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On the Empirical Evidence of Mutual Fund Strategic Risk Taking

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Abstract

We reexamine empirical evidence on strategic risk-taking behavior by mutual fund managers. Several studies suggest that fund performance in the first semester of a year influences risk-taking in the second semester. However, we show that previous empirical studies implicitly assume that idiosyncratic fund returns (in a factor model) are uncorrelated across funds. We present generalized methodologies (based on both contingency tables and regression analysis) that accommodate the case of a general error structure. We show that the correlation between idiosyncratic fund returns is essential to the analysis and, when it is taken into account, the empirical evidence of strategic risk taking by fund managers disappears.

KEYWORDS: Strict factor structure, Tournament hypothesis.
JEL CLASSIFICATION: G11

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1 Introduction

During the last two decades, the mutual fund industry experienced tremendous growth both in number of funds and amount of assets under management. It is not surprising that it attracts a lot of attention of the regulatory agencies that would like to ensure that fund managers select investment strategies that are optimal from the investors' point of view. The joint occurrence of two well-established facts in the mutual fund industry may lead to an agency conflict between mutual fund managers and mutual fund shareholders. First, managers' compensation is typically based on a percentage of the fund's net assets (see, e.g., Khorana, 1996). Second, the top-performing funds receive the bulk of new cash inflows, while bad performance does not lead to significant outflows (see, e.g., Sirri and Tufano, 1998). Together, these effects suggest that mutual funds participate in annual tournaments where they compete for the top rankings. This leads to the conjecture that funds performing badly during the first part of the year have an incentive to increase risk in the second part of the year in order to try to catch up with mid-year winners at the end of the year. This conjecture is called the *tournament hypothesis*. Chen and Pennacchi (1999) provide a theoretical model for risk-taking assuming that fund managers are evaluated with respect to an exogenous benchmark index. They show that, in their model, poor performing funds do not necessarily increase the volatility of their fund's returns.

A number of studies verifies the tournament hypothesis empirically. Brown, Harlow, and Starks (1996) find evidence supporting the tournament hypothesis using a contingency table methodology applied to monthly data. Busse (1998) uses the same methodology with daily data and finds that mid-year losers do not increase their risk relative to better performing funds, contrary to the tournament hypothesis. Koski and Pontiff (1998) use regression analysis and find a negative relation between interim performance and subsequent change in risk, in line with the tournament hypothesis. Finally, Chevalier and Ellison (1997) obtain different regression results depending on whether fund risk is measured on the basis of fund portfolio holdings or monthly fund returns.

In this paper, we show that all test procedures employed so far in the literature implicitly assume that fund returns follow a factor structure with *uncorrelated* idiosyncratic errors across funds. This is what Chamberlain and Rothchild (1983) have named a *strict factor structure*. We generalize both the contingency table and regression methodologies used before to the case of a general error structure. We find that the evidence of the strategic risk behavior by fund managers disappears, when possible correlation between idiosyncratic fund returns is taken into account.

The structure of the paper is as follows. In Section 2, we discuss the empirical findings in the literature on the impact of past performance on funds' risk taking. We replicate these analyses on our dataset which leads to the same results. In Section 3, we demonstrate the validity of the methodologies used in previous papers in a strict factor structure. We show that these methodologies tend to reject the null (i.e., absence of strategic risk taking) too often when there is no strict factor structure. We also show how to extend the methodologies to the case of a general (i.e., non-strict) factor structure. Our empirical results, in Section 3, show that the empirical evidence reported in the literature disappears when possible correlation between idiosyncratic fund returns is accounted for. Section 4 concludes.

2 Mutual fund strategic risk taking: empirical evidence

All empirical studies on the tournament hypothesis referred to above use one of two different methodologies. The first methodology is a contingency table approach where χ^2-tests of independence are used to test whether risk-taking during the second half of the year is independent of realized performance during the first part of the year. The second methodology is based on regression techniques to test the same hypothesis. We discuss both methodologies, and the empirical results based on them, in more detail now.

2.1 Contingency table approach

Brown, Harlow, and Starks (1996) and Busse (1998) investigate changes in mutual fund risk policies within a calendar year using 2×2-contingency tables. The change in risk from the first to the second part of the year of fund i is measured as the ratio of the standard deviations of returns in the corresponding periods: $\sigma_i^{(2)}/\sigma_i^{(1)}$, where $\sigma_i^{(k)}$ denotes the standard deviation of monthly returns of fund i in the k-th part of the year, $k = 1, 2$. This ratio is called the *risk adjustment ratio.* According to the tournament hypothesis, the risk adjustment ratio should be higher for interim losers (funds ranked relatively low after the first part of the year) than for interim winners.

In the main specification, the first part of the year comprises the first seven months of the year. The results remain virtually unchanged when the interim assessment period is taken to be equal to the first six months of the year. We will use the latter specification in this paper. Moreover, interim losers (winners) are defined as funds with a return over the first part of the year below (above) the median return for all funds. In an alternative specification, Brown, Harlow, and Starks (1996) define winners (losers) as funds in the top (bottom) quartile of returns over the first part of the year. For simplicity, we restrict ourselves to the description of the main specification in the sequel.

In order to test the tournament hypothesis, 2×2-contingency tables are constructed. Each cell represents the funds with interim return above (below) the median return and risk adjustment ratio above (below) the median risk adjustment ratio. Under the null hypothesis that the level of the interim performance and subsequent change in risk are independent from each other, all frequencies should be equal to

25%. The Low-High frequency, for example, represents the fraction of funds with a return over the first six months below the median return and a risk adjustment ratio above median. The tournament hypothesis then states that the Low-High frequency is above 25%. A standard χ^2-statistic for independence is then used in the empirical analysis. The statistic is given by

$$Q = 16N(f - 0.25)^2, \tag{2.1}$$

where N denotes the number of funds and f denotes the Low-High frequency defined above. The null hypothesis is rejected in favor of the tournament hypothesis if the χ^2-statistic (2.1) has a p-value (based on a χ^2_1-distribution) below the required significance level.

Brown, Harlow, and Starks (1996) examine monthly returns of 334 US growth-oriented mutual funds during the period from 1980 to 1991. The Low-High frequency for the whole sample appears significantly different from 25% in the predicted direction. Similar results for the whole sample are obtained for the alternative specifications when the first part of the year comprises the first 6 months and division into winners and losers is based on quartiles. The empirical results reported by Brown, Harlow, and Starks (1996) suggest that the results obtained are sensitive to the time period taken. Contrary to the tournament hypothesis, the Low-High frequency is (insignificantly) below 25% in the first half of the sample. The positive finding for the whole sample appears to be driven by the last six years of the sample. In general, the Low-High frequency uniformly increases with time from 22.43% in 1980-1982 to 31.22% in 1989-1991. The authors explain the observed pattern by "the growth of the mutual fund industry and the increased investor scrutiny that attended that expansion".

Busse (1998) applies the methodology of Brown, Harlow, and Starks (1996) to daily returns of 230 US domestic equity funds during the period from 1985 to 1995. When using monthly returns computed from daily data, he finds results equivalent to those of Brown, Harlow, and Starks (1996). However, he finds that the Low-High frequency based on daily returns is not significantly larger than 25% in the total period and in most subperiods.

We replicate the contingency table analysis in each of the annual tournaments from 1976 to 1994, in the total period, and in the subperiod 1980-1991. Our dataset consists of monthly returns of 811 US growth funds obtained from Morningstar Mutual Fund Database. The time span is from 1976 to 1994 including the 1989-1994 time period for which our data are free from survivorship bias. The dataset also includes the starting date and size (as of the end of 1994) for the funds that survived till that time. These data will be used later on to discriminate between small and large as well as young and old funds. For the first fifteen years, our dataset is virtually the same as the dataset of Brown, Harlow, and Starks (1996).

The third and fourth columns of Table 1 report the Low-High frequencies f and corresponding χ^2-statistics for each of the annual periods from 1976 to 1994, the period 1980-1991, and the total time span of our dataset. The most striking finding is that the χ^2-statistics vary a lot from year to year. In five consecutive years (from 1987 to 1991), the Low-High frequency appears significantly above 25% in full accordance with the tournament hypothesis. However, there are also four years (1977, 1978, 1983, and 1993) where the Low-High frequency appears to be significantly below 25%, which contradicts the tournament hypothesis. Moreover, the Low-High frequency for the overall sample seems insignificantly different from 25%. We defer an explanation of these effects to Section 3.

2.2 Regression based approach

Chevalier and Ellison (1997) and Koski and Pontiff (1998) test the relation between interim performance and change in risk by considering the following relation for fund i in year t:

$$\sigma_{i,t}^{(2)} - \sigma_{i,t}^{(1)} = \alpha_0 + \alpha_1 \sigma_{i,t}^{(1)} + \alpha_2 P_{i,t}^{(1)} + \beta^T C_{i,t} + \varepsilon_{i,t}, \qquad (2.2)$$

where $\sigma_{i,t}^{(1)}$ and $\sigma_{i,t}^{(2)}$ are the standard deviation of monthly returns for fund i in the first and second part of year t, respectively, and $C_{i,t}$ includes different controlling variables such as year and category dummies. $P_{i,t}^{(1)}$ represents a measure of fund i's performance in the first part of year t. This is either fund i's return in excess of the market (Chevalier and Ellison, 1997) or in excess of the mean return of funds with the same investment objective (Koski and Pontiff, 1998). The level of risk in the first part of the year $\sigma_{i,t}^{(1)}$ is included in the regression in order to control for mean reversion in the noisy component of the risk measure employed.

Chevalier and Ellison (1997) examine 449 US growth and growth and income funds in 1983-1993 and find a positive coefficient on $P_{i,t}^{(1)}$, which contradicts the tournament hypothesis. However, they obtain opposite results when fund risk is measured on the basis of historical returns of stocks comprising the fund equity portfolio. Koski and Pontiff (1998) use the dataset of 798 US equity funds and find a negative relation between interim performance and subsequent change in risk, in line with the tournament hypothesis.

We also replicate the regression analysis in each of the annual tournaments from 1976 to 1994, in the total period, and in the subperiods corresponding to other studies. We specified $P_{i,t}^{(1)}$ simply as fund i's return in the first part of year t. With one fund category and year dummies, we would get the same results if we would specify performance as an excess return. The third and fourth columns of Table 2 report the coefficients on $P_{i,t}^{(1)}$ and corresponding t-statistics for the annual periods, the sample periods of other studies, and the total time span of our dataset. Similarly to the results based on contingency tables, there is a lot of variation between performance coefficients across years. The relation between risk and performance appears significantly positive in seven years (1976, 1977, 1978, 1983, 1986, 1987, and 1993) and significantly negative in three years (1984, 1991, and 1994). The performance coefficients measured over the longer time spans seem significantly positive in three out of four cases.

Summarizing, for both the contingency table approach and the regression approach mixed evidence with respect to the tournament hypothesis has been reported in the literature. Using our dataset, which differs slightly from those used in other papers, we obtain the same results. In the next section, we take a closer look at the statistical properties of the tests, which will enable us to explain these findings. Moreover, this analysis allows us to adapt p-values and unify the answers of all testing methodologies.

3 Detailed discussion of tournament tests

In order to explain the contribution of the present paper, we recall the different uses of the term "factor model" in the financial and statistical literature. In any factor model, the return of fund i in month t is written as

$$R_{i,t} = \alpha_i + \beta_i^T F_t + \varepsilon_{i,t}, \tag{3.1}$$

where F_t denotes the (vector valued) factor for month t. For each month t, the vector of error terms $\varepsilon_t \equiv (\varepsilon_{1,t}, ..., \varepsilon_{N,t})^T$ is, by construction, uncorrelated with the factors F_t. Without further conditions, (3.1) is nothing but an orthogonal decomposition of returns into a part explained by the factors and a part orthogonal to the factors. Thus, it does not describe a testable restriction. Content is only added to (3.1) by imposing extra restrictions. In finance, following the seminal research by Fama and French, the term "factor model" is used to denote the situation where, for each asset i, the constant term α_i is related to asset-specific factor-loadings β_i and asset-independent risk-premiums for the factors. In the statistical literature, on the contrary, the term "factor model" is used to denote the situation where the idiosyncratic errors $\varepsilon_{i,t}$ are uncorrelated across funds, i.e., $\Sigma_\varepsilon = var(\varepsilon_t)$ is diagonal. This second situation is what Chamberlain and Rothchild (1983) have named a *strict factor structure*.

The size properties of the contingency table approach as well as the regression approach are based on standard central limit arguments. Whether or not fund returns satisfy a Fama-French type factor structure is irrelevant for the behavior of the contingency table or regression tests as described in Section 2. However, a necessary condition for the central limit arguments is that fund returns are "sufficiently independent". In the appendix, we prove rigorously that, for the contingency table approach, the χ^2-statistic indeed has a χ^2_1 limiting null distribution if fund returns follow a strict factor model. Using the same line of reasoning, the limiting null distribution of the t-statistic (in the regression approach) is indeed standard normal for the strict factor case. However, when the idiosyncratic errors of individual funds are cross-correlated, i.e., when the variance matrix of the errors is not diagonal, the χ^2-statistic (2.1) and the t-statistic on the performance coefficient α_2 in 2.2 are more variable and the null hypothesis will be rejected too often if χ^2_1 and standard-normal p-values are used.

Mutual funds often belong to a limited number of mutual fund families. In that case, it seems reasonable that idiosyncratic errors in some factor model are correlated across funds. In order to accommodate this situation, we determine the distribution of the tournament tests, under the null of no strategic risk-taking, using simulation based on (3.1). The exact choice of the factors (which is, of course, material for pricing applications) is irrelevant for the problem at hand as we will explain shortly. For each month t, the vector of error terms ε_t is assumed to be normally distributed with variance matrix Σ_ε). Using factor loadings and variances that are estimated from observed fund returns using standard regression, we simulate realized fund returns from (3.1) imposing no tournament effect and calculate the realization of both the χ^2- and t-statistic. This is replicated 10,000 times from which the empirical p-values for both methodologies are obtained.

This way of simulating adapted p-values has a particularly nice invariance property. The simulated fund returns (and, consequently, the simulated p-values) are independent of the choice of the factors F_t. Hence, in the null simulation we assume without loss of generality that $\beta_i = 0$ and α_i equals the observed average return for fund i. The variance is then simply equal to the sample variance of the fund returns. Note that our simulations assume normality of monthly fund returns. Clearly, this normality assumption is innocuous, if sufficient regularity conditions are satisfied for a central limit theorem to hold true. It is important that the simulation setup allows idiosyncratic errors to be correlated across funds.

The simulation approach is the same for both the contingency table approach and the regression approach. We discuss the empirical results for them separately. First, we simulated 10,000 replications of the contingency tables for each year from 1976 to 1994 and the two time spans of interest: 1980-1991 and 1976-1994. In each replication, we compute the Low-High frequency and the χ^2-statistic (2.1). Given the empirical distribution of the χ^2-statistics, we calculate adapted p-values for the actual χ^2-statistics (see Column 6 of Table 1). The adapted p-values are much larger than the p-values of the χ^2_1 distribution that have been reported in the literature[1]. This is due to the fact that the dependencies induce much less degrees of freedom than the number of observations suggests.[2] These results imply that using χ^2_1-based p-values for the χ^2-statistic (2.1) may lead to incorrect inference, namely rejecting the null hypothesis too often. When we use adapted p-values, then only in one year out of 19 (year 1991), the null hypothesis is rejected at the 5% level. We attribute

[1] Using a bootstrap procedure which maintains the cross correlation across funds, Busse (1998) also finds adapted p-values much larger than χ^2_1-based p-values. However, he does not explain the source of this finding.

[2] For completeness, we also simulated assuming a strict factor model, i.e. assuming that the variance matrix Σ_ε is diagonal. As expected, the simulated p-values in this case coincide with the p-values of the χ^2_1 distribution.

this to sampling error.

Brown, Harlow, and Starks (1996) argue that small funds and new funds are more likely to adjust their risk in response to the tournament incentives. Indeed, they find that the Low-High frequency for small funds and new funds is typically larger than among large and old funds. In order to check the robustness of these results, we repeat our analysis for the subsets of small funds and young funds (see Tables 3 and 4, respectively). We define small (young) funds as funds with size (age) below median in a given year. The Low-High frequencies for small and young funds seem to be more variable than among all funds. However, most of them appear insignificantly different from 25% when we use adapted p-values. For both small and young fund subsets, we reject the null hypothesis at the 5% level in only two years (1983 and 1991 for small funds and 1978 and 1983 for young funds).

We use the same methodology to obtain the null distribution of the t-statistic for the performance coefficient α_2 in regression (2.2). We perform the analysis for each year from 1976 to 1994 and for three longer time spans: 1983-1993, 1992-1994 and 1976-1994. The first two of the three time spans correspond to the sample periods of Chevalier and Ellison (1997) and Koski and Pontiff (1998), respectively. The last one is our full sample period. In each of 10,000 replications, we estimate the performance coefficient α_2 and the corresponding t-statistic. Using the empirical distribution of this t-statistic, we calculate adapted (one-sided) p-values (see Column 6 of Table 2). As in the case of the contingency table approach, the adapted p-values for the t-statistics are much larger than the p-values of the Student distribution. Using adapted p-values, we reject the null hypothesis at the 5% level only in two years out of nineteen (1978 and 1983). Similar results are obtained for the subsets of small and young funds.

Thus, when we relax the assumption of the strict factor structure for mutual fund returns, the evidence of strategic risk-taking behavior among mutual funds disappears, irrespectively of the sample period and methodology used. Taking the correlation between idiosyncratic errors into account, there seems to be no evidence of excessive risk taking of mutual fund managers caused by tournament behavior. The same conclusion applies to the subsets of small and young funds.

4 Conclusion

The empirical evidence on a convex relation between mutual fund flows and their past performance (see, e.g., Sirri and Tufano, 1998) inspired numerous studies of funds' risk-taking behavior. Most of them investigate how a change in risk between the first and second semester is influenced by fund performance in the first semester. Two basic research techniques have been used: contingency tables (see Brown, Harlow, and Starks, 1996, and Busse, 1998) and regressions (see Chevalier and Ellison, 1997, and Koski and Pontiff, 1998). In this paper, we demonstrate that both methodologies implicitly assume that fund returns are generated from a strict factor structure.

We propose a generalization based on simulated p-values that does not rely on this assumption. Using this technique, we find no evidence of strategic risk-taking irrespective of the methodology or sample period used.

A Appendix: Limiting distribution of the test statistics

In this appendix, we derive the limiting distribution of both the χ^2- and t- test statistics mentioned in the main text assuming that mutual fund returns are generated from a strict factor model. Thus, we assume for the moment that, for fund returns in month t,

$$R_{i,t} = \alpha_i + \beta_i^T F_t + \varepsilon_{i,t}, \tag{A.1}$$

where F_t denotes the vector of factors and where the idiosyncratic errors $\varepsilon_{i,t}$ are independently $N(0, \sigma_i^2)$ distributed[3]. Define the sample average and the sample volatility of fund i's returns in semester k as $\hat{\mu}_i^{(k)}$ and $\hat{\sigma}_i^{(k)}$, respectively:

$$\begin{aligned}
\hat{\mu}_i^{(k)} &= \frac{1}{6} \sum_{t=1+6(k-1)}^{6k} R_{i,t}, \\
\hat{\sigma}_i^{(k)} &= \sqrt{\frac{1}{6} \sum_{t=1+6(k-1)}^{6k} (R_{i,t} - \hat{\mu}_i^{(k)})^2}.
\end{aligned}$$

Let $\mathcal{F}$ denote the information in the factors over the complete observational period, i.e. $\mathcal{F} = \sigma(F_1, F_2, \ldots)$. Now, conditionally on $\mathcal{F}$ and under the null hypothesis, the statistics $\hat{\mu}_i^{(1)}$, $\hat{\mu}_i^{(2)}$, $\hat{\sigma}_i^{(1)}$, and $\hat{\sigma}_i^{(2)}$ are independently distributed. For the χ^2-statistic, the independence of the risk-adjustment-ratio $\hat{\sigma}_i^{(2)}/\hat{\sigma}_i^{(1)}$ and the first semester returns, implies that (conditionally on $\mathcal{F}$ and under the null) the standard χ^2-test statistic for independence Q in (2.1) follows, asymptotically, a χ_1^2 distribution. Formally, under the null hypothesis,

$$\mathcal{L}(Q|\mathcal{F}) \to \chi_1^2.$$

For regression tests, the independence of the idiosyncratic errors $\varepsilon_{i,t}$ across funds, guarantees the validity of the standard t-test by the same arguments.

In case the idiosyncratic errors $\varepsilon_{i,t}$ are correlated across funds, the arguments above no longer hold, even asymptotically. In that case, the number of unbounded eigenvalues of the variance of fund returns is generally infinite and limiting results can no longer be established analytically in general.

[3] Clearly, normality is, asymptotically, irrelevant for the main results in this appendix as long as variances exist.

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Year	# funds	Low-High frequency	χ^2-statistic	p-value (χ^2_1)	p-value (adapted)
1976	119	25.21	0.01	0.9270	0.9409
1977	123	16.26	15.03	0.0001	0.1393
1978	128	14.06	24.50	0.0000	0.0697
1979	131	26.34	0.37	0.5408	0.7637
1980	132	27.27	1.09	0.2963	0.6629
1981	139	21.58	2.60	0.1071	0.5520
1982	144	23.61	0.44	0.5050	0.7146
1983	160	17.19	15.63	0.0001	0.0939
1984	181	24.03	0.27	0.6029	0.8304
1985	203	24.88	0.00	0.9440	0.9543
1986	235	23.40	0.96	0.3278	0.7357
1987	271	31.00	15.59	0.0001	0.2450
1988	315	29.68	11.05	0.0009	0.3986
1989	336	27.68	3.86	0.0495	0.5732
1990	357	29.69	12.57	0.0004	0.2968
1991	392	34.82	60.50	0.0000	0.0386
1992	425	24.94	0.00	0.9613	0.9816
1993	520	18.75	32.50	0.0000	0.1852
1994	635	26.30	1.71	0.1903	0.7638
1980-91	2865	26.86	15.84	0.0001	0.2217
1976-94	4946	25.01	0.00	0.9773	0.9876

Table 1: Results of the contingency table approach for all funds. The Low-High column gives the percentage of funds with both a total return over the first six months below median and a risk adjustment ratio above median. The χ^2-statistic tests the null hypothesis that population percentages are equal to 25%. Column five presents the p-values of the χ^2-statistic based on the χ^2_1 distribution. The last column reports adapted p-values for the χ^2-statistic. See main text for details.

Year	# funds	α_2	t-statistic	p-value (Student)	p-value (adapted)
1976	119	0.04	2.75	0.0034	0.3464
1977	123	0.07	6.08	0.0000	0.0982
1978	128	0.27	10.03	0.0000	0.0474
1979	131	0.03	1.77	0.0399	0.5106
1980	132	0.04	1.43	0.0772	0.5385
1981	139	-0.02	-1.26	0.1045	0.4626
1982	144	-0.02	-1.27	0.1037	0.3590
1983	160	0.09	9.05	0.0000	0.0265
1984	181	-0.09	-4.04	0.0000	0.3117
1985	203	0.03	1.93	0.0276	0.4190
1986	235	0.04	3.81	0.0001	0.2649
1987	271	0.09	3.89	0.0001	0.2958
1988	315	0.01	0.77	0.2222	0.5160
1989	336	0.01	0.69	0.2449	0.6019
1990	357	-0.01	-0.69	0.2592	0.4888
1991	392	-0.04	-3.58	0.0002	0.1297
1992	425	0.00	-0.55	0.2900	0.4716
1993	520	0.03	5.53	0.0000	0.2090
1994	635	-0.03	-6.10	0.0000	0.1993
1983-93	3395	0.02	6.01	0.0000	0.2839
1992-94	1580	0.00	0.32	0.3732	0.4894
1976-94	4946	0.02	7.30	0.0000	0.2627

Table 2: Results of the regression analysis for all funds. The third and fourth columns present the coefficient on interim performance and corresponding t-statistic. Column five presents the p-values of the t-statistic based on the Student distribution. The last column reports adapted p-values of the t-statistic. See main text for details.

Year	# funds	Low-High frequency	χ^2-statistic	p-value (χ_1^2)	p-value (adapted)
1976	57	22.81	0.44	0.5078	0.6825
1977	59	16.10	7.47	0.0063	0.1587
1978	61	13.11	13.79	0.0002	0.0665
1979	63	28.57	1.29	0.2568	0.5517
1980	63	19.84	2.68	0.1015	0.3800
1981	66	18.18	4.91	0.0267	0.3378
1982	69	22.46	0.71	0.3994	0.6779
1983	75	13.33	16.33	0.0001	0.0225
1984	83	25.30	0.01	0.9126	1.0000
1985	93	23.66	0.27	0.6041	0.7168
1986	107	22.90	0.76	0.3843	0.7220
1987	123	31.71	8.85	0.0029	0.2034
1988	142	29.58	4.76	0.0291	0.4592
1989	154	25.97	0.23	0.6287	0.9012
1990	167	28.44	3.17	0.0751	0.4863
1991	184	36.41	38.35	0.0000	0.0112
1992	203	24.88	0.00	0.9440	1.0000
1993	249	18.88	14.94	0.0001	0.1763
1994	314	27.07	2.15	0.1423	0.6643
1980-91	1326	26.70	6.11	0.0135	0.2821
1976-94	2332	25.00	0.00	1.0000	1.0000

Table 3: Results of the contingency table approach for small funds. The Low-High column gives the percentage of small funds with both a total return over the first six months below median and a risk adjustment ratio above median. The χ^2-statistic tests the null hypothesis that population percentages are equal to 25%. Column five presents the p-values of the χ^2-statistic based on the χ_1^2 distribution. The last column reports adapted p-values of the χ^2-statistic. See main text for details.

Year	# funds	Low-High frequency	χ^2-statistic	p-value (χ_1^2)	p-value (adapted)
1976	54	25.93	0.07	0.7855	0.7701
1977	56	14.29	10.29	0.0013	0.0932
1978	57	11.40	16.86	0.0000	0.0419
1979	59	26.27	0.15	0.6961	0.7730
1980	59	20.34	2.05	0.1521	0.4411
1981	62	19.35	3.16	0.0754	0.3197
1982	65	23.85	0.14	0.7098	0.7713
1983	70	15.71	9.66	0.0019	0.0475
1984	79	22.78	0.62	0.4310	0.6558
1985	88	23.86	0.18	0.6698	0.7310
1986	101	24.26	0.09	0.7653	0.8474
1987	117	30.34	5.34	0.0208	0.3167
1988	135	28.52	2.67	0.1020	0.5688
1989	147	30.27	6.54	0.0106	0.3078
1990	160	29.38	4.90	0.0269	0.3280
1991	177	35.03	28.48	0.0000	0.0547
1992	199	27.14	1.45	0.2282	0.6918
1993	249	17.87	20.24	0.0000	0.1132
1994	314	22.93	2.15	0.1423	0.6150
1980-91	1260	26.75	6.15	0.0132	0.2792
1976-94	2248	24.51	0.86	0.3534	0.6999

Table 4: Results of the contingency table approach for young funds. The Low-High column gives the percentage of young funds with both a total return over the first six months below median and a risk adjustment ratio above median. The χ^2-statistic tests the null hypothesis that population percentages are equal to 25%. Column five presents the p-values of the χ^2-statistic based on the χ_1^2 distribution. The last column reports adapted p-values of the χ^2-statistic. See main text for details.