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Another Look at Mutual Fund Tournaments

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Abstract

Daily returns are used to examine how mutual funds actively alter the risk of their portfolios in response to past performance. Compared to monthly data, daily returns produce much more efficient estimates of fund volatility, which give vastly different inferences about the behavior of fund managers. In particular, monthly results consistent with under-performers increasing their risk relative to better performing funds disappear with daily data. The differences in the monthly and daily results arise from biases in the monthly volatility estimates attributable to daily return autocorrelation.

I. Introduction

In a recent paper, Brown, Harlow, and Starks (1996) (hereafter BHS) identify an interesting behavior pattern in the mutual fund industry. Using a sample of monthly fund returns, the authors find that mid-year "losers," funds that earn returns below the median, increase their risk relative to mid-year "winners." The authors attribute this behavior to fee contracts that base compensation on the total amount of assets under management. The idea is that fund cash flows are an asymmetric function of fund performance; high-performing funds receive large inflows, but funds that under-perform are not equally penalized with outflows (see, e.g., Sirri and Tufano (1998)). BHS argue that investors pay particular attention to annual performance rankings reported at the end of the year and, hence, fund managers are especially motivated to enhance their calendar year performance. By increasing fund volatility, mid-year losers increase their probability of finishing the "tournament" among the end of year winners and, in so doing, increase expected fund inflows and fees. The test statistics reported by BHS appear very strong, especially during the more recent period of their study, a consequence, the authors speculate, of increasing competition in the mutual fund industry.

In another recent study of monthly fund returns, Koski and Pontiff (1999) also document an increase in risk for mid-year under-performing funds. Chevalier

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and Ellison (1997) examine several related issues and, although many of their results are consistent with BHS, some of their findings are difficult to rationalize in the earlier paper's framework. For example, when the authors use monthly returns, they find "higher January–September excess returns are clearly correlated with larger risk increases" (Chevalier and Ellison (1997), p. 1196), a result at odds with BHS.

In this paper, I use a sample of daily fund returns to further explore the hypothesis that fund managers actively alter the risk of their portfolios in response to past performance. With more than 20 times as many observations as monthly data, daily data produce much more precise estimates of volatility. The results are striking. When I compound the daily returns into monthly returns, I find the same pattern documented by BHS. However, when I use the same data at a daily frequency, any apparent tendency for poorly performing funds to increase risk relative to better performers completely disappears.

The differences in the monthly and daily results arise from biases in the monthly standard deviation estimates. The biases arise from autocorrelation patterns in the daily returns attributable to disparate exposure to small capitalization stocks. When I redo the tournament analysis with unbiased monthly standard deviation estimates, the tournament patterns disappear. Furthermore, when I use the statistical characteristics of the actual daily fund returns to simulate a mutual fund environment in which managers do not strategically alter their risk, the actual monthly results are consistent with the null hypothesis of no tournament behavior.

I estimate what a fund's end of year volatility would be if it did not change its factor loadings or residual risk from the beginning of the year, and I find that the predicted volatility explains most of the fund's actual end of year risk. This indicates that a large portion of a fund's intra-year change in risk arises from changes in the volatility of common stock market risk factors, which, in turn, suggests that very little is attributable to the deliberate actions of the fund manager.

The paper is organized as follows. Section II discusses the methodology used in the empirical analysis. Section III describes the mutual fund sample and analytically compares the efficiency of monthly and daily volatility estimates. Section IV presents the empirical results. Section V concludes.

II. Methodology

The central prediction of the tournament hypothesis is that funds with below median returns during the first several months of the year (losers) increase their total risk during the rest of the year relative to the higher performing funds (winners). Thus, on average,

$$\frac{\sigma_{L2}}{\sigma_{L1}} > \frac{\sigma_{W2}}{\sigma_{W1}}, \tag{1}$$

where σ_{Lt} is the volatility of loser fund returns during time period t, σ_{Wt} is the volatility of winner fund returns during time period t, and t refers to the first half or the last half of the year.

Each year, I take performance for fund p during the evaluation period to be the compounded total return,

$$\text{(2)} \qquad \text{RTN}_{py} = \prod_{d=1}^{D}(1 + r_{pd}) - 1,$$

where r_{pd} is the daily return for fund p on day d, and there are D daily returns during the year y evaluation period. To check the sensitivity to the evaluation period, I separate the evaluation period from the latter part of the year at five different break points: after April, May, June, July, and August.

For fund p, I compute fund volatility ratios each year in two different ways. First, assuming the daily returns are independent,

$$\text{(3)} \qquad \text{SDR}_{py} = \left[\frac{\frac{1}{(D_y - D) - 1} \sum_{d=D+1}^{D_y} \left(r_{pd} - \bar{r}_{p(D+1:D_y)}\right)^2}{\frac{1}{D-1} \sum_{d=1}^{D} \left(r_{pd} - \bar{r}_{p(1:D)}\right)^2} \right]^{\frac{1}{2}},$$

where $d = 1$ to D refers to the evaluation period, $d = D + 1$ to D_y refers to the post-evaluation period, and there are D_y trading days during year y.

Second, to account for positive first-order serial correlation in the returns, I model the fund returns as a moving average (MA(1)) process. For each fund, each year, I estimate the moving average process twice, once for the evaluation period and once for the rest of the year,

$$\text{(4)} \qquad \begin{aligned} r_{pd} &= \mu_{p1} + \theta_{p1}\varepsilon_{p1,d-1} + \varepsilon_{p1d}, \qquad d = 1 \text{ to } D, \\ r_{pd} &= \mu_{p2} + \theta_{p2}\varepsilon_{p2,d-1} + \varepsilon_{p2d}, \qquad d = D + 1 \text{ to } D_y. \end{aligned}$$

I take the MA(1) conditional standard deviation ratio to be

$$\text{(5)} \qquad \text{SDR}_{py} = \frac{\sigma(\varepsilon_{p2})}{\sigma(\varepsilon_{p1})}.$$

The statistics in equations (2) and (3) are identical to those of BHS, except I replace monthly returns with daily returns. For each fund, I compute equations (2), (3), and (5) for one of five assessment periods for each full year that the fund exists. An assessment period consists of a beginning of the year evaluation period (e.g., January through June) and a year-end post-evaluation period (e.g., July through December). I then allocate each fund to one of four cells in a two-by-two contingency table each year based on the fund's RTN relative to the median fund RTN and the fund's SDR relative to the median fund SDR. The null hypothesis is that an equal percentage of funds (25%) falls into each cell; that is, there is no difference in relative volatility between winners and losers. A χ^2 test with one degree of freedom determines whether the null hypothesis can be rejected in favor of the hypothesis that losers increase their post-evaluation period risk relative to winners.

I also examine the daily data compounded into a monthly frequency. By doing so, I can directly investigate how the frequency of the data impacts the results. I compute the monthly return on fund p during month m as

$$(6) \qquad r_{pm} = \prod_{d=1}^{D_m}(1 + r_{pd}) - 1,$$

where there are D_m trading days in the month.[1] Morningstar and Standard and Poor's Micropal, two widely used sources of monthly data, use the same procedure to compute monthly returns. I compute the monthly standard deviation ratios with the monthly returns,

$$(7) \qquad \mathrm{SDR}_{py} = \left[\frac{\frac{1}{(12-M)-1}\sum_{m=M+1}^{12}\left(r_{pm} - \overline{r}_{p(M+1:12)}\right)^2}{\frac{1}{M-1}\sum_{m=1}^{M}\left(r_{pm} - \overline{r}_{p(1:M)}\right)^2}\right]^{\frac{1}{2}},$$

where there are M months during the evaluation period. RTN is unaffected by the frequency of the data.

Fund managers should have more control over beta and residual risk than over total variance, which is affected by the aggregate behavior of all market participants. Consequently, I repeat the tournament analysis with beta and residual risk. I examine single- and four-factor specifications,

$$(8) \qquad R_{pd} = \alpha_{p1} + \sum_{j=1}^{k}(\beta_{pj1}R_{jd} + L_{pj1}R_{j,d-1}) + \varepsilon_{p1d}, \qquad d = 1 \text{ to } D,$$

$$R_{pd} = \alpha_{p2} + \sum_{j=1}^{k}(\beta_{pj2}R_{jd} + L_{pj2}R_{j,d-1}) + \varepsilon_{p2d}, \qquad d = D+1 \text{ to } D_y$$

with $k = 1$ or 4. R_{pd} is the excess return of fund p on day d; R_{jd} is the return of factor j on day d; β_{pj1} (β_{pj2}) is fund p's regression coefficient on factor j during (after) the evaluation period; L_{pj1} (L_{pj2}) is fund p's one-day lag regression coefficient on factor j during (after) the evaluation period; α_{p1} (α_{p2}) is fund p's abnormal return during (after) the evaluation period; and ε_{pd} is fund p's idiosyncratic return on day d. The single-factor is the excess return on the S&P 500 index (including dividends). The four-factor specification adds factors that capture the differential dynamics of small cap stocks compared to large cap stocks (small minus big, SMB), high book-to-market stocks compared to low book-to-market stocks (HML), and momentum stocks compared to contrarian stocks (MMC). The SMB and HML indices are similar to those of Fama and French (1993), except at a daily frequency.[2] The MMC index is similar to the momentum index used by

[1] Although the NAV goes down when a fund makes a distribution, the daily return incorporates the distribution on the day the NAV drops. The monthly return also accounts for the distribution because it is compounded from the individual daily returns.

[2] There remains some controversy, on both theoretical and empirical grounds, over the validity of the Fama-French factors as asset pricing factors. See, for example, Ferson, Sarkissian, and Simin (1999) and Ferson and Harvey (1999).

Carhart (1997), except value-weighted and at a daily frequency.[3] The lag factors are to control for the non-synchronous trading problems that Dimson (1979) shows affect regression estimates of individual securities.

For year y, I take fund p's systematic risk ratio for factor j to be

$$\text{(9)} \qquad \text{SYSR}_{pjy} = \frac{\beta_{pj2} + L_{pj2}}{\beta_{pj1} + L_{pj1}},$$

and residual risk ratio to be

$$\text{(10)} \qquad \text{RESR}_{py} = \frac{\sigma(\varepsilon_{p2})}{\sigma(\varepsilon_{p1})}.$$

III. Data

A. Sample

The mutual fund sample, taken from Busse (1999), consists of daily returns from January 2, 1985, through December 29, 1995, for 230 domestic equity funds. The funds have a "common stock" investment policy and a "maximum capital gains," "growth" or "growth and income" investment objective, and more than \$15 million in total net assets according to the December 1984 version of Wiesenberger's *Mutual Funds Panorama.* The sample excludes sector (e.g., technology or health care), balanced, and index funds. This sample is not survivorship biased to any great extent because it includes funds that subsequently merge. However, the sample is biased to some extent because it excludes seven funds that switched into an excluded fund type (e.g., became a sector fund). In addition, the sample does not include new entrants after December 1984. Table 1 reports summary return statistics of the sample.

TABLE 1

Return Statistics of Mutual Fund Sample

Fund Group	No. of Funds	Mean Return	Mean Std. Dev.
All	230	0.0562%	0.898%
Max Capital Gains	68	0.0553	0.979
Growth	107	0.0570	0.894
Growth & Income	55	0.0557	0.805
Survivors	196	0.0574	0.879
Non-Survivors	34	0.0492	1.005

The table shows the daily return statistics of the mutual fund sample by subgroup. Survivors exist during the entire sample period; non-survivors either merge or liquidate. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

[3] I orthogonalize the factors to facilitate estimation of the factor contributions in Section IV.F. The orthogonal SMB factor is the intercept plus residuals from a regression of the SMB factor on the excess returns of the S&P 500. The orthogonal HML factor is the intercept plus residuals of a regression of the HML factor on the excess returns of the S&P 500 and the orthogonal SMB factor. The orthogonal MMC factor is the intercept plus residuals of a regression of the MMC factor on the excess returns of the S&P 500, the orthogonal SMB factor, and the orthogonal HML factor.

B. Efficiency of Estimates

With more than 20 times as many observations, daily returns provide much more information about volatility than monthly returns. Under the simplifying assumptions that returns are independent and normally distributed, if there are 21 daily returns for every monthly return, the efficiency of a daily volatility estimate relative to a monthly estimate is

$$\text{(11)} \qquad \text{efficiency} = \frac{\text{var}(s_m)}{\text{var}\left(\sqrt{21}s_d\right)},$$

where s_m is the standard deviation estimate of monthly returns, and s_d is the standard deviation estimate of daily returns. For a time series of n returns, the unbiased estimator of the variance σ^2 is given by

$$\text{(12)} \qquad s^2 = \frac{1}{n-1}\sum_{t=1}^{n}(r_t - \bar{r})^2.$$

For independent, normal returns, the quantity $(n-1)s^2/\sigma^2$ is distributed as $\chi^2(n-1)$, from which I compute the variance of s_m and s_d.[4] For a six-month estimation period, the efficiency given by equation (11) is 23.7. Relative to monthly estimates, daily estimates are very precise.

Since the ratio of post-evaluation period standard deviation to evaluation period standard deviation is of primary interest, I also examine the efficiency gain in this ratio. Again, I assume returns are independent and normally distributed.

The efficiency of the daily volatility ratio estimate relative to the monthly estimate is given by

$$\text{(13)} \qquad \text{efficiency} = \frac{\text{var}\left(\frac{s_{m2}}{s_{m1}}\right)}{\text{var}\left(\frac{s_{d2}}{s_{d1}}\right)},$$

where s_{m1} (s_{m2}) is the standard deviation estimate of monthly returns from the beginning (end) of the year, and s_{d1} (s_{d2}) is the standard deviation estimate of daily returns from the beginning (end) of the year. The random variables $(n_1 - 1)s_1^2/\sigma_1^2$ and $(n_2 - 1)s_2^2/\sigma_2^2$ have independent χ^2 distributions with $n_1 - 1$ and $n_2 - 1$ degrees of freedom, respectively, where n_1 and n_2 denote the number of observations used to compute volatility during the evaluation period and post-evaluation period, respectively. Therefore,

$$\text{(14)} \qquad f = \frac{(n_2-1)s_2^2/\left[\sigma_2^2(n_2-1)\right]}{(n_1-1)s_1^2/\left[\sigma_1^2(n_1-1)\right]} = \left(\frac{s_2\sigma_1}{s_1\sigma_2}\right)^2$$

has an F distribution with $n_2 - 1$ and $n_1 - 1$ degrees of freedom, from which I compute the variance of s_{m2}/s_{m1} and s_{d2}/s_{d1}. For a January through June, July

[4]The technical details of this section are available upon request.

through December assessment period, the efficiency given by equation (13) is 47.3, which indicates that the standard deviation ratios are considerably more precise when computed with daily rather than monthly returns.[5]

IV. Empirical Analysis

A. Main Results

I compute the RTN and SDR measures for the daily data and for monthly data (compounded from the daily data). Table 2 shows the results for various assessment periods. The percentages in the table reflect the 11 individual annual tournaments. For example, I sum up the number of funds classified as low RTN, high SDR each year and divide by the total number of funds in all four classifications over 11 years. I classify funds (high or low RTN and high or low SDR) relative to funds of the same investment objective.

TABLE 2

Frequency Distributions of Two-by-Two Contingency Tables of Return and Standard Deviation Ratio by Assessment Period

		Sample Frequency					
		Low RTN		High RTN			
Assessment Period	Obs	Low SDR	High SDR	Low SDR	High SDR	χ^2	*p*-Value
Panel A. Monthly Returns							
(4,8)	2302	24.59%	25.54%	25.46%	24.41%	0.84	0.359
(5,7)	2302	23.41	26.50	26.59	23.50	8.51	0.004
(6,6)	2302	23.24	26.80	26.59	23.37	10.30	0.001
(7,5)	2302	22.11	27.76	27.93	22.20	29.36	0.000
(8,4)	2302	23.37	26.72	26.50	23.41	9.26	0.002
Panel B. Independent Daily Returns							
(4,8)	2302	25.28	24.67	24.67	25.37	0.34	0.560
(5,7)	2303	24.88	24.97	25.10	25.05	0.00	0.983
(6,6)	2303	26.23	23.80	23.75	26.23	5.35	0.021
(7,5)	2302	25.50	24.59	24.41	25.50	0.84	0.359
(8,4)	2303	26.01	24.06	23.80	26.14	4.09	0.043
Panel C. MA(1) Daily Returns							
(4,8)	2302	25.46	24.46	24.59	25.50	0.77	0.381
(5,7)	2303	24.92	25.10	25.05	24.92	0.01	0.917
(6,6)	2304	26.39	23.57	23.57	26.48	7.33	0.007
(7,5)	2303	25.88	24.19	24.06	25.88	2.71	0.100
(8,4)	2303	26.40	23.75	23.40	26.44	7.23	0.007

The table shows the percentage of funds allotted to each of four cells in two-by-two contingency tables based on total return during an evaluation period (RTN) and the ratio of return standard deviation after the evaluation period to return standard deviation during the evaluation period (SDR). The results depict percentages of aggregations of the individual annual tournaments. The (x, y) assessment period refers to an evaluation period consisting of the first x months of the year. Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. Panel A shows the results of the daily returns compounded into monthly returns. Panel B shows the results of the daily returns at a daily frequency, assuming the returns are independent. Panel C shows the results of the daily returns at a daily frequency, assuming the returns follow an MA(1) process. The χ^2 test is with one degree of freedom. The sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

[5]Nelson (1991) also argues for more robustness of a high frequency volatility estimator.

The monthly results in panel A closely match those of BHS.[6] The percentage of funds that fall into the low RTN, high SDR cell is significantly greater than the null expectation of 25% for all assessment periods except the earliest. As in BHS, the most significant departures from the null occur with an evaluation period ending after July. The results for the January–July, August–December assessment period are consistent with approximately 11% of loser funds deliberately increasing their end of year risk.[7]

The daily results are much different. Regardless of the evaluation period, there is no evidence that mid-year losers increase end of year risk more than winners. If anything, the results indicate the opposite, although I cannot reject the null hypothesis that each cell contains the expected 25% except at the June and August cutoffs, where the pattern runs counter to that predicted by the tournament hypothesis. Whether I assume returns are independent (panel B) or model the return series as a moving average process (panel C), the daily results do not reject the null hypothesis.

Table 3 shows the results for various groups of funds. I focus on the (6,6) assessment period (January–June, July–December) and the moving average specification. (The results from assuming independent returns are not materially different.) The monthly results, assuming iid returns, appear consistent with the tournament hypothesis for all investment objectives and among funds that existed over the entire sample period (survivors) or either merged or liquidated (non-survivors). The results for growth and surviving funds have the lowest p-values, but the results for maximum capital gains, growth and income, and non-surviving funds are not statistically significant.

At a daily frequency, the pattern for maximum capital gains, growth, and surviving funds runs counter to the tournament hypothesis. The growth and income funds more closely approximate the monthly pattern, although any evidence of tournament behavior fails to attain statistical significance.

Table 4 shows the same tests as Table 3, by sub-period. The monthly results again suggest that losers increase risk relative to winners for all periods. The daily data produce this pattern only during the earliest sub-period (1985–1987), and it is not statistically significant.

When I repeat the tournament analysis on systematic and residual risk (equations (9) and (10)), there is no evidence of a relation between performance and any of the betas or residual risk from daily regressions of the single- or four-factor specifications. For example, 24.41% of funds are classified as low January–June return, high four-factor $\beta_{S\&P,Jul-Dec}/\beta_{S\&P,Jan-Jun}$, and 25.50% of funds are classified as low January–June return, high four-factor $\sigma(\varepsilon_{Jul-Dec})/\sigma(\varepsilon_{Jan-Jun})$.

Since the daily risk estimates are much more precise than the monthly estimates, the failure to reject equal cell frequencies with daily data casts doubt on

[6]For a (7,5) assessment period, 27.78% of BHS's funds are classified as low return and high risk adjustment, giving a χ^2 statistic of 29.79 (Brown, Harlow, and Starks (1996), p. 95).

[7]For example, suppose there are 100 funds. Under the null, 25 of the 50 loser funds are classified as high SDR. If 11% of the loser funds (5.5 funds) deliberately increase their end of year risk, then, on average, half of them (2.75 funds) would already be classified as high SDR, and the other half would switch from low to high SDR, resulting in 27.75 low RTN, high SDR.

TABLE 3

Frequency Distributions of Two-by-Two Contingency Tables of Return and Standard Deviation Ratio for a January–June, July–December Assessment Period by Fund Group

		Sample Frequency					
		Low RTN		High RTN			
Fund Group	Obs	Low SDR	High SDR	Low SDR	High SDR	χ^2	*p*-Value
Panel A. Monthly Returns							
Max Capital Gains	679	23.27%	26.80%	26.80%	23.12%	3.25	0.071
Growth	1058	22.78	27.32	26.94	22.97	7.32	0.007
Growth & Income	565	24.07	25.84	25.66	24.42	0.40	0.528
Survivors	2119	23.50	26.57	26.47	23.45	7.61	0.006
Non-Survivors	178	22.47	26.97	25.84	24.72	0.37	0.545
Panel B. Daily MA(1) Returns							
Max Capital Gains	679	27.10	22.83	22.83	27.25	4.78	0.029
Growth	1059	27.10	22.85	22.85	27.20	7.48	0.006
Growth & Income	566	24.20	25.80	25.80	24.20	0.45	0.501
Survivors	2119	26.66	23.36	23.41	26.57	8.60	0.003
Non-Survivors	180	23.89	26.67	23.89	25.56	0.00	0.995

The table shows the percentage of funds allotted to each of four cells in two-by-two contingency tables based on total return during the first six months of the year (RTN) and the ratio of return standard deviation during the last six months of the year to return standard deviation during the first six months of the year (SDR). The results depict percentages of aggregations of the individual annual tournaments. Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. Panel A shows the results of the daily returns compounded into monthly returns. Panel B shows the results of the daily returns at a daily frequency, assuming the returns follow an MA(1) process. The χ^2 test is with one degree of freedom. The sample consists of 230 mutual funds. Survivors exist during the entire sample period; non-survivors either merge or liquidate. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

the hypothesis that managers actively alter their portfolio risk in response to past performance.

I also sort funds on mean returns in the second half of the year and then compute the monthly SDR as before. Over the 1985–1995 sample period, 26.37% of funds are classified low July–December RTN, high monthly SDR. The χ^2 test statistic of 7.57 is strongly significant (p-value $= 0.006$). Since I find similar results sorting on returns in the first and second halves of the year, and managers could not respond to second half performance at mid year, this casts further doubt on the idea that tournaments drive the monthly results. However, the difference between the daily results here and monthly results of BHS remains to be resolved.

B. Simulations

Daily fund returns are autocorrelated and cross-correlated. The autocorrelation could be a result of market frictions, such as non-synchronous trading of the component securities (Kadlec and Patterson (1999) and Chalmers, Edelen, and Kadlec (2000)); time-varying economic premiums (Hameed (1997)); institutional investor trading patterns (Sias and Starks (1997)); or psychological factors (e.g., Jegadeesh and Titman (1993)). Cross-correlation arises because the prices of the portfolio holdings often respond in the same direction to economic news. Correlations violate the independence assumptions used in deriving the χ^2 tests for equal cell frequencies. Therefore, I simulate tournaments under the null hypothe-

TABLE 4

Frequency Distributions of Two-by-Two Contingency Tables of Return and Standard Deviation Ratio for a January–June, July–December Assessment Period by Sub-Period

		Sample Frequency					
		Low RTN		High RTN			
Sample Period	Obs	Low SDR	High SDR	Low SDR	High SDR	χ^2	*p*-Value
Panel A. Monthly Returns							
A1. Entire Sample Period							
1985–1995	2302	23.24%	26.80%	26.59%	23.37%	10.30	0.001
A2. Six- and Five-Year Periods							
1985–1990	1308	22.94	27.14	26.91	23.01	8.27	0.004
1991–1995	994	23.64	26.36	26.16	23.84	2.32	0.128
A3. Three- and Two-Year Periods							
1985–1987	661	24.36	25.42	25.57	24.66	0.18	0.669
1988–1990	647	21.48	28.90	28.28	21.33	12.79	0.000
1991–1993	605	23.64	26.28	26.12	23.97	1.21	0.272
1994–1995	389	23.65	26.48	26.22	23.65	0.93	0.335
Panel B. Daily MA(1) Returns							
B1. Entire Sample Period							
1985–1995	2304	26.39	23.57	23.57	26.48	7.33	0.007
B2. Six- and Five-Year Periods							
1985–1990	1309	25.06	24.90	24.90	25.06	0.01	0.934
1991–1995	995	28.14	21.81	21.81	28.24	15.70	0.000
B3. Three- and Two-Year Periods							
1985–1987	661	23.75	26.02	26.17	24.05	1.10	0.294
1988–1990	648	26.39	23.77	23.61	26.23	1.58	0.209
1991–1993	606	27.23	22.77	22.77	27.23	4.46	0.035
1994–1995	389	29.56	20.31	20.31	29.82	12.96	0.000

The table shows the percentage of funds allotted to each of four cells in two-by-two contingency tables based on total return during the first six months of the year (RTN) and the ratio of return standard deviation during the last six months of the year to return standard deviation during the first six months of the year (SDR). The results depict percentages of aggregations of the individual annual tournaments. Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. Panel A shows the results of the daily returns compounded into monthly returns. Panel B shows the results of the daily returns at a daily frequency, assuming the returns follow an MA(1) process. The χ^2 test is with one degree of freedom. The sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

sis of no strategic managerial behavior, but allowing for dependence, to examine the size of the χ^2 tests and to estimate empirical p-values.

In the simulations, I want to remove any relation between performance and relative volatility. For each fund, each year, I run the daily four-factor model,

$$(15) \quad R_{pd} \quad = \quad \alpha_{py} + \sum_{j=1}^{4} (\beta_{pjy} R_{jd} + L_{pjy} R_{j,d-1}) + \varepsilon_{pd}, \qquad d = 1 \text{ to } D_y.$$

For each year of the 11-year sample period, I arrange the four factors and residuals from the regressions into two matrices. The factor matrix consists of D_y rows and four columns, where D_y is the number of daily returns in year y. The residual matrix consists of D_y rows and 230 columns, where there are 230 funds in the sample. To simulate factors, I randomly select a row from the factor matrix and then use the following $D_y - 1$ rows in order, continuing with row one of the factor matrix after row D_y. To simulate residuals, I re-sample randomly with replacement D_y rows from the residual matrix. I then build up the simulated daily returns using the sum betas $(\beta_{pjy} + L_{pjy})$ and intercepts from regression equation (15) with the simulated factors and simulated residuals. This preserves cross-correlation in the factors and residuals and most of the autocorrelation in the factors, and captures a large amount of randomness in the actual data that is due to the factors. Using non-zero alphas with constant factor loadings throughout the year and re-sampling the residuals removes any relation between performance and residual risk. Furthermore, re-sampling randomly for the first half of the year, independent of the second half, removes any tournament effects that may be present in the actual data.

I compute the RTN and SDR for each artificial fund over a January–June, July–December assessment period and allot funds to cells in two-by-two contingency tables based on the median fund RTN and the median fund SDR. The standard deviation estimates assume returns are independent. I repeat the process 10,000 times, generating an empirical distribution of the daily two-by-two contingency table allotments under the null hypothesis.

I also construct simulated distributions for monthly frequency data by compounding the simulated daily returns into the monthly frequency, computing the SDRs, and combining the RTNs and SDRs. As with the daily simulations, I construct the simulated monthly distributions over a January–June, July–December assessment period.

Figure 1 shows the monthly and daily distributions. The monthly (daily) distribution is centered to the right (left) of the null expectation of 25%, and both have fatter tails than the χ^2. Based on the two-tailed 5% χ^2 critical values, 39.3% of the monthly simulations would reject the null hypothesis. This indicates that the size of the standard χ^2 test is wrong. The daily simulations are similarly susceptible to erroneous rejections of the null. Clearly, it is important to evaluate the actual results empirically, rather than with the theoretical χ^2 statistic.

When I evaluate the results empirically, I find that the actual monthly result and the actual daily result both fall within the 95% confidence interval of the simulated null distributions. Neither the monthly result (two-tailed empirical p-value = 0.191) nor the daily result (two-tailed empirical p-value = 1.000) rejects the null hypothesis that there are no tournaments.

I repeat the simulations as before, except I remove autocorrelation in the factors. From the actual four-factor and residual matrices, I re-sample randomly with replacement D_y rows from the four factors and, independently, D_y rows from the residuals. I build up the simulated daily returns using the sum betas $(\beta_{pjy}+L_{pjy})$ and intercepts from regression equation (15) with these random draws.

Figure 2 shows the results. The distributions are now centered closer to the null expectation of 25%, which suggests that autocorrelation in the daily returns could contribute to the differences in the actual monthly and daily results. I explore this in greater detail in the following section. Once again, the distributions have fatter tails than the χ^2. The actual monthly result and the actual daily result again fall within the 95% confidence interval of the simulated null distributions.

I also use a Monte Carlo approach as a check, assuming the normality on which the statistics are based. I draw the four factors randomly from normal distributions with means and covariance matrix matching those of the actual daily factors. I draw the residuals independently, also from normal distributions with a

FIGURE 1

Simulated Frequency Distributions under the Null Hypothesis with Autocorrelation

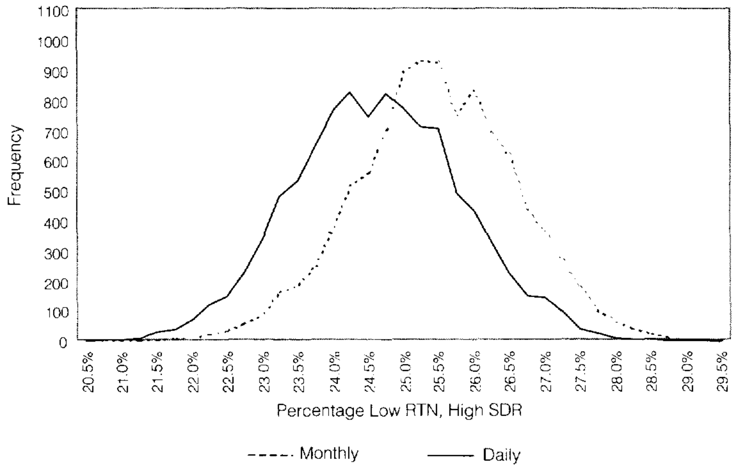

Figure 1 shows monthly and daily frequency distributions of the percentage of funds allotted to the low RTN, high SDR cell in two-by-two contingency tables based on total return during the first six months of the year (RTN) and the ratio of return standard deviation during the last six months of the year to return standard deviation during the first six months of the year (SDR). The distributions are based on 10,000 simulations under the null hypothesis that risk does not change. The simulations incorporate autocorrelation and cross-correlation in the daily returns. Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. The simulated sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

covariance matrix that matches that of the actual residuals. Using the sum betas $(\beta_{pjy}+L_{pjy})$ and intercepts from regression equation (15) with these random draws, I build up the simulated daily returns.

Figure 3 shows the results. Although the Monte Carlo distributions are more narrow than the distributions of the simulations that use the actual return data, neither the monthly result (two-tailed empirical p-value $= 0.067$) nor the daily result (two-tailed empirical p-value $= 1.000$) is significantly greater than the null expectation of 25% low return, high relative volatility. The simulated distributions are not materially different when I use the contemporaneous and lag betas separately instead of combining them into sum betas.[8] Thus, the Monte Carlo experiment confirms that neither the actual monthly ratios nor the actual daily ratios can reject the hypothesis of no tournaments.

C. Explaining the Results

Since the assignment of funds to cells based on average returns in the evaluation period is invariant to the frequency of the data, the different monthly and daily results could reflect autocorrelation patterns in the daily returns. In particular, daily return autocorrelation can bias estimates of monthly standard deviation.

[8]Additional simulations indicate that the distributions narrow as the cross-correlations decrease and as the monthly returns (compounded from the daily) more closely approximate a normal distribution.

FIGURE 2

Simulated Frequency Distributions under the Null Hypothesis without Autocorrelation

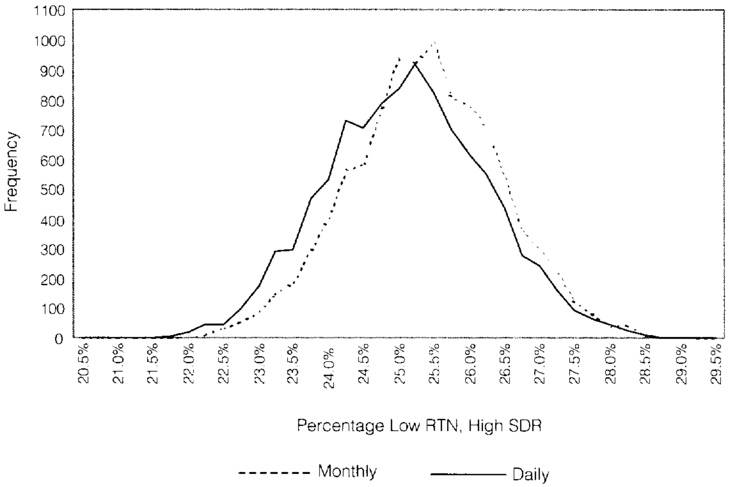

Figure 2 shows monthly and daily frequency distributions of the percentage of funds allotted to the low RTN, high SDR cell in two-by-two contingency tables based on total return during the first six months of the year (RTN) and the ratio of return standard deviation during the last six months of the year to return standard deviation during the first six months of the year (SDR). The distributions are based on 10,000 simulations under the null hypothesis that risk does not change. The simulations incorporate cross-correlation in the daily returns. Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. The simulated sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

If funds with low returns in the evaluation period also have higher autocorrelation in the second half of the year, their relative standard deviations can be biased upward in the second part of the year.

To explore this explanation for the monthly ratios, I focus on funds that have conflicting monthly and daily SDR classifications. Table 5, panel A shows the number of funds that fall into each of eight categories, based on the intersections of the RTN and monthly and daily SDR classifications. About 37% of the SDR classifications differ with monthly and daily data.

Table 5, panel B shows average autocorrelation patterns for the eight categories. For each RTN, daily SDR grouping, the funds classified as high monthly SDR have smaller average January–June MA(1) coefficients than the corresponding low monthly SDR funds. Also, funds classified as high monthly SDR have larger average increases in autocorrelation from the beginning to the end of the year. The same pattern holds in 37 out of 44 annual tournament groupings: controlling for daily SDR, the intra-year increase in autocorrelation is greater for high monthly SDR funds than for low monthly SDR funds. The MA(1) coefficient of high monthly SDR funds increases 38% on average from January–June to July–December, more than double that of low monthly SDR funds. Since daily autocorrelations positively bias monthly standard deviation estimates, this suggests that the autocorrelation pattern in the daily returns drives the difference in the monthly and daily tournament results.

FIGURE 3

Monte Carlo Frequency Distributions under the Null Hypothesis

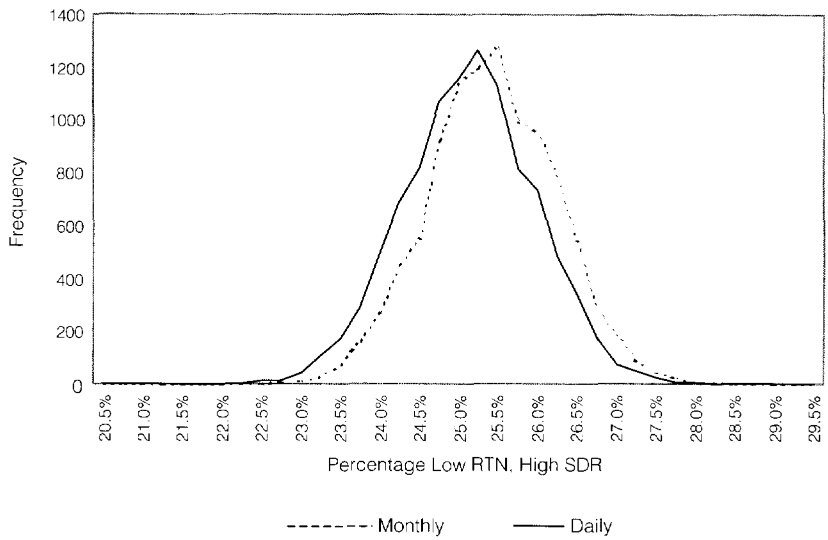

Figure 3 shows monthly and daily frequency distributions of the percentage of funds allotted to the low RTN, high SDR cell in two-by-two contingency tables based on total return during the first six months of the year (RTN) and the ratio of return standard deviation during the last six months of the year to return standard deviation during the first six months of the year (SDR). The distributions are based on 10,000 Monte Carlo simulations under the null hypothesis that risk does not change. The simulations incorporate cross-correlation in the daily returns. Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. The simulated sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

To explore whether there is a relation between average returns and autocorrelation that leads to the results, I first estimate January–June factor loadings from regression equation (8) for funds divided into two groups based on their January–June MA(1) coefficient. The average four-factor loadings for funds with high (low) January–June MA(1) coefficients are 0.887 (0.847) for the S&P 500, 0.272 (0.178) for SMB, −0.133 (−0.099) for HML, and 0.091 (0.056) for MMC. The largest difference in factor loading is on the small stock factor. Funds with greater daily return autocorrelation have greater exposure to small capitalization stocks, possibly because small cap stocks are more susceptible to non-synchronous trading than are large cap stocks (e.g., see Boudoukh, Richardson, and Whitelaw (1994)). Table 5, panel C confirms that for each RTN, daily SDR grouping, the funds classified as low monthly SDR have larger average small stock loadings during the first six months of the year than the high monthly SDR funds.

Small cap stocks outperform large cap stocks from January–June, 1985–1995 by an average of about 3.2% per year, largely because of strong January returns (1.8% of the 3.2% (also see Keim (1983) and Reinganum (1983)). The January–June regression coefficients for winner (loser) funds are 0.887 (0.853) for the S&P 500, 0.458 (0.429) for SMB, −0.183 (−0.187) for HML, and 0.093 (0.081) for MMC, consistent with less small cap stock exposure for low return funds.

TABLE 5

Daily Autocorrelation and Small Stock Exposure

	Low RTN				High RTN			
	Low Daily SDR		High Daily SDR		Low Daily SDR		High Daily SDR	
	High Monthly SDR	Low Monthly SDR	High Monthly SDR	Low Monthly SDR	High Monthly SDR	Low Monthly SDR	High Monthly SDR	Low Monthly SDR
Panel A. Number								
No.	251	352	361	179	181	363	354	244
Panel B. Autocorrelation								
Jan–Jun MA(1)	0.114	0.139	0.129	0.178	0.140	0.152	0.150	0.168
Jul–Dec MA(1)	0.174	0.184	0.168	0.179	0.196	0.186	0.200	0.184
MA(1) Change	0.059	0.044	0.039	0.001	0.056	0.034	0.051	0.016
Panel C. Small Stock Exposure								
Jan–Jun β_{SMB}	0.362	0.470	0.362	0.587	0.356	0.466	0.442	0.555
Jul–Dec β_{SMB}	0.382	0.408	0.467	0.563	0.418	0.453	0.513	0.514
β_{SMB} Change	0.020	−0.061	0.105	−0.024	0.062	−0.013	0.071	−0.041

The table shows intra-year autocorrelation and small stock exposure patterns of the intersections of funds allotted to cells based on: i) total return during the first six months of the year (RTN); ii) the ratio of daily return standard deviation during the last six months of the year to daily return standard deviation during the first six months of the year (daily SDR); and iii) the ratio of monthly return standard deviation during the last six months of the year to monthly return standard deviation during the first six months of the year (monthly SDR). Low RTN funds have an RTN below the median. High SDR funds have an SDR above the median. Panel A shows the number of funds. Panel B shows the average January–June MA(1) coefficient, July–December MA(1) coefficient, and change in MA(1) coefficient. Panel C shows the average January–June β_{SMB}, July–December β_{SMB}, and change in β_{SMB}. The sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

These results indicate that there is a relation between daily return autocorrelation, average returns, and small cap stock exposure. Less exposure to small cap stocks leads to lower returns, lower January–June autocorrelation, and lower estimates of January–June monthly standard deviation.

The end of the year regression coefficients for January–June winner (loser) funds are 0.895 (0.841) for the S&P 500, 0.477 (0.445) for SMB, −0.158 (−0.131) for HML, and 0.138 (0.078) for MMC. Since both winner and loser funds increase SMB factor exposure at the end of the year, there is no clear pattern (or statistically significant relation) between mid-year fund return and changes in small stock exposure. However, a clear pattern emerges in Table 5, panel C, which shows changes in small stock exposure for funds with different monthly and daily SDR classifications. The funds classified as high monthly SDR have greater average increases in small stock exposure than the corresponding funds classified as low monthly SDR. On average, the small stock loading of high monthly SDR funds increases 17.9% from January–June to July–December; the small stock loading of low monthly SDR funds decreases 7.1%. This suggests that the monthly results reflect risk estimation biases attributable to daily return autocorrelation arising from small cap stock exposure.

These results do not suggest that, relative to winners, losers move into small cap stocks in the second half of the year, but only that for those funds that have conflicting monthly and daily SDRs, the funds with high monthly SDRs move into small cap stocks relative to those with low monthly SDRs. Overall, 48.7% of the 1,143 low RTN funds increase their small cap stock exposure relative to the median of all 2,285 funds.

The monthly tournament pattern arises because there are more low RTN funds that are classified as low daily SDR, high monthly SDR than as high daily SDR, low monthly SDR. Across the entire sample of funds, there is a large increase in return autocorrelation from the beginning to the end of the year. Funds with lower January–June autocorrelation have larger average increases in autocorrelation from the beginning to the end of the year. Ceteris paribus, this leads to larger average increases in the bias in relative monthly standard deviation for these funds.

To the extent that stocks with high returns at the beginning of the year have high average daily return autocorrelations, the results might not be a fluke of the sample period. Since small cap stocks also have high average January–June returns and large, positive daily autocorrelation over the 1963–1984 period, the monthly and daily results could also diverge over earlier sample periods.

Momentum strategies are associated with autocorrelated returns and higher average returns (see Grinblatt, Titman, and Wermers (1995)). This suggests that momentum trading could contribute to the monthly pattern if some low RTN funds moved into momentum securities in the second half of the year. However, autocorrelation is more strongly related to small cap stock exposure than to momentum trading. For example, 74.8% of the funds with MA(1) coefficients above the median also have SMB factor coefficients above the median; 54.3% of the high MA(1) funds have MMC factor coefficients above the median. When I examine changes in MMC factor exposure for funds with different monthly and daily SDR classifications (analogous to Table 5, panel C), I find no systematic difference between the high monthly SDR funds and the low monthly SDR funds.

D. Unbiased Monthly Estimates

I compute monthly standard deviations that are unbiased in the presence of autocorrelation to examine the impact of estimation biases on the monthly tournament results.

For each fund, each half year, I generate random daily data that matches the fund's mean return, standard deviation of return, and one-day autocorrelation of return. I then compound the random daily data into monthly data and compute the standard deviation of monthly return. I fit the daily random data to an MA(1) specification (similar to equation (4)), and I compute the standard deviation of daily residuals. I estimate the bias in the monthly standard deviation of return with the ratio,

$$B_p = \frac{\sigma\left(R^r_{mp}\right)}{\sqrt{21}\sigma\left(\varepsilon^r_{dp}\right)}, \tag{16}$$

where R^r_{mp} are fund p's random monthly returns, ε^r_{dp} are fund p's random daily MA(1) residuals, and there are approximately 21 daily returns per month. I repeat this procedure 10,000 times and compute an average B_p for each fund.

I use the bias ratio to estimate monthly standard deviations that are unbiased in the presence of autocorrelation,

$$\sigma_u(R_{mp}) = \frac{\sigma(R_{mp})}{B_p}, \tag{17}$$

where R_{mp} are fund p's actual monthly returns. I then repeat the tournament analysis with the unbiased measures.

When I redo the tournament analysis with the unbiased monthly measures, the tournament patterns disappear. For all funds over a (6,6) assessment period from 1985–1995, 25.07% of funds are classified low RTN, high SDR. Over the 1985–1990 sub-period, 24.62% of funds are low RTN, high SDR; from 1991–1995, 25.65% of funds are low RTN, high SDR. The unbiased analysis supports the claim that the monthly results are due to a systematic bias in the monthly ratios.

E. Regression Methodology

The literature that studies the relation between fund performance and change in risk does not rely exclusively on contingency tables to draw its conclusions. If we dismiss the monthly contingency table results, what would we then conclude about the other evidence? To answer this question, I examine the tournament story with regressions similar to those in Koski and Pontiff (1999) (hereafter KP).

For each fund, each year, I run a single-index time-series regression twice, once from January through June and once from July through December,

$$\begin{aligned} R_{pt} &= \alpha_{p1} + \beta_{py1} R_{mt} + \varepsilon_{pt}, \qquad t = 1 \text{ to } T, \\ R_{pt} &= \alpha_{p2} + \beta_{py2} R_{mt} + \varepsilon_{pt}, \qquad t = T+1 \text{ to } T_y, \end{aligned} \tag{18}$$

where R_{mt} is the excess return on the S&P 500 index (including dividends) during period t, and there are T periods from January through June and T_y periods during the year. I run the regressions in equation (18) separately with monthly returns and daily returns. I compute the beta and residuals in each monthly regression from six returns, similar to KP; I compute those in the daily regressions from an average of 126 returns.

I examine the relation between fund performance and change in risk with cross-sectional regressions,

$$\text{Risk}_{py2} - \text{Risk}_{py1} = a + \gamma \text{Perf}_{py1} + \phi \text{Risk}_{py1} + \varepsilon_{py}, \tag{19}$$

where Risk_{py1} (Risk_{py2}) is the estimate of fund risk for fund p from January–June (July–December) of year y, and Perf_{py1} is the difference between fund p's January–June fund return and the average return of funds with the same investment objective. I use three different estimates of risk: $\sigma(R_{py})$, the standard deviation of excess fund returns; $\sigma(\varepsilon_{py})$, the standard deviation of residuals from regression equation (18); and β_{py}, the systematic risk estimate from regression equation (18).

I focus on the 1985–1995 sample period and the shorter 1992–1994 period for comparison with KP. I run pooled cross-sectional regressions over multiple years (as in KP) and separate cross-sectional regressions each year.

Table 6 shows the results. The results from the pooled cross-sectional regressions with monthly data over the 1992–1994 period are directionally consistent with those of KP and the tournament hypothesis. Since the pooled regressions from 1992–1994 in Table 6 use approximately one third as many observations as KP's regressions, it is not surprising that the performance coefficients do not have t-statistics as large as those in KP. Interestingly, the results from the other monthly cross-sectional regressions (pooled, 1985–1995; annual, 1992–1994; and annual, 1985–1995) are not consistent with mid-year losers increasing risk. These latter results cannot be compared with KP, because they only examine pooled regressions from 1992–1994.

The most interesting result is that none of the daily regressions support the tournament story. Focusing on the averages of the 11 annual cross-sectional regression coefficients from 1985–1995, there is no evidence that managers alter the risk of their portfolios based on their relative performance.

I also repeat the regressions using unbiased monthly standard deviation estimates as the measure of risk. I compute the unbiased estimates using equation (17). The results are not consistent with mutual fund tournaments. The γ coefficient for a pooled cross-sectional regression is positive over a 1985–1995 sample period and -0.0206 (t-statistic $= -0.57$) from 1992–1994. The regression results confirm the daily contingency table results that cast doubt on the tournament story.

F. Common Factor Volatility

By relying on standard deviation ratios, the BHS methodology implicitly assumes that changes in market volatility affect individual fund volatility similarly. However, part of the change in a fund's volatility can potentially be attributed to its unique set of exposures to various asset classes. In this section, I estimate the portion of a fund's intra-year change in risk that is attributable to changes in the volatility of common stock market risk factors.

First, I estimate a fund's end of year volatility assuming it maintains its four-factor loadings and residual risk from the beginning of the year,

$$\text{(20)} \qquad \text{CFS}_{py2} = \left[\sum_{j=1}^{4} \beta_{pj1}^2 \sigma^2(R_{j2}) + \sigma^2(\varepsilon_{p1})\right]^{\frac{1}{2}},$$

where β_{pj1} and $\sigma(\varepsilon_{p1})$ are fund p's sum beta on orthogonal factor j ($\beta_{pj1} + L_{pj1}$) and residual risk, respectively, from regression equation (8) from January–June; $\sigma(R_{j2})$ is orthogonal factor j's standard deviation from July–December; and CFS refers to the constant factor standard deviation.

I then regress each fund's actual change in risk from the beginning to the end of the year on the difference between its constant factor standard deviation computed from equation (20) and beginning of the year risk,

$$\text{(21)} \qquad \sigma(R_{py2}) - \sigma(R_{py1}) = a + \gamma[\text{CFS}_{py2} - \sigma(R_{py1})] + \varepsilon_{py}.$$

Pooled estimation of regression equation (21) over the 2,338 observations from 1985–1995 gives a γ coefficient of 1.0814 (t-statistic $=$ 147.33) and an r^2

TABLE 6

Coefficients from Regressions of Change in Risk vs. Performance

Sample Period	Pooled Regressions Obs	Intercept	Perf	Risk	Annual Regressions Obs	Intercept	Perf	Risk
Panel A. Monthly Returns								
A1. Return Standard Deviation								
1992–1994	600	0.013	−0.049	−0.456	200	0.014	−0.015	−0.485
		(17.60)	(−1.53)	(−18.51)		(10.93)	(−0.76)	(−11.67)
1985–1995	2338	0.004	−0.078	0.167	213	0.023	0.031	−0.388
		(3.61)	(−1.34)	(5.69)		(10.74)	(0.21)	(−8.25)
A2. Residual Standard Deviation								
1992–1994	600	0.005	−0.019	−0.480	200	0.005	0.007	−0.483
		(11.20)	(−0.66)	(−22.53)		(6.85)	(−0.51)	(−13.77)
1985–1995	2338	0.006	0.000	−0.494	213	0.006	−0.008	−0.453
		(24.73)	(0.02)	(−36.86)		(7.00)	(−0.22)	(−10.79)
A3. Beta								
1992–1994	600	0.987	−3.91	−0.97	200	0.800	−0.560	−0.828
		(40.40)	(−2.72)	(−38.95)		(19.99)	(−0.84)	(−17.30)
1985–1995	2338	0.881	3.117	−0.891	213	0.654	1.644	−0.686
		(73.44)	(4.67)	(−74.25)		(16.91)	(0.76)	(−16.93)
Panel B. Daily Returns								
B1. Return Standard Deviation								
1992–1994	600	0.000	0.395	−0.249	200	0.000	0.140	−0.258
		(2.98)	(4.92)	(−16.89)		(2.12)	(1.05)	(−10.22)
1985–1995	2338	0.001	0.790	−0.007	213	0.002	0.348	−0.051
		(3.74)	(3.02)	(−0.16)		(3.14)	(0.99)	(−4.51)
B2. Residual Standard Deviation								
1992–1994	600	0.000	0.367	−0.166	200	0.000	0.185	−0.184
		(1.71)	(4.59)	(−9.66)		(1.92)	(1.55)	(−7.51)
1985–1995	2338	0.001	0.162	−0.094	213	0.001	0.021	−0.088
		(7.30)	(1.69)	(−4.35)		(3.25)	(0.68)	(−3.41)
B3. Beta								
1992–1994	600	0.167	13.359	−0.256	200	0.147	−11.084	−0.235
		(7.72)	(0.94)	(−13.42)		(4.03)	(−0.38)	(−7.32)
1985–1995	2338	0.240	43.149	−0.230	213	0.168	13.904	−0.149
		(17.69)	(4.39)	(−16.37)		(4.04)	(0.55)	(−4.05)

The table shows the coefficients from cross-sectional regressions of the difference between July–December fund risk and January–June fund risk on: i) the difference between January–June fund return and the average January–June return of funds with the same investment objective (Perf); and ii) January–June risk (Risk). Panel A uses monthly returns, and Panel B uses daily returns. Three different measures of fund risk are examined: return standard deviation (panels A1 and B1), residual standard deviation (panels A2 and B2), and systematic risk (panels A3 and B3). The January–June and July–December systematic risk and residual standard deviation are computed from time-series regressions of the excess fund return on the excess return on the S&P 500. Each pooled cross-sectional regression result is from one cross-sectional regression from 1992–1994 or 1985–1995. The annual regression results are averages of three (1992–1994) or 11 (1985–1995) annual regressions. *t*-statistics are in parentheses. Obs. is the number of observations in the cross-sectional regressions. The sample consists of 230 mutual funds. The sample period is from Jan. 2, 1985, to Dec. 29, 1995.

of 90.3%. This indicates that a large portion of the intra-year change in risk arises from changes in common factor volatility and suggests that very little is attributable to the deliberate actions of the fund managers, unless they trade to intentionally keep loadings fixed. For instance, the regression,

$$\sigma(R_{py2}) - \sigma(R_{py1}) = a + \gamma[\sigma(R_{py2}) - \text{CFS}_{py2}] + \varepsilon_{py}, \quad (22)$$

estimates the change in risk that is due to changing factor loadings and residual risk. Regression equations (21) and (22) are complementary regressions, where the sum of the two regressions is a regression of $\sigma(R_{py2}) - \sigma(R_{py1})$ on itself. The slope coefficient and high r^2 in regression equation (21) implies little explanatory power for regression equation (22).[9]

These results suggest that subsequent analysis of changes in fund risk should differentiate between changes that are due to the common factors and changes attributable to the fund manager.[10]

V. Conclusion

Using monthly returns, Brown, Harlow, and Starks (1996) argue that, when lagging in performance, funds increase portfolio risk in an attempt to boost returns. The expectation is that superior returns will attract additional dollar inflows and an increase in the manager's asset-based fee.

The main drawback to using monthly data to estimate risk over annual time periods is that the paucity of data precludes efficient estimation. My analysis indicates that monthly volatility estimates are biased by daily return autocorrelation. Compared to winners, mid-year losers have lower January–June autocorrelation, leading to the monthly pattern of losers showing increased monthly estimates of risk. When I redo the tournament analysis with daily or unbiased monthly standard deviation estimates, the tournament patterns go away.

The daily data also indicate that most of a fund's intra-year change in risk is attributable to changes in the volatility of common stock market risk factors and is not related to changing factor exposures or residual risk. Since the daily data provide more precise estimates of volatility, these results cast serious doubt on the hypothesis that fund managers actively alter the risk of their portfolio in response to past performance.

With fee contracts that reward cash inflows and strong evidence that exemplary performance attracts large inflows, it is not difficult to envision manager behavior similar to that anticipated by BHS. However, it is not clear when managers would strategically alter portfolio risk, since mutual fund performance is widely reported daily and cash flows accrue to funds throughout the year. Un-

[9]Interpreting the results of regression equations (21) and (22) is complicated by having an identical variable on both sides of the equation. The cross-sectional standard deviations of $\sigma(R_{py2})$ (0.0053) and CFS_{py2} (0.0049) are much greater than the cross-sectional standard deviation of $\sigma(R_{py1})$ (0.0023). Simulations show that estimating regression equation (22) gives a spuriously high r^2 because the lower variance $\sigma(R_{py1})$ is only on one side of the equation. Simulations also show that this complication is mitigated to a large extent in regression equation (21) because $\sigma(R_{py1})$ is subtracted from both sides.

[10]I use these results to formulate a new test of the tournament hypothesis. Instead of comparing a fund's SDR to the median fund SDR, I compare a fund's *constant factor* SDR (CFSDR),

$$\text{CFSDR}_{py} = \frac{\sigma(R_{py2})}{\text{CFS}_{py2}},$$

to the median fund CFSDR. The CFSDR indicates whether the fund increased or decreased its risk, after accounting for changes in the volatility of the underlying factors. When I allot funds to cells based on RTN and CFSDR, the results are not consistent with the tournament story for any assessment period, sub-period, or fund group.

covering a potentially more complex behavior pattern should be a fruitful area for future research.

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