Why Do Hedge Funds Stop Reporting Performance?

It isn't because they're successful.

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The assets managed by hedge funds have grown dramatically, particularly in recent years. It is estimated that as of the end of 2005, more than one trillion U.S. dollars were invested in hedge funds around the globe.[1]

Despite their large global presence, hedge funds remain relatively free from many requirements of the Securities and Exchange Commission or other regulatory bodies. This relative freedom includes exemption from obligatory performance reporting. The hedge fund performance data from data-gathering services such as TASS are available only because of hedge funds' willingness to supply them.

Thus, it would be interesting to examine the characteristics of funds that choose to report versus those that do not. As such an empirical analysis cannot be undertaken, given the lack of data on funds that choose not to report. We instead examine the funds that reported performance to the TASS database at some time and then chose to cease reporting. We explore their likely reasons for ceasing to report and compare their characteristics with those that continue to report their performance.

The financial literature presents two competing explanations for why some hedge funds stop reporting their performance data. We, like others, have argued that funds stop reporting when they perform more poorly than other funds (see, for example, Malkiel and Saha [2005]). Funds stop reporting because they fail (as well as for other reasons that are unrelated to performance, such as merger or name change).

Other researchers suggest a competing explanation, arguing that funds that perform well do not have an incentive to continue reporting performance because they do

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not need to attract additional capital. Ackermann, McEnally, and Ravenscraft [1999, p. 867] contend:

> Excluding disappearing funds has virtually no impact on our assessment on overall performance. This self-selection bias has two interesting implications for hedge funds research. First, some hedge funds may not actively seek new money, because there may be diminishing returns to their arbitrage strategies. Second, some of the best hedge fund managers may be opting out of the databases.

Insight into which of these two competing hypotheses is true is provided, in part, by the degree of survivorship bias in average hedge fund performance estimates. Survivorship bias is evident when, for example, the annual average returns of all funds (both reporting and non-reporting) are lower than the average return of only the surviving funds. If it were true that the performance of funds that stop reporting is comparable to that of the funds that continue to report, then the average returns of the two groups would be very similar, and there would be no evidence of survivorship bias.

Yet many studies on the hedge fund industry have found evidence of survivorship bias, although estimates of it vary considerably. Survivorship bias estimates range from 0.16% (Ackermann, McEnally, and Ravenscraft [1999]) to 4.50% per year (Malkiel and Saha [2005]). Other researchers estimate survivorship bias to be 2.24% (Liang [2000]), 3% (Brown, Goetzmann, and Ibbotson [1999]), or 3.48% (Fung and Hsieh [1997]). The fact that all these survivorship bias estimates are positive suggests, if indirectly, that funds that cease to report are generally worse performers than those that continue to report.

We attempt to directly address the reasons hedge funds cease reporting performance results. Using the TASS dataset of hedge funds, we first analyze the returns of funds that stop reporting. We find that these funds' returns significantly worsen at the end of their reporting lives, which suggests that the majority of funds stop reporting because they fail. We then use survival time analysis techniques to examine the funds' time to failure and changes in the hazard rate (i.e., the probability of failure) over time. We also estimate the effects of funds' performance, size, and other characteristics on the hazard rate.

Consistent with the finding on returns at the end of reporting lives, we find that better-performing and larger hedge funds have lower hazard rates.

PRIOR STUDIES

Several published studies have examined the exit probability of hedge funds. Using the TASS database, Brown, Goetzmann, and Park [2001] estimate several alternative models of hedge fund failure, and find that younger hedge funds disappear faster than more established funds. They also conclude that style-adjusted return risk has a significant impact on fund failure probability. Howell [2001] concludes that the probability of hedge funds failing is 7.4% in the first year after inception, increasing to 20.3% in the second year.

While Baquero, ter Horst, and Verbeek [2005] focus on examining persistence in hedge fund performance, they model the liquidation process of hedge funds with a probit model. Using TASS data for 1994-2000, they find that the impact of historical returns on hedge fund survival is positive and significant; funds with high returns are much less likely to liquidate than those with low returns.

The study most closely related to ours is Gregoriou [2002], which examines the pattern of survival times of hedge funds using various survival models, including an accelerated failure time model and the Cox proportional hazard model. The sample is from the Zurich Capital Markets database for 1990 through 2001.

Gregoriou concludes:

> New funds struggle during the first two to three years of operation, but then establish themselves so that the risk of failure (the hazard) decreases from then on. . . . The main conclusion reached is that investors should consider hedge funds as the ideal classification because of its highest survival time and because of its diversification effects for traditional investment portfolios [2002, pp. 245, 250].

Our conclusions are markedly different. We find that failure rates for hedge funds are high, and rates remain high even for long-standing funds. We believe there are two explanations for the difference in conclusions. First, while the last year considered in Gregoriou's study is 2001, we examine TASS data through April 2004. Between January 1994 and December 2003, 1,392 funds left the TASS database. Of these, 541 funds or nearly 40% exited the database after 2001, in 2002 and 2003. Thus, inclusion of these two years of data with a large number of exits is very likely to lead to different conclusions.[3]

Second, in estimating an accelerated failure time model, Gregoriou adopts a Weibull distribution. The problem in using this distribution for modeling the change in failure rate over time (loosely speaking, the hazard function) is that it does not have the flexibility to accommodate a U-shaped or an inverted U-shaped hazard function.[4]

The Weibull hazard function is either monotonically increasing or monotonically declining. Our analysis shows that the Weibull distribution is unambiguously rejected by data in favor of the log-logistic distribution, which yields an inverted U-shaped hazard function. This estimated shape of the hazard function in our study suggests that the failure rate increases during the first six years of a fund's existence, reaches a peak, and then declines. As the estimated hazard rate falls minimally from the peak after ten years of life, the risk of failure for hedge funds remains relatively high, even after operating for a fairly long time.

TASS DATABASE

We use the TASS database to study the characteristics of hedge fund returns. Tremont Capital Management purchased the TASS service in March 1999, and tried to encourage the hedge funds that reported to it and to other database services to begin reporting to TASS. As a result, TASS has become one of the most comprehensive services covering a wide variety of funds. We believe it is broadly representative of the hedge fund universe.

We obtain from TASS data not only on currently existing funds but also on so-called dead or defunct funds (funds that either no longer exist or have stopped reporting to the TASS service but still exist). The TASS database does not provide specific information about why a fund chooses to cease reporting.

Exit Pattern

The exiting funds are identified in our dataset by those that stopped reporting performance data to TASS before March 31, 2004. Funds that continued to report on or after this date are classified as *alive*. Our comparative performance analysis runs from January 1996 through April 2004. In earlier years, particularly 1994 and 1995, there is a high proportion of back-filled data in the TASS database. Back-filling occurs when a fund opts to report its returns of prior years at a later date. Studies have shown that this practice introduces a bias because back-filling occurs selectively; funds choose to back-fill the earlier years' returns only when they are favorable.[5]

Exhibit 1 compares the performance of exiting funds in the final three, six, and nine months before they exit the TASS database and their prior performance (that is, after January 1996 and before the final three, six, and nine months of life). We use two measures of performance: 1) the fund's average monthly return (calculated as the geometric mean of all the fund's returns); and 2) the fund's Sharpe ratio.

EXHIBIT 1
Performance of Funds that Have Stopped Reporting: 1996-2004

		(1)	(2)
A.	**Last Three Months**		
		Entire Period[a]	**Last 3 Months**
	Returns[b]	0.49%	-0.61%
	Sharpe Ratio[c]	0.102	-1.859
B.	**Last Six Months**		
		Entire Period	**Last 6 Months**
	Returns	0.65%	-0.56%
	Sharpe Ratio	0.146	-1.293
C.	**Last Nine Months**		
		Entire Period	**Last 9 Months**
	Returns	0.85%	-0.45%
	Sharpe Ratio	0.153	-1.551

[a]*Excluding the last three, six, or nine months.*
[b]*Intrafund returns are calculated using geometric returns. Comparisons across funds are calculated using an arithmetic mean.*
[c]*Sharpe ratios are computed using the 3-month Treasury bill converted to monthly returns as the risk-free rate. It is the geometric mean of relevant monthly hedge fund returns minus the relevant geometric mean of risk-free returns divided by the relevant hedge return volatility.*

Exhibit 1 indicates a markedly worse performance in the period immediately before the funds stop reporting. For example, in the final six months, the exiting funds' average monthly return is –0.56%, compared to an average monthly return of 0.65% during their reporting lives (excluding the final six months). In the last three months, the average return falls to –0.61%, compared to an average monthly return of 0.49% during reporting lives prior to the last three months.

Exhibit 1 also shows that the average fund Sharpe ratios closely follow the pattern displayed by the average monthly returns. The average Sharpe ratios during the final months are consistently lower than the averages for the preceding period.

The unambiguous pattern of declining performance during funds' final months before ceasing to report suggests that, on average, it is poor performance, and very likely failure, that explains hedge funds' decision to stop reporting to the TASS database. The hypothesis that successful funds stop reporting because they do not want to attract additional capital does not seem to be supported by the data.

Hedge Funds' Time to Failure

To examine the time to exit for funds that cease reporting to the TASS database, we use survival time analysis techniques widely used by researchers who have examined *duration data.* Applications of duration analysis include the length of unemployment (Lancaster [1979]) or welfare spells (Blank [1989]); job duration (Gronberg and Reed [1994]); length of time firms remain under Chapter 11 bankruptcy protection (Bandopadhaya [1994]); and duration of marketing time for residential housing (Haurin [1988]). Excellent reviews and numerous other examples are provided by Kiefer [1988] and Lancaster [1990]

In survival analysis models, the variable of interest is the length of the spell, which in our case is the length of time from a hedge fund's inception until it fails or stops reporting. Central to our duration analysis is the survival function:

$$S(t) = \Pr(T \geq t) \tag{1}$$

which gives the probability that the random variable, T, denoting duration, will equal or exceed the particular value of t.

Even though the survival time is the underlying process that is modeled, it makes more sense to think about the spells in terms of hazard rates. The *hazard rate* is the rate at which spells are completed, given that they lasted until that moment. The hazard function is defined as:

$$\lambda(t) = -\frac{\dot{S}}{S} = \frac{dS(t)/dt}{S(t)} \tag{2}$$

In this study, the hazard function is the rate at which funds stop reporting at time t, given that they have continued to report until t. The hazard function describes how the rate of failure changes over time; the *failure event* is a fund's ceasing to report. A monotonically increasing hazard function, for example, implies that the likelihood of failure increases with time (although in many applications hazard functions can be non-monotonic and can be U-shaped or inverted U-shaped).

A priori, one would expect the hazard function for hedge funds' survival time to be inverted U-shaped. This shape would imply that a fund is unlikely to fail immediately after inception; if failure occurs, it is more likely to occur in the first few years of operation. Once a fund has survived the formative years and has established a favorable track record, however, its likelihood of failure is expected to decline over time.

For each fund that exited the TASS database, we compute the length of time between its inception and the month it stopped reporting. Of course, for a fund that has continued to report, the duration time is simply the time between the fund's inception and April 2004, the last month of data in the database.

Exhibit 2 shows the distribution of survival times for the funds in our sample. Clearly, after the first three or four years of funds' lives, the number of failing funds in each additional year declines.

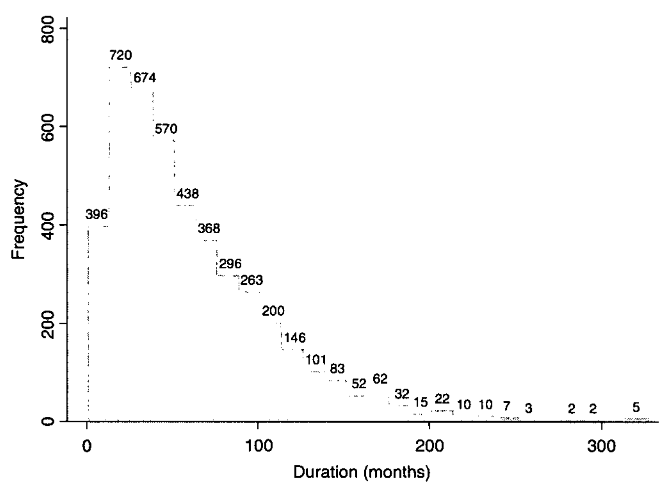
Conclusions regarding the rate of funds' exit are sensitive to the choice of functional form for the hazard function. For example, the exponential distribution imposes a flat-line hazard function (implying that the hazard rate does not change over time); the hazard function of the Weibull distribution is either monotonically increasing or monotonically declining. The lognormal or the log-logistic distribution, however, can accommodate an inverted U-shaped hazard function.

The choice of the distribution that fits the data best can be made using Akaike's information criterion (AIC), which is based on the highest log-likelihood value. The log-likelihood values for the four alternative specifications are:

Exponential:	−4004.7
Weibull:	−3932.7

Exhibit 2

Hedge Fund Survival Times



Lognormal: −3898.3
Log-logistic: −3897.2

Thus, according to this criterion, the log-logistic distribution fits the data the best, closely followed by the lognormal specification, both of which allow for an inverted U-shaped hazard function—the shape one would expect a priori. The exponential and the Weibull distributions are clearly rejected by our data.

Exhibit 3 shows the estimated hazard function computed using the log-logistic distribution.[6] According to the log-logistic estimates, the hazard rate increases rapidly during the first five years of a fund's life. Approximately five and a half years after inception, it reaches its maximum of 1% per month, which corresponds to roughly 12% per year.

Note in Exhibit 3 that the decline in the hazard rate after it reaches its maximum (at month 66) is extremely gradual; even after ten years of operation, the estimated hazard rate falls minimally from the peak of 12% per year to 11% per year. Indeed, the estimated likelihood of failure of a ten-year old hedge fund is not significantly different from the likelihood of failure of a five and a half-year old fund.

These findings suggest that the risk of failure for hedge funds remains relatively high, even after operation for a fairly long time. Interestingly, this finding on hedge funds stands in sharp contrast to the estimated hazard rates for mutual funds found by Lunde, Timmermann, and Blake [1999] for a dataset of U.K. funds. They find that the estimated hazard rate drops sharply for a typical mutual fund after it has survived for approximately ten years.

One reason the risk of failure remains higher for hedge funds is that incentive fees depend on "High-Water" marks. Suppose a hedge fund has enjoyed strong long-run performance but then suffers a sharp loss in net asset value in a single year. The fund manager will not only fail to earn an incentive fee (usually about 20% of any profits) during that poor year, but will also be less likely to earn an incentive in the following years. This is so because the incentive will be earned only if the net asset value exceeds the previous high net asset value. Thus, the manager may prefer to close the fund and open a new fund that is not burdened by a high water mark that will limit incentive compensation. This will be especially true if assets under management are relatively small.

FACTORS THAT AFFECT TIME UNTIL FAILURE

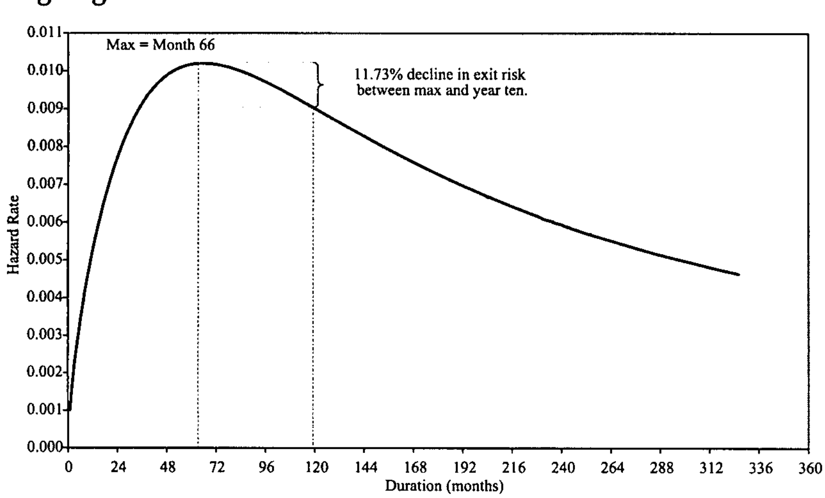
A variety of factors affect hedge funds' hazard rates, including fund characteristics such as size, performance, and investment style.

Exhibit 4 shows the means and standard deviations of the variables that reflect the fund characteristics of interest. The duration variable represents the number of days between a hedge fund's inception and the time it stops reporting, or until April 2004 if the fund has continued to report.

The Sharpe ratio for a fund is computed by dividing the difference between the geometric mean of the fund's monthly returns and the geometric mean of risk-free returns (three-month Treasury bill returns) by the fund's volatility of returns. Volatility is the variance in a fund's monthly returns over the entire reporting life of the fund between January 1996 and April 2004. Assets under management are the fund's average reported assets in millions of U.S. dollars over its entire reporting life.

To compute performance relative to funds in the same primary category, we first calculate the difference between a fund's average return (geometric mean) and average returns of all hedge funds in the same primary category. We then divide this difference by the standard deviation of the returns of all funds in that same primary category. Performance relative to all hedge funds is

EXHIBIT 3
Log-Logistic Hazard Function



Rate at which a hedge fund dies, given that it has lasted the number of months shown on the horizontal axis.

EXHIBIT 4

Summary Statistics—4,328 Funds

	Mean	Std. Dev.
Duration	1,866.5	1,404.4
Sharpe Ratio	0.224	0.744
Volatility	0.042	0.040
Assets under management in ($millions)	75.8	225.6
Performance relative to funds in the same primary category	0.003	0.260
Performance relative to all funds in the database	0.004	0.261
Indicator variable for Equity Hedge Funds	0.382	0.486
Indicator variable for International Hedge Funds	0.110	0.313
Indicator variable for Fund of Funds	0.201	0.401
Indicator variable for Other Funds	0.307	0.461

computed in a similar fashion, except now the benchmark is the average return of all hedge funds in the TASS database.

Finally, we construct several indicator variables that reflect the fund's investment style by separating funds into four groups: equity hedge funds (1,706 funds); international hedge funds (495 funds); funds of funds (914 funds); and other funds (1,374 funds).[7]

RESULTS

We examine the relation between fund characteristics and hazard rates using both semiparametric and parametric models. In Exhibit 5, the first column shows the coefficient estimates using a Cox semiparametric hazard model; the second column shows the results of the parametric estimation using a log-logistic survival model.[8]

The coefficient estimates from the two models must be interpreted with caution. Because the explained variable in the Cox model is the hazard rate, while in the log-logistic model it is the time to failure, the estimated coefficients are expected to have opposite signs. For example, a negative estimated coefficient for a particular variable in the Cox model signifies that the variable reduces the hazard rate (the conditional probability of failure). A positive estimated coefficient for the same variable in the log-logistic model signifies that the time to failure is increased by the variable, consistent with the Cox model result.

Exhibit 5 shows that the signs on all the estimated coefficients (except for performance relative to all funds) are consistent across the Cox and log-logistic models, as one might expect. The Cox model estimates show that the Sharpe ratio is a statistically significant predictor of the likelihood of a fund's failure at the 99% confidence level, suggesting that a higher Sharpe ratio leads to a lower likelihood of fund failure. The positive coefficient in the log-logistic specification (also significant at the 99% confidence level) indicates that a higher Sharpe ratio leads to an increase in a fund's survival time. This is an especially powerful result, supporting our earlier finding that poor performance, and not success, explains funds' ceasing to report.[9]

The estimated coefficient on the volatility variable has the expected sign and is significant at the 95% confidence level in the Cox model, suggesting that funds with higher volatility of returns have a higher likelihood of failure.

The estimated coefficient on assets under management implies that a fund's size is a strong predictor of a hedge fund's likelihood of survival; the larger a fund, the less likely is its failure. The estimated coefficient of the assets variable is statistically significant at the 99% confidence level in both the Cox and log-logistic specifications. These results are inconsistent with the hypothesis that funds stop reporting because they have become too big.

The Cox model results in Exhibit 5 show that a fund performing better than its peers in the same primary category has a lower hazard rate. The estimated coefficient of the variable measuring performance relative to all hedge funds is insignificant in the Cox model, but statistically significant and with the expected sign in the log-logistic specification.

Of all the fund category indicator variables, only one—the funds of funds category—is statistically significant in both the Cox and log-logistic specifications. The results imply that hedge funds classified as funds of funds have a lower hazard rate than the benchmark equity hedge funds category. This finding seems to suggest that funds of funds, which hold portfolios of other hedge funds, are more successful in diversifying their risks, reducing their likelihood of failure.

CONCLUSIONS

We have investigated two competing hypotheses as to why hedge funds stop reporting to data-gathering

EXHIBIT 5
Estimated Coefficients of Hazard and Survival Analysis Models

	Cox Model	Log-Logistic Model
Sharpe Ratio	−0.513	0.847
	[11.09]**	[9.68]**
Volatility	1.047	−0.573
	[2.00]*	[1.15]
Assets under management	−0.003	0.002
	[9.93]**	[8.13]*
Performance relative to funds in the same primary category	−0.860	0.083
	[3.51]**	[0.39]
Performance relative to all funds in the database	0.228	0.576
	[1.02]	[2.69]**
Indicator variable for International Hedge Funds	0.105	-0.022
	[1.46]	[0.36]
Indicator variable for Fund of Funds	-0.203	0.195
	[2.96]**	[3.59]**
Indicator variable for Other Funds	0.007	-0.011
	[0.14]	[0.25]
Constant		7.463
		[175.29]**

Absolute values of z-statistics are in brackets.
Equity Hedge Funds is the benchmark category.
**Significant at 5%; **significant at 1%.*

services such as TASS. Some authors argue that poor performance, if not outright failure, is the main reason. Others suggest that funds stop reporting because they do not need to attract new capital—that is, because of success rather than failure.

Our empirical evidence refutes the latter hypothesis. First, we show that, in the months before they stop reporting, funds tend to perform significantly more poorly than they did in the preceding time period. Second, using hazard function analysis, we find that the likelihood a fund will stop reporting reaches a peak at around five and a half years of operation, and then declines gradually over time. This finding is consistent with the intuition that the first few formative years are critical for a fund's survival; funds that fail are likely to fail in the first few years. Finally, we find that better-performing funds (funds with higher Sharpe ratios), larger funds, and funds that outperform their peers are less likely to stop reporting performance.

All three findings suggest the same conclusion. Most funds stop reporting not because they are too successful, but rather because they fail. Interestingly, we also find that funds of funds typically have a lower likelihood of failure. As we point out in Malkiel and Saha [2005], however, such funds tend to underperform the average hedge fund.

These results have important implications for investors. The fact that hedge funds cease reporting because of unfavorable results implies extremely high failure rates for hedge funds. While some hedge funds have provided generous returns, investors are at high risk of buying a poorly performing fund or, even worse, a failing one. Moreover, since failure rates remain high, even for funds with several years of operation, this risk cannot be mitigated by restricting one's purchases to funds with a long record of past success.

ENDNOTES

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[1]According to Van Hedge Fund Advisors International.

[2]Similar arguments are made by other authors. Gregoriou [2002, p. 240] writes: "Successful hedge funds with good records are frequently closed because managers have understood that size may have a negative impact on performance." Baquero, ter Horst, and Verbeek [2005, p. 495] write: "Thus, self-selection bias exists either because underperformers do not wish to make their performance known, or because funds that performed well have less incentive to report to data vendors."

[3]See Exhibit 7 in Malkiel and Saha [2005].

[4]Curiously, while Gregoriou [2002, p. 251] writes: "the results indicate that an inverse U-shaped hazard function may be harmonious, since hedge funds go through the learning process," he uses a Weibull distribution that is incapable of accommodating an inverted U-shaped hazard function.

[5]See, for example, Malkiel and Saha [2005].

[6]The log-logistic distribution imposes the inverted U-shape for the hazard function. In addition to providing the

best fit, the inverted U-shape for the hazard function is confirmed by undertaking a Kaplan-Meier non-parametric analysis—which is free from the assumption of any specific distribution—of the survival time data for hedge funds.

[7]These four groups are created using the "primary category" variable in the TASS database.

[8]The Cox semiparametric estimation technique allows the fund characteristics to have a multiplicative effect on the hazard function as follows: $\lambda(t) = \lambda_0(t)\exp(\mathbf{X}'\boldsymbol{\beta})$, where $\mathbf{X}$ is the vector of fund characteristics, $\boldsymbol{\beta}$ is the vector of parameters, and $\lambda_0(t)$ is the baseline hazard function. The log-logistic survival function has the form $S(t) = \{1 + (\lambda t)^{1/\lambda}\}^{-1}$ and is implemented by parameterizing $\lambda_j = \exp(-\mathbf{X}_j\beta)$ and treating the scale parameter γ as an ancillary parameter to be estimated from data.

[9]In estimating the Cox and log-logistic specifications, we account for left truncation as well as right censoring. These problems typically arise in duration data. Left truncation in our dataset arises for funds that came into being before 1996, the beginning of our data period. Right censoring arises for funds that were still alive as of April 2004, the last month in our data period. For these funds, the duration is censored because we do not know how long those funds will continue to survive beyond April 2004; thus, the observed length of their lifetime constitutes a lower bound on their survival time.

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