0.32	0.41
	(0.05)	(0.09)		(0.15)	(0.15)	(0.12)
Age_3	0.35	0.41	—	0.26	0.27	0.36
	(0.06)	(0.10)		(0.15)	(0.15)	(0.12)
Age_4	0.33	0.40	—	0.32	0.28	0.44
	(0.06)	(0.10)		(0.14)	(0.14)	(0.11)
Age_5	0.31	0.38	—	0.37	0.32	0.45
	(0.06)	(0.10)		(0.14)	(0.13)	(0.11)
$Age\_6\text{-}7$	0.28	—	0.26	0.21	0.17	0.38
	(0.06)		(0.06)	(0.13)	(0.13)	(0.11)
$Age\_8\text{-}10$	0.23	—	0.21	0.14	0.16	0.25
	(0.06)		(0.07)	(0.14)	(0.14)	(0.12)
Age_11+	0.20	—	0.18	0.21	0.20	0.24
	(0.05)		(0.05)	(0.11)	(0.11)	(0.11)
Excess $return_{t-1}$	1.22	1.80	1.01	1.59	1.54	1.71
	(0.12)	(0.24)	(0.14)	(0.26)	(0.26)	(0.24)
Excess $return_{t-2}$	0.52	0.89	0.44	0.07	-0.02	0.40
	(0.13)	(0.30)	(0.15)	(0.30)	(0.31)	(0.32)
Excess $return_{t+1}$	1.62	1.57	1.62	3.15	3.26	2.45
	(0.14)	(0.26)	(0.16)	(0.32)	(0.32)	(0.27)
$IndustryGrowth_{t+1}$	0.43	0.58	0.37	0.56	0.58	0.22
	(0.06)	(0.12)	(0.07)	(0.14)	(0.14)	(0.12)
$\log(Assets)$	-0.04	-0.07	-0.04	-0.04	-0.05	-0.04
	(0.01)	(0.02)	(0.01)	0.02	(0.02)	(0.02)
N	3036	780	2256	560	560	1102
R^2	0.21	0.36	0.15	0.32	0.32	0.23

* Estimated standard errors in parentheses.

vious studies. The effect of period $t-1$ returns is smaller than that of period t returns (for any age group) and is clearly significant. The point estimate for the coefficient for period $t-2$ returns is less than one-half of the coefficient for period $t-1$ returns, but still has a statistically significant effect on flows. The other control variables: period $t+1$ returns, growth in industry assets, and the logarithm of the fund's period t end-of-year assets all have the expected signs and are highly significant.

When estimating our nonlinear model, we will divide the dataset into the subsamples of "young" and "old" funds. The second and third columns of Table 2 report the coefficient estimates from separate regressions run, respectively, on the 780 funds of age 2-5 and on the 2256 funds of age 6 or more. While this specification allows for the possibility that variables other than the year t excess return have effects which are age dependent, the results are quite similar to those we have already presented. However, flows into young funds appear to be somewhat more sensitive to year $t-1$ and $t-2$ returns and to the growth of the mutual fund industry as a whole than flows into older funds.[10]

In the context of this linear model we examined our basic specification in a number of ways.[11] First, to see whether the incorporation of additional information on the cost to consumers of investing in each fund might be warranted we separately added turnover (a proxy for tax costs imposed by the fund), expense ratios and sales load charges to our basic flow regression. None of them had a statistically significant effect on flows.

Next, while Patel, Zeckhauser, and Hendricks (1990), Ippolito (1992), and Sirri and Tufano (1993) have previously reported both that risk adjustments based on historical betas fail to have additional explanatory power and make little difference in the coefficient estimates in their flow regressions, we thought it prudent to examine whether our model was grossly inadequate in focusing on consumers' reactions to simple excess returns. To do so, we reestimated the basic flow regression using both $r_{it}-\beta rm_t$ and $r_{it}-rm_t$ as the year t excess

[10]The differential sensitivities to $t-1$ returns and to the growth of the fund industry are significant at the 5% level.

[11]The opportunity which the linear model provides to perform such tests is, in fact, one of the main motivations for presenting the results of this section. We felt that it would be unsatisfying to examine the inclusion of additional explanatory variables, etc. only in the context of our semiparametric model where the imprecision of the estimates would seem to stack the deck in favor of not rejecting the simplest specification.

return variable on the subsample of funds where portfolio data was available.[12] Coefficient estimates are presented in columns 4 and 5 of Table 2, respectively. The estimates and goodness of fit of the two regressions are very similar, so given the difficulty of obtaining reliable betas for our full sample, we will focus on simple excess returns in our subsequent (data intensive) semiparametric estimates.

We have tried to keep the specification as simple as possible in other ways as well. While year dummies are jointly significant when added to the regression in place of the growth in industry assets, adding them produces only very minor changes in the other coefficients and in the goodness of fit, and few of them are individually significant. When further lagged returns are added to the regression, they also have small and insignificant coefficients and thus they have also been omitted.

To see whether the age-return interactions we found might actually reflect size-return interactions, we estimated several models adding variously specified size-return interactions and found them not to be significant and not to affect our other coefficient estimates. Finally, to look for possible effects of survivorship or backfilling bias, we reestimated the base model of column 1 for the subsample of funds for which we had year-end equity holding information (which eliminates the backfilling problem) for the period from 1989 to 1992 (which eliminates the survivorship problem). The results presented in column 6 are very similar to those of our base model.

3.2 Evidence for Nonlinearity

Our primary interest in the flow-performance relationship is in understanding how nonlinearities in the relationship create incentives for mutual funds to manipulate their portfolios. Ippolito (1992) and Sirri and Tufano (1993) have previously noted statistically significant nonlinearities by fitting two- and three-segment piecewise linear models, respectively. While these models are useful descriptively, the strong restrictions they impose make them seem a

[12]More precisely, the sample consists of the subset of the 839 funds discussed in Section 5 for which we had both end-of-September and end-of-December portfolios for which we had flow data and for which we were able to estimate an end-of-year beta.

priori to be inappropriate for estimating the nature of incentives to take risks.[13] Using non-parametric techniques we can reject statistically not only a linear specification for the effect on flow of period t returns, but also two- and three-segment piecewise linear specifications of the relationship.

To see that none of these specifications fully captures the nature of the relationship, we apply a nonparametric specification test described in Ellison and Ellison (1993). They propose testing the hypothesis that a parametric model is correctly specified by looking at a test statistic of the form

$$T = \frac{\hat{\epsilon}' W \hat{\epsilon}}{\sqrt{2}\hat{\sigma}^2 ||W||},$$

where $\hat{\epsilon}$ is the vector of residuals from the null model, W is a nonnegative symmetric matrix indicating which observations are to be considered "close" for the purpose of detecting nonlinearities and $||W|| = (\sum_{ij} w_{ij}^2)^{1/2}$. For our purposes we chose W to be a matrix of kernel weights based solely on differences in year t excess returns.[14] Critical values for the tests were obtained by evaluating the test statistic on 1000 simulated datasets which were created by sampling with replacement from the empirical distribution of the residuals. In the full sample, we can reject our linear specification, a specification which follows Ippolito (1992) in allowing separate coefficients on positive and negative year t excess returns, and a specification which follows Sirri and Tufano (1993) in allowing separate coefficients for period t excess returns in the top, middle three, and bottom quintiles, all at the 1% level. Looking separately at the young- and old-fund subsamples, we again are able to reject our linear specification, and the two piecewise linear specifications at the 1% level for the older funds. All three of the specifications are rejected at the 10% level for the younger funds. From these results, we conclude both that there is strong evidence for nonlinearity in the flow-performance relationship, and that we perhaps have enough data to use semiparametric methods to obtain a more detailed view of the relationship than piecewise linear models provide.

[13]For example, with Ippolito's specification, the incentive to take risks is be constrained to be symmetric about zero, always of the same sign, and with a magnitude smoothly declining in the distance from zero.

[14]The Epanechnikov kernel was used for a range of window widths between 0.02 and 0.04.

3.3 A Semiparametric Model

So far, we have seen that the flow-performance relationship is nonlinear and dependent on the age of the fund. We now use a semiparametric model to investigate further the shape of the relationship. The basic model we estimate is of the form

$$Flow_{it+1} = (1 + \sum_k \gamma_k Age\_k_{it}) f(r_{it} - rm_t) + \sum_k \delta_k Age\_k_{it} + \alpha X_{it} + \epsilon_{it+1},$$

where X_{it} represents the vector of additional explanatory variables from our basic linear model.[15] The model differs from our basic linear model only in that the effect of year t excess return on year $t+1$ flow now follows the nonlinear function f which is also to be estimated. We estimate the specification separately for funds ages 2-5 and for funds age 6 or older to allow the shape of the flow-performance relationship to vary across the groups. Otherwise, to conserve degrees of freedom we assume that the flow-excess return relationship has the same basic shape for all age categories in a single specification. We do, however, include dummy variables which shift and scale the function f so that the mean flow and the sensitivity of flow to performance can vary across the age groups. In order to identify the model it is necessary to omit dummy variables for one age category. If $\gamma_k > 0$ then the function f is scaled up and flow is more sensitive to performance for funds in the k^{th} age category than for funds in the omitted age category. If $\delta_k > 0$ then the curve is shifted upwards so that the expected flow is greater for funds in the k^{th} age category than for funds in the omitted category.[16]

We estimate the model by a three-step process: first estimating the α coefficients, then the γ's and δ's, and finally estimating the function f. For the first step, we note that for each subsample of the data consisting of those observations in a single age category we may obtain a consistent estimate of α by the nonparametric partialing out procedure described by Robinson(1988): performing kernel regressions of both $Flow_{it+1}$ and X_{it} on $r_{it} - rm_t$, and then regressing the residuals on the residuals. The estimate $\hat{\alpha}$ we use is obtained by

[15] Actually, we have made one minor change in the additional explanatory variables – scaling the *Assets* variable by its sample geometric mean $\bar{A}$ so that the figures below are easier to interpret.

[16] Strictly speaking this is necessarily true only at the year t excess return level such that $f(r - rm) = 0$. If in addition $\gamma_k = 0$ this is true at all return levels.

computing separate estimates for each subsample and taking a sample size weighted average of the estimates.

Next to obtain estimates $\hat{\gamma}$ and $\hat{\delta}$ we note that for each age category k we may consistently estimate the function $(1+\gamma_k)f + \delta_k$ from the subsample of the data in that age category using a kernel regression of $Flow_{it+1} - \hat{\alpha}X_{it}$ on $r_{it} - rm_t$. Writing $\hat{g}^k$ for the this estimate (and $\hat{g}^0$ for the estimate obtained from the subsample corresponding to the age category whose dummy is omitted), there are clearly a large number of ways to obtain consistent estimates of γ and δ using the functions $\{\hat{g}^k\}$. For example, one very simple (and likely very inefficient) method would be simply to set

$$\hat{\gamma}_k = \frac{\hat{g}^k(x_1) - \hat{g}^k(x_0)}{\hat{g}^0(x_1) - \hat{g}^0(x_0)} - 1 \qquad \text{and} \qquad \hat{\delta}_k = \hat{g}^k(x_0) - (1+\hat{\gamma}_k)\hat{g}^0(x_0)$$

for some pair of points x_0 and x_1. The estimates we use are obtained by evaluating each $\hat{g}^k$ on a grid of points in the center of the data and then regressing the values of each $\hat{g}^k$ on the values of $\hat{g}^0$ using $r_{it} - rm_t$ as an instrument.[17]

Finally to obtain an estimate $\hat{f}$ of the function f we perform a kernel regression of

$$\hat{y}_t \equiv \frac{Flow_{it+1} - \sum_k \hat{\delta}_k Age\_k_{it} - \hat{\alpha}X}{1 + \sum_k \hat{\gamma}_k Age\_k_{it}}$$

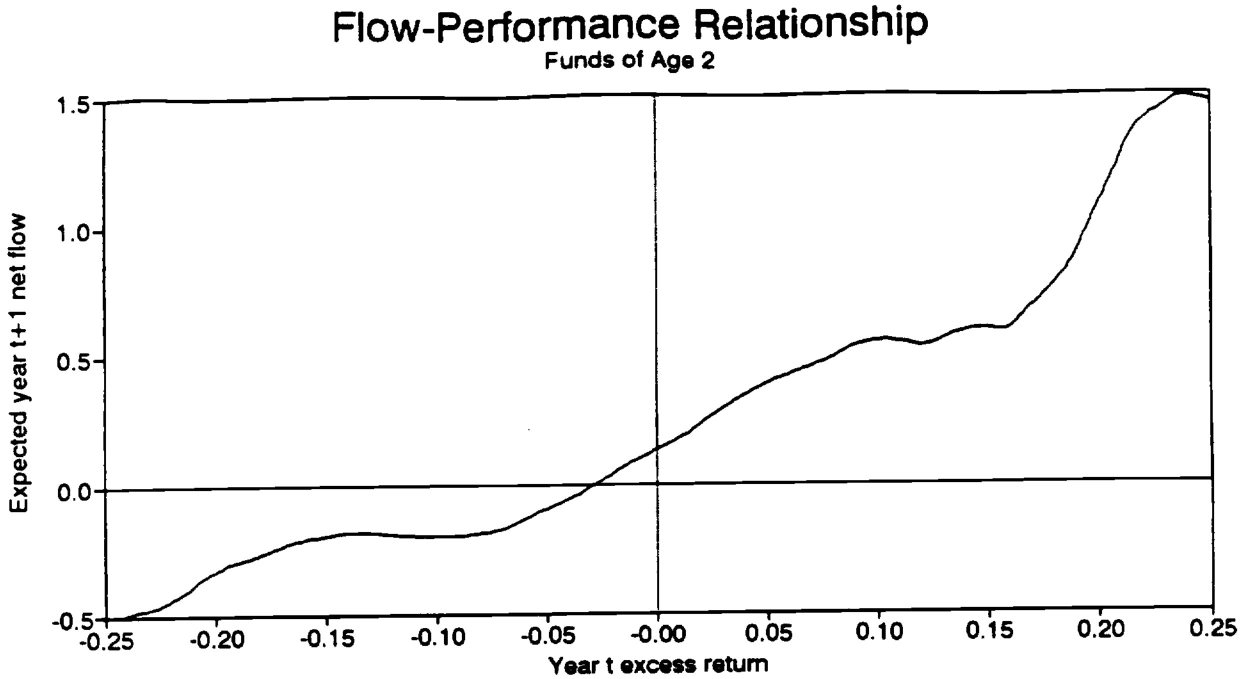
on $r_{it} - rm_t$. In this and all other kernel regressions we have used an Epanechnikov kernel with a window width which varies across the data so that more smoothing is done near the edges than in the middle of the excess return distribution. Specifically, in any regression involving n data points we use the window width $(0.3+0.1|r_{it}-rm_t|)(n/1000)^{-1/5}$. Standard errors for all of the parameter estimates were obtained by simulations which allowed for nonnormality of the error distribution and a degree of heteroskedasticity by sampling errors with replacement from the set of residuals corresponding to observations within the same age category.

With this model, we are finally in a position to discuss the most interesting aspect of the flow-performance relationship — the nature of the nonlinearities which may create incentives for funds to manipulate their portfolios. Figure 1 presents a graph of the function $\hat{f}$ obtained from the subset of young funds. Given the normalizations we have made, the

[17]The support of the grid used was $[-0.17, 0.17]$.

graph may be interpreted as presenting the expected growth rate in year $t+1$ of a two year old fund as a function of its year t excess return (assuming also that the fund's excess return is zero in years $t-2$, $t-1$, and $t+1$, that the fund's total assets match the geometric mean of our sample, and that the industry as a whole experiences zero growth.) For example, such a fund would be expected to grow by approximately 15% in year $t+1$ if its year t return matches the return on the market, and to grow by approximately 55% if its return is ten points greater than the market return.

Figure 1: Nonlinear Flow-Performance Relationship $\hat{f}$ for Young Funds



While we do not attempt in this paper to test formal models of consumer behavior, the relationship in the figure appears to be roughly consistent with a model in which heterogeneously informed potential investors try to assess the quality of various funds.[18] When the firm's return is fifteen or more points below the market, funds flow out quickly with the rate being sensitive to performance, as if increasingly even investors who pay

[18] We would like to emphasize that we are not trying to test any particular hypothesis of consumer behavior only to provide an intuitive mental model which may help the reader to remember the empirically identified pattern. We recognize that by varying the type of heterogeneity, the relative informativeness of different signals, etc. a wide variety of patterns could have been explained.

little attention begin to take notice of the fund's poor performance.[19] For somewhat less disastrous results (say between fifteen and eight points below the market) the curve appears to be largely flat, as if the fund attracts few or no new investors but does retain many of its old investors. At more typical performance levels, flow is increasing in year t excess returns. The marginal value of each unit of return appears perhaps to diminish once the excess return reaches ten points and then increases sharply at excess return levels above fifteen points. This pattern is consistent with a model where very large returns bring sharply higher flows as a fund starts to make annual "Best Fund" lists and therefore comes to the attention of relatively uninformed potential investors.

Regardless of whatever behavior has generated the flow-performance relationship illustrated in Figure 1, the shape clearly suggests that interesting incentives to manipulate portfolios may exist. In particular, the graph suggests that the relationship may be convex in some regions and concave in others. Whenever the relationship is convex, funds will have an incentive to increase their unsystematic risk as the end of the year approaches. When the relationship is concave, the incentive will be to index the market. If the flow-performance relationship is indeed concave in some regions and convex in others and funds react to these incentives, intermediate returns could be used to predict end-of-year portfolio changes. We develop these ideas further and also discuss the statistical significance of the patterns we have described in the following section.

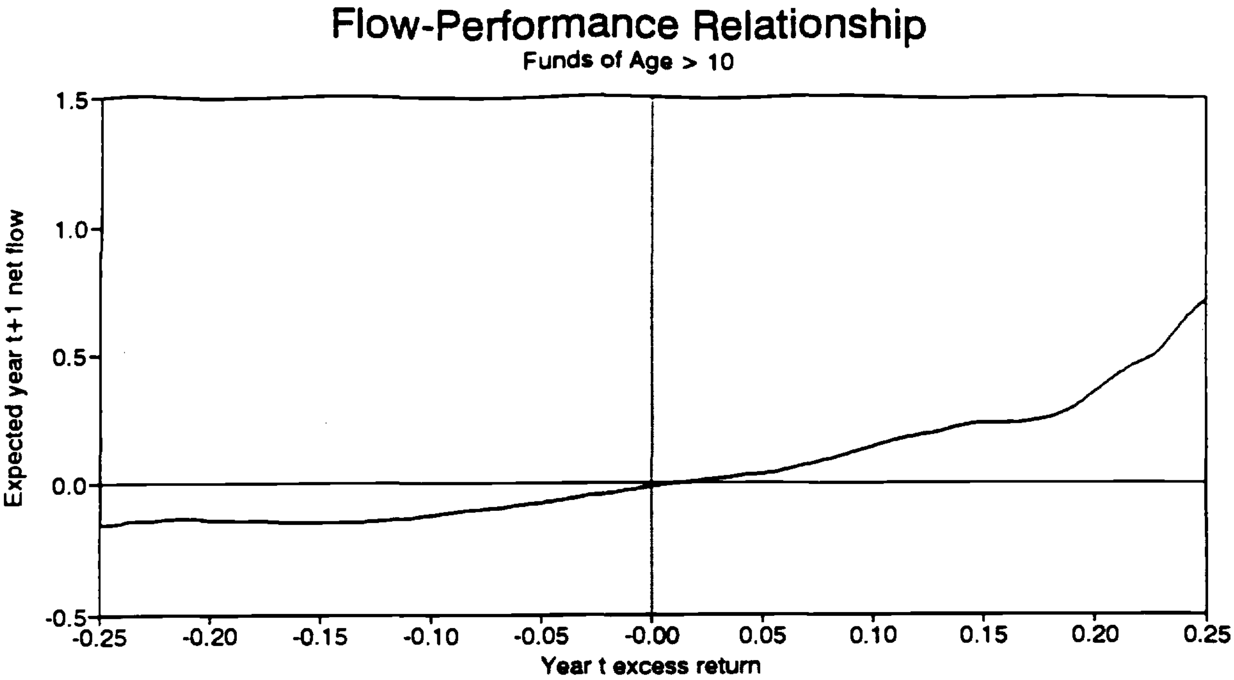
The function $\hat{f}$ estimated from the sample of older funds is presented in Figure 2. Here, we have omitted the dummy for funds of age 11 and above, so that the graph can be interpreted as presenting the expected growth rate of a fund of this age group in year $t+1$ as a function its year t excess return.[20] The estimated expected flows for these funds are clearly less sensitive to year t excess returns than are those for two year old funds, never falling below -15% or rising above 75% for a fund whose return is within twenty five points of the market. The most striking feature of this graph is its generally convex shape which

[19] Here we should note that the left side of this figure may be affected by selection bias. Funds which perform very poorly are more likely to "die" and have their flow omitted from our dataset. Treating these deaths as substantial outflows would likely result in a picture which was more steeply sloped at low performance levels.

[20] In both subsamples we took the omitted age dummy to be that for the category with the largest number of observations hoping that this would provide the best estimate of γ.

suggests that incentives to carry unsystematic risk may be fairly universal. In contrast to the pattern for younger funds we do not see outflows increase dramatically at the worst performance levels. Flows do, however, again increase sharply for the best performing funds.

Figure 2: Nonlinear Flow-Performance Relationship $\hat{f}$ for Old Funds



The semiparametric models involve also scaling factors and the same control variables as in the linear model. Estimates of the parameters are presented in Table 3. Where they are comparable, the estimates are generally similar to those from the linear models presented in Table 2, and despite our having shifted to a semiparametric model most of these coefficients remain highly significant. The main differences in the coefficients on the control variables are that the estimated effect of year $t+1$ returns is larger than before, as is the effect of industry growth.

To interpret the estimated γ's, it should be kept in mind that the omitted age dummies are for two year old and eleven year old and older funds in the two subsamples. To obtain, for example, a graph of the expected growth rate of a four year old fund (having otherwise the standard characteristics) one would multiply the curve in Figure 1 by a factor of 0.66

Table 3: Coefficients from Semiparametric Flow-Performance Model

Independent Variables	Dependent Variable: $Flow_{t+1}$	
	Young Funds	Old Funds
Multiplicative *Age_3* (γ_3)	-0.28	—
	(0.25)	
Multiplicative *Age_4* (γ_4)	-0.34	—
	(0.20)	
Multiplicative *Age_5* (γ_5)	-0.46	—
	(0.22)	
Multiplicative *Age_6-7* (γ_{67})	—	0.30
		(0.79)
Multiplicative *Age_8-10* (γ_{810})	—	0.35
		(0.38)
Additive *Age_3* (δ_3)	0.06	—
	(0.07)	
Additive *Age_4* (δ_4)	-0.02	—
	(0.06)	
Additive *Age_5* (δ_5)	-0.01	—
	(0.06)	
Additive *Age_6-7* (δ_{67})	—	0.03
		(0.09)
Additive *Age_8-10* (δ_{810})	—	0.02
		(0.04)
Excess return$_{t-1}$	1.86	1.00
	(0.25)	(0.14)
Excess return$_{t-2}$	0.73	0.29
	(0.31)	(0.16)
Excess return$_{t+1}$	2.49	2.44
	(0.26)	(0.16)
$IndustryGrowth_{t+1}$	1.07	0.85
	(0.12)	(0.07)
$\log(Assets/\bar{A})$	-0.07	-0.04
	(0.02)	(0.01)

* Estimated standard errors in parentheses.

(=1-0.34) and then shift it down by 0.02. Hence a four year old fund which matches the market return would be expected to grow by about 8%, with the expected growth increasing to about 36% if its return is ten points above the market. That the multiplicative terms γ_3, γ_4, and γ_5 for funds of age three to five are negative and monotonically decreasing indicates that the older funds' flows are increasingly less sensitive to their most recent performance. While these parameters are not very precisely estimated, the sensitivity of the four- and five year old funds to year t returns is significantly smaller than that for two year old funds at the 5% level in a one tailed test. In the subsample of older funds our point estimates indicate that flows into the six to seven and eight to ten year old funds are more sensitive to year t returns than are flows into funds which are eleven years of age or more, although the differences fail to be significant.

4 Estimation of Risk Incentives

In this section we discuss how the flow-performance relationship viewed as an incentive scheme may induce mutual funds to manipulate the riskiness of their portfolios toward the end of the year. We take the basic agency problem between a mutual fund and its investors to be that while investors would like the fund to use whatever private information it may have to maximize risk adjusted returns, the mutual fund itself will instead take whatever action maximizes its value as a concern given the incentives it faces.[21] Because management fees in the industry are usually charged as a percentage of assets (within some size range), the value of a mutual fund (holding future expected growth and the level of management fees constant) is to a first approximation proportional to its assets under management. Because many potential investors see and react to year-end returns, a fund may at times increase its expected inflow of investment (and hence its value) by altering the riskiness of its portfolio.

Given that a mutual fund wishes to maximize its value as a concern how might it have

[21]Note that in doing so we assume away any agency problems between mutual fund companies and their managers.

an incentive to distort its portfolio? For a simple illustration consider the case of a two year old fund which by the end of September of year t has fallen eight percentage points behind the market and which finds itself confronted by the flow-performance relationship of Figure 1. If the fund indexes the market for the remainder of the year it will finish the year eight points below the market and see an expected outflow of 14% of its value in year $t+1$. If in the final quarter the fund loses five more points and finishes the year 13 points behind the market the expected outflow will be about the same. If instead the fund outperforms the market by five points in the final quarter it will finish the year three points behind the market — a position sufficient to provide (in expectation) a small positive expected inflow in year $t+1$. Clearly, the fund's expected size at the end of year $t+1$ is far greater if it holds a portfolio which is equally likely to gain or lose five points than if it indexes the market, *i.e.* the fund is tempted to gamble and try to catch up with the market. In contrast, suppose the fund were instead eight points ahead of the market by the end of September. Inflows would now be only slightly higher with a small improvement in performance, but would be sharply lower with an inferior performance. Hence, the fund benefits from "locking-in" its gains by indexing the market throughout the fourth quarter.

The incentives to alter the riskiness of a portfolio described above are derived from the fact that flows (or our estimates of them) are a nonlinear function of calendar year returns.[22] If instead flows were a separable function of the returns in each quarter, a fund's position relative to the market at the end of September would be irrelevant to its behavior in the final quarter. Why should we believe that there is something "magic" about calendar year returns? We believe that the calendar return in the most recent year is important because calendar year data appear to be most generally available to consumers. The calendar year return is the format used in the comprehensive listing of mutual funds published annually in *US News and World Report*, *Money*, *Kiplinger's*, and *Business Week* (total circulation of approximately 6.4 million). Potential investors can obtain comprehensive listings of returns quarterly from the *Wall Street Journal* or *Barrons* (total circulation of approximately 2 million) or obtain annual returns calculated during the third quarter from

[22]That such incentives exist when agents can alter their behavior in continuous time is the core of Holmstrom and Milgrom's (1987) argument that linear incentive schemes may be optimal in such situations.

Fortune (total circulation of approximately 0.9 million), but certainly some investors do not see this information. The annual return format is also used in the annual comprehensive fund listings produced by Morningstar and others. Furthermore, the annual return format is required in prospectuses, although these may contain fiscal rather than calendar year returns.

How can we quantify the incentive of a mutual fund to increase or decrease the amount of risk it holds toward the end of the year? In this section we take the simplest approach possible in trying to capture this incentive in looking solely at the incentives derived from a fund's desire to maximize its expected growth rate in the following year. In particular, we note that at the end of September of year t a k year old fund's expected year $t+1$ growth rate takes the form

$$E[Flow_{it+1}] = E[(1+\gamma_k)f(r_{Sep}+u) + \delta_k + \alpha X_{it}],$$

where r_{Sep} is the fund's year-to-date excess return and u is a random variable representing the fund's excess return in the final quarter of year t. Assuming that u is an appropriately distributed random variable with mean zero and standard deviation σ, and that v has mean zero and standard deviation $\sigma+\Delta\sigma$, then the expected increase in a fund's year $t+1$ growth rate which results from increasing its quarterly standard deviation from σ to $\sigma+\Delta\sigma$ (or more precisely changing its fourth quarter excess return distribution from u to v) is

$$h_k(r_{Sep};\sigma,\Delta\sigma) = E[(1+\gamma_k)(f(r_{Sep}+v) - f(r_{Sep}+u))].$$

Note that this measure of a benefit of increased risk is simply a linear functional of the function f we estimated in the previous section. We can thus estimate h_k consistently (on a bounded set of r values) by simply plugging our estimates of $\hat{f}()$ and $\hat{\gamma}_k$ into the formula above (at least provided that u and v have bounded support.)

The function $h_k()$, of course, does not fully capture the complex effect that an increase in the riskiness of a mutual fund's portfolio has on its value. A fund's calendar year t excess return affects as well its growth rate in years t, $t+2$ and $t+3$. While a change in the riskiness of the year t portfolio does not affect the expected growth rates in these years given our linear specification, the fact that growth rates are higher in future years when the base asset values to which these growth rates apply are high implies that in a full dynamic value function calculation there will be a small additional incentive to carry risk. Performing such a calculation is difficult computationally, and also requires assumptions about the discounting of profit flows and the time path of industry growth. More importantly, the additional incentives such a calculation finds will be quite sensitive to the functional forms we have specified and not estimated for the effect of year t excess returns on growth rates in years other than $t+1$. Given these difficulties and our expectation that the dynamic effects are small, we feel that the simpler approach of focusing on year $t+1$ growth rates yields a more convincing measure of the incentives to take risks.[23]

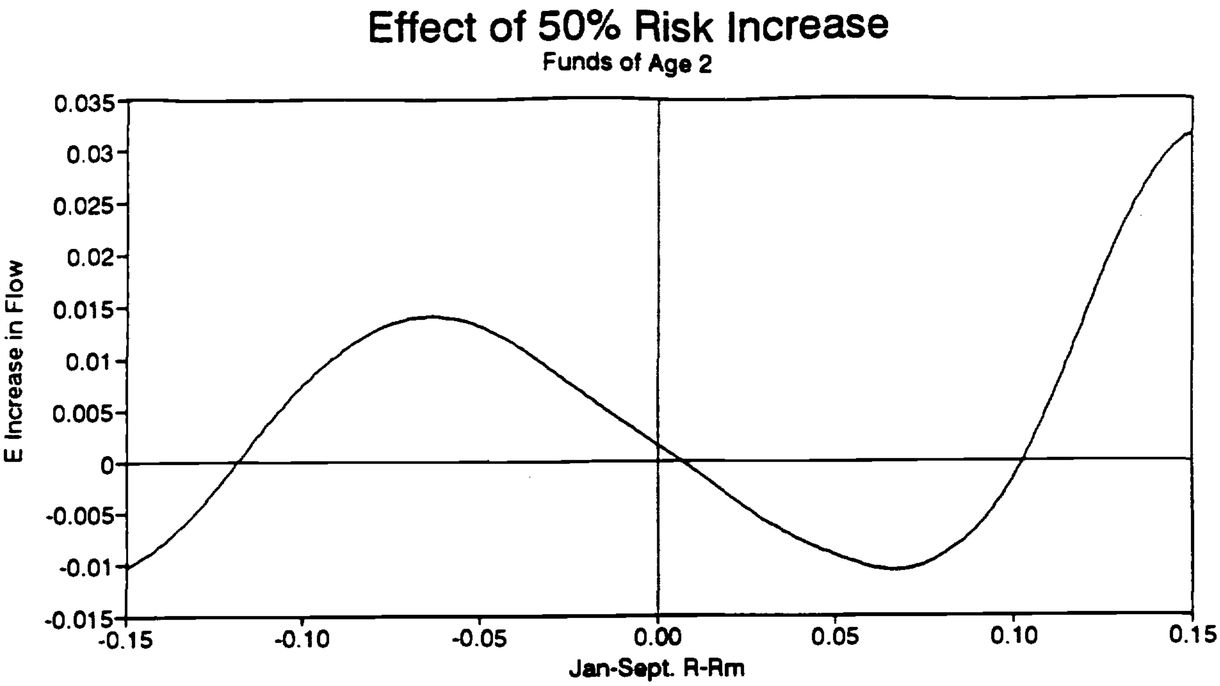
Figure 3 provides our first clear look at the incentives to take risks created by the flow-performance relationship. The figure presents an estimate of the function $h_2(r_{Sep}; \bar{\sigma}, 0.5\bar{\sigma})$, *i.e.* of the expected increase in the year $t+1$ growth rate of a two year old fund which results from its increasing its risk in the fourth quarter of year t from the sample average to 50% above this average.[24] In accord with the intuition developed above, the point estimates graphed in the figure indicate that funds who are somewhat behind the market have an incentive to gamble and try to catch up while funds which are somewhat ahead of the market have an incentive to lock in their gains. The figure suggests in addition that these incentives reverse at extreme positions: funds who are well behind the market may want to reduce their risk, while funds who are well ahead of the market may have a strong incentive to gamble. The figure also quantifies the incentives – such an increase in risk increases the expected growth rate of a fund which is somewhat behind the market by one percentage point, and may increase the expected growth rate of a fund which is well above the market by over three percentage points. Note also that given our functional form assumptions and the estimated γ's the incentives for three, four, and five year old funds are identical in shape to the graph shown here, but scaled down by 28%, 34%, and 46% respectively.

Figure 4 presents the corresponding graph for funds of age eleven or more. Note first

[23]We have also ignored the possibility that flows do not fully capture the short term effect on profits because funds anticipating increased demand may increase their management fees.

[24]More precisely, $\bar{\sigma}(=0.037)$ was set to sample standard deviation of fourth quarter excess returns in the complete set of growth and growth and income funds in *Mutual Funds OnDisc*. The distributions of u and v were taken to be truncated normals.

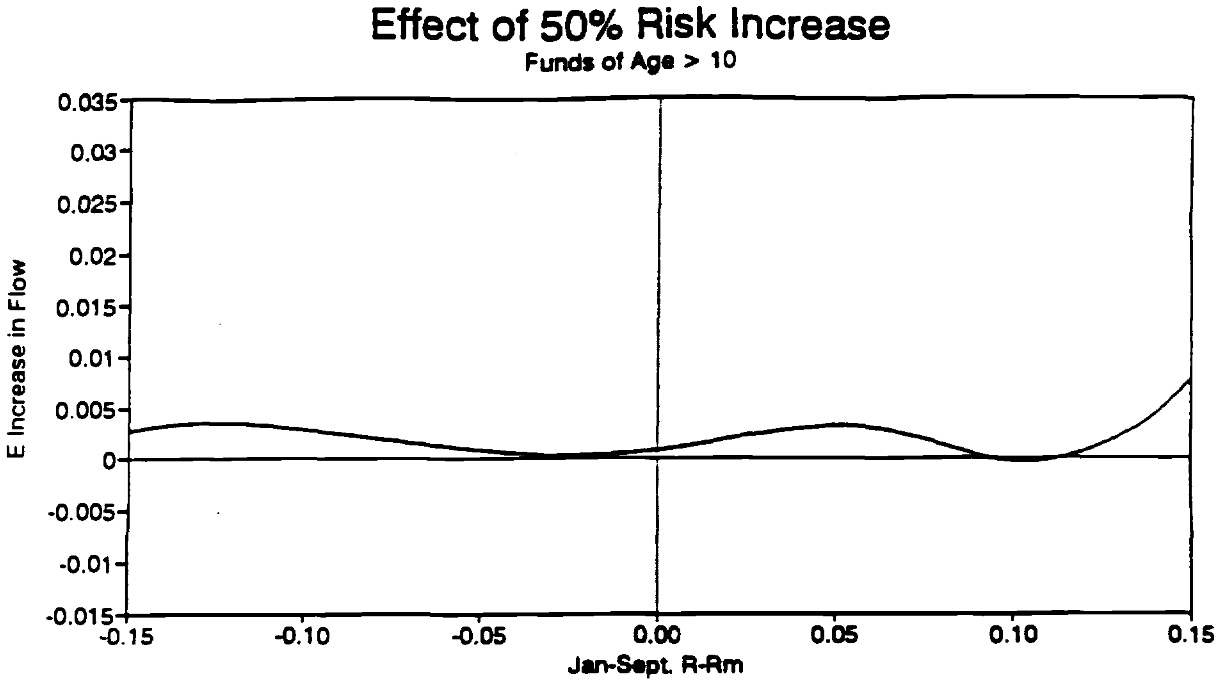
Figure 3: Incentive to Increase Risk for Two Year Old Funds



that, as might be expected given that flows into these funds are much less sensitive to recent performance than are flows into younger funds, the estimated incentives are much weaker than for the two year old funds. The potential increase in the year $t+1$ growth rate is estimated to exceed one-half of one percentage point only for funds who are very far above to the market. In addition, the pattern of the estimated incentives is much less striking. The older funds appear frequently to have an incentive to increase their riskiness toward the end of the year, but we do not observe clearly defined regions where the incentives are much stronger or weaker.

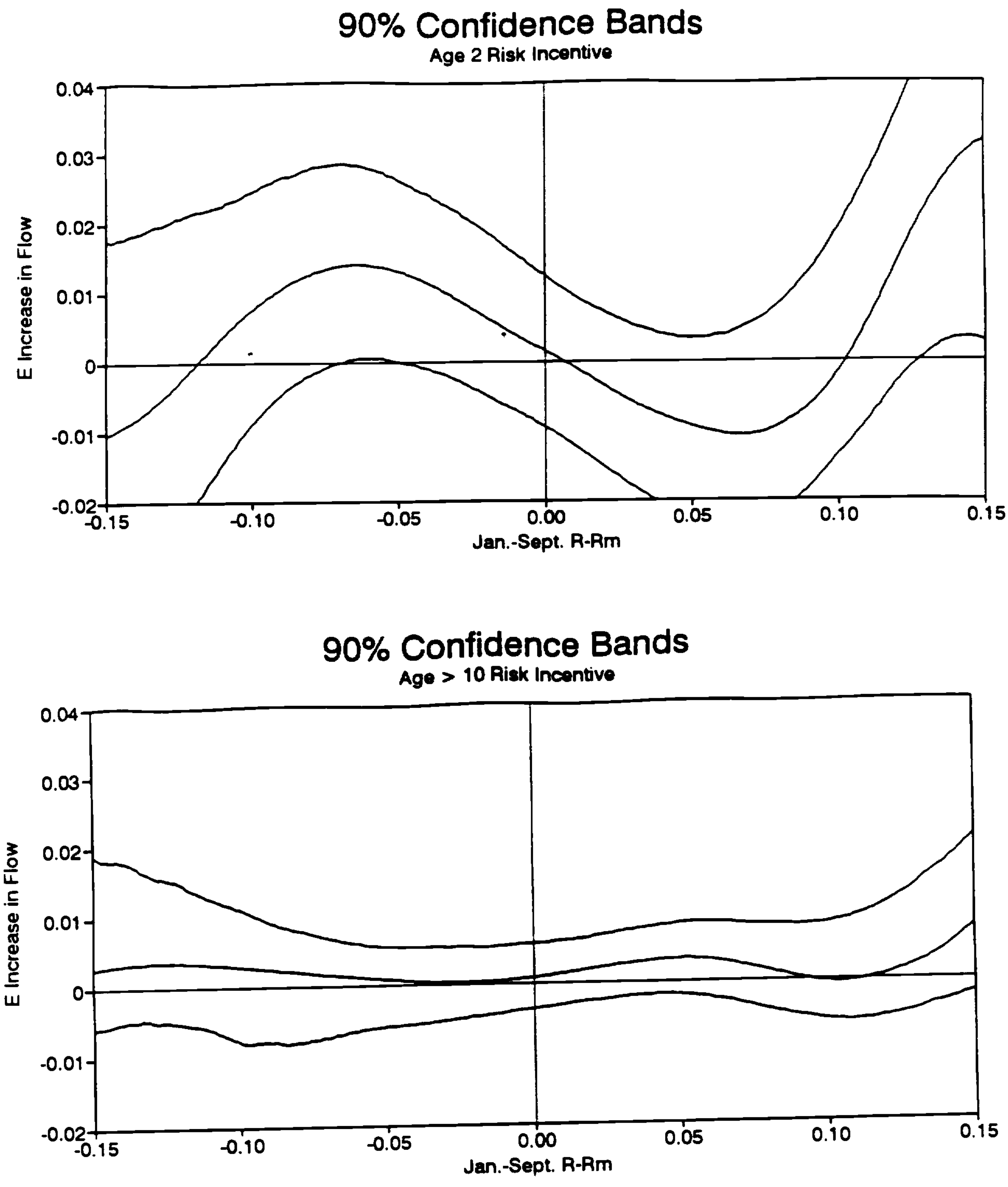
In the previous section, we deferred any discussion of the statistical significance of the nonlinear patterns visible in the flow-performance graphs beyond simply noting from the specification tests that globally the departures from linearity were significant. Now that we have finally derived quantitative results from the estimated flow relationship, it is time to return to this issue. In particular, we should discuss whether our model provides statistically significant evidence of the existence of incentives to alter risk levels. To address this question, we estimated the flow-performance relationship and derived the risk incentive

Figure 4: Incentive to Increase Risk for Eleven+ Year Old Funds



functions $\hat{h}_2$ and $\hat{h}_{11+}$ on 7900 simulated datasets which were created as before by sampling with replacement from the age-specific empirical distribution of residuals from our base semiparametric models. Figure 5 presents the pointwise 90% confidence bands obtained from these simulations. In the case of the young funds, the incentives are significantly greater than zero at the 10% level for funds which are well ahead of the market and for funds which are a little more than five points behind the market. The incentive to lock in gains falls just short of significance at this level for funds who are about five points ahead of the market. In the case of the older funds, the confidence bands are tighter, but we obtain far less in the way of significant results. In a pointwise test we are unable to reject that the incentive at any intermediate return level is zero. In a joint test, however, the average across all the return levels in the figure is significantly positive at the 10% level.

Figure 5: 90% Confidence Bands for Risk Incentives



5 Do Funds Alter their Risk in Response to these Incentives?

In this section, we finally come to the question which most interests us, investigating whether mutual funds adjust the riskiness of their portfolios in response to the incentives created by the flow-performance relationship. We have already seen that the incentive of a mutual fund to hold unsystematic risk in its portfolio is affected by the fund's position relative to the market portfolio at the end of September. Here, we explore the ways in which mutual funds actually alter their portfolios between the end of September and the end of December.

The primary focus of this section is on detailed data on the *equity* portion of funds' portfolios — data which contain complete listings of the common stock holdings of 398 growth and growth and income mutual funds both at the end of September and at the end of December of certain years (giving a total of 839 fund-years of data). With these data, we analyze how funds alter the riskiness of their portfolios toward the end of the year and show that these changes appear to be related to the incentives to take risks we have previously identified. Subsequently, to allay fears that the changes we find in the equity portion of portfolios may not reflect the nature of overall portfolio changes we look also at (less detailed) data on changes in portfolio composition (*e.g.* stocks vs. cash) and in measures of riskiness constructed from time series data. Finally, we discuss the robustness of our results in several respects.

Before beginning with our analysis, it is useful to say a few words about how we might expect portfolios to change between September and December given the results of the previous section. The simplest way to think about this question is to imagine that each mutual fund has some private information about which stocks are likely to increase in value and is allowed to change its holdings on exactly two dates each year – January 1st and October 1st. If a fund is acting solely in the best interest of its shareholders, the fund would, on each occasion, select whatever portfolio it believes will have the highest risk-adjusted return. If, however, the fund is motivated by a desire to maximize its expected growth rate, it will depart from this strategy and adjust the riskiness of its portfolio up or down, with the amount of the adjustment determined by trading off the benefit of the higher or lower risk level with the cost of a decreased expected return from not using its information optimally. In January, the incentives to alter the riskiness of a portfolio are generally fairly weak. By the end of September when a fund finds itself ahead of or behind the market, we have seen that the incentives to alter risk levels may be fairly strong. On October 1st, therefore, we might expect firms to change their risk levels in the direction of the incentive we have previously identified — a change we could observe by comparing the end-of-September and end-of-December portfolios.

In the real world, of course, opportunities to alter a portfolio arrive in continuous time. Funds which have a strong incentive to carry unsystematic risk in the final quarter may have already increased their riskiness before September is over. They might also begin to reduce their risk back toward the level which will be optimal in January before the end of December. Nonetheless, given the structure of the data available to us it seems reasonable to hope that these effects are not so large as to eliminate any correlations entirely, and to ask whether portfolio changes are in the direction we would predict from the incentives we have identified.

In addressing this question, our primary measure of the riskiness of a fund's portfolio at a point in time is the sample standard deviation of the difference between the return of the portfolio and the return on the market portfolio (calculated from historical data on the component securities). Because of the implicit assumption in our flow regressions that investors react to the simple difference between a fund's return and the market return, it is in terms of this measure that we computed incentives to change risk levels. Note that the total variance of a portfolio in this sense can be decomposed into two parts,

$$\mathrm{Var}(r_i - rm) = \mathrm{Var}(r_i - \beta rm) + (\beta - 1)^2 \mathrm{Var}(rm).$$

The first term in the expression above is the fund's unsystematic risk, the part of risk not associated with movements in the market. The second is increasing in the distance of a fund's beta from unity reflecting variance from implicit bets with or against the market as a whole. At times we will also explore changes in each of these components of riskiness separately.

5.1 Changes in the riskiness of equity portfolios

In this subsection, we use data on funds' equity holdings to generate measures of end-of-year risk changes. We use a simple regression to show that risk changes are related to the incentives we have previously identified, and then analyze risk changes in more detail.

We focus solely on the equity portion of funds' portfolios here because our detailed security-level data is limited in two ways. First, our data contain the share of fund assets that are held in cash, bonds, and other securities only for a subset of the funds for which we have equity portfolio data. Second, even when we do know the shares of the portfolio held in cash or bonds, the data do not contain security level descriptions of the bond holdings, derivative positions, etc., so that we can only give crude estimates of the riskiness of the fund's complete portfolio. Because the mutual funds in this study are garden-variety growth or growth and income funds, the vast majority of the funds' holdings are in common stocks. For the funds in our sample for which we have holdings data, the median fund has 88% of its holdings in common stocks (and no derivatives). Hence we may hope that changes in the equity portfolio provide a meaningful reflection of risk changes.

For each equity portfolio, risk measures were calculated from the CRSP daily return data for the prior year. Thus, for example, when calculating the beta for a stock held by a mutual fund in September or December of 1990, we examined the covariance of the stock's return with the return on the market portfolio for January through December of 1989.[25] Prior year data were used so that changes in portfolio risk reflect actual changes in the portfolio, not changes in the measured riskiness of the component securities. The beta of a portfolio was calculated by taking the weighted average of the betas for the component securities, and the standard deviation measures were calculated by taking the appropriate weighted sum of the variances and covariances of the returns of the individual securities. One difficulty with these calculations is that it was impossible to calculate the risk measures for every security in every portfolio because matches to the CRSP database could not always be made. In the regressions below, we use data only from those mutual funds for which we could match and obtain historical data on at least 85 percent of the total holdings (by

[25] Our market return proxy is a value weighted combination of NYSE, AMEX and NASDAQ returns.

value) in the September portfolio.

5.1.1 Basic tests of reactions to incentives

The basic hypothesis generated by the analysis of the flow-performance relationship is that mutual funds alter the variance of their portfolio returns around the return of the market in order to increase the expected flow of funds into the mutual fund. We test this hypothesis first via several simple cross section regressions. The dependent variable in each specification is the change in a measure of the riskiness of each portfolio between the end of September and the end of December. The primary independent variable of interest, $RiskIncentive$, is a measure of the incentive of each fund to increase its riskiness calculated in much the same manner as we calculated the incentive to increase risk as a function of the end-of-September position relative to the market in the previous section. The only differences are that the incentives are scaled up or down by the factor γ_k appropriate to the age of the fund, and that the risk incentives are calculated as the incentive to increase the standard deviation not from the mean but instead from its end-of-September level. Note that the incentive variable has already been scaled to take into account each fund's age, etc. so that it is natural for the variable to enter additively with a constant coefficient. Because increasing or decreasing the overall risk level of the portfolio may be more difficult for larger portfolios, we do also include in the regression the risk incentive measure multiplied by the natural log of total fund assets. A negative coefficient for this variable would indicate that, for a given risk incentive, larger mutual funds adjust their overall risk level less than smaller mutual funds. To allow for the possibility of mean-reversion in measured portfolio riskiness, we include also the September level of the risk measure in the regression. Finally, we also include in the regression the natural log of total assets of the fund.

We exclude from the estimations the set of funds mentioned before for which we thought the flow-performance relationship might differ from that of standard retail growth and growth and income funds. Specifically, we excluded index funds, funds which were closed to new investors, funds which have a high minimum initial purchase requirements, funds with very high expense ratios, funds with total assets of less than $10 million, and funds which merged during the fund-year. Summary statistics are reported in Table 4.

Table 4: Summary Statistics for Risk Change Regressions

Variable	Mean	St.Dev.
Sept. $SD(r - rm)$	0.053	0.022
Sept. $SD(r - \beta rm)$	0.048	0.020
Sept. $\lvert\beta - 1\rvert$	0.153	0.115
$\Delta SD(r - rm)$	0.0019	0.008
$\Delta SD(r - \beta rm)$	0.0017	0.007
$\Delta\lvert\beta - 1\rvert$	0.006	0.045
$RiskIncentive$	0.0017	0.004
$\log(Assets)$	5.269	1.475
Sept. share matched	0.936	
Dec. share matched	0.918	

The regression results are reported in Table 5. The first column shows the results for the basic hypothesis test. The risk measure used, $\Delta SD(r - rm)$ is the change in the standard deviation of the difference between fund return and the return on the market portfolio. The coefficient for the risk incentive measure is positive, while the coefficient on the interaction of the risk incentive measure and $log(Assets)$ is negative, indicating that small funds at least do adjust their riskiness in the direction of the incentive we have measured, and that the magnitude of the response is larger for smaller funds. Each coefficient is significant at the five percent level. It is, however, important to note that the estimated response of portfolio risk changes to the risk incentive diminishes quickly as fund size rises. In a one-tailed test we can reject at the 5% level the null hypothesis that the coefficient for the risk incentive measure plus the coefficient for the risk incentive measure multiplied by the log of assets equals zero only for fund sizes which are below the 40th percentile in our sample.

The magnitude of the effect is fairly small, but still of practical relevance. For example, for a two year old fund the $RiskIncentive$ variable may take on a value of 0.01 for a fund which is a few points behind the market and 0.03 for a fund which is well ahead of the market. For the smallest funds we are using (those with an asset value of approximately $10 million) the coefficients in the regression imply that the expected increases in the standard deviation are approximately 0.005 and 0.015 in the two situations. Such changes would require increasing the variance of the mean portfolio in our sample by about 17% and 48% respectively. Contrary to what we might have expected, there seems to be no evidence of mean reversion in portfolio riskiness.

Table 5: September-December Risk Changes and Incentives

Independent Variables	Dependent Variable		
	$\Delta SD(r - rm)$	$\Delta SD(r - \beta rm)$	$\Delta\|\beta - 1\|$
$RiskIncentive$	0.83	0.70	1.98
	(0.36)	(0.32)	(2.06)
$RiskIncentive \cdot \log(Assets)$	-0.14	-0.11	-0.52
	(0.07)	(0.06)	(0.38)
$\log(Assets)$	0.00008	-0.00002	0.002
	(0.0003)	(0.0002)	(0.002)
Sept. Risk Level	0.05	0.03	-0.007
	(0.02)	(0.02)	(0.02)
Constant	-0.001	-0.00001	-0.005
	(0.002)	(0.002)	(0.009)
N	464	464	464
R^2	0.03	0.03	0.01

* Estimated standard errors in parentheses.

As we noted above, we may decompose the riskiness of a portfolio (in the sense we have used it) into the portfolio's level of unsystematic risk and the departure of its beta from unity. The second column of Table 5 repeats the standard regression with our measure of the change in unsystematic risk, $\Delta SD(r - \beta rm)$, as the dependent variable. The results are very much like those discussed above, with each coefficient again being significant at the 5% level in a one tailed test.

If consumers do indeed react to the simple difference between a fund's return and the market return as they do in our econometric specification, then a fund which wishes to increase its level of risk may also do so by moving its beta away from unity. We would like to emphasize, however, that our specification of flows as a function of $r - rm$ instead of

$r - \beta rm$ was dictated by data constraints, and that we do not regard our results or anyone else's as providing any convincing evidence on the extent to which consumers take betas into account in judging performance.[26] While we will therefore be hesitant to claim that any regression explaining changes in betas is a clean test of reactions to incentives, we do feel that such a regression is at least of substantial descriptive interest. The third column of Table 5 repeats the basic risk change specifications of the first two columns, with $\Delta|\beta - 1|$ as the dependent variable and Sept $|\beta - 1|$ as the initial risk level. The results show a positive coefficient for the risk incentives measure, and a negative coefficient for the risk incentive measure interacted with size. However, neither coefficient is significantly different from zero at standard confidence levels.

5.1.2 A more detailed picture of equity risk changes

While the simple regressions above provide a straightforward test of the hypothesis that funds react to the incentives we have identified, they may leave one wondering exactly how sharp the correspondence between the patterns of actual incentives and behavior is. We thus turn now to the task of providing a more detailed picture of actual risk changes.

Recall from Section 4 that the pattern of incentives to manipulate the riskiness of a mutual fund depends on the age of the fund. For "young" funds, the payoff to increasing risk (pictured in Figure 3) is negative for funds who are far behind the market, increases with a fund's January-September excess return until reaching a local maximum at about six points behind the market, then decreases to a minimum for funds which are about seven points ahead of the market, and finally increases sharply to reach its highest level for funds who are far ahead of the market. For "old" funds, an incentive to increase risk (pictured in Figure 4) appears to exist fairly generally, although the precise pattern of the incentive is less clear.

To assess whether actual risk changes follow such patterns in detail, we felt it would be most valuable simply to produce pictures of actual changes which could be compared visu-

[26] Given informational limitations, however, we do feel that it seems unlikely that investors could react much to a short-term change in a fund's beta.

ally with Figures 3 and 4. Because of the limited number of funds for which we have portfolio data, we chose not to attempt another semiparametric analysis, but instead simply to fit a piecewise linear model to the relationship between risk changes and January-September excess returns. Specifically, we used nonlinear least squares to estimate the equation

$$\Delta SD(r_i - rm) = \alpha_0 + \alpha_1 \log(Assets) + \alpha_2 Sept.SD(r_i - rm) + h(\text{Jan.-Sept.}r_i - rm) + \epsilon_i$$

where $h(x)$ was a continuous, piecewise linear function having five parameters: the locations of two kinkpoints ($KINK1$ and $KINK2$) and the slopes in the regions to the left of both kinks ($SLOPELEFT$), between the two ($SLOPEMID$), and to the right of both ($SLOPERIGHT$). For the sample of young funds, for example, if the pattern of actual risk changes closely matched the estimated incentives to take risks shown in Figure 3, we would expect to find that $KINK1$ was approximately -0.06 and $KINK2$ was approximately 0.07. Figure 3 also suggests that we would expect to find that $SLOPELEFT$ and $SLOPERIGHT$ are positive, while $SLOPEMID$ should be negative.

Coefficient estimates from the piecewise linear model for the subsample of young funds are presented in column 1 of Table 6. The correspondence between actual changes and incentives is fairly strong. The first estimated kinkpoint, $KINK1$ is located at -0.06, with the estimate being highly significant. The second turning point, $KINK2$, is estimated very imprecisely, with the estimate of 0.001 not being significantly different from 0.07. The estimated slope of the first segment, $SLOPELEFT$, is positive as predicted, and significantly different from zero at the 5% level. The estimated slope of the second segment, $SLOPEMID$, is negative as predicted, but not significantly different from zero. $SLOPEMID$ is, however, significantly different from $SLOPELEFT$. The slope of the third segment, $SLOPERIGHT$, is positive although very small and again not significant. To facilitate comparisons with the incentives shown in Figure 3, predicted values from this regression are graphed in the top panel of Figure 6. From the graph it appears that the most salient feature of the actual risk change data is that funds who are somewhat behind the market do tend to increase the riskiness of their portfolios toward the end of the year as if trying to gamble and catch the market.

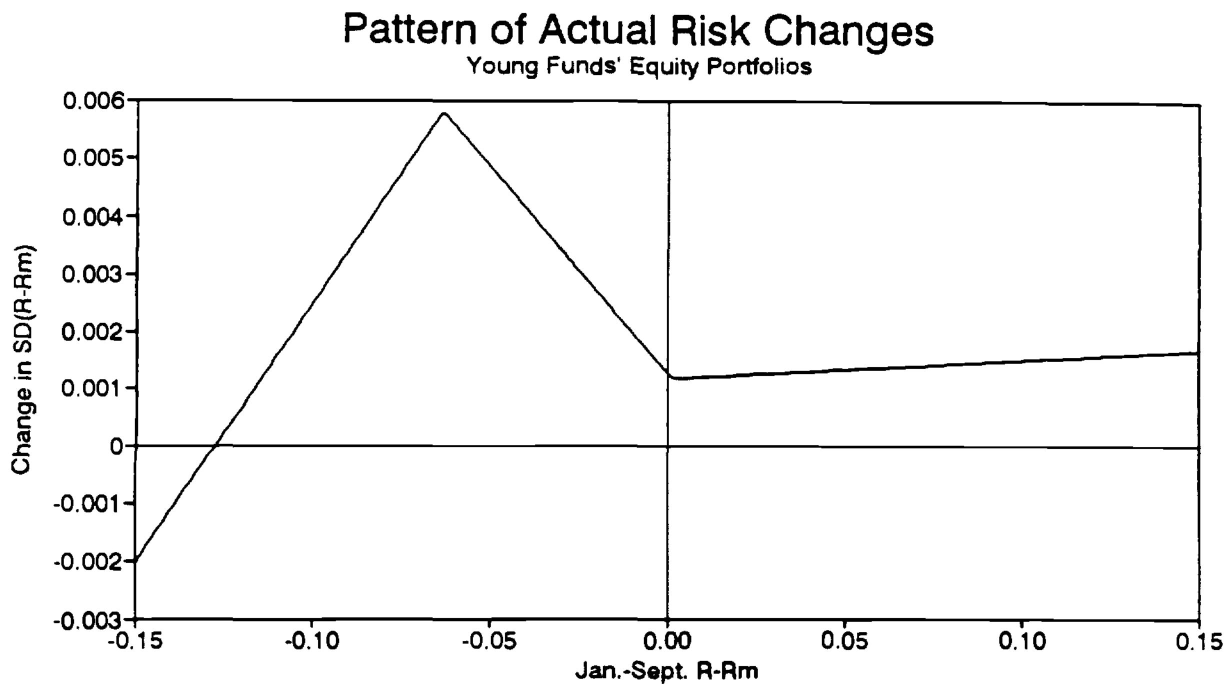
Our analysis of risk incentives for older funds did not reveal a clear pattern. Therefore,

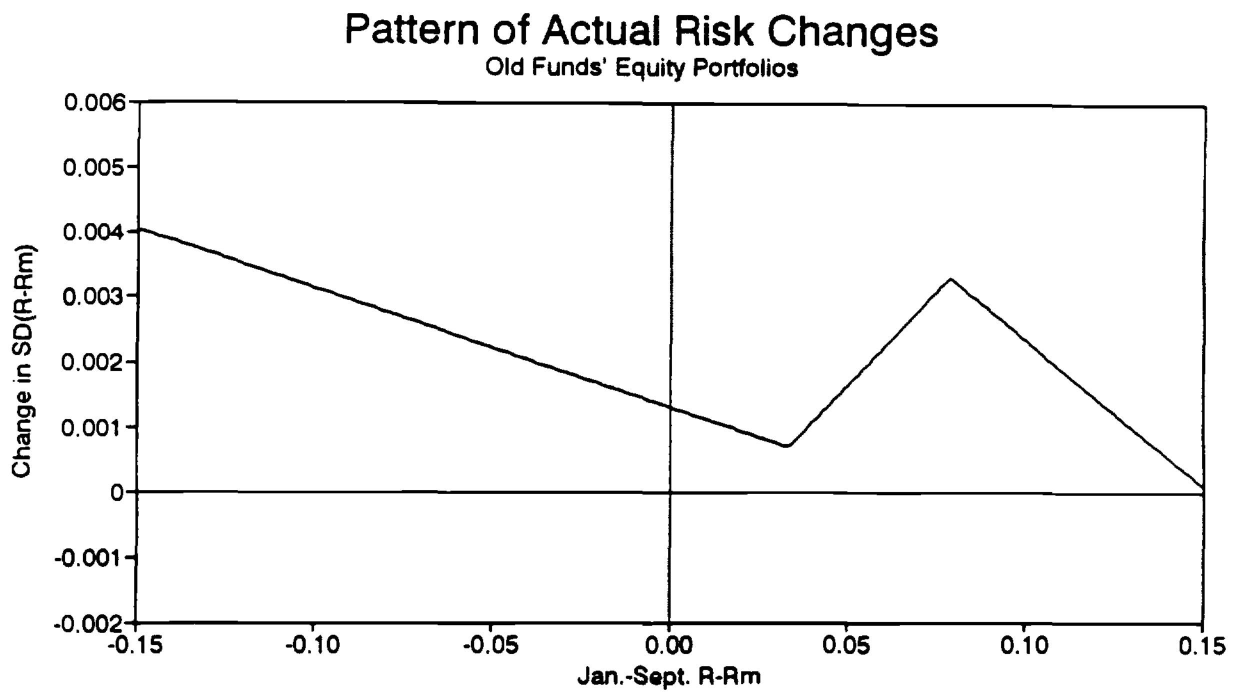
Table 6: Actual Risk Changes as a Function of Jan.-Sept. Returns

Independent Variables	Dependent Variable: $\Delta SD(r - rm)$ Young Funds	Old Funds
Constant	-0.02	-0.003
	(0.006)	(0.002)
$KINK1$	-0.06	0.03
	(0.02)	(0.03)
$KINK2$	0.001	0.08
	(0.04)	(0.03)
$SLOPELEFT$	0.09	-0.02
	(0.04)	(0.01)
$SLOPEMID$	-0.07	0.06
	(0.07)	(.08)
$SLOPERIGHT$	0.003	-0.05
	(0.02)	(0.04)
$\log(Assets)$	-0.0007	0.00002
	(0.0006)	(0.0003)
Sept. $SD(r - rm)$	-0.02	0.09
	(0.04)	(0.02)

* Estimated standard errors in parentheses.

Figure 6: Risk Changes: Fitted Values from Piecewise Linear Model





it is not surprising that no clear patterns of actual risk changes appear in column 2 of Table 6 which presents estimates of the same piecewise linear function on the subsample of "old" funds. Neither of the turning points are estimated precisely, and only the first of the estimated slopes is significantly different from zero at the ten percent level. Predicted values from this regression are graphed in the bottom panel of Figure 6. [27] The one potentially interesting regularity in the figure is that we find that over a wide range of January-September excess return levels funds do tend to increase their riskiness toward the end of the year. While this in very much in line with the incentives we have identified, we hesitate to emphasize the result because of the potential for our sample selection having biased the results.[28]

5.2 Changes in total portfolio riskiness

So far, we have used the detailed data available to us to show that changes in the riskiness of the equity portion of funds' portfolios reflect the incentive to attract investment flows. While we lack data of a similar quality on the remainder of funds' holdings, we attempt here to look at measures of risk of the broader portfolios and provide some assurance that changes in the riskiness of equity holdings are not undone by other changes. We take two distinct approaches — one exploiting composition data and the other time series data on returns.

5.2.1 Portfolio composition

In this section, we present some simple descriptive statistics on changes in the broad composition of fund holdings, and then combine this data with our equity data to provide rough estimates of changes in the riskiness of funds' complete portfolios.

[27]The one borderline significant relationship in the old funds regression suggests that, for the poorest-performing group of funds in September, risk increases are decreasing as January to September returns increase. This is roughly consistent with the risk incentives pictured in Figure 4.

[28]Recall that we require 85% of the securities in the September portfolio to be successfully matched to CRSP, and impose no match quality restriction on the December portfolio. The direction of the bias this creates is not clear.

For 602 of the 839 fund-years for which we have equity portfolios, we also have available the share of the mutual fund held in cash, bonds, common stocks, preferred stocks, convertible securities and "other" both at the end of September and at the end of December. Descriptive statistics on this sample are provided in Table 7. The table gives the mean and median share invested in each of the categories, along with the mean and median of the absolute value of the September-December changes. Note that the majority of mutual funds in our sample have zero positions in bonds, preferreds, convertibles, and "other" securities, and that common stocks are by far the largest component of the typical portfolio.

Table 7: Summary Statistics for Composition Data

	Mean Sept. Share	Mean Dec. Share	Mean Abs. Sept-Dec Change	Median Sept. Share	Median Dec. Share	Med. Abs. Sept-Dec Change
Cash	10.9	10.3	4.6	8.1	7.3	2.6
Bonds	2.6	2.4	1.4	0	0	0
Stocks	84.6	85.4	4.9	88.0	88.9	2.6
Preferreds	0.2	0.3	0.2	0	0	0
Convertibles	1.3	1.3	0.5	0	0	0
Other	0.2	0.2	0.2	0	0	0

Given that the largest part of the portfolio changes which occur in these funds are between stocks and cash, a significant portion of the changes may be attributable to short run cash flows resulting from purchases and sales of blocks of stock, inflows of investments, or a need to meet anticipated redemptions. If, however, September-December changes in the composition of portfolios are also systematically related to January-September excess returns, we might very well find that these reallocations are an additional tool for risk-shifting in response to incentives, or that changes in the equity portfolio are being counterbalanced by compositional shifts. Table 8 presents coefficient estimates from regressions in which the September-December change in the shares of each fund's portfolio held in cash, bonds, stocks, etc. are the dependent variables, and the primary independent variables of interest are dummy variables for January-September excess returns falling into four categories: less than -0.05, between -0.05 and zero, between zero and 0.05, and greater than 0.05. Included also in the regression as controls are the September share of the portfolio in the corresponding category and the natural log of the fund's total assets.

Table 8: Changes in Portfolio Composition

Independent Variables	Dependent Variable: Sept.-Dec. Change in Share of Stock	Cash	Bonds	Preferred	Convertibles	"Other"
Dummy $r - rm < -.05$	-0.94	-0.05	0.22	0.54	0.19	0.15
	(0.79)	(0.61)	(0.40)	(0.30)	(0.14)	(0.14)
Dummy $-.05 < r - rm < 0$	2.82	-2.12	-0.85	0.002	0.12	-0.02
	(0.67)	(0.51)	(0.34)	(0.25)	(0.12)	(0.12)
Dummy $0 < r - rm < .05$	2.09	-1.65	-0.48	-0.04	-0.06	0.004
	(0.75)	(0.57)	(0.38)	(0.28)	(0.13)	(0.13)
Dummy $.05 < r - rm$	-0.02	-0.03	0.13	-0.03	0.08	0.06
	(0.92)	(0.70)	(0.47)	(0.35)	(0.16)	(0.16)
Sept. Share	-0.23	-0.26	-0.37	-0.42	-0.01	0.14
	(0.02)	(0.02)	(0.02)	(0.12)	(0.02)	(0.04)
$\log(Assets)$	-0.20	0.17	0.12	-0.07	-0.03	-0.05
	(0.21)	(0.16)	(0.11)	(0.08)	(0.04)	(0.04)
R-squared	0.15	0.19	0.33	0.03	0.01	0.03

The one significant pattern which appears in the table and which might be potentially relevant to a discussion of the manipulation of portfolio risk levels is that funds whose returns are close to the market appear to be shifting into stocks and out of cash and bonds more than funds whose intermediate returns are further from the market. Given that young funds which are slightly ahead and slightly behind the market have opposite incentives as far as increasing risk goes, however, it does not seem likely that these shifts are undoing the patterns previously reported. Other than this, the most notable coefficients in the table are those on the September composition of the portfolio, which clearly indicate that there is significant mean reversion in the shares of stocks, cash, bonds, and preferreds. This fits fairly well with the view that much of the reallocations are a result of cash flow considerations.

A rough calculation may provide additional confidence that the results of our analysis of equity portfolios are not undone by compositional shifts. For funds for which we have both equity portfolio and composition data we may roughly approximate the beta and riskiness of the complete portfolios by ignoring investments in preferreds, convertibles, and "other" securities (the shares of which are usually very small) and assuming that both cash and bonds (the share of which is also usually small) return the risk-free rate.

Table 9 repeats the specifications of Table 5 using as the dependent variables changes in risk measures which have been calculated with this approximation.[29] Column 1 of Table 9 shows that there is a positive relationship between incentives to take risk and the change in the standard deviation of fund return minus the return on the market. The coefficients on the risk incentive measure and the risk incentive-log($Assets$) interaction remain significant at the 5 percent level (in a one-tailed test) and are approximately the same in magnitude as was the case when we looked only at the riskiness of the equity portfolio. Columns 2 and 3 break the standard deviation of the return on the fund minus the return of the market into two components: changes in unsystematic risk and changes in the absolute value of beta minus one. The coefficient estimates for the risk incentive measures have the expected signs in both cases. They are statistically significant at the five percent level for the beta changes specification.

5.2.2 Complete portfolio risk via time series return data

An obvious alternate methodology for examining changes in the riskiness of mutual funds (used by Brown, Harlow, and Starks (1994)) is to try to estimate the riskiness at separate points in time using time series data on fund returns. From Morningstar's *Mutual Funds OnDisc* we have available monthly return data for a large sample of funds and can construct noisy estimates of the change in a fund's riskiness by comparing the sample variance of a fund's monthly excess returns for the January-September and October-December periods.

Examining risk changes in this way introduces a number of measurement error problems. First, absent high frequency return data the risk measures that such an approach

[29] The risk incentive variable has also been recalculated to take into account the new measure of initial riskiness

Table 9: Complete Portfolio Risk Changes

Independent Variables	Dependent Variable		
	$\Delta SD(r - rm)$	$\Delta SD(r - \beta rm)$	$\Delta\lvert\beta - 1\rvert$
$RiskIncentive$	0.89	0.22	7.79
	(0.45)	(0.40)	(3.92)
$RiskIncentive \cdot \log(Assets)$	-0.16	-0.05	-1.25
	(0.09)	(0.08)	(0.75)
$\log(Assets)$	0.00004	0.0003	0.001
	(0.0003)	(0.0003)	(0.003)
Sept. Risk Level	-0.01	0.003	-0.17
	(0.02)	(0.02)	(0.03)
Constant	-0.003	0.004	0.02
	(0.002)	(0.002)	(0.02)
N	352	352	352
R^2	0.02	0.01	0.10

* Estimated standard errors in parentheses.

relies on will be quite noisy (being estimated from as few as three data points). This problem is, however, ameliorated by our being able to use a much larger sample because we require much less data about each individual fund. Second, and perhaps more importantly, because mutual funds change their composition over time, an estimate of the variance of the September portfolio computed from January to September returns will be biased, with the bias correlated with the level of January to September excess returns — our primary explanatory variable.[30] Ignoring these problems, we now proceed with such an analysis.

The data available to us contain monthly returns for for a sample of growth and growth and income funds between 1983 and 1993 (giving a total of 3163 fund-years). For each fund, we construct a measure of the change in the variance of the fund's simple excess return by

$$\Delta TS\mathrm{Var}(r_i - rm) = \frac{1}{3}\sum_{j=Oct}^{Dec}(r_{ij} - rm_j)^2 - \frac{1}{9}\sum_{j=Jan}^{Sep}(r_{ij} - rm_j)^2.$$

To explore how end-of-year risk changes measured in this way vary with a fund's January-

[30]One can regard Brown, Harlow, and Starks' (1994) decision to simply compare the end-of-year riskiness of the groups ahead and behind the market in September as an attempt to overcome this problem if one assumes that the biases will be equal for funds which are symmetrically ahead and behind the market so that the bias cancels from the comparison. Such an approach, however, is of less help if we want to explore the pattern of risk changes in more detail.

September excess return we computed nonlinear least squares estimates of a piecewise linear model similar to that used in Section 5.1.2. (but omitting controls for fund size and initial riskiness).

Coefficient estimates from the subsamples of "young" and "old" funds are presented in Table 10, with the predicted values of the functions graphed in Figure 7 so that they may be compared both with the incentives pictured in Figures 3 and 4 and the estimates of risk changes from the equity data pictured in Figure 6. For the young funds, the point estimates on the three slopes again follow a positive, negative, positive pattern with one kink to the left of zero and the other to the right of zero. However, the middle slope is not nearly as negative as the risk incentive picture suggests it should be, and the locations of the kinks are not estimated precisely.

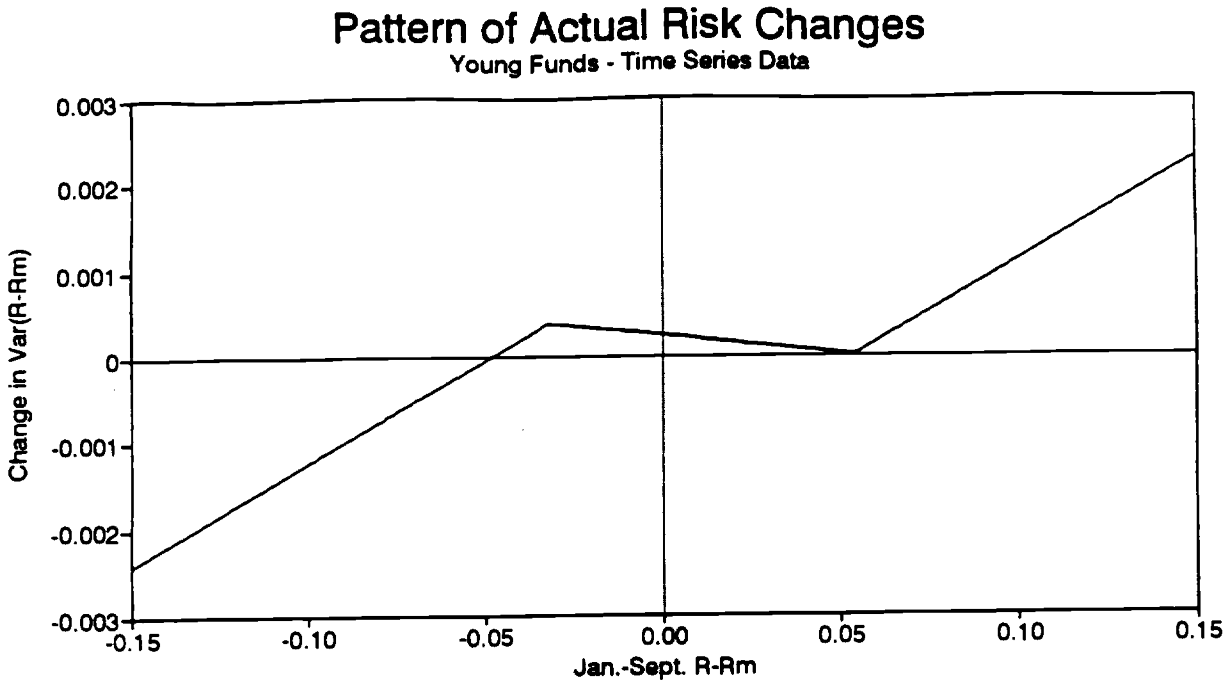
Table 10: Risk Changes from Time Series as a Function of Jan.-Sept. Returns

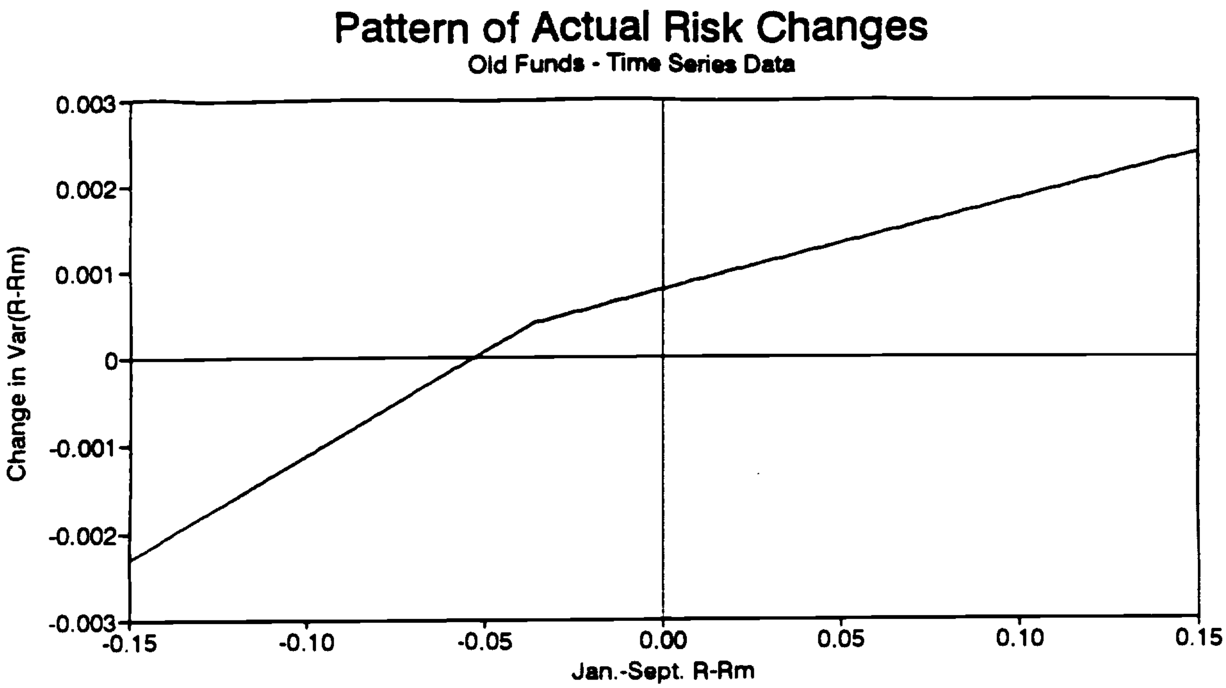
Independent Variables	Dependent Variable: $\Delta TS\text{Var}(r - rm)$ Young Funds	Old Funds
Constant	0.001	0.001
	(0.0008)	(0.0005)
$KINK1$	-0.032	-0.036
	(0.030)	(0.032)
$KINK2$	0.054	0.217
	(0.037)	(0.043)
$SLOPELEFT$	0.024	0.023
	(0.010)	(0.006)
$SLOPEMID$	-0.004	0.011
	(0.013)	(0.003)
$SLOPERIGHT$	0.024	0.085
	(0.010)	(0.040)

* Estimated standard errors in parentheses.

In the data on older funds, we see that risk changes do again exhibit something of a tendency to be positive. The one clear regularity in the data which is somewhat puzzling in contrast with our earlier results is that higher January-September excess returns are clearly correlated with larger risk increases. This pattern is quite compatible with the results of

Figure 7: Risk Changes via Time Series: Fitted Values from Piecewise Linear Model





Brown, Harlow and Starks' (1994) analysis of monthly return time series. Looking back at the top panels of Figures 6 and 7 we see that the time series approach produces a more positive correlation between excess returns and risk increases than is visible in the equity portfolios for the young funds also. Why this occurs is not clear to us.

5.3 Additional results on robustness

In this section, we undertake some alternative specifications of the basic equity risk change regressions in order to gauge the robustness of the basic equity risk change results. We explore the effects of measurement error and survivorship bias, the differential response to risk incentives of old vs. young funds, and the behavior of mutual funds that may use derivative securities to alter their riskiness.

5.3.1 Measurement error and survivorship bias

Measurement error is a major source of concern for the main regressions which examine the relationship between risk incentives and changes in equity portfolio risk. Measurement error in the right hand side variables will cause the coefficient estimates to be biased.[31] In particular, the risk incentive measure has been estimated using the flow-performance relationship and is thus measured with error. Unfortunately, there are no obvious instruments for the risk incentive measure which would be uncorrelated with this measurement error.

Another source of measurement error stems from the fact that, for some mutual fund portfolios, we were unsuccessful in matching all of the fund holdings to the CRSP database; the portfolio risk measures are constructed for the subset of the portfolio for which we have data. In the tests above, we study portfolios for which the equity risk measures are calculable for at least 85% of the total assets of the fund. To obtain a sample where such measurement errors may be smaller, we reestimated our basic regression of risk changes keeping only funds where the fraction of securities matched was higher. Requiring a 90%

[31] We have also not corrected the standard errors to account for the fact that the regressors have been generated.

matching of the securities results in a loss of 106 observations; requiring a 95% match results in a loss of 266 observations. In the estimation of overall and unsystematic risk changes, when we require a higher degree of matching, the coefficients of interest have approximately the same point estimates, but have smaller standard errors and thus, have greater statistical significance than in the specifications which we presented above (despite the datasets being much smaller). R-squared measures for the regressions also tend to rise. For the regressions examining changes in systematic risk, $|\beta - 1|$, the coefficients for the risk incentive measure become very close to zero when the 90% or 95% matching requirements are imposed. The low explanatory power of the regressions presented may be symptomatic of the measurement error problem. Columns 1, 2, and 3 of Table 11 reestimate columns 1, 2, and 3 of Table 5 using a 90% matching requirement.

While we have no reason to think that survivorship bias would tend to make risk changes appear to be aligned with incentives, we nonetheless reestimated our basic risk change regression for the subsample of fund-years from 1989 to the present, which is not survivorship biased. The point estimates are very similar to those in the base model. However, when we exclude the pre-1989 data the standard errors of the regressions shrink slightly and the explanatory power of the regressions rises by more than 50%. The results for the risk change measure, $\Delta SD(r - rm)$ for the non-survivorship-biased subsample are shown in Column 4 of Table 11 These results may suggest that improved data accuracy (the Morningstar data was more likely to contain tickers in the later years) leads to smaller measurement error for this later subperiod.

5.3.2 Results for old vs. young funds

The risk incentive measures which we have calculated are age-specific. Thus, we have no particular reason to expect different coefficients for the risk incentive measures for the two age groups. Column 5 of Table 11 shows regression results when we repeat the specification of Table 5, column 1, allowing old and young funds to have different coefficients for the risk incentive measures. The risk incentive measure is multiplied by "Old Dummy", a

Table 11: Risk Changes and Incentives: Robustness Checks

Independent Variables	Model/Dependent Variable					
	90% Matching Models			Post-88	Age Effects	Derivatives
	ΔSD(r-rm)	ΔSD(r-βrm)	$\Delta\|\beta-1\|$	ΔSD(r-rm)	ΔSD(r-rm)	ΔSD(r-rm)
$RiskIncentive$	0.80	0.76	-0.06	1.04		
	(0.29)	(0.26)	(1.97)	(0.44)		
$RiskIncentive \cdot \log A$	-0.13	-0.12	-0.10	-0.18		
	(0.06)	(0.05)	(0.37)	(0.08)		
$\log(Assets)$	0.0002	-0.0001	0.002	-0.00002	0.0001	-0.0001
	(0.0002)	(0.0002)	(0.001)	(0.0003)	(0.0003)	(0.0003)
Sept. Risk Level	0.02	0.01	-0.02	0.06	0.05	0.06
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-0.0009	-0.000009	-0.003	-0.001	-0.001	-0.0004
	(0.002)	(0.001)	(0.008)	(0.002)	(0.002)	(0.002)
$RiskIn$·Old					0.91	
					(0.52)	
$RiskIn$·Young					0.70	
					(0.52)	
$RiskIn$·No Other						1.08
						(0.45)
$RiskIn$·Other						-1.46
						(2.49)
$RiskIn$ log A Old					-0.11	
					(0.11)	
$RiskIn$ log A Young					-0.16	
					(0.09)	
$RiskIn$ log A No Oth						-0.17
						(0.08)
$RiskIn$ log A Other						0.25
						(0.50)
N	358	358	358	342	464	351
R^2	0.03	0.03	0.01	0.05	0.03	0.05

* Estimated standard errors in parentheses.

dummy variable which takes the value of one if the fund is of age 6 or older. The risk incentive measure is also multiplied by "Young Dummy", a dummy variable which takes the value of one if the fund is between ages 2 and 5. These dummy variables are also used to create separate coefficients for young and old firms for interaction between the risk incentive measure and the log of assets. While the significance of the coefficients is predictably reduced, the coefficients for the young and old funds are remarkably similar with no significant differences between them. The reader should keep in mind that the magnitude of the risk incentive measure is typicaly much larger for younger funds, so that their predicted risk changes are larger.

5.3.3 Are these effects undone using derivatives?

Next, we examine the role of derivative securities. Although we have previously seen that the funds in our sample have little of their holdings in derivatives, it is possible that the small holdings are sufficient to undo the changes in risk we observe when we examine the fund's equity portfolio. While we do not have data on the specific holdings of derivative securities by mutual funds, we can say something about this.

Many mutual funds have provisions outlined in the fund prospectus which forbid the fund to use derivative securities. It would thus be interesting to determine whether the relationship between changes in the riskiness of equity holdings and incentives is weaker or stronger for mutual funds that do use derivative securities. If the measured risk change-flow-performance relationship is stronger for funds that do use derivatives, we might worry that the unobserved derivatives portfolio is undoing the risk changes that are observed in the equity portfolio. The opposite result might suggest funds that can hold options and futures use these securities to alter the riskiness of their portfolios, while mutual funds which do not use derivatives instead alter fund riskiness via their common stock holdings.

While our dataset does not contain explicit information about derivative securities, for funds for which portfolio composition data is available these securities will show up as a nonzero number in the "other" category. For 214 of the 351 fund-years for which we have data on both the portfolio and holdings of "other" securities, the fund has a zero position in "other" securities in both September and December. For 137 fund-years, the fund has a non-zero position in "other" securities in either September and December (or both).

Column 6 of Table 11 repeats the specification of column one of Table 5, examining equity risk changes but estimating separate coefficients for the risk incentive measure for funds which are observed to hold "other" securities in that year, and for funds which are not. The positive and significant relationship between risk incentives and changes in the riskiness of the equity portfolio continues to appear only for those funds which do not hold "other" securities. Clearly, the pattern of equity risk changes in response to incentives is not a result of changes which are being simultaneously undone using derivatives. While we cannot reject the hypothesis that the coefficient for funds that do not hold "other" securities is the same as the coefficient for funds that do not hold "other" securities, the differences are suggestive that funds which can use options and futures alter fund riskiness be doing so rather than incurring larger transactions costs in to changing the riskiness of their equity portfolios.

6 Conclusion

In this paper we interpret the flow-performance relationship as an incentive scheme implicitly given to mutual fund companies by mutual fund investors. We show that the flow-performance relationship can generate incentives for mutual fund companies to increase or decrease the riskiness of their portfolios. Finally, we show that mutual fund companies respond to this incentive scheme; funds alter their portfolios between September and December in a manner consistent with the September incentive to take risk calculated from the flow-performance relationship.

The methodology of treating the flow-performance relationship as an incentive scheme could be used to examine other hypotheses about the behavior of mutual funds or institutional asset managers. For example, Scharfstein and Stein (1990) and Zwiebel (1995) present models in which optimal performance evaluation gives managers an incentive to "herd". Lakonishok, Shleifer, and Vishny (1992) and Grinblatt, Titman and Wermers (1993) have used data on institutional asset managers and mutual funds, respectively, to examine whether asset managers exhibit "herd" behavior. An interesting extension of the methodology in this paper would be to test the performance evaluation component of Scharfstein and Stein's and Zwiebel's models directly and see if mutual funds receive a larger payoff if they herd. If, for example, we were to find no evidence that institutional investors disproportionately invest with asset management firms in a manner which would encourage them to herd, this could help to explain why Lakonishok, Shleifer, and Vishny (1992) found little evidence that these investment managers have a tendency to herd.

Similarly, Lakonishok, Shleifer, Thaler, and Vishny (1991) have examined whether institutional asset managers engage in "window-dressing", selling off poor-performing assets from their portfolios prior to issuing year-end holdings reports. Their results suggest that very little window-dressing is undertaken by their sample of managers. An extension of the methodology of this paper would be to examine whether investors believe that window-dressing managers are of higher quality than managers with equal performance who have not window dressed. For example, one could test whether, controlling for the overall returns of the portfolios, are investors less likely to invest with a management company which reports holding many "losers" in its year-end report. If investment flows do not systematically differ for funds with the same performance but different amounts of window-dressing, then we should not expect that funds would engage in the costly activity of window-dressing.[32]

Finally, our examination of the flow-performance relationship could serve as a starting point for further examination of decision-making by investors. A comparison of the shape of the flow-performance relationship for the retail mutual funds which we have studied to the shape of the flow-performance relationship for products purchased exclusively by institutional investors may provide insight into the evaluative procedures used by different types of investors.

[32]Our preliminary forays in this direction suggest that retail mutual fund companies are not rewarded for window-dressing. It would be interesting to know if the same is true for managers of institutional assets.

References

Asch, Beth (1990): "Do Incentives Matter? The Case of Navy Recruiters," *Industrial and Labor Relations Review* 43: 89-107.

Becker, Brian E. and Mark A. Huselid (1992): "The Incentive Effects of Tournament Compensation Systems," *Administrative Science Quarterly* 37: 336-350.

Borenstein, Severin and Martin B. Zimmerman (1988): "Market Incentives for Safe Commercial Airline Operation," *American Economic Review* 78: 913-935.

Borland, Jeff (1992): "Career Concerns: Incentives and Endogenous Learning in Labour Markets," *Journal of Economic Surveys* 6, 251-270.

Bronars, Stephen (1987): "Risk Taking Behavior in Tournaments," working paper, University of California-Santa Barbara.

Brown, Keith C., W. V. Harlow and Laura T. Starks (1994): "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry," working paper, University of Texas.

Bull, Clive, Andrew Schotter and Keith Weigelt (1987): "Tournaments and Piece Rates: An Experimental Study," *Journal of Political Economy* 95: 1-33.

Ehrenberg, Ronald G. and Michael L. Bognanno (1990): "Do Tournaments Have Incentive Effects?" *Journal of Political Economy* 98, 1307-1324.

Ehrenberg, R. and M. Bognanno (1990): "The Incentive Effects of Tournaments Revisited: Evidence from the European PGA Tour," *Industrial and Labor Relations Review* 43: 74-89.

Ellison, Glenn, and Sara Fisher Ellison (1993): "A Simple Framework for Nonparametric Specification Testing," Harvard Institute of Economic Research Discussion Paper 1662.

Goetzmann, William N. and Nadav Peles (1993): "Cognitive Dissonance and Mutual Fund Investors", working paper.

Grinblatt, Mark and Sheridan Titman (1989a): "Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings," *Journal of Business* 62, 394-415.

Grinblatt, Mark and Sheridan Titman (1989b): "Portfolio Performance Evaluation: Old Issues and New Insights," *The Review of Financial Studies* 2, 394-415.

Grinblatt, Mark and Sheridan Titman (1992): "The Persistence of Mutual Fund Performance," *Journal of Finance* 47, 1977-1984.

Grinblatt, Mark and Sheridan Titman (1993a): "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns," *Journal of Business* 66, 47-68.

Grinblatt, Mark, Sheridan Titman and Russ Wermers (1993b): "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," working paper.

Healy, Paul (1985): "The Effect of Bonus Schemes on Accounting Decisions," *Journal of Accounting and Economics* 7: 85-107.

Holmstrom, Bengt (1982): "Managerial Incentive Problems — A Dynamic Perspective," in *Essays in Economics and Management in Honor of Lars Wahlbeck.* Helsinki: Swedish School of Economics.

Holmstrom, Bengt and Paul Milgrom (1987): "Aggregation and Linearity in the Provision of Intertemporal Incentives, *Econometrica* 55, 303 - 328.

Ippolito, Richard A. (1992): "Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry", *Journal of Law and Economics* 35, 45-70.

Lakonishok, Joseph, Andrei Shleifer, Richard Thaler, and Robert W. Vishny (1991): "Window Dressing by Pension Fund Managers," *American Economic Review, Papers and Proceedings* 81, 227-231.

Lakonishok, Joseph, Andrei Shleifer, and Robert W. Vishny (1992): "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics* 47, 23-43.

Patel, Jayendu, Richard Zeckhauser, and Darryll Hendricks (1990): "Investment Flows and Performance: Evidence from Mutual Funds, Cross-Border Investments, and New Issues," working paper.

Robinson, Peter M. (1988): "Root - N Consistent Semiparametric Regression" *Econometrica* 56, 931-54.

Scharfstein, David S. and Jeremy C. Stein (1990): "Herd Behavior and Investment," *American Economic Review* 80, 465-489.

Sirri, Erik R. and Peter Tufano (1993): "Buying and Selling Mutual Funds: Flows, Performance, Fees, and Services", working paper, Division of Research, Harvard Business School.

Smith, K. V. (1978): "Is Fund Growth Related to Fund Performance?," *Journal of Portfolio Management* 5: 49-54.

Spitz, A. E. (1970): "Mutual Fund Performance and Cash Inflow," *Applied Economics* 2: 141-145.

Wermers, Russ (1993a): "Herding, Trade Reversals, and Cascading by Institutional Investors", working paper.

Wermers, Russ (1993b): "An Optimum Test of Correlated Trading by Institutional Investors", working paper.

Zwiebel, Jeffrey (1995): "Corporate Conservatism and Relative Compensation," *Journal of Political Economy* 103, 1-25.