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SURVIVAL OF THE FITTEST: AN EMPIRICAL ANALYSIS OF IPOs IN THE POST-SEBI ERA

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ABSTRACT

The Indian primary market has seen several fluctuations in the post-SEBI era. The introduction of SEBI and abolition of CCI created 'hot issue phenomenon' in the market wherein several new issues entered the market, however, only a few managed to survive in the aftermarket. This paper explores the survival profile of 3125 IPOs issued during 1992-1996 using most sophisticated methodologies i.e., Logistic Regression and Survival Analysis. The models take a range of information concerning offering, market, and corporate specific characteristics of IPOs. The empirical investigation reveals that most of the IPOs entered the market in hot issue period (1992-1996) but they failed to survive longer in the market. Overall, the Kaplan-Meier estimation exhibits a significant decline in survival rate and a growth in hazard rate during the first 50-60 months of listing. The offering characteristics such as issue size, lead manager's reputation, and IPO demand exhibit a positive influence, whereas initial returns, risk, and list delay exhibit a negative influence on the endurance of IPOs. The analysis of market specific variables and survival profile of IPOs reveals that issues in the period of high IPO activity fails to sustain longer on the exchange. The results of corporate specific variables validates that age of the company not only enhances the odds of survival of IPOs but also accelerates their survival duration in the aftermarket. The survival profile of IPOs varies across the several industries as well. The findings of this study will have fruitful implication for the issuers, investors, regulators, and the entire capital market as they can evaluate the future prospects of IPOs and can take rational decisions accordingly.

KEYWORDS: IPO, Kaplan-Meier, Logistic regression, Survival Analysis.

INTRODUCTION

Going public is an important phase in the life cycle of a company. The first stage in a company is generation of an entrepreneurial idea or concept that is initially nurtured with private equity capital. Then, at a subsequent stage in its development, the firm attempts to raise additional capital through an IPO. However, in post-IPO phase, the firm can evolve into one of three basic states. It may continue to operate as a viable concern, acquired by another firm, chooses to go private again, or liquidates. In the worst scenario, because of poor performance or any such reason, a company may be delisted i.e., dropped from the exchange on which its securities are

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traded (Jain and Kini, 1999; Peristiani and Hong, 2004). In other words, “the life of a firm is a roller coaster ride wherein death is even more difficult to define, especially for public firms” (Bhattacharya *et al.*, 2011).

Over a period, the issue of corporate failure has become a matter of concern in economic as well as business area. ‘Failure’ simply refers to the inability of a firm to meet its desirable objectives and viewed as the opposite of success (Walter, 1957; Donaldson, 1962; Li and Lui, 2010). One such kind of failure is the delisting of issue from the market. Delisting is a traumatic event for both the firm as well as the shareholders (Li *et al.*, 2006). The failure of issue on the trading exchange may lead to bankruptcy, liquidation or momentous changes in the control of a firm and consequently results in huge losses to firm (Noor and Iskandar, 2012). Further, it hampers the interest of investors, creditors, and the economy at large. In the past few years, investors in IPOs had truly a bittersweet experience due to such failures in the aftermarket (Peristiani, 2003). Agarwal and Gort (2002) observed that roughly 5-10 percent of the firms in the US left the market over the span of a single year. Similarly, Fama and French (2004) reported a significant increase in the number of new listings on the NASDAQ during the period 1973 and 2001 followed by a sharp decline in survival rates as well. Apart from issuers and investors, the efficiency as well as the functioning of the entire market is highly influenced when an issue fails to survive on the exchange. Since, the survival of IPO holds huge importance not only for the issuer but also for the investors as well as the economy at large, the research efforts in this area suddenly got a thrust.

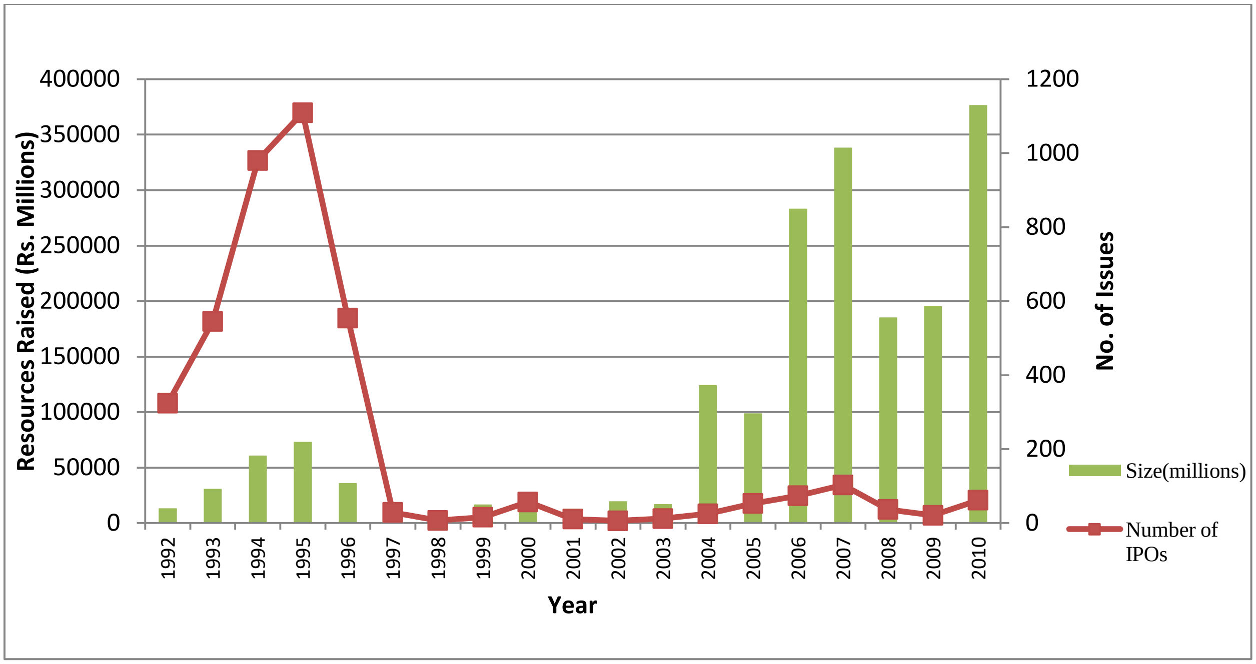
Researchers across the world have start exploring the status of initial public offerings in terms of their survival or failure (Hensler *et al.*, 1997; Peristiani and Hong, 2004; Demers and Joos, 2007, Rath, 2008, to name a few). In unfolding the puzzle of most fitted IPO in the aftermarket, several measures have been used by the researchers. Hensler *et al.* (1997) examined the survival of US IPOs during 1975 to 1984 using certain issue, market, and company specific characteristics. The study revealed a positive influence of issue size, firm age, and initial returns whereas a negative influence of market level at the time of offerings and number of risk characteristics on the survival duration of IPOs in the aftermarket. Following this, Jain and Kini (2000) analyzed the effect of venture capitalist involvement on the survival of 877 US IPOs during 1977-1990. Fama and French (2004) examined how the changing characteristics of newly listed firms affect their post-listing status. Kooli and Meknassi (2007) conducted a research on survival profile of 6235 IPO issuers from 1985 to 2005. They found that larger IPOs exhibit a lower probability of delisting, whereas, higher underpricing and hot period increases the probability of failure or becoming a target. Jain and Kini (2008) applied the Cox proportional hazard model to examine the influence of certain strategic investment variables and control variables on IPO survival. Hamza and Kooli (2010) conducted a research on the effect of venture capitalist reputation on the survival profile of 6235 US IPOs from 1985 to 2005. They observed that having a prestigious underwriter improves the probability of survival for IPO firms. However, high level of underpricing, hot period, and internet sector boost up the likelihood of non-survival relative to survival. Lui and Li (2014) analyzed the life cycle of IPOs in China using Cox PH model and they found that delisting is predominantly influenced by the company' pre-IPO operating performance, as well as financial indicators and governance structure at the time of the IPO. Recently, Espenlaub *et al*. (2016) examined the impact of the legal system on survival of IPO survival 32 countries. They found that IPOs in countries with better investor protections remain listed for longer.

A different strand of literature, predominantly from the field of accounting and finance, relates the survival and failure of IPOs to various financial ratios based on their capital market and accounting information (Cockburn and Wagner, 2007; Bhabra and Pettway, 2003; Peristiani and Hong, 2004; Demers and Joos, 2007; Cockburn and Wagner, 2007; Chou *et al.*, 2007; Rath, 2008; Adjei *et al.*, 2008). Whereas, certain researchers have associated the long run endurance of initial public offerings with certain corporate governance measures as well. Fischer and Pollock (2004), Rath (2008), Chancharat *et al.* (2008), Audretsch and Lehmann (2005), Howton (2006) and so on, used certain governance mechanism in different contexts and with different combination reaching to varied conclusions. Within this broad umbrella of survival measures, researchers have empirically examined the large number of determinants that influence the survival of IPOs in the aftermarket. The thorough analysis of literature provides the evidence that issue, company, and market specific variables mainly determine the survival profile of IPOs.

Although, the efforts have been started across the world to explore the status of IPOs in the aftermarket, yet the reasons and consequences of delisting of IPOs are quite less explored especially in India. As far as Indian IPO market is concerned, Raju and Prabhudesai (2012) explored the high failure rate of IPOs in light of global credit crunch and the US recession in 2007-2008. However, the empirical evidences on the survival profile of IPOs in the post-SEBI era are quite scarce. Hence, the dearth of literature on the survival profile of IPOs in India opens a scope for more research contribution.

The Indian IPO market has experienced several structural changes in the post-SEBI (Securities and Exchange Board of India) era. The abolition of the Controller of Capital Issues (CCI), establishment of SEBI, introduction of free pricing mechanism, and increase in participation by Foreign Institutional Investors (FIIs) has brought a sea change in the entire IPO market. The effect of such changes is evident from the upward trend in the IPO market during the period 1992-1996 (see figure1). However, along with this, several malpractices, discretionary allotments, and fly-by-night operators also entered the market that disrupted the smooth functioning of this market. Moreover, the Southeast crisis and the Internet bubble burst generated the negative sentiments among the investors and decelerated the growth of this market significantly.

Figure 1: Trends in Indian IPO Market



Source: Prime Database

During such period, several new issues failed to maintain their identity, whereas a few managed to sustain their status on the exchange. This signifies that surviving firms possess some distinctive factors that ensure their sustenance in such a volatile environment. The present study is an endeavor to explore such factors that influence the sustenance of IPOs in the post-SEBI era.

The aims of this paper is to fill the gap in the literature by identifying the extent to which the post-IPO outcome varies, along with the determinants of the success of fittest IPOs in the aftermarket. The study addresses this issue from four main perspectives. First, the paper extends the previous studies of post-IPO market, covering the operating performance of IPOs as the main concern, to post-IPO outcomes in terms of their survival or failure. Second, this study applies the survival analysis methodology, which is a unique way of exploring the duration of IPOs in the aftermarket. Third, it tracks down the effect of covariates on the post-listing status of IPOs that help in analyzing the significance of each factor in underpinning the two post-IPO outcomes. Finally, the study explores the role of timings of issue (hot or cold) in determining the success of IPOs on the exchange. The 'hot issue' period refers to the duration in which a large number of issues enter the market, whereas cold period attracts less number of issues (Ibbotson and Jaffe, 1975; Jain and Kini, 1999; Loughran and Ritter, 2004; Demers and Joos, 2007; Carpentier and Suret, 2008; Kooli and Meknassi, 2007). Researchers assert that hot issue period gives an immense number of issues in the market, but such issues are of low quality. Mainly, such low quality firms enter the market just to take the benefit of favorable market conditions, but in reality, they do not have the capacity to withstand the rough market conditions due to which they fail to survive in the aftermarket (Hensler *et al.*, 1997; Demers and Joos, 2007). However, in cold periods, stronger firms are more likely to succeed with their IPOs (Boubakri *et al.*, 2005). This situation is also known as 'Window of Opportunity' hypothesis. The present study attempts to empirically examine whether the phenomenon of 'Hot issue period' or 'Window of Opportunity' hypothesis have any significant influence on the survival profile of IPOs in India.

The present study offers a distinct contribution to IPO literature in general and survival in particular. Further, it contributes in the area of survival analysis that has not been widely applied in the field of finance. The findings will be of great use for the issuers as they can critically evaluate the factors that are crucial for their survival and can build their strategies for the issues that would ensure their long run endurance on the exchange. In this way, they can uncover the reasons that are actually responsible for the failure of IPOs that needs to be given special attention. Apart from issuers, investors can evaluate the issue, market, and company specific factors in order to ensure that their decision to invest in an issue should turn out to be profitable in the aftermarket. In practical terms, the findings of this study can inform public policy decision makers who are concerned with regulating the market. In other words, the study would provide a base for the regulators and policy makers to update their laws and formulate such kind of policies that would not only create a lucrative and more sustained market but will also protect the interest of investors in the aftermarket. In nutshell, the significance of analyzing the most fitted IPO is immensely fruitful for every associated party of an IPO.

This article is organized into four main sections. Section 1 introduces the topic, discusses the problem, and presents the literature in the area of IPO survival, Section 2 presents the database and methodology, Section 3 discusses the empirical results, and finally section 4 summarizes and concludes this paper.

DATABASE AND METHODOLOGY

***Data and Sample selection*:** The initial data consists of IPOs that entered the market in the post-SEBI and hot issue period i.e., from 1992 to 1996. For sample selection, the data for various variables i.e., Share prices, issue size, subscription, name of lead managers, NIC code, and year of incorporation must be available. These criteria resulted in 3125 IPOs that got listed on Bombay Stock Exchange (BSE) from 1992-1996 and they are analyzed till the end of 2011.

***Sources for data collection*:** Data for the variables i.e., Issue size, issue price, times subscribed, and IPO activity have been compiled from Prime database and Capitaline database. Incorporation year of each IPO and their National Industrial Classification (NIC 2008) codes has been obtained from Prowess database maintained by CMIE (Centre for Monitoring Indian

Economy Pvt. Ltd.) on the basis of which IPOs have been classified into 10 major industries. The market returns for underpricing and market level have been computed by taking the closing values of Sensex from the official website of BSE. The data for post-listing IPO status, date and reason for delisting has been taken from BSE and Moneycontrol websites.

Measurement of Variables**:** The study defines an IPO as 'survivor' if it continues to list on the stock exchange and 'non-survivor' if it delists from the stock exchange due to liquidation, permanent suspension, compulsion by SEBI or any other reason, except due to its merger or movement to another stock exchange (Hensler *et al*., 1997; Rath, 2008; Bhattacharya *et al*., 2011). In order to predict the trajectories following the IPO, three sets of variables concerning offering, market, and corporate specific characteristics are taken. Table 1 presents the measurements of these variables.

Table 1: Measurement of Variables

Variable	Variable defined	Expected relationship to survival
Offering Characteristics		
Issue Size	The natural logarithm of the size of the offering listed in the prospectus, or the amount raised by the company in the issue.	+
Lead manager's reputation	Megginson and Weiss (1991) reputation measure based upon a number of issues and total size of issues managed. On the basis of number of issues managed by lead managers: LM Reputation (n)= Percentage of number of issues managed by lead managers i.e. Total number of issues managed by LM/ Total number of issues in the sample On the basis of size of issues managed by lead managers: LM Reputation (size)= Percentage of total issue size managed by lead managers i.e. Total issues size managed by LM/ Total issue size of all the issues in the sample In case an issue has more than one lead manager, the average of lead manager's share is used as a measure of quality (Meggison and Weiss, 1990, p.13).	+
Initial Returns (MAER or underpricing)	Raw returns= (Closing price on the listing day– Offering price) / (Offering price) Market returns= Closing value of Sensex on listing date- Closing value of Sensex on Issue date/ Closing value of Sensex on Issue date Market adjusted excess returns (MAER) = Raw returns- Market returns	+/-
IPO demand	The natural logarithm of the number of times issue has been subscribed.	+
Risk	Standard deviation of first 30 trading days of aftermarket returns (Jain and Kini, 1999)	-
List delay	The natural logarithm of the difference between Issue date and List date	-

Continued…

Market Characteristics		
Market Level	Return on Sensex for the month of issue.	-
IPO Activity	The natural logarithm of the number of issues in the calendar quarter of the offering.	-
Corporate Characteristics		
Age of Company	The natural logarithm of the one plus the difference between incorporation year and the year of issue.	+
Industry	Binary industry dummies based upon NIC 2008 classification	+/-

Source: Compiled from various studies

***Empirical specifications*:** The empirical analysis involves two dimensions. The determinants of IPO survival are empirically examined using ‘Logistic Regression model’, whereas the survival time of IPOs is explored using ‘Survival Analysis methodology’.

Logistic Regression is a family of discrete choice models in which the dependent variable is categorical and independent variables can be continuous as well as categorical (Field, 2005, p. 218). The aim of this model is to assess how well the set of independent variables predicts the occurrence of the categorical dependent variable. The probability function in logistic regression is as follows:

$$L_i = \ln \left[\frac{Pi}{1-Pi}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta n\, Xn + \varepsilon i$$

Here, L_i is the log of odds ratio; P_i is the probability that Y_i=1 (i.e., An IPO continues to list on the exchange), and (1-P_i) = probability that Yi=0 (i.e., An IPO delists from the exchange); β_0 is the constant; $\beta_1, \beta_2, \beta_3 \ldots\beta_n$ are the coefficients to be estimated.

Although the logit model is capable of predicting whether the event will occur or not, yet it gives no idea about the timings of that event. In other words, it makes no distinction between the firms failing in six months and the firms failing after two years (Lowers *et al*., 1999; Kooli and Meknassi, 2007; Raju and Prabhudesai, 2012). Hence, to overcome this problem, survival analysis methodology is best suited. The survival analysis models not only examine the occurrence of the event, but also consider the timing of such event (Mills, 2010). In addition, this methodology deals with the censored data as well as time series data. Since IPO market possesses both these features, hence this methodology is quite fruitful (Hamza and Kooli, 2010; Raju and Prabhudesai, 2012).

There are two main functions in survival analysis i.e, survival function and hazard function. The survival function refers to the probability that an individual will continue to survive until the end of the study period (Kleinbaum and Klein, 2005, p. 9) and is written as follows:

$$S(t) = \Pr(T > t) = 1 - \mathrm{F(t)}$$

Here, *S(t)* = cumulative survival rate; *T* = time until the firm experiences the event (trading months); *t* = study time period; *F(t)* = cumulative density function= Pr $(T \leq t)$

Whereas, the hazard function is the measures of conditional probability that an IPO is delisted instantaneously, given that it has survived up to time *t*. It is denoted as (Lee and Wang, 2003, p. 11):

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}$$

Here, *f (t)* is the probability function that is the product of survival and the hazard function:

$$f(t) = S(t)\, h(t)$$

The survival analysis model follows several distribution forms such as non-parametric, semi-parametric, and parametric. The suitability of all such forms has been tested and accordingly non-parametric 'Kaplan Meier Estimation' method and parametric 'Accelerated Failure Time' (AFT) model has been employed. The model is written in log-linear as follows (Bradburn *et al*., 2003):

$$\mathrm{Ln}\ (T) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots. + \beta p\, Xp + \varepsilon$$

Here, Ln (T) is the log of survival time, which is the dependent variable; β_0 is the constant; $\beta_1\, \beta_{2\ldots.}$ are coefficients of the covariates; X_1, X_2, $X_3 \ldots X_P$ are the covariates; ε is the error term.

EMPIRICAL RESULTS

The survival of fittest IPOs are analyzed using different methodologies in the following sections:

Descriptive Statistics: Firstly, in order to gain an insight into the basic features of IPOs that entered the market in the post-SEBI era, their descriptive statistics are analyzed and compared across survivors and non-survivors using independent sample t test and Wilcoxon Z test. The tests exhibit that survived IPOs have a significantly higher issue size, demand, lead manager's reputation, and age. However, the issues that are ill-fitted or fail to survive in the market conditions have significantly higher underpricing, risk, listing delay, market level, and IPO activity. Table 2 displays the results of this analysis.

Table 2: IPO characteristics across survivors and non-survivors

Variables	Survivor IPOs (2258)			Non-Survivor IPOs (867)			T value	Wilcoxon Z value
	Mean	Median	Std. Deviation	Mean	Median	Std. Deviation		
Offering Characteristics								
Issue size (Crores)	6.86	3.00	41.76	4.22	3.16	4.87	1.856*	-1.23
IPO Demand (No. of times)	7.96	2.19	22.88	4.79	1.21	9.51	3.962***	-9.84***
Initial Returns (Percentage)	43.59	20.12	129.53	45.83	19.69	109.45	-0.451	-1.46
Lead manager rep. (n) (Percentage)	1.70	1.13	1.61	1.60	0.93	1.61	1.526	-2.35***
Lead manager rep. (size) (Percentage)	1.47	0.23	2.70	0.92	0.18	1.90	5.511***	-4.50***
Risk (Percentage)	0.13	0.09	0.43	0.13	0.11	0.13	-.0.352	-6.62***
List Delay (Days)	133.22	82.00	240.62	148.70	87.00	184.80	-1.710*	-5.49***
Market Characteristics								
Market Level (Percentage)	0.44	-1.30	8.86	0.90	-0.68	8.60	-1.302	-1.86*
IPO Activity (No. of issues)	237.84	231.00	108.47	230.00	230.00	95.44	1.868*	-1.08
Corporate Characteristics								
Age (Years)	7.31	5.00	7.64	6.14	5.00	5.89	4.076***	-3.11***

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Note: ***Significant at 1% level, ** Significant at 5% level,* Significant at 10% level

Survival Pattern of IPOs: The survival probabilities of IPOs can be assessed non-parametrically from the observed survival time for censored as well as non-censored observations through 'Kaplan-Meier estimation Method' (Kaplan and Meier, 1958). This method gives an in-depth understanding of survival as well as hazard patterns of IPOs in the aftermarket. It generates table and plots of survival as well as hazard function for event history data (Garson, 2012).

The mean and median of survival time is presented in table 3. This indicates that 95% of the IPOs fit to survive in between the period of 105 to 112 months (approx) in the aftermarket. Although the average months are 108 but the median time of survival is 54 months (approx).

Table 3: Means and Medians for Survival Time

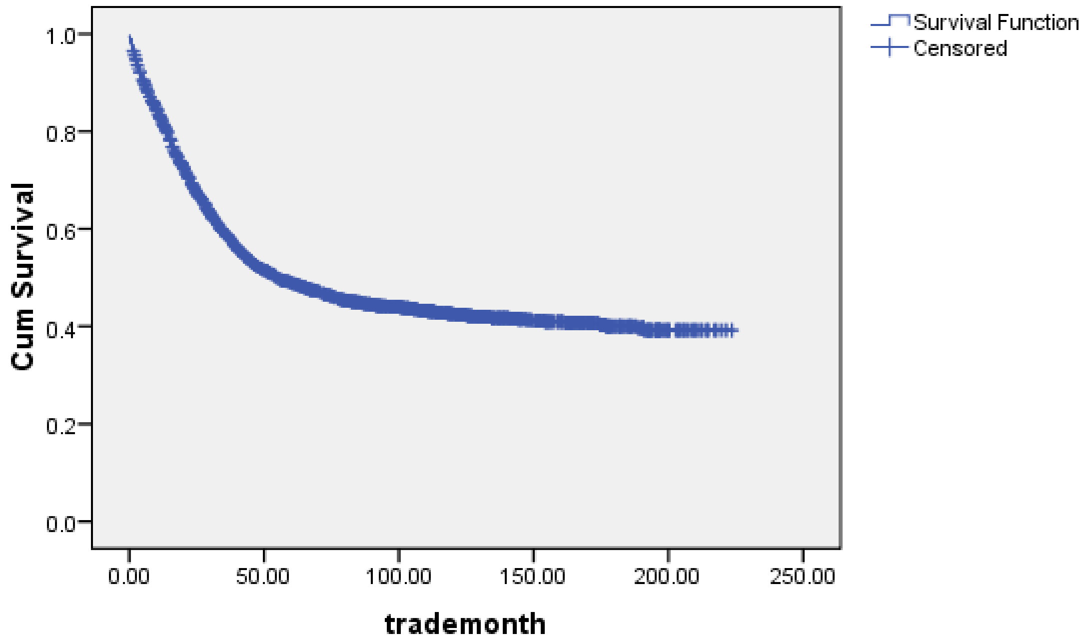
Mean			Median		
Estimate	95% Confidence Interval		Estimate	95% Confidence Interval	
	Lower Bound	Upper Bound		Lower Bound	Upper Bound
108.924	105.274	112.573	54.619	47.136	62.102

Source : Author's estimation

Further, this method obtains the information of survived as well as failed IPOs and constructs the survival and hazard function plots over time. Such plots are known as 'Kaplan-Meier curves' (KM) which are the series of horizontal steps of declining magnitude. The KM survival curve is shown in figure 2, which summarizes the entire survival pattern of IPOs that entered the market during 1992-1996 and they are tracked until the end of 2011. The survival probability of IPOs is plotted against trading months, wherein the probability of survival of IPOs at that time is the percentage of cumulative survival at any given time. Further, the survival duration of IPOs determines the steepness of the curve. In order to show the sharpness of survival curve more clearly and closely to time, the plot of log survival function has been taken wherein the survival function is plotted on a logarithmic scale on the Y-axis (Garson, 2012).

In line with the findings of Boubakri *et al.* (2005), the survival function exhibits that the probability of surviving falls as the time from the issuance of IPO rises. A significant decline has been seen in this curve from zero to 50 months, which indicates a huge rate of non-survival during the initial years of IPOs. Thereafter, the rate of decline becomes moderate forming an elbow at around 50-60 months. This fall in survival function shows that chance of survival of IPOs in India is quite low during the first four to five years of issue i.e., during the hot issue period of 1992-1996. However, as the time increases, the rate of decline slows down and sustains around the probability value of 0.4 after 60 months of the issue.

Figure 2: Survival Function of IPOs



Source: Stata

Figure 3 exhibits the hazard function, which is exactly the opposite of survival function. It shows that the cumulative force of mortality of IPOs is very high in the first 50 months and reaches around the probability value of 0.6. Thereafter, an upward movement has been observed in the curve and the hazard probability remains closer to 0.9.

Figure 3: Hazard Function of IPOs

Source: Stata

In other words, the hot issue period (1992-1996) brought several new issues in India, but most of such issues were ill fitted as they were of low quality and hence failed to survive longer in the aftermarket. This supports the 'Window of Opportunity' hypothesis which claims that most of the issues follow the herd behavior and enter the market in hot period, but in reality such issues are of low quality and hence they fail to fit in the rough market conditions (Raju and Prabhudesai, 2012; Demers and Joos, 2007; Kooli and Meknassi, 2007; Chi *et al*., 2010).

Survival Probability of IPOs: The empirical investigation of the impact of several offering, market, and corporate variables on the survival probability of IPOs is conducted using logistic regression model. In this model, each IPO is tracked from the date of its listing until the next five years in order to classify it as 'survivor' or 'non-survivor'. Majority of studies have tracked the status of IPOs for 5 years of listing as it is believed that five years is a sufficient period for analyzing their status in the market (Jain and Kini, 1999; Bhabra and Pettway, 2003; Peristiani and Hong, 2004; Demers and Joos, 2007; Howton, 2006; Chou *et al.*, 2007; Rath, 2008; Jain and Kini, 2008, to name a few). In addition, the period of five years covers major movements of a business cycle and is sufficient to examine the future prospects of an issue (Rath, 2008). Moreover, the KM curves also exhibit that most of the IPOs in India failed to survive beyond this period. Hence, based upon this classification, out of 3125 IPOs from 1992 to 1996, 2258 are categorized as 'survivors' and 867 as 'non-survivors'.

The Model: Following logit model is estimated:

$$\begin{aligned} Logit(p) = \alpha + \ & \beta 1\, Issue\ Size + \beta 2\, IPO\ Demand + \beta 3\, Initial\ Returns \\ & + \beta 4\, LM\ Reputation\ (n) + \beta 5\, LM\ reputation\ (size) + \beta 5\, Risk \\ & + \beta 6\, List\ Delay + \beta 7\, Market\ Level + \beta 8\, IPO\ Activity + \beta 9\, Age \\ & + \beta 10\, Industry\ dummies \end{aligned}$$

Dependent Variable: The binary dependent variable in logit model takes the value '1' if an IPO continues to survive for five years and '0' if it gets delisted or stop trading from the exchange within this period.

Explanatory Variables: As revealed from the literature, several offering, market, and corporate specific factors are crucial in determining the success or failure of IPOs in the aftermarket. Hence, based upon the review, such factors are taken as explanatory variables in the model and their influence on the likelihood of survival is examined. All such variables along with their labels, hypothesis, and expected signs are summarized in table 4.

Table 4: Description of Explanatory Variables

Labels	Name	Definition and Hypothesis		Expected relationship with likelihood of survival of IPOs
	Dependent Variable			
Yi	IPO survival		For Logistic Regression Model: Binary variable 1 for the survival and 0 for non-survival	
	Survival Duration		For Log-logistic AFT model: Number of trading months for which IPO remains listed on the exchange	
	Independent Variables*			
X_1	Issue Size	For Logistic Regression Model: H_{1a}: Issues with larger size are less likely to be delisted from the exchange.		+
		For Log-logistic AFT model: H_{1b}: Issues with larger offer size survive longer in the aftermarket.		
X_2	IPO demand	For Logistic Regression Model: H_{2a}: Issues which are more subscribed are less likely to be delisted from the exchange.		+
		For Log-logistic AFT model: H_{2b}: Issues which are more subscribed survive longer in the aftermarket.		
X_3	Initial Returns (MAER)	For Logistic Regression Model: H_{3a}: There is a significant influence of initial returns on the likelihood of survival of IPOs.		+/-
		For Log-logistic AFT model: H_{3b}: There is a significant influence of initial returns on the survival duration of IPOs in the aftermarket		
X_4	Lead manager's reputation	For Logistic Regression Model: H_{4a}: Issues backed by reputed lead managers are less likely to be delisted from the exchange.		+
		For Log-logistic AFT model: H_{4b}: Issues backed by reputed lead managers survive longer in the aftermarket.		
X_5	Risk	For Logistic Regression Model: H_{5a}: Issues with higher risk are more likely to be delisted from the exchange.		-
		For Log-logistic AFT model: H_{5b}: Issues with higher risk survive for shorter duration in the aftermarket.		
X_6	List delay	For Logistic Regression Model: H_{6a}: Issues with delay in listing are more likely to be delisted from the exchange.		-
		For Log-logistic AFT model: H_{6b}: Issues with delay in listing survive for		

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		shorter duration in the aftermarket.		
X_7	Market Level	For Logistic Regression Model: H_{7a}: Issues during the period of high market level are more likely to be delisted from the exchange.		-
		For Log-logistic AFT model: H_{7b}: Issues during the period of high market level survive for shorter duration in the aftermarket.		
X_8	IPO Activity	For Logistic Regression Model: H_{8a}: Issues during the hot issue period are more likely to be delisted from the exchange.		-
		For Log-logistic AFT model: H_{8b}: Issues during the hot issue period survive for shorter duration in the aftermarket.		
X_9	Age of Company	For Logistic Regression Model: H_{9a}: Issues of older firms are less likely to be delisted from the exchange.		+
		For Log-logistic AFT model: H_{9b}: Issues of older firms survive longer in the aftermarket.		
X_{10}	Industry	For Logistic Regression Model: H_{10a}: There is a significant influence of industry on the likelihood of survival of IPOs.		+/-
		For Log-logistic AFT model: H_{10b}: There is a significant influence of industry on survival duration of IPOs in the aftermarket		

Note: The definition of explanatory variables is same as explained in table 1

IPO demand, which represents the number of times an issue is subscribed, exhibits a positive and significant influence on the odds of survival of IPOs in the aftermarket. It clearly shows that the interest of investors towards an issue is crucial in determining its fitness on the exchange. The result corroborates with the findings of Kooli and Meknassi, 2007; Goot *et al.*, 2011; Raju and Prabhudesai, 2012, who also support the higher probability of survival of IPOs with higher demand.

Another offering specific variable, which exhibits a positive and significant influence on the survival prospects of IPOs, is lead manager’s reputation (measured on the basis of size of issues they manage). This finding supports that lead managers by the virtue of their expertise, reputed capital, wider network, and interlocking arrangements provide stronger support to the IPO firms that improves their survival profile in the aftermarket (Jain and Kini, 1999, Jain and Kini, 2000; Chou *et al.*, 2007; Kooli and Meknassi, 2007; Rath, 2008; Hamza and Kooli, 2010).

However, Initial returns, which refers to the returns on the first day of listing, exhibits a negative and significant influence on the post-listing status of IPOs. The rationale behind this negative impact is supported by several researchers who assert that issue with significant underpricing generates high indirect cost, less collected funds, and more financial difficulties on the firm which in turn decreases the likelihood of survival of its IPO in the aftermarket (Kooli and Meknassi, 2007; Hamza and Kooli, 2010; Raju and Prabhudesai, 2012).

Similarly, 'List delay', i.e. the difference between the issue day and listing day, depicts a negative and significant influence on the odds of survival of IPOs in the aftermarket. The Indian primary market has faced a unique experience of a very long delay between the issue day and the listing day. Such delay is mainly due to time-consuming administrative procedure and postponement of the listing day by the IPO issuing company. Hence, during this time lag, the market receives the sensitive information that may adversely affect the underpricing and initial volatility on the listing day (Shah, 1995; Chakrabarty and Ghosh, 2006). In other words, the issues with higher delay in listing exhibit lower chances of survival in the aftermarket. Hence, it is important that IPOs should be listed within the time limit as stipulated by SEBI otherwise it could prove to be detrimental for their survival on the exchange (Sehgal and Singh, 2008).

As far as other issue specific variables are concerned, such as issue size, risk, and lead manager's reputation (measured as per number of issues they manage), no significant influence is found in the model. The influence of market scenario is tested by taking two major variables i.e., Market level and IPO activity, but they also failed to exhibit any significant influence on the odds of survival of IPOs in the aftermarket.

Out of corporate specific variables, age of the firm at the time of issue comes out to be one of the highly significant variables that positively influence the chance of survival of IPO in the aftermarket. It validates the hypothesis that older firms by the virtue of their experience and wider knowledge about the market demonstrate a strong fit in the prevailing environment. However, the younger firms with a shorter operating history are more speculative and hence less likely to survive in the aftermarket (Hensler *et al.*, 1997; Peristiani and Hong, 2004; Audretsch and Lehmann, 2005; Demers and Joos, 2007; Carpentier and Suret, 2008; Chancharat *et al.*, 2008; Rath, 2008; Chi *et al.*, 2010). The odds ratio of age shows that each added year in a firm age leads to higher odds of survival of its IPO on the exchange. This clearly depicts that age of a firm at the time of its issue acts as a good predictor of the success of its IPO in the aftermarket.

The survival profile of IPOs varies across several industries as well. Taking manufacturing sector with the largest number of issues as a base, the model shows that out of all sectors, agriculture and administration sectors have a negative influence on the survival prospects of IPOs issued in these sectors. However, IPOs in mining, construction, wholesale and retail, accommodation, information and communication, finance and insurance, and others sectors have shown a higher likelihood of survival in the post-SEBI era. However, transportation and storage sector exhibits insignificant results.

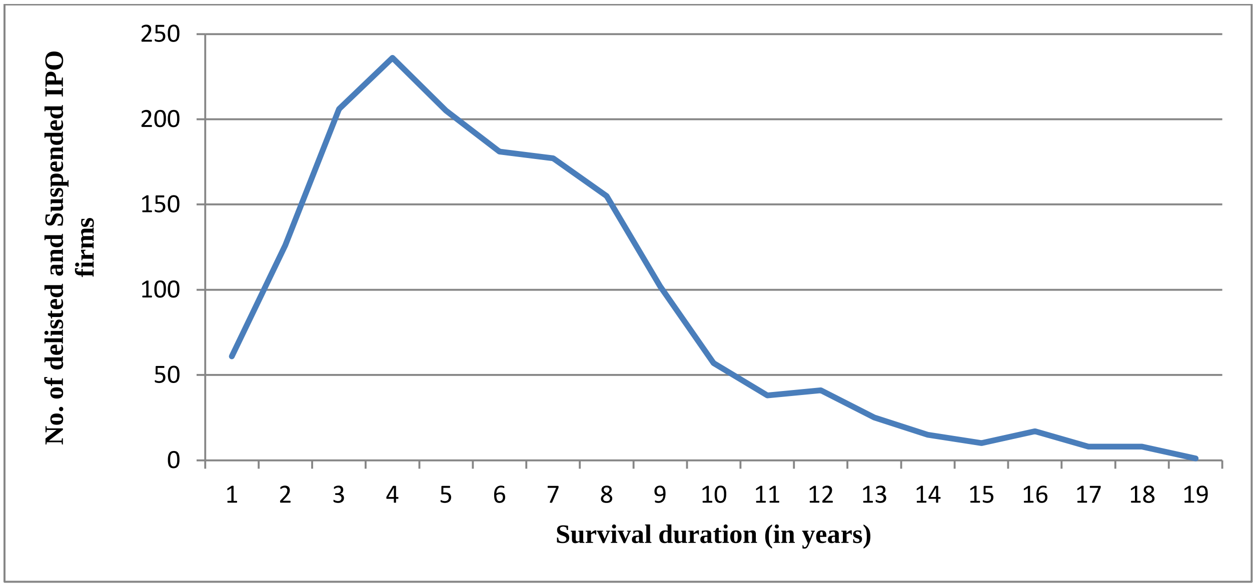
The results obtained are consistent with Raju and Prabhudesai (2012) who found the highest survival rate for finance and IT sector in India. Apart from India, the results are consistent with the studies across the world, such as Hensler *et al.* (1997) who observed higher survival for wholesale, computers, and restaurant sector, Boubakri *et al.* (2005) who revealed higher survivors in the mining sector as compared to other sectors, Howton (2006) who observed the technology dummy to be positive and significant for survival rather than failure, Demers and Joos (2007) who found that the amount of time that a firm takes for failing is longer for technology firm, Kooli and Meknassi (2007) who found smallest failure rate in energy and mining sector and highest survival rate in finance sector, Rath (2008) who found highest survival rate in IPOs belonging to natural resources and finance sectors as compared to other sectors. Mainly, the literature supports that certain peculiar features of the industry such as environment of the industry, entry barriers, growth prospects, competition level, technological changes, and the level of demand etc., perhaps determine the fitness of IPOs in the aftermarket (Audretsch, 1995; Jain and Kini, 1999; Agarwal and Gort, 2002; Peristiani and Hong 2004).

The goodness of fit of logit model is tested through 'Omnibus test of model coefficient' and 'Hosmer and lemeshow'. The significant value of omnibus test and the insignificant value of Hosmer and lemeshow indicate that the model has a good fit. The value of Nagelkerke R square comes out to be 13.3 per cent, which is quite closer to pseudo R square obtained by several researchers (Raju and Prabhudesai, 2012; Adjei *et al*., 2008; Kooli and Meknassi, 2007; Chou *et al*., 2007; Chi *et al*., 2010). The overall classification percentage is 74.5 percent, which indicates that the model is quite good in predicting the correct category for survivors and non-survivors.

Survival Duration of IPOs: The results of logistic regression shows that the offering, market, and corporate characteristics have an influence on the survival probability of IPOs, however, it ignores the survival duration of IPOs on the trading exchange. Hence, in order to explore the influence of such variables on the duration of IPOs in the aftermarket, the survival analysis methodology is best suited. Out of several models of survival analysis, the most efficient 'Accelerated Failure Time' (AFT) model is applied in order to check the robustness of results obtained from logistic regression (Hensler *et al*., 1997; Jain and Kini, 2000; Kooli and Meknassi, 2007; Raju and Prabhudesai, 2012).

Functional Form of AFT model: Since AFT is a parametric model, the baseline hazard function assumes to follow some distribution. There are several distribution forms of the AFT model such as Log-Normal, Log-Logistic, Exponential, Weibull and Gamma, out of which the best form is to be selected. In order to test the distribution form, the number of delisted and suspended companies is plotted against the time. Figure 4 shows that the peak of delisting reaches to its maximum and thereafter it slowly declines monotonically. This non-monotonic pattern in hazard suggests that log-normal or log-logistic functional forms are best suited for AFT model. Although both forms are quite similar in shapes, yet researchers support the log-logistic over log-normal as it captures the censored data well and is not sensitive to smaller duration (Hensler *et al.*, 1997, Raju and Prabhudesai, 2012).

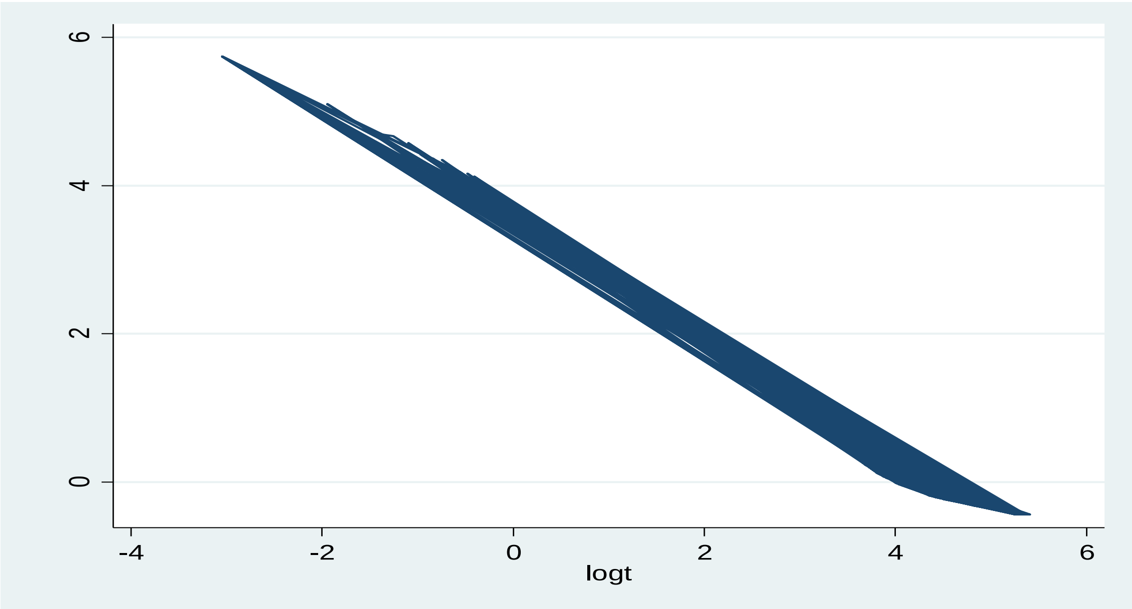
Figure 4: Delisting frequency distribution



Source: Author's calculation

Another way of testing the distribution form is plotting the log-odds ratio of survival against the log survival time. As per Kleinbaum and Klein (2005), in order to assess the appropriateness of log-logistic assumption, the log-odds of survival should be a linear function with log of time with slope –ρ. Figure 5 shows the resultant output.

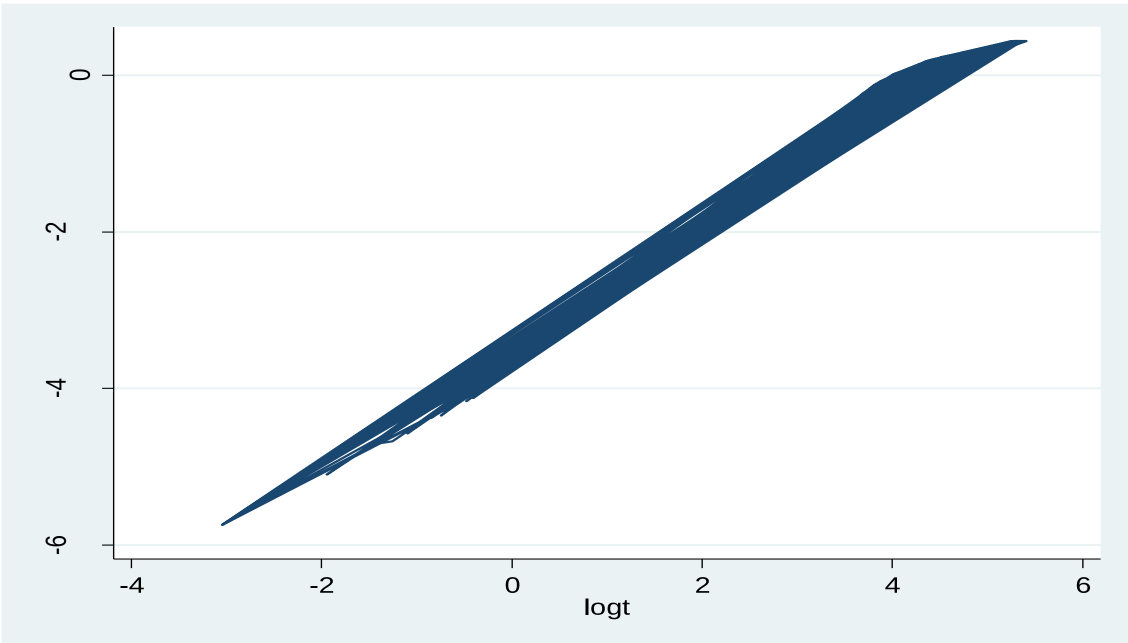
Figure 5: Survival Plot



Source: Stata

On the other hand, log-odds ratio of failure is also plotted against the log-survival time and is shown in figure 6.

Figure 6: Failure Plot



Source: Stata

Both the figures (5 & 6) shows a clear straight line, which validates that log-logistic is the best-fitted form of AFT model (Bradburn *et al*., 2003; Kleinbaum and Klein, 2005, p. 279).

Log-Logistic AFT Model: The log-logistic AFT model is estimated with the data previously described. In this, each of 3125 IPOs (1992-1996) are tracked from the date of their listing until the date of delisting or the end of 2011, whichever is earlier. This categorization resulted in 1450 survivors and 1675 non-survivors. Taking this data, the following model is estimated in which the natural logarithm of survival time is presented in linear function of explanatory variables:

$$\begin{aligned} Ln(Tj) = \alpha + \ & \beta 1\ Issue\ Size + \beta 2\ IPO\ Demand + \beta 3\ Initial\ Returns \\ & + \beta 4\ LM\ Reputation(n) + \ \beta 5\ LM\ reputation\ (size) + \beta 5\ Risk \\ & + \beta 6\ List\ Delay + \beta 7\ Market\ Level + \ \beta 8\ IPO\ Activity + \beta 9\ Age \\ & + \beta 10\ Industry\ dummies \end{aligned}$$

Dependent variable: In survival analysis, the dependent variable is the number of trading months of IPOs from the date of listing until the date of delisting or the end of 2011, whichever is earlier. Since the time window is different for each issue, the probability of survival or failure varies as per the length of post-issue period (Raju and Prabhudesai, 2012).

Explanatory variables: The offering, market, and corporate specific variables are taken as explanatory variables in the model whose influence on the post-listing duration of IPOs is examined. All such variables along with their labels, hypothesis, and expected signs are summarized in table 4.

The results of log-logistic AFT model confirms that offering characteristics of IPOs such as issue size, lead manager’s reputation, and IPO demand accelerates the survival duration of IPOs, whereas, initial returns (MAER), risk, and list delay decelerates their duration on the trading exchange. Although the issue size variable was found to be insignificant in logit model (taking five year window) but is found to be highly significant in survival analysis model. Hence, this finding provides a strong support to the hypothesis and is in line with the liability of smallness theory of firm survival which asserts that large organizations have better prospects of survival than small firms (Aldrich, 1979; Bruderl *et al.*, 1992; Perez and Catillejo, 2008). In other words, issues with large size exhibits more market confidence as well as ability to withstand the rough market situations in the aftermarket and hence they survive longer in the market (Jain and Kini, 1994; Hensler *et al.*, 1997, Fischer and Pollock, 2004; Boubakri *et al.*, 2005; Zhao, 2005; Goot *et al.*, 2011; Ahmad, 2012; Raju and Prabhudesai, 2012). This finding corroborates with the theoretical argument of Zingales (1995) who emphasized on having an optimal size at which a firm chooses to go public to sustain longer in the market.

Similarly, in line with the hypothesis and the findings of Chou *et al*. (2007) and Jain and Kini (2000), it is found that lead manager's reputation (measured on the basis of size of issue managed) ensures the longer endurance of IPOs on the exchange. This depicts that expertise and effective monitoring services of reputed lead manager is very significant in accelerating the survival time of IPOs in the market. Also, the time ratio of IPO demand variable validates that when the demand for an issue increases, the survival time significantly accelerates in the aftermarket (Kooli and Meknassi, 2007; Goot *et al.*, 2011; Raju and Prabhudesai, 2012).

In line with the hypothesis and the results of logit model, it is found that higher underpricing lowers the survival duration of IPOs in the marketplace. Also, the issues with higher listing delay fails to survive longer on the exchange. However, risk variable was found to be insignificant in logit model, but in AFT model this variable proves the hypothesis to be correct and support that that level of risk in the issue significantly lowers the survival duration of IPOs on the trading exchange (Bhabra and Pettway, 2003; Rath, 2008; Chi *et al.*, 2010; Goot *et al.*, 2011).

The results of AFT model for market related variables exhibit that out of both variables, IPO activity exhibits a negative and significant influence on the survival duration of IPOs in the aftermarket. This supports that hot issue period creates a conducive environment for the inferior firms to go for public issue, but such firms survive for shorter duration in the aftermarket (Demer and Joos, 2007; Kooli and Meknassi, 2007; Chi *et al.*, 2010; Raju and Prabhudesai, 2012). Hence, the results of market specific variables demonstrate the importance of market timings as well as the favorable market conditions for the longevity of IPOs on the trading exchange (Zhao, 2005).

The corporate specific findings corroborate with the hypothesis as well as with the results of logit model. The positive influence of age on the survival duration goes in the line with the liability of newness theory of firm survival which suggests that since the new organization are highly dependent upon the cooperation of strangers and do not possess the ability to compete effectively against the established firms, hence they fail to survive longer than older firms (Stinchcombe, 1965). Finally, it is obtained from the model that IPOs in agriculture and administration sectors survive for shorter duration, whereas IPOs in construction, wholesale and retail, accommodation, information and communication, finance and insurance, and others sectors survive longer in the aftermarket. However, no significant results are obtained from mining and transportation sector.

CONCLUSION

This paper explores the survival profile of initial public offerings in India during the post-SEBI and hot-issue period of 1992-1996. The introduction of SEBI and the abolition of CCI brought the tremendous changes in the Indian primary market. During this fluctuative period, several firms followed the herd behavior and introduced their new issues in the market, however only a few managed to sustain their identity in the aftermarket. This phenomenon is provided in the 'Window of Opportunity' hypothesis or 'Hot issue' phenomenon. The present study examines this theory in light of IPOs in the hot issue period by taking their offering, market, and corporate specific characteristics. The sample of this study comprises of 3125 IPOs during 1992-1996 and they are tracked till the end of 2011. The empirical analysis has been done using most sophisticated methodologies i.e, Logistic Regression model, Kaplan-Meier estimation, and Log-Logistic Accelerated Failure Time (AFT) model.

The study validates the theory of 'Window of Opportunity'and exhibits that most of the issues in the hot period are of low quality who just entered the market to take the benefit of favorable market environment, but in reality they do not possess the ability to withstand the tough market conditions and hence they failed to survive in the aftermarket (Hensler *et al.*, 1997; Boubakri *et al.*, 2005; Demers and Joos, 2007). The survival profile of IPOs across offering characteristics reveals that issue size, lead manager's reputation, and IPO demand have a positive influence, whereas initial returns, risk, and list delay have a negative influence on the endurance of IPOs on the trading exchange. Further, the analysis of market specific variables reveals that issues in the period of high IPO activity fail to sustain longer in the aftermarket. The empirical analysis of age of the firm at the time of issue supports the hypothesis that older firms have more potential to sustain longer on the exchange as compared to younger firms. The survival profile of IPOs has been tested across the several industries as well, which exhibits that IPOs in agriculture and administration sectors have lower likelihood of survival and smaller survival duration, whereas IPOs in information and communication, construction, accommodation, wholesale and retail, finance and insurance, and other sectors have higher likelihood of survival and longer survival duration in the aftermarket. However, no significant influence could be obtained from mining and transport sectors. Overall, the KM estimation method shows a significant decline in the survival rate and a growth in the hazard rate during the first 50-60 months of listing of IPOs on BSE.

The present study contributes to the IPO literature in general and survival in particular. Also, the findings of this study provide useful insight to the issuers, investors, regulators and policy makers. Issuers can take important decisions about the issue considering the long term prospects of IPO whereas investors can take the rational investment decisions based upon the chance of survival as well as their duration in the future (Ahmad, 2012). The regulators can formulate the stringent laws and policies so as to ensure a lucrative and more sustained market that will protect the interest of investors in the aftermarket.

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Table 5: Results of Logistic Regression Model and Survival Analysis

Categories	Independent variables	Logistic Regression Model				AFT model			
		β	SE	Wald	Exp β	B	SE	Wald	Time Ratio(Exp β)
Offering Characteristics	Issue size (Crore)	-.033	.067	.251	.967	0.125	0.056	2.23**	0.882
	Lead Manager's reputation_size (Percentage)	.106	.027	15.494***	1.111	0.089	0.020	4.47***	1.093
	Lead Manager's reputation _n (Percentage)	-.018	.035	.248	.983	0.005	0.029	0.20	1.005
	Initial Returns (Percentage)	-.002	.000	18.426***	.998	-0.0019	0.00035	-5.54***	0.998
	IPO demand (No. of times)	.371	.043	74.045***	1.450	0.529	0.369	14.33***	1.697
	Risk (Percentage)	.096	.142	.454	1.100	-0.281	0.0926	-3.03***	0.755
	List delay (No. of days)	-.301	.081	13.740***	.740	-0.337	0.0797	-4.24***	0.713
Market Characteristics	Market level (Percentage)	-.005	.005	1.184	.995	-0.0065	0.0042	-1.54	0.993
	IPO Activity (Number of issues)	-.133	.095	1.952	.875	-0.161	0.0853	-1.89*	0.851
Corporate Characteristics	Age (Years)	.027	.007	13.005***	1.027	0.145	0.0513	2.83***	1.156

	Industry Dummies								
	Agriculture	-.951	.218	19.052***	.386	-1.045	0.194	-5.38***	0.351
	Mining	.639	.346	3.413*	1.895	0.114	0.279	0.41	1.120
	Construction	.718	.266	7.293***	2.050	1.277	0.248	5.13***	3.585
	Wholesale and retail	.831	.212	15.289***	2.295	0.409	0.167	2.44**	1.505
	Transport and storage	.311	.444	.490	1.365	0.285	0.385	0.74	1.329
	Accommodation	.853	.456	3.504*	2.346	1.04	0.386	2.69***	2.829
	Information and communication	2.538	.404	39.521***	12.652	1.988	0.209	9.50***	7.300
	Finance and insurance	.330	.125	6.895**	1.390	0.258	0.117	2.20**	1.294
	Administration and support services	-.996	.310	10.359***	.369	-0.762	0.285	-2.67***	0.466
	Others	1.061	.338	9.878***	2.890	1.175	0.290	4.04***	3.238
	Constant	2.388	.775	9.504***	10.896	5.500	0.72289	7.55***	244.691
Omnibus Tests of Model Coefficients (Chi square (p value))				302.356(0.000)		Log Likelihood	-4482.259		
Nagelkerke R Square				0.133					
Hosmer and Lemeshow(Chi square (p value))				4.320(0.827)		LR (Chi square, p value)	522.45(0.000)		
Overall Classification percentage				72.5%					

Note: ***Significant at 1% level, ** Significant at 5% level,* Significant at 10% level; β =Beta; SE=Standard Error; Exp β stands for Exponential Bet