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Exposing Survivorship Bias in Mutual Fund Data

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Abstract

We revisit survivorship bias within domestic equity mutual funds from the middle of 1998 to the middle of 2004. Using Morningstar Principia and tracking both disappearing funds and name changes, we report a statistically significant performance difference between the complete sample and the survivorship-biased sample. We correlate this potential for a disproportional weighting of better performing funds to market conditions and show that changes in stock market indices and interest rates have a bearing on the level of survivorship bias. We also analyze the time series properties of survivorship and demonstrate that mutual fund survivorship bias follows a mean-reverting process.

INTRODUCTION

In this paper we examine survivorship bias within domestic equity mutual funds. The prevailing evidence shows that the bias is due to a disproportional weighting of better performing funds in the reporting databases. In other words, the attrition we see in the industry tends to be poor performing funds dropping out. While the reported decline in the number of funds tracked, or fund attrition, can be explained in some cases by successful funds shutting out new investors, survivorship bias has come to mean that the performance of the mutual fund industry, on average, is worse than reported.

In a widely referenced study, Malkiel (1995) found that poor performing mutual funds tend to disappear, usually by merging into more successful funds, thus burying the fund's bad record with it. Since the worst funds cease to exist, after a few years the survivors that define the industry tend to have better than average results. For example, we often see fund companies advertising the spectacular performance that their funds have achieved in the past, without mentioning that some of their funds have disappeared during the same period.

All of the commercial fund databases, including Morningstar, CDA, and ICDI, ascribe to a certain degree of survivorship bias in reported returns. Even the Center for Research in Security Prices (CRSP), a mutual fund database that claims to be survivorship bias free and is becoming popular among researchers, has a form of survivorship bias that is referred to as omission bias.[1] Omission bias arises because the data reported in CRSP is monthly for some funds but annual for others. Given that the reporting of liquidation rates is lower in monthly data, the CRSP sample will tend to understate the proportion of liquidations and thus overstate the performance for their fund population. In addition, since CRSP collects fund data from different sources data inconsistency is also a potential problem.

Attrition rates of mutual funds are surprisingly high and have been increasing through time. According to Carhart et al. (2002), the average annual fund attrition rate from 1962 to 1995 is about 3.6% per year. In addition, aggressive growth funds fall off at the higher rate of about 4.5%, while the rate of loss for long-term growth funds is lower at about 2.9%. Our study reports a much larger attrition of just over 2% quarterly, almost 9% annually, over the time period studied. Hence one of the implications of our research is that in the mutual fund arena, survivorship bias still exists and is growing.

Our objective is to examine the mutual fund bias over the more recent and volatile market regime of the late 1990's and early 2000's, and to examine the cross-sectional properties of the performance bias. We are particularly interested in the potential for survivorship bias to be related to market conditions, something that previous researchers have yet to show.

SURVIVORSHIP BIAS AS REPORTED IN PREVIOUS STUDIES

Past research has examined survivorship bias from a number of perspectives. One straightforward approach compares a sample of surviving funds to another sample that includes the universe of funds. Wermers (1997) looks at the performance of mutual funds from 1976 to 1994 and finds that the surviving group earned about 100 basis points more per year compared with the fund universe.[2] Brown and Goetzmann's (1995) study reports a survivorship bias that is, on average, 80 basis points per year.[3] An even higher estimate of survivorship bias is reported by Malkiel[4] (1995) whose comparison finds that the return boost to the surviving fund sample is in the neighborhood of 150 basis points per year.

Grinblatt and Titman (1989), defining survivorship bias as the differences in alpha between a sample of surviving funds versus the universe of funds, report a bias between 10 and 40 basis points per year. Similar to Grinblatt and Titman (1989), Elton, Gruber, and Blake (1996) show through alphas[5] a bias that ranges from 40 basis points to one full percentage point, depending on the length of the sample period used.

In the context of mutual fund performance persistence, Carhart (1997) defines survivorship bias as the difference in alpha between equally-weighted portfolios of surviving funds and non-surviving funds. Carhart finds that small funds (which disappear more frequently than large funds) have higher portfolio turnover and buy smaller stocks, thus incurring higher transaction costs than large funds. Instead of providing a direct estimate of the survivorship bias, Carhart estimates the difference in alpha between these portfolios to be between 3% and 5% per year.

Carhart et al. (2002), comparing the performance of surviving and non-surviving funds, examine the cross-sectional averages of the group-adjusted returns and four-factor alphas of individual funds. Non-surviving funds exhibit considerably poorer performance than surviving funds. By these measures, non-surviving funds underperform survivors by about 4% (group-adjusted) per year. Using four-factor model estimates, the performances of the portfolios of survivors and non-survivors are considerably different, as the survivors achieve abnormal performance of -0.07% per month while non-survivors earn -0.33%.[6]

In the fixed income markets, Blake, Elton and Gruber (1993) look at the difference in excess risk-adjusted return between bond funds that survive and those that do not. According to their estimates, the average alpha of those failed funds is, on average, lower than the survivors by about one percentage point per year.

Our objectives are to report survivorship bias during the most recent rise and then fall in the stock market, and to examine some of the cross-sectional properties of survivorship bias. It would be intuitive to expect that the bias should rise and fall across time with the market. This line of reasoning suggests that systematic risk will force more funds to drop out in down markets while fewer funds will blow up in advancing markets. But the prevailing evidence is not consistent with this prediction. Elton et al (1996) look at the bias over time and report a (near) constant survival rate. Wermers (1997) compares the differences in survivorship bias across several sub-periods and finds no significant differences. In a similar way, we would expect that survivorship varies across different asset locations. But Elton et al. (1996) again fails to find a difference between fund survival and investment objective, and Wermers (1997) concludes that there is no significant difference between survivorship bias and fund categories.

And so we are motivated to reexamine survivorship bias in what we would argue to be a cleaner and better positioned sample of mutual fund performance. First, nearly all of the previous studies collect fund data from more than one data source. For example, Carhart (1997) uses data from *FundScope Magazine, the Investment Dealer's Digest, United Babson Reports, Wiesenberger Investment Companies, the Wall Street Journal*, and past printed reports from ICDI. These data sources can cause inconsistency that in turn can alter the conclusions. Second, the time period examined can alter the conclusions. Many previous studies report results over a healthy bull market. In contrast our sample is derived from one data source, Morningstar, and is conducted over a six-year period that includes the first few years of a raging bull market and the last few years of a prolonged downtrend. If the incidence of survivorship bias is related to data clarity and market conditions, then our study is best designed to pick up these effects.

DATA AND METHODOLOGY

We use *Morningstar Principia* as our only data source and construct a survivorship bias free fund sample in the following way. Our data set represents the combined fund sample of 24 quarterly *Morningstar Principia* CDs, covering the time period October 1998 through September 2004. Records over this period incorporate all new funds and include complete returns[7] dating back to the fund's inception date. We then adjust the combined fund sample for name changes by retaining as data points only the most recently named fund, thus deleting any redundant return records.[8] In the end we have a complete set of all funds, live or dead, that existed in a given month. TABLE 1 provides a first look at the whole fund universe, separated by funds added and funds removed. We report an average quarterly attrition rate is 2.27%.

We define survivorship bias as the difference in return between the set of surviving equity funds and the entire equity fund sample:

(1) $$SB_t = RS_t - RC_t$$

Table 1. Additions, Removals, and Attrition Rates of Mutual Funds over Time

Reported are the number of funds, additions, and removals of the whole fund universe by quarter from the 4th quarter of 1998 to the 3rd quarter of 2004. Quarterly addition rate and attrition rate are also provided. Δ=addition rate – attrition rate.

Quarter	Quarter start	Additions	Removals	Quarter end	Addition rate (%)	Attrition Rate (%)	Δ (%)
1998 4th qtr				10,373			
1999 1st qtr	10,373	359	117	10,615	3.46	1.13	2.33
1999 2nd qtr	10,615	593	220	10,988	5.59	2.07	3.52
1999 3rd qtr	10,988	288	178	11,098	2.62	1.62	1.00
1999 4th qtr	11,098	171	138	11,131	1.54	1.24	0.3
2000 1st qtr	11,131	261	105	11,287	2.34	0.94	1.4
2000 2nd qtr	11,287	303	117	11,473	2.68	1.04	1.64
2000 3rd qtr	11,473	588	327	11,734	5.13	2.85	2.28
2000 4th qtr	11,734	596	249	12,081	5.08	2.12	2.96
2001 1st qtr	12,081	854	386	12,549	7.07	3.20	3.87
2001 2nd qtr	12,549	762	205	13,106	6.07	1.63	4.44
2001 3rd qtr	13,106	759	320	13,545	5.79	2.44	3.35
2001 4th qtr	13,545	614	387	13,772	4.53	2.86	1.67
2002 1st qtr	13,772	893	368	14,297	6.48	2.67	3.81
2002 2nd qtr	14,297	339	334	14,302	2.37	2.34	0.03
2002 3rd qtr	14,302	663	356	14,609	4.64	2.49	2.15
2002 4th qtr	14,609	413	349	14,673	2.83	2.39	0.44
2003 1st qtr	14,673	813	377	15,109	5.54	2.57	2.97
2003 2nd qtr	15,109	598	506	15,201	3.96	3.35	0.61
2003 3rd qtr	15,201	1262	847	15,616	8.30	5.57	2.73
2003 4th qtr	15,616	714	345	15,985	4.57	2.21	2.36
2004 1st qtr	15,985	1006	268	16,723	6.29	1.68	4.61
2004 2nd qtr	16,723	412	188	16,947	2.46	1.12	1.34
2004 3rd qtr	16,947	439	256	17,130	2.59	1.51	1.08
Average quarterly rate					4.43%	2.22%	2.21%

Where SB_t is the survivorship bias in month t, RS_t is the average return of equally-weighted surviving funds in month t, and RC_t is the average return of the equally-weighted complete equity fund sample, both live and dead, in month t.

The general design of our tests can be specified as follows. We will first perform a t-test for the difference between the raw returns of survivorship-biased sample and complete sample. In order to see whether survivorship bias can be explained away by common market risk factors, we will also use the CAPM, Fama-French three-factor and four-factor models to examine the significance of the alphas. Equations (2), (3), and (4) represent CAPM, Fama-French three-factor and four-factor models, respectively:

(2) $SB_t = a_i + b_i R_{m,t} + e_i$

(3) $SB_t = a_i + b_i R_{m,t} + s_i SMB_t + h_i HML_t + e_i$

(4) $SB_t = a_i + b_i R_{m},t + s_i SMB_{,t} + h_i HML_{,t} + UMD_t + e_i$

Where $R_{m,t}$ is the excess return on a value-weighted aggregate market proxy, SMB and HML are returns on value-weighted, zero-investment portfolios for size and book-to-market equity in stock returns, and UMD is a momentum factor[9] by Fama and French. A positive and significant alpha in either CAPM or French-French models will indicate that survivorship bias is significant in the context of risk-adjusted returns.

As a preliminary test on the relation between survivorship bias and market states, we will set up a regression model with the monthly return of S&P 500 index as the only dummy variable (D). Specifically, D is equal to one if the monthly return of S&P 500 index is greater than zero, otherwise D is set to be zero. A dummy variable that is statistically different from zero indicates a significant relationship between survivorship bias and market states. Once the relation between survivorship bias and the market is confirmed, we will move on to locate the driving factors behind survivorship bias.

EMPIRICAL FINDINGS

Table 2 examines the importance of survivorship bias in a number of ways. First, how does the performance of the full mutual fund sample differ from the survivorship-biased sample? Panel A shows that the difference to be 0.078% per month, or just under 1% per year, statistically significant at the 1% level. And so mutual fund performance can be off as much as 1% based solely on the inability to account for failed or removed funds.

Panel B examines survivorship bias in CAPM, Fama-French three-factor and four-factor models. We find that the alpha in any of the three models is statistically different from zero at 1% significance level with a positive sign, meaning that survivorship bias can inflate fund performance even if we use risk-adjusted returns.

In Panel C we ask whether or not survivorship bias is related to movements in the market. Recall from our previous discussion that this is an unresolved issue, and that most previous research has found no existence of a market trend in survivorship bias. In these tests we use monthly returns on the S&P 500 index as a measure of the market, and identify market conditions through a dummy variable that takes a value of one in an up market (monthly return of S&P 500>0) and a value of zero in a down market (monthly return of S&P 500<0). We report negative and statistically significant coefficients at the 1% level, such that the bias is greatest (least) when the market is poor (strong).

TABLE 2. Survivorship and Market Variables

Table 2 examines survivorship bias of equity funds from three perspectives over the time period October 1998 through October 2004. Panel A shows the results of a t-test for difference in raw return between the survivorship biased sample and the complete sample, where CL represents confidence limits of the estimated difference in mean returns. In Panel B, we test whether Fama-French three-factor and four-factor models can explain survivorship bias away. The Newy-West (1987) method is used in estimating parameters. *t*-statistics are in parentheses. Panel C is a dummy variable regression model, where D = 1 if the monthly return of S&P500 Index is greater than zero and zero otherwise.

Panel A: Difference in Return Between Survivorship-biased Sample and Complete Sample

Difference in returns	Lower CL mean	Mean	Upper CL mean	*t*-statistic
Survivorship bias	0.0425	0.078	0.1134	4.34 **

Panel B: Survivorship Bias and Fama-French Three-factor and Four-factor Models

Dependent variable	Intercept	Loadings on RMRF	Loadings on SMB	Loadings on HML	Loadings on UMD	Adj-R^2
Monthly SB_t	0.07453 (5.28)**	-0.01329 (-4.84)**				0.5084
Monthly SB_t	0.070788 (4.83)**	-0.02012 (-4.02)**	0.011998 (2.07)*	0.000154 (0.06)		0.5223
Monthly SB_t	0.072603 (4.82)**	-0.02273 (-5.15)**	0.015083 (2.73)**	-0.00152 (-0.52)	-0.00422 (-1.54)	0.5343

Panel C: Survivorship Bias and S&P 500

Dependent variable	Intercept	$D_{S\&P500}$	Adj-R^2
Monthly SB_t	0.146847 (4.61)**	-0.12916 (-3.48)**	0.1815

**Indicates statistical significance at the 0.01 level.
*Indicates statistical significance at the 0.05 level.

Table 3 expands our market tests to examine sub-market indices, including the S&P 500 for large-caps, the S&P 400 for mid-caps, and the S&P 600 for small-cap stocks.[10] We see that when examined individually, survivorship bias is statistically related to all of the market variables, and that the coefficients all have the expected sign. Particularly, the interest rate indices have positive signs. We believe that this is due to the inverse relationship between the stock market and interest rates. Funds tend to flow into the stock market under low interest rates and vice versa, and so more mutual funds will be terminated when the interest rate is high. Comparing equity indices, the S&P 500 index clearly has the highest explanatory value, and comparing fixed income indices, survivorship bias is more sensitive to short-term interest rate fluctuations. In all of our regression models the Newy-West method[11] is used to adjust for potential autocorrelation and heteroskedasticity. Meanwhile VIFs[12] in all the multivariate models are well below 5, indicating that multicollinearity does not pose a problem to our estimation.

Table 3. Survivorship and Equity Indexes

Survivorship bias of equity funds, as the dependent variable, is examined against three equity indexes and two interest rate variables. The sample period is from October 1998 to October 2004. The Newey-West method is used in estimating parameters. VIFs measure the degree of multicollinearity in multivariate regression models. Typically a VIF value greater than 10 is of concern. T-statistics are in parentheses.

Depend Variable: Monthly Survivorship Bias SB_t							
Model	Intercept	S&P large-cap 500	S&P mid-cap 400	S&P small-cap 600	3-month T-bill	30-year T-bond	Adj-R^2
1	0.0830 (4.79)**	-0.0169 (-3.34)**					0.2846
2	0.0907 (4.51)**		-0.0120 (-2.73)**				0.1685
3	0.0881 (4.35)**			-0.0099 (-2.47)*			0.1256
4	0.0757 (4.63)**	-0.0206 (-3.10)** VIF=3.61	0.0036 (0.74) VIF=3.61				0.2917
5	0.0787 (4.59)**	-0.0171 (-3.03)** VIF=1.88		-0.0001 (-0.04) VIF=1.88			0.2871
6	-0.0078 (-0.32)				0.3177 (2.79)**		0.1135
7	-0.2485 (-1.98)*					0.7405 (2.58)*	0.0224
8	0.2220 (0.89)				0.4156 (2.04)* VIF=2.15	-0.5823 (-0.88) VIF=2.15	0.1113
9	0.0020 (0.09)	-0.0166 (-3.68)** VIF=1.00			0.3036 (3.20)** VIF=1.00		0.3925
10	-0.1858 (-1.24)	-0.0166 (-3.25)** VIF=1.00				0.6115 (1.85) VIF=1.00	0.2995

**Indicates statistical significance at the 0.01 level.
*Indicates statistical significance at the 0.05 level.

We next look at survivorship bias as a function of investment style. For example, might the survival rate of growth funds differ from that of income funds? Based on the relevant Morningstar indices, Table 4 provides a representation of growth versus income (value) by size, separating investment style by capitalization of the underlying stocks. Not surprisingly, the coefficients on all growth funds are negative and significant at 1% level, while those for the income funds show no relationship (except for the Morningstar large-cap value index which is significant at the 5% level). In fact, the adjusted R-square values report that over half the variation in survivorship is explained by a growth investment style. Size and investment style of the underlying stocks also matters -- the

Table 4. Survivorship and Investment Style

Table 4 examines the relationship between survivorship bias and a series of Morningstar market indices, controlling for size and style of the underlying assets. The Newy-West method is used in estimating parameters. The dependent variable is monthly survivorship bias SB_t of domestic equity funds. The sample period spans from October 1998 to October 2004. T-statistics are in parentheses.

Depend Variable: Monthly Survivorship Bias SB_t									
Model	Intercept	Large growth index	Large value index	Mid growth index	Mid value index	Small growth index	Small value index	3-month T-bill	Adj-R^2
1	0.0745 (5.28)**	-0.0133 (-4.84)**							0.5084
2	0.0808 (4.10)**		-0.0082 (-2.07)*						0.0477
3	0.0717 (4.89)**	-0.0152 (-4.55)** VIF=1.28	0.0012 (0.29) VIF=1.28						0.5085
4	0.0809 (5.64)**			-0.0095 (-5.78)**					0.3870
5	0.0789 (4.18)**				-0.0021 (-0.66)				-0.0101
6	0.0801 (4.81)**			-0.0138 (-3.63)* VIF=1.10	-0.0037 (-0.48) VIF=1.10				0.4194
7	0.0847 (5.90)**					-0.0089 (-5.92)**			0.3244
8	0.0810 (4.16)**						-0.0034 (-1.13)		-0.0025
9	0.0767 (4.14)**					-0.0118 (-1.90)* VIF=1.21	0.0004 (0.05) VIF=1.21		0.3311
10	0.0752 (5.16)**	-0.0126 (-2.98)** VIF=4.67		-0.0007 (-0.23) VIF=4.67					0.5016
11	0.7418 (5.03)**	-0.0136 (-3.65)** VIF=2.98				0.0003 (0.16) VIF=2.98			0.5014
12	-0.0013 (-0.07)	-0.0129 (-5.51)** VIF=1.00						0.2847 (3.71)** VIF=1.00	0.6050

**Indicates statistical significance at the 0.01 level.
*Indicates statistical significance at the 0.05 level.

large-cap stock index has more explanatory power than the small-cap stock index, while the growth stock index has more explanatory power than the value stock index. Altogether, the large-cap growth index is the most significant market factor that drives survivorship bias. The three-month T-bill is also significant at 1% level with a positive sign, meaning that higher short-term interest rate would increase the chance of a fund going out of business. It is clear that large-cap growth index and short-term interest rate are the two most important market factors that drive survivorship bias.

The dynamics of the market's association with survivorship is examined further in Table 5. Because our data spans a volatile market period, we are able to test these relationships separately in distinctive markets. Panel A excludes data over the down market period of July 2000 through June 2002, while Panel B excludes data over the up market period of October 1998 to June 2000. Excluding the down market shows that the relation between survivorship bias and market movements disappears, while excluding the up market magnifies the market variable as the t-values more than double and the adjusted R-square approaches 80%. In contrast, the explanatory power of short-term interest rate is immune from the market conditions. Thus, our earlier hypothesis that survivorship bias is related to market conditions is supported by our tests.

Table 5. Market States and Survivorship

Table 5 examines market movements over different market regimes. Panel A excludes a prolonged down period (July 2000 through June 2002) while Panel B excludes a prolonged up period (October 1998 to June 2000). The Newy-West method is used in estimating parameters. The dependent variable is monthly survivorship bias SB_t of domestic equity funds. The sample period spans from October 1998 to October 2004. T-values are in parentheses.

Panel A: Excluding The Down Market Period Of July 2000 Through June 2002				
Model	Intercept	Large growth index	3-month T-bill	Adj-R^2
1	-0.0086 (-0.84)	-0.0017 (-0.81)	0.2116 (4.46)**	0.2616
2	0.0401 (4.10)**	-0.0006 (-0.23)		-0.0188
3	-0.0087 (-0.79)		0.1995 (3.78)**	0.2522
Panel B: Excluding The Up Market Period of October 1998 Through June 2000				
	Intercept	Large growth index	3-month T-bill	Adj-R^2
4	0.0023 (0.13)	-0.0171 (-9.27)**	0.2314 (2.67)*	0.7890
5	0.0471 (4.48)**	-0.0185 (-9.70)**		0.7535
6	-0.0287 (-1.03)		0.5175 (2.63)*	0.2011

**Indicates statistical significance at the 0.01 level.
*Indicates statistical significance at the 0.05 level.

ROBUSTNESS CHECK USING GRANGER CAUSALITY TEST

As a robustness check, the Granger causality test is conducted to investigate whether there are causal relations among survivorship bias, large-cap growth index, and the 3-month T-bill. From Table 6 we can see that the large-cap growth index Granger causes survivorship bias, whereas survivorship bias does not Granger-cause the large-cap growth index. Moreover, there is a two-way causality between T-bill and survivorship bias. The 3-month T-bill Granger causes survivorship bias while survivorship bias also Granger causes the 3-month T-bill. The Granger Causality test confirms the robustness of our results.

Table 6. Granger Causality Test

As a robustness check, Granger Causality is conducted to investigate the relation among survivorship bias, the large growth index, and the 3-month T-bill. Panel A shows the result of this stationarity test for the three time series variables. We can see that both survivorship bias and large growth index are stationary, while the T-bill becomes stationary after the first difference. The Granger Causality test in Panel B shows that both the large growth index and the T-bill Granger Cause survivorship bias, while survivorship bias also Granger causes the T-bill.

Panel A: Stationarity Test				
	Augmented Dickey-Fuller test statistic		First difference	
Variables	*t*-statistic	*p* -value	*t*-statistic	*p* -value
Survivorship bias	-6.83	0.0000		
Large growth index	-7.98	0.0000		
3-month T-bill	-0.98	0.7555	-4.67	0.0003

Panel B: Granger Causality Test		
Null hypothesis	*F*-statistic	*p* -value
Large growth index does not Granger Cause survivorship bias	3.26	0.0452
Survivorship bias does not Granger Cause large growth index	1.41	0.2519
T-bill does not Granger Cause survivorship bias	4.42	0.0163
Survivorship bias does not Granger Cause the T-bill	11.33	0.0001

TIME SERIES PROPERTIES OF SURVIVORSHIP BIAS

In this section we examine the time-varying properties of survivorship bias based on exponential models, including Brown's one-parameter model which only incorporates a level component, Holt's two-parameter model accounting for both level and trend components, and Winter's additive seasonal model which takes level, trend and seasonal patterns into account.[13] Panel A in Table 7 provides the summary statistics for survivorship bias based on the three models.

Table 7. Times Series Properties of Fund Survivorship Bias

Panel A of this exhibit reports modeling results of three exponential smoothing models; Panel B explains the procedure of setting up a mean-reverting model for monthly survivorship bias. Sample period spans from October 1998 to October 2004. T-statistics are in parentheses. Parameter estimates are given in percentage points..

Panel A: Alternative exponential smoothing models of survivorship bias

Smoothing model	Level weight	Smoothed level	Trend weight	Seasonal weight	Theil's U
Brown's model	0.04448 (3.1552)**	0.06849			0.0795
Holt's model	0.01667 (1.0694)	0.04683	0.00100 (0.0215)		0.1543
Winter additive model	0.01757 (0.8938)	0.04632	0.00100 (0.0225)	0.00100 (0.007602)	0.3029

Panel B: Mean-reverting model of survivorship bias

Dependent variable=S_{t+1}-S_t (Survivorship bias change between t and t+1)
Independent variable=X_t (Survivorship bias in t)

variable	Intercept	Slope	Residual Standard deviation	Adjusted R-square
Parameter estimate	0.07002 (4.12)	-0.8079 (-8.40)**	0.146825	0.5904
P value	0.0001	0.0001		

Mean reverting rate=negative of slope=-(-0.8079)=0.8079
Long run mean=Intercept/Speed=0.07002/0.8079=0.0867
Volatility=Residual volatility/Long run mean=0.146825/0.0867=1.6935

**Indicates statistical significance at the 0.01 level.
*Indicates statistical significance at the 0.05 level.

Panel A in Table 7 demonstrates that only the level component in Brown's one-parameter model is significantly different from zero, which is 0.06849% per month. Panel A also shows that survivorship bias does not have a significant trend component, nor does it have a significant seasonal pattern. Although the Theil's Us[14] in all three models are lower than 1, Brown's model has the lowest value in U, thus Brown's one-parameter model is best in depicting the time-varying movement of survivorship bias. Since survivorship bias follows a mean-reverting process with monthly smoothed level of 0.06849%, the mean-reverting level of monthly survivorship bias is 0.06849%. In addition to the mean-reverting level, the mean reverting rate (or speed) is the other key component for a mean-reverting process. In order to get a better understanding of the survivorship bias, we next set up a mean-reverting model for survivorship bias to depict its time series properties. Mathematically a mean-reverting model is given as:

(5) $$dSt = a(S^* - St) + \sigma dWt$$ [15]

Where $dSt = S_{t+1} - St$ is the expected change in survivorship bias from t to t+1, S^* is the mean-reverting level or long-run equilibrium level of survivorship bias, S_t is the monthly survivorship bias in month t, a is the mean-reverting rate, σ is the volatility, and dWt is a Wiener process representing random shock to survivorship bias from t to t+1.[16]

From equation (5) we can see that the mean-reverting component or "drift" term $a(S^*-St)$ is governed by the distance between the current level of survivorship bias and the mean-reverting level as well as by the mean reversion rate. Particularly, if the current level of survivorship bias is below the reverting level, the mean-reverting component will be positive, pushing survivorship bias up to the equilibrium level. Alternatively, if survivorship bias is above the mean reversion level, the mean-reverting component will be negative, pulling survivorship bias down to the equilibrium level. This pattern will create a path over time for survivorship bias to drift towards the mean reversion level at a speed determined by the reverting rate.

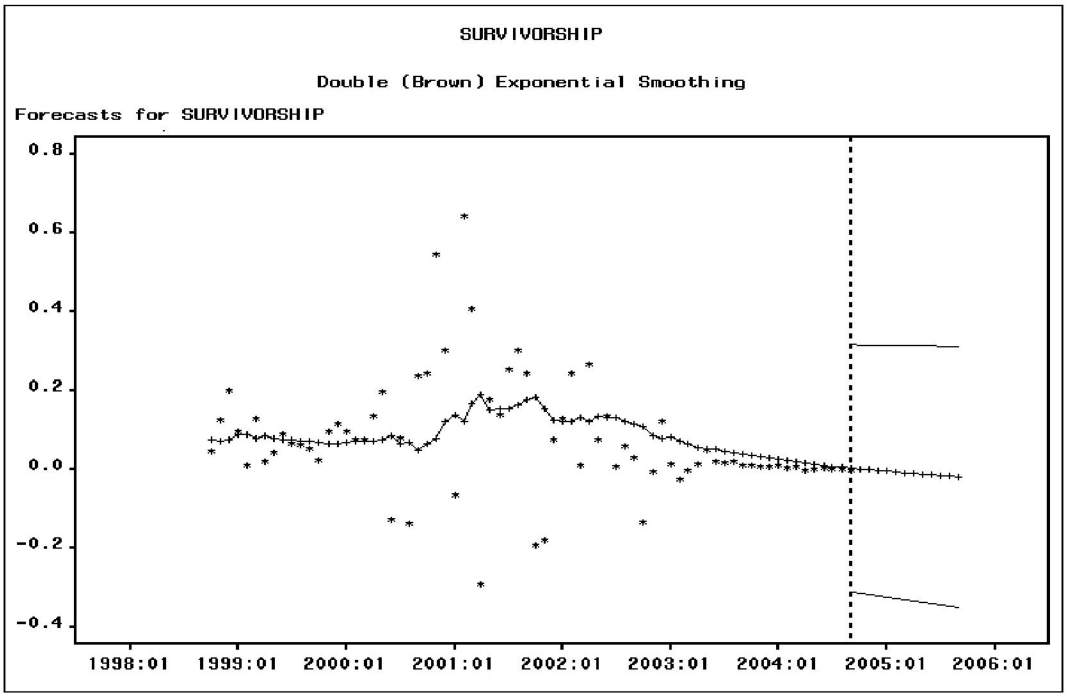
The mean-reverting rate can be estimated by regressing the absolute value of survivorship bias changes against its previous levels. In equation (5) we can see that the mean-reverting rate is the negative value of the slope, whereas the long-term mean is the intercept estimate of that regression divided by the reverting speed, and that the volatility of survivorship bias changes is given by the residual standard deviation. Panel B in TABLE 7 summarizes the regression results. Based on the test results, the mean-reverting model of monthly survivorship bias in our sample period is given in equation (6).

(6) $$dSt=0.8079*(0.0867-St)+1.6935*dWt$$

Note that the equilibrium level of survivorship bias is 0.0867% per month, which is close to 0.06849% from Brown's one-parameter model. We can see that the mean-reverting speed during our sample period is 0.8079%. This means that if survivorship bias deviates 1% away from the equilibrium level, survivorship bias will tend to drift back at a speed of 0.8079%.

Lastly, in Figure 1 we provide the exponential smoothing chart of monthly survivorship bias based on Brown's one-parameter model. Figure 1 also includes a 12-month forecast for the survivorship bias under discussion. Based on the forecast, we expect that the survivorship bias of domestic equity funds will continue to go downward slowly from October 2004 to October 2005.

Figure 1. Exponential Smoothing of Monthly Survivorship Bias



CONCLUSION

Mutual fund survivorship bias refers to the tendency of poor-performing funds to disappear while strong performers continue to exist. Survivorship bias can cloud the performance evaluation of funds, that is, the comparison between actively managed funds and passively managed funds. While the existence of this bias has been the subject of previous research, no consensus has been reached, although there is general agreement that the net effect of the bias is inflated performance.

Using Morningstar Principia as the single data source, we investigate the survivorship bias of domestic equity funds from 1998 to 2004. Since Morningstar Principia is the most popular mutual fund database in the industry, also because our sample period covers both bull and bear markets, our study can examine both the existence and properties of survivorship bias. Indeed, one of the main contributions of this study is to test the relationship between mutual fund survivorship bias and market conditions.

We find that the large-cap growth index and the three-month T-bill rate are the two major determinants of mutual fund survivorship bias. The large-cap growth index has the highest explanatory power but its significance is sensitive to the market fluctuations, whereas the three-month T-bill's explanatory power is immune from this problem. In addition, we find that a pattern between size and style, meaning that the large-cap stock index has more explanatory power than the small-cap stock index. Our results also show that the growth stock index has more explanatory power than the value stock index, thus the large-cap growth index becomes the most significant market factor that drives survivorship bias. Granger Causality tests confirm these relationships. Furthermore, we prove that survivorship bias follows a mean-reverting process, and a model is set up to depict the time series properties of survivorship bias.

Thus, our study not only confirms the potential of exaggerated mutual fund performance, but shows that the main of this impact occurs during prolonged bear markets. While no mutual fund data can be 100% survivorship bias free, we show a more complete road map to fund performance evaluation that will best serve investors.

ENDNOTES

[1] See Elton et. al.(2001).
[2] Wermers found that surviving funds exhibited an average pre-expense return of 23 basis points (on a risk-adjusted basis) per year above that of all funds (surviving or not), and that the annual survivorship bias is 100 basis points in terms of gross return most of the years. He attributes (at least in part) the larger survivorship bias found by other researchers to significantly higher transaction costs and fund expenses among non-survivors than among survivors.
[3] Brown and Goetzmann found that the difference between raw returns composed of an equally weighted entire fund sample and returns of an equally-weighted surviving fund sample to be 0.8 percent per year.
[4] Malkiel found that survivorship bias appears to be more important than other studies had estimated. The differences in value-weighted returns between surviving funds and all funds are about 150 basis points per year.
[5] The index alpha is Jensen's alpha using excess return over S&P500 as the only regressor while the three-index alpha compares the performance of the fund to a passive portfolio of large stocks, small stocks, bonds, and T-bills.
[6] According to Carhart et al (2002), cross-sectional average monthly performance is the cross-sectional average of the performance estimates of individual funds based on the complete time-series of their returns. Group-adjusted performance is the difference between a fund's return and the average return on all other funds with the same declared fund objective. Four-factor alpha is the intercept from a time-series regression of a fund's excess returns on the four-factor model factor-mimicking portfolios over the fund's complete history. The four-factors are RMRF, SMB, and HML Fama and French's (1993) market proxy and factor-mimicking portfolios for size and book-to-market equity, and a factor-mimicking portfolio for one-year return momentum.
[7] Morningstar does not adjust total returns for sales charges (such as front-end, deferred or redemption fees). The total returns include management fees, administrative fees, 12b-1 fees, and other costs automatically taken out of fund assets. Brokerage costs are not included in total returns. In the calculation of returns dividends are assumed to be used to purchase additional shares in the fund at the reinvestment net asset value that is available to shareholders of the fund.
[8] On average, over 2,500 funds out of the whole fund universe change their names each year during our sample period.
[9] Fama and French use six value-weight portfolios formed on size and prior (2-12) returns to construct the momentum factor UMD (Up Minus Down), defined as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. See French's web site for detail.
[10] It might be of concern that the use of stock indices creates the potential for a new bias. Because the constituent stocks in the index change over time, the indices themselves suffer from survivorship bias. However, we think that this concern is unwarranted for two reasons. First, companies are not only deleted by are added over time in order to better reflect the condition of the represented markets. Second, our monthly returns are representative of the concurrent indices during a particular month such that the effect of survivorship bias in stock indices can be ignored.
[11] New-West method is an estimation procedure based on New-West(1987) covariance matrix, which is heteroskedasticity and autocorrelation consistent.
[12] Variance inflation factor (VIF) is a common way for detecting multicollinearity. It measures the impact of collinearity among the independent variables in a regression model. It expresses the degree to which

collinearity among the predictors degrades the precision of an estimate. Typically a VIF value greater than 10 is of concern.

[13] Following is the error-correction form of these three models, the equations of forecasted values are also given:

a. Brown's one-parameter exponential smoothing model

$L_t=L_{t-1}+ae_t$ Where $e_t=X_t-L_{t-1}$

$\mathbf{X}_{t+1}=\mathbf{X}_t+ae_t$ Where $e_t=X_t-X_{t-1}$

Forecast: $\mathbf{X}_t(h)=Lt$, $h=1,2,3,\ldots\ldots$

b. Holt's two parameter model, which includes parameters for level and trend.

$L_t=L_{t-1}+T_{t-1}+ae_t$ Where $et=X_t-L_{t-1}-T_{t-1}$ and $T_t=T_{t-1}+a\beta et$

Forecast: $\mathbf{X}_t(h)=L_t+hT_t$, $h=1,2,3,\ldots\ldots$

c. Winter's additive seasonal model, this is a three-parameter model for level, trend, and season.

$L_t=L_{t-1}+T_{t-1}+ae_t$ Where $e_t=X_t-L_{t-1}-T_{t-1}-F_{t-s}$ and $T_t=T_{t-1}+a\beta e_t$

$F_t=F_t\text{-}s+\gamma[(1-a)e_t]$

Forecast: $\mathbf{X}_t(h)=L_t+hT_t+F_{t+h-s}$, $h=1,2,3,\ldots\ldots,s$

[14] Meaning that they all are better than naïve no-change model.

[15] a(S*-St) sometimes are also regarded as the mean reversion component and σdWt as the random component.

[16] A stochastic process {X(t), T>=0} is said to be a Wiener process or Brownian motion process if (i) X(0)=0;(ii) {X(t), t>=0} has stationary and independent increments; (iii) for every t>0, X(t) is normally distributed with mean 0 and variance σ^2t.

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