CENTRUM VOOR ECONOMISCHE STUDIEN

DISCUSSION PAPER

ELIMINATING BIASES IN EVALUATING MUTUAL FUND PERFORMANCE FROM A SURVIVORSHIP FREE SAMPLE

by

Jenke R. TER HORST
Theo E. NIJMAN
Marno VERBEEK

Econometrics

Center for Economic Studies
Discussion Paper Series DPS 98.20

Katholieke Universiteit Leuven
Departement Economie
Naamsestraat 69
B-3000 Leuven

Eliminating Biases in Evaluating Mutual Fund Performance from a Survivorship Free Sample[1]

Jenke R. ter Horst[2], Theo E. Nijman[3] and Marno Verbeek[4]

May 29, 1998
Revision October 23, 1998

Key words: Mutual Funds, Performance Evaluation, Survivorship Bias

JEL classification: G11, G23, C34

[1]Financial support by the Netherlands Organization for Scientific Research (N.W.O.) is gratefully acknowledged by the first author. We are grateful to Frank de Jong and Jon Danielsson for helpful comments on a previous version and to Mark Carhart for providing data used in Section 7.

[2]Department of Econometrics, Tilburg University, PO Box 90153, 5000 LE Tilburg, The Netherlands. E-mail: J.R.terHorst@kub.nl.

[3]CentER for Economic Research and Department of Econometrics, Tilburg University.

[4]Center for Economic Studies, K.U. Leuven and Department of Econometrics, Tilburg University.

Abstract

Poor performing mutual funds are less likely to be observed in the data sets that are typically provided by data providers. This so-called survivor problem can induce a substantial bias in measures of the performance of the funds and the persistence of this performance. Many studies have recently argued that survivorship bias can be avoided by analyzing a sample that contains returns on each fund up to the period of disappearance using standard techniques. Such data sets are usually referred to as 'survivorship free'. In this paper we show that the use of standard methods of analysis on a 'survivorship free' data-set typically still suffers from a bias and we show how one can easily correct for this using weights based on probit regressions.

Using a sample with quarterly returns on U.S. based equity funds, we first of all model how survival probabilities depend upon historical returns, the age of the fund and upon aggregate economy-wide shocks. Subsequently we employ a Monte Carlo study to analyze the size and shape of the survivorship bias in various performance measures that arise when a 'survivorship free database' is used with standard techniques. In particular, we show that survivorship bias induces a spurious U-shape pattern in performance persistence. Finally, we show how a weighting procedure based upon probit regressions can be used to correct for the bias. In this way, we obtain bias-corrected estimates of abnormal performance relative to a one-factor and the Carhart [1997a] four-factor model, as well as its persistence. Our results are in accordance with the persistence pattern found by Carhart [1997a], and do not support the existence of a hot hand phenomenon in mutual fund performance.

1 Introduction

Many empirical studies in finance potentially suffer from survivorship bias. This point has recently been stressed by e.g. Brown, Goetzmann and Ross [1995] and Carhart [1997b]. In this paper we focus on the impact of survivorship bias in measuring mutual fund performance. Poor performing mutual funds are less likely to be observed in the data sets that are typically available. This so-called survivor problem can induce a substantial bias in measures of the performance of the funds and the persistence of this performance. Many studies (see, e.g. Grinblatt and Titman [1989], Brown and Goetzmann [1995], Malkiel [1995] and Wermers [1997]) have recently argued that survivorship bias can be avoided by using standard techniques on a sample that contains returns on each fund up to the period of disappearance. Such data-sets are usually referred to as 'survivorship free'. As stressed by Carhart [1997b], the analysis of a 'survivorship free' database with standard techniques will in general still yield biased estimates of performance measures, because poor performing funds are underrepresented. Carhart [1997b] refers to this bias as a 'look ahead bias'. In this paper we analyze the relative size of these biases for U.S. based equity funds and show how these biases can be eliminated using appropriate correction methods.

Empirical studies by Brown and Goetzmann [1995], and Elton, Gruber and Blake [1996] indicate, as may be expected, that a bad record of returns is one of the main reasons for fund disappearance. If this is the case, a simple analysis of average returns for a sample of mutual funds still in existence at the end of the sample period tends to be upward biased due to the relative absence of low returns. Because of cross-sectional variation in expected returns, this bias does not necessarily disappear in a survivorship free sample. It is sometimes claimed (Grinblatt and Titman [1989], Blake, Elton and Gruber [1993]) that the effect of survivorship bias on average returns is between 0.1% and 0.4% per year, although the implicit underlying assumptions on the survival process are not clear. For alternative and more sophisticated measures of performance, and its persistence, survivorship can lead to a wide range of spurious empirical regularities, the form of which will depend upon the survival process (see, e.g. Brown et al. [1992], Brown, Goetzmann and Ross [1995] and Hendricks, Patel and Zeckhauser [1997]).

In this paper we empirically study the performance of U.S. based open-end mutual funds for the period 1989-1995, explicitly taking into account the problem of survivorship bias. Following the micro-economics literature on sample selection (starting with Heckman [1976, 1979]), we model the process that determines attrition from the sample, and subsequently analyze it jointly with (the underlying model of) performance evaluation. As a consequence, the goal of this paper is threefold. First, we determine the factors that affect a fund's probability to close or merge and leave the sample. The longitudinal probit model that we propose extends the model in Brown and Goetzmann [1995] by allowing for aggregate macro-economic shocks. Second, we analyze the effects of this survival process on a range of performance measures using a Monte Carlo experiment and, third, we show how one can correct for these survivorship biases and apply this to the sample of equity funds. Our results show that historical returns are an important determinant for fund survival, that survivorship bias in performance measurement can be substantial, and that knowledge of the survival process enables fairly simple corrections for survivorship biases. Using Carhart's [1997a] four-factor model for evaluating mutual fund performance, we find a persistence pattern that is similar to the one reported in Carhart [1997a], although the latter may be subject to bias.

The remainder of this paper is organized as follows. A stylized example in Section 2 illustrates the potential problem of survivorship bias in performance measurement using a survivorship free as well as a survivors-only sample of mutual funds. In Section 3 we describe the sample of U.S. based mutual funds that we employ. We show that the total number of funds that leaves the sample is substantial and their average return is substantially less than for surviving funds. This indicates the potential for survivorship bias and the need to correct for it. In Section 4 we model survival probabilities and examine factors that determine fund disappearance. We also analyze whether funds with different investment objectives, such as growth stocks or foreign stocks, have different probabilities of survival. A Monte Carlo study, presented in Section 7, shows the effect of survivorship bias on various methods analyzing mutual fund performance. The empirical survival process, in which historical returns over at most three years play a role, induces a spurious pattern of performance persistence that is U-shaped, rather than J-shaped as in Hendricks, Patel and Zeckhauser [1997]. In Section 8 we show how the survival model can be used to construct weights that can be applied to correct for survivorship biases. The empirical implementation of this approach is presented in Section 9, where we examine persistence in the performance of U.S. open-end equity funds over the period 1989-1994, using a simple one-factor model and Carhart [1997a]'s four-factor model. By and large, our results support the findings of Carhart [1997a] and do not indicate the existence of a hot hands phenomenon in mutual fund performance. Section 10 summarizes the main results and presents some concluding remarks.

2 A Stylized Example

In order to show that the use of a survivorship free sample to evaluate mutual fund performance still yields biased estimates, we will in this section analyze a simple example that illustrates the causes and sizes of the impact that survivorship effects can have on performance measures. More explicitly, we will examine the effect on the average return of a mutual fund or a sample of funds given that mutual fund survival depends on past returns.

Assume that a population of mutual funds exists, indexed $i = 1, .., M$. In two consecutive sample periods, each of them realizes a return μ^H with probability p_i, or $\mu^L < \mu^H$ with probability $1 - p_i$, where p_i comes from a cross-sectional distribution with mean p. Consequently, the expected return on mutual fund i is:

$$\mu_i = p_i \mu^H + (1 - p_i)\mu^L,$$

while the expected return on an arbitrary fund (the cross-sectional average) is given by

$$\mu = p\mu^H + (1 - p)\mu^L.$$

In the first sample period each fund is observed, while in the second period we observe a fund with probability one if it had a return $r_{it} = \mu^H$ in the previous period and with probability q if it had return $r_{it} = \mu^L$. Indexing data availability in the second period by $y_i = 1$, we thus have that

$$P\{y_i = 1|r_{i1}\} = q + (1 - q)\frac{r_{i1} - \mu^L}{\mu^H - \mu^L} \tag{1}$$

and

$$P\{y_i = 1\} = p_i + (1 - p_i)q. \tag{2}$$

The standard estimator for the expected return μ_i of fund i from a 'survivorship free' database is

$$\hat{\mu}_i = \frac{r_{i1} + y_i r_{i2}}{1 + y_i}. \tag{3}$$

(Note that r_{i2} is missing if $y_i = 0$.) By using the probabilities for each of the possible outcomes, it is easily verified that this is not an unbiased estimator for μ_i. In particular, it can be shown that

$$E\{\hat{\mu}_i\} - \mu_i = [\frac{1}{2}p_i(1-p_i)(1-q)](\mu^L - \mu^H), \tag{4}$$

indicating that (3) underestimates the expected return μ_i. Consequently, even a survivorship free sample is not free of survivorship effects in the sense that the properties of standard estimators can be affected by the survival process. The bias increases as the probability of survival q decreases. Not surprisingly, the bias disappears if $\mu^H = \mu^L$, if the survival probability q equals one or if $p_i = 0$ or $p_i = 1$.

Conditional upon fund survival in period 2, the expected value of $\hat{\mu}_i = \frac{1}{2}(r_{i1} + r_{i2})$ is given by

$$E\{\hat{\mu}_i | y_i = 1\} - \mu_i = \frac{\frac{1}{2}p_i(1-p_i)(1-q)}{p_i + (1-p_i)q}(\mu^H - \mu^L), \tag{5}$$

which indicates that the estimator based upon the survivors-only sample overestimates the expected return μ_i. This is due to the relative absence of bad returns.

Intuitively, the fact that the estimator for the expected return conditional upon fund survival yields a positive bias, due to the relative absence of low returns, suggests that in order to obtain an unbiased estimate the weight for the observed low returns should be increased, while the observed high returns should have a lower weight. In Section 8 we show that using a weight factor that equals the inverse of the normalized probability that fund i is kept in the sample yields unbiased estimates. Consequently, to estimate the expected return μ_i for fund i, the appropriate weight is the ratio of the unconditional (2) and conditional survival probability (1) and is given by

$$w_i = \frac{p_i + (1-p_i)q}{q + (1-q)\frac{r_{i1} - \mu^L}{\mu^H - \mu^L}}. \tag{6}$$

It is easily verified that the adjusted estimator $\tilde{\mu}_i = \frac{1}{2}w_i(r_{i1} + r_{i2})$ is an unbiased estimator based upon the sample characterized by $y_i = 1$. Note that the weights w_i depend upon returns, r_{i1} in this case, and are thus endogenous. Moreover, they depend upon the unknown parameters p_i and q. This is not a problem if we can identify funds with identical p_i values from the survivorship free sample.

If we are interested in the cross-sectional average of expected returns μ, the numerator in (6) is replaced by the unconditional probability $p + (1 - p)q$, which is directly identifiable from the data using observations on all funds. By adjusting the numerator in (6) we can thus estimate expected returns for different subsets of funds. In particular, the numerator should equal the unconditional survival probability within a given subsample, such that, within the subsample, $E\{\frac{1}{w_i}\} = 1$. Note that this implies that all weights equal 1 and no correction is needed if we are interested in the expected return in period 2 conditional upon the return realized in period 1. The reason is that, given the initial return, survival does not depend upon the period 2 return.

3 Stylized Facts on Survival of U.S. Equity Funds

In order to examine the importance of the effect of conditioning upon survival for empirical performance studies, we employ a data set selected from the Morningstar Mutual Funds Ondisc database (February 1995 edition). This database contains monthly information on more than 6000 U.S. based open-end equity as well as fixed income mutual funds. This sample suffers from survivorship because only funds that existed at the end of the sample period (February 1995) are included. Many mutual funds have disappeared from the sample because they have merged with other funds or are closed down completely. In the latter case it is possible that the management of the fund has decided to change to a closed-end fund, or that the investors of the fund are offered the opportunity to withdraw their money and invest it in another fund of the same investment company. A first step in obtaining results free of survivorship bias, is the inclusion of attrited funds in the sample. We did so by extending the database with the mutual funds that disappeared between the first month of 1989 and the last month of 1994. In the sequel we will refer to this data set, covering 1989-1994, as the combined 'survivorship free' sample[1].

In this paper, following previous studies, we concentrate on equity funds. During the period January 1989 to December 1994, we observe 2678 funds

[1] Unfortunately, Morningstar was unable to provide information about funds that ceased to exist before 1989.

with their name, objective, the year of fund inception, and monthly returns until the month of disappearance. In contrast to Carhart [1997b] we also included specialty funds (i.e. 273 sector funds), internationally diversified U.S. based funds (490) and a number of funds which advertise as 'balanced fund' and invest less than 50% in fixed income securities (180). For 79 funds Morningstar did not report an investment objective. For 33 funds of this group the investment objective was obvious from their name. The remaining 46 funds were classified as having an 'other' investment objective. Table 1 presents the number of funds by inception year and the number of them that did not survive the period January 1989 to December 1994, aggregated to a yearly level. Note that we aggregated all funds with an inception date before 1977, which explains the relative large number of 279 funds with inception year 1976.

Table 1 shows that 498 of the mutual funds in our sample disappeared between January 1989 and December 1994 due to merger or liquidation, which corresponds with a yearly average of 5.3%. This estimate differs from Carhart [1997b], who reports a non-survival rate of 3.6% over the period 1962 to 1995, which increases to 4.6 % for the period 1989 to 1994. The remaining difference with our yearly average is due to inclusion of types of funds in our sample that have relatively low survival rates (compare Table 3 below). Furthermore, looking at, for instance, the 173 funds that started in 1990, 29.5% of them already disappeared within the next four years. A similar pattern seems to hold for other years, so that a first conclusion would be that a large part of the defunct funds disappeared at a relatively young age, age being defined as the time elapsed since fund inception. Apparently, it is not only the case that the number of mutual funds has grown at an increasing rate over the last decade, but also that the relative number of funds that has closed down or merged has increased significantly. At a more disaggregated level (not reported in the table), it appears that in some months relatively many mutual funds leave the sample while in other months almost no funds disappear, indicating that common aggregate factors may play a role in fund disappearance as well.

It is often claimed that a bad record of fund returns is one of the main reasons that funds disappear from a sample (see, e.g. Elton, Gruber and Blake [1996]). Low returns compared to other funds as well as low returns relative to some benchmark portfolio seem to be a reason for the management of the fund to close down the fund or to let the fund merge (see Brown and Goetzmann [1995]). Table 2 presents the average quarterly returns for the

Table 1: **Number of Non-survivors.** The table reports the annual number of funds by inception year since 1976 and the annual number that ceased to exist between 1989 through 1994 . The row labelled 'Non-surv. Rate' contains the number of disappearing funds divided by the total number of funds at the beginning of the year.

Inception year	total in	out in year: 1989	1990	1991	1992	1993	1994	total out
≤1976	279	5	3	4	7	16	8	43
1977	14		1		1	2		4
1978	13			2	2			4
1979	11	1		1		1		3
1980	10					1		1
1981	26	2		1	1			4
1982	33	1		2	2	3	1	9
1983	58	4	3	3	3	3	2	18
1984	75		2	3	2	3	5	15
1985	98	2	5	5	3	6	4	25
1986	143	1	11	8	9	13	7	49
1987	162	3	6	9	7	16	11	52
1988	140	2	2	7	13	14	10	48
1989	107		3	5	4	12	7	31
1990	173			11	6	18	16	51
1991	187				8	7	23	38
1992	277					17	15	32
1993	550					13	40	53
1994	322						18	18
total:	2678	21	36	61	68	145	167	498
Non-surv. Rate (%/yr)		1.98	3.14	4.75	4.82	8.95	8.25	5.31

period 1989-1994 for the funds that survived until the end of 1994, for the funds that did not survive, and for the combined sample. For comparison, we also added the quarterly returns on the Standard and Poor 500 and the returns on a three month Treasury Bill over the same period.

In accordance with other studies, like Malkiel [1995], it appears that in almost all quarters the surviving funds had a higher average return than the non-surviving funds, indicating that low returns increase the probability of disappearance. Furthermore, the average annual return over the period 1989 through 1994 for the sample containing the surviving funds is 0.64% higher than for the combined sample of funds, i.e. 11.44 % versus 10.80 %. In contrast, Malkiel [1995] finds a difference of 1.50 % over the period 1982 through 1991, Elton, Gruber and Blake [1995] even find a difference of 1.87 % for 1976 through 1993, while Brown and Goetzmann [1995] report a difference of 0.80 % over the period 1977-1987. Note that all estimates for this effect of survivorship in computing average returns are higher than the at most 0.40 %, that was claimed by Grinblatt and Titman [1989]. In most quarters the average return of the mutual funds underperforms the S&P500 which could be due to the fact that the equity funds hold bonds and liquidities as well. On an annual basis we find a difference between the S&P500 and the combined sample of funds of 1.52 %, i.e. 12.32 % versus 10.80 %.

In order to examine whether the survival rate varies with the funds' investment objective, we broke down the sample by investment styles. While Morningstar reports investment objectives in thirteen different categories, we chose to follow other studies (Malkiel [1995], Brown and Goetzmann [1995]), and decided to split the sample, for ease of comparison, into six categories. The category 'other' represents the equity funds that could not be clearly assigned to any of the other five categories, so it contains, for instance, the funds that advertise as equity fund and invest less than 50% in fixed income securities as well as the funds with unknown investment objective. Table 3 presents the average quarterly return over the period 1989-1994 for all funds as well as for the subset of funds that survived until the end of 1994 for each of the six investment objectives[2]. It appears that the categories 'specialty' and 'other' had the highest percentage of non-survivors. Moreover, the difference between the average annual returns for the 'specialty' category is 1.40%, which is much higher than the 0.64% for the aggregated sample of

[2]Note that a fund's investment objective is self-reported and can therefore easily lead to gaming to improve relative ex post return rankings (see Brown and Goetzmann [1997]).

Table 2: **Average quarterly returns.** The table reports the average quarterly returns for the funds that survived until the end of 1994, average quarterly returns for the funds that ceased to exist during 1989-1994, and the average return for the combined sample. Furthermore, we present the quarterly returns for the Standard and Poor 500 and Treasury bills. The columns labelled 'Number' contain the number of funds over which the average quarterly return is calculated.

quarter	Surviving Funds Mean return	Number	Non-Survivors Mean return	Number	Combined Mean return	return S&P500	return t-bill
1989/01	6.50	819	5.06	296	6.12	7.03	1.85
/02	6.36	830	5.28	294	6.08	8.80	2.19
/03	9.79	843	7.97	289	9.32	10.64	2.10
/04	0.34	858	-0.45	286	0.14	2.05	1.98
1990/01	-2.72	888	-2.78	298	-2.74	-3.02	1.79
/02	5.75	921	4.65	306	5.47	6.29	2.00
/03	-14.91	951	-13.35	300	-14.54	-13.78	1.95
/04	6.83	980	5.01	301	6.40	8.95	1.86
1991/01	15.16	1025	12.30	308	14.50	14.56	1.44
/02	-0.79	1058	-1.21	301	-0.88	-0.21	1.43
/03	6.91	1095	5.99	284	6.72	5.38	1.41
/04	7.24	1129	6.03	278	7.00	8.36	1.20
1992/01	-0.63	1184	-1.75	274	-0.84	-2.55	0.96
/02	-1.07	1213	-1.34	265	-1.12	1.97	0.92
/03	1.44	1298	0.93	254	1.36	3.10	0.83
/04	6.84	1374	5.63	242	6.66	5.10	0.75
1993/01	4.88	1515	3.59	241	4.70	4.28	0.71
/02	2.86	1603	2.10	253	2.75	0.51	0.71
/03	5.69	1732	4.51	164	5.59	2.56	0.75
/04	4.19	1871	2.36	150	4.05	2.31	0.70
1994/01	-3.13	2043	-3.46	136	-3.15	-3.82	0.73
/02	-2.03	2181	-2.61	115	-2.06	0.41	0.90
/03	5.69	2183	2.77	21	5.66	4.92	1.01
/04	-2.45	2184	.	.	-2.45	-0.03	1.20
Mean	2.86	.	.	.	2.70	3.08	1.31

Table 3: **Summary Statistics by Objective Category.** The table shows for six investment objectives categories the average quarterly return for the combined sample and the average quarterly return for the funds that survived until the end of 1994 as well as the number of funds in each category, the number of non-survivors and the corresponding drop-out percentage.

Group Objective	Combined mean return	Combined Number	Surviving Funds mean return	Surviving Funds Number	Drop out %
1: Aggressive Growth	3.70	95	3.88	77	18.9
2: Growth/Small Companies	3.12	1052	3.22	904	14.1
3: Income/Growth-Income	2.49	540	2.59	434	19.6
4: Specialty	2.51	273	2.86	201	26.4
5: Foreign/World	2.04	490	2.18	429	12.4
6: Other	2.05	226	2.17	138	38.9

mutual funds.

4 What Determines Mutual Fund Survival?

In Section 2 we showed that the use of a survivorship free sample does not guarantee that standard estimators of mutual fund performance yield unbiased estimates. Moreover, as we briefly showed in Section 2 and what will be more extensively be discussed in Section 8, the use of a simple weight factor based on the ratio of the unconditional and conditional survival probability is sufficient to correct for survivorship bias in standard estimators. Consequently, in order to correct for survivorship bias we first of all have to determine the factors that affect mutual fund survival probabilities, which moreover, allows us to analyze the effects of survivorship on a variety of performance evaluation techniques.

In the previous section we noted that mutual funds that leave the sample have on average lower returns. Moreover, most of the disappearance occurs at a relatively young age, indicating that a bad record of returns in the first few years of its existence seriously decreases a fund's survival probabilities. It can also be noted that in particular months fund disappearance is much larger than can be expected on the basis of observed returns. To account for this, we include a common time effect in our specification.

Let y_{it} be an indicator variable that indicates whether or not fund i has an observed return in period t. Our first specification describes the probability of fund survival ($y_{it} = 1$) using a longitudinal probit model, such that a fund survives if an underlying latent variable, y^*_{it} is positive. That is,

$$\begin{aligned} y^*_{it} &= \alpha + \sum_{j=1}^{J} \gamma_{ij}(r_{i,t-j} - \theta) + \phi age_{i,t-1} + \lambda_t + \eta_{it} \qquad (7) \\ y_{it} &= 1 \text{ if fund } i \text{ is observed in quarter } t \ (y^*_{it} > 0) \\ y_{it} &= 0 \text{ otherwise} \end{aligned}$$

where $r_{i,t-j}$ is the return of fund i in quarter $t-j$, θ is an unknown constant, $age_{i,t-1}$ is the time in years since fund inception, and λ_t denotes a time effect describing economy wide effects. The error term η_{it} is assumed to be standard normally distributed, independently over funds and periods. i.e. $\eta_{it} \sim IIN(0,1)$. The γ coefficients measure the impact of historical returns and, potentially, vary over funds and lags. To prevent that the model only applies to funds that have a return history of at least J quarters, and is thus conditional upon having survived these J quarters, we employ a flexible parametrization of the effects of lagged returns such that the model is conditional upon the observed return history only. In addition, to avoid dimensionality problems, we assume that the γ_{ij}'s can be described by a polynomial in j, multiplied by a factor that depends upon the number of lagged returns that is available. Let m_{it} denote the number of lagged quarterly returns that is available for fund i in quarter t, with a maximum of J. Then, we assume the following structure for the lagged quarterly returns coefficients[3]

$$\gamma_{ij} = (1 + \xi \ln[J + 1 - m_{it}]) \sum_{k=0}^{3} a_k j^k . I(j \leq m_{it}), \qquad (8)$$

where $\sum_{k=0}^{3} a_k j^k$ is a polynomial of degree three, and $I(\,)$ is the indicator function that equals 1 if j is smaller than or equal to m_{it} and 0 otherwise. Note that for mutual funds with a return record of more than J quarters, the lagged quarterly returns coefficients can simply be described by $\sum_{k=0}^{3} a_k j^k$. The advantage of a polynomial lag structure is that we only have to estimate a restricted number of parameters, increasing precision of the estimates, and, moreover, a smooth pattern of the coefficients is automatically imposed. As

[3]For notational simplicity, the fact that the γ_{ij} coefficients vary over time as a function of m_{it} (for a subsample of the funds) is not reflected in their indices.

it is implicitly assumed that further lags of the returns are irrelevant, we restrict the polynomial coefficients such that the hypothetical coefficient for lag $J+1$ is zero. This gives an additional restriction that can be substituted in (7) and reduces the number of parameters describing variation in γ_{ij} to four. It should be noted, because of the presence of the time effects and the truncation of m_{it}, that both ξ and θ are only identified from information contained in funds that exist less than 12 quarters.

We estimate (7) with four ($J = 4$), eight ($J = 8$) and twelve ($J = 12$) lagged quarterly returns included, over the period 1989/01 through 1994/04. Table 4 reports the estimates for the lagged quarterly return parameters γ_1 through γ_J, the constant fund return parameter θ and the age parameter ϕ. The coefficient estimates for the time dummies can be found in Table 9 (Appendix B). It appears that lagged quarterly returns, age of the fund and the aggregate time effect have a significant effect on fund disappearance (at the 5% level). Low returns for a number of consecutive quarters increase the probability of leaving the sample. The positive coefficient for age indicates that, *ceteris paribus*, the older the fund, the more likely it is to survive. It is also clear from the results that the probability of fund disappearance varies significantly over the quarters, even if returns have not changed. Note that the time effects capture all fund-invariant variables, including, for example, the return on the market portfolio and the term structure of interest rates. Most strikingly, during the third quarters of 1993 and 1994, fund disappearance has been much more likely than in other quarters.

The estimated values for ξ vary a lot between the specifications and are not significantly different from zero. This indicates that the absolute weights of recent historical returns do not increase for funds with a short history. Put differently, the returns in, say, the last four quarters are equally important irrespective of whether the fund has a history of just these four or more than twelve quarterly returns. The coefficient θ serves the purpose of adjusting the mean of the probit function when m_{it} changes, such that the number of returns included does not give a spurious effect on the survival probabilities through their nonzero means.

The three specifications in Table 4 are tested against each other and against more general alternatives. Note that the number of parameters in each of the three models is the same. To test whether the inclusion of additional lags would improve the models, we applied variable addition test to the three specifications. These tests are Lagrange Multiplier tests for the null hypotheses that the coefficients for one or more additional lags, added

Table 4: **Estimation results.** The table presents estimation results for probit specification (7) with four ($J = 4$), eight ($J = 8$) and twelve ($J = 12$) lagged quarterly returns, a constant fund return θ, age of the fund (in years) and 24 time dummies as explanatory variables. We do not report the estimates for the polynomial coefficients, but only report the implied estimates for the lagged quarterly returns under the condition that a fund has more than J quarterly returns available. Note that for funds with less than J historical returns available, the coefficients for the lagged return should be inflated by a factor (see main text). The total number of observations is 36311.

	$J = 4$		$J = 8$		$J = 12$	
	estimate	std. err	estimate	std. err	estimate	std. err
α	3.208	0.231	3.416	0.224	3.257	0.213
r_{t-1}	0.013	0.003	0.014	0.003	0.014	0.003
r_{t-2}	0.016	0.003	0.012	0.002	0.014	0.002
r_{t-3}	0.019	0.003	0.013	0.002	0.015	0.002
r_{t-4}	0.015	0.003	0.014	0.002	0.015	0.002
r_{t-5}	.		0.016	0.002	0.015	0.002
r_{t-6}	.		0.016	0.002	0.014	0.002
r_{t-7}	.		0.014	0.002	0.013	0.002
r_{t-8}	.		0.009	0.002	0.012	0.002
r_{t-9}	.		.		0.010	0.002
r_{t-10}	.		.		0.008	0.002
r_{t-11}	.		.		0.006	0.002
r_{t-12}	.		.		0.003	0.001
θ	11.394	2.229	8.390	1.215	6.878	0.795
ξ	-0.603	0.309	0.087	0.107	-0.066	0.064
age_{t-1}	0.016	0.004	0.019	0.004	0.025	0.005

unrestrictedly to the model, are zero. More details about this and subsequent tests are provided in Appendix A.

Panel A of Table 4 presents the outcome of the tests for the inclusion of additional lagged returns. Clearly, the specifications with $J = 4$ and $J = 8$ are overly restrictive and have to be rejected against alternatives with additional lags. For the model with three years of quarterly returns ($J = 12$) it cannot be rejected that further lags have zero coefficients. As it is well known that violation of the assumption of homoskedastic error terms typically leads to inconsistency of the maximum likelihood estimators in limited dependent variable models (see, e.g. Amemiya [1986 p. 268 ff.]), we also test the specification with $J = 12$ against heteroskedastic alternatives, the error variance being functions of lagged returns, fund age or both. The results of the Lagrange Multiplier tests, presented in Table 4, do not cause any doubt on the validity of the homoskedasticity assumption. Another crucial assumption is that of normality, which we tested against the more general Pearson family of distributions, as described by Newey [1985]. Somewhat surprisingly given the large number of observations, we are not able to reject normality either. Finally, we tested the inclusion of nonlinear functions of age and once more do not reject the model.

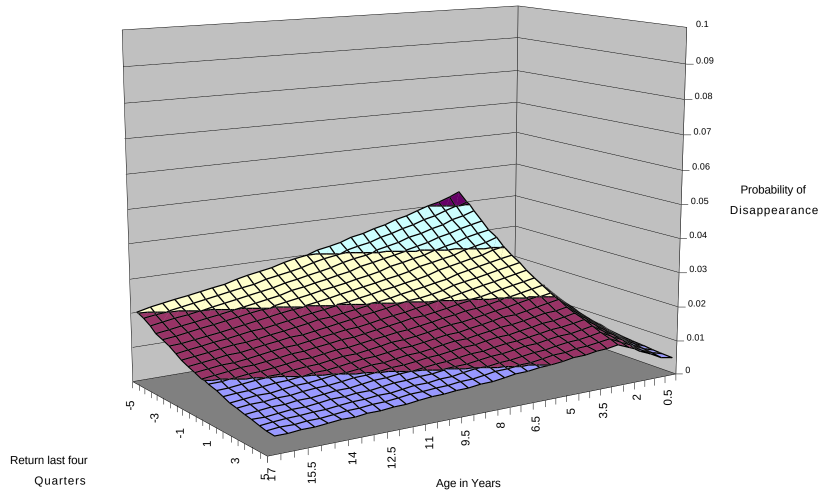
Let us now look at our preferred specification with $J = 12$ in more detail. For funds with a return history of less than 12 months, the coefficients in Table 4 are not appropriate and should be adjusted with the estimated factor $\xi \ln(J + 1 - m_{it})$ and set to zero for the unavailable returns. The results of this exercise are presented in Table 10 in Appendix B. Using the estimates for the panel data probit model with 12 quarterly returns included, we can compute the probability that a fund will disappear in the next quarter given the past record of returns and the age of the fund[4]. In Figure 3 we show the probability of disappearance for funds with different ages, where the past record of returns varies from -5% to $+5\%$ for each of the last four quarters and the quarterly returns for the quarters $t-5$ through $t-12$ are fixed at 3.00 %, corresponding to the average quarterly return over the period 1989-1994. The probabilities are averaged over the 24 different quarters. Alternatively,

[4]Because of the inclusion of the fixed time effects, probabilities are also conditional upon aggregate market movements. As these may not be observed in advance, the probabilities of survival do not correspond to ex ante probabilities, as employed in Brown, Goetzmann and Ross [1995]. Eliminating biases, which is an ex post exercise, does not require knowledge of these ex ante probabilities, but rather the survival probabilities conditional upon other observables.

Table 5: **Results of misspecification tests.** The table reports for the specifications (7) and (9) outcomes of LM tests for missing impacts of past performance of the fund, its style and the specification of age. All test statistics have an asymptotic null distribution that is Chi-squared with degrees of freedom given by DF. A * indicates rejection at the 5% level. See Appendix A for details

Panel A: Variable Addition Test				
Specification	Additional variable(s)	DF	LM-statistic	p-value
(7) $J = 4$	r_{t-5}	1	7.43*	0.006
	$r_{t-5}...r_{t-8}$	4	45.99*	0.000
(7) $J = 8$	r_{t-9}	1	7.91*	0.005
	$r_{t-9}...r_{t-12}$	4	12.89*	0.012
(7) $J = 12$	r_{t-13}	1	1.77	0.183
	r_{t-13}, r_{t-14}	2	2.54	0.280
	style dummies $g_1...g_5$	5	57.61*	0.000
	age_{t-1}^2	1	2.28	0.131
	$\sqrt{age_{t-1}}$	1	3.54	0.060
(9) $J = 12$	r_{t-13}	1	1.32	0.251
	r_{t-13}, r_{t-14}	2	2.01	0.366
	age_{t-1}^2	1	2.64	0.104
	$\sqrt{age_{t-1}}$	1	3.31	0.069
Panel B: Heteroskedasticity Test				
Specification	Variable(s)	DF	LM-statistic	p-value
(7) $J = 12$	$r_{t-1}...r_{t-12}$	3	0.13	0.988
	$r_{t-1}...r_{t-12}$, age_{t-1}	4	0.21	0.995
(9) $J = 12$	$r_{t-1}...r_{t-12}$, age_{t-1}	4	0.13	0.998
	$r_{t-1}...r_{t-12}$, $age_{t-1}, g_1..g_5$	9	0.43	0.999
Panel C: Normality Test				
Specification		DF	LM-statistic	p-value
(7) $J = 12$		2	4.16	0.125
(9) $J = 12$		2	2.82	0.244

Figure 1: **Non-Survival Probabilities.** The figure shows the probability of disappearance for different years since fund inception (Age). The return for each of the last four quarters, i.e. $r_{t-1}...r_{t-4}$, varies between -5% to +5%, while the returns over the quarters r_{t-5}... r_{t-12} is fixed at 3% per quarter.



we could have fixed the time effect to its average over the quarters.

It appears that, for instance, a 3-year old fund with a return of -5% for each of the last four quarters has a probability of almost 4% to disappear in the next quarter, while a 16-year old fund with a comparable return record only has a probability of almost 2% to disappear. On the other hand, the probability of attrition drops below 1% if a fund of age sixteen had a return of +5% for the last four quarters.

The signs we find for the estimated coefficients in the probit specifications are in accordance with the results of Brown and Goetzmann [1995]. Our specification can be interpreted as a reduced form specification of their model, that also includes the size of the fund and the expense ratio as explanatory variables. While we do not observe the size of a fund during the entire sample period, it has been well documented (see, e.g., Rockinger [1995] and Sirri and Tufano [1998]) that (relative) historical returns are key determinants of capital flows to mutual funds. In contrast to our reduced form model, Brown and Goetzmann [1995] did not include time effects nor test for their presence. It is important to allow for fixed time effects to incorporate common aggregate shocks that affect the survival of all funds, such as bad returns on the stock market as a whole. Omitting the time effects, which may be correlated with the regressors, yields inconsistent parameter estimates (Baltagi [1995, p. 178 ff.]) and inappropriate bias corrections. The model with fixed time effects (or any other fund-invariant variables) can only be estimated consistently for the number of funds tending to infinity. We shall therefore assume that the cross-section of funds is sufficiently large (compare footnote 10).

In order to examine whether mutual funds with different investment objectives have different probabilities of leaving the sample, we tested whether the inclusion of investment objective dummies significantly improves the model. Given that this test strongly rejects (see Table 4), we extended the survival model in (7) to include dummies for each investment objective. This leads to:

$$\begin{aligned} y_{it}^* &= \alpha + \sum_{j=1}^{J} \gamma_{ij}(r_{it-j} - \theta) + \phi age_{i,t-1} + \\ &\quad \delta_1 g_{1i} + \delta_2 g_{2i} + \delta_3 g_{3i} + \delta_4 g_{4i} + \delta_5 g_{5i} + \lambda_t + \eta_{it} \\ y_{it} &= 1 \text{ if fund } i \text{ is observed in quarter } t \ (y_{it}^* > 0) \\ y_{it} &= 0 \text{ otherwise} \end{aligned} \tag{9}$$

where g_{1i} through g_{5i} denote the investment objective dummies, corresponding to the classification in Table 3. As before, we assume that the structure for the lagged quarterly return coefficients γ_{ij} can be described by (8). Table 6 reports the estimates for specification (9) with twelve lagged quarterly returns included ($J = 12$), while the coefficient estimates for the time dummies can be found in Table 9 (Appendix B). In Table 4, we also report the outcomes for the tests of the homoskedasticity and normality assumption in specification (9).

From Table 6, it appears that U.S. based internationally investing mutual funds, i.e. investment objective 'foreign', have, *ceteris paribus*, the highest probability to survive. Moreover, the positive coefficients for the investment dummies in the majority of cases indicates that the mutual funds with investment objective 'aggressive growth' and investment objective summarized by the category 'other' have the highest probability to disappear. The estimated coefficients for the lagged returns, and age are similar to those for specification (7). While specification (9) describes survival probabilities conditional on a larger information set that includes investment objective, the significance of the investment dummies suggests that it can be expected that the

Table 6: **Estimation results Investment Categories dummies.** The table presents estimation results for probit specification (9) with twelve ($J = 12$) lagged quarterly returns, a dummy for the investment objective, a constant fund return θ, age of the fund (in years) and 24 time dummies as explanatory variables. We do not report the estimates for the polynomial coefficients, but only report the implied estimates for the lagged quarterly returns under the condition that a fund has more than 12 quarterly returns available. The total number of observations is 36311

$J = 12$					
	estimate	std. err		estimate	std.err
α	3.161	0.232			
r_{t-1}	0.013	0.003	δ_1 : Growth	0.163	0.102
r_{t-2}	0.014	0.002	δ_2 : Income	0.090	0.105
r_{t-3}	0.015	0.002	δ_3 : Specialty	0.085	0.112
r_{t-4}	0.015	0.002	δ_4 : Foreign	0.310	0.112
r_{t-5}	0.015	0.002	δ_5 : Other	-0.287	0.073
r_{t-6}	0.015	0.002	θ	6.617	0.761
r_{t-7}	0.014	0.002	ξ	-0.063	0.068
r_{t-8}	0.013	0.002	$\phi : age_{t-1}$	0.024	0.005
r_{t-9}	0.011	0.002			
r_{t-10}	0.009	0.002			
r_{t-11}	0.006	0.002			
r_{t-12}	0.003	0.001			

error term η_{it} in (7) exhibits fund-specific serial correlation. We will therefore use specification (9) in the empirical analysis. For the Monte Carlo experiments in Sections 7 and 8, where we do not distinguish different investment styles, we use specification (7).

5 The Effects of Survivorship on Performance Measures

In Section 2 we examined in a stylized example the effect of non-random attrition on a simple performance measure like the average fund return using a survivorship free sample as well as a sample plagued by survivorship. Let us now look at a more realistic example, where interest lies in the estimation of fund alphas and their persistence. To do so, we perform a Monte Carlo simulation experiment. Following the set-up of Brown, Goetzmann, Ibbotson and Ross [1992], we generate quarterly returns from the following one factor model

$$r_{it} = r_{ft} + \beta_i(R_{mt} - r_{ft}) + u_{it} \tag{10}$$

where r_{ft} is the short term interest rate and $R_{mt} - r_{ft}$ is the quarterly excess return on the market portfolio. The idiosyncratic error term u_{it} is independent of the quarterly risk premium and is assumed to be normal with mean zero and variance σ_i^2, given by

$$\sigma_i^2 = k(1 - \beta_i)^2. \tag{11}$$

This relationship is a rough approximation to the relationship between non-systematic risk and β that is often observed in mutual funds data. We employ a set of parameter values in the return generating process that closely matches the first two sample moments of returns and beta. The quarterly excess return on a market portfolio is i.i.d. normal with mean 0.0215 and standard deviation 0.104, β is i.i.d. normal with mean 0.93 and standard deviation 0.37 and the value of k equals[5] 0.01997. Moreover, we assume that

[5] The value of k that we employ is based on the sample average of $\hat{\sigma}_i^2/(1 - \hat{\beta}_i)^2$.

the short term interest rate can be described by an AR(1) model given by[6] [7]

$$r_{ft} = \mu + \rho(r_{ft-1} - \mu) + \epsilon_t, \quad \epsilon_t \ i.i.d. \ N(0, \sigma_\epsilon^2). \tag{12}$$

The simulation experiment proceeds as follows. We start with a 'random' number of funds such that an average 2% increase per quarter leads to 2500 mutual funds in the final quarter. This leads to a sample where the number of funds increases each quarter, while none of the funds drops out. Next, we apply the survival model of the previous section, i.e. equation (7) with twelve lagged returns ($J = 12$), to determine for each fund in each period the probability that it leaves the sample. This means that from the record of historical returns, the age of the fund and an aggregate time effect, a probability $\hat{p}_{it}$ of leaving the sample in the next quarter is determined. Then fund i leaves the sample in period t with a probability $\hat{p}_{it}$. Note that this assumes that η_{it} is independent of current returns, that is, the probability of survival only depends upon age and historical returns, and – conditional upon those – not upon current returns. Since the age of the fund, defined as the years since fund inception, is a significant factor in fund disappearance, we decided to draw a random age for the funds that already exist in the first quarter, closely corresponding to the observed age distribution in our sample of mutual funds, i.e. $age_1 \sim abs(N(0, 16))$. The survivorship process used in our simulations is thus more complicated but also more realistic than the rules applied by Brown, Goetzmann, Ibbotson and Ross [1992] and Hendricks, Patel and Zeckhauser [1997], who simply remove, for instance, the worst performing 10% of the mutual funds in each period.

Note that the estimated time effects in probit specification (7) reflect aggregate shocks. We take the potential dependence between the time effects and observed aggregate variables in the model into account by running a number of regressions on variables such as the return on the S&P500 and the return on a three-month Treasury Bill over the period 1989-1994. Table 11 in Appendix B presents the estimation results for a number of specifications. It appears that the time effect is significantly correlated with the risk-free return on Treasury bills. Accordingly, the random effect that is used in the simulations is drawn from a normal distribution with mean $\mu_{\lambda_t} = 2.29 +$

[6] An OLS estimation of the short rate AR(1) process over the period 1976-1994 yields $r_{ft} = 0.140 + 0.922 * r_{ft-1} + \epsilon_t$, with $\hat{\sigma}_\epsilon = 0.003$.

[7] In the simulations, the average T-bill return over 1976-94 of 0.018 is used to start the process. Moreover, if a risk free rate smaller than zero happens to be generated, we set it equal to zero.

Table 7: **Simulated average quarterly returns and betas** The table presents average quarterly returns and betas for 500 simulated samples of surviving funds, non-surviving mutual funds, the combined sample as well as the sample without attrition. Standard errors in parentheses. Averages are computed over 36 quarterly mean returns.

	Average return		Average β
Without	3.72	(0.02)	0.93
Survivors	3.80	(0.02)	0.93
Combined	3.68	(0.02)	0.92
Non-Survivors	2.42	(0.01)	0.90

$0.332 * r_{ft}$ and variance equal to $\sigma_\lambda = 0.079$. Note that a high risk-free rate leads to, on average, higher time effects, but the effect on the survival rate might be balanced by higher (nominal) returns. The numbers presented below refer to averages or standard deviations over 500 replications. In order to prevent sensitivity to the starting conditions, we do not use the first 24 quarterly returns, i.e. fund returns are generated from quarter 1 onwards, while the survival process starts operating from quarter 13 and further.

We now construct four different samples. The first sample is the one without attrition and contains all funds up to the last period. We will refer to this hypothetical complete sample as "without" and we will only use it in a few cases. The second sample suffers from survivorship, as generated by our model, and contains only those funds that happened to survive until the end of the last quarter. We refer to this sample as "survivors". A third sample consists of the survivors sample completed with observations on those funds that left the sample before the last quarter. We refer to this sample as "combined". Most recent empirical studies (e.g. Brown and Goetzmann [1995], Carhart [1997a], Wermers [1997]) employ such survivorship free samples. A fourth and last sample named "non-survivors" is used for comparisons only and contains only the non-surviving funds.

First, Table 7 presents average quarterly returns over 36 quarters in the different samples. As expected, the mean return of the surviving funds substantially exceeds (i.e. 0.48% on an annual basis) the mean return for the combined or 'survivorship bias free' sample, at least if the parameter values in the simulation have been chosen to match the sample means. Furthermore, it appears that the non-surviving funds have, on average, a lower β than the surviving mutual funds.

Another important topic in performance analysis of mutual funds is the persistence in returns. Empirical studies by Brown and Goetzmann [1995], Malkiel [1995] and Carhart [1997a] examine whether 'winning' mutual funds, where winning is defined as exceeding the median fund return in a given period, are more likely to be winners in the next period. Studies of Brown, Goetzmann, Ibbotson and Ross [1992] and Hendricks, Patel and Zeckhauser [1997] show that survivorship bias induces spurious persistence patterns if there is cross-sectional variation in expected returns or risk. Instead of hypothesizing a certain survival process, we use the empirical survival model that matches the sample of U.S. equity funds, to redo the calculations of Hendricks, Patel and Zeckhauser [1997], who found a spurious J-shape pattern in performance persistence. As we generated fund returns such that any abnormal return is the result of (unpredictable) luck, any regularity found in performance measures is necessarily spurious and due to survivorship bias.

The performance of the funds is evaluated by estimating Jensen's α from the one-factor model in (16), over four three-year periods. We sort the funds on the basis of the estimated α's in each three-year period into eight groups. For each octile group, we calculate the average Jensen's α in the subsequent three-year period. Table 8 presents the average α for each group for the sample that only contains the surviving mutual funds, the sample that also contains the funds that ceased to exist before the final quarter, and the hypothetically complete sample, not affected by attrition.

It appears that the sample of surviving mutual funds exhibits a strong pattern of spurious persistence in performance. Furthermore, this is also the case for the combined sample, that includes funds that did not survive until the final quarter, although the pattern is somewhat weaker. Clearly, the fact that the data is survivorship free does not imply that a standard analysis is free of survivorship bias. Although the spurious persistence pattern is not exactly J-shaped, the simulation results more or less confirm the bias found by Hendricks, Patel and Zeckhauser [1997]. The argument for such a pattern is a risk argument. Funds in one of the extreme ranks are more likely to be 'high risk' funds and thus less likely to survive. Conditional on the fact that they did survive in the second subperiod, they will have made better returns than average. Compared to Hendricks, Patel and Zeckhauser, we find an additional upward bias in Jensen's α for the lower octiles. The reason for this is that our survival process is dynamic. Funds with a low rank realized relatively bad returns in the first twelve quarters. As this will decrease a fund's probability over the next twelve quarters to survive, these

Table 8: **Simulated performance persistence.** The table presents the subsequent period performances for simulated samples of surviving funds, for samples that also contain the non-surviving funds until the quarter of disappearance and for samples that are not effected by survivorship. Standard errors in parentheses.

Initial Period Rank	Performance Subsequent Period					
	Survivors		Combined		Without	
1	0.162	(0.007)	0.117	(0.006)	0.004	(0.005)
2	0.064	(0.005)	0.045	(0.004)	-0.001	(0.004)
3	0.035	(0.003)	0.024	(0.003)	0.001	(0.003)
4	0.018	(0.002)	0.014	(0.002)	0.001	(0.002)
5	0.024	(0.003)	0.017	(0.003)	-0.002	(0.002)
6	0.045	(0.004)	0.031	(0.004)	-0.002	(0.003)
7	0.064	(0.005)	0.042	(0.005)	-0.001	(0.004)
8	0.143	(0.008)	0.095	(0.008)	-0.000	(0.006)

funds must have made up for these bad returns given that they have survived. Apparently, with our parameter values this effect is large enough to change the J-shape into a (more or less) U-shape. As expected, the sample that is not affected by survivorship does not exhibit a spurious persistence pattern.

6 Correcting for Survivorship Effects

Knowledge of the survival process is a key to correcting for the survivorship effects as discussed in the previous sections. In Section 4 survival of a fund was modelled as a function of historical returns, age and an aggregate time effect. We will show, in this section, how inferences can be corrected for survivorship effects if it can be assumed that fund survival in period t is independent of the return in period t, after conditioning upon lagged returns, fund age and time[8]. Technically, this imposes that η_{it} in (1) is independent of r_{it}, as was assumed in the previous section. The corrections, based upon work of Moffitt, Fitzgerald and Gottschalk [1997], are relatively simple to apply and involve the use of weights as shown in Section 2. As these weights depend upon fund returns, they are endogenous and their use has implications for

[8]Econometric approaches of sample selection and attrition problems based upon the work of Heckman [1979] and Hausman and Wise [1979], assume that the model of interest is conditional upon the same set of variables, which is inappropriate in this case.

consistency of the estimators used.

In general, let R_i denote a vector of returns for fund i that is used in an empirical analysis, for example in constructing a contingency table. Let $Y_i = 1$ if fund i is used in the analysis and 0 otherwise. While Y_i is determined by the researcher, we shall assume that it is a function of y_{it}'s only. The distribution of returns for the funds used in the analysis, conditional on some observed characteristics X_i, is described by $f(R_i|X_i, Y_i = 1)$, where f is generic notation for a density/probability mass function. Because Y_i is not independent of the returns, this distribution differs from the one unconditional upon survival $f(R_i|X_i)$, which is what we are interested in. The set of variables in X_i is chosen by the researcher and could be empty, but could also reflect a fund's investment style, its return history, or its relative historical performance. Let Z_i denote observable fund characteristics that affect the probability of survival. Then it follows, using standard conditioning arguments (see Moffitt et al. [1997] or Fitzgerald et al. [1998]), that we can write

$$f(R_i, Z_i|X_i) = w_i f(R_i, Z_i|X_i, Y_i = 1), \tag{13}$$

where w_i is a weight factor given by

$$w_i = \frac{P\{Y_i = 1|X_i\}}{P\{Y_i = 1|R_i, X_i, Z_i\}}. \tag{14}$$

This weight equals the inverse of the normalized probability that fund i is kept in the sample for funds of type X_i. The left hand side of (19) provides the (un)conditional distribution of returns we are interested in. The right hand side is the conditional observable distribution of returns times a weight factor. If the weights w_i are known, any inference based upon the observed distribution of returns can directly be adjusted to reflect the unconditional distribution. For example, the expected returns of fund i satisfy

$$\begin{aligned} E[r_{it}] &= \\ \int R_i f(R_i, Z_i) dR_i dZ_i &= \int w_i R_i f(R_i, Z_i|Y_i = 1) dR_i dZ_i \\ &= E[w_i r_{it}|Y_i = 1], \end{aligned} \tag{15}$$

which implies that the average of $w_i r_{it}$ rather than the average of r_{it} provides an unbiased estimate of the fund's mean return if r_{it} is observed if $Y_i = 1$ only. Similarly, a fund's alpha can be estimated as

$$\tilde{\alpha}_i = w_i \hat{\alpha}_i, \tag{16}$$

where $\hat{\alpha}_i$ is the usual (uncorrected) ordinary least squares estimate.

Going back to our sample of U.S. equity funds, suppose we are interested in performance as measured by alpha over a period of 12 quarters. This implies that we can only use funds in the analysis that have observed returns for 12 consecutive periods s to $s+11$, and we have that $Y_i = \prod_{t=s}^{s+11} y_{is}$. The probability that $Y_i = 1$ given the fund's returns R_i and characteristics Z_i, X_i is then described by our survival model, provided that X_i is included in the model (or can be assumed to have a zero coefficient), and provided that we assume that, conditional upon historical returns, Z_i and X_i, the probability of attrition in any given period does not depend upon (potentially unobserved) returns in that or future periods. In that case, we can write[9]

$$P\{Y_i = 1|R_i, Z_i, X_i) = \prod_{t=s}^{s+11} P\{y_{it} = 1|r_{i,t-1}, ..., age_i, X_i). \qquad (17)$$

If X_i denotes investment style, the latter probabilities are directly obtained from the survival model in (9). If X_i is empty, one should employ the survival model that does not include investment style, as was done in the simulation exercise. If X_i includes both investment style and historical performance, specification (9) can be used assuming that survival depends upon historical performance only through historical returns. The numerator in (20) reflects the probability of survival for a given X_i. When X_i is empty, and one is interested in returns for arbitrary funds, this can easily be estimated by the ratio of the number of funds that survived from period s to $s+11$ and number of funds that was in the sample in period $s-1$. If X_i denotes investment style or a fund's initial performance ranking, this computation has to be done for each style or ranking separately. Together, this provides estimated weights $\hat{w}_i$ that are consistent for $N \to \infty$. Consequently, we can estimate the alpha of an individual fund asymptotically unbiasedly[10] using (22) with $\hat{w}_i$ instead of w_i.

The approach above is generally applicable as long as it is clear what selection process a researcher is conditioning upon. In order to estimate unconditional expected returns in a given period t, for example, the conditioning is upon participation of each fund in that particular period and the

[9] This assumes that there is no autocorrelation in η_{it} in (3).

[10] Asymptotically unbiased means that the expected value of the estimator equals the true value if the number of funds N goes to infinity. The asymptotics underly consistent estimation of the survival process.

weights simply reflect the probability that $y_{it} = 1$. Averaging over periods then, does not require additional corrections.

In order to illustrate the use of the proposed correction method, we applied it for possible biases in simulated samples generated in Section 7. Recall that in the performance persistence analysis we found a spurious U-shape pattern in the risk-adjusted returns of the formed octiles in the combined as well as survivors-only samples. To correct contingency Table 8 for these biases, we first estimate initial period alphas and their ranking, using funds that have observations over 12 consecutive quarters, and correct these OLS estimates using weights based upon these 12 periods. Next, for the alphas estimated over the second subperiod, which are conditional upon survival of another 12 quarters, we apply a weight correction based upon survival over these 12 periods. As interest lies in the distribution of alphas conditional upon a fund's initial rank, the numerators in the weights correspond to survival probabilities for a given octile.

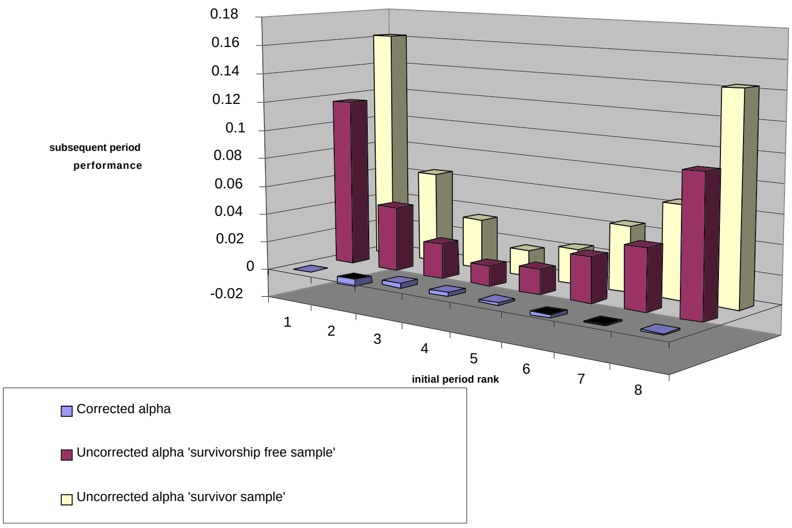
In Figure 4 we present the average corrected Jensen's alpha in the subsequent three-year period for each octile group, where octile one represents the worst performing funds of the initial period. For comparison, the figure also contains the uncorrected results for the samples of surviving funds only and the samples that also contain the non-surviving funds until the quarter of disappearance, as given in Table 8.

It is quite clear that the spurious persistence pattern that was present in the combined sample of funds has disappeared. While not reported, the standard errors show that the average corrected Jensen's alphas of the octile groups are not significantly different from zero anymore. Furthermore, while the Monte Carlo results show how the spurious persistence pattern can be eliminated if there is no genuine persistence, the correction with weights can also be applied to obtain estimates of performance persistence that do not suffer from biases.

7 Empirical Results

A substantial number of empirical papers report persistence in the performance of mutual funds over one to three year horizons, see, e.g., Hendricks, Patel and Zeckhauser [1993], Gruber [1996], Carhart [1997a] or Wermers [1997]. Mostly, these papers suggest that their results are free of survivorship bias and no attempts are made to correct for potential biases, apart

Figure 2: **Simulation results survivorship bias correction on alpha.** The figure shows the subsequent period performances for simulated samples of surviving funds (Uncorrected alpha 'survivor sample'), for samples that also contain the non-surviving funds (Uncorrected alpha 'survivorship free sample'), and for samples that contain the non-surviving funds but with performance correction for look-ahead bias (Corrected alpha).



from the inclusion of attrited funds' returns in the sample. In this section, we address the question of short-term predictability of mutual fund performance correcting for survivorship biases using the methodology discussed in the previous section.

As our sample of attrited funds goes back to only January 1989 we can estimate survival probabilities only over the period 1989/1-1994/4, and our survivorship bias free methodology is limited to equity funds over this period. While this sample period is relatively short, we do not feel that this is a serious drawback. Given the huge increase in the number of mutual funds, and their holdings, over the last decade, it may be hard to argue that information from the 1960s and 1970s is relevant for current investment decisions. Thus, we prefer to work with a short but recent time period, with a fairly large cross-sectional dimension, as required by our methodology (compare footnote 10).

Contrary to the simulation experiment, where a one-factor pricing model was adequate to price all assets, we cannot be sure about the model with respect to which risk-adjusted or abnormal returns should be defined. First, we shall apply a simple one-factor model, given by:

$$r_{i,t+1} - r_{f,t+1} = \alpha_i + \beta_i(r^m_{t+1} - r_{f,t+1}) + \varepsilon_{i,t+1}, \tag{18}$$

where $r_{i,t+1}$ is the return on mutual fund i in period $t+1$, r^m_{t+1} is the return on the market portfolio in period $t+1$ and $r_{f,t+1}$ is the return on a risk free asset. Second, we use Carhart's [1997a] four-factor model given by:

$$r_{i,t+1} - r_{f,t+1} = \alpha_i + \beta_{mi}(r^m_{t+1} - r_{f,t+1}) + \beta_{si}r^{smb}_{t+1} + \beta_{hi}r^{hml}_{t+1} + \beta_{pi}r^{pr1yr}_{t+1} + \varepsilon_{i,t+1}, \tag{19}$$

where r^{smb}_{t+1} is the difference between the returns on a portfolio of small stocks and one of big stocks, r^{hml}_{t+1} is the difference between the returns on a portfolio of high book-to-market and a portfolio of low book-to-market stocks and r^{pr1yr}_{t+1} is the difference between the return on a portfolio of stocks with the highest return over the previous year and a portfolio of stocks with the lowest return over the previous year[11]. We shall refer to α_i in (24) and (25) as the Jensen's alpha.

The question we try to answer is to what extent the ranking of a fund's alpha, over the subperiod 1989/1-1991/4, is informative about its alpha in the second subperiod 1992/1-1994/4. We do so by first estimating Jensen's alphas from (24) and (25) over the initial three-year period for all funds in the sample that survived these twelve quarters. These least squares estimates are biased because they are conditional upon survival. To correct for these biases, we employ the estimated survival probabilities as described by model (9) that also includes the investment style of a mutual fund. Using the technique of Section 8, we correct the estimated α for survivorship bias using

$$\tilde{\alpha}_i = \frac{\hat{q}_s}{\Pi_{s=1}^{s+11}\hat{p}_{is}}\hat{\alpha}_i, \tag{20}$$

where $\hat{p}_{is}$ is the estimated probability that fund i leaves the sample in period s, and $\hat{q}_s$ is the ratio of the number of funds in the same investment category as fund i that survived from period s to $s+11$, and the number of funds in

[11]We are very grateful to Mark Carhart for providing the data with returns on the market index, SMB portfolio, HML portfolio and PR1YR portfolio.

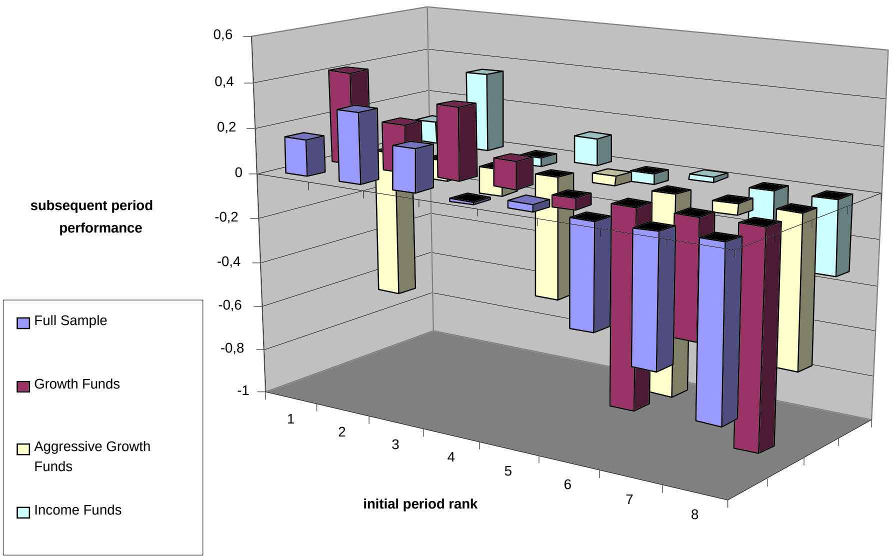
that category that was in the sample at $s-1$. In the next step, we sort the funds into octiles on the basis of the corrected Jensen's α. For the subsequent three year period, i.e. 1992-1994, we estimate alphas, again correcting the OLS estimates using (26), where $\hat{q}_s$ now corresponds to the proportion of survived funds in the corresponding octile.

The results are summarized in Figures 5 and 6. These figures present the average corrected Jensen's α in the subsequent three year period for each octile group of a number of different subsamples, where octile one represents the worst performing funds of the initial period. Figure 5 is based on the one-factor model given in (24), while Figure 6 represents the four-factor model given in (25). Both pictures show the persistence patterns for the funds with investment objectives 'growth', 'aggressive growth' and 'income', as well as that for the combined sample that combines these three investment objectives ('full sample'). Because neither factor model seems particularly adequate in explaining returns for funds in one of the remaining investment categories ('specialty', 'foreign' and 'other'), we excluded these categories from the figures.

For the one-factor model, the full sample of funds does not exhibit any positive persistence. Funds with a risk-adjusted return in the initial period that is below the median, have the highest Jensen's alpha in the subsequent period, and, on average, outperform the model by about 0.2% per quarter. On the other hand, the best performing funds of the initial period even have a negative average alpha in the evaluation period, corresponding to an underperformance of 0.6% per quarter. The result that we find for the one-factor model is in contrast with the strong evidence for a 'hot hand' phenomenon reported by Malkiel [1995]. Note that Malkiel used a survivorship free sample, but did not correct for the potential presence of survivorship bias. At a disaggregate level, 'growth' funds have a similar reverse pattern as the full sample of funds, while 'aggressive growth' funds show a negative U-shape pattern in the subsequent period. The 'income' funds do not exhibit a clear pattern of performance persistence, but it seems that the best performing funds of the initial period belong to the worst performing in the second period.

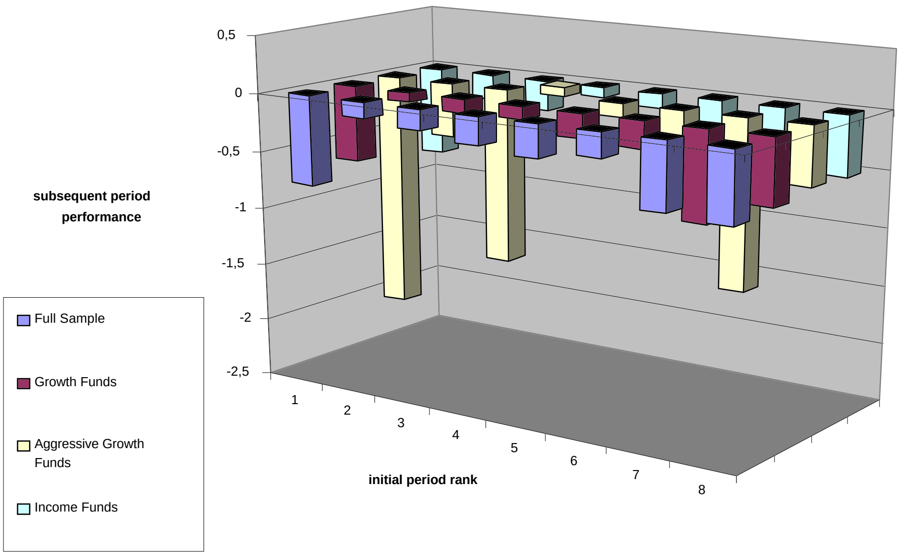
However, if we move away from the one-factor model and concentrate on Carhart's four-factor model, we find that for the full sample of funds, as well as its subsamples, the (reverse) persistence patterns have disappeared. There is no octile for any of the subsamples that significantly outperforms the model. Alternatively, this can be interpreted that the four factors in (25) account for the reverse persistence pattern of the one-factor model. It

Figure 3: **Empirical results for the bias corrected one-factor performance persistence pattern.** The figure shows the subsequent period performance measured by a one-factor model for the full sample of funds and for the funds with as investment objective: growth, aggressive growth and income. All results are corrected for bias using the procedure outlined in the text.



appears that the worst performing funds of the initial period are also the worst performing in the subsequent period, with an underperformance of 1% per quarter, implying persistence of bad performance for this group of funds. The pattern we find for the four-factor model is in accordance with the one reported by Carhart [1997a], indicating that our results do not support a hot hand phenomenon in mutual fund performance. However, in contrast to our findings, the best performing funds of Carhart's initial period have a slightly positive Jensen's alpha in the subsequent period. Moreover, the worst performing funds of Carhart's sample show less underperformance than the worst performing funds in the sample that we employ. There are two possible explanations for this difference in result. First of all, the difference in sample period, i.e. 1966-1993 vs 1989-1994. Second, recalling the spurious persistence pattern we found in the simulation experiment, we found that the worst performing funds had a higher persistence bias than the best

Figure 4: **Empirical results for the bias corrected four-factor performance persistence pattern.** The figure shows the subsequent period performance measured by Carhart's four-factor model, for the full sample of funds, and for the funds with as investment objective: growth, aggressive growth and income. All results are corrected for bias using the procedure outlined in the text.



performing mutual funds. Since Carhart's methodology is not free of this survivorship bias (look ahead bias), the difference in the two extreme octiles might be due to this effect.

8 Concluding Remarks

In the recent literature, the importance of survivorship bias in empirical studies in finance has been sufficiently acknowledged. Most studies emphasize the potential biases that can arise from analyzing data conditional upon survival, using more or less ad hoc theoretical models that determine survival. Attempts to correct for these biases are scarce and this paper fills this gap.

We showed how inferences on mutual fund performance can be corrected for survivorship bias using a simple weighting strategy, based upon the estimated survival model. A Monte Carlo experiment showed that the spurious U-shape pattern that arises in estimating performance persistence using traditional techniques disappears with the correction that we propose. In addition, the approach was applied to U.S. equity funds using a one-factor and Carhart's four-factor model. Using the latter model, we do not find any evidence for 1989-1994 of the hypothesis that mutual funds that performed well in the past continue to perform well in the future.

In the paper, we analyzed the potential effect of survivorship bias on various mutual fund performance measures, on the basis of an empirical model of survival, fitted to U.S. equity funds over the period 1989/1-1994/4. This required us to extend the study of Brown and Goetzmann [1995], by examining which factors are important in determining mutual fund survival probabilities. From an extensive analysis of various specifications, it appeared that a specification with twelve lagged quarterly returns, time since fund inception, aggregate time effects and dummies reflecting the investment style has to be preferred. The specification of the survival model was chosen in such a way that it is not conditional upon the existence of a three-year history of returns, so that it also models survival for 'young' funds.

In order to obtain insight in the size of survivorship effects in various performance evaluation measures, a number of Monte Carlo simulation experiments have been performed. By dropping funds from the sample based on the estimated survival probabilities, we analyzed the effect of survivorship on average returns and persistence in risk-adjusted returns, thus extending the analysis in Hendricks, Patel and Zeckhauser [1997]. Although the results are sensitive to the parameter values of the return generating process, we find that, as expected, average returns of samples of surviving funds only, are biased upward. Both the sample with surviving funds, as well as the sample that include returns of both survived and attrited funds, are affected by survivorship bias and generate a spurious persistence in performance. This is important, as it is generally believed and suggested that such survivorship free samples are free of survivorship bias. With the dynamic survival model that was estimated, a spurious U-shape pattern was found in the persistence of risk-adjusted returns, similar to but different from J-shape found in Hendricks, Patel and Zeckhauser [1997].

A Misspecification Tests in the Probit Model

In this appendix we briefly indicate how the different misspecification tests for the probit model have been computed. In particular, we consider Lagrange multiplier (or conditional moment) tests for omitted variables, heteroskedasticity and nonnormality. More details can be found in, e.g., Newey [1985] or Pagan and Vella [1989].

Variable addition tests

Let x_{it} denote the k-dimensional vector of explanatory variables in the probit model, including the time dummies. The log likelihood function for the probit model is given by

$$L(\beta|X,y) = \sum_{i,t} y_{it} \log \Phi(x_{it}'\beta) + \sum_{i,t}(1-y_{it}) \log(1-\Phi(x_{it}'\beta)), \tag{21}$$

so that the first order conditions can be written as

$$\sum_{i,t}\left[\frac{y_{it}-\Phi(x_{it}'\hat{\beta})}{\Phi(x_{it}'\hat{\beta})(1-\Phi(x_{it}'\hat{\beta}))}\phi(x_{it}'\hat{\beta})\right]x_{it} = \sum_{i,t}\hat{\varepsilon}_{it}^{G}x_{it} = 0, \tag{22}$$

where ϕ is the standard normal density function and Φ is the corresponding distribution function. The term in square brackets is referred to as the generalized residual (see Gourieroux et al. [1987]) and denoted $\hat{\varepsilon}_{it}^{G}$. The first order conditions can be interpreted to say as that each explanatory variable should be orthogonal to the generalized residual (over the whole sample).

If r additional variables z_{it} were to be included in the model, it would not change the current estimates if the current estimates already satisfy the additional first order conditions. This means that if

$$\sum_{i,t}\hat{\varepsilon}_{it}^{G}z_{it} = 0 \tag{23}$$

then including z_{it} in the model would not change the current estimates. To test whether the left hand side of (29) significantly differs from zero, we compute the Lagrange Multiplier test statistic as

$$\xi_{LM} = \iota' R(R'R)^{-1}R'\iota \tag{24}$$

where R is a matrix of individual gradients of the loglikelihood function, with typical row

$$(\hat{\varepsilon}_{it}^{G}x_{it}', \hat{\varepsilon}_{it}^{G}z_{it}'),$$

and ι is a vector of ones. It can be shown that under the null hypothesis that z_{it} does not enter the probit specification in (27), the Lagrange multiplier test ξ_{LM} is asymptotically χ^2 distributed with r degrees of freedom.

Testing for heteroskedasticity

Suppose that ε_{it} has a variance of

$$V[\varepsilon_{it}] = h_{it} = h(z'_{it}\gamma)$$

for some function $h > 0$ with $h(0) = 1$ (normalization condition), where z_{it} is of dimension r. Using this specification for the variance the loglikelihood changes to the following form

$$L(\beta, \gamma|X, y) = \sum_{i,t} y_{it} \log \Phi\left(\frac{x'_{it}\beta}{\sqrt{h(z'_{it}\gamma)}}\right) + \sum_{i,t}(1-y_{it}) \log\left(1 - \Phi\left(\frac{x'_{it}\beta}{\sqrt{h(z'_{it}\gamma)}}\right)\right). \tag{25}$$

Now the first order conditions for γ, evaluated under the null hypothesis $H_0 : \gamma = 0$ are

$$\sum_{i,t} \hat{\varepsilon}^G_{it}(x'_{it}\beta)z_{it} = 0.$$

Consequently, it is easy to test $H_0 : \gamma = 0$ using the Lagrange Multiplier test statistic given in (30) using a matrix R that has typical row

$$(\hat{\varepsilon}^G_{it}x'_{it}, \hat{\varepsilon}^G_{it}(x_{it}\hat{\beta})z'_{it}).$$

Testing for non-normality

A test for normality can be derived by specifying an the alternative distribution function as $\Phi(x'\beta + \gamma_2(x'\beta)^2 + \gamma_3((x'\beta)^3)$ (compare Newey, 1985). The null hypothesis of normality corresponds to $\gamma_2 = \gamma_3 = 0$. This can be tested by using (30), where the matrix R now contains

$$(\hat{\varepsilon}^G_{it}x'_{it}, \hat{\varepsilon}^G_{it}(x'_{it}\beta)^2, \hat{\varepsilon}^G_{it}(x'_{it}\beta)^3).$$

B Additional Tables

Table 9: **Estimates time dummy coefficients.** The table reports the estimates for the time dummies for a probit specification with four ($J = 4$), eight ($J = 8$) and twelve ($J = 12$) lagged quarterly returns, and age of the fund (in years) as explanatory variables. The column $J = 12^*$ contains the estimates for the time dummies with as additional explanatory variable a dummy for the investment objective.

	$J = 4$		$J = 8$		$J = 12$		$J = 12^*$	
λ	estimate	std. err	estimate	std. err	estimate	std. err	estimate	std.err
89/02	-0.067	0.259	-0.006	0.261	-0.115	0.260	-0.091	0.263
89/03	-0.289	0.240	-0.266	0.242	-0.351	0.240	-0.341	0.240
89/04	-0.575	0.230	-0.555	0.233	-0.570	0.232	-0.544	0.232
90/01	-0.118	0.275	-0.227	0.275	-0.075	0.279	-0.054	0.280
90/02	-0.182	0.248	-0.306	0.252	-0.176	0.257	-0.165	0.258
90/03	-0.544	0.218	-0.771	0.219	-0.652	0.224	-0.627	0.225
90/04	-0.120	0.231	-0.450	0.230	-0.347	0.234	-0.336	0.235
91/01	0.070	0.243	-0.238	0.241	-0.147	0.242	-0.160	0.243
91/02	-0.572	0.220	-0.796	0.215	-0.744	0.215	-0.725	0.217
91/03	-0.626	0.226	-0.719	0.212	-0.751	0.213	-0.746	0.214
91/04	-0.449	0.233	-0.287	0.236	-0.355	0.235	-0.366	0.235
92/01	-0.636	0.220	-0.576	0.225	-0.598	0.223	-0.616	0.223
92/02	-0.522	0.219	-0.631	0.223	-0.584	0.221	-0.606	0.222
92/03	-0.483	0.218	-0.638	0.221	-0.539	0.223	-0.561	0.224
92/04	-0.510	0.212	-0.818	0.213	-0.634	0.218	-0.654	0.219
93/01	-0.287	0.222	-0.598	0.220	-0.476	0.224	-0.509	0.224
93/02	-0.193	0.233	-0.372	0.230	-0.345	0.233	-0.369	0.233
93/03	-1.286	0.202	-1.410	0.201	-1.407	0.203	-1.442	0.203
93/04	-0.648	0.211	-0.736	0.212	-0.772	0.213	-0.804	0.214
94/01	-0.476	0.215	-0.619	0.217	-0.631	0.217	-0.656	0.218
94/02	-0.533	0.210	-0.715	0.212	-0.684	0.212	-0.712	0.213
94/03	-0.980	0.201	-1.200	0.202	-1.145	0.204	-1.182	0.204
94/04	-0.311	0.212	-0.592	0.210	-0.535	0.213	-0.560	0.213

Table 10: **Quarterly return coefficients (* 100).** The table presents the implied estimates in the probit specification for survival probabilities for the quarterly return coefficients multiplied by 100 for funds with less than $J = 12$ returns available (m_{it})

pm.\ml	1	2	3	4	5	6	7	8	9	10	11	12
γ_1	1.14	1.15	1.16	1.17	1.18	1.19	1.20	1.22	1.24	1.27	1.30	1.36
γ_2	0	1.21	1.22	1.23	1.24	1.25	1.27	1.29	1.31	1.33	1.37	1.44
γ_3	0	0	1.25	1.26	1.28	1.29	1.30	1.32	1.34	1.37	1.41	1.48
γ_4	0	0	0	1.27	1.28	1.29	1.31	1.33	1.35	1.38	1.42	1.48
γ_5	0	0	0	0	1.26	1.27	1.28	1.30	1.32	1.35	1.39	1.46
γ_6	0	0	0	0	0	1.22	1.23	1.25	1.27	1.29	1.33	1.39
γ_7	0	0	0	0	0	0	1.14	1.16	1.18	1.20	1.24	1.30
γ_8	0	0	0	0	0	0	0	1.04	1.06	1.08	1.11	1.17
γ_9	0	0	0	0	0	0	0	0	0.91	0.93	0.96	1.00
γ_{10}	0	0	0	0	0	0	0	0	0	0.75	0.77	0.80
γ_{11}	0	0	0	0	0	0	0	0	0	0	0.54	0.57
γ_{12}	0	0	0	0	0	0	0	0	0	0	0	0.30

Table 11: **Dependence time effect and aggregate variables.** The table presents the estimation results for a regression of the estimated time dummies λ_1 through λ_{24} on a number of fund invariant variables. The variable c denotes a constant.

Independent Variables	Estimate	Std. error	adjR^2
c	2.296	0.155	
Treasury Bill	0.333	0.110	0.26
c	2.677	0.074	
S&P 500	0.017	0.015	0.32
c	2.289	0.154	
Treasury Bill	0.308	0.111	
S&P 500	0.012	0.010	0.28

References

Amemiya, T., 1985, *Advanced Econometrics*, Cambridge: Harvard University Press.

Baltagi, B.H., 1995, *Econometric Analysis of Panel Data*, Wiley.

Blake, C.R., E.J. Elton and M.J. Gruber, 1993, The Performance of Bond Mutual Funds, *Journal of Business,* 66, 371-403.

Brown, S.J. and W.N. Goetzmann, 1995, Performance Persistence, *The Journal of Finance*, 50, 679-698.

Brown, S.J., W.N. Goetzmann, R.G. Ibbotson and S.A. Ross, 1992, Survivorship Bias in Performance Studies, *Review of Financial Studies*, 5, 553-580.

Brown, S.J., W.N. Goetzmann and S.A. Ross, 1995, Survival, *The Journal of Finance*, 50, 853-874.

Brown, S.J. and W.N. Goetzmann, 1997, Mutual Fund Styles, *Journal of Financial Economics*, 43, 373-399.

Carhart, M.M., 1997a, On Persistence in Mutual Fund Performance, *The Journal of Finance*, 52, 57-82.

Carhart, M.M., 1997b, Mutual Fund Survivorship, Working Paper, Marshall School of Business, U.S.C.

Elton E.J., M.J. Gruber and C.R. Blake, 1995, Survivorship Bias and Mutual Fund Performance, *The Review of Financial Studies*, 9, 1097-1120.

Fitzgerald, J., P. Gottschalk, and R. Moffitt, 1998, An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics, *Journal of Human Resources*, 33, 251-299.

Gourieroux C., A. Monfort, E. Renault, A. Trognon, 1987, Generalized Residuals, *Journal of Econometrics*, 34, 5-32.

Grinblatt, M. and S. Titman, 1989, Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings, *Journal of Business,* 62, 393-416.

Gruber, M.J., 1996, Another Puzzle: The Growth in Actively Managed Mutual Funds, *Journal of Finance*, 51, 783-811.

Hausman, J.A. and D. Wise, 1979, Attrition Bias in Experimental and Panel Data: The Gary Income Maintenance Experiment, *Econometrica*, 47, 455-473.

Heckman, J., 1976, The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models, *The Annals of Economic and Social Measurement,* 5, 475-492.

Heckman, J., 1979, Sample Selection Bias as a Specification Error, *Econometrica,* 47, 153-161.

Hendricks, D., J. Patel and R. Zeckhauser, 1997, The J-shape of performance Persistence given Survivorship Bias, *The Review of Economics and Statistics*, 79, 161-170.

Malkiel, B.G., 1995, Returns from Investing in Equity Mutual Funds 1971 to 1991, *The Journal of Finance*, 50, 549-572.

Moffitt, R., J. Fitzgerald and P. Gottschalk, 1997, Sample Attrition in Panel Data: The Role of Selection on Observables, paper presented at the 7th International Conference on Panel Data, Paris, 19-20 June, 1997.

Newey, W.K., 1985, Maximum Likelihood Specification Testing and Conditional Moment Tests, *Econometrica*, 53, 1047-1070.

Pagan, A. and F. Vella, 1989, Diagnostic Tests for Models Based on Individual Data: A Survey, *Journal of Applied Econometrics*, 4, S29-S59.

Rockinger, M., 1995, Determinants of Capital Flows to Mutual Funds, Working Paper, HEC, France.

Sirri, E.R. and P. Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance*, 53, xxx-xxx.

DISCUSSION PAPERS 1997

DPS 97.01 Hans Dewachter, Geert Gielens and Dirk Veestraeten, *An Assessment of Central Banks'. Stand on Exchange Rate Stabilization Policies,* February. (International Economics).

DPS 97.02 Anneleen Peeters, *How Hiring and Firing Costs Affect Labour Demand in a Model of Uncertainty,* February. (International Economics).

DPS 97.03 Hans Eyssen, *Are West-African Immigrants Discriminated in Cote D'Ivoire?,* March. (Development Economics).

DPS 97.04 Wim Lagae, *The Absorption of the Effects of Debt Relief Operations by European Export Credit Agencies: An Institutional Analysis*, March. (Development Economics).

DPS 97.05 Jenke ter Horst and Marno Verbeek, *Estimating Short-Run Persistence in Mutual Fund Performance*, March. (Econometrics).

DPS 97.06 Hans Dewachter and Hanno Lustig, *A Cross-Country Comparison of CPI as a Measure of Inflation,* April. (Financial Economics).

DPS 97.07 Yunus Aksoy and Yohanes E. Riyanto, *Exchange Rate Pass-Through in Vertically Related Markets*, May. (International Economics).

DPS 97.08 Paul De Grauwe, *The Indeterminacy of the Euro Conversion Rates. Why it Matters and how it can be solved*, June. (International Economics).

DPS 97.09 Jozef Konings, Hylke Vandenbussche and Reinhilde Veugelers, *Union Wage Bargaining and European Antidumping Policy*, June (Financial Economics).

DPS 97.10 Francis Vella and Marno Verbeek, *Using Rank Order as an Instrumental Variable: An Application to the Return to Schooling,* May. (Econometrics).

DPS 97.11 Jozef Konings and Patrick P. Walsh, *The Effect of Real Exchange Rate Movements and Ownership on the Life Cycle of Manufacturing Plants in Ireland (1973-1994),* June. (Financial Economics).

DPS 97.12 Johan Eyckmans, *Balancedness of games with multilateral environmental externalities*, August. (Public Economics).

DPS 97.13 Patrick Van Cayseele and Dave FURTH, *Price Leadership and Buyouts,* September. (Financial Economics).

DPS 97.14 Mark De Broeck, Dominique Guillaume and Emmanuel Van der Stichele, *Small and Big Bangs in Bond Markets*, September (Financial Economics).

DPS 97.15 Hanno Lustig, *Re-examining the Synchronization of European Business Cycles*, September (Financial Economics).

DPS 97.16 João P. Cocco, Francisco J. Gomes and Pascal J. Maenhout, *A Two-Period Model of Consumption and Portfolio Choice With Incomplete Markets*, June (Financial Economics).

DPS 97.17 Stefan Dercon and Daniel Ayalew, *Demobilisation and Reintegration of Ex-Soldiers in Ehtiopia*, October (Development Economics).

DPS 97.18 Stefan Dercon and Pramila Krishnan, *In Sickness and in Health…Risk-Sharing within Households in Rural Ethiopia*, October (Development Economics).

DPS 97.19 Paul Collier, Stefan Dercon and John Mackinnon, *Density versus Quality in Health Care Provision: The Use of Household Data for Budgetary Choices in Ehtiopia* October (Development Economics).

DPS 97.20 van der Lijn Nick and Marno Verbeek, *Excess demand, repressed inflation, and forced saving in the Soviet Union,* October (Econometrics).

DPS 97.21 Lorelei Crisologo-Mendoza and Dirk Van de gaer, *Population Growth and Customary Law on Land: The Case of Cordillera Villages in the Philippines,* October (Development Economics).

DPS 97.22 Tom Van Puyenbroeck, *Two-stage optimal control problems subject to an isoperimetric constraint,* October (Public Economics).

DPS 97.23 Erik Schokkaert, Geert Dhaene and Carine Van de Voorde, *Risk Adjustment and the Trade-off Between Efficiency and Risk Selection*, November (Public Economics).

DPS 97.24 Paul De Grauwe, Hans Dewachter and Dirk Veestraeten, *Stochastic Process Switching and Stage III of EMU*, November (International Economics).

DPS 97.25 Dirk Heremans, *Regulation of Banking and Financial Intermediation,* November (Financial Economics).

DPS 97.26 Knud J. Munk, *Agricultural Policy a Public Economic Explanation,* November (Public Economics).

DPS 97.27 Hans Dewachter, *Can Markov Switching Models Replicate Chartist Profits in the Foreign Exchange Market?* November (International Economics).

DPS 97.28 Paul De Grauwe and Frauke Skudelny, *The Impact of EMU on Trade Flows,* December (International Economics).

DISCUSSION PAPERS 1998

DPS 98.01 Louis Baeck, *Thematisation and Canon Building in Post-War Development Studies*, January (Development Economics).

DPS 98.02 Hans Dewachter and Hanno Lustig, *Sticky Prices and the Nominal Effects of Real Shocks*, January (International Economics).

DPS 98.03 Ilse Frederickx, *Health in Rural Tanzania: The Determinants of Health Status, Health Care Demand and Health Care Choice,* January (Development Economics).

DPS 98.04 Paul De Grauwe, *European Unemployment. A Tale of Demand and Supply,* February (International Economics).

DPS 98.05 João Cocco, Francisco Gomes and Pascal Maenhout, *Consumption and Portfolio Choice over the Life-Cycle,* March (Financial Economics).

DPS 98.06 Yunus Aksoy and Hanno Lustig, *Circular Aspects of Exchange Rates and Market Structure,* January (International Economics).

DPS 98.07 André Decoster and Frederic Vermeulen, *Evaluation of the Empirical Performance of Two-Stage Budgeting AIDS, QUAIDS and Rotterdam Models Based on Weak Separability,* April (Public Economics).

DPS 98.08 Erik Schokkaert and Luc Van Ootegem, *Preference Variation and Private Donations,* April (Public Economics).

DPS 98.09 Erik Schokkaert, *Mr. Fairmind is Post-Welfarist: Opinions on Distributive Justice,* April (Public Economics).

DPS 98.10 Dirk Van de gaer, Michel Martinez and Erik Schokkaert, *Measuring Intergenerational Mobility and Equality of Opportunity*, April (Public Economics).

DPS 98.11 Paulo Augusto Nunes, *Testing the Validity of WTP values from a Contingent Valuation Survey in Portugal*, April (Public Economics).

DPS 98.12 Paulo Augusto Nunes, *Measuring the WTP for Recreation and Biodiversity Protection Programs,* April (Public Economics).

DPS 98.13 Laurens Cherchye and Tom Van Puyenbroeck, *Learning from Input-Output Mixes in DEA: A Proportional Measure for Slack-Based Efficient Projections,* February (Public Economics).

DPS 98.14 Jerzy Mycielski and Yohanes Riyanto, *On the Interaction between Taste and Distance and Its Implications on the Vertical Distribution Arrangement*, May (Financial Economics).

DPS 98.15 Jerzy Mycielski, Yohanes Riyanto and Filip Wuyts, *Product Differentiation and the Equilibrium Structure of the Manufacturer-Retailer Relationship,* May (Financial Economics).

DPS 98.16 Hans Degryse and Patrick Van Cayseele, *Relationship Lending within a Bank-based System: Evidence from European Small Business Data,* April (Financial Economics).

DPS 98.17 Pramila Krishnan, Tesfaye Gebre Selassie and Stefan Dercon, *The Urban Labour Market During Structural Adjustment: Ethiopia 1990-1997*, April (Development Economics).

DPS 98.18 Bart Capéau and Stefan Dercon, *Prices, Local Measurement Units and Subsistence Consumption in Rural Surveys: An Econometric Approach with an Application to Ethiopia*, March (Development Economics).

DPS 98.19 Stefan Dercon and Pramila Krishnan, *Changes in Poverty in Rural Ethiopia 1989-1995: Measurement, Robustness Tests and Decomposition*, March (Development Economics).

DPS 98.20 Jenke R. ter Horst, Theo E. Nijman and Marno Verbeek, *Eliminating Biases in Evaluating Mutual Fund Performance from a Survivorship Free Sample,* June (Econometrics).

DPS 98.21 Hilke Vandenbussche and Jozef Konings, *Globalization and the effects of national versus international competition on the labour market. Theory and evidence from Belgian firm level data,* August (Financial Economics).

DPS 98.22 Wim Moesen and Laurens Cherchye, *The Macroeconomic Performance of Nations Measurement and Perception,* August (Public Economics).

DPS 98.23 Anneleen Peeters, *Interim Employment and a Leading Indicator for the Belgian Labour Market*, September (International Economics, IERP 137).

DPS 98.24 Wessel Marquering and Marno Verbeek, *An Empirical Analysis of Intertemporal Asset Pricing Models with Transaction Costs and Habit Persistence,* September (Econometrics).

DPS 98.25 Filip Abraham and Joeri Van Rompuy, *Is Belgium ready for EMU? A look at national, sectoral and regional developments,* September (International Economics, IERP 138).

DPS 98.26 Sara Ochelen, Stef Proost and Kurt Van Dender, *Optimal Pricing for Urban Road Transport Externalities,* September (Public Economics).

DPS 98.27 Knud Munk, *Optimal Support to Low-skilled Households*, July (Public Economics).

DPS 98.28 Wim Moesen and Philippe Van Cauwenberge, *The Status of the Budget Constraint, Federalism and the Relative Size of Government: A Bureaucracy Approach,* September (Public Economics).

DPS 98.29 Laurens Cherchye, *The Measurement of Macroeconomic Performance: Comparison of DEA-Based Alternatives,* August (Public Economics).

DPS 98.30 Jürgen Janssens, *Volatility and Risk Premia on Belgian Secondary Long Term Government Bond Markets,* October (Financial Economics).

DPS 98.31 Stef Proost and Kurt Van Dender, *Effectiveness and Welfare Impacts of Alternative Policies to Address Atmospheric Pollution in Urban Road Transport* (Public Economics).

DPS 98.32 Inge Mayeres and Stef Proost, *Marginal Tax Reform, Externalities and Income Distribution*, (Public Economics).

DPS 98.33 André Decoster and Guy Van Camp, *The unit of analysis in microsimulation models for personal income taxes: fiscal unit or household?* (Public Economics).

DPS 98.34 Paul De Grauwe, Hans Dewachter and Yunus Aksoy, *The European Central Bank: Decision Rules and Macroeconomic Performance*, (International Economics).

DPS 98.35 Laurent Franckx, *The use of ambient inspections in environmental monitoring and enforcement when the inspection agency cannot commit itself to announced inspection probabilities*, (Public Economics).