THE JOURNAL OF FINANCE • VOL. LIV, NO. 2 • APRIL 1999

How Are Derivatives Used? Evidence from the Mutual Fund Industry

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ABSTRACT

We investigate investment managers' use of derivatives by comparing return distributions for equity mutual funds that use and do not use derivatives. In contrast to public perception, derivative users have risk exposure and return performance that are similar to nonusers. We also analyze changes in fund risk in response to prior fund performance. Changes in risk are substantially less severe for funds using derivatives, consistent with the explanation that managers use derivatives to reduce the impact of performance on risk. We provide new evidence regarding the implications of cash flows and managerial gaming for the relation between performance and risk.

DERIVATIVE SECURITIES GENERATE PROFITS that are functions of changes in the price of underlying assets. How does derivative use by investment managers affect portfolio performance? Theoretical work advocates derivatives as useful tools that allow investment managers to utilize information better, manage risk, and reduce transaction costs (Scholes (1981), Silber (1985), Stoll and Whaley (1985), and Merton (1995)). If so, then portfolios whose managers use derivatives should demonstrate improved performance relative to otherwise comparable portfolios that do not use derivatives. In contrast, recent popular press commonly portrays derivatives as speculative, high-risk investments (see, e.g., McGough (1995a, 1995b)), implying that portfolios that include derivatives will be riskier than those that do not. Public concern has been strong enough to prompt the Securities and Exchange Commission to reevaluate risk disclosure requirements for mutual funds (Taylor and Calian (1995)) and to provoke possible regulatory initiatives (Anderson (1994)).

* School of Business Administration, University of Washington. We thank Keith Brown, Diane Del Guercio, Roger Edelen, Wayne Ferson, Mark Grinblatt, Avi Kamara, Stanley Kon, Paul Malatesta, Greg Niehaus, Ed Rice, and Catherine Schrand for their comments, and David Myers, Douglas Rolph, Mark Thorpe, and Amanda Westlake for valuable research assistance. We also thank James Curtis, René Stulz (the editor), and an anonymous referee. Helpful comments have been received from seminar participants at Arizona State University, Harvard Business School, Katholieke Universiteit Leuven, Norwegian School of Management, Securities and Exchange Commission, Stockholm School of Economics, University of California–Davis, University of California–Los Angeles, University of Michigan, University of Southern California, University of Texas at Austin, and University of Washington. We also thank participants in the 1996 Wharton Financial Institutions Center Conference on Risk Management in Insurance Firms.

Mutual fund derivative use is likely to remain in the public spotlight. For tax purposes, mutual funds are organized as pass-through entities in which the fund does not incur any taxes. Instead, the capital gains and dividend taxation are passed through to the fund's shareholders, as though they held the securities in personal accounts. Until recently, mutual funds were subject to the "short-short" rule, which eliminates preferential pass-through tax status for funds that realize more than 30 percent of their capital gains from positions held less than three months. This rule inhibited derivative use because some derivative securities such as options and futures contracts involve realizing capital gains for holding periods of less than three months. The Taxpayer Relief Act of 1997 included repeal of the short-short rule, a move that is likely to lead to increased derivative use by mutual funds.

Although derivative use has generated substantial attention from many communities, no evidence documents how derivative securities are actually used by investment managers. This paper analyzes the use of derivatives by equity mutual funds by comparing the return characteristics of funds that use derivatives to those that do not. We study portfolio returns, instead of individual trading in derivatives, because the ability to trade derivatives is likely to affect managers' decisions to trade nonderivatives. We focus on three alternative ways derivatives may affect a mutual fund's returns. First, depending on whether derivatives are used to speculate or to hedge, funds that use derivatives may have higher or lower risk than funds that do not use derivatives. Second, managers who use derivatives may improve net portfolio performance, either due to lower transaction costs or because the managers better utilize information.[1] Third, we examine how derivatives affect the intertemporal relation between fund performance and risk. Specifically, recent research documents changes in mutual fund risk in response to interim fund performance. Previous studies hypothesize that these intertemporal changes occur when managers game incentive systems. We propose an alternative hypothesis, that fund risk changes in response to cash flows into and out of a fund, and distinguish between these two hypotheses with information about derivative use.

The primary contributions of this research are as follows. First, we provide direct empirical evidence about the use of derivatives by one specific type of investor, equity mutual funds. Our findings show that most equity mutual funds do not use derivatives. From our sample of 679 general, domestic equity mutual funds, only 21 percent use derivative securities. The use of derivatives is not concentrated in a particular investment category. The most significant determinant of derivative use is membership in a family of funds; funds in complexes are more likely to use derivatives.

[1] In the absence of transaction costs, derivative securities are typically redundant because strategies that trade the underlying securities can duplicate the derivative's payoff. Holding transaction costs constant, derivatives may allow a wider range of possible risk profiles. Holding risk constant, derivatives may allow trading at lower cost. Therefore, we analyze both risk and portfolio performance after transaction costs.

Although we find substantial variations in risk related to self-stated investment objectives, we find no differences between funds that use derivatives and those that do not. Funds that use derivatives have similar standard deviation, idiosyncratic risk, exposure to market risk, market timing, skewness, and kurtosis as funds that do not use derivatives. Derivative use is also unrelated to net return performance. The risk-adjusted returns that accrue to funds that use derivatives do not differ significantly from the returns for funds that do not use derivatives. Investment managers who decide to use derivatives combine them with nonderivative investments so that net portfolio returns are comparable to returns for funds that do not use derivatives.

We also analyze how derivative use affects the relation between past performance and risk. Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) show that past performance and changes in risk are negatively related, which they attribute to managerial incentive gaming. However, we propose an alternative explanation, that managers may respond slowly to new cash flows. Specifically, after strong performance, new cash flows into a fund, and fund risk decreases until managers fully invest the cash. Similarly, after poor performance, investors redeem shares, and fund risk increases as managers borrow to meet redemptions. Furthermore, if managers use derivatives to manage cash flows, funds using derivatives will be able to maintain desired risk exposure more easily. On the other hand, if managers want to game performance systems, derivatives provide a low cost way to change risk, so funds that use derivatives should have a stronger relation between performance and changes in risk.

Our results show that change in risk is significantly related to prior performance, and that these changes are consistently less severe for derivative users. Our findings suggest the use of market-based derivatives, since the relation between change in risk and prior performance is significant for systematic risk but not idiosyncratic risk. Change in risk is significantly negatively related to prior, interim performance within one calendar year. However, change in fund risk during the early part of one year is significantly positively related to fund performance during the end of the prior year. We interpret the fact that calendar year-end affects the relation between fund risk and prior performance as relatively more consistent with incentive compensation-based explanations.

Although there is no previous evidence regarding use of derivatives by investment managers, several recent papers examine use of derivatives in other industries. Sinkey and Carter (1995) identify firm characteristics associated with derivative use by commercial banks, and Gorton and Rosen (1995) analyze the risk of interest rate swap positions for the U.S. commercial banking system as a whole. Nance, Smith, and Smithson (1993) and Géczy, Minton, and Schrand (1997) analyze characteristics of corporations that are associated with the decision to use derivatives. Tufano (1996) uses detailed information about derivative investments to examine risk management activities of North American gold mining companies. Cummins, Phillips, and Smith (1996) examine characteristics associated with the use of derivatives by insurance companies, and summarize related literature. None of these papers specifically analyzes use of derivatives by professional investment managers. Furthermore, the primary focus of most of this research is determining firm asset characteristics associated with the decision to use derivatives and the choice of derivative security in various contexts. Our study is unique in its focus on the implications of derivative use for returns.

The remainder of this paper is organized as follows. Section I describes the sample. Results concerning risk, performance, and risk management are contained in Sections II, III, and IV, respectively. Section V concludes.

I. Sample

A. Sample Selection Criteria

To construct the sample, we consider all general, domestic equity mutual funds as classified by *Morningstar Mutual Funds OnDisc* as of December 31, 1993. We exclude funds that are primarily bond funds; because of the wide variety and complexity of fixed income derivative securities, it is difficult to define what constitutes a derivative security for purposes of this research. Equity funds primarily use relatively simpler derivative securities, particularly options and futures contracts (Schultz (1994)). Because of our focus on equity funds, we implicitly use a relatively narrow institutional definition of derivative. We exclude specialty equity funds and global funds for tractability. The initial sample includes 798 funds classified by Morningstar as Aggressive Growth, Equity-Income, Growth and Income, Growth, or Small Company funds.[2]

Data for returns on the funds included in the sample come from *Morningstar Mutual Funds OnDisc*, January 1995, providing monthly returns data through December 1994. We include returns for the period January 1992 through December 1994.[3] Information on whether the fund used derivatives is obtained primarily by telephone. Appendix A describes in detail the collection of data about derivative use. The final sample includes 679 funds that meet the following criteria: (1) the fund is included on *Morningstar Mutual Funds OnDisc* as of December 31, 1993, and December 31, 1994, in one of the five equity fund classifications listed above, and (2) data concerning derivative use is available from telephone interviews, or if interviews were inconclusive, from fund prospectuses or annual reports.

[2] Much of the recent negative publicity about mutual funds and derivatives centers on losses due to interest rate movements for money-market funds. We do not analyze this type of fund.

[3] Using returns from a longer time period would improve precision of our variable estimates, but would also increase the length of time between the date of the returns and the date of our information about investment in derivatives. This time period is chosen as a compromise between these two considerations. Previous drafts of this paper used two years of data (1992–1993) with similar results.

Table I

Summary of Use of Derivatives by Sample Funds

Sample of 679 equity mutual funds from Morningstar. Derivative use is self-reported during telephone interviews. Numbers in parentheses represent the percentage of funds for a given investment objective.

Investment Objective	Number of Funds	Number (%) of Funds Using Derivatives	Number (%) of Funds Not Using Derivatives
Equity-Income	53	14 (26.4%)	39 (73.6%)
Growth and Income	184	43 (23.4%)	141 (76.6%)
Growth	296	55 (18.6%)	241 (81.4%)
Small Company	102	17 (16.7%)	85 (83.3%)
Aggressive Growth	44	12 (27.3%)	32 (72.7%)
Overall sample	679	141 (20.8%)	538 (79.2%)

We expect the results of the telephone inquiries to be very reliable because there are potential legal implications for a respondent who denies using derivatives when the mutual fund actually does use derivatives. Given the current public perception regarding derivatives, we also consider it unlikely that a fund would claim to use derivatives when it does not. However, in order to verify the accuracy of the telephone interviews, we pursue additional information for all Growth and Income funds that claimed not to use derivatives. For this subsample of funds, we check the accuracy of the telephone interview with the information regarding asset holdings in the fund's reports where available. Of 141 such funds, we have prospectus information for 118. Ten of these funds (8.5 percent) had options or futures listed as assets in their portfolio holdings, even though fund representatives denied using derivatives on the phone. Another 84 funds stated in their prospectus that they were allowed to use derivatives; it is probable that most of these funds did not use derivatives even though the fund charter allowed it. We classify funds that are allowed to use derivatives but do not do so as nonusers of derivatives in most of our analyses, although we explore the sensitivity of results to this classification below.

B. Descriptive Characteristics

Table I summarizes the number of funds by fund type and use of derivatives. Of the 679 funds in the total sample, 141, or 20.8 percent, use derivatives. The proportion of funds using derivatives for each fund type ranges from 16.7 percent of the Small Company funds to 27.3 percent of the Aggressive Growth funds, but these differences in the proportions are not significant (χ^2 test, p-value = 0.28). Approximately 45 percent of funds report using derivatives primarily for hedging, and only a small number (12 funds, or 8.5 percent) report using derivatives only for speculative purposes. Almost two-thirds of funds that use derivatives report using options and/or futures contracts. Given the limitations inherent in a telephone survey and the relatively large sample size, we were unable to obtain more in-depth information from each fund about the choice and purpose of specific instruments. We leave these issues as a topic for future research, as improved data become available.

Table II (Panel A) reports results of a descriptive logit analysis relating the use of derivatives to various fund characteristics for individual funds. We include explanatory variables representing the size of the fund, the age of the fund, and the length of time the current manager has managed the fund to determine whether the choice to use derivatives is related to the size or age of a fund. Further, derivatives may require an up-front investment, which makes derivative use more economical for funds that belong to families. One example is fixed investment in computer-related accounting systems. Prior to 1997, derivative users had to monitor realized capital gains for their portfolio in order to comply with the Internal Revenue Service's short-short rule. For funds that use derivatives to market time or to attain target risk levels, systems are needed to monitor portfolio risk exposure as well as new cash flows. Along these lines, fund advisors must employ individuals who are familiar with derivatives, which is more likely for larger advisors who have a larger number of employees. There are governance issues regarding derivative use as well, since the fund's charter must be amended if derivatives are not allowed in the original charter. Because of the constraints discussed above, once one charter is amended, the marginal cost of changing more charters within the family is almost zero. In order to address the role of fund families for derivative use, we include a dummy variable equal to one if the fund is a member of a family with at least one other fund in our sample.

A large component of fund expenses is investment advisory fees. More sophisticated, better-trained advisors will be able to earn economic rents on their skill and training through advisory fees. If sophisticated advisors are more likely to use derivatives, fund expenses will be related to derivative use. In order to investigate this hypothesis, we include the fund expense ratio in our estimation. We also include a dummy variable equal to one if the fund has no front-end or deferred (back-end) load fees. Load fees discourage excessive variation in investor redemptions and deposits. If derivatives are used to manage inflows and outflows from investors, then load funds should be less likely to use derivatives, since derivatives are less useful for these funds. We include dummy variables representing the fund investment objectives. Our estimation also includes measures of fund turnover and income dividend yield. We expect that these measures control for dimensions of investment style that are not captured by the investment objective classifications.

In Table II (Panel A), we report the marginal probabilities for each variable (analogous to an ordinary least squares slope coefficient), evaluating all independent variables at their means. These results show that derivative use is positively related to turnover. Funds with greater trading activity as measured by turnover are more likely to use derivatives. Results also show

Table II

Relation between Characteristics of Funds and Derivative Use

Panel A reports results of a logit analysis for individual funds in which the dependent variable equals one if the fund uses derivatives, and zero otherwise. Panel B reports results of a fund-family level weighted least squares regression in which the dependent variable equals the percentage of funds in the family that use derivatives. Manager tenure is in years. Net asset value is the log of the fund's net asset value (in millions of dollars). Turnover is the log of annual turnover (in percent). The fund inception date is the year that the fund was organized. Dividend yield is the fund's income dividend yield (in percent). No load is a dummy variable that is equal to one if the fund has no sales load fee. At the individual fund level, Big family is a dummy equal to one if the fund is a member of a family with at least one other fund in our sample. For fund families, Big family is a dummy equal to one if the family consists of more than one fund in our sample, and Net asset value is the log of total net asset value of funds in the family. All other independent variables in the family level regression represent mean values across all funds in the family. Marginal Probabilities are the derivative estimates of the coefficients, calculated at the mean values of the independent variables. *p*-value is the *p*-value from a χ^2 test of the null hypothesis that the coefficient equals zero. The analysis is based on 675 individual funds or 295 fund families with data for the independent variables. In Panel B, each observation is weighted by the inverse of the square root of the number of funds in the family.

Panel A: Individual Fund Level

Variable	Marginal Probabilities	*p*-value
Intercept	−2.229	(0.000)
Big family	0.440	(0.014)
Net asset value	0.016	(0.712)
Manager tenure	0.019	(0.120)
Expense ratio	−0.038	(0.719)
Turnover	0.128	(0.058)
Fund inception date	0.003	(0.530)
Dividend yield	−0.003	(0.951)
No load	0.094	(0.463)
Dummy: Equity-Income	0.279	(0.228)
Dummy: Growth and Income	0.187	(0.211)
Dummy: Small Company	−0.071	(0.721)
Dummy: Aggressive Growth	0.320	(0.185)

Panel B: Fund Family Level

Variable	Parameter Estimates	*p*-value
Intercept	0.262	(0.173)
Big family	0.139	(0.011)
Net asset value	−0.025	(0.083)
Mean manager tenure	−0.002	(0.480)
Mean expense ratio	−0.025	(0.409)
Mean turnover	0.047	(0.016)
Mean fund inception date	−0.003	(0.064)
Mean dividend yield	−0.000	(0.998)
Mean no load	0.094	(0.020)
Dummy: Equity-Income	0.006	(0.938)
Dummy: Growth and Income	0.129	(0.015)
Dummy: Small Company	0.021	(0.735)
Dummy: Aggressive Growth	0.031	(0.724)

that funds that are members of families are significantly more likely to use derivative securities than those that are not; membership in a family increases the probability of derivative use by 44 percent.

To explore the role of fund families with respect to derivative use, we analyze the relation between the use of derivatives and characteristics of the fund at the fund-family level.[4] Table II (Panel B) reports results of a fund-family level weighted least squares regression in which the dependent variable is the percentage of funds in the family that use derivatives. In this analysis, we use similar explanatory variables to those outlined above, replacing the values for the individual funds with the mean value for all funds in a family. Results show that the percentage of funds in a family using derivatives is significantly positively related to trading activity as measured by the mean turnover of funds in the family, to the absence of load fees, and to whether the fund is a Growth and Income fund. It is also significantly related to a dummy variable equal to one if the family has more than one fund. The use of derivatives in the family is also marginally significantly related to the size and age of the fund. Growth and Income funds, and funds in families with more members, with higher average turnover, with lower average load fees, with older average age (earlier average inception dates), and of smaller size are all more likely to use derivatives.

II. Results: Risk

This section analyzes the impact of derivative use on the higher moments of return distributions, and the next section examines expected returns.

A. Definition of Variables

Our first test examines whether cross-sectional variation in fund risk is related to use of derivatives. To analyze this issue, we define three different variables to measure risk:

1. *Standard deviation* (STD): the standard deviation of the monthly return for a fund over the period from January 1992 to December 1994. Standard deviation is computed as $\sqrt{((1/(N-1))\sum_{i=1}^{N}(r_i - \bar{r})^2)}$, where N is the number of months, r_i is the return for month i, and $\bar{r}$ is the mean return for the fund.
2. *Idiosyncratic risk* (IDIO): the standard deviation of the residual terms from a market model regression of fund return in excess of the risk-free rate on a constant and the CRSP value-weighted return in excess of the risk-free rate.[5] This term is computed as $\sqrt{((1/(N-2))\sum_{i=1}^{N} e_i^2)}$, where e_i equals the market model residual.

[4] Of the 679 funds included in the sample, 155 funds are unrelated to any other fund in our sample, and the remaining 524 funds are members of 142 different families. The largest family includes 19 funds in our sample.

[5] For the regressions to estimate IDIO, BETA, and UPBETA, we use the one-month Treasury bill rate from Datastream as the risk-free rate.

3. *Beta* (BETA): the estimated beta coefficient in a market model regression of fund return in excess of the risk-free rate on a constant and the CRSP value-weighted return in excess of the risk-free rate.

We choose these variables to measure total risk (STD), and its decomposition into idiosyncratic risk (IDIO) and systematic risk (BETA). The SEC is considering requiring disclosure of either beta or standard deviation as a measure of fund risk. In the spirit of Merton and Henriksson (1981), we also estimate a market timing beta:

4. *Timing Beta* (UPBETA): the estimated slope coefficient on a variable equal to the maximum of the excess return on the market and zero, when this variable is added as an independent variable to the market model regression used to estimate BETA (described above).

The coefficient on UPBETA measures the increase of fund beta when the market return is greater than the return on the risk-free asset. Managers with market timing ability will increase their portfolios' market betas during periods of high market returns, and decrease market betas during periods of low market returns. This activity will be captured by a positive market timing beta. If derivatives enable managers to respond quickly to private information regarding market movements, then funds that use derivatives will have higher market timing betas than will funds of nonusers.

Given that derivatives may be used to truncate return distributions, for example to hedge against losses, or to generate income from writing covered call options and limiting upside gains, we also examine skewness. This statistic will measure symmetry, or lack thereof, of the return distribution:

5. *Skewness* (SKEW): the skewness of the monthly return of a fund, January 1992 to December 1994. Skewness is computed as

$$\sum_{i=1}^{N} z_i^3 N/(N-1)(N-2),$$

where $z_i = (r_i - \bar{r})/STD$.

We include kurtosis (KURT) to measure peakedness. If fund return standard deviation varies from month to month, the distribution of returns will have a higher peak and fatter tails (see, e.g., Press (1967) and Roll (1988)). This feature will be reflected in a higher kurtosis statistic. Mutual fund managers may lower kurtosis by using derivatives to hedge against extreme returns, or to smooth month-to-month variation in risk.

6. *Kurtosis* (KURT): the kurtosis of the monthly return of a fund, January 1992 to December 1994. Kurtosis is computed as

$$\left(\sum_{i=1}^{N} \frac{z_i^4 N(N+1)}{(N-1)(N-2)(N-3)}\right) - \left(\frac{3(N-1)^2}{(N-2)(N-3)}\right). \tag{1}$$

Morningstar classifies funds into the five investment categories we analyze: Aggressive Growth, Equity-Income, Growth and Income, Growth, and Small Company. A fund's category is determined by its marketing materials, not by a statistical analysis of its risk characteristics. These five fund investment categories capture variation in fund risk measures. Tests of differences in mean estimates of the six return parameters described above across investment objective strongly reject the hypothesis that funds in different investment objective categories have the same standard deviation, idiosyncratic risk, beta, timing beta, skewness, or kurtosis. Since investment objectives capture important differences in fund distribution, we use this classification to control for exogenous fund characteristics.[6]

B. Comparison of Distributional Parameters

For each type of fund, Table III reports the cross-sectional mean values of each variable for the overall sample, and for subgroups of funds that do and do not use derivatives. Standard deviation and beta are monotonically increasing across the fund investment objective types, from least to most risky as follows: Equity-Income, Growth and Income, Growth, Small Company, and Aggressive Growth. Idiosyncratic risk, timing beta, and skewness exhibit similar (although not strictly monotonic) trends across investment objective for the overall samples.[7] Unlike most of the other variables, the kurtosis measure does not exhibit the same strong pattern.[8] The finding of negative timing beta is consistent with Cumby and Glen (1990) and Ferson and Schadt (1996). Figure 1 contains a graphical representation of the results in Table III.

Comparing funds that use derivatives to those that do not, the most notable result is that there is no significant difference between the two groups for most of the investment objectives and variables considered. A few cases exhibit differences, but there are no systematic patterns in these results.

[6] To explore the robustness of our results to the control for underlying risk, we also analyze funds by two alternative classifications: Morningstar investment style, and Morningstar size (see *Morningstar Mutual Funds OnDisc Operations Manual*, p. 102). Morningstar characterizes funds by investment style as being growth, value, or a blend of the two. These classifications are based on price/earnings and price/book ratios relative to similar ratios for the Standard and Poor's 500 Index. Morningstar also classifies funds based on size as small (market capitalization less than $1 billion), medium ($1 billion to $5 billion), and large (greater than $5 billion). Results based on these classifications also support our conclusions.

[7] Because option strategies can have a pronounced effect on portfolio skewness, we also compare skewness for option users and nonusers. From the telephone survey, 76 funds denoted as derivative users specifically use options (38 use options, 35 use options and futures, and 3 use options, futures, and other derivatives). We perform a regression of skewness on a dummy variable for option use, four dummy variables for fund types, and four dummy variables for portfolio styles. The slope coefficient for option use was −0.02 (this sign of which is consistent with the strategy of writing covered calls), although the *t*-statistic of −0.64 is not statistically significant.

[8] The kurtosis of the CRSP value-weighted index during this sample period was −0.61. Our kurtosis findings are consistent with market conditions during this period.

Table III

Mean Risk and Higher Moments by Investment Objective and Use of Derivatives

Mean estimates of the risk variables standard deviation, idiosyncratic risk, beta, and timing beta, and of higher moments, skewness and kurtosis, by investment objective. Results are reported for all funds, and for funds that do and do not invest in derivatives. Timing Beta is the incremental market beta of the fund in periods where the market outperforms the risk-free rate. Tests of Differences represent tests of the null hypothesis that mean variable estimates are equal for users and nonusers of derivatives. Wilcoxon is a nonparametric location test. Monthly returns are in percent.

	Overall		Users		Nonusers		Tests of Differences	
Investment Objective	N	Mean	N	Mean	N	Mean	t-test (p-value)	Wilcoxon Test (p-value)
Standard deviation								
Equity-Income	53	2.17	14	2.24	39	2.15	1.26 (0.21)	1.10 (0.27)
Growth & Income	184	2.37	43	2.30	141	2.39	−1.23 (0.22)	−1.42 (0.15)
Growth	296	2.92	55	2.95	241	2.91	0.35 (0.73)	0.50 (0.62)
Small Company	102	3.72	17	3.97	85	3.67	1.02 (0.31)	0.99 (0.32)
Aggressive Growth	44	3.83	12	3.50	32	3.95	−1.28 (0.21)	−1.01 (0.31)
Idiosyncratic risk								
Equity-Income	53	1.06	14	1.09	39	1.05	0.46 (0.65)	0.76 (0.45)
Growth & Income	184	1.04	43	0.99	141	1.06	−0.75 (0.46)	−1.48 (0.14)
Growth	296	1.73	55	1.73	241	1.73	−0.00 (0.99)	0.24 (0.81)
Small Company	102	2.91	17	3.08	85	2.88	0.79 (0.43)	0.44 (0.66)
Aggressive Growth	44	2.88	12	2.76	32	2.93	−0.49 (0.63)	−0.38 (0.70)
Beta								
Equity-Income	53	0.84	14	0.87	39	0.82	1.28 (0.21)	0.82 (0.41)
Growth & Income	184	0.93	43	0.89	141	0.94	−1.63 (0.10)	−0.80 (0.42)
Growth	296	1.03	55	1.05	241	1.03	0.72 (0.47)	1.01 (0.31)
Small Company	102	1.04	17	1.12	85	1.02	1.26 (0.21)	1.35 (0.18)
Aggressive Growth	44	1.09	12	0.92	32	1.16	−2.15 (0.04)	−1.73 (0.08)
Timing beta								
Equity-Income	53	−0.22	14	−0.23	39	−0.22	−0.14 (0.89)	−0.17 (0.86)
Growth & Income	184	−0.07	43	−0.07	141	−0.07	−0.15 (0.88)	0.08 (0.94)
Growth	296	−0.01	55	−0.06	241	−0.00	−0.99 (0.32)	−1.20 (0.23)
Small Company	102	−0.10	17	−0.13	85	−0.10	−0.23 (0.82)	0.04 (0.96)
Aggressive Growth	44	−0.08	12	−0.34	32	0.01	−1.59 (0.12)	−2.02 (0.04)
Skewness								
Equity-Income	53	−0.38	14	−0.35	39	−0.40	0.69 (0.49)	1.10 (0.27)
Growth & Income	184	−0.30	43	−0.30	141	−0.30	−0.06 (0.95)	−0.01 (0.99)
Growth	296	−0.14	55	−0.16	241	−0.13	−0.67 (0.50)	−0.17 (0.87)
Small Company	102	0.00	17	−0.08	85	0.02	−1.26 (0.21)	−1.07 (0.29)
Aggressive Growth	44	−0.01	12	−0.00	32	−0.02	0.19 (0.85)	0.51 (0.61)
Kurtosis								
Equity-Income	53	−0.10	14	−0.14	39	−0.09	−0.27 (0.79)	−0.33 (0.74)
Growth & Income	184	−0.46	43	−0.52	141	−0.44	−0.65 (0.51)	−0.61 (0.54)
Growth	296	−0.51	55	−0.64	241	−0.48	−1.56 (0.12)	−0.96 (0.34)
Small Company	102	−0.39	17	−0.64	85	−0.34	−1.90 (0.06)	−1.85 (0.06)
Aggressive Growth	44	−0.43	12	0.03	32	−0.60	2.56 (0.01)	1.41 (0.16)

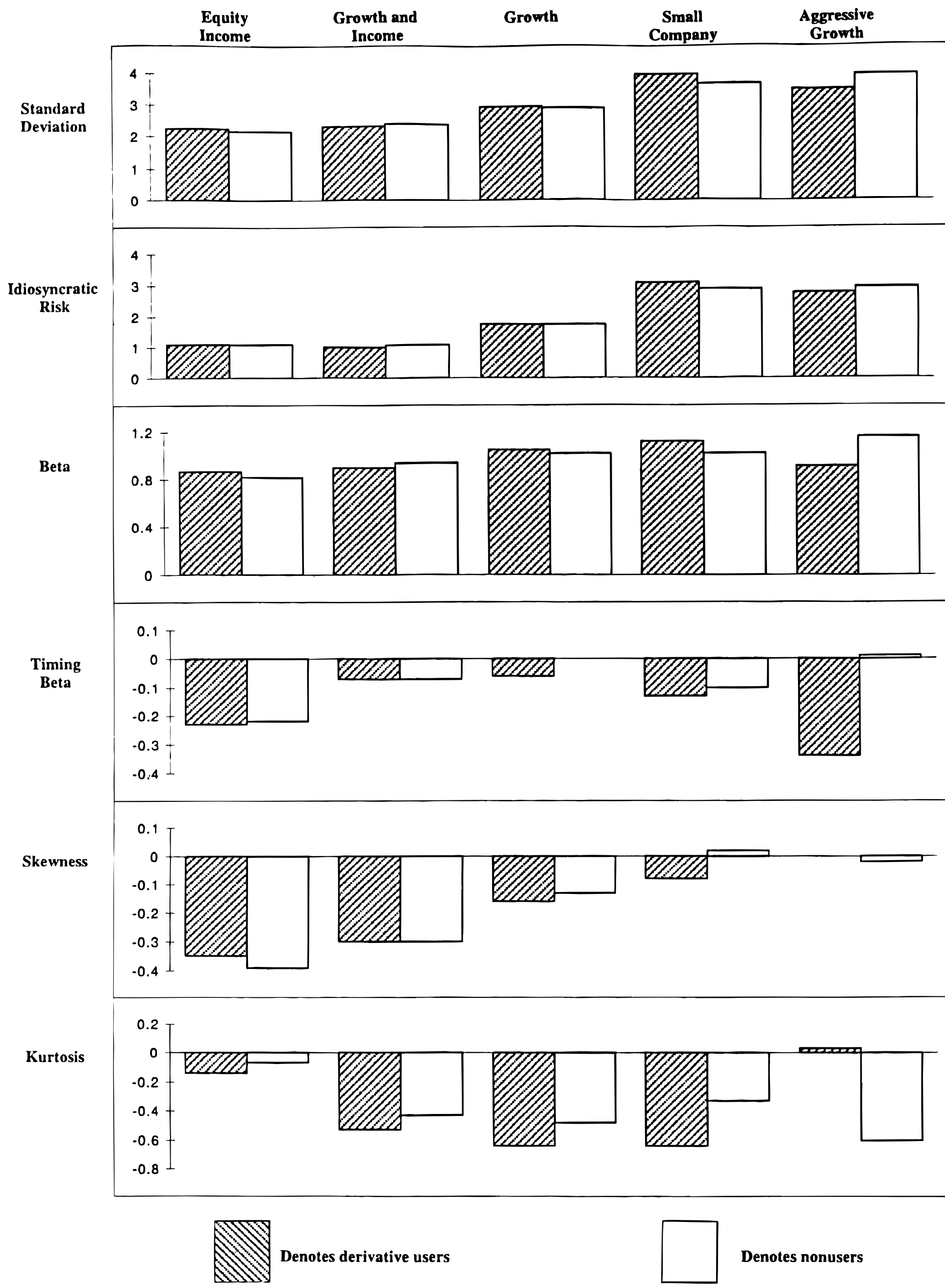

Figure 1. Comparison of risk measures for mutual funds that use and do not use derivatives. Constructed from Table III data. Mean estimates of standard deviation, idiosyncratic risk, beta, timing beta, and of higher moments, skewness, and kurtosis, by investment objective.

Figure 1 highlights the major results of this section; substantial variations in risk are associated with investment objective, but not with derivative use.

To examine the robustness of our results to our identification of users and nonusers of derivatives, we repeat the experiment reported in Table III for all of the Growth and Income funds for which we have portfolio holdings information in the funds' reports. Specifically, we include as "nonusers" only those funds that: (a) report by telephone that they do not use derivatives, and (b) state in their prospectus that they are not allowed to use derivatives. This classification eliminates all funds that are allowed to use derivatives but deny doing so because these funds are the most likely to be misclassified. This classification produces similar results, not reported for brevity.

C. Dispersion of Distributional Parameters

Results in Table III support the hypothesis that there is no difference in average risk measures between funds that do and do not use derivatives. However, similarities in average parameter values may obscure greater variation in distributions. It is possible that some funds that use derivatives have higher standard deviations due to speculative activity, and others have lower standard deviations as a result of hedging. Table III reports only the mean values of the risk variables, which will not reflect variation in the extreme values. The concerns detailed in the popular press may more accurately reflect concerns about a few funds with a high degree of risk as a result of derivative investments.

To examine these issues, Table IV reports data concerning the dispersion of the distributional parameters summarized in Table III. This table reports the standard deviation of each variable (i.e., the standard deviation of the beta or idiosyncratic risk estimates for the funds in each category), and the 10th and 90th percentiles. Results in Table IV show that there is no systematic tendency for funds that use derivatives to have greater (or less) variation in the risk measures than funds that do not use derivatives. The 90th percentile values of the risk variables (corresponding to the most risky funds) for funds that use derivatives are neither systematically higher nor lower than for nonusers. An F-test comparing the variance of risk measures for funds using derivatives to those that do not shows that there are a few fund types for which specific risk variables are more widely dispersed for funds using derivatives than for nonusers. However, most of these results are only marginally significant and are not consistent across fund type or risk measure.

We also investigate the dispersion of nonrisk measures—in particular, skewness and kurtosis. Funds that use derivatives typically have more similar skewness and kurtosis than funds that do not use derivatives. The exception is Aggressive Growth funds, for which derivative users have more diverse skewness and kurtosis than nonusers. Overall, however, it appears that results concerning mean variable estimates do not obscure a great deal of variation in the extreme fund values.

Table IV

Dispersion of Distributional Parameters

Standard deviation and 10th and 90th percentiles of the estimates of standard deviation, idiosyncratic risk, beta, timing beta, skewness, and kurtosis reported in Table III. Timing beta is the incremental market beta of the fund in periods where the market outperforms the risk-free rate. Results are reported for funds that use derivatives and for funds that do not. *N* denotes the number of observations. *SD* represents the standard deviation of the variable. 10% and 90% are the 10th and 90th percentiles. *F*-Test *p*-value is the *p*-value for an *F*-test of equality of variances between the sample of funds using derivatives and the sample of funds not using derivatives. Monthly returns are in percent.

	Users				Nonusers				
Investment Objective	*N*	*SD*	10%	90%	*N*	*SD*	10%	90%	*F*-Test *p*-value
Standard deviation									
Equity-Income	14	0.31	1.92	2.43	39	0.21	1.91	2.44	0.06
Growth & Income	43	0.47	1.90	2.77	141	0.40	1.96	2.87	0.22
Growth	55	0.70	2.15	3.93	241	0.69	2.21	3.95	0.95
Small Company	17	1.13	2.82	6.17	85	1.09	2.46	5.01	0.77
Aggressive Growth	12	1.33	1.91	5.29	32	0.89	2.99	4.78	0.08
Idiosyncratic risk									
Equity-Income	14	0.25	0.85	1.39	39	0.32	0.66	1.45	0.32
Growth & Income	43	0.61	0.35	1.66	141	0.48	0.57	1.66	0.03
Growth	55	0.70	0.99	2.61	241	0.75	0.96	2.89	0.59
Small Company	17	1.13	1.57	5.12	85	0.95	1.86	4.00	0.32
Aggressive Growth	12	1.19	1.21	4.64	32	0.97	2.03	3.82	0.36
Beta									
Equity-Income	14	0.13	0.74	0.96	39	0.11	0.67	0.95	0.48
Growth & Income	43	0.19	0.65	1.05	141	0.15	0.78	1.09	0.09
Growth	55	0.23	0.77	1.32	241	0.21	0.79	1.25	0.31
Small Company	17	0.21	0.82	1.35	85	0.30	0.63	1.45	0.12
Aggressive Growth	12	0.47	0.08	1.36	32	0.27	0.76	1.40	0.01
Timing beta									
Equity-Income	14	0.26	−0.59	0.16	39	0.25	−0.63	0.08	0.77
Growth & Income	43	0.38	−0.62	0.50	141	0.31	−0.42	0.30	0.09
Growth	55	0.34	−0.44	0.34	241	0.40	−0.52	0.49	0.12
Small Company	17	0.29	−0.48	0.21	85	0.44	−0.57	0.44	0.06
Aggressive Growth	12	0.74	−1.35	0.11	32	0.63	−0.41	0.67	0.47
Skewness									
Equity-Income	14	0.21	−0.78	−0.10	39	0.21	−0.67	−0.13	0.93
Growth & Income	43	0.28	−0.61	0.02	141	0.30	−0.58	−0.03	0.69
Growth	55	0.22	−0.42	0.08	241	0.29	−0.41	0.23	0.01
Small Company	17	0.15	−0.25	0.18	85	0.30	−0.26	0.46	0.00
Aggressive Growth	12	0.42	−0.22	0.34	32	0.18	−0.24	0.22	0.00
Kurtosis									
Equity-Income	14	0.42	−0.51	0.62	39	0.68	−0.75	0.64	0.07
Growth & Income	43	0.53	−0.95	0.02	141	0.81	−0.91	0.07	0.00
Growth	55	0.34	−1.00	−0.17	241	0.73	−1.00	0.09	0.00
Small Company	17	0.32	−1.07	−0.15	85	0.64	−0.93	0.46	0.00
Aggressive Growth	12	1.32	−0.94	2.22	32	0.33	−0.99	−0.09	0.00

We conclude that derivative use is cross-sectionally unrelated to risk exposure and the higher moments of return distributions.

III. Results: Performance

Results in Section II suggest that use of derivatives is not cross-sectionally related to fund risk. Derivative users have neither increased risk due to speculation nor decreased risk from hedging. Given that derivatives do not seem to be associated with the higher moments of the distribution of fund returns, our second test examines whether derivatives affect mean returns by allowing trading at lower cost.[9] The opportunity to use derivatives may allow a fund manager to implement trades at lower cost, and to manage more efficiently the inflows and outflows of money to and from the fund (Silber (1985)). If so, then funds that use derivatives should achieve higher returns (after trading costs) than those that do not.[10]

To analyze this question, we compute a multivariate analog to Jensen's alpha for each fund type. Our specification controls for three types of risk exposure: market risk, small stock risk, and interest rate risk. Following Shanken (1990), the beta coefficients on all three types of risk are modeled as functions of previous performance, dividend yields, and interest rates. Mutual funds are a natural extension for models that capture risk exposure variation. For example, a similar specification is utilized by Pontiff (1995) to estimate variation in closed-end fund risk, and by Ferson and Schadt (1996) to estimate variation in open-end fund risk. Our decision to incorporate information from dividend yields and interest rates follows Ferson and Schadt. We incorporate information about performance because we expect risk to change based on performance. (Section IV presents a full examination of this topic.)

Alpha is computed as the estimate of α in the regression

$$r_t - r_{ft} = \alpha_t + \beta_t^{MKT}(MKT_t - r_{ft}) + \beta_t^{CAP} CAP_t + \beta_t^{BOND} BOND_t + \epsilon_t, \qquad (2)$$

[9] As noted by *The Wall Street Journal* (McGee (1995)), "[S]tock futures not only boast greater liquidity but also lower transaction costs than traditional trading methods. Portfolio managers stress that in today's fast-moving markets, it's critical to implement decisions quickly. For giant mutual and pension funds eager to keep assets fully invested, shifting billions around through stock-index futures is much easier than trying to identify individual stocks to buy and sell."

[10] Morningstar's *Operations Manual* states that "Morningstar's calculation of total return is computed each month by taking the change in monthly net asset value, reinvesting all income and capital-gains distributions during that month, and dividing by the starting NAV. . . . Morningstar does not adjust the total returns in this section for sales charges (such as front-end and deferred charges and redemption fees). . . . The total returns do account for management, administrative, and 12b-1 fees and other costs automatically taken out of funds assets" (pp. 116–117).

where

$$\beta_t^{MKT} = \delta_0^{MKT} + \delta_1^{MKT} DIVYIELD_{t-1} + \delta_2^{MKT} PERF_{t-1} + \delta_3^{MKT} r_{ft}, \tag{3}$$

$$\beta_t^{CAP} = \delta_0^{CAP} + \delta_1^{CAP} DIVYIELD_{t-1} + \delta_2^{CAP} PERF_{t-1} + \delta_3^{CAP} r_{ft}, \tag{4}$$

$$\beta_t^{BOND} = \delta_0^{BOND} + \delta_1^{BOND} DIVYIELD_{t-1} + \delta_2^{BOND} PERF_{t-1} + \delta_3^{BOND} r_{ft}, \tag{5}$$

and r_t = the mutual fund's return for month t, r_{ft} = the risk-free rate at month t, MKT_t = the return on the CRSP value-weighted index for month t, CAP_t = the difference between the return on the 10th decile (small firm) CRSP capitalization portfolio and the 1st decile (large firm) capitalization portfolio, $BOND_t$ = the return on the CRSP long-term corporate bond index (GBTRET) minus the one-month T-bill yield at month t, $DIVYIELD_{t\text{-}1}$ = the return difference between the CRSP value-weighted index with and without dividends in month $t-1$, and $PERF_{t\text{-}1}$ = the difference between the fund's return and the CRSP value-weighted index return in month $t-1$.

We use ordinary least squares to estimate this model. Table V contains the results.[11] We find positive abnormal performance for the funds in our sample. This finding may be attributable to a survivorship bias, since we only include funds that remain in the sample through the entire three-year period (see, e.g., Malkiel (1995)). The magnitude of the abnormal returns is consistent with the findings of Carhart (1997). Unless derivative use is correlated with survivorship, our findings regarding derivatives will not be affected by this bias. For three of the five fund types the alphas for funds using derivatives are greater than those for funds that do not use derivatives. These differences are generally neither statistically nor economically significant. Results show that there is no significant difference in performance as measured by alpha between the funds that use derivatives and those that do not.

IV. Results: Risk Management

Results so far indicate that derivative use is not related significantly to the unconditional distribution of returns. This section examines the relation between derivative use and the distribution of returns conditional on previous performance. Two recent studies document a relation between past performance and changes in risk: Brown et al. (1996) and Chevalier and Ellison (1997). According to their hypotheses, managers should increase risk after

[11] Bookstaber and Clarke (1984, 1985) argue that investment in options skews the distribution of portfolio returns so that traditional mean-variance analyses are not appropriate. Results in Section II suggest that the skewness of funds that use derivatives does not differ significantly from those that do not. Therefore, funds in this sample that use derivatives do not appear to use options extensively enough to alter skewness, and we proceed with this mean-variance analysis.

Table V

Mean Manager Alpha by Investment Objective and Use of Derivatives

Alpha is computed as the estimate of α in the regression

$$r_t - r_{ft} = \alpha_t + \beta_t^{MKT}(MKT_t - r_{ft}) + \beta_t^{CAP}CAP_t + \beta_t^{BOND}BOND_t + \epsilon_t,$$

where

$$\beta_t^{MKT} = \delta_0^{MKT} + \delta_1^{MKT}DIVYIELD_{t-1} + \delta_2^{MKT}PERF_{t-1} + \delta_3^{MKT}r_{ft},$$

$$\beta_t^{CAP} = \delta_0^{CAP} + \delta_1^{CAP}DIVYIELD_{t-1} + \delta_2^{CAP}PERF_{t-1} + \delta_3^{CAP}r_{ft},$$

$$\beta_t^{BOND} = \delta_0^{BOND} + \delta_1^{BOND}DIVYIELD_{t-1} + \delta_2^{BOND}PERF_{t-1} + \delta_3^{BOND}r_{ft},$$

and r_t = the mutual fund's return for month t, r_{ft} = the risk-free rate at month t, MKT_t = the return on the CRSP value-weighted index for month t, CAP_t = the difference between the return on the 10th decile (small firm) CRSP capitalization portfolio and the 1st decile (large firm) capitalization portfolio, $BOND_t$ = the return on the CRSP long-term corporate bond index (GBTRET) minus the one-month T-bill yield at month t, $DIVYIELD_{t-1}$ = the return difference between the CRSP value-weighted index with and without dividends in month $t-1$, and $PERF_{t-1}$ = the difference between the fund's return and the CRSP value-weighted index return in month $t-1$. Users and Nonusers refer to funds that use and do not use derivatives, respectively. Tests of Differences represent tests of the null hypothesis that mean variable estimates are equal for users and nonusers of derivatives. Wilcoxon is a nonparametric location test. Monthly returns are in percent.

	Overall		Users		Nonusers		Tests of Differences	
Investment Objective	N	Mean Alpha	N	Mean Alpha	N	Mean Alpha	t-test (p-value)	Wilcoxon (p-value)
Equity-Income	53	0.073	14	0.168	39	0.038	1.61	0.98
							(0.11)	(0.33)
Growth and Income	184	0.024	43	0.057	141	0.014	0.92	0.52
							(0.36)	(0.60)
Growth	296	0.013	55	−0.024	241	0.021	−0.82	−0.69
							(0.42)	(0.49)
Small Company	102	0.150	17	0.089	85	0.162	−0.65	0.27
							(0.52)	(0.79)
Aggressive Growth	44	0.016	12	0.123	32	−0.024	0.73	0.49
							(0.47)	(0.63)
Overall sample	679	0.041	141	0.046	538	0.040	0.17	0.24
							(0.86)	(0.81)

poor performance and decrease risk after good performance in order to maximize payoffs from incentive compensation contracts (see also Grinblatt and Titman (1989)). Both studies conclude that past performance and changes in risk are negatively related, which they attribute to managerial incentive gaming.

We argue that there is an alternative explanation for the negative relation between past performance and change in risk. In particular, Ippolito (1992) shows that cash flows are related to fund performance; money flows into funds that perform well and out of funds that perform poorly.[12] Managers may be reluctant to invest in or divest their funds of securities immediately in response to cash flows if the timing of cash flows does not correspond to managers' information about optimal trading. Edelen (1995), for example, shows that mutual fund trades that are related to cash flows are less profitable than trades that are not influenced by cash inflows. Managers who are unable to invest new cash immediately cause the fund's cash position to increase after periods of good performance, which leads to a decrease in fund risk. Likewise, after poor performance investors will redeem shares, and fund risk will increase if managers borrow to meet redemptions.

The prior incentive compensation hypothesis and our hypothesis about fund cash flows both predict that fund risk will increase after periods of poor performance and decrease after periods of good performance. We propose to use derivatives to distinguish between these two hypotheses by appealing to the notion that derivatives are a low cost way to achieve a desired risk exposure. Specifically, if managers game performance systems by increasing risk after poor performance and decreasing risk after good performance, then changes in risk conditional on prior performance are endogenous and desired by managers. Managers who use derivatives will be able to accentuate changes in risk relative to managers who do not use derivatives.[13] In this case, we expect that the relation between prior performance and changes in risk will be stronger for funds that use derivatives. Conversely, if fund risk conditional on performance changes because of variations in cash flows, changes in risk are exogenous and undesirable. Managers who use derivatives will be able to dampen the impact of performance on risk relative to those who do not. Our alternative hypothesis is that if fund risk changes due to cash flows, then the relation between prior performance and changes in risk will be weaker for funds that use derivatives than for those that do not.

To test the relation between prior fund performance and use of derivatives to alter fund risk characteristics, we estimate the following pooled cross-sectional regression:[14]

$$\Delta RISK = \alpha + \beta_1 D + \beta_2 PERF + \beta_3 D * PERF + \beta_4 LagRISK + \sum_j \beta_j Dummy_j, \tag{6}$$

[12] A similar finding using aggregate data is documented by Warther (1995).

[13] This hypothesis assumes that derivative use does not attract increased scrutiny relative to alternative ways to change risk. We thank Keith Brown for noting this issue.

[14] Beta is calculated from a regression of fund return on the return of the Standard and Poor's 500 Index, since managers have access to Standard and Poor's 500 derivative securities.

where $\Delta RISK$ is the change in variable (STD, IDIO, or BETA) between the first six months and the second six months of the year, D is a dummy variable equal to one if the fund uses derivatives, PERF is the difference between the mean excess return on the fund and the mean excess return for funds with the same investment objective during the first six months of the year, and LagRISK is the value of the risk variable during the first six months.[15,16] We include dummy independent variables for subperiods, fund types, Morningstar investment style and size classifications (defined in footnote 6), interactions between the subperiod and fund type dummies, and interactions between the subperiod and Morningstar classification dummies. Ferson and Schadt (1996) provide evidence that funds in similar objective categories exhibit risk that is related to economy-wide factors. In order to control for changes in risk that are related to an entire group of funds, we include these dummy variables for period and fund type.

From this regression we can infer the relation between past performance and risk for funds that do not use derivatives from parameter β_2. From β_3, we can infer the incremental effect that derivative holdings have on this relation. Our risk measures are summary statistics and are measured with error. In periods in which measured risk is high, we expect lower risk in the next period due to mean reversion in the noise component of our estimate. Thus we include lagged risk in our specification because we expect that this variable will capture mean reversion in risk changes that is caused by mismeasurement.

Table VI reports the regression estimates using ordinary least squares (OLS) and weighted least squares (WLS). Weights for the weighted least squares are computed by running a first-pass ordinary least squares regression. The residual terms from this regression are used to compute a fund-specific standard deviation. The inverse of this term is used as the weight in the second-pass weighted least squares regression. This specification controls for fund-specific heteroskedasticity.

For all three risk measures—STD, IDIO, and BETA—the slope coefficients on past performance are negative, and statistically significant in most cases. These results are similar to the findings of Brown et al. (1996) and Chevalier and Ellison (1997). Overall, these results support both the incentive gaming conjecture and the cash flow management conjecture.

[15] Our estimation procedure uses return performance as a proxy for cash flow. We do not directly use cash flow for two reasons. First, we have limited access to cash flow data. Second, trading will be related to unexpected cash flows. Calculating a reliable unexpected cash flow measure is problematic because our time series is relatively short. Overall, return performance should be a very good proxy for unexpected cash flows. Using aggregate fund data, Warther (1995) finds the correlation between return and unexpected cash flow to be 0.73 (the correlation between return and cash flow is 0.48).

[16] Our decision to use a peer group benchmark is influenced by Farnsworth et al. (1995), who show that peer group benchmarks are very informative about future returns. Performance was also estimated using the CRSP value-weighted index as a benchmark. This specification had no material impact on any of the results.

Table VI

Regressions of Change in Risk on Past Performance during the Same Calendar Year

Results of regression analyses testing relation between the change in risk variable between the first six months and the second six months of the year, and mutual fund performance during the first six months of the year. The dependent variable is $\Delta RISK$, the change in risk variable (STD, IDIO, or BETA) between the first six months and the second six months of the year. Independent variables include D (dummy variable equal to one if the fund invests in derivatives), *PERF* (the difference between the mean excess return on the fund and the mean excess return for funds with the same investment objective during the first six months), and *LagRISK* (the value of the risk variable during the first six months). Each regression also includes dummy independent variables (not reported) for subperiods, fund types, Morningstar investment style and size classifications, interactions between the subperiod and fund type dummies, and interactions between the subperiod and Morningstar classification dummies. Returns are in percent. p-values for tests of the null hypothesis that the coefficient equals zero are in parentheses. Results are reported using ordinary least squares and weighted least squares. The inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

Variable	Intercept	*D*	*PERF*	*D ∗ PERF*	*LagRISK*
Six-month subperiods, ordinary least squares					
ΔSTD	1.537	0.006	−0.007	0.014	−0.540
	(0.00)	(0.87)	(0.02)	(0.04)	(0.00)
ΔIDIO	0.655	−0.003	−0.003	0.009	−0.602
	(0.00)	(0.93)	(0.33)	(0.17)	(0.00)
ΔBETA	0.858	0.011	−0.004	0.002	−0.759
	(0.00)	(0.48)	(0.00)	(0.61)	(0.00)
Six-month subperiods, weighted least squares					
ΔSTD	1.475	−0.156	−0.016	0.017	−0.486
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔIDIO	0.583	−0.146	−0.006	0.002	−0.600
	(0.00)	(0.00)	(0.00)	(0.49)	(0.00)
ΔBETA	0.800	−0.035	−0.011	0.005	−0.695
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

The coefficient on the interaction between derivatives and performance is positive for all three risk parameters, and significant for standard deviation (OLS and WLS) and beta (WLS only). The negative relation between previous performance and change in risk is weaker for funds that use derivatives, indicating that past performance has a relatively weaker impact on risk for users than for nonusers. One explanation is that fund risk changes through time as a function of prior performance because of fund cash flows, and that managers who use derivatives are able to dampen the impact of performance on risk. An alternative explanation is that managers with the ability to manage risk are also those who are allowed to use derivatives, so derivative use is associated with smaller changes in risk conditional on performance.[17] For the idiosyncratic risk regression, the slope coefficient on the interaction variable is insignificant in both regressions. This result is consistent with mutual fund managers who manage risk with market-based derivatives such as options and futures on the Standard and Poor's 500 Index.

We propose an additional test to distinguish between the impact of prior performance on fund risk due to managerial incentive gaming and due to cash flows. Brown et al. (1996) analyze changes in fund risk within one calendar year, under the assumption that performance evaluations are based on relative annual (calendar year) performance.[18] If fund managers are evaluated on their performance for one calendar year, then manipulation of fund risk for incentive compensation reasons should be concentrated within calendar years. On the other hand, if fund risk changes because of cash investments and redemptions, changes in risk may span the calendar year-end.

To test these hypotheses, we repeat the regression analysis in Table VI, with two changes. First, we consider changes in risk over consecutive subperiods, regardless of whether or not they span a calendar year-end. Second, we add a dummy variable to the regression equal to one if the change in risk is calculated from the end of one calendar year to the beginning of the next. Our hypotheses are that if fund risk changes for cash flow reasons and is therefore unrelated to calendar year-end, then the coefficient on this dummy variable interacted with prior performance should equal zero. On the other hand, if fund risk changes for incentive compensation reasons, then the coefficient on this term should be positive and equal in magnitude to the negative coefficient during the calendar year (implying no net effect across calendar year-end).

Results of this (WLS) regression analysis are reported in Table VII. We conduct the analysis with consecutive six-month subperiods. To explore the robustness of results to the length of the subperiods, we also report results for consecutive four-month subperiods (see Brown et al. (1996)). Results in Table VII are consistent with prior results: change in risk is negatively related to prior performance, but the relation is weaker for funds that use derivatives. These effects are present for both four- and six-month subperiods, and are concentrated in total risk and systematic risk rather than idiosyncratic risk. However, results for the dummy variable FIRST, equal to one if the consecutive subperiods span a calendar year-end, show that the coefficient on the interaction of this dummy variable with prior performance is significantly positive. These results are relatively more consistent with

[17] Additionally, recall from Table II that derivative use is positively related to manager tenure for individual funds. As suggested to us by the editor, perhaps established managers are more likely to use derivatives, and also have fewer incentives to play games. In this case, we would also observe a weaker relation between past performance and changes in risk for funds that use derivatives than for those that do not.

[18] Brown et al. (1996, p. 90) note: "Following the most prevalent industry practice, we make the simplifying assumption that the tournaments are held on an annual basis and that all funds have their performance judged on the same cycle."

Table VII

Regressions of Change in Risk on Performance during the Previous Calendar Year

Results of regression analyses testing the relation between change in risk variable between two subperiods, and mutual fund performance during the first subperiod. Results are reported for six- and four-month subperiods. The dependent variable is Δ*RISK*, the change in risk variable (STD, IDIO, or BETA) between the two subperiods. Independent variables include *D* (dummy variable equal to one if the fund invests in derivatives), *PERF* (the difference between the mean excess return on the fund and the mean excess return for funds with the same investment objective during the first subperiod), *D* ∗ *PERF*, *FIRST* (a dummy variable equal to one if Δ*RISK* represents the change in risk from the last subperiod of one calendar year to the first subperiod of the next calendar year), *FIRST* ∗ *D* ∗ *PERF* and *LagRISK* (the value of the risk variable during the first subperiod). Each regression also includes dummy independent variables (not reported) for subperiods, fund types, Morningstar investment style and size classifications, interactions between the subperiod and fund type dummies, and interactions between the subperiods and Morningstar classifications. Returns are in percent. *p*-values for tests of the null hypothesis that the coefficient equals zero are in parentheses. Results are reported using weighted least squares. The inverse of the per fund standard deviation of the residual terms from the first-pass ordinary least squares regression is used as the weight in the second-pass weighted least squares regression.

Variable	Intercept	*D*	*PERF*	*D* ∗ *PERF*	*FIRST* ∗ *PERF*	*FIRST* ∗ *D* ∗ *PERF*	*LagRISK*
Six-month subperiods							
ΔSTD	1.127	−0.015	−0.014	0.008	0.080	−0.028	−0.396
	(0.00)	(0.44)	(0.00)	(0.19)	(0.00)	(0.01)	(0.00)
ΔIDIO	0.176	−0.043	−0.001	−0.001	0.053	−0.005	−0.390
	(0.00)	(0.01)	(0.78)	(0.93)	(0.00)	(0.60)	(0.00)
ΔBETA	0.740	−0.021	−0.011	0.009	0.038	−0.013	−0.658
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Four-month subperiods							
ΔSTD	1.905	−0.024	−0.015	0.014	0.070	−0.028	−0.574
	(0.00)	(0.22)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
ΔIDIO	0.371	−0.082	0.006	−0.001	0.071	−0.021	−0.610
	(0.00)	(0.00)	(0.01)	(0.83)	(0.00)	(0.02)	(0.00)
ΔBETA	0.816	0.006	−0.013	0.010	0.025	−0.012	−0.776
	(0.00)	(0.50)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)

managerial gaming than the cash flow explanation. We also conduct a test of the null hypothesis that this coefficient is equal in magnitude to the negative coefficient on PERF, implying no net effect across calendar year-end. We reject this null hypothesis; change in risk during the first subperiod of a year shows a net, significantly positive relation to performance during the last subperiod of the prior year. This surprising result is not predicted by either hypothesis. Finally, we note that the impact of performance on risk is consistently less severe for funds that use derivatives than for those that do not, both within and across calendar year-ends.

Overall, the negative relation between change in fund risk and prior performance within calendar years is consistent with both managerial incentive gaming and with changes in fund risk due to cash inflows and outflows. This relation is weaker for funds that use derivatives, results we interpret as relatively more consistent with the cash flow explanation. Because the calendar year-end affects the relation between fund risk and prior performance, we also find some evidence supportive of managerial incentive gaming. In all cases, the relation between changes in fund risk and prior performance is concentrated in total and systematic risk, and is significantly weaker for funds that use derivatives. Managers who use derivatives are able to manage the impact of performance on fund risk. The significant positive relation between change in risk and prior performance across the calendar year-end is not predicted by either theory.

V. Conclusions

This paper provides evidence about the ways in which mutual fund managers use derivatives. Almost 21 percent of the equity mutual funds analyzed in this paper use derivatives. The primary characteristic determining derivative use is membership in a family of funds.

Fund risk is associated with self-stated investment objective and with Morningstar style, but not with derivative use. We find no systematic differences in various risk measures and the higher moments of return distributions between funds that do and do not use derivatives. Managers who decide to use derivatives combine them with nonderivative assets to maintain net portfolio risk and return comparable to those of funds that do not use derivatives. This finding contradicts the popular association of derivative use with increased risk exposure. We also find that funds that use derivatives have similar performance as funds that do not use derivatives.

Finally, changes in fund risk in response to previous performance are substantially less severe for funds that use derivatives, consistent with the explanation that managers use derivatives to reduce the impact of performance on risk. Derivative use is significantly related to changes in systematic risk, but not to changes in idiosyncratic risk, suggesting use of stock index derivatives.

Appendix: Collection of Information about the Use of Derivatives

> Fund-tracking services such as Morningstar Inc. and Lipper Analytical Services Inc. generally find it difficult to compile lists of funds that are active users of derivatives. That's because of the inconsistency of disclosure and the fact that certain bonds—such as kitchen-sink bonds or structured notes—don't lend themselves to easy identification. . . . Michael Lipper, president of Lipper, laments that funds can buy and sell a derivative security between financial-statement dates, leaving no trace. . . . So what's a shareholder to do? [One] suggestion is to call the

> fund companies and ask if they use derivatives, and if so, how and why they use them. A fund prospectus often can state that the fund manager has the authority to invest in complex derivatives. But, in fact, the manager may act only rarely on that authority. [Schultz (1994)]

During the period December 1994 through June 1995, we attempted to contact 798 funds classified as Aggressive Growth, Equity-Income, Growth and Income, Growth, or Small Company funds by *Morningstar Mutual Funds OnDisc*. We called each fund at the telephone number listed in the Operations Information section of the Morningstar database. Each successful telephone interview gathered responses to the following questions:

1. Has Fund _____ invested in derivatives in the last couple of years?
   1a. For example, has Fund ______ invested in options or futures in the last couple of years?
2. If so, what types of derivatives (options, futures, or other derivatives)?
3. What does the fund use derivatives for?

Question 1 was designed to identify funds that use derivatives, and Question 1a to verify the response. Questions 2 and 3 were designed to collect additional information about the use of derivatives. Also, each fund was asked to mail a copy of the fund prospectus and annual report to us.

The telephone respondents demonstrated a wide variety of knowledge about the funds themselves and finance in general. Some fund representatives had no idea what derivatives were, despite repeated explanations on our part. At least one fund manager delivered a hostile lecture arguing that derivatives were not evil securities. Each time we had doubts about the knowledge of the respondent or the accuracy of the response, we asked to speak to the fund manager or someone more knowledgeable. Also, all questionable responses were verified by another phone call and/or review of the prospectus.

From the telephone calls, we obtained information about derivative use for 663 of the 798 funds. We were missing information from the funds for the following general reasons: the telephone number was disconnected or there was no response after repeated attempts, the fund had merged, liquidated, or was otherwise closed to new investors, or the person responding to the call did not know the answer and was unable to provide the name of someone who did. For the 135 funds missing information after the telephone calls, we reviewed the prospectus (if available) to attempt to classify derivative use. We reviewed both the investment objective description and the balance sheet data. The investment objective indicated whether the fund was allowed to invest in derivatives, and the balance sheet indicated derivative positions as of a particular date. More than half of the funds reviewed are allowed to invest in derivatives, but many do not actually do so. Therefore, we considered only those funds with positive positions listed on their balance sheets as investing in derivatives. We obtained information for 42 additional funds from the prospectus, for a sample of 705 funds. We lost an additional 26 funds when we extended the sample period through December 1994, for a final sample of 679 funds.

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