Racing the Clock: Benchmarking or Tournaments in Mutual Fund Risk-Shifting?[1]

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ABSTRACT

We find that mutual fund managers tend to shift risk in response to beating the S&P 500, and we find no such shift in response to beating the median of fund performance. As suggested in Basak, Pavlova and Shapiro (2004), we find that funds decrease risk after beating the benchmark; funds beating the benchmark reduce the log standard deviation of returns by 0.004 per month compared with their non-benchmark beating counterparts. Furthermore, we find that funds beating the median of fund performance show no significant decrease in risk. We investigate changes in mutual fund stock holdings before and after beating the benchmark, and we find that funds that do not beat the benchmark by mid-year reduce the market value of S&P 500 stock holdings while those that do beat the benchmark show no such reduction.

[1] We acknowledge the comments and suggestions of Greg Brown, Eitan Goldman, David Musto and Laura Starks. All errors are our own.

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The measurement of mutual fund managers' skill has been the subject of a long line of research including Jensen (1968). One of the keys to determining the investment skill of fund managers is identifying the relevant benchmark. In many cases, a broad market index, such as the S&P 500, is used as a yardstick for manager performance. Managers, recognizing the evaluation benchmark, have incentives to change their investment policy after conditioning on their investments' performance with respect to the benchmark.

Previous studies such as Brown, Harlow and Starks (1996), hereafter referred to as BHS (1996), have shown that fund managers increase risk when their performance is below that of their peers. Specifically, managers whose mid-year performance is above the median fund's performance show a relatively lower standard deviation through the rest of the year than funds with mid-year performance below the median. In this study, we show that mutual fund managers respond to year-to-date performance measured in comparison to the market index instead of relative to each other. We show that mutual fund managers reduce risk after beating the S&P 500 but not after beating the median.

Papers such as BHS (1996) are measuring the risk shifting that would be a natural outcome of the incentives generated by the convex flow-performance relationship identified in Chevalier and Ellison (1997) and Sirri and Tufano (1998). In a sense, it would be surprising if funds responded to anything but each other based on this flow-performance ratio. Similarly, results in Carhart, Kaniel, Musto and Reed (2002) show that funds do not seem to mark the close in an attempt to jump past the S&P 500 on the last day of the year. However, if, as in Ou-Yang (2003), fund managers are compensated based on their performance relative to a benchmark, then the benchmark-based risk shifting could be a strong effect.

This paper explores the hypothesis that beating the S&P 500 is an important determinant of the mutual fund manager's attitude towards risk. Similar in thinking to Basak, Pavlova, and Shapiro (2003), we find that mutual fund managers appear to take larger risks before beating the S&P 500, and if they do beat that benchmark, the managers tend to reduce risk. Basak, Pavlova and Shapiro (2003) formulate a model in which managers respond to the incentives of benchmarking, and this paper verifies their main hypothesis empirically.

The balance of this paper proceeds as follows. Section two describes the data, section three describes our model and estimation approach, section four describes our results, and section five concludes.

II. Data

In this paper, we combine daily returns data from Micropal with holdings data from Thompson Financial. The combined database has returns and holdings data from January 1985 through August 1997. Summary statistics are presented in Table I.

A. Daily Returns Data

To analyze any potential risk shifting behavior in mutual fund returns, we construct a database of daily returns for 3,262 funds using daily price, dividend, and dividend reinvestment NAV data from Micropal (now owned by Standard & Poor's). Our database comprises diversified open-end equity mutual funds in the Aggressive Growth,

Growth and Income, and Long-term Growth categories as defined by Carhart (1997), and it runs from January 2, 1985 to September 22, 1997. To focus on actively managed U.S. equity mutual funds, we apply the following filters: funds in the database have ICDI objective codes equal to 'AG','GI','IN','LG', *or* CRSP objective codes equal to 'G','G-I','G-I-S','G-S','G-S-I','I','I-G','I-G-S','I-S','I-S-G','S','S-G-I','S-I','S-I-G','GCI','IEQ','LTG' *or* Strategic Insight Objective codes equal to 'AGG','GRI','GRO','ING' *and* CRSP investment policy codes equal to 'CS', 'I-S', 'MF'.

There is some survivor bias in the early years of Micropal data[3]. We calculate total-return time series (reinvesting dividends on ex-dates), and these returns are used in the time-series and cross-sectional tests. Table I shows that the majority of the observations in the daily returns database are found in the 1991 to 1997 range.

B. Mutual Funds Holdings Data.

We can not generally observe a fund's portfolio but we can observe its semiannual or quarterly statutory disclosures in the CDA/Spectrum database (see Wermers (1999) for a description), which we have from 1984 to 1998. Table 1 shows the intersection of the two databases. Since some of the following results are based on holdings measured before and after the end of the daily returns date range, the holdings data spans the years before and after the date range of the daily returns database: 1984 through 1998.

[3] For example, 0 of the 463 funds with Micropal data for some of 1985 die in 1985, whereas 1 of the 493 similarly-defined funds in the CRSP monthly mutual-fund database with data for some of 1985 dies in 1985. The analogous numbers for 1990 are 29 out of 807 in Micropal and 8 of 700 in CRSP, and for 1995 it is 66 of 2,063 in Micropal and 67 of 1,979 in CRSP.

III. Model Setup

We develop a model that builds on the econometric findings of previous papers. Busse (2001) shows that daily returns provide much more efficient estimates of fund volatility. The paper shows that the volatility shifting result in BHS (1996) does not hold in daily data. However, Goriaev, Nijman and Werker (2003) shows that the daily return analysis will not hold if returns are correlated across funds, and that monthly returns can be more robust to autocorrelation effects.

Let fund returns be described by the following general process:

$$r_{i,y,m,d} = \left(\psi(L)\varepsilon_{i,y,m,d}\right)e^{h_{i,y,m}}$$

Where $r_{i,y,m,d}$ is the return on fund i in year y, month m and day d. In this specification, returns may be autocorrelated within each month; $\psi(L)$ is the generalized lag operator. $\varepsilon_{i,y,m,d}$'s are independent error terms normally distributed with mean zero and standard deviation 1. h's are defined as half log volatility, and their functional form is as follows:

$$h_{i,y,m} = \ell(\sigma_{sp\ y,m}) + f(m, y, I_{i,k}) + \omega_{i,y,m}$$

h's will be linear functions of the volatility of the sp500, and they will be allowed to be functions of month and year. $I_{i,k}$ is a function indicating whether fund i beat benchmark k. We will assume that h's are constant within each month, and we will assume that the error terms, ε, are distributed normally with mean zero and variance-covariance matrix Ω. We will assume that ε's and ω's are independent.

Next, we need to specify functional forms for the above general specification. Figure 1 shows the autocorrelograms of daily fund returns in our sample. The immediate decay of daily returns in Figure 1B leads us to choose a MA(1) process for returns:

$\psi(L) = 1 + \delta L$.

Define the ratio λ_i as the ratio of a fund's volatility this month to its volatility last month.

$$\lambda_i = \frac{\sigma^2{}_{i,m}}{\sigma^2{}_{i,m-1}}$$

If funds adjust volatility from one month to the next, λ_i will not be equal to one. Taking $\sigma_{i,m} = exp(h_{i,m})$, notice that: $\sqrt{\text{var}(r_{i,y,m,d})} = \sqrt{(1+\delta^2)}\sigma_{i,m}$

Taking logs,

$$\log\sqrt{\text{var}(r_{i,y,m.d})} = \frac{1}{2}\log(1+\delta^2) + h_{i,m}$$

After a first-order expansion,

$$= \frac{1}{2}\log(1+\delta^2) + h_{i,0} + m\log\lambda_i$$

Where the month-by-month differences in the log variance of daily returns is given by $\log \lambda_i$.

In estimating the equations above, we use the sample standard deviation of daily returns in each month

$$STD_{i,y,m} = \sqrt{\frac{\sum_{d=1}^{n}\left(r_{i,y,m,d} - \overline{r_{i,y,m}}\right)^2}{n-1}}$$

to approximate $\sqrt{\text{var}(r_{i,y,m.d})}$.

Testing whether on average funds adjust risk (H_0: l =1) is equivalent to testing (H_0: ρ =0) in the following regression:

$$\log STD_{i,y,m} = \theta + \rho\, m + \omega_{i,m}$$

We can also group the observations according to certain criteria and test $H_0\!:\rho_{j1} = \rho_{j2}$

$$\log STD_{i,m} = \theta_j + \rho_j m + \omega_{i,m}$$

Since *h*'s can also be a functions of year and quarterly seasonal effects and linear functions of factors such as the standard deviation of the S&P 500, we consider the following model:

$$\ln(STD_{i,y,m}) = \theta_j + \rho_j m + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \lambda_j * \ln(STDsp_{y,m}) + \omega_{i,y,m}$$

Where $[\omega_{i,y,m}] \sim N(0,\Omega)$, j =0,1,..N. Figures 2A and 2B show that there is a strong end-of quarter and end-of year pattern in volatility as suggested by Carhart et al. (2002). Therefore, we control for month-of-quarter effects with nqrt = 1,2,3 representing the nth month of each quarter and year-end effects with 12m, a dummy variable for December. In order to handle the heteroscadascity in ω's and the possibility of ω's being autocorrelated for repeated observations of each fund, we let Ω be a diagonal block matrix, where Ω_i is the autocorrelation matrix of fund i.

$$\Omega \equiv \begin{bmatrix} \Omega_1 & & & & \\ & \Omega_2 & & & \\ & & \cdot & & \\ & & & \cdot & \\ & & & & \cdot \\ & & & & & \Omega_N \end{bmatrix}$$

We test the three different forms of autocorrelation structure for square matrixes Ω_i.

$$\Omega_i^{Baisc} \equiv \begin{bmatrix} \sigma_i^2 & 0 & 0 & 0 \\ 0 & \sigma_i^2 & 0 & 0 \\ 0 & 0 & \sigma_i^2 & 0 \\ 0 & 0 & 0 & \sigma_i^2 \end{bmatrix} \qquad \Omega_i^{MA(1)} \equiv \begin{bmatrix} \sigma_i^2 & \sigma_{i1} & 0 & 0 \\ \sigma_{i1} & \sigma_i^2 & \sigma_{i1} & 0 \\ 0 & \sigma_{i1} & \sigma_i^2 & \sigma_{i1} \\ 0 & 0 & \sigma_{i1} & \sigma_i^2 \end{bmatrix} \qquad \Omega_i^{ARMA(1,1)} \equiv \sigma_i^2 \begin{bmatrix} 1 & \gamma & \gamma\rho & \gamma\rho^2 \\ \gamma & 1 & \gamma & \gamma\rho \\ \gamma\rho & \gamma & 1 & \gamma \\ \gamma\rho^2 & \gamma\rho & \gamma & 1 \end{bmatrix}$$

Moreover, instead of year fixed effects, we also test the models using year as a random effect.

$$\ln(STD_{i,y,m}) = \alpha_j + \beta_j * m + \gamma_{nqrt} + \lambda * \ln(STDsp_{y,m}) + \omega_y + \omega_{i,y,m}$$

Where $\omega_y \sim N(0,\sigma^2)$

We use both restricted maximum likelihood estimation (REML) and maximum likelihood estimation and get very close results.

IV. Results

In this section we measure mutual fund managers' response to their past performance relative to the S&P 500 index. The approach is two fold. First, we measure changes in volatility with a regression of funds' standard deviation on time and various controls. Second, we look directly for strategy changes by looking at the stock holdings before and after beating the benchmark.

A. Pooled regressions.

We test the hypotheses that mutual fund managers change their strategies in response to their past performance relative to the benchmark. Specifically, we look at return-based measures of risk in the following general regression:

$$\ln(STD_{i,y,m}) = \theta + \rho_1 m + \rho_2 m^2 + \lambda \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

This parameterization, described fully in Section III, allows us to look for changes in risk characteristics throughout the year. Specifically, the coefficients ρ_1 and ρ_2 should be zero if fund managers do not change their exposure to S&P 500 risk during the year. Table 3 shows that ρ_1 and ρ_2 are both significantly different than zero; specifically, our estimate for ρ_1 is -0.013 and our estimate for ρ_2 is 0.001. Our estimation reveals that fund managers change their exposure to risk over the year. Figure 3 shows the changing risk profile as a function of time. The standard deviation is falling during the first half of the year and rising in the second half of the year.

In order to make comparisons across groups more easily, we also estimate a piecewise linear version of the regression equation:

$$\ln(STD_{i,y,m}) = \theta + \rho_1 m_1 + \rho_2 m_2 + \lambda \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

Where m_1 is a step function going from one to six indicating each of the months from January through June and m_2 is a step function step function going from one to six indicating each of the months from July through December. Table 4 indicates that fund managers do change their risk throughout the year; ρ_1 and ρ_2 are both significantly different from zero; the coefficient estimates are -0.0037 and 0.0100, respectively. Figure 4 shows the pattern in risk as a function of time. In this piecewise linear framework, managers seem to reduce risk in the first half of the year and increase risk in the second half.

In linear and non-linear regression frameworks, we find that managers change risk over the year. Specifically, we find that managers reduce risk in the first half-year and increase risk in the second half-year. Up to this point, we have not separated out funds that beat the benchmark from those that do not beat the benchmark. In the following sections we will look at how past performance vis-à-vis the benchmark affects managers' risk.

B. Performance Categories

On average, it is clear that managers change their risk throughout the year. To test our risk-shifting hypothesis, we need to look for differences in risk-shifting across groups of managers who have differences in their performance relative to the benchmark. First, we define three windows of performance: performance up to last year's year-end, LASTDEC, performance up to last year's mid-point, LASTJUN, and performance up to this year's mid-point, THISJUN. Furthermore, we look at two different benchmarks, the first being the performance of the median fund in the sample, M, and the performance of the S&P 500, SP. Combined, there are six performance metrics, LASTDEC_M, LASTDEC_SP, LASTJUN_M, LASTJUN_SP, THISJUN_M and THISJUN_SP. Funds will fall into one of two groups for each metric: funds that beat the benchmark and funds that don't.

If the tournaments literature is correct in predicting that funds are competing against one another, then the performance metrics will show losing funds increase risk more than winning funds relative to the median as in BHS (1996). If, however, benchmark-beating is an important determinant of risk-shifting, then performance metrics will show losing funds increasing risk more than winning funds relative to the S&P 500. Table 5 shows estimation results from the following three regression models:

$$\text{Model I}: \ln(STD_{i,y,m}) = \theta_j + \rho_j m + \omega_{i,y,m}$$

$$\text{Model II}: \ln(STD_{i,y,m}) = \theta_j + \rho_j m + \lambda_j \ln(STDsp_{i,y,m}) + \omega_{i,y,m}$$

$$\text{Model III}: \ln(STD_{i,y,m}) = \theta_j + \rho_{1j} m_1 + \rho_{1j} m_2 + \lambda_j \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

Model I is a close approximation to previous literature. We find that S&P 500 winners reduce risk throughout the year relative to S&P 500 losers; the difference in coefficients on the month variable, $\rho_1 - \rho_0$, is a negative and statistically significant -0.0101. Furthermore, the result is reversed for performance relative to the median. Funds leading the median increase risk relative to funds lagging the median; the estimated difference, $\rho_1 - \rho_0$, is a positive and statistically significant 0.0057. Our methodology, which allows fund returns to be autocorrelated, finds that funds beating the median reduce risk in response to beating the S&P 500, but they do not reduce risk relative to peer performance.

As pointed out by Goriaev, Nijiman, and Werker (2003), the analysis in previous studies will be invalid if market model errors are correlated across funds. Model II allows use to capture a large portion of the cross-sectional correlation in funds' risk profile by controlling for changes in market risk throughout the year. Using Model II, we find that winning funds respond symmetrically to both benchmarks; they increase risk throughout the year, and they have higher sensitivities to market risk.

As seen in the previous sub-section, risk profiles are non-linear, and respond to seasonal effect throughout the year. In Model III, we allow funds to shift risk differently throughout the year, and we control for year, month-in-quarter, year-end effects. In this most general model, we find results that echo Model I. We find that both future median and future S&P beaters increase risk in the fist half of the year; the significantly positive coefficient estimate difference, $\rho_{11} - \rho_{10}$, is 0.0097 for the S&P benchmark and 0.018 for the median benchmark. We find that funds respond to beating the S&P differently than they respond to beating the median. Funds that beat the S&P reduce risk in the second half of the year; the coefficient estimate difference, $\rho_{21} - \rho_{20}$, is -0.004. Funds that beat the median do not change their risk profile in the second half of the year; the coefficient estimate difference, $\rho_{21} - \rho_{20}$, is 0.0003, and it is not statistically different from zero.

Overall, we find evidence that funds respond to beating the S&P 500 by reducing risk, and we find that funds that beat the median fund in the sample show no such decrease in risk. In the next section, we attempt to investigate the risk-shifting more closely by looking at changes in funds' stock holdings.

C. Evidence from Holdings Data.

In addition to using returns data to get a sense of what strategies mutual fund managers are employing, we can detect any potential shift in fund strategies by looking directly at the funds' holdings. If fund managers try to lock in any performance gains once they beat the benchmark, then we would expect to see an increase in both the number and value of S&P 500 holdings as a percentage of overall portfolio holdings.

We define groups based on whether funds beat the S&P last year and in the current half year. The group labeled [0,0] is a group of funds that haven't beaten the S&P 500 last year, and they haven't beaten the S&P 500 in the current half-year. The group labeled [1,0] is a group of funds that beat the S&P last year, and they haven't beaten the S&P in the current half-year. The other two groups, [0,1] and [1,1] are defined similarly.

In Table VIII, we show differences in holdings across performance-based fund groups. Interestingly, we see that funds tend to add stocks whether or not they have beaten the S&P 500 in June. The significantly positive coefficients of 0.019, 0.052 and 0.094 indicate that funds beating either last year's benchmark or this year's year-to date benchmark add more unique stocks in the second half year compared with funds that don't beat the benchmark. Furthermore, all of the performance-based groups seem to add more S&P 500 stocks in the second half year. The statistically positive coefficients of 0.014, 0.024 and 0.053 show that funds that beat the benchmark in the current or previous year add more stocks in the S&P 500 in the second half year. However, when we look at the market value of stocks reduced, we see a different pattern. The significantly negative coefficient of -0.542 indicates that funds that beat the S&P last year but haven't beaten the S&P 500 by current mid-year significantly reduce their non-S&P 500 holdings relative to their counterparts who did not beat the S&P last year. Furthermore, the insignificant coefficients of -0.079 and -0.279 indicate that funds that do beat the S&P 500 by mid-year do not significantly reduce their S&P 500 holdings. Overall, the holdings results are consistent with the idea that finds beating the S&P 500 by mid-year respond to their past performance by reducing risk. In particular, funds that do not beat the benchmark by mid-year reduce the market value of S&P 500 stock holdings while those that do beat the benchmark show no such reduction.

V. Conclusion

In this paper we find that mutual fund managers tend to shift their strategy in response to beating a benchmark as opposed to previous literature, such as BHS (1996), which suggests funds respond to beating each other. As in Basak, Pavlova and Shapiro (2004), year-end performance evaluation for fund managers could be driving the benchmark-beating response—beating the benchmark is not necessarily the goal according to previous literature such as Chevalier and Ellison (1997) and Sirri and Tufano (1998).

We find that funds decrease risk after beating the S&P 500; funds beating this benchmark reduce their log standard deviation by -0.004 per month in the second-half year relative to their non-benchmark beating counterparts. Furthermore, funds beating each other show no such change in risk. Funds beating the median of fund returns show an insignificant change in their risk in the second half year relative to their non-median beating counterparts.

We also investigate our hypothesis directly by looking at changes in mutual fund holdings before and after beating the benchmark. Funds that do not beat the benchmark by mid-year reduce the market value of S&P 500 stock holdings while those that do beat the benchmark show no corresponding reduction. Taken together, we present evidence that fund managers lock in their position relative to the index after beating it by switching into strategies which reduce their risk.

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Table I.
Data Description

The following is a description of the combined holdings and daily returns mutual fund database. The daily return database begins 1/1/1985 and ends 9/22/1997. There are 3262 funds in the sample, and there are a total of 3095320 daily return observations. The sample is limited to actively managed U.S. equity funds; funds in the database have ICDI objective codes equal to 'AG','GI','IN','LG', *or* CRSP objective codes equal to 'G','G-I','G-I-S','G-S','G-S-I','I','I-G','I-G-S','I-S','I-S-G','S','S-G-I','S-I','S-I-G','GCI','IEQ','LTG' *or* Strategic Insight Objective codes equal to 'AGG','GRI','GRO','ING' *and* CRSP investment policy codes equal to 'CS', 'I-S', 'MF'. Each fund has at least 720 observations and has data for 6 month in each year and 12 days in each month.

Year	Thomson Financial CDA/Spectrum Mutual Funds Holding	Micropal Mutual Fund Returns	
	No of observations	No of Funds	No of observations
1984	124373		
1985	135688	298	3520
1986	155489	353	4111
1987	179853	412	4815
1988	194051	492	5837
1989	199859	499	5960
1990	230785	573	6839
1991	295986	598	7090
1992	352806	877	10322
1993	471853	1043	12257
1994	601711	1356	16066
1995	685296	1682	19940
1996	788664	1654	19626
1997	928997	1624	12874
1998	1091706		

Table II.
Summary Statistics

The table gives the summary statistics for Ln(STD), $\hat{\alpha}$ and $\hat{\beta}$ by group.

$$STD_{i,y,m} = \sqrt{\frac{\sum_{d=1}^{n}\left(r_{i,y,m,d} - \overline{r_{i,y,m}}\right)}{n-1}} \qquad r_{i,y,m,d} = \hat{\alpha}_{i,y,m} + \hat{\beta}_{i,y,m} rsp_{i,y,m,d} + \hat{\varepsilon}_{i,y,m,d}$$

LAST DEC_M = 1 Last December Median Beaters
LAST JUN_M = 1 Last June Median Beaters
THIS JUN_M = 1 This June Median Beaters

LAST DEC_SP = 1 Last December S&P Beaters
LAST JUN_SP = 1 Last June S&P Beaters
THIS JUN_SP = 1 This June S&P Beaters

	Group	LAST DEC_M		LAST DEC_SP		LAST JUN_M		LAST JUN_SP		THIS JUN_M		THIS JUN_SP		[LAST DEC_M, THIS JUN_M]				[LAST DEC_SP, THIS JUN_SP]			
		0	1	0	1	0	1	0	1	0	1	0	1	[0,0]	[0,1]	[1,0]	[0,1]	[0,0]	[0,1]	[1,0]	[0,1]
	No of observations	55308	51352	49822	56838	44908	48008	49661	50355	50844	55816	56005	50655	24155	21837	21981	29371	28180	21642	27825	29013
Panel A	Alpha	(In 0.01)																			
	MEAN	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.03	0	0.03	0	0.03	0.01	0.03	0	0.03	0.01	0.03
	STD	0.12	0.11	0.12	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.11	0.13	0.11	0.11	0.12	0.13	0.11	0.12	0.11
	MEDIAN	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0.02	0.01	0.03	0.01	0.02
	MAD	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Panel B	Beta																				
	MEAN	0.76	0.78	0.74	0.79	0.77	0.77	0.76	0.77	0.74	0.79	0.75	0.78	0.73	0.79	0.75	0.8	0.73	0.76	0.78	0.8
	STD	0.32	0.3	0.32	0.31	0.34	0.28	0.34	0.28	0.32	0.3	0.32	0.3	0.32	0.31	0.31	0.29	0.32	0.31	0.33	0.29
	MEDIAN	0.77	0.79	0.75	0.8	0.77	0.79	0.77	0.79	0.75	0.8	0.76	0.8	0.74	0.8	0.75	0.81	0.74	0.77	0.78	0.81
	MAD	0.18	0.17	0.17	0.17	0.18	0.16	0.18	0.17	0.18	0.16	0.18	0.17	0.19	0.16	0.17	0.16	0.17	0.17	0.18	0.17
Panel C	Ln(STD)																				
	MEAN	-5.08	-5.05	-5.06	-5.07	-5.06	-5.06	-5.06	-5.06	-5.09	-5.04	-5.07	-5.06	-5.09	-5.06	-5.08	-5.02	-5.07	-5.05	-5.07	-5.06
	STD	0.47	0.45	0.48	0.45	0.45	0.46	0.46	0.46	0.47	0.46	0.48	0.45	0.48	0.46	0.45	0.44	0.48	0.47	0.47	0.43
	MEDIAN	-5.07	-5.04	-5.05	-5.06	-5.05	-5.05	-5.05	-5.06	-5.07	-5.05	-5.06	-5.06	-5.08	-5.06	-5.07	-5.02	-5.06	-5.04	-5.06	-5.07
	MAD	0.28	0.28	0.28	0.29	0.26	0.29	0.26	0.3	0.29	0.28	0.29	0.27	0.29	0.27	0.28	0.28	0.29	0.26	0.3	0.28

Table III.
Non-linear regressions for monthly log standard deviation, beta and alpha

The table gives the estimates for the regression model

$$\ln(STD_{i,y,m}) = \theta + \rho_1 m + \rho_2 m^2 + \lambda \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\beta}_{i,y,m} = \theta + \rho_1 m + \rho_2 m^2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\alpha}_{i,y,m} = \theta + \rho_1 m + \rho_2 m^2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

Here m is month, γ_y is the year fixed effect, γ_{nqrt} the fixed effect of the nth month of each quarter; and $STDsp_{i,y,m}$ is the monthly standard deviation of S&P500 index. $\omega_{i,y,m} \sim N(O, \Omega)$. Ω is a diagonal block matrix, where Ω_i is the autocorrelation matrix of fund i, basic heteroskadasticity structure is tested for the square matrices, Ω_i's.

$$\Omega \equiv \begin{bmatrix} \Omega_1 & & & & \\ & \Omega_2 & & & \\ & & \cdot & & \\ & & & \cdot & \\ & & & & \cdot & \\ & & & & & \Omega_N \end{bmatrix} \qquad \Omega_i^{Baisc} \equiv \begin{bmatrix} \sigma_i^2 & 0 & 0 & 0 \\ 0 & \sigma_i^2 & 0 & 0 \\ 0 & 0 & \sigma_i^2 & 0 \\ 0 & 0 & 0 & \sigma_i^2 \end{bmatrix}$$

Using daily return of each month, monthly log sample standard deviation, log standard deviation $\ln(STD_{i,y,m})$, beta $\hat{\beta}_{i,y,m}$ and alpha $\hat{\alpha}_{i,y,m}$ is calculated for each firm as the independent variables.

$$STD_{i,y,m} = \sqrt{\frac{\sum_{d=1}^{n}\left(r_{i,y,m,d} - \overline{r_{i,y,m}}\right)}{n-1}}$$

$$r_{i,y,m,d} = \hat{\alpha}_{i,y,m} + \hat{\beta}_{i,y,m} rsp_{i,y,m,d} + \hat{\varepsilon}_{i,y,m,d}$$

	ln(STD)		Beta		Alpha	
Effect	Estimate	Probt	Estimate	Probt	Estimate	Probt
α	-0.947	<.0001	0.747	<.0001	-0.001	0.034
ρ_1	-0.013	<.0001	-0.015	<.0001	0.001	0.006
ρ_2	0.001	<.0001	0.002	<.0001	0.000	0.002
λ	0.836	<.0001	-		-	
γ_y	YES		YES		NO	
$\gamma_{nqrt1}-\gamma_{nqrt3}$	0.023	<.0001	0.023	<.0001	0.000	0.662
$\gamma_{nqrt2}-\gamma_{nqrt3}$	-0.043	<.0001	-0.031	<.0001	0.001	0.032
γ_{12m}	-0.055	<.0001	-0.094	<.0001	0.001	0.014
-2 log likelihood	92422		53683		-436435	
AIC	92462		53723		-436395	
AICC	92462		53723		-436395	
BIC	92574		53834		-436283	

Table IV.
Piecewise-linear regressions for monthly log standard deviation, beta and alpha.

This table gives the estimates for the regression model

$$\ln(STD_{i,y,m}) = \theta + \rho_1 m_1 + \rho_2 m_2 + \lambda \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\beta}_{i,y,m} = \theta + \rho_1 m_1 + \rho_2 m_2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\alpha}_{i,y,m} = \theta + \rho_1 m_1 + \rho_2 m_2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

The only differences from the specifications in Table 3 are, instead of m and m^2, m_1=min (month, 6) and m_2=min(month-6, 0) are the dependent variables to test the time trend.

	ln(STD)		Beta		Alpha	
Effect	**Estimate**	**Probt**	**Estimate**	**Probt**	**Estimate**	**Probt**
α	-0.9570	<.0001	0.7254	<.0001	-0.0008	0.1172
ρ_1	-0.0037	0.0006	-0.0036	<.0001	0.0002	0.0331
ρ_2	0.0100	<.0001	0.0073	0.0057	-0.0002	0.0019
λ	0.8361	<.0001	-	-	-	-
γ_y	YES		YES		NO	
γ_{nqrt1}-γ_{nqrt3}	0.0212	<.0001	0.0216	0.8274	0.0002	0.5428
γ_{nqrt2}-γ_{nqrt3}	-0.0438	<.0001	-0.0299	<.0001	0.0005	0.0373
γ_{12m}	-0.0463	<.0001	-0.0794	<.0001	0.0010	0.0483
-2 log likelihood	92411		53507		-436430	
AIC	92451		53549		-436392	
AICC	92451		53549		-436392	
BIC	92563		53667		-436285	

Table V.
Regressions of Ln(STD) by group

This table gives the contrasts of the coefficients between groups for three regression models

Regression I: $\ln(STD_{i,y,m}) = \theta_j + \rho_j m + \omega_{i,y,m}$

Regression II: $\ln(STD_{i,y,m}) = \theta_j + \rho_j m + \lambda_j \ln(STDsp_{i,y,m}) + \omega_{i,y,m}$

Regression III: $\ln(STD_{i,y,m}) = \theta_j + \rho_{1j} m_1 + \rho_{1j} m_2 + \lambda_j \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$

Where $STD_{i,y,m} = \sqrt{\frac{\sum_{d=1}^{n}\left(r_{i,y,m,d} - \overline{r_{i,y,m}}\right)}{n-1}}$; m is month, m_1=min (month, 6) and m_2=min(month-6, 0) ; γ_y is the year fixed effect, γ_{nqrt} the fixed effect of the nth month of each quarter; and $STDsp_{i,y,m}$ is the monthly standard deviation of S&P500 index.

LAST DEC_M = 1 Last December Median Beaters
LAST JUN_M = 1 Last June Median Beaters
THIS JUN_M = 1 This June Median Beaters
LAST DEC_SP = 1 Last December S&P Beaters
LAST JUN_SP = 1 Last June S&P Beaters
THIS JUN_SP = 1 This June S&P Beaters

Regression		LAST DEC_SP		LAST DEC_M		LAST JUN_SP		LAST JUN_M		THIS JUN_SP		THIS JUN_M	
I	$\rho_1 - \rho_0$	-0.0019	0.0210	-0.0080	<.0001	-0.0038	<.0001	-0.0072	<.0001	-0.0101	<.0001	0.0057	<.0001
II	$\rho_1 - \rho_0$	-0.0003	0.6605	-0.0007	0.3369	-0.0019	0.1076	-0.0012	0.0886	0.0023	0.0021	0.0070	<.0001
	$\lambda_1 - \lambda_0$	0.0758	<.0001	0.0790	<.0001	0.3093	<.0001	0.3168	<.0001	0.0955	<.0001	0.0852	<.0001
III	$\rho_{11} - \rho_{10}$	0.0039	0.0600	-0.0088	<.0001	0.0015	0.5729	0.0058	0.0281	0.0097	0.0003	0.0180	<.0001
	$\rho_{21} - \rho_{20}$	-0.0025	0.0662	0.0021	0.1164	-0.0024	0.1661	-0.0055	0.0016	-0.0040	0.0457	0.0003	0.8515
	$\lambda_1 - \lambda_0$	0.0818	<.0001	0.0698	<.0001	0.3277	<.0001	0.3209	<.0001	0.0635	<.0001	0.0872	<.0001

Table VI.
Regressions of $\hat{\beta}$ by group

This table gives the contrasts of the coefficients between groups for two regression models

Regression I: $\hat{\beta}_i = \theta_j + \rho_j m + \omega_{i,y,m}$

Regression II: $\hat{\beta}_i = \theta_j + \rho_{1j} m_1 + \rho_{2j} m_2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$

Where $r_{i,y,m,d} = \hat{\alpha}_{i,y,m} + \hat{\beta}_{i,y,m} rsp_{i,y,m,d} + \hat{\varepsilon}_{i,y,m,d}$; m is month, m_1=min (month, 6) and m_2=min(month-6, 0) ; γ_y is the year fixed effect, γ_{nqrt} the fixed effect of the nth month of each quarter.

LAST DEC_M = 1 Last December Median Beaters
LAST JUN_M = 1 Last June Median Beaters
THIS JUN_M = 1 This June Median Beaters
LAST DEC_SP = 1 Last December S&P Beaters
LAST JUN_SP = 1 Last June S&P Beaters
THIS JUN_SP = 1 This June S&P Beaters

Regression		LAST DEC_SP		LAST DEC_M		LAST JUN_SP		LAST JUN_M		THIS JUN_SP		THIS JUN_M	
I	$\rho_1 - \rho_0$	-0.0041	<.0001	-0.0042	<.0001	-0.0068	<.0001	-0.0059	<.0001	0.0005	0.4285	0.0031	<.0001
II	$\rho_{11} - \rho_{10}$	-0.0158	<.0001	-0.0033	0.1391	-0.0067	0.0024	0.0027	0.2268	0.0194	<.0001	0.0163	<.0001
	$\rho_{21} - \rho_{20}$	0.0022	0.1333	-0.0051	0.0006	-0.0056	0.0001	-0.0110	<.0001	-0.0129	<.0001	-0.005	0.0007

Table VII.
Regressions of $\hat{\alpha}$ by group

Regression I: $\hat{\alpha}_i = \theta_j + \rho_j m + \omega_{i,y,m}$

Regression II: $\hat{\alpha}_i = \theta_j + \rho_{1j} m_1 + \rho_{2j} m_2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$

Where $r_{i,y,m,d} = \hat{\alpha}_{i,y,m} + \hat{\beta}_{i,y,m} rsp_{i,y,m,d} + \hat{\varepsilon}_{i,y,m,d}$; m is month, m_1=min (month, 6) and m_2=min(month-6, 0) ; γ_y is the year fixed effect, γ_{nqrt} the fixed effect of the nth month of each quarter.

LAST DEC_M = 1 Last December Median Beaters
LAST JUN_M = 1 Last June Median Beaters
THIS JUN_M = 1 This June Median Beaters
LAST DEC_SP = 1 Last December S&P Beaters
LAST JUN_SP = 1 Last June S&P Beaters
THIS JUN_SP = 1 This June S&P Beaters

Regression		LAST DEC_SP		LAST DEC_M		LAST JUN_SP		LAST JUN_M		THIS JUN_SP		THIS JUN_M	
I	$\rho_1 - \rho_0$	-0.0001	0.4495	-0.0001	0.3669	0.0000	<.0001	0.0000	0.0980	-0.0001	<.0001	-0.0001	<.0001
II	$\rho_{11} - \rho_{10}$	0.0001	0.4005	0.0002	0.3697	0.0001	<.0001	0.0000	0.1664	-0.0002	<.0001	-0.0002	<.0001
	$\rho_{21} - \rho_{20}$	-0.0002	0.1367	-0.0002	0.1095	0.0000	0.3489	0.0000	0.3063	0.0000	0.0003	0.0000	<.0001

Table VIII.
Test of Risk Shifting based on Change of Portfolio Holdings

Using quarterly portfolio holding data, a set of independent variables are constructed. The table gives the contrast of λ between groups based on the joint performance relative to S&P500 in the past and in the current midyear.

$$IND_{i,qrt} = \lambda_{j,halfyear} + \gamma_{year} + \varepsilon_{i,qrt}$$

where j = [LAST DEC_SP, THIS JUN_SP]

LAST DEC_M = 1 Last December Median Beaters THIS JUN_SP = 1 This June S&P Beaters

Half year	Group by YTD return relative to SP500	No. of sp500 stocks added	Market Value of sp500 stocks added	No. of stocks changed	Market Value of changed stocks	No. of stocks added/ No. of stocks changed	No of sp500 stocks added/ No of stocks changed	No. of SP500 stock reduced/ No. of changed	Market value of SP500 stock reduced/ Market value. of stocks changed
1st	[0,1]-[0,0]	(0.213)	(15230000)**	(11.124)**	(17580000)	(0.000)	0.008	0.017	(0.154)
	[1,0]-[0,0]	2.368	6341272	(1.098)	48237202***	0.057***	0.024***	(0.004)	(0.174)
	[1,1]-[0,0]	19.972	8181562	34.639	65528390***	0.076***	0.051	0.000	(0.122)
2nd	[0,1]-[0,0]	1.590	(7875147)	(1.141)	(10480000)	0.019*	0.014***	(0.007)	(0.079)
	[1,0]-[0,0]	3.800	10865899	9.434 *	60022826***	0.052***	0.024***	(0.013) ***	(0.542)**
	[1,1]-[0,0]	20.372	15444436**	46.136***	80962064***	0.094***	0.053***	(0.025) ***	(0.279)
2nd-1st	[0,0]	(1.464)	(8526240)	(7.194)	(13860000)	(0.020)**	(0.007)	0.019	0.075
	[1,0]	0.339	(1169533)	2.789	(6763158)	(0.001)	(0.001)	(0.005)	0.150
	[0,1]	(0.032)	(4001613)	3.338	(2074072)	(0.025)***	(0.007)	0.010	(0.294)
	[1,1]	(1.064)	(1263366)	4.302	1573977	(0.001)	(0.005)	(0.006)	(0.082)
2nd-1st	[0,1]-[0,0]	1.803	7356707	9.984	7096538	0.019*	0.006	(0.025)***	0.075
	[1,0]-[0,0]	1.432	4524627	10.532	11785624	(0.005)	0.000	(0.010)	(0.368)
	[1,1]-[0,0]	0.400	7262874	11.497	15433673	0.019	0.002	(0.025)***	(0.156)

* Significant in 10% level
** Significant in 5% level
***Significant in 1% level

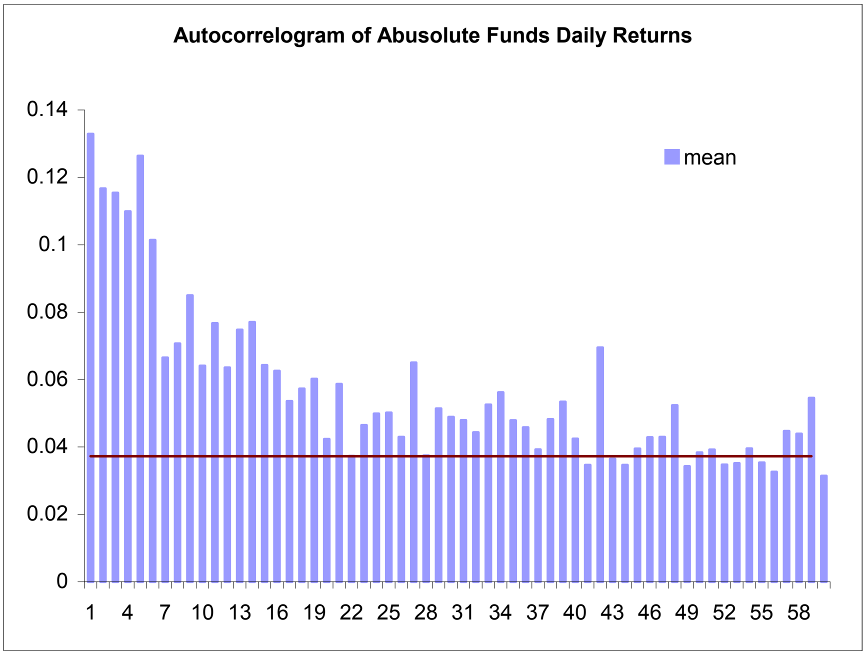

Figure 1A
The first 60 autocorrelations of the absolute value of the daily returns for each fund are averaged for each lag of days. Since each fund has at least 720 observations, the horizontal line at $1/\sqrt{720}$ is the upper bound of the critical value.

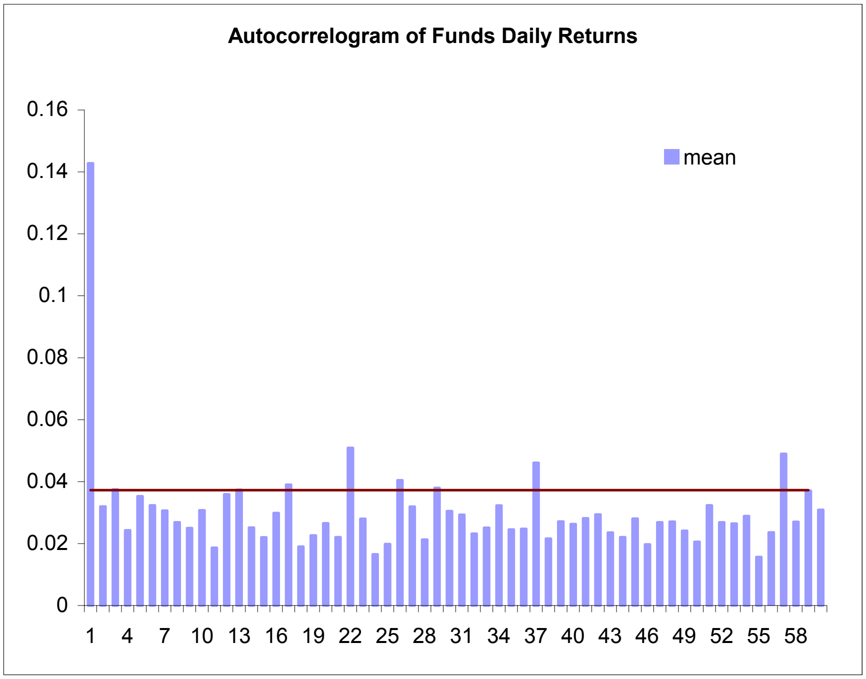

Figure 1B
The absolute values of the first 60 autocorrelations of the daily returns for each fund are averaged for each lag of days. Since each fund has at least 720 observations, the horizontal line at $1/\sqrt{720}$ is the upper bound of the critical value.

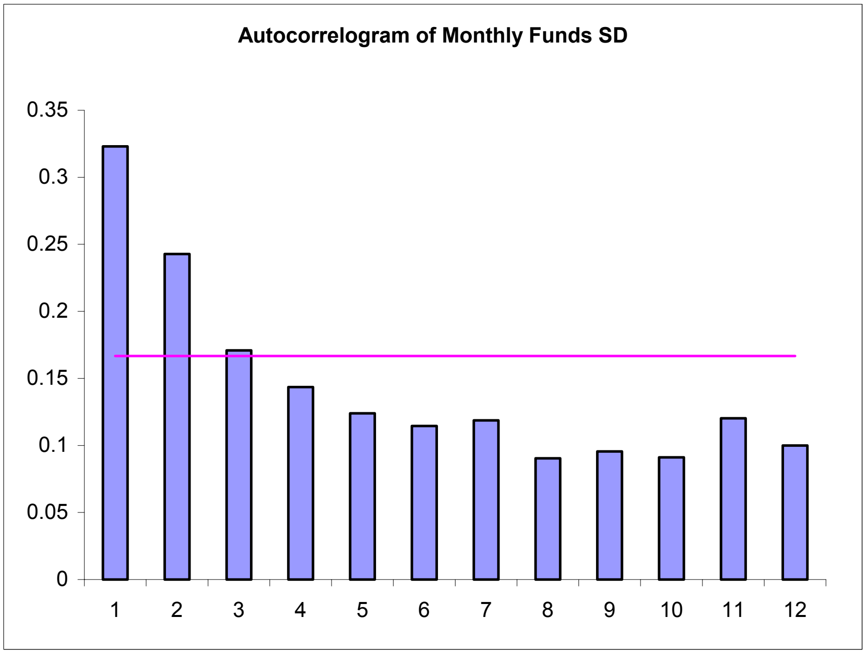

Figure 1C
The absolute values of the first 12 autocorrelations of the monthly standard deviations for each fund are averaged for each lag of months. Since each fund has at least 36 observations, the horizontal line at $1/6$ is the upper bound of the critical value.

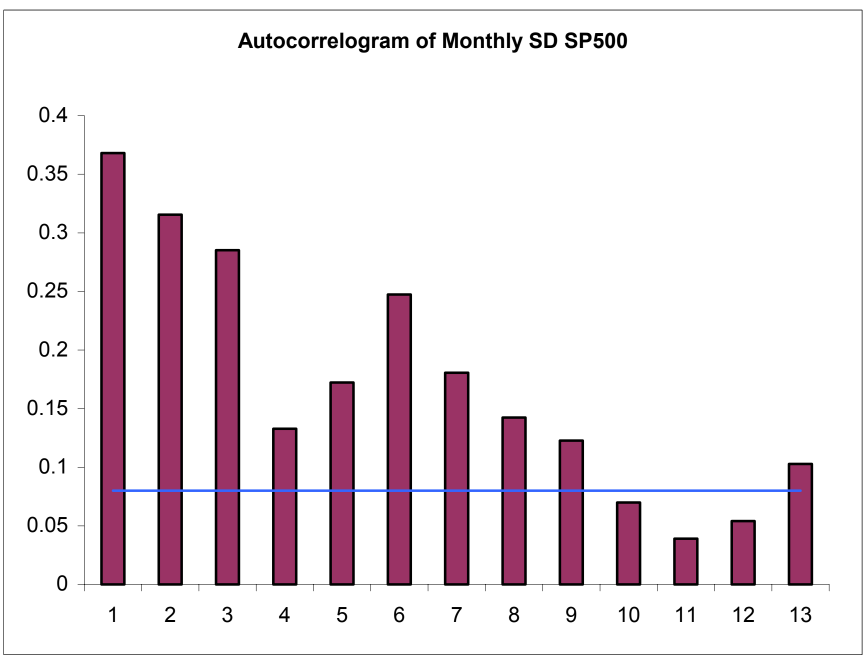

Figure 1D
The first 12 autocorrelation coefficients of the monthly standard deviations of daily returns for SP500 index.

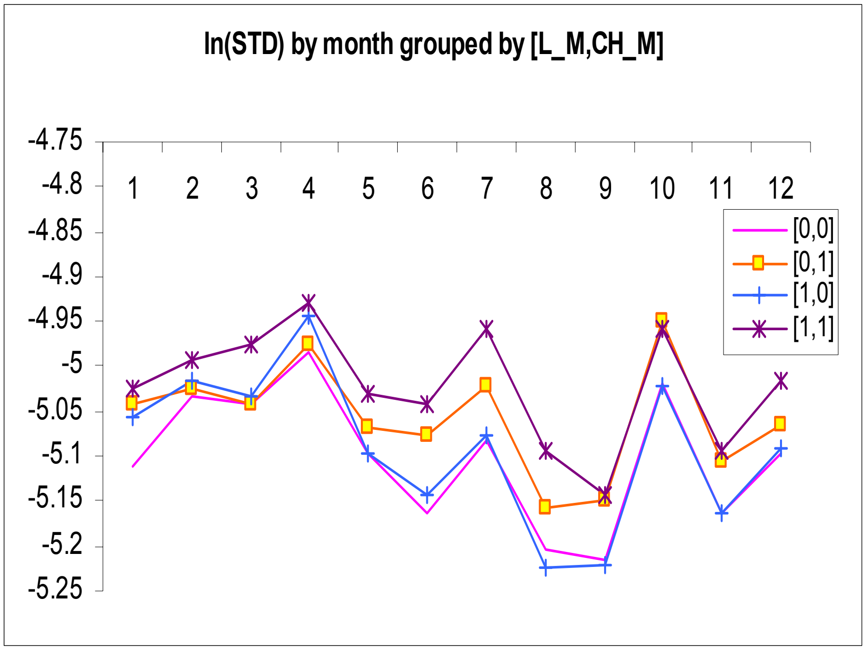

Figure 2A

Fixed effect of month $\gamma_{j,m}$ by group based on funds' past year year-end return and current midyear return relative to that of the median fund.

$$\ln(STD_{i,y,m}) = \theta + \gamma_{j,m} + \omega_{i,y,m}$$

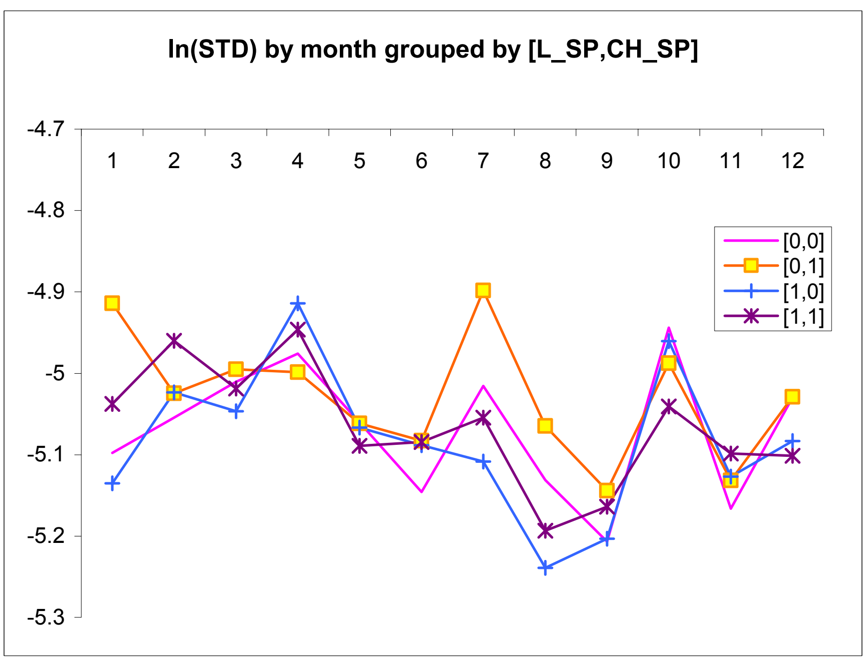

Figure 2B

Fixed effect of month $\gamma_{j,m}$ by group based on funds' past year year-end return and current midyear return relative to that of the S&P500 index.

$$\ln(STD_{i,y,m}) = \theta + \gamma_{j,m} + \omega_{i,y,m} ..$$

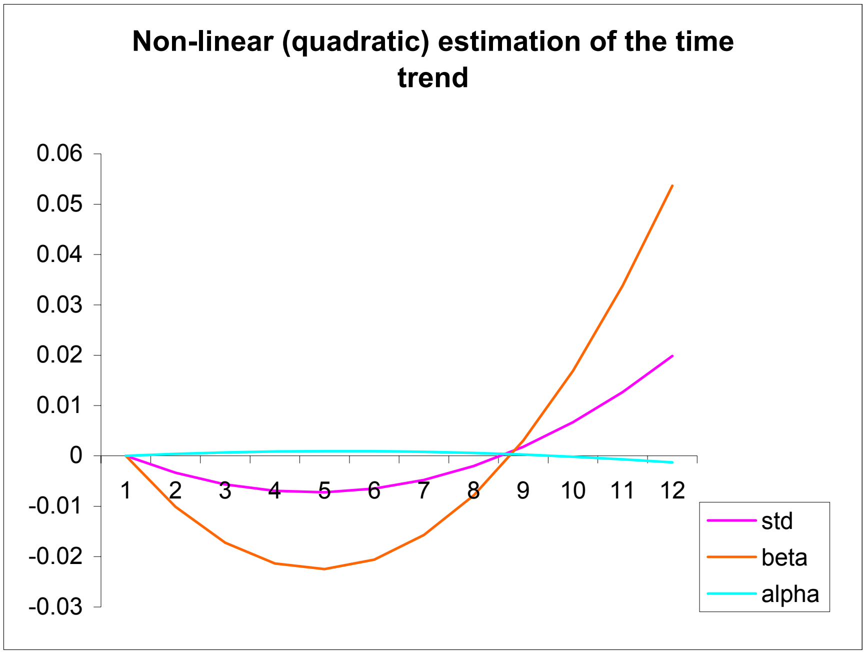

Figure 3

The estimated monthly trend of STD, Beta and Alpha based on the non-linear regression in Table 3.

$$\ln(STD_{i,y,m}) = \theta + \rho_1 m + \rho_2 m^2 + \lambda \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\beta}_{i,y,m} = \theta + \rho_1 m + \rho_2 m^2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\alpha}_{i,y,m} = \theta + \rho_1 m + \rho_2 m^2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

Here m is month, γ_y is the year fixed effect, γ_{nqrt} the fixed effect of the nth month of each quarter; and $STDsp_{i,y,m}$ is the monthly standard deviation of S&P500 index. $\omega_{i,y,m} \sim$ N(O, Ω). The starting points are set to zero.

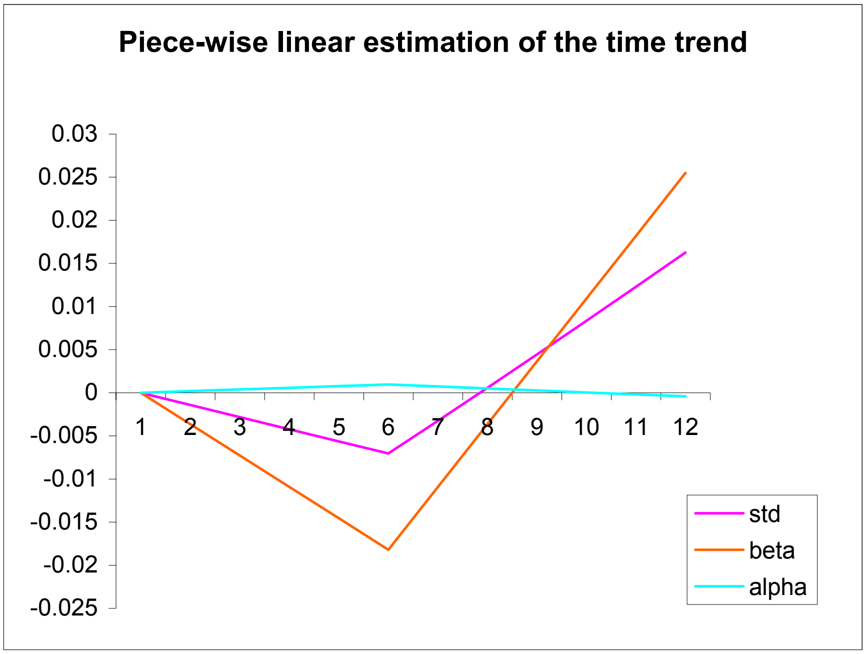

Figure 4

The estimated monthly trend of STD, Beta and Alpha based on the piecewise-linear regression in Table 4. The starting points are set to zero.

$$\ln(STD_{i,y,m}) = \theta + \rho_1 m_1 + \rho_2 m_2 + \lambda \ln(STDsp_{i,y,m}) + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\beta}_{i,y,m} = \theta + \rho_1 m_1 + \rho_2 m_2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

$$\hat{\alpha}_{i,y,m} = \theta + \rho_1 m_1 + \rho_2 m_2 + \gamma_y + \gamma_{nqrt} + \gamma_{12m} + \omega_{i,y,m}$$

Here m_1=min (month, 6) and m_2=min(month-6, 0).