A SURVIVAL ANALYSIS OF AUSTRALIAN EQUITY MUTUAL FUNDS

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Abstract:
Determining which types of mutual (or managed) investment funds are good financial investments is complicated by potential survivorship biases. This project adds to a small recent international literature on the patterns and determinants of mutual fund survivorship. We use statistical techniques for survival data that are rarely applied in finance. Of specific interest is the hazard rate of fund closure, which gives the variation over time in the conditional probability of fund closure given fund survival to date.

For a sample of 251 retail investment funds in Australia from 1980 to 1999 we identify a hump-shaped hazard function that reaches its maximum after about five or six years, a pattern similar to the UK findings of Lunde, Timmermann and Blake (1999). We also consider the impact of monthly and annual fund performance (gross and relative to a market benchmark). Returns relative to the benchmark are much more important than gross returns, with higher relative returns associated with lower hazard of fund closure. There appears to be an asymmetric response to performance, with positive shocks having a larger impact on the hazard rate than negative shocks.

JEL Classification: C14; G14; G23
Key Words: Mutual funds, Survivorship bias, Duration Analysis, Cox regression.

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This version: 15 April 2003

1. Introduction

Mutual funds are rapidly growing in most developed nations as a preferred investment vehicle. In Australia this movement has been further exacerbated by the introduction of compulsory superannuation and the plans to allow individuals to manage their superannuation funds. Figure 1 illustrates this growth in funds under management, and as of June 2002 over $645 billion was invested in mutual funds, representing an annual growth rate of 11.2% since June 1988 when $145 billion was invested.

**** Figure 1 about here ****

A major area of international research in finance has been the evaluation of the financial performance of mutual funds. For example, do actively managed funds outperform a relevant benchmark market index by an amount sufficient to warrant their higher expenses? (See *inter alia* Brown and Goetzmann (1995), Carhart (1997), Grinblatt and Titman (1992), Lehmann and Modest (1987) and Malkiel (1995)). Several recent studies have criticized earlier studies for restricting attention to funds in existence for a long period of time, say ten years, and failing to take into account funds that are closed in a shorter period of time. In particular, the performance of mutual funds is overstated if only well-performing funds survive for a long period of time, while poorly performing finds are likely to be closed. This problem is called one of survivorship bias (see *inter alia* Brown, Goetzmann, Ibbotson and Ross (1992), Elton, Gruber and Blake (1996) and Malkiel (1995)).

In this paper we model the causes of fund closure using statistical techniques for survival data. Investigating the factors affecting managed fund attrition is important for several reasons. It provides a methodology to explore the magnitude of "survivorship bias", as the average life of a fund and the relationship between a fund's abnormal performance and its probability of closure affects the size of the "survivorship bias". The estimated persistence of fund performance is affected by fund attrition to the extent that those that close are the ones with relatively poor track records. Measuring the attrition profile of funds may be important for understanding incentives under which fund managers with a range of products operate. And if funds are most likely to close as a result of lack of investor interest due to poor performance, the termination process itself may be informative about both the investment strategies pursued by individuals and the process by which they inform themselves about the relative quality of investment vehicles.

There has been relatively little attention paid to the reasons for the closure of mutual funds. Brown and Goetzmann (1995) estimate a probit model for a sample of U.S. mutual funds. Lunde, Timmermann and Blake (1999) estimate hazard rates for a sample of U.K. funds. Both investigations conclude that past relative performance is a significant determinant of fund attrition. There is little published academic research into the Australian managed investment fund sector and none that address the issue of persistence in performance, survivorship bias or the determinants of fund attrition.

2. Models for Fund Survivorship

Interest lies in the reasons for fund death, such as the sector in which the fund focuses, fund returns and the size of the fund. The pattern of survival times is also of interest. Specifically, after controlling for fund characteristics, does success feed on itself in the sense that the longer the fund has been in existence the lower is the conditional probability that the fund will cease to exist.

These questions are answered using regression models with dependent variable defined to be the duration of time until the fund is closed. Possible explanatory regressors include fund size, fund sector, measures of fund performance, measures of fund performance relative to other comparable funds, and the volatility of fund performance.

Standard regression models cannot be applied, because of the special nature of the dependent variable and the method of sampling. The dependent variable cannot be negative and from stochastic process theory is likely to be distributed as exponential (or a generalization of exponential). More substantively, regression analysis is greatly complicated because the data is censored. That is, data on the complete length of time that the fund exists is unavailable for funds that have not yet closed.

One approach for censored survival data is to use the proportional hazard model, estimated by the partial likelihood method. This approach, due to Cox (1972, 1975) has the attraction of controlling for censoring under relatively weak distributional assumptions. Standard references include Kalbfleisch and Prentice (1980, 2002), Lawless (1982) and Fleming and Harrington (1991). The method is extensively used in biostatistics but is rarely used in economics, aside from applications in labor economics to data on the length of unemployment spells, and even more rarely used in finance. We therefore provide a brief presentation of the method.

Let t denote the period of time that the mutual fund is in operation, with density function $f(t)$, cumulative distribution function $F(t)$, and survivor or survival function $S(t)$ = 1- $F(t)$. The starting point is the instantaneous probability of the fund closing, given that to date it has not yet closed. Formally this is called the hazard function

$$\lambda(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1-F(t)}.$$

Regressors X are introduced by assuming that the hazard function has the proportional hazards functional form

$$\lambda(t, X) = \lambda_0(t) * \exp(X'\beta),$$

where for k regressors, the X and β are kX1 vectors. Note that the roles of t and X have been separated. The function $\lambda_0(t)$ does not depend on X and is called the baseline hazard rate. This is multiplied by an amount that does vary with the regressors X and the unknown parameters β. The regressors are not deterministic functions of time, though the regressor values may vary over time. The term "proportional" is used as the hazard for any X is proportional to the baseline hazard $\lambda_0(t)$.

The goal of estimation is obtain estimates of β and of the baseline hazard rate $\lambda_0(t)$. To interpret the parameter β, note that

$$\frac{\partial\lambda(t,X)}{\partial X} = \lambda_0(t) * \exp(X'\beta) * \beta = \beta\lambda(t,X).$$

Thus the effect of a one unit change in X is to multiply the hazard by β. For example, let one of the regressors be the excess rate of return on a fund (measured in decimals). Then a coefficient of –2.0 means that an increase of 0.01 (that is 1 percentage point) in the excess rate of return of the fund leads to a 0.02 decrease in the instantaneous probability of fund closure, given survival to date. Note that the impact on the hazard rate, rather than on the mean duration time, is being directly measured. A decrease in the hazard corresponds to an increase in the mean duration time.

The baseline hazard rate $\lambda_0(t)$ is also interpretable. In particular, the conditional probability of death of a mutual fund increases or decreases or does not vary with time according to whether $\lambda_0(t)$ is an increasing, decreasing or constant function of *t*.

We now consider estimation based on a sample of size *n*, $(t_1, X_1),...,(t_n, X_n)$. Cox (1972) proposed an ingenious method to estimate β without having to specify a functional form for the baseline hazard function $\lambda_0(t)$. Suppose we have a sample of *n* funds, with durations $t_1,...,t_n$. Define the risk set $R(t_i) = \{ j \mid t_j \geq t_i \}$, which is the set of all funds that have lasted at least t_i and are therefore at risk of failing at time t_i. The probability that spell *i* is the spell during which a fund fails is

$$\frac{\Pr(T_i = t_i \mid T_i \geq t_i)}{\sum_{j\in R(t_i)} \Pr(T_j = t_j \mid T_j \geq t_i)} = \frac{\lambda_i(t_i)}{\sum_{j\in R(t_i)} \lambda_j(t_j)} = \frac{\exp(X_i'\beta)}{\sum_{j\in R(t_i)} \exp(X_j'\beta)},$$

where the proportional hazards functional form permits the final simplification whereby the baseline hazard drops out. The so-called partial likelihood is obtained by combining such probabilities over the distinct failure times. Cox showed that the estimator of β which maximizes the partial likelihood is consistent and asymptotically normal, regardless of the form of the baseline hazard. Methods to then estimate $\lambda_0(t)$, given estimates of β, are given in, for example, Kalbfleisch and Prentice (1980, 2002) and Fleming and Harrington (1991). This estimate of $\lambda_0(t)$ becomes increasingly imprecise at longer durations as then relatively few spells are at risk of failure.

An alternative approach is a fully parametric one that permits more precise estimation particularly of the baseline hazard. One class of parametric models is of the proportional hazards form given above, with different parametric functional forms for $\lambda_0(t)$ yielding different models. Popular choices are those that correspond to the exponential, Weibull and Gompertz distributions.

A second class of parametric models is that of accelerated time models. These specify a regression model for the natural logarithm of spell duration time

$$\ln(t_i) = X_i\beta + \varepsilon_i,$$

where ε_i is an error with density $f(\varepsilon)$. A positive regression parameter means that an increase in the regressor leads to an increase in the duration time. This corresponds to a **decrease** in the hazard rate. Different distributions of the error term lead to different parametric models. If $f(\varepsilon)$ is the normal density we obtain the lognormal duration model; if $f(\varepsilon)$ is the logistic density we obtain the log-logistic duration model; if $f(\varepsilon)$ is the extreme-value density, we obtain the Weibull duration model; and if $f(\varepsilon)$ is a three parameter gamma density, the generalised gamma duration model results. The Weibull and exponential are unique in being both proportional hazard models and accelerated failure time models. For both classes of parametric models estimation is by maximum likelihood, controlling for censoring due to some spells being incomplete. These parametric and non-parametric models can be estimated using either of the readily available commercial statistical packages STATA and S-PLUS, leading survival analysis packages for, respectively, the social sciences and biostatistics.

The different parametric models place different restrictions on the shape of the hazard function. The exponential distribution has hazard function that is constant, whereas the Weibull and Gompertz models, both of which nest the exponential model, can have hazards that are constant, monotonic increasing or monotonic decreasing. By contrast, the lognormal and log-logistic exhibit non-monotonic hazard rates, initially increasing and then decreasing. The hazard function of the generalised gamma distribution is extremely flexible, allowing for a large number of possible shapes. This provides some advantages in modelling, as it nests the exponential, Weibull and lognormal duration models.

3. Data

A key element of this study is the availability of a data set that is unusually rich by international standards. The data set, sourced from FPG Research, tracks all unlisted managed investment funds in Australia from 1968 to March 1999. This is one of three commercially available products used by Australian investment advisers, and includes information on variables such as the fund return (income and growth), size of the fund, management expense ratios, entry and exit fees, as well as the investment strategy of the fund manager. The focus of this study is the retail sector of Australian Equity Trusts, on which monthly data was available from November 1974 to March 1999. This encompasses 251 Funds of which 89 closed (failed) during that period. The FPG Research database does not provide information on whether a closed fund actually failed, or whether it was absorbed into another investment fund.

Table 1 summarizes the birth and death rate of these funds. Steady growth in the number of funds to 1982 was followed by high growth rates up to 1989. The first closures of funds occurred in 1989. In each of the calendar years 1989 to 1993 there were more closures of funds than new funds created. The years from 1994 to 1998 all experienced a net growth in the number of managed funds.

**** Table 1 about here ****

From the FPG Research database we were able to extract monthly values for the dependent variable, Age of Fund (measured in months), and the following time-varying covariates:

1. Fund Return (based on an accumulation index computed by FPG Research)
2. Cumulated Fund Return (a rolling 12 month accumulation of Fund Return)
3. Excess Return (defined as the excess of the Fund Return over the return on the All Ordinaries Accumulation Index)
4. Cumulated Excess Return (a rolling 12 month accumulation of Excess Return)
5. Fund Volatility (the absolute value of Fund Return), and
6. Cumulated Fund Volatility (the absolute value of Cumulated Fund Return).

The returns are monthly returns, with the sample average of fund return equal to 0.0077. Although some data was available on Fund Size and Management Expense Ratios, there was not sufficient coverage to utilise these covariates.

The data on the age of the funds is both left censored (that is funds could have failed before observations on their covariates were available) and right censored (by March 1999 there were 162 Funds still operating). Both of these types of censoring are properly accounted for in the subsequent analysis, which was obtained using the STATA (2003) statistical package. After cleaning the data set, the analysis reported in this paper is based on 247 Funds, of which there were 88 observed failures, with a total number of 21,677 months at risk of failure.

Figure 2 reports the age distribution of the 88 closed funds. The median age of closed funds is 66 months, the shortest life 8 months and the longest life 326 months. At first glance it seems that funds are most likely to close at a young age, but this interpretation could be wrong as the sample includes many recent entrants that, should they close, can necessarily only close at a young age. The next section controls for this complication.

*** Figure 2 about here ***

4. Nonparametric and Semiparametric Survival Models

Before introducing regressors we present an estimate of the distribution of fund duration. The standard procedure in duration analysis is to estimate the survivor function, $S(t) = 1 - F(t)$, controlling for censoring by using the nonparametric Kaplan-Meier estimate

$$\hat{S}(t) = \prod_{j|t_j \le t} \left(\frac{n_j - d_j}{n_j} \right),$$

where n_j is the number of funds in the risk set $R(t_j)$ at time t_j and d_j is the number of funds to fail at time t_j. This indicates that 75 percent of funds survive for at least 74 months (six years), 50 percent survive for 182 months (fifteen years) and 25 percent survive for at least twenty-five years. In particular, the median time to fund closure is fifteen years.

The estimated survivor function, along with the 95% confidence bands, is presented in Figure 3. The estimates become imprecise after about fifteen years, a consequence of the sample including many recent entrants and relatively few funds with long durations of either incomplete or complete spells.

*** Figure 3 about here ***

*** Table 2 about here ***

The first column of Table 2 reports parameter estimates of the semiparametric Cox Proportional Hazard Model. The null hypothesis that all of the coefficients are zero can be rejected at a high level of significance. The estimated coefficients of the variables Excess Return (-7.56) and Cumulative Excess Return (-2.52) are statistically significant at 5 percent and negative, indicating that returns in excess of the All Ordinaries Index benchmark lead to a decrease in the hazard rate. The estimated coefficients of Fund Return (0.84) and Cumulative Fund Return (-0.62) are close to zero and statistically very insignificant, indicating that it is not returns per se but returns relative to the benchmark that matter. The estimated coefficients of Absolute Fund Return (-5.35) and Absolute Cumulative Fund Return (-3.92) are both negative. If these are interpreted as proxies for short term and long-term volatility, then increases in the volatility of fund returns reduce the hazard rate. On the other hand, if they are interpreted as allowing asymmetric responses the estimated coefficients imply that positive shocks to Fund Return and Cumulative Fund Return have much larger impacts on the hazard function than negative shocks.

*** Figure 4a about here ***

The explanatory variables in the Cox model are all mean corrected, so the resulting baseline survivor function reported in Figure 4a is evaluated at the mean of each of the explanatory variables. The estimated baseline survivor function is similar to the Kaplan-Meier estimate in Figure 3 that did not control for regressors.

*** Figure 4b about here ***

The baseline hazard can also be estimated and is given in Figure 4b. The hazard peaks at around 75 months and then falls. It then rises again, but the estimate is extremely imprecise at longer durations due to very few observations at long durations. More precise estimation of the hazard at durations beyond ten or so years requires fully parametric models, and even then we choose to plot only the first twenty years.

*** Table 3 about here ***

Tests of the proportional hazard assumption, as implemented by STATA, are reported in Table 3, and on the basis of the individual tests and the global test there is no reason to reject the proportional hazard model.

5. Parametric Survival Models

The remaining columns of Table 2 give the estimated parameters of the various parametric survival models. All parameterisations are presented in Accelerated Failure Time (AFT) model form, except the Gompertz model, which is necessarily reported in Proportional Hazard (PH) form. As already explained the sign of beta is reversed in going from the PH to the AFT parameterisation. The coefficient estimates are quite similar to those from the Cox model, suggesting that the regression parameter estimates are relatively robust to the additional parametric assumptions. The estimates are generally more precise, as is expected in going to a more parametric model, though the gain is not great. An increase in the Excess Return and in Cumulative Excess Return reduces the hazard rate. Similarly increases in both absolute return regressors reduce the hazard rate, with interpretation similar to that discussed for the Cox model, though Absolute Fund Return is marginally insignificant. Controlling for excess returns and absolute fund returns both level of Fund Return regressors are statistically insignificant and close to zero.

*** Figures 5a and 5b about here ***

The associated baseline hazard and survivor functions for the six parametric models, evaluated at the means of the explanatory variables are presented in Figures 5a and 5b. The estimated survivor functions are very similar for each of the six models, but there is clear distinction between the estimated hazard functions. As expected the estimated hazard for the exponential model is constant, with the Weibull and Gompertz models displaying monotonic increasing hazards. However the generalized gamma, log-logistic and lognormal all exhibit humped-shape estimated baseline hazard functions. On the basis of hypothesis testing and the maximum Akaike Information Criterion, the lognormal model is the preferred model. The estimated baseline hazard function for this model increases up to a maximum of just over 0.004 after a period of five to six years, and then declines to a value of 0.002 after twenty years.

*** Figures 6a and 6b about here ***

To obtain some insight into the comparative statics of the estimated lognormal model, with coefficient estimates given in the final column of Table 2, the hazard function and survivor functions are evaluated at the quartile values for each regressor variable. Figures 6a and 6b present the results. For each of the six explanatory variables in turn, the hazard function and survivor function are evaluated at the quartile values of the variable, while keeping the remaining five variables at their mean values. Since all regression coefficients are positive, being in the upper quartile produces the lowest hazard function and highest survivor function for all the regressors. For the first two regressors there is essentially no change in the hazard or survival functions, due to the relatively low estimated coefficients once the other regressors are included in the model. The functions are most sensitive to the Cumulated Fund Return and Absolute Cumulated Fund Return variables, with the highest relative impact being around the lifetime at which the hazard function peaks.

6. Conclusions

In considering the failure of retail investment funds in Australia from 1980 to 1999, we have identified a hump shaped hazard function that reaches its maximum after about five or six years, a pattern similar to the UK findings of Lunde, Timmerman and Blake (1999). As these authors point out this is consistent with a learning process in which investors gradually extract information on fund performance, and when it is recognised that a fund is under-performing, withdrawals lead to fund closure. From the estimated survivor functions 25% of funds terminated after about six years and 50% after about twelve years.

We have quantified the impact of short-term fund performance and annual fund performance (gross and relative to the market) on both the fund's hazard function and the fund's survivor function. Relative returns are much more important than gross returns, with higher relative returns associated with lower conditional probability of fund closure. There appears to be an asymmetric response to performance, with positive shocks having a larger impact on the hazard rate than negative shocks.

Acknowledgements
We are grateful for helpful comments from the participants at the *Stock Markets, Risk, Return and Pricing* Symposium held in December 2002 at the Queensland University of Technology, and for able research assistance from Thuy-Duong Tô. We acknowledge financial support from the ARC Small Grants Scheme.

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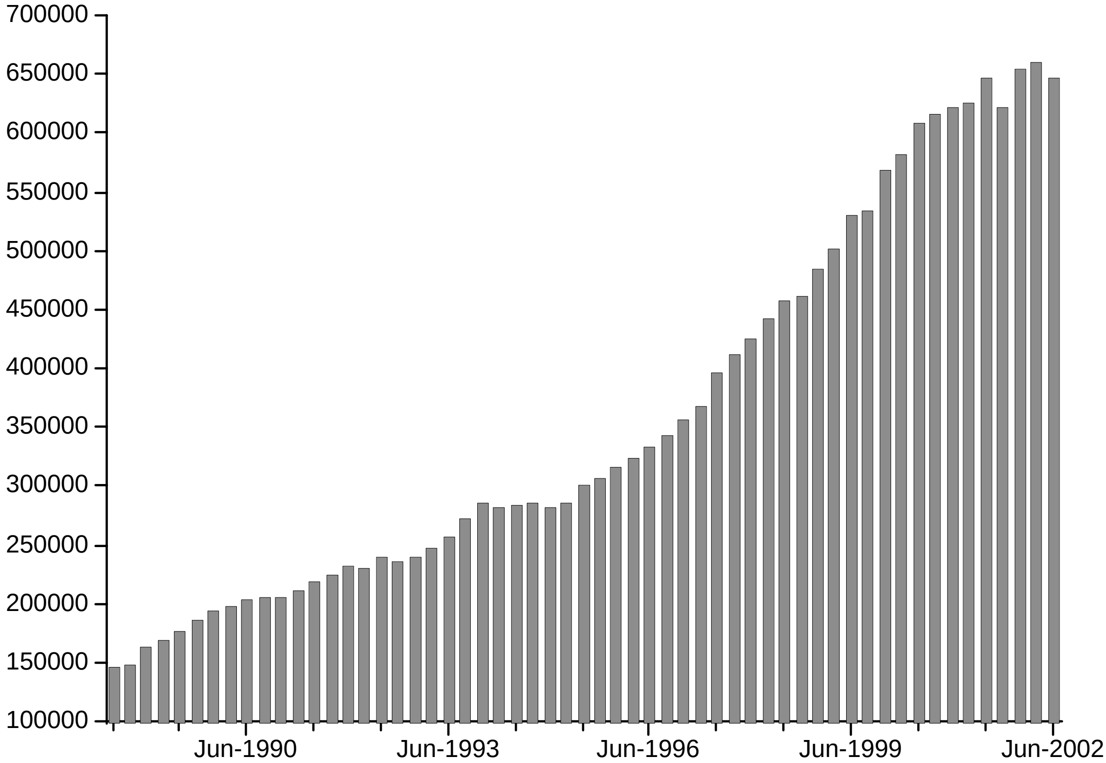
Figure 1: Total of all Australian Managed Funds (Consolidated, $millions)



Source: Reserve Bank of Australia, Table B.15, Series BMFTFC.

Figure 2: Histogram of the age distribution of Funds that closed.

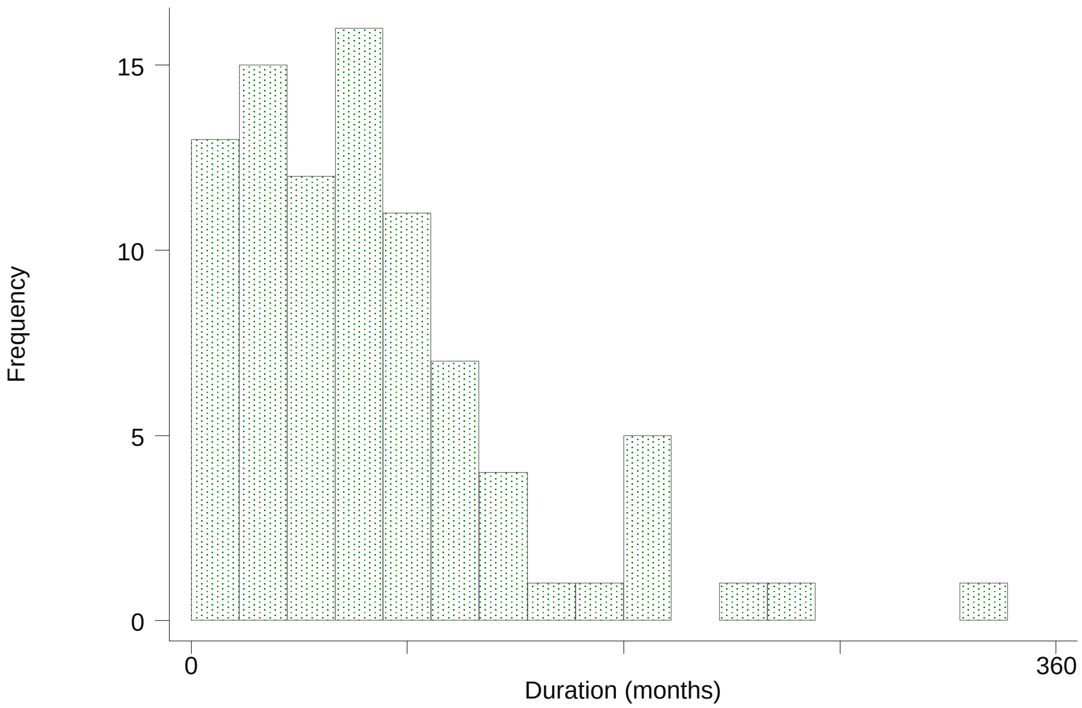


Figure 3: Estimated Survival Function with no regressors: Nonparametric Kaplan-Meier Estimate

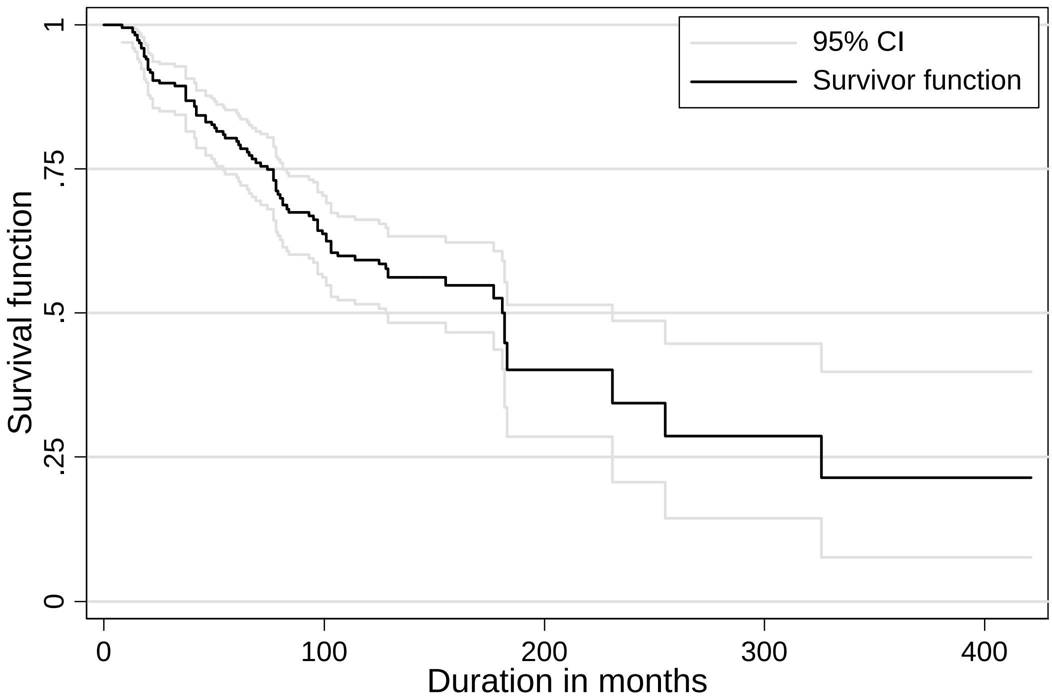


Figure 4a: Estimated Baseline Survival Function after Cox Semiparametric Regression

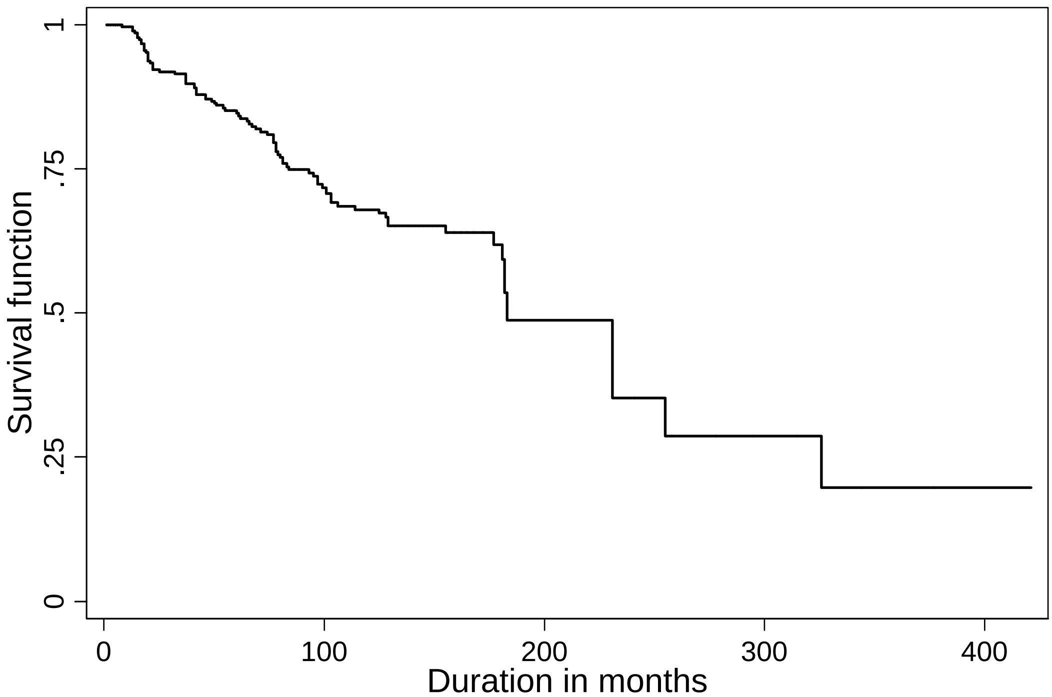


Figure 4b: Estimated Baseline Hazard Function (kernel smoothed) after Cox Semiparametric Regression

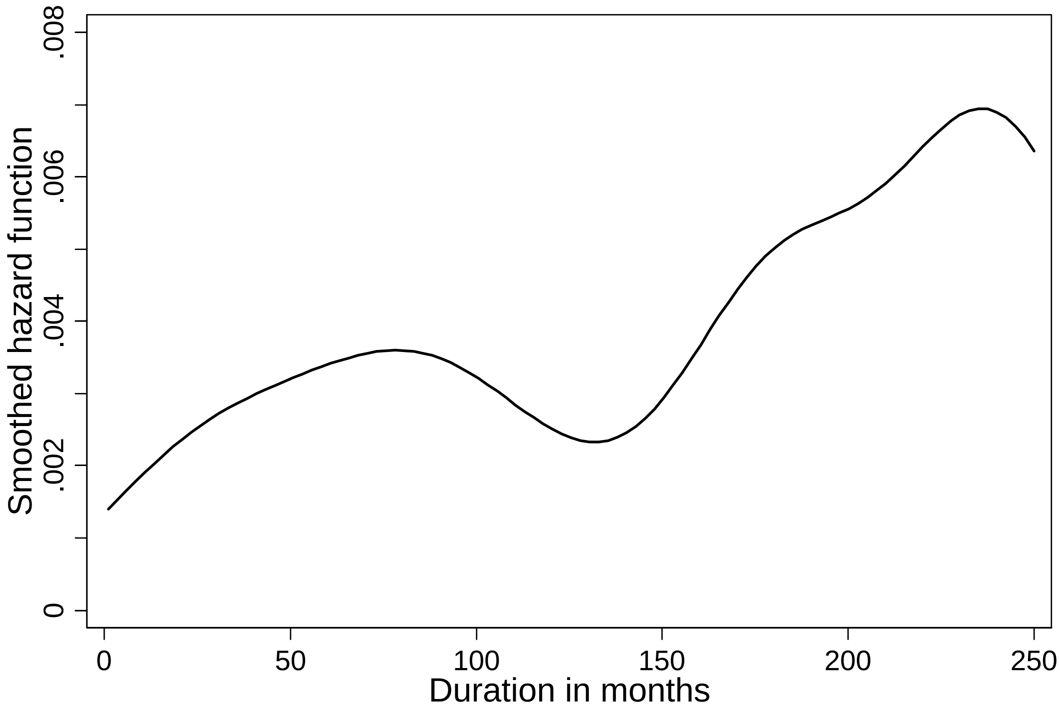


Figure 5a: Estimated Baseline Hazard Functions after Parametric Regression for the Exponential, Weibull, Gompertz, Generalized Gamma, Lognormal and Log-logistic Distributions

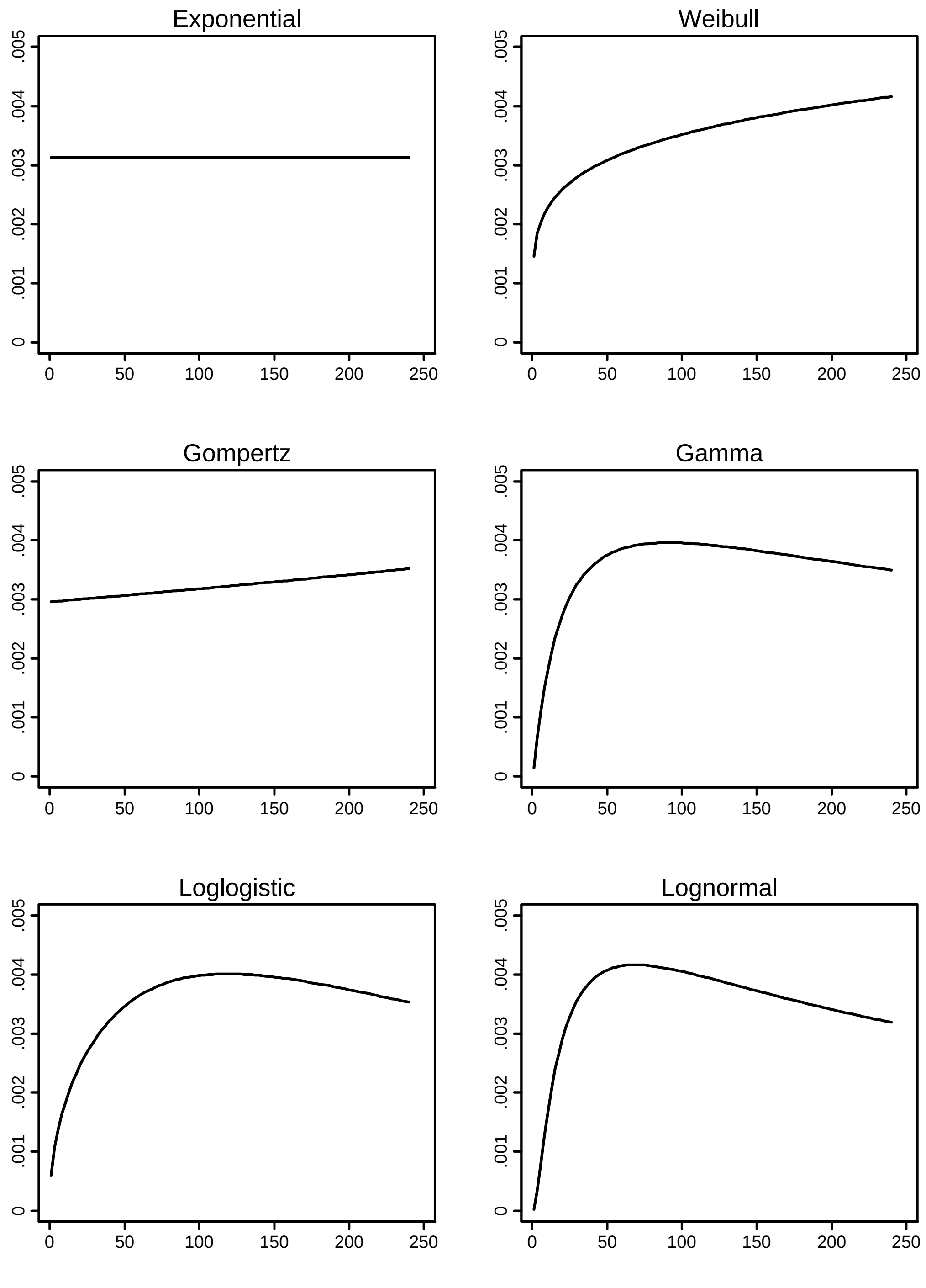


Figure 5b: Estimated Baseline Survival Functions after Parametric Regression for the Exponetial, Weibull, Gompertz, Lognormal, Generalised Gamma and Log-logistic Distributions

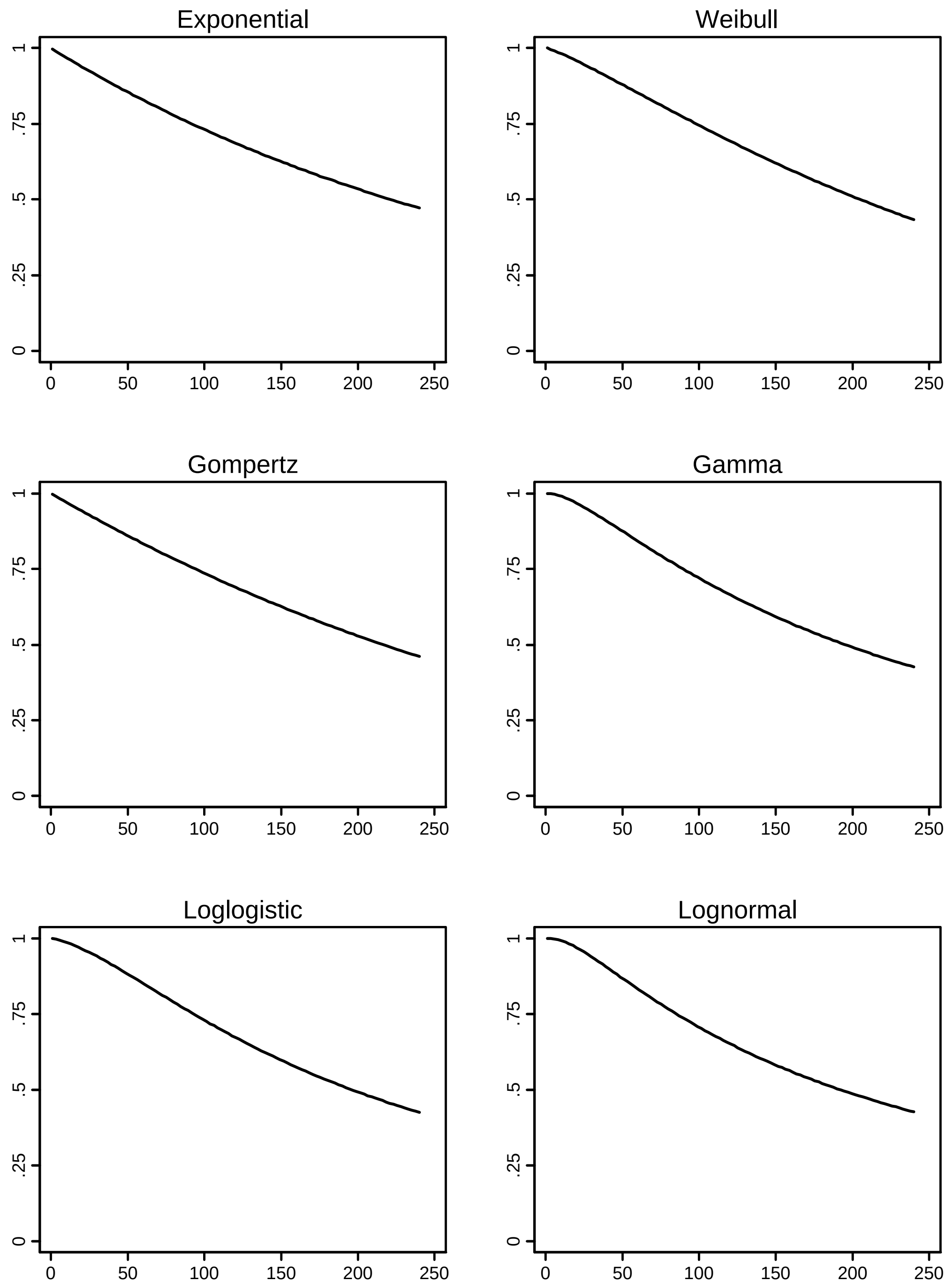


Figure 6a: Impact on the Lognormal Parametric Hazard Function of Changes in each of the Regressors.

Note: The hazard is evaluated at the lower quartile (topmost hazard), median (middle hazard) and upper quartile (lowest hazard) for each regressor, with all other regressors evaluated at sample means. For the first two regressors there is essentially no impact on the hazard.

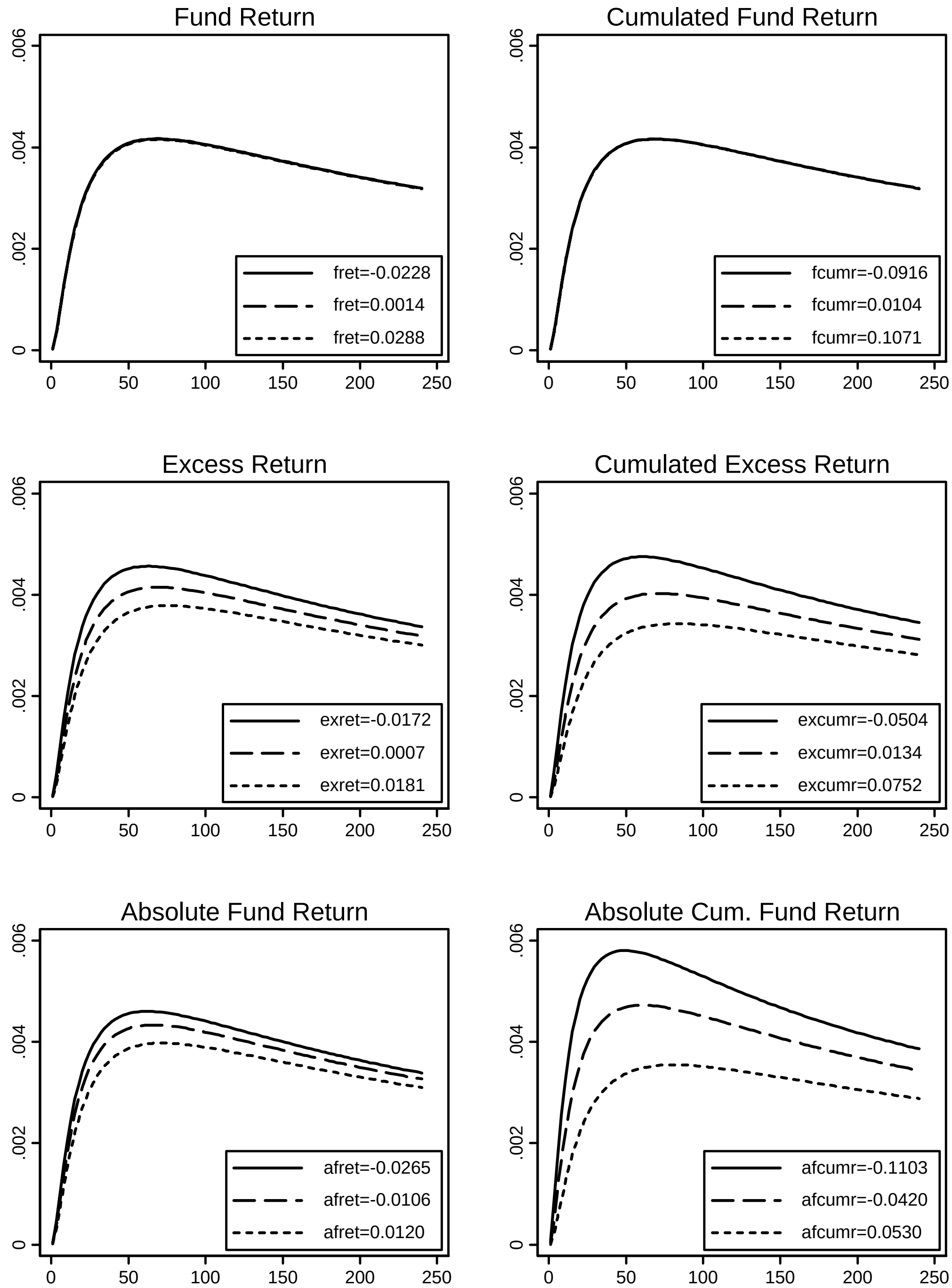


Figure 6b: Impact on the Lognormal Parametric Survival Function of Changes in each of the Regressors.

Note: The survival function is evaluated at the lower quartile (lowest survival function), median (middle survival function) and upper quartile (topmost survival function) for each regressor, with all other regressors evaluated at sample means. For the first two regressors there is essentially no impact on the survival function.

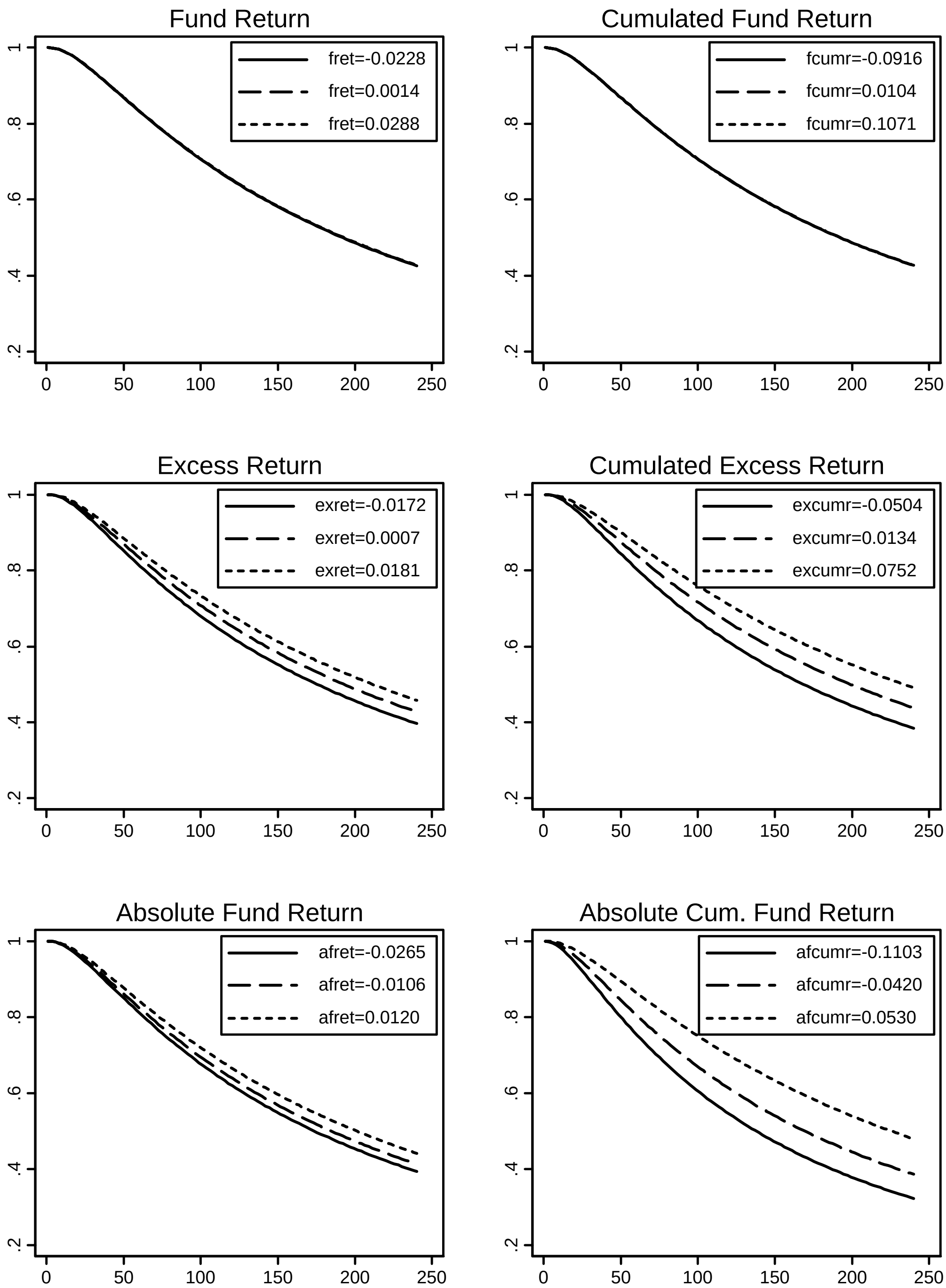


Table 1: Fund births and deaths from 1980 to 1999.

Year	Funds born during year	Birth rate (%)	Funds dying during year	Death rate (%)	Funds alive at the end of year
1980	0	0.0%	0	0.0%	16
1981	3	18.8%	0	0.0%	19
1982	2	10.5%	0	0.0%	21
1983	9	42.9%	0	0.0%	30
1984	9	30.0%	0	0.0%	39
1985	14	35.9%	0	0.0%	53
1986	26	49.1%	0	0.0%	79
1987	29	36.7%	0	0.0%	108
1988	26	24.1%	0	0.0%	134
1989	12	9.0%	9	6.7%	137
1990	7	5.1%	13	9.5%	131
1991	3	2.3%	6	4.6%	128
1992	4	3.1%	8	6.3%	124
1993	6	4.8%	9	7.3%	121
1994	17	14.0%	8	6.6%	130
1995	18	13.8%	3	2.3%	145
1996	16	11.0%	4	2.8%	157
1997	17	10.8%	6	3.8%	168
1998	16	9.5%	8	4.8%	176
1999#	1	0.6%	15	8.5%	162

Data January to March 1999
Source: FPG Research.

Table 2: Estimated Coefficients from Regression of Duration to Fund Closure (in months) for Cox Semiparametric Model and for six Parametric Models.

	Cox Model	Exponen-tial	Weibull	Gompertz	General Gamma	Log-Logistic	Log-normal
Specification	PH	AFT	AFT	PH	AFT	AFT	AFT
Fund Return	0.84 (2.80)	-0.05 (2.80)	-0.33 (2.40)	0.09 (2.82)	-0.09 (2.32)	0.05 (2.27)	0.09 (2.26)
Cumulative Fund Return	-0.62 (0.66)	0.06 (0.67)	0.18 (0.593)	-0.07 (0.67)	0.05 (0.60)	-0.02 (0.62)	0.00 (0.59)
Excess Return	-7.56 (3.66)	6.67 (3.49)	6.07 (3.06)	-6.75 (3.53)	5.72 (2.92)	6.09 (3.16)	5.32 (2.73)
Cumulative Excess Return	-2.52 (0.84)	2.74 (0.78)	2.19 (0.70)	-2.73 (0.78)	2.57 (0.86)	2.82 (0.95)	2.59 (0.88)
Absolute Fund Return	-5.35 (3.18)	5.13 (3.39)	4.45 (2.91)	-5.17 (3.39)	4.11 (2.88)	3.70 (3.58)	3.81 (2.88)
Absolute Cumulative Fund Return	-3.92 (1.22)	3.37 (1.12)	3.02 (0.92)	-3.40 (0.04)	3.05 (0.81)	3.08 (0.79)	3.01 (0.78)
Constant	na	5.77 (0.13)	5.63 (0.12)	na	5.38 (0.19)	5.28 (0.12)	5.26 (0.13)
Ancillary	na	na	1.19 (0.08)	0.0007 (0.0014)	0.10 (0.15)	0.68 (0.05)	1.20 (0.08)
Kappa	na	na	na	na	0.29 (0.35)	na	na
Log Likelihood	-392.29	-201.23	-199.24	-201.13	-197.18	-197.98	-197.48
AIC		412.46	410.49	414.26	412.36	411.96	410.97
Chi2(6) p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes:

1. Estimates based on 247 subjects, 88 failures and 21,677 months at risk.
2. Robust standard errors adjusted for clustering on funds in parentheses.
3. Specification: PH = proportional hazard, AFT = accelerated failure time. The AFT parameters can be compared to the PH parameters upon changing the sign. See text.
4. Chi2(6) p-val = Probability value for test of the null hypothesis that all covariate parameters are zero.
5. All results obtained using STATA; na = not applicable.

Table 3: Test of the Proportional Hazard Assumption in the Cox Semiparametric Model

	rho	χ^2	df	Prob > χ^2
Fund Return	0.150	2.60	1	0.107
Cumulative Fund Return	0.007	0.01	1	0.929
Excess Fund Return	-0.071	0.81	1	0.367
Cumulative Excess Return	0.048	0.45	1	0.504
Absolute Fund Return	0.083	0.67	1	0.412
Absolute Cumulative Excess Return	-0.098	5.70	1	0.017
Global Test		7.42	6	0.284

Note: Based on the estimates in column one of Table 2. The test reported is the generalised Grambsch and Thernau test of non-zero slopes in a generalised linear regression of the scaled Schoenfeld residuals on the rank of time, and is equivalent to testing that the log hazard ratio function is constant over time. See the STATA manual for details of the procedure: STPHTEST.