Is AIM A Casino?

A study of the survival of new listings on the UK Alternative Investment Market (AIM)

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Abstract

In this paper we study the survival rate of firms listing on the junior segment of London Stock Exchange, the Alternative Investment Market (AIM). The results show that on average AIM IPOs have high survival rates over the windows we study (up to five years post-flotation). We conclude that, contrary to recent allegations by the head of the US Securities and Exchange Commission (SEC), AIM is not a casino. Sufficient quality controls appear to be in place to ensure that firms admitted to the AIM have good chances of survival post-issue. Examining the determinants of survival rates of IPO firms over a window of five years post-IPO, we find that the probability of survival increases with firm age and size at the time of IPO. IPOs incorporated in the UK have higher survival rate than non-UK incorporated IPOs. IPO firms operating in the financial, cyclical-service and resource sectors have higher survival rates than IPOs operating in other sectors. New listings of the technology companies are particularly short-lived. Our results on the signs of the relationships between the probability of survival, on one hand, and initial returns and venture-capital backing are in line with previous findings for U.S. listings. However, in our study the relationships are not statistically significant. Finally, we examine the reasons for delistings, and differentiate between favourable and unfavourable reasons for delisting from investors' perspective. The main category of favourable delistings is deemed to be mergers and acquisitions. Investigating the determinants of the probability of delisting due to a merger or acquisition, we find that it is inversely related to the size of the firm at the time of IPO.

1. INTRODUCTION

"*The US Securities and Exchange Commission described London's junior Aim market as a casino on which 30 per cent of listings were gone within a year.*"

(The Financial Times, March 9 2007, Headline story)"

Earlier this year, the head of the US Securities and Exchange Commission (SEC) described the Alternative Investment Market (AIM) as a highly risky market where nearly one third of the new listings were gone within one year of listing. This claim was covered by the Financial Times as their headline news and motivates us to examine the survival rates of newly listed firms on AIM.

Since its creation in the 1995, the AIM has come to be seen as one of the most successful second-tier markets in the world. Even in the period following the bursting of the dotcom bubble, when most stock markets were seeing a large drop in the number of IPOs, AIM continued to attract new listings. It has attracted more non-domestic companies than NASDAQ. The AIM market is designed for smaller and growing companies. To its critics the AIM listing rules are viewed as light-touch allowing unsuitable companies to float. This raises questions of whether the AIM attracts companies that are of sufficiently good quality and are likely to survive.

Once a company lists on a stock market, its continued presence in the market is of considerable interest to all the stakeholders. New investors are concerned with the value of their investment, which to some extent may depend on the continued listing of the stock. Company managers have an interest in firm-survival as their careers and the value of their firm-specific human capital depend on the survival of their firm. Policy makers are keen to know whether the regulations and rules in place are effective and sufficient to protect investors and the reputation of the market.

Conducting an IPO offers benefits to the issuing firm, but also triggers organizational changes in terms of changes to strategy, structure, control process and operating procedures. These changes can be disruptive to the existing internal and external routines and may increase the short term risk of failure of the firm. The survival rate during such a period of organizational transformation becomes an important issue. Prior research (Schultz 1993; Hensler, Rutherford and Springer 1997; Jain and Kini 1999) focuses only on the long-term survival of new listings (typically over five or more years) in U.S. markets. These studies ignore the short-term risk of failure associated with the organizational transformation from private to public corporation. However, it seems of particular importance to examine the short-term probability of survival. The changes in ownership and organizational form triggered by flotation can be hazardous to newly floated firms struggling to adapt their strategies and internal operations to be compatible with their new forms. These changes can increase the failure rate as the firm's resources are diverted to reorganize the structure of the company as a public corporation (Amurgey, Kelly and Barnett 1993). Therefore, we investigate survival rates both over short and long-term periods following the IPO (specifically, during the first one, two and five years post-IPO).

We define surviving firms as firms that continue to be listed on AIM as independent organisations. A firm that is delisted due to merger or acquisition, suspension, liquidation or for any reason other than a transfer to the Main Market (or Official List) of the LSE is classified as a non-survivor. Delisting due to a merger or acquisition is not always bad news for its investors. Therefore, we differentiate mergers and acquisitions as comparatively "favourable" delistings, from investors' point of view, from other "unfavourable" reasons for delisting. We employ firm characteristics at the time of IPO such as age, size, industry and year of listing to model the probability of delisting due to merger or acquisition, against the probability of delisting for any reasons other than a merger/acquisition.

Prior research on UK IPOs has examined issues such as IPO underpricing and the ownership and corporate governance of IPO companies. There has also been research on the long-term stock and operating performance of IPOs. However, the issue of the survival profile of UK IPOs remains an unexplored area. To the best of our knowledge, this is the first IPO survival study to examine the survival time of the AIM IPOs.

This paper examines the survival rate of the AIM IPOs in the short-run (one and two years post-IPO) and long-run (five years) using survival analysis. Survival analysis complements other performance measure as it tests whether a firm has performed well enough to survive the competitive nature of the capital market in the sense of maintaining its corporate identity as an independent public corporation. Another attractive feature of survival analysis is that it allows us to examine both the likelihood of failure and the time to failure.

The short-run analysis involves estimating the survival rates over a period of two years for all firms that went public between 2000 and 2004 using an event-time approach. Descriptive statistics are also provided on survival rates over one year post-IPO. The relationship between the survival time and firm characteristics at the time of the IPO is examined in the long-run using both event-time and calendar-time approaches. These two approaches vary in relation to the tracking periods of the IPO firms. A comparison between the event time and calendar time results allows detection of any bias induced by different tracking periods of the IPO firms. In our analysis of the determinants of survival we use the following explanatory variables: age and size of the firm at the time of the IPO, initial IPO returns, the country of incorporation (UK or non-UK), venture-capital backing, and year and industry dummies.

For a sample of IPOs issued during the years 2000 to 2004, we find that the short-run probability of survival of AIM IPOs is high.[1] Firm age and size are positively related to the survival time in the long-run. IPOs incorporated in the UK have a higher survival rate than non-UK incorporated IPOs. The survival rate also depends on the industry of the IPO firm. For example, IPOs operating in the financial, cyclical-service and resource sectors have higher survival rates than those operating in the information technology sector. Unlike the evidence from the US (Jain and Kini 2000), we do not find any statistically significant relationship between initial returns, presence or absence of VCs and the probability of survival. Our results also show that the functional form of the probability of failure is better modeled by a log-normal distribution.[2]

Finally, we examine the reasons for delistings, and differentiate between favourable and unfavourable reasons for delisting from investors' perspective. Favourable delistings are deemed to be mergers and acquisitions (including buyouts). Investigating the determinants of the probability of delisting due to a merger or acquisition, we find that it smaller for larger IPO firms.[3]

[1] The probability of survival of IPOs that came to the market in the year 2000 is relatively low. This could be because of the difficult market conditions just after the dot com bubble.
[2] The AIC suggests the superiority of the log-normal over the log-logistic.

[3] Moeller et al (2004) find that most acquiring firms are large and medium sized firms.

The rest of the paper is organized as follow: Section 2 provides some back-ground information on the AIM market since its inception. Section 3 reviews the literature on survival analysis and bankruptcy. Section 4 describes the hypothesis, the data sources and methodology. Empirical findings are discussed in Section 5, while the conclusion is presented in Section 6.

2. BACKGROUND OF THE AIM

The Alternative Investment Market (AIM) was established in 1995, by the London Stock Exchange (LSE). The AIM is intended to provide a market for smaller and growing companies especially those may not be able to meet the Main market regulations. Securities listed on the AIM are currently treated as unquoted for the tax purpose thus providing potential tax benefits for the companies as well as the investors.[4] There are various business sectors on the AIM and many companies listed on the Main market have used the AIM at some point in their corporate lives, as a stepping stone, prior to full listing. The advantage of the AIM over the Main market is that AIM-companies are not required to fulfill the Listing Rules of the UK Authority.

The AIM imposes no restrictions on the type of business or the industry sector in which the company operates. The market is open to companies from all sectors and all countries around the world. The admission requirements for the AIM are relatively simple and less complicated compared to the Main market. The AIM does not require a trading record, which is generally the case with the admission to the Main market, and there is no minimum requirement for free float. Companies which apply for an admission to the AIM must comply with the AIM Rules and relevant legislation. Applicants must produce an admission document, which complies with the requirements of the Public Offers of Securities Regulations 1995 (POS Regulations).

There are many benefits on the AIM market similar to NASDAQ, but it also offers additional benefits to growing companies. The NASDAQ has grown from junior market into a senior market dominated by large and more established business. The AIM approach to governance is viewed as well balanced, protecting investors without adding compliance costs to newly quoted

[4] However, from April 2008, there will be no capital gain tax advantages. Instead there will be a flat rate of 18% for all capital gains. (The Daily Reckoning UK Edition, 18th Oct, 2007)

companies. In addition, the AIM offers a level of engagement for medium-sized firms that is not available in the senior markets such as the Main market of LSE, NYSE and NASDAQ.

Since the inception of the AIM, more than 2500 firms have been admitted to the market, raising approximately £31 billion through initial and further offerings. However, some companies have been delisted due to merger and acquisitions, while others have chosen to move to the Main market. Fig 1 gives information on the domestic and international firms that have been admitted to the AIM from 1995 to May 2007. It can be seen that the number of firms joining the AIM has been increasing since 2004. In 2006, the number of non-UK companies joining the AIM reached 124, which is 100 percent more than in 2004 and more than seven times the number of firms admitted in 2003.

[FIGURE 1 HERE]

2.1 Attractiveness of the AIM

Many international companies are joining the AIM as the market has an important part to play in building a sound foundation for entrepreneurship and growth across Europe. At present the AIM is known as the world's leading market for smaller growing companies from all part of the world. The market continues to attract ambitious companies; many UK and non-UK companies have chosen the AIM to gain a public quote. Companies joining the AIM also gain many advantages experienced by their counter-part listed companies on the Main market such as access to a globally respected investor and capital, enhance company profile, increase status and credibility of the firm. Table 1 summarizes the difference of the admission requirements between the AIM and Main market. The admission requirements for the AIM-companies are undoubtedly minimal and lighter than the Main market.

[TABLE 1 HERE]

Companies are allowed to join the AIM regardless of their country of origin or sector of activity. The main requirement for a firm seeking listing on the AIM is that the firm is appropriate for the market and any firm satisfies this requirement is eligible for listing. Nonetheless, this judgment is made by company's nominated advisor (NOMAD). The AIM market made easier for companies to join across the world using fast-track route. Under the fast-track process companies, which have had their securities traded on AIM designed market over the last 18 months can apply to admission without any admission documents.[5]

However, companies using the fast track route are also required to make a detailed pre-admission announcement. These announcements include:

- Confirmation that the company abides by the legal requirement of the relevant AIM designated markets.
- Details of the business and strategy following admission.
- A description of any significant change in the financial position or trading strategy.
- A statement showing that the directors are confident and working capital is sufficient at least for the next 12 months.
- The rights attaching to the arrangement for settling transaction in the shares being admitted.
- Disclose any information required by the AIM and not being made public.
- Address of the company web containing the latest published account.

3. LITERATURE REVIEW

Survival analysis is widely applied in the bankruptcy literature, but over the last decade, the technique has received an increasing attention in the IPO literature. The IPO firms are delisted for various reasons, so evaluating firm characteristics that contribute to the probability of delisting/failure is now an attractive area of research. Surprisingly, most studies of the IPO survivals are based on the US markets, while the UK markets remained unexplored.

[5] AIM designated markets are the main markets of Australian Stock Exchange, Euronext, Deutsche Borse, Johannesburg Stock Exchange, NASDAQ, NYSE, Stockholmsborsen, Swiss Exchange, Toronto Stock Exchange, UKLA Official List.

Queen and Roll (1987) examine whether a firm mortality is predictable using market data such as size of the firm, price, total returns, total volatility and beta. They argue that there are many drawbacks related to the use of accounting data including time-issues and accounting methods. Accounting data are subject to measurement error, in that two alternative accounting methods are likely to provide different results. Their results show that the size of the firm is inversely related to the firm's mortality, suggesting that large firms have lower mortality rate relative to small firms. The total return, price and volatility are positively related to the mortality indicating that the mortality rate increases with increase in the total returns, price and volatility. These relationships are significant at 1% level, whereas the relation between the mortality and beta is negative, but statistically insignificant. Queen and Roll conclude that the firm size is the best predictor of the mortality rate over the long term and short term period.

Schultz (1993) examines unit offerings (composed of shares and warrants) and shares issued on the NASDAQ and finds that firms that issue units are more likely to be delisted than firms that issue shares only. The control variables employed as the predictors of the probability of delisting are size of the firms, age, initial returns, average income before the IPO to the IPO proceeds, total assets to the IPO proceeds, sales to the IPO proceeds and long term liabilities to the IPO proceeds. Using the logistic analysis, his results show that the probability of delisting is negatively related to the age of the IPO firm and its size. Schultz concludes that the probability of delisting is high for firms with lower age, smaller size and lower initial returns. However, the probability of delisting is better modeled using survival model rather than logistic model. The logistic model does not distinguish between firms that failed 2 months or 3 months following the IPO. While the survival model assign the probability of survival for each firm based on their survival time.

Hensler et al (1997) investigate the relation between the survival rate of US IPO firms and firm characteristics using accelerated failure time model. The firm characteristics include size of the firm, age, initial returns, IPO activity, market level, number of risk factors reported in the prospectus, insider ownership and industry performance. Their findings show that the survival rates are positively related to the age, size of the firms, initial returns, IPO activity, insider ownership, optical and drug industries. These relationships are statistically significant between 5 and 10 percent levels. Hence, increase in the age, size of the firm and initial returns are predicted to increase the survival time post IPO. Hensler et al argue that the log-logistic distribution fits the survival data better and the probability of delisting increases and then decreases (nonmonotonic). However, the nonmonotonicity is also modeled by log-normal distribution and the choice between the two distributions is determined by lower AIC value.

Jaini and Kini (1999) examine the probability of surviving post-IPO using multinomial logit model. The sample of the IPO firms is compiled from 1977 to 1990. The results indicate that the size of the IPO firms at the time of IPO, pre-IPO operating performance and investment bankers' prestige are positively related to the survival of the IPO firms. Further, firm risk, industry barriers to entry and higher industry concentration are negatively related to the survival time.

Jain and Kini (2000) examine whether Venture Capital (VC) involvement improves the survival profile of IPO firms. The explanatory variables employed to predict the probability of survival post IPO period are natural logarithm of the gross proceeds raised at the IPO, managerial ownership retention, the R&D expenditure over total assets prior to the IPO year, analyst reputations, the number of lead bank and analyst tracking the IPO firms, and the reputation of the investment bank. The findings indicate that the probability of survival post IPO is positively related to the firm characteristics' and statistically significant except the managerial ownership retention, which is negative and insignificant. Jain and Kini find that the functional form of the probability of failure for the IPO firms is nonmonotonic and follows log-logistic distribution, which compliment the results of Hensler et al.

Jain and Martin (2005) investigate the relationship between audit quality and post-IPO survival using proportional hazard model. The sample consists of 800 firms that went public during 1980-1990 and tracked them until the end of 1996. Various firm characteristics are used including age, initial returns, ownership retention and the quality of the auditors to examine the impact of these characteristics to the probability of survival post-IPO. The findings show that the hazard rate is negatively related to the auditors' quality, age, size and investment bank reputations.

Cochrane, Darrat and Elkhal (2006) investigate the probability of failure in the internet industry mainly Dotcom firms applying Cox proportional hazard model on event-time and calendar-time approaches. The sample consists of 225 firms and collected from 1997 to 2001. Cochrane et al find that the net income to total assets, cash flow to total liabilities and total assets as important predictors of the Dotcom firms' failure. Other control variables used in their model include annual stock returns, total liabilities to total assets, net working capital to total assets, net sale to total assets and cash flow to total assets.

The results show that the Dotcom firms' failure is positively related to the total assets and negatively related to net income to total assets, and cash flow to total liabilities. These suggest that the higher the net income to total assets, and cash flow to total liability the lower the probability of failure, whereas higher total assets lead to higher probability of failure. However, the evidence of higher total assets associated with higher probability of failures contradicts the evidence reported in other studies such as Altman (1968), and Opler and Titman (1994). Further, the liquidity (cash flow to total assets) is important variable in predicting the probability of failure one year prior to the failure and less important three years prior to the failure. The stock returns, total liabilities to total assets, and working capital to total assets are insignificant variables to predict the failure, using the event-time and calendar-time.

Prior studies (Schultz 1993; Hensler et al 1997; Jain and Kini 1999 and 2000) have applied survival analysis to examine the relationship between the probability of survival and firm characteristics at the time of IPO. However, these studies focus on the long-run survival, ignoring the implication of the short-run survival for the IPO firms. This paper investigates the survival rates of the AIM-IPOs in the long-run and short-run. The short-run study accounts for the short-term risk caused by going public process and organisation transformation from private to public corporation. The long-run study extends the literature pioneered by Hensler et al (1997) and Jain and Kini (2000), but employing the log-normal distribution rather than their log-logistic specification.

4. MOTIVATIONS, DATA AND METHODOLOGY

4.1 Motivations

In order to investigate the survival rates of the AIM IPOs and factors that influence the survival at the time of IPO, we use variables employed in the survival analysis to predict the survival rate of the IPO firms. Hensler at al (1997) find that larger firms have a higher probability of survival relative to small firms. Hence, firms' size at the time of IPO is positively related to the survival rate. Schultz (1993) finds that the probability of delisting decreases as the age of the IPO firm increases. Therefore, the age is expected to be positively associated with the survival time. Hensler et al (1997) finds a significant positive relation between the initial returns and the survival rate, while Schultz (1993) finds no significant relation between the initial returns and the probability of failure over two year or three years post IPO. Since the results are mixed, the relation between the survival rates and the initial returns is expected to be positive, but likely to be significant or insignificant.

Jain and Kini (2000) find that VC-backed IPOs have a higher survival rate than non-VC-backed IPOs, so we expect the survival rate of the VC-backed IPO to be higher than non VC-backed. Information technology sector is riskier than the financials, cyclical service and resource sectors. Therefore, the survival rates of the financial, cyclical service and resource sectors are expected to be higher than that of information technology sector. IPOs incorporated in the UK are likely to have higher survival rate than non-UK incorporated IPOs. This is because investors are biased and pessimistic toward investing in non-domestic companies.

4.2 Data

This paper uses various sources of data to investigate the probability of survival for all AIM IPOs between 2000 and 2004. The list of the IPO firms, offer price, market capitalization, country of incorporation and industry sectors are obtained from the London Stock Exchange (LSE). The age of the firms and the date in which the firm becomes inactive are collected from the World Scope database and cross referenced with London Share Price Database (LSPD). The first day closing stock prices are gathered from the Datastream and Perfect Analysis databases. The list of the VC and non VC-backed IPOs is provided by the British Venture Capital Association (BVCA).

The survival analysis is applied in the short-run and long-run periods. The short-run test involves estimating the survival rates over a two year period for a sample of 641 IPO firms that went public from 2000 to 2004 using event-time approach. The approach involves tracking an IPO firm over a two year period from the IPO date. The probability of delisting due to a merger/acquisition is estimated for a sample of 139 firms that are delisted during 2000-2004. The long-run test involves evaluating the effect of firm characteristics on the survival time using event-time and calendar time approaches for a sample of 316 firms that went public during 2000-

mid 2002. The calendar time approach involves tracking an IPO firm from the event day to the end of the study period. The problem of the calendar-time approach is that it is likely to induce bias, since the IPO firms are tracked at different windows. For instance, Jain and Martin (2005) compile their IPO firms for the period 1980-1990 and track them until the end of 1996. This means that firms that went public in 1986 are tracked for 10 years compared to 6 years for firms that went public in 1990.

Table 2 illustrates the descriptive statistics of the age, size of the firm and initial returns for all firms that went public from 2000 to mid 2002. These variables have been identified in the IPO survival (Schultz 1993; Hensler et al 1997; Jain and Kini 2000) as the key predictors of the survival rates. The average age of the IPO firm joining the AIM during 2000- mid 2002 is 6 years, while the average size is £22 million and the average initial returns is approximately 8 percent. The age and the size of the firms are highly skewed with excessive kurtosis, while the logarithm transformations reduce the skewness and kurtosis significantly. The test of correlation between the control variables indicates that the variables are not highly correlated and there is no evidence of multicollinearity.[6]

[TABLE 2 HERE]

The distribution of the IPO firms are presented by industry in table 3, using FTSE Global Classification System. The four industries with the most IPO firms between 2000 and 2004 are Financial sector, Cyclical Service, Information Technology and Resource sectors. The number of firms floated in 2000 is more than twice the number of firms floated in 2002 and 2003.

[TABLE 3 HERE]

Table 4 shows the number of IPO firms delisted within one year and two years following the IPO. The Financial sector has experienced a higher failure rate during 200-2004, followed by cyclical service, resources and information technology sectors. In addition, the table shows that the IPO firms floated in 2000 have the highest probability of failure, whilst those floated in 2002 have the lowest failure rate. However, table 3 & 4 demonstrate that the rate of failure for the AIM IPOs between 2000 and 2004 is relatively low.

[6] See the appendix table 1 the correlation matrix between the variables.

[TABLE 4 HERE]

The IPO firms are delisted for different reasons table 5 provides a brief description of the delisted firms that went public from 2000 to 2004 using LSPD delisting codes. Many IPO firms delisted due to suspension, receivership and liquidation, while only a small fraction of the IPO firms delisted due to merger/acquisitions.

[TABLE 5 HERE]

Table 6 provides information on the presence of VCs in the AIM IPO market during the years 2000 to 2004. The table exhibits that not many VC-backed IPO firms approach the AIM for placing, despite the attractive features of the market.

[TABLE 6 HERE]

4.3 Methodology

4.3.1. Short-run

Survival analysis is an appropriate statistical technique that has been applied to examine the occurrence of some event (Hensler et al 1997; Jaini and Kini 2000; Jaini and Martin 2005). The survival analysis is different from other regression analysis due to its ability to account for time and handle censored observation. Censor refers to incomplete observation, in another word a situation where the event of interest has not occurred. For instance, a large proportion of the IPO firms in our sample have not yet experienced failure and remain operating until the end of the tracking period. So the survival analysis technique incorporates both censored and uncensored observation to provide consistent estimators (Allison 2000). Shumway (2001) finds that survival models as theoretically and empirically better than static models in terms of out of sample forecasts. Survivor is defined as a firm that continues to operate as an independent public corporation. Non-survivor is a firm that have been delisted from trading exchange due to suspension, liquidation, acquisition or for any reason other than moving to the Main market.

The survival rates for the IPO firms, are estimated using *Kaplan-Meier* method. The fundamental assumptions of this method are the survival times are independent and censuring occurs independent of the survival.

The *Kaplan-Meier* method involves estimating the survival rate non-parametrically using the following equations:

$$\widehat{S}(t) = \prod_{i|t_i \leq t} \frac{n_i - d_i}{n_i} \tag{1.1}$$

This is equivalent to

$$S(t) = \left(\frac{n_i - d_i}{n_i} \right) S_{i-1} \tag{1.2}$$

Where *S(t)* is the survival rate, n_i is the number of the IPO firms that are listed and participating in the study, d_i is the number of the IPO firms delisted during the tracking period. We apply equation (1.2) for each strata separately.[7] The survival rate is the probability of survival past time t_{i-1} , times the probability of survival at time t_i conditional on a firm being listed at time t_{i-1}.

The variance of the *product-limit* estimator is computed through Green-woods formula:

$$\widehat{V}[S_i] = S(t)^2 \sum_{i|t_i \leq t} \frac{d_i}{n_i(n_i - d_i)} \tag{1.3}$$

The standard error of the *product-limit* estimator is the square root of equation (1.3) scaled by $\sqrt{n}$, where n is the number of firms that are listed and participating in the study. The Log rank and Wilcoxon tests of equality are used to asses if for instance, the IPO groups share the same survival rates. The relevancy of these tests is that the failure rates are classified into observed failure and expected failure rates if the groups share the same survival functions. If the observed

[7] We apply equation (1.2) to estimate the survival rates of each IPO group separately based on the year of IPO. Similar approach is used to estimate the industry survival rates, VC and non-VC backed IPOs, UK and non-UK incorporated IPOs.

failure rate is significantly different from the expected failure rate, we reject the null hypothesis that the survivor functions of the groups are the same.

The logit regression is used to model the probability of delisting due to merger/acquisitions versus non merger/acquisitions. The dependent variable takes a value of 1 if the delisting is due to a merger/acquisition and 0 otherwise. The cumulative conditional probability of an event is given by:

$$P_i = E(y=1|X_i) = \frac{e^{X_i\beta}}{1+e^{X_i\beta}} \tag{1.4}$$

Where X_i is a vector of explanatory variables and P_i is the probability of being delisted due to merger. β is the coefficient estimated through maximum likelihood estimation. The marginal effect of change in X_i is given by the partial derivatives of the equation (1.4) and hence:

$$\frac{\partial L(X_i'\beta)}{\partial X_{ik}} = \frac{e^{X_i'\beta}}{(1+e^{X_i'\beta})^2}\beta_k \tag{1.5}$$

We run logit regression controlling for logarithm of age, logarithm of firm size, industry dummies and year dummy using the following expression.[8]

$$\begin{aligned} \mathrm{Ln}\left(\frac{P_i}{1-P_i}\right) = {} & \beta_1 \mathrm{Lnage} + \beta_2 \mathrm{Lnsize} + \beta_3 \mathrm{Financials} + \beta_4 \mathrm{Cyc\text{-}service} + \beta_5 \mathit{Re}\mathrm{source} \\ & + \beta_6 \mathrm{Year\text{-}dummy} + \varepsilon \end{aligned} \tag{1.6}$$

4.3.2. Long-run

The Cox (1972) hazard methodology is applied to examine factors at the time of IPO that influence the survivability of the IPO firms.

The general form of the hazard model is

$$T(t \mid X_i) = h_0(t)\exp(X_i\beta_x) \tag{1.7}$$

[8] Long and Freese (2006, p:77) state that using ML may not be convenient for a sample smaller than 100. The size of our sample is 139 firms that have been delisted during 2000-2004.

Where $T(t \mid X_i)$ is the length of trading period measured in months conditional on some covariates, $h_0(t)$ is the baseline hazard function, which measures the risk of failure at the beginning of a time period and the shape of the hazard function. The β_x are the probabilities of failure and are estimated from the data using maximum likelihood estimation. The X_i are the covariates at the time of the IPO, which influence the probability of failure post-IPO. The effect of the covariates is assumed to accelerate time to failure by a factor $\exp(-X_i\beta_x)$. If $\exp(-X_i\beta_x) > 1$, then time to failure for the IPO firm is accelerated and hence the failure is expected to occur over a shorter interval. If $\exp(-X_i\beta_x) < 1$, then the time to failure is decelerated and therefore the failure for the IPO firm is expected to occur over a longer period.

The likelihood ratio or Wald test is used to determine the appropriate parametric Accelerated Failure Time (AFT) model, when the AFT models are nested such as Weibull versus exponential, or gamma versus Weibull or log-normal. However, Akaike Information Criterion (AIC) is the appropriate test to select the best-fitting model in the case of non-nested models such as log-logistic versus log-normal distribution. The AIC is defined as

$$AIC = -2\mathrm{LnL} + 2(k+c) \tag{1.8}$$

Where LnL is the log likelihood ratio, *k* is the number of model covariates and *c* is the number of model-specific distributional parameters. Nonetheless, the log-normal and log-logistic models have two distributional parameters ($c = 2$). The AIC test suggests that the best fitting model is the model with the lower value of the AIC, regardless of how significant is the difference between the AIC values. Based on the AIC value the probability of failure for the AIM IPOs is better modeled by log-normal distribution.

The AFT model for the log-normal is

$$\begin{aligned} \mathrm{Ln}(t_j) = {} & \beta_1 \mathrm{Lnage} + \beta_2 \mathrm{Lnsize} + \beta_3 \mathrm{Initial-return} + \beta_4 \mathrm{DVC} + \beta_5 \mathrm{DYear} \\ & + \beta_6 \mathrm{UK-Firms} + \beta_7 \mathrm{DFinancial} + \beta_8 \mathrm{DCyclical} + \beta_9 \mathrm{DResources} + \varepsilon_t \end{aligned} \tag{1.9}$$

Where $Ln(t_j)$ is the accelerated failure time. Lnage is the logarithm of the firm age, while Lnsize is the logarithm of the firm size. Dvc is a dummy variable taking a value of 1 or zero depending on whether the IPO firm is VC or non VC-backed. Dyear is a year dummy taking a value of 1 if the IPO firm went public in 2000 and zero otherwise. DUk-firm is a dummy variable taking a value of 1 for the UK incorporated IPOs and zero for the non-UK incorporated IPOs. Dfinancial , Dcyclical and Dresources are industry dummies taking a value of 1 if the IPO firm operates in the fianancial sector, cyclical service or resource sector and zero otherwise. The information technology sector is used as the base sector to compare its survival rates with that of the financial, cyclical service and resource sectors.[9]

The general form of likelihood functions is

$$L_j(\beta_x, \Theta) = \frac{\{S(t_j \mid x_j\beta_x\Theta)\}^{1-d}\{f(t_j \mid x_j\beta_x, \Theta)\}^d}{S(t_{0j} \mid x_j\beta_x, \Theta)} \qquad (1.10)$$

Where *f* ( ) is the log-normal distribution, *S*( ) is the corresponding survival function, and (t_0, t_j, d, x_j) is the information on the *j*th observation. The β_x are the coefficients on **x**, and Θ are ancillary parameters for the log-normal distribution ($\Theta = \mu, \sigma$).[10]

[9] The intercept is not included in the model as the mean variation of the response variable is close to zero. As Baum (2006) states, including an intercept makes no sense especially in a model where the mean variation of the dependent variable is approximately zero and all regressors' coefficients are significant.

[10] Pseudo R^2 is used a measure of goodness of fit, which is an extension to the R^2 of the linear regression model. However, the pseudo R^2 resembles the R^2 measure in many aspects except that it does not measure the proportion of variation in the dependent variable explained by the independent variables, but rather provides a value to reflect how well the model fits the data in some vaguer sense

$\text{psuedo} - R^2 = 1 - \frac{L_{ur}}{L_0}$, where the L_{ur} is the log-likelihood function for the full model and L_0 is the log-likelihood function in the model with only an intercept. If the independent variables have no explanatory power, the $\frac{L_{ur}}{L_0} = 1$ and hence the pseudo R^2 is zero, which is similar to the R^2 in the linear regression model, when the covariates have no explanatory power.

5. ANALYSIS AND INTERPRETATION.

5.1. Short-run survival analysis results

The survival rates of the AIM IPOs are estimated over the two years after the IPO date using the event time approach. Figure 2 shows the survival rates of all IPO firms between 2000 and 2004. It can be seen that the rate of survival declines gradually within two and four months following the IPO except for firms that had their IPOs in 2001.

The rate of failures ranges between 3 and 15 percent over the first year and between 8 and 35 percent over the first two years following the IPO. The failure rate is higher in 2000 relative to all years, indicating that AIM IPOs had lower survival rate in 2000 compared to all the years between 2001 and 2004. The evidence does not support the view that the AIM market attracts low quality companies. The results also show that the AIM IPOs have higher survival rates on average and the short-run risk of failure is relatively low. The survival rates of firms that went public between 2001 and 2003 are similar to those reported by Schultz (1993) for NASDQ IPOs. AIM IPOs have high probability of surviving within a year or two post –IPO regardless of their country of incorporation.

[FIGURE 2]

Figure 3 shows the survival rates for IPOs issued during 2000-2004 by industry (i.e. pooling all IPO years). The rate of survival for the IPO firms operating in the Cyclical Consumer Goods industry falls by 8 percent over a period of seven months following the IPO, and further 5 percent in month 12 and constant over the remaining period. None of the IPO firms operating in the Utility sector failed over the two year period[11], while those IPOs operating in the financial sector had the highest failure rate during the same period. The industry failure rates vary in a range of 0 to 20 percent over the two years following the IPO. These failure rates are comparable with the rates reported by Hensler et al (1997). Hensler et al report 1.7 percent average failure rate for the IPO firms operating in the Health sector compared to 2 percent for the AIM IPOs operating in the same sector. However, a drawback for our analysis of these differing survival rates is that some

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[11] The results for the utility sector should be interpreted with caution as the sample size coming from this section is too small.

industries have more firms than others, and the rate of survival in any given industry might be greatly influenced by the number of firms operating in that industry.

[FIGURE 3]

The survival rates of the UK incorporated IPOs, non-UK incorporated IPOs, VC, and non VC-backed IPOs are shown in figure 4, over the two years period after the IPO. The survival rate of the UK incorporated IPOs declines 1 month following the IPO date compared to 3 months for the non UK incorporated IPOs. Similarly, the survival profile of the VC and non VC-backed IPOs falls at different rates a month after the IPO. Nonetheless, the survival rate of the UK firms remained higher over the two years period than non-UK firms. During the same period, the VC-backed IPOs have lower survival rates than non-VC-backed, which is inconsistent with Jain and Kini findings.

[FIGURE 4]

Table 7 illustrates the results of the log rank and Wilcoxon tests of equality, which are global tests in a sense that they do not test the equality at specific time point. The survival rates of the IPO firms are different for firms that went public between 2001and 2004. The difference between the observed delisting and the expected delisting is significant producing a highly significant chi-square value. On the other hand, the observed and the expected delisting for the VC and non VC-backed IPOs, the industries and the UK and non UK incorporated firms are close, generating a low chi-square value.

[TABLE 7]

The logit model is applied to estimate the probability of delisting due to merger/acquisition versus the probability of delisting for any other reason. Table 8 shows the results of the IPO firms delisted from 2000 to 2004. The probability of delisting due to merger reduces significantly the larger the size of the firm at the time of IPO. Nonetheless, there is no evidence to suggest that the age of the firm at the time of IPO reduces the probability of delisting for the merger/acquisition.

[TABLE 8]

5.2.Long-run results from calendar-time approach

The accelerated failure time model is applied to investigate the relation between the survival time and the effect of firm characteristics at the time of IPO. The IPO firms are divided into two categories: Table 9 shows the results of the IPO firms that went public between 2000 and mid 2002 and tracked until mid 2007 using calendar-time approach, while Table 10 shows the results of the same IPO firms tracked over five years period from the IPO date, using the event time approach.

[TABLE 9]

Model 1 shows the relation between the probability of survival post IPO and all covariates, whereas model 2 shows similar relation excluding insignificant covariates from model 1. The probability of surviving is positively related to the log of age, log of size of the firm, initial returns, VC-backed IPOs, UK firms, Financials, Cyclical service and Resource sector, and negatively related to the year dummy. However, initial returns and VC-backed IPOs are statistically insignificant, while other coefficients are significant between 5 and 1 percent levels. These results persist across the two models and are consistent with the previous studies.

The model predicts that an increase in the logarithm of age by one unit holding all other variables constant is expected to increase the probability of survival by 2 to 3 period based on time ratio or 57 percent based on the exponentiated coefficient. This suggests that old firms at the time of IPO have higher probability of surviving post IPO relative to young firms. The logarithm of the firm size is expected to increase the probability of survival post IPO by 1 to 2 periods or 33 percent. The UK incorporated IPOs have higher probability of survival than non UK incorporated IPOs by 90 percent and the difference between the survival rates for UK and non-UK IPOs is statistically significant. The VC-backed IPOs have higher survival rates than non VC-backed, but the difference between the survival rates is statistically insignificant. AIM IPO operating in the Financial sector, Cyclical service and Resource sectors have higher probability of survival post IPO than IPOs operating in the Technology sector. This evidence is statistically significant between 5 and 1 percent level. Firms that went public in 2000 have lower survival rates than firms that went public during 2001-mid 2002.

The AIC test provides evidence that the log-normal distribution is a better specification than the log-logistic distribution. The log-likelihood ratio test (LR test) does not reject the null, that the effects of the initial returns and the VC-backed IPOs are insignificant to the probability of surviving post IPO. The results are consistent with Schultz (1993), Hensler et al (1997) and Jain and Kini (2000), but there is no statistical evidence on the AIM market to support the findings of Jain and Kini that the VC-backed IPOs have higher survival rate than non VC-backed IPOs.

5.3 Results from event time approach

Table 10 shows the results of the event time approach, the probability of surviving is positively related to the log of age, log of size, initial returns, VC-backed IPOs, UK firms, Financials, Cyclical service and Resource sector, and negatively related to the year dummy. Nonetheless, the initial returns and VC-backed IPOs remained insignificant, while the other covariates are statistically significant.

[TABLE 10]

The event time results provide robustness to the calendar time results regarding the association between the probability of surviving post IPO and the effect of firm characteristic at the time of IPO. The estimated coefficients of the event-time and calendar-time approaches are approximately identical in terms of signs and size. However, the coefficient for the Financials becomes significant at 10 percent from 5 percent level. Further, the results provide evidence that the event time and calendar time approach are identical when the tracking periods of the IPO firms vary by 12 to 24 months. On the contrary, the two approaches are more likely to provide different results the larger the difference between the tracking periods of the IPO firms, as it is the case in the previous.

The short-term results provide evidence that the AIM-IPOs have high survival rates on average and the probability of delisting due to merger/acquisition is lower the larger the size of the firm at the time of IPO. The long-run results show that the logarithm of age and size at the time of IPO is positively related to the survival time post-IPO. This supports the findings of the previous studies (Schultz 1993; Hensler et al 1997; Jain and Kini 1999 and 2000; Jain and Martin 2005) that the age and size at the time of IPO improve the survivability post-IPO.

6. SUMMARY AND CONCLUSIONS.

This paper examines the survival rates of the AIM IPOs both in the short-run and in the long-run. The short-run results show that AIM IPOs have high probability of survival post-IPO. The probability of delisting post-IPO due to merger/acquisition reduces as the size of the IPO firm increases. The long-run results show that the survival time of the IPOs increase with age and size of the firms, while the initial returns have no impact on the survival time of the IPO firms. This evidence is consistent using both the event-time and calendar-time approaches.

Testing for inter-industry difference for four industries, the results show that IPOs operating in the Information technology sector have higher probability of failure five years after the IPOs than IPOs operating in the Financial, Cyclical service and Resource sectors. Further, UK incorporated IPOs have higher probability of surviving post IPO than non-UK IPOs. We do not find any statistically significant relationship between VC-backing and survival rates.

Table 1

Difference between the AIM and Main admissions

AIM	Main Market
• No minimum shares required in public hand	• Minimum 25% shares required in public hand
• Trading records are not required	• Three years trading records are required
• No shareholder approval required for transactions	• Shareholders approvals required for acquisition and disposal
• Admission documents are not examined by the UKLA	• Admission documents are investigated by the UKLA
• Nominated advisors required for all transaction	• Advisors needed only for certain transaction
• No minimum market capitalisation	• Minimum market capitalisation £10m

UKLA: UK Listing Authority.

Source: A Professional Handbook 2007.

Table 2
Descriptive statistics

Variables	Mean	Standard deviation	Skewness	Kurtosis	N
Panel A					
Age	5.5696	5.0519	7.9216	97.0489	316
Size	22.4433	36.3200	8.6405	112.5979	
Initial returns	0.0774	0.1840	3.5729	37.7338	
Panel B					
LnAga	1.5617	0.4927	1.3225	6.5595	
LnSize	2.4623	1.2047	-0.3027	2.8563	

Initial return is computed as the first day closing price less the offer price divided by the offer price

Firm’s age is the year from incorporation date to the IPO.

Size is the offer price x the number of shares issued.

Table 3
Industry Distribution of IPO firms from 2000 to 2004

	IPOs					
FTSE Global Classification System	2000	2001	2002	2003	2004	**Total**
Cyclical Service	**41**	**27**	**17**	**19**	**61**	**165**
General Retailers	3	2	2	-	5	12
Leisure, Entertainment & Hotels	9	3	5	5	14	36
Media & Photography	15	12	7	4	16	54
Support Services	12	10	3	9	17	51
Transport	2	-	-	1	9	12
Financials	**51**	**21**	**15**	**19**	**68**	**174**
Insurance	4	1	-	-	1	6
Investment Companies	1	6	2	1	7	17
Real Estate	6	4	1	3	4	18
Speciality & Other Finance	39	10	12	14	54	129
Investment Entities	1	-	-	1	2	4
General Industrials	**12**	**1**	**3**	**3**	**14**	**33**
Aerospace & Defence	-	-	1	-	3	4
Electronic & Electrical Equipment	5	-	-	-	6	11
Engineering & Machinery	7	1	2	3	5	18
Information Technology	**27**	**13**	**7**	**8**	**30**	**85**
Information Technology Hardware	5	3	2	-	1	11
Software & Computer Services	22	10	5	8	29	74
Non-cyclical Consumer goods	**15**	**9**	**6**	**4**	**32**	**66**
Beverages	-	1	1	-	2	4
Food Producers & Processors	1	1	-	2	5	9
Health	8	-	1	1	11	21
Personal Care & Household Products	-	1	-	-	-	1
Pharmaceuticals & Biotechnology	6	6	4	1	14	31
Resources	**17**	**18**	**9**	**10**	**23**	**77**
Mining	11	13	8	7	15	54
Oil & Gas	6	5	1	3	8	23
Others	**16**	**5**	**3**	**3**	**14**	**41**
Chemicals	5	1	-	1	3	10
Construction & Building Materials	2	1	-	-	2	5
Packaging	-	1	-	-	-	1
Automobiles & Parts	2	-	-	1	1	4
Household Goods & Textiles	3	-	2	1	3	9
Food & Drug Retailers	-	-	-	-	1	1
Telecommunication Services	4	2	1	-	3	10
Electricity	-	-	-	-	1	1
Total	**179**	**94**	**60**	**66**	**242**	**641**

Table 4

IPOs firms delisted between one and two years after the IPO industry

	IPOs										
	2000		2001		2002		2003		2004		
FTSE Global Classification System	year1	years2	year1	years2	year1	years2	year1	years2	year1	years2	**Total**
Cyclical Service	9	5	1	-	-	-	-	1	6	7	29
Financials	7	10	2	4	1	2	-	2	7	10	45
General Industries	2	3	-	-	-	-	-	-	1	-	6
Information Technology	4	5	1	-	-	-	1	1	1	6	19
Non-cyclical Consumer goods	3	2	1	-	-	-	1	-	4	1	12
Resources	2	2	2	1	-	1	1	1	6	5	21
Others	4	2	-	-	-	-	1	-	-	-	7
Total	**31**	**29**	**7**	**5**	**1**	**3**	**4**	**5**	**25**	**29**	**139**

Table 5

Reasons for delisting by industry

	Delisting reasons					
FTSE Global Classification System	Merger & Acquisition	Quotation Suspended	Administrative Receivership	Voluntary Liquidation	Others	**Total**
Cyclical Service	5	7	5	4	4	25
Financials	8	15	6	7	13	49
General Industries	2	1	1	-	2	6
Information Technology	4	9	3	-	4	20
Non-cyclical Consumer goods	1	5	3	-	3	12
Resources	9	5	-	2	4	20
Others	2	3	1		1	7
Total	**31**	**45**	**19**	**13**	**31**	**139**

Table 6
VC and non VC-backed IPO firms on the AIM
Between 2000 and 2004

	2000	2001	2002	2003	2004	Total
VC-backed IPOs	10	8	2	3	14	37
Non VC-backed IPOs	169	86	58	63	228	604
Total	179	94	60	66	242	641

Table 7
Log-rank and Wilcoxon tests of equality for the survival function

Groups	Observed delisting	Expected delisting	Log-rank Test	Wilcoxon Test
By industries	**139**	**139**	6.84	6.6
Basic industries	2	4	(0.6545)	'(0.6783)
Cyclical Consumer Goods	2	3		
Cyclical Serivce	29	36		
Financials	45	37		
General Industries	6	7		
Information Technology	19	19		
Non-cyclical Consumer Goods	12	14		
Non-Cyclical Service	3	2		
Resources	21	16		
By IPO year	**139**	**139**	31.4	32.55
IPO 2000	60	36	(0.000)	(0.000)
IPO2001	12	22		
IPO 2002	4	14		
IPO 2003	9	15		
IPO 2004	54	53		
UK & non UK	**139**	**139**	0.32	0.28
UK firms	123	125	(0.5701)	(0.5973)
Non-UK firms	16	14		
VC & non VC	**139**	**139**	0.82	0.93
VC-backed	10	8	(0.364)	(0.3337)
Non VC-backed	129	131		

The null hypothesis for the log rank and Wilcoxon tests is that the survival function for the groups is the same. The alternative is that the survival function is not the same. The test rank the delisting into observed delisting and expected delisting if the groups share the same survival functions. If the observed delisting is significantly different from the expected delisting, we reject the null; otherwise, we do not reject the null. The values in the parenthesis are chi-square p-values.

Table 8

The coefficients estimated from logit model between 2000 and 2004

$$Ln\ (P_i\ /1\text{-}P_i) = \beta_1 \text{LnAge} + \beta_2 \text{LnSize} + \beta_3 \text{Financials} + \beta_4 \text{Cyc-service} + \beta_5 \text{Resource} + \beta_6 \text{Year-dummy} + \varepsilon$$

Variables	**Coefficients**	**Marginal Probability**
LnAge	-0.0369	-0.0069
	(0.857)	(0.857)
LnSize	-0.2806**	-0.0531***
	(0.014)	(0.008)
Financials	-0.7387*	-0.1310**
	(0.09)	(0.059)
Cyc-service	-0.1030	-0.0192
	(0.819)	(0.815)
Resource	-0.9415*	-0.1491**
	(0.107)	(0.039)
Year Dummy	0.1680	0.032
	(0.723)	(0.725)
Number of observations	139	
$Pr(Y=1\|X_i)$	0.2541	
$Pr(Y=0\|X_i)$	0.7459	
Obs with Dep=0	105	
Obs with Dep=1	34	
Pseudo R^2	**0.2**	

The dependent variable equal to 1 if the delisting is due to merger/acquisitions and zero otherwise. The values in parenthesis are the p-values.

*** Significant at 1% level

**Significant at 5% level

*Significant at 10% level

Table 9

Coefficients estimates from parametric Hazard Model using calendar-time approach from 2000 to 2005

$$Ln(Survival\ time) = \beta_1 LnAge + \beta_2 LnSize + \beta_3 Initial\text{-}return + \beta_4 VC + \beta_5\ Year + \beta_6\ UK\text{-}firms + \beta_7\ Financials + \beta_8\ Cyclical\ service + \beta_9 Resources + \varepsilon$$

	Model 1		*Model 2*	
Variables	**Coefficients**	**Time ratios**	**Coefficients**	**Time ratios**
LnAge	0.8589***	2.3607***	0.8752***	2.3994***
	(0.000)	(0.000)	(0.000)	(0.000)
LnSize	0.3922***	1.4802***	0.4041***	1.4979***
	(0.000)	(0.000)	(0.000)	(0.000)
Initial returns	0.05412	1.0556	-	-
	(0.368)	(0.368)	-	-
VC-backed	0.8108	2.249	-	-
	(0.125)	(0.125)	-	-
Year Dummy	-0.8472***	0.4285***	-0.8255***	0.4380***
	(0.001)	(0.001)	(0.001)	(0.001)
UK firms	2.3201***	10.1772***	2.3345***	10.3246***
	(0.000)	(0.000)	(0.000)	(0.000)
Financials	0.5534**	1.7392**	0.5597**	1.7502**
	(0.050)	(0.050)	(0.048)	(0.048)
Cyc-service	0.8069***	2.2409***	0.7979***	2.2210***
	(0.007)	(0.007)	(0.008)	(0.008)
Resource	1.1165***	3.0542***	1.1719***	3.2282***
	(0.002)	(0.002)	(0.002)	(0.002)
Number of observation	316			
LR test Chi square			3.29	
Prob>chi^2			0.1926	
Pseudo R^2	0.25		0.25	

The values in parenthesis are the p-values. Financials, cyclical service and resource are dummy variables taking a value of 1 or zero, depending on the industry.
Time ratios measure the time in which one-unit increase in the covariate would delay the time to failure by one month. AIC for log-normal is 763.22 and 768.44 for log-logistic distribution respectively.
*** Significant at 1% level
**Significant at 5% level
*Significant at 10% level

Table 10

Coefficients estimates from parametric Hazard Model using event time approach from 2002 to 2007

$$Ln(h_t) = \beta_1\text{LnAge} + \beta_2\text{LnSize} + \beta_3\text{Initial-return} + \beta_4\text{VC} + \beta_5\text{ Year} + \beta_6\text{ UK-firms} + \beta_7\text{ Financials} + \beta_8\text{ Cyclical service} + \beta_9\text{Resources} + \varepsilon$$

	Model 1		*Model 2*	
Variables	**Coefficients**	**Time ratios**	**Coefficients**	**Time ratios**
LnAge	0.8455***	2.3291***	0.8622***	2.3693***
	(0.000)	(0.000)	(0.000)	(0.000)
LnSize	0.3983***	1.4893***	0.4101***	1.5070***
	(0.000)	(0.000)	(0.000)	(0.000)
Initial returns	0.05443	1.0559	-	-
	(0.364)	(0.364)	-	-
VC-backed	0.8138	2.2566	-	-
	(0.123)	(0.123)	-	-
Year Dummy	-0.8285***	0.4366***	-0.8071***	0.4461***
	(0.001)	(0.001)	(0.001)	(0.001)
UK firms	2.3129***	10.1037***	2.3274***	10.2520***
	(0.000)	(0.000)	(0.000)	(0.000)
Financials	0.5363*	1.7096*	0.5428*	1.7209*
	(0.057)	(0.057)	(0.056)	(0.056)
Cyc-service	0.8062***	2.2390***	0.7970**	2.2189**
	(0.007)	(0.007)	(0.008)	(0.008)
Resource	1.1132***	3.0443***	1.1689***	3.2186***
	(0.002)	(0.002)	(0.001)	(0.001)
Number of observation	316			
LR test Chi square			3.33	
Prob>chi^2			0.1892	
Pseudo R^2	0.25		0.25	

The values in parenthesis are the p-values. AIC for log-normal is 763.22 and 768.44 for log-logistic distribution respectively.
*** Significant at 1% level
**Significant at 5% level
*Significant at 10% level

FIGURE 1
IPOs on AIM of UK and Non-UK incorporated firms

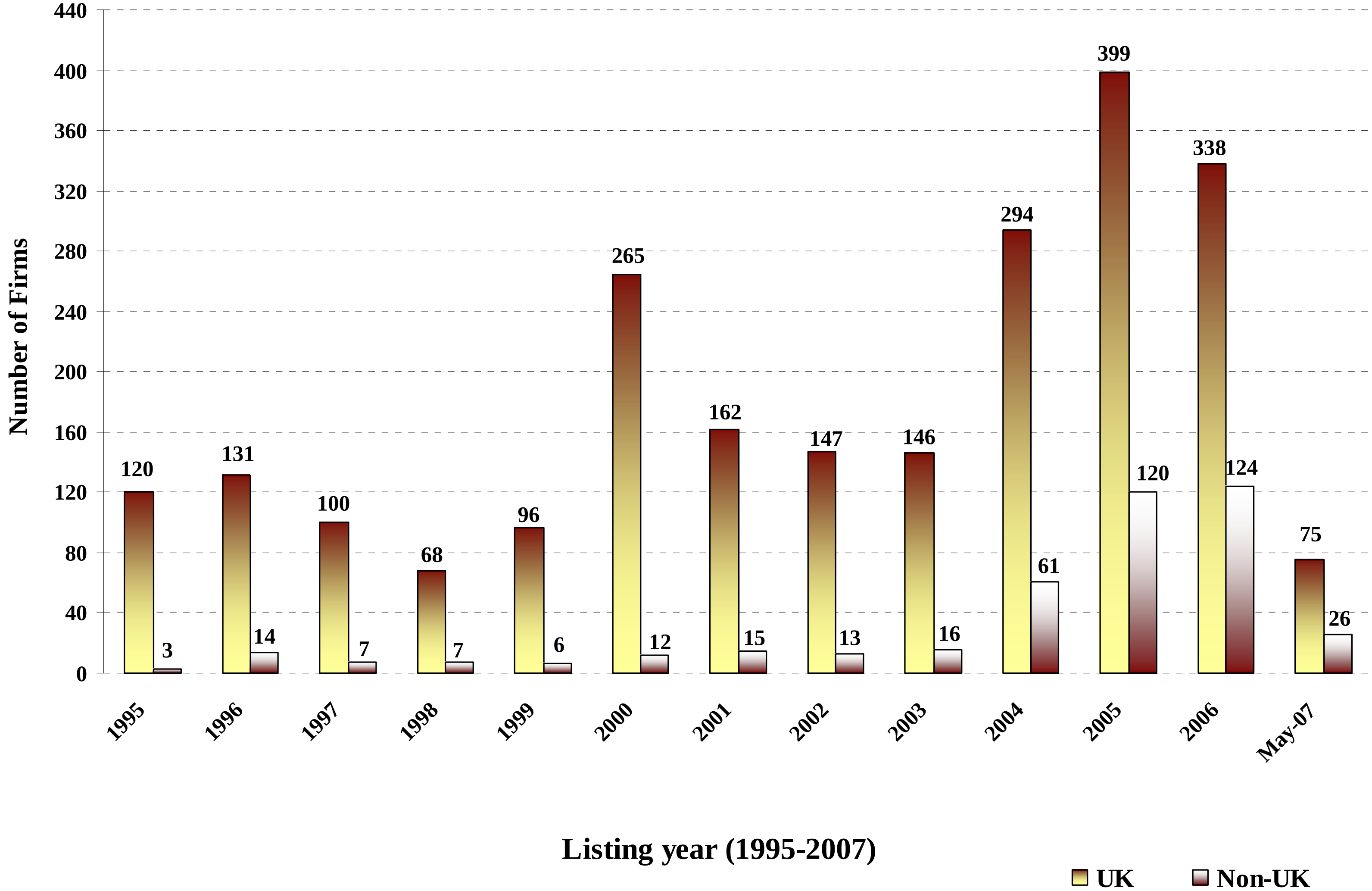


FIGURE 2
The Kaplan-Meier survival rate by year of IPO

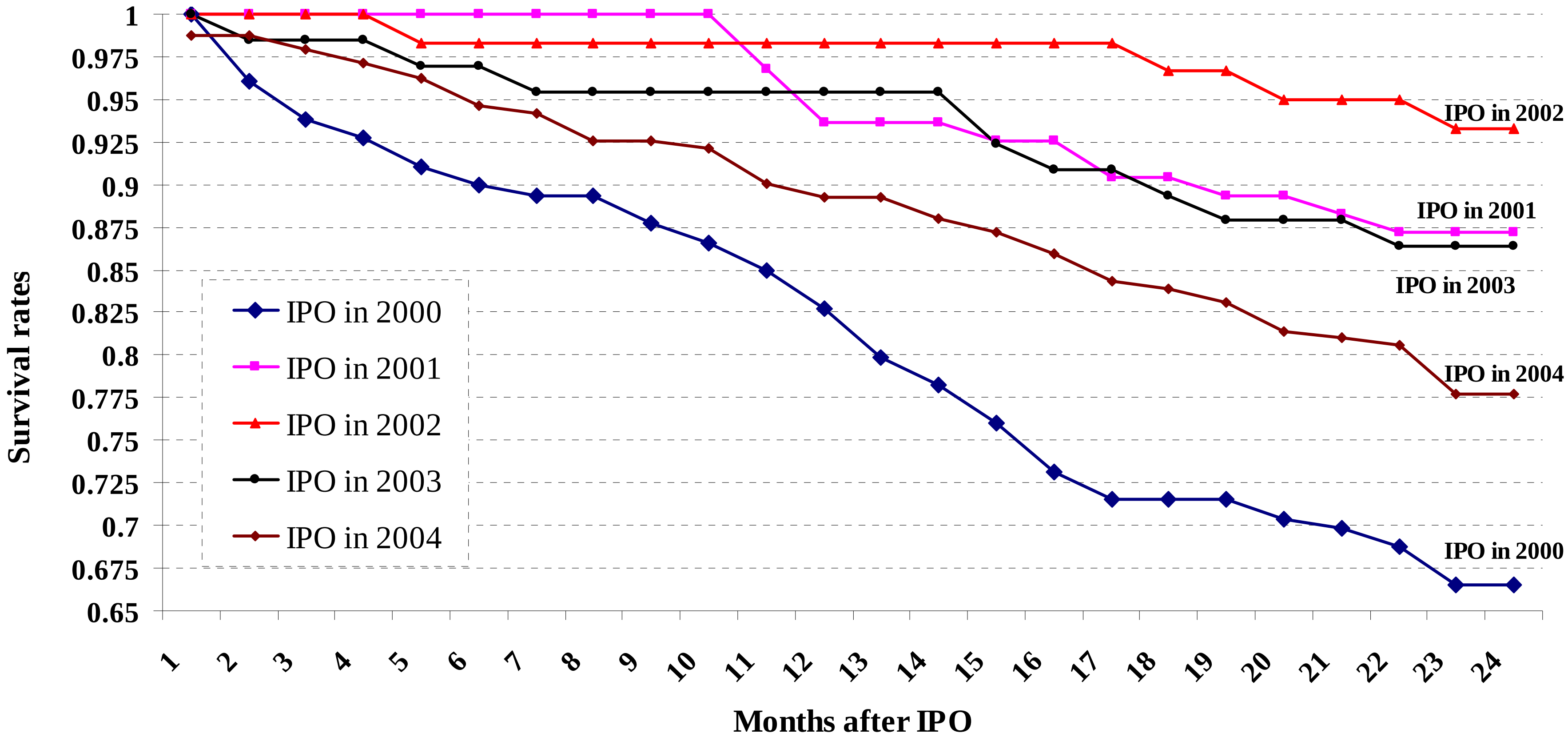


FIGURE 3
The Kaplan-Meier survival rate by industry

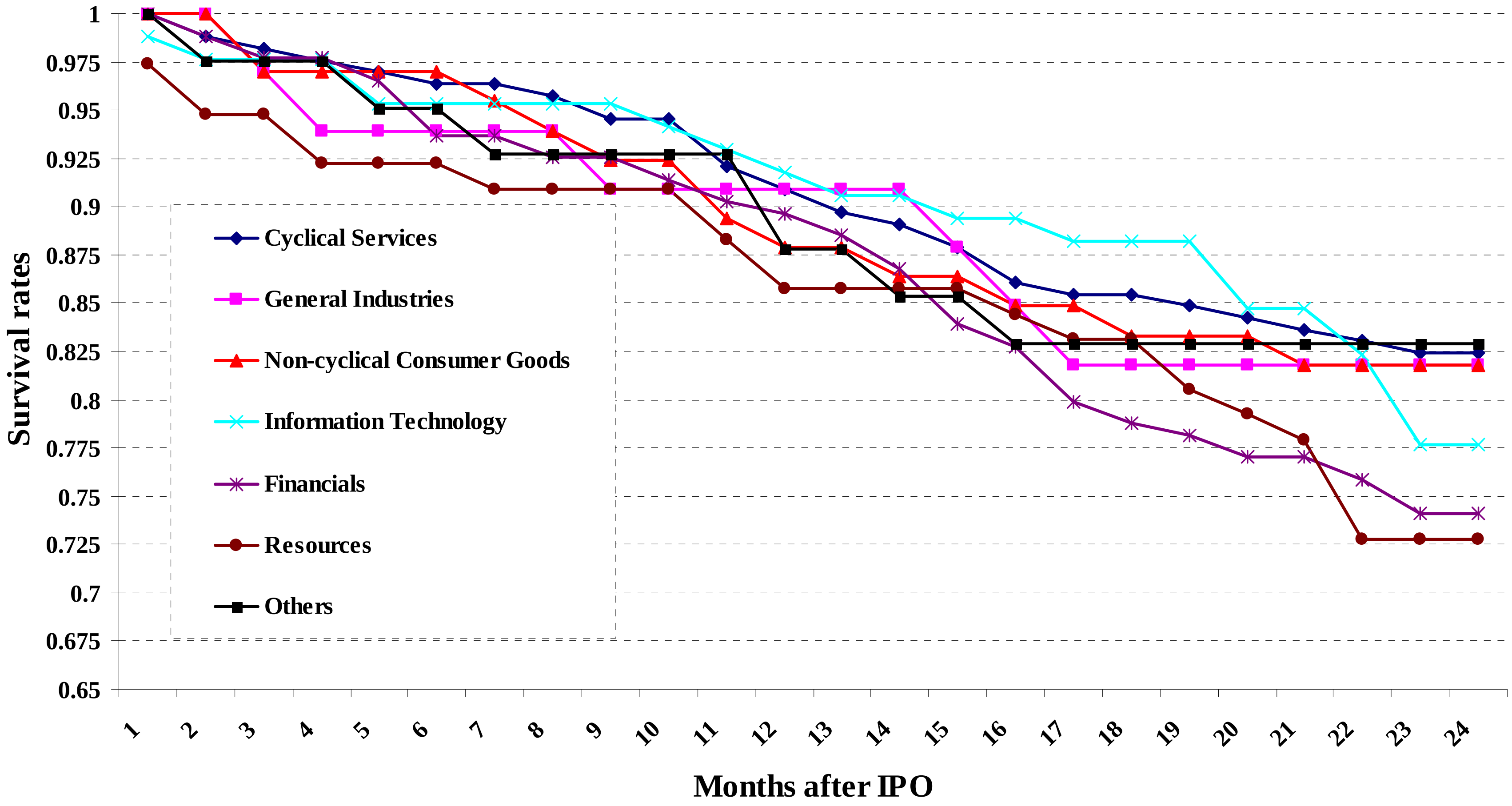
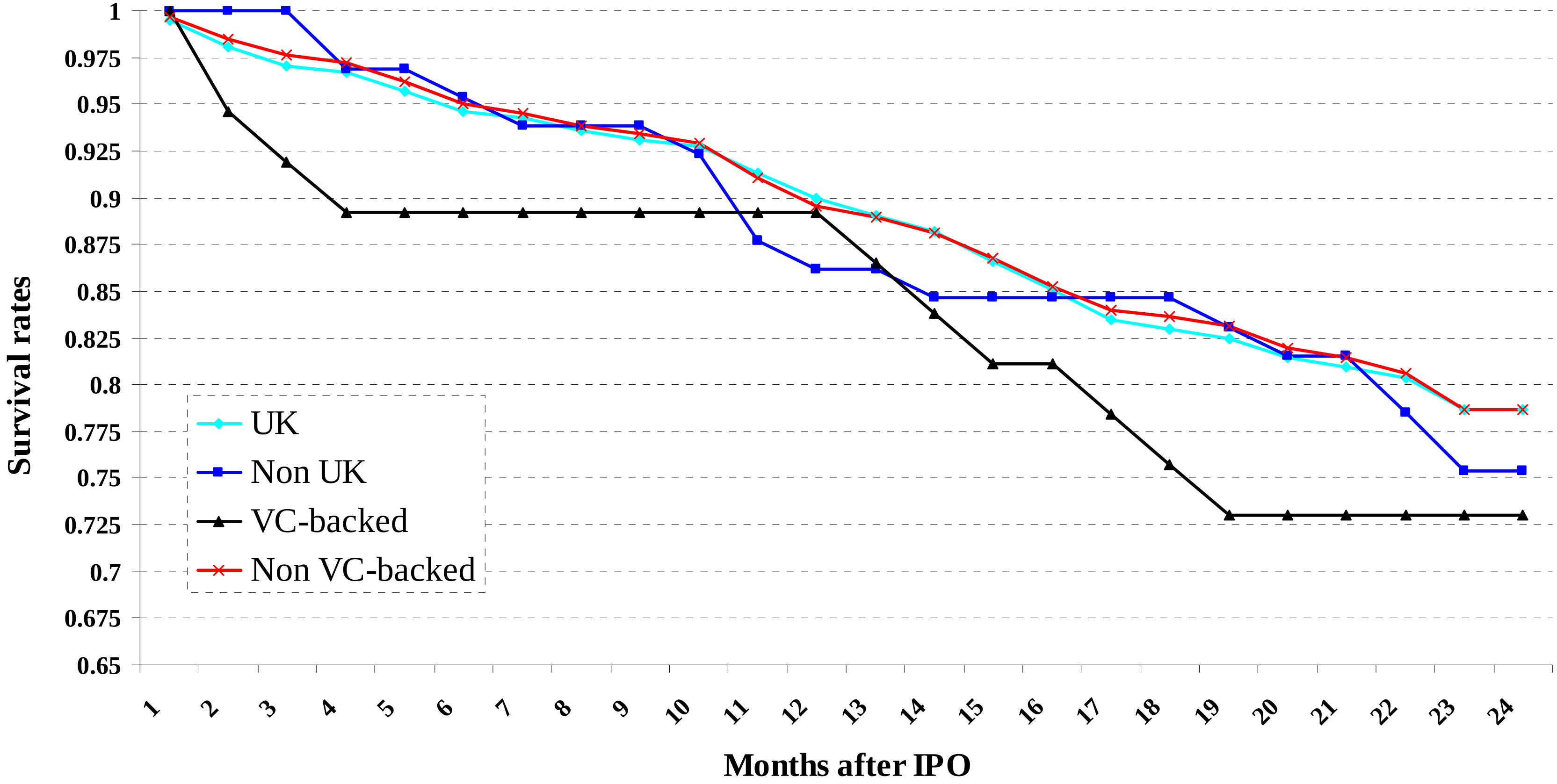


FIGURE 4
The Kaplan-Meier survival rate by country of incorporation and VC-backing



REFERENCE

Allison, P. (2000). Survival analysis using the SAS system: A practical guide. *SAS Institute Publishing*

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance,* 23: 589-609.

Amurgey, T., Kelly, D., Barnett, W. (1993). Strategic momentum: The dynamic of organisational change and failure. *Administrative Science Quarterly,* 38:335-348.

Audertsch, D., and Mahmood, T. (1995). New firm survival: New results using a hazard function. *Review of Economics and Statistics,* 97-103.

Baum, C. (2006). An introduction to modern econometrics using Stata. *A Stata Press Publication, Texas.* P: 78-82

Caves, R. (1998). Industrial organisation and new findings on the turnover and mobility of firms. *Journal of Economics Literature,* 36: 1947-1982.

Chochran, J., Darrat, A., and Elkhal, K. (2006). On the bankruptcy on internet companies: An empirical inquiry. *Journal of Business Research,* 59: 1193-1200.

Cleves, M., Gould, W., and Gutierrez, R. (2004). An introduction to survival analysis using Stata. *A Stata Press Publication, Texas.*

Cohen, N., Blackwell, D., and Grant, J. (2007). Top securities official calls AIM a 'casino'. *Financial Times,* p: 1

Congsheng,W., and Chuck,C. (2007). Long-run performance of global versus domestic initial public offerings. *Journal of Banking & Finance,* 31: 609-627.

Cox, D. (1972). Regression models and life tables. *Journal of Statistics Society,* 34: 187-220.

Cox, D., and OAKES, D. (1984). Analysis Of Survival Data. *University Printing House, Cambridge, London*

Deshmukh, S. (2003). Dividend initiations and asymmetric information: A hazard model. *The Financial Review,* 38: 351-368.

GREENE, W. (2003). Econometrical analysis. Fifth edition. *New Jersey. United*

Hamilton, L. (2006). Statistics with Stata. *A Stata Press Publication, Texas.*

Hensler, D., Rutherford, R., and Springer, Thomas. (1997). The survival of initial public offerings in the aftermarket. *Journal of Financial Research,* 93-110.

Jain, B., and Kini, O. (1999). The life cycle of initial public offerings. *Journal of Business Finance and Accounting.* 26: 1281-1307.

Jain, B., and Kini, O. (2000). Does the presence of venture capitalists improve the survival profile of IPO firms?. *Journal of Business Finance & Accounting,* 27: 1139-1176.

Jain, B., and Martin, C. (2005). The association between audit quality and post-IPO performance: A survival analysis approach. *Review of Accounting and Finance.* 4: 50-75.

Khurshed, A., Paleari, S., and Vismara, S. (2005). The operating performance of Initial Public Offerings, *Working-Paper,* University of Manchester and University of Bergamo.

Kleinbaum, D. (1996). Survival analysis: A self-learning text. *Springer Verlag, New York States of America*

Long, J., Freese, J. (2006). Regression models for categorical dependent variables using Stata. *A Stata Press Publication, Texas.*

LSE. (2007). The AIM rules, for Nominated Advisors (NOMAD), on-line www.omm.com.

Merali, M., Partner., and Marc, S. (2005). Role of the reporting accountant in an AIM floatation: A professional Handbook. *WHIreland.*

Moeller. S., Schlingemann, F., and Stulz, R. (2004). Firm size and the gains from acquisions. *Journal of Financial Economics,* 73: 201-228.

Opler, T., and Titman, S. (1994). Financial distress and corporate performance. *Journal of Finance,* 49: 1015-1055.

Osborne, C. (2006). Is AIM the new NASDAQ?. On-line *Osborneclarke.com.*

Page. Nigel (2006). AIM: The most successful growth market in the world. *White Page Ltd.*

Queen, M., and Roll, R. (1987). Firm mortality: Using market indicators to predict survival. *Financial Analyst journal,* 43:9-26

Ritter, J. (1991). The long-run performance of initial public offerings. *Journal of Finance*. 42: 365-94.

Schultz, P. (1993). Unit initial public offerings. *Journal of Financial Economics,* 34: 199-229

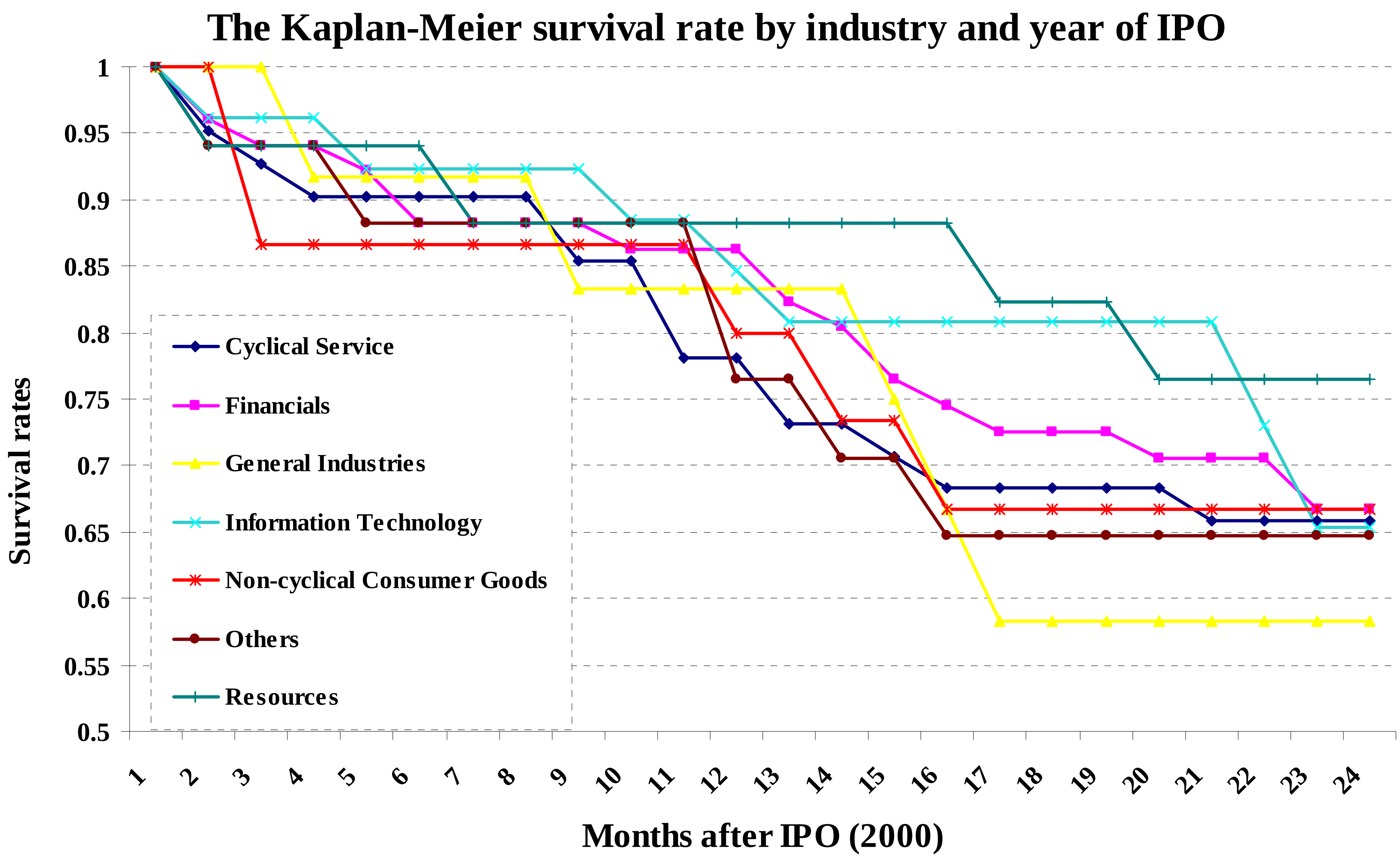
Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business,*74: 101-124.

APPENDIX

Table 1
Correlation matrix between age, firm size, initial returns

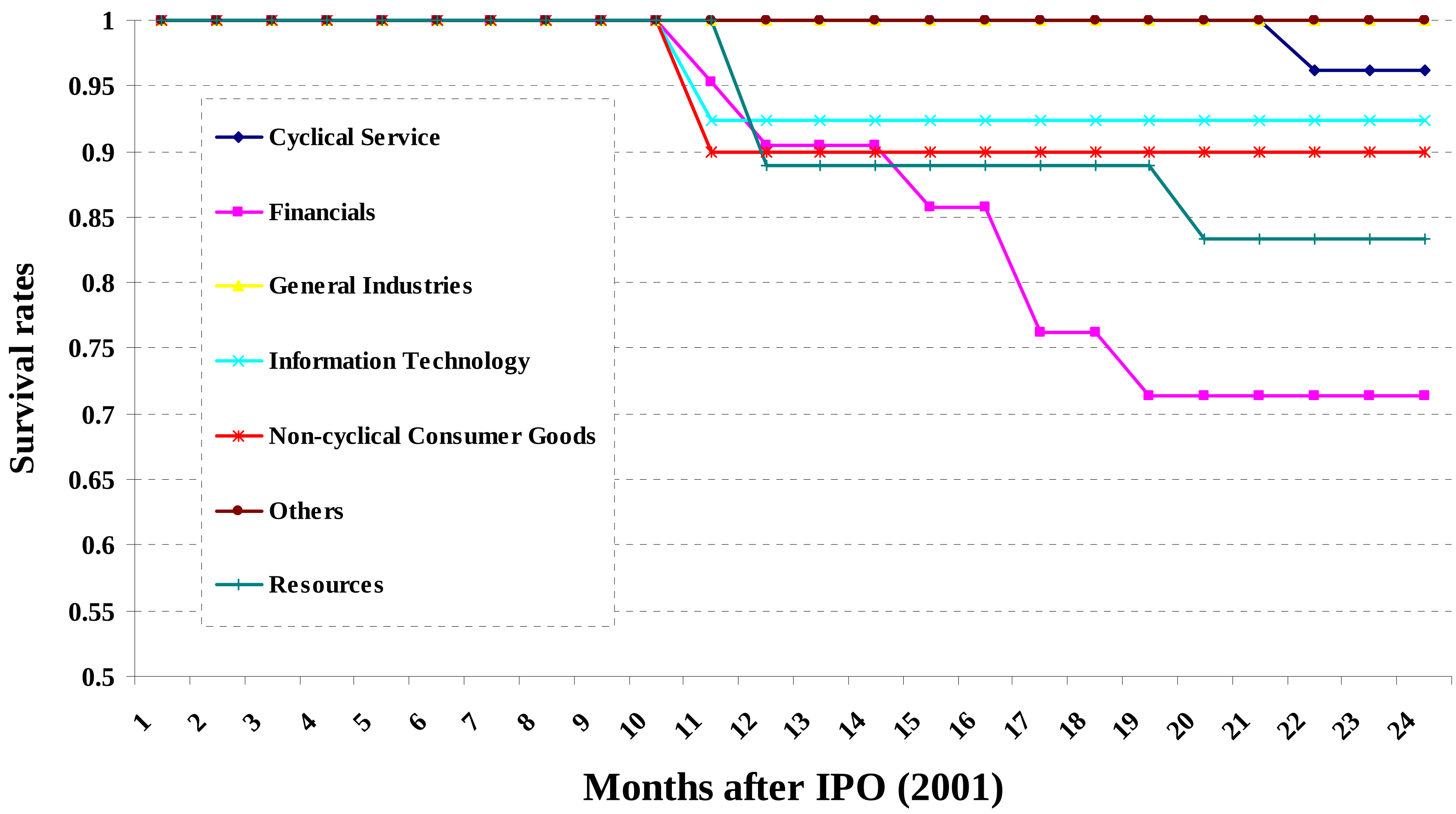
Variables	Age	Size	Initial returns	N
Age	1	0.0410	-0.0082	316
Size	0.0410	1	0.4052	
Initial returns	-0.0082	0.4052	1	

Appendix Figure 1



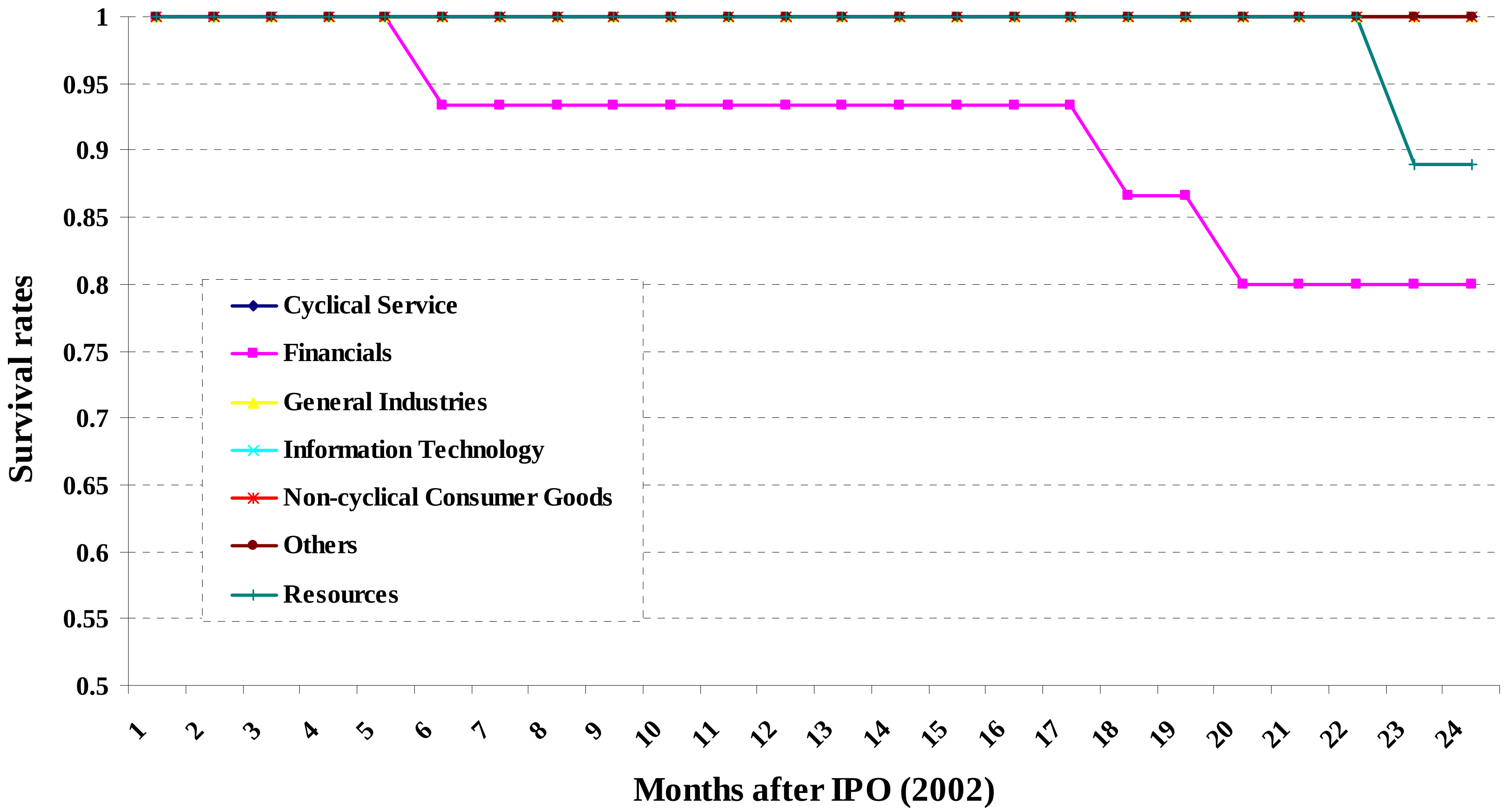
Appendix Figure 2

The Kaplan-Meier survival rate by industry and year of IPO



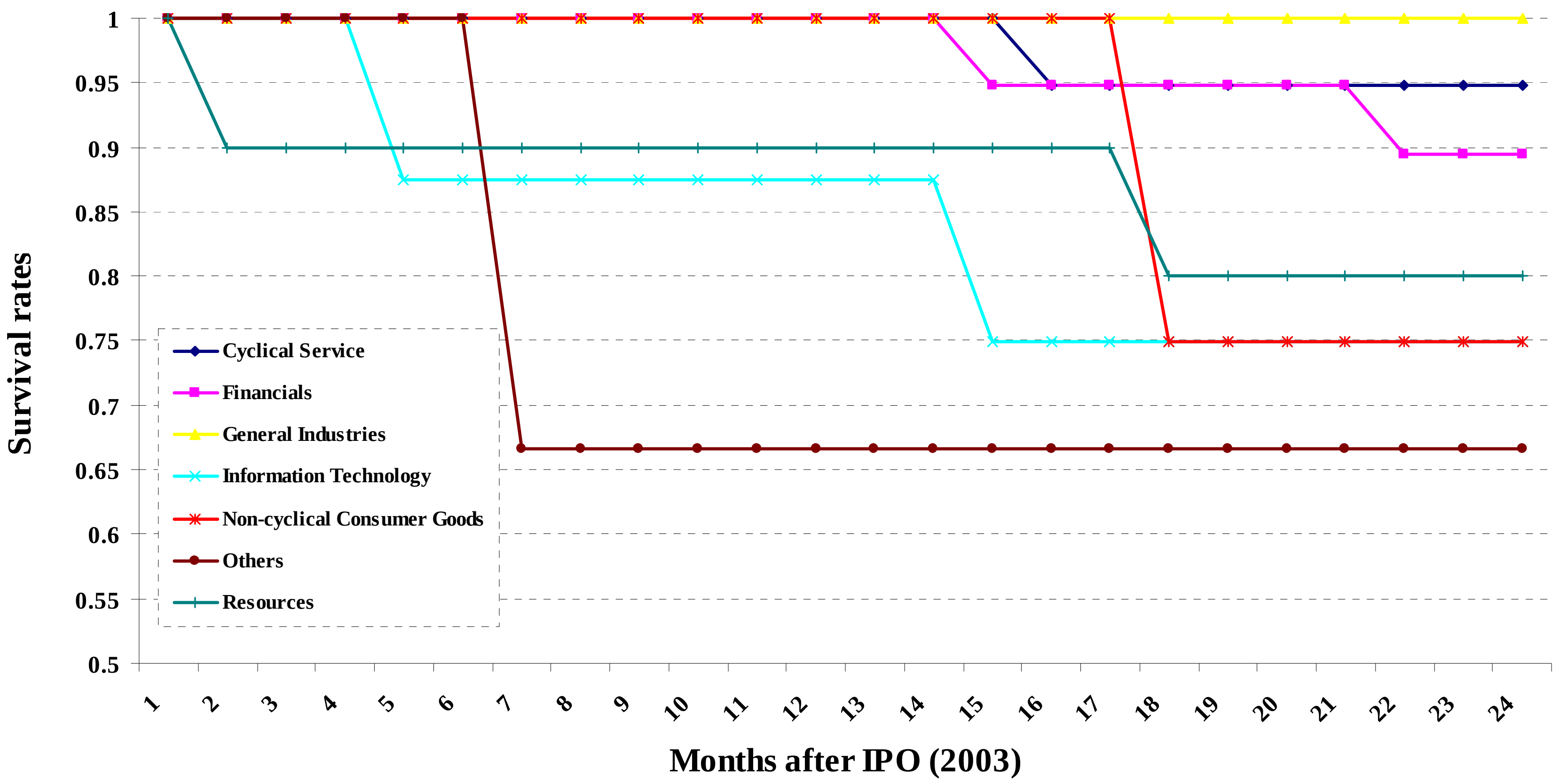
Appendix Figure 3

The Kaplan-Meier survival rate by industry and year of IPO



Appendix Figure 4

The Kaplan-Meier survival rate by industry and year of IPO



Appendix Figure 5

The Kaplan-Meier survival rate by industry and year of IPO