ABSTRACT

We examine the drivers of Internet firm survival using a multi-method survival analysis. Based on previous literature on business failure and recent IS research on e-commerce business models, we test the impact of sector-, firm- and e-commerce-specific factors on an Internet firm’s duration after its IPO. We first provide a descriptive analysis of Internet firm survival using non-parametric survival analysis, which indicates the existence of differences in exit timing for different e-commerce firms. We next explore the relative strengths of the explanatory factors in predicting different outcomes using semi-parametric survival analyses. Our results suggest that the impact of the sector-, firm- and e-commerce-specific factors are different for different outcomes such as bankruptcy, merger and acquisition. A favorable capital market, reflected in a high IPO entry rate, and the selling of digital goods can enhance an Internet firm’s chances of survival. One limitation of our research is the generalizability of the results since the Internet sector is still in its early stage of development and we only include publicly-traded Internet firms in our data analysis. In addition, results from our semi-parametric analyses might not apply to publicly-traded B2B firms, which are not included since there were no observations of bankruptcies, mergers and acquisitions.

KEYWORDS: Internet firms, econometric analysis, electronic commerce, empirical research, strategic morphing, survival analysis.

1. Introduction

During the past several years, we witnessed the proliferation of Internet firms and the subsequent large-scale failure in the Internet sector that triggered an economic downturn. According to Webmergers.com [15], more than 800 Internet firms have folded since January 2000. Those that remain adapt to the marketplace by changing their organizational strategies. But why have so many so many firms failed?

Based on prior research, we identify explanatory factors that might influence DotCom or Internet firm survival. We perform a multi-method survival analysis to test the impact of these explanatory factors on the duration of Internet firms following their initial public offerings (IPOs). Barua et al. [5] defined a DotCom as an Internet intermediary or commerce firm generating all its revenues through the Internet. Barua et al. [4] reduced the cutoff to 95%, recognizing most Internet firms also allow purchases through telephone and fax. We use 90% as the cutoff, and include only Layer 3 and 4 firms [3]. Layer 3 intermediaries provide e-transaction marketplaces; Layer 4 firms sell products or services via the Internet.

The fact that some Internet firms survived while others did not reveals there is a difference among Internet firms that deserves a closer examination. In this research, we try to answer the following questions:

- Can we build an explanatory model that can explain survival rates for Internet firms?
- Are the explanatory factors able to predict different outcomes, such as bankruptcy, merger and acquisition?

2. Literature

Two streams of literature are helpful in formulating the theory: research on business failure and current IS research on different Internet business models.

2.1 Business failure

Previous research on business failure indicates both industry and firm factors have impact on survival of new
businesses. Industry characteristics include the technical regime of the industry and rate of new firm entry. In the manufacturing sector, Audretsch and Mahmood [1, 2] find that firm survival in different industries is due to differences in technological environments. New entrants are less likely to survive in an industry that is characterized by a routinized technological regime, where the initial setup costs for new businesses are high and it is difficult to obtain new technology for their operations to reach optimal scale. On the other hand, in an industry that is characterized by an entrepreneurial regime, new entrants are more likely to survive because of their technological innovative advantage over market incumbents. In an analysis on the survival of Japanese manufacturing firms, Honjo [11] finds that new firms are less likely to survive in an industry that has a high entry rate due to the higher competitive pressure.

Firm factors that influence survival include financial capital, startup size, post-entry firm size, founding time, and whether the firm is a new startup or a new branch or subsidiary of an existing business. Audretsch and Mahmood [2] normalize startup size and post-entry firm size by the minimum efficient scale (MES) of the industry. They found that when a firm operates at a size below the MES, it is more likely to fail; it incurs a cost disadvantage. Larger startups can reduce the difference between its current size and MES, hence reducing its risk of failure [1]. Audretsch and Mahmood [2] explore the influences of two ownership structures in the manufacturing industry: independent new startups and new branches or subsidiaries of existing companies. New firms are more likely to fail than the new branches or subsidiaries of existing firms.

Honjo [11] finds that financial capital and firm size are both significant when they are incorporated in the model independently. However, when both are present, only financial capital is significant. Honjo concludes that findings of a significant relationship between firm size and survival might be actually capturing the effect of financial capital since smaller firms tend to have limited financial resources. Also firms established around a market crash are less likely to survive.

There is research that suggests a negative relationship between firm size and the risk of failure, though the opposite results are known. Das and Srinivasan [8] examine new firm survival in the Indian computer hardware industry and find larger startup size is associated with higher risk of exit. Thus we do not hypothesize the direction for the relationship between firm size and survival.

Hensler, et al. [10] analyze firm duration after their IPOs in the stock market. In their study, failure occurs when a firm has been delisted from a stock exchange due to negative reasons. This can occur when the equity price for a firm is lower than a minimum price level, when there is an insufficient trading volume, or when the number of shareholders is too small to make a market viable to maintain liquidity and effectively establish prices. The authors analyze an IPO data set during the period from 1975 to 1984. The factors that can enhance an IPO’s survival are firm size, the age of the firm at the offering, the initial return on investment in the stock issue, the number of IPOs co-occurring in the market, and the percentage of the firm owned by insiders. In contrast, factors such as a higher average price level in the stock market at the time of IPO and a higher number of risk characteristics associated with the firm as reported in the prospectus lead to higher risk of failure. The authors also report an industry effect where firms in the optical or pharmaceutical industries enjoy a longer survival time than firms in industries such as computer and data, wholesale, restaurant, and airline.

### 2.2 Assessment of Internet business models

A number of recent IS studies help us formulate factors that might explain the observed Internet firm casualties. In their analysis of the impact of e-commerce initiative announcements, Subramani and Walden [14] find that cumulative abnormal returns to shareholders are higher for B2C announcements than those for B2B announcements. They also show that the cumulative abnormal returns to shareholders for tangible goods announcements are higher than those for digital goods.

Barua et al. [5] differentiate two types of Internet firms. A digital Internet firm is a firm that provides digital products and services and directly delivers them via the Internet. A physical Internet firm uses the digital channel to sell physical goods but product delivery is realized through the physical world. They find that digital goods firms enjoy higher productivity gains, and argue that the reason for the difference is a higher level of digitization of business strategies and processes. Close-to-zero marginal costs of production and nearly negligible delivery costs reduce overall costs, allowing them to enjoy higher productivity than physical Internet firms. Since productivity and profitability directly relate to a firm’s survivability, we expect digital Internet firms to be less likely to fail than physical Internet firms.

Overall, we expect e-commerce-related factors such as the sector that the firm operates in -- B2C, B2B or both -- and the product sold will have an impact on firm survival.

### 2.3 Preliminary conceptual model

Thus, we identify the following three types of factors crucial to the survival of a new business:

- **Industry and market characteristics.** They include the technological regime of the industry, the rate of new firm entry, the number of IPOs co-occurring at the time of the
offering, and stock market index levels at the time of the offering.

- **Firm characteristics.** Financial capital, startup size, post-entry firm size, founding time, the age of the firm at the time of offering, the initial return on investment in the stock issue, insider ownership, and whether the firm is a new startup or a new branch or subsidiary of an existing business.

- **E-commerce-related characteristics.** They include the business model and the types of products or services provided.

Not all these factors are directly applicable in our research context. For example, in their research on new firm survival in the manufacturing sector, Audretsch and Mahmood [2] operationalize the technological regime of the industry as the total innovation rate for the industry. This is not applicable to the Internet intermediaries and e-commerce firms in our sample. As an initial attempt to examine the impact of various factors on Internet firm survival, we try to develop a model that encompass the above three types of factors yet concise enough to permit empirical testing. Of the industry-related factors, the rate of firm entry has been reported significant in previous study [11]. Because we could not obtain data on the rate of new Internet firm entry in different industries, we use the number of Internet firm IPOs in the stock market as a proxy. However, the recent economy reveals periods when there were numerous Internet firm IPOs, and when tech stock performance was strong. Other evidence exists, too. Croson et al. [7] found that the potential for extraordinary financial returns via IPO “cash outs” probably drove firm entry into B2B e-markets more so operational profit maximization. As a result, the number of new IPOs might also be an indicator of the abundance of financial capital and investors’ unwary willingness to invest in Internet stocks. As a result, we will not hypothesize any direction for the relationship between new IPOs and firm survival. Rather, we view our empirical results as indicative of which factor -- the competitive pressure due to the entry of competing firms, or the availability of financial capital -- played a more important role in determining survival during our sample period. For firm-related factors, we include financial capital and firm size because these two variables have been most often included in previous research and often found to be explanatory of firm survival. The e-commerce-related factors that we include are the operating sector for the firm and the kind of products it sells. We formulate our conceptual model of Internet firm duration after IPO as follows:

$$\text{Survival} = f(\text{IPOEntry}, \text{FinancialCapital}, \text{FirmSize}, \text{Sector}, \text{ProductSold})$$

We also will control for the impact of the macroeconomy on firm survival. This model will be further refined based on results of our data collection and econometric issues that we identify.

### 3. Data Collection and Methodology

We now turn to a discussion of our data collection and empirical analysis methods.

#### 3.1 Data

The observations in our sample are publicly-traded Internet firms. No privately held firms are included. Firms that switched their lines of business to e-commerce after their IPOs are not included. We used FIS Online to identify the relevant firms, which yielded about 3000 hits. We then determined whether a firm met our inclusion criterion. For companies with Internet and physical channel operations, we then searched their annual reports to determine revenue shares generated online. We also searched multiple sources such as FIS Online, EDGAR Online IPO Express and corporate filings at the SEC Web site for IPO date information for the Internet firms. Those with IPO dates missing or that were not Internet firms at the time of their IPOs were eliminated. We used COMPUSTAT for quarterly and annual financials. 103 Internet firms constitute the final sample.

Table 1 summarizes the sample’s descriptive statistics. (See Table 1.) We define *duration* in terms of the number of quarters that have elapsed since the date of the firm’s IPO to the time it was delisted from the stock market, or the ending of the study period if the observation is censored, whichever is sooner. Similar to the definitions Subramani and Walden [14] use, we define a B2C firm as a business that has consumers as their customers, and a B2B firm as a business that has other companies as their customers. We also have an additional category, B2B2C firms, which target both

<table>
<thead>
<tr>
<th>Firm Type</th>
<th>Number of Obs</th>
<th>Duration (in quarters)</th>
<th>Quarterly Revenues (in million dollars)</th>
<th>Firm Size (# of employees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B2C</td>
<td>67</td>
<td>9.25 ± 4.02</td>
<td>43.73 ± 108.67</td>
<td>483 ± 1035</td>
</tr>
<tr>
<td>B2B</td>
<td>8</td>
<td>8.50 ± 4.78</td>
<td>16.08 ± 12.97</td>
<td>291 ± 240</td>
</tr>
<tr>
<td>B2B2C</td>
<td>28</td>
<td>10.43 ± 3.80</td>
<td>24.31 ± 36.87</td>
<td>382 ± 625</td>
</tr>
<tr>
<td>Total</td>
<td>103</td>
<td>9.60 ± 4.00</td>
<td>35.86 ± 89.03</td>
<td>438 ± 881</td>
</tr>
</tbody>
</table>
consumer and business markets.

3.2 Data analysis

We perform a multi-method survival analysis, a well-established technique in public health and criminology used in the analysis of failure processes, such as patient disease treatment and criminal recidivism. Four concepts are starting points to understand the methodology: duration, censoring, hazard rate, and survival function. Based on a starting time, duration is either the time an event occurred or the time that the study ended if the subject is still at risk at that time. In the second case, the observation is said to be right-censored. The hazard rate is the instantaneous failure rate at time \( t \) assuming that an individual has survived up until \( t \). The survival function is the probability of observing a duration time longer than \( t \) [13].

When we do not make any distributional or parametric shape assumptions about the hazard rate and the survival function, we use non-parametric survival analysis to compare the hazard rates among different groups. Semi-parametric analysis, in contrast, especially the Cox proportional hazards model [6], involves assumptions about explanatory variables but not the baseline hazard function. In this research, we will perform non-parametric analysis, and then test various explanatory factors for Internet firm survival using the semi-parametric Cox proportional hazards model.

3.3 Firm survival outcomes

Even though bankruptcies are generally thought of as a “failure” of the firm, the reasons for mergers and acquisitions are more complex, and cannot so easily be thought of as failures. Owners of a financially-troubled business might seek a merger or to be acquired to obtain additional capital. On the other hand, a healthy business might also be acquired due to its growth potential or as a result of the stockholders’ strategy to maximize their returns. In this research, we recognize the complex nature of the drivers of different survival outcomes. In the non-parametric analysis that follows, we will not differentiate among the various firm exit outcomes. Rather, we will define the outcome when the firm remains viable as a “default.” In the semi-parametric analyses, however, we will perform tests that differentiate among these outcomes and examine in greater detail the drivers that cause the various exit strategies to be observed.

3.4 Non-parametric analysis

We use the Kaplan-Meier estimator to non-parametrically characterize the survival function [13]:

\[
\hat{S}(t) = \prod_{\{i \leq t\}} \frac{n_i - d_i}{n_i}
\]

where \( n_i \) is the number of firms that are still at risk at time \( t_i \) and \( d_i \) is the number of businesses had events at time \( t_i \). Because the survival history of all firms before \( t_i \) is also taken into account in calculating the survival function at time \( t_i \), Kaplan-Meier permits us to estimate the likelihood of survival at \( t_i \) based on information at time \( t_i \) and prior periods. The results are usually displayed as a Kaplan-Meier curve, where survival rate is plotted against duration.

We plot the Kaplan-Meier curve for all 103 Internet firms in our sample in Figure 1. (See Figure 1.) Figures 1 and 2 illustrate the survival functions we obtain. The circles indicate censored observations.

The results indicate that during the first four quarters after our Internet firms went public, the shakeout was gradual. More exits begin to appear
Quarter 4 and continue until Year 5. The horizontal survival function after Quarter 19 indicates that after surviving the initial shakeout, an Internet firm will be more likely to survive. Figure 2 displays the curves for different types of Internet firms. (See Figure 2.)

The horizontal survival function indicates that no sample B2B firms failed during the study period. The pattern for initial survival for B2C and B2B2C firms is similar; the two curves diverge in Quarter 7. From Quarters 7 to 13, B2C firms experienced near constant hazard rates. Afterwards, the hazard rate starts to decrease. The survival of B2B2C firms after Quarter 7 tells a different story. From Quarters 7 to 11, the hazard rate is low. The majority of changes occur between Quarters 12 and 16; about half of B2B2C firms exited during this period.

The Kaplan-Meier curves suggest that the hazard rates and survival functions for B2C, B2B and B2B2C firms are different. To formally test this, we perform semi-parametric analyses that include the influences of other industry and firm factors on Internet firm survival.

3.5 Semi-parametric analyses

We perform three semi-parametric analyses using the Cox proportional hazards model. Our first analysis does not differentiate among the different types of exits in its test of the impact of various industry, firm and e-commerce factors on Internet firm survival. Our second analysis, in contrast, differentiates among different outcomes, including bankruptcy, acquisition, and merger. It tests competing risks [12], and allows us to discern differences on the impact of the explanatory factors on the exit types. The final test considers the different outcomes as different degrees of failure. We perform a semi-parametric analysis on the impact of the explanatory variables. Because no B2B firms in our sample failed during the study observation period, we have an imbalanced sample problem. Thus, we dropped all eight B2B firms from further analysis.

The Cox proportional hazards model. This model occurs in previous research on new firm survival [1, 2, 11]. We use it to analyze duration data for Internet firms since when they went public. The Cox model assumes a hazard rate at time \( t \) proportional to a baseline hazard function, \( h_0(t) \), based on age of the firm and explanatory variables that vary across firms over time:

\[
h(t, X, \beta) = h_0(t) e^{X\beta}
\]

With this hazard function, we obtain the survival function:

\[
S(t, x, \beta) = [S_0(t)]^{\exp(x\beta)}
\]

\( S_0(t) \in \{0,1\} \) is the baseline survival function. It represents the probability that a firm will not have failed by time \( t \) considering the baseline survival function for all firms and the set of explanatory factors that bear values specific to this firm. This analysis is conditional on the assumption that the firm has been in continuous operation in prior periods to which the sample pertains.

Given that a firm \( i \) is still at risk at time \( t_i \), the likelihood that it fails at time \( t_i \) compared to other firms that are at risk at time \( t_i \) is

\[
L_i(\beta) = \frac{h(t_i, x_i, \beta)}{\sum_{j \in R(t_i)} h(t_j, x_j, \beta)} = \frac{e^{x_i\beta}}{\sum_{j \in R(t_i)} e^{x_j\beta}}
\]

In Equation 3, \( R(t_i) \) is the risk set and includes all firms that are still at risk at time \( t_i \). For a data set that contains \( n \) firms, the partial likelihood is:
\[ L_p(\beta) = \prod_{i=1}^{n} \left[ \frac{e^{x_i'\beta}}{\sum_{j \in R(i)} e^{x_j'\beta}} \right]^{c_i} \quad (5) \]

In Equation 4, \( c_i \) is 0 if the observation is censored and 1 otherwise. Using this partial likelihood function, we can estimate parameters without specifying the baseline hazard function.

**Dependent variables.** The dependent variables are the duration of the firm’s survival since its IPO and an indicator for firm status. In the first analysis we do not differentiate exit types. The status variable is binary and indicates whether duration is determined by time of bankruptcy, merger or acquisition, or if the firm is still at risk but censored up to the last period for which we collected data. Otherwise, the status indicator is categorical and we perform separate analyses for the occurrence of different outcomes. (See Table 2.)

**Explanatory variables.** There are six independent variables and we summarize their definitions below. (See Table 2 again.)

We identify three categories of variables related to Internet firm survival: industry, firm and e-commerce. We could not obtain data for new firm entry for each industry for the digital marketplace. So we use the number of Internet firm IPOs in each quarter as a proxy. We define this for the IPO firm’s sector (i.e., the firm is a B2C, B2B or B2B2C company). In addition, we only calculate relevant competing IPO entries. Thus, a B2C firm competes with other B2C and B2B2C firms, while a B2B2C firm competes not only with B2C and B2B2C firms but also with B2B firms. We use the six-month U.S. treasury bill interest rate as a control for the impact of the macroeconomy on firm survival [2].

Our data are quarterly and the study period is early 1996 to September 2001. The only exception is firm size, which is measured annually. Public firms only report this figure annually. In trying to predict the survival status of an Internet firm in a quarter, we typically used one quarter-lagged data. However, financial data in the quarter immediately before bankruptcy, merger or acquisition are not available. Thus, values for explanatory variables are from 1996 to March 2001 for financial capital and up to June 2001 for the rest.

We also removed one firm that existed for two quarters due to unavailable financial data. Thus, final semi-parametric sample size is 94. The subset of 42 failed firms includes 13 firms that filed for bankruptcy, 16 that merged, and 15 acquired by other businesses. No two explanatory variables are correlated beyond 0.50. Moreover, no variable has a Belsley Kuh Welsch condition index larger than 20 [9]; multicollinearity is not a problem.

The hazard function for the estimation of model parameters is:

\[ h(t) = h_0(t) \exp[\beta_1 IPOEntry_{t-1} + \beta_2 Size_{t-1} + \beta_3 Capital_{t-2} + \beta_4 Product + \beta_5 B2B2C + \beta_6 InterestRate_{t-1}] \quad (6) \]

The time-varying covariates include IPOEntry, Size, Capital, and InterestRate. We next present results from our three semi-parametric analyses. In presenting the results, we differentiate hazard ratio from hazard rate. The former is the marginal effect of a one-unit increase in the explanatory variable on the hazard rate. It is calculated as \( \exp(\beta_i) \), where \( \beta_i \) is the parameter estimate for the explanatory variable.

No differentiation among different failure types. Table 3 summarizes the results for Model 1 based on the Cox model with aggregated types (i.e., bankruptcy, acquisition or merger are all treated as failures). Overall, Model 1 has a likelihood ratio of 21.74 (p < .01).

The sector-related variable IPOEntry is significant at the .10 level. However, contrary to the results from previous research, IPOEntry has a parameter estimate of -0.0747, which results in a hazard ratio of 0.928. It indicates that with one additional new competing Internet firm IPO, the hazard rate of an existing publicly-traded Internet firm falls to 92.8% of its original value. The only firm-related factor that is significant is Product, which has a parameter estimate of -0.871 (p<.05). The estimated hazard ratio is 0.419; thus the hazard rate for an Internet firm selling digital goods is about 41.9% of that for an Internet firm selling physical goods, ceteris paribus. The control variable InterestRate is significant at the .01 level and has a parameter estimator of -0.378. The hazard ratio is 0.685, indicating with one percent increase in interest rate, the hazard rate of a public Internet firm falls to about 68.5% of its original value.

Our results show that firm Size and financial Capital are not significant. Even though B2B2C firms have estimated parameters indicating lower hazard rates as indicated by the estimated hazard ratio of 0.685 over B2C firms, this parameter is not significant.

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1. Audretsch and Mahmood (1995) also used UnemploymentRate as a control. We investigated whether this was appropriate. However, it had a -0.62 correlation with InterestRate. Since it carried information already in our model, we excluded it.

2. Our model initially included percentage change in the NASDAQ Composite Index. However, this variable had a 0.58 correlation with IPOEntry, so we removed it.
Testing for competing risks. We can distinguish among exit types and view bankruptcy, merger and acquisition being explainable in different ways. Our competing risks analysis allows us to further look into the impact of the explanatory factors on each different type of outcome and test the hypothesis that the parameter estimates are the same across the three different exit types. In examining each exit type, we view only the occurrence of that specific outcome as the occurrence of an event, and treat all other observations as censored. (See Table 4.)

In Model 2A we test the impact of the explanatory variables on bankruptcy. IPOEntry of -0.929 is weakly significant ($p < .10$), suggesting that with the entry of one competing firm's IPO in a period, an existing public firm's hazard rate due to bankruptcy falls to about 39.5% of its previous value. The parameter estimate for Product is moderately significant at -1.277 ($p < .05$), indicating the marginal impact on the hazard rate for Internet firms selling digital versus physical goods is 27.9%. Overall, the model has a likelihood ratio statistic of 19.82 ($p < .01$).

In Model 2B, where we only consider exit due to merger, Size and InterestRate are both weakly significant. Size has a parameter estimate of -2.145 ($p < .10$), indicating the hazard rate declines to about 11.7%
of its original value with a marginal change in firm Size, as we define it. The parameter estimate for InterestRate is -0.542 ($p < .10$), which suggests with 1% increase in the 6-month Treasury bill rate, the hazard rate declines by 41.8%. However, the overall model is close to marginally significant (likelihood ratio = 10.57, $p = .1025$); the reader should recognize the limitations of this part of our results.

In the estimation for the explanatory variables’ impacts on acquisition in Model 2C, no variable is significant (model likelihood ratio = 14.39; $p < .05$). With smaller samples, there are going to be limitations to what we can conclude and can learn from our data, as we see here.

Finally, the likelihood ratio for equal parameter estimates across the three exit types is 18.63 ($p < .10$). This indicates that the impact of the explanatory variables on bankruptcy, merger and acquisition is probably different, as we had expected when we formulated the econometrics model in this way.

**Testing for different degrees of failure.** We can order the different outcomes from most constraining to least constraining as follows: bankruptcy, acquisition, merger, and survival. Bankruptcy is the least desirable outcome since it indicates the inability of the firm to continue operation under its current condition. Acquisition may be a less restrictive circumstance than bankruptcy, but probably less attractive to managers at the firm than a merger. Why? It is usually the case that weaker firms are acquired outright and that mergers are more likely to represent the formation of one synergistic business by two firms with complementary resources that have greater market value in proximity to one another. Survival, by the same token, might be viewed as the most attractive outcome. Based on this ordering, there are three possible analyses.

First, when we view bankrupt Internet firms as one group and the other three (acquisitions, mergers, and survived firms) as another group, we test the impact of the explanatory factors on bankruptcy only. The results

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**Table 4. Results of testing three models for competing risks (Model 2A, 2B and 2C)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Std Dev</th>
<th>Chi-Square</th>
<th>Hazard Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 2A -- Failure due to bankruptcy (N=94, 13 events)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPOEntry</td>
<td>-0.929</td>
<td>0.934</td>
<td>3.394***</td>
<td>0.365</td>
</tr>
<tr>
<td>Size</td>
<td>0.168</td>
<td>0.290</td>
<td>0.336</td>
<td>1.183</td>
</tr>
<tr>
<td>Capital</td>
<td>-0.00760</td>
<td>0.00116</td>
<td>0.431</td>
<td>0.959</td>
</tr>
<tr>
<td>Product</td>
<td>-1.277</td>
<td>0.627</td>
<td>4.153**</td>
<td>0.279</td>
</tr>
<tr>
<td>B882C</td>
<td>-0.535</td>
<td>0.853</td>
<td>0.393</td>
<td>0.586</td>
</tr>
<tr>
<td>InterestRate</td>
<td>0.229</td>
<td>0.567</td>
<td>0.391</td>
<td>1.238</td>
</tr>
</tbody>
</table>

Likelihood ratio statistic for failure due to bankruptcy = 19.82***

| **Model 2B -- Failure due to merger (N=94, 16 events)** | | | | |
| IPOEntry | 0.107 | 0.466 | 0.050 | 1.010 |
| Size | -2.145 | 1.102 | 3.788** | 0.117 |
| Capital | 0.000372 | 0.000931 | 0.160 | 1.000 |
| Product | -0.846 | 0.621 | 1.818 | 0.429 |
| B882C | -0.337 | 0.606 | 0.408 | 0.679 |
| InterestRate | -0.542 | 0.321 | 2.844** | 0.082 |

Likelihood ratio statistic for failure due to merger = 10.57, not significant

| **Model 2C -- Failure due to acquisition (N=94, 15 events)** | | | | |
| IPOEntry | 0.148 | 0.103 | 2.029 | 0.862 |
| Size | -0.999 | 0.847 | 1.263 | 0.266 |
| Capital | 0.00259 | 0.00238 | 0.812 | 0.697 |
| Product | -0.333 | 0.658 | 1.251 | 0.279 |
| B882C | -0.060 | 0.415 | 0.010 | 0.942 |
| InterestRate | -0.407 | 0.234 | 2.568 | 0.114 |

Likelihood ratio statistic for failure due to acquisition = 14.39**

**Note:** The likelihood ratio statistic for the hypothesis of equal parameters across failure types is 18.63, and is significant at the .10 level. Significance levels for the explanatory variables in this table are given by:

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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3 Note the difference between various stakeholders. Stockholders and firm managers benefit little from bankruptcy, other than as a means to protect themselves from debtholders. Stockholders and managers may view acquisition and merger differently. Stockholders prefer high equity value, even if ownership changes hands. Managers recognize the probability of being dismissed may be greater for acquisitions than mergers.
are the same as the analysis in the previous section where we only test failure due to bankruptcy. Second, we can combine the occurrence of bankruptcy and acquisition as a somewhat less restrictive operationalization of failure, and define merger and survival as censored cases. We summarize these results in Table 5. (See Table 5.)

*IPOEntry* and *Product* are both significant; no others are. The parameter estimate for *IPOEntry* is -0.270 \( (p < .05) \) and the hazard rate is predicted to fall to 76.5% of its original value with each additional competing IPO. *Product* has a parameter estimate of -0.922 \( (p < .05) \), suggesting a hazard rate that is 39.8% less for firms selling digital goods. Overall, the model has a likelihood ratio of 23.60 \( (p < .01) \).

Third, the last case is similar to the first analysis where we do not differentiate the different exit types, so we do not report additional results.

4. Conclusion

We tested for the impact of different factors on Internet firm survival. Our analyses reveal a number of results. First, the non-parametric analysis for the expected duration of all Internet firms provides a descriptive picture of the hazard rate during their life spans. It suggests the hazard rates for different types of Internet firms are different. B2B Internet firms experienced no failure during our observation period. For B2C firms, the shakeout occurs during the early stages of their life, which continues till Year 3. This result indicates a B2C firm is more likely to survive once it passes through a critical period. For B2B2C firms, the shakeout occurs later. About half of the B2B2C firms failed during Year 3 to Year 4. Thereafter, the B2B2C firms had lower hazard rates and were more likely to survive.

Second, our test for exit due to competing risks suggests the impact of the explanatory factors on bankruptcy, acquisition and merger are different. For exit due to bankruptcy, a firm selling digital goods has a lower hazard rate. This result is consistent with Barua et al. [5]. Higher productivity DotComs selling digital goods take advantage of the electronic channel in delivering products. They incur lower operation costs, resulting in higher efficiency and profitability, improving survivability.

Entry of competing Internet firms (through their issuance of IPOs) also can reduce the hazard rate for existing public Internet firms. As a result, even though new entrants exert competitive pressure on market incumbents, abundant financial capital, as indicated by a large number of firms going IPO, may be the more critical factor in determining Internet firm survival during our sample period.

Firm size and interest rates are significant in predicting Internet firm mergers. Logically, larger firms are less likely to be merged. With higher interest rates, indicating greater demand for financial capital in a prosperous economy, a firm’s hazard rates due to merger also decline. No other sector, firm or e-commerce factors are significant. Our acquisition model reveals no significant explanatory variables. Bankruptcy usually indicates problems. However, mergers and acquisitions can be result from either failure or success. A healthy firm might be acquired due to its growth potential. Firms in financial difficulty might be acquired to obtain financial capital to remain viable. Thus, the lack of significance of some explanatory variables turns out to be reasonable.

Third, our analysis for different operational definitions of failure reveals the predictive power of competing IPO entry and the products the company sells. Both variables are significant in all three different groupings. Market capital sufficiency, as reflected in a high IPO entry, is critical to Internet firm survival during our study period. Firms selling digital goods have lower hazard rates.

The current study has limitations. First, because the Internet sector is in an early stage of development, the results might not be generalizable. However, given the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Std Dev</th>
<th>Chi-Square</th>
<th>Hazard Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPOEntry</td>
<td>-0.270</td>
<td>0.121</td>
<td>4.938**</td>
<td>0.765</td>
</tr>
<tr>
<td>Size</td>
<td>-0.186</td>
<td>0.235</td>
<td>0.626</td>
<td>0.831</td>
</tr>
<tr>
<td>Capital</td>
<td>-0.000639</td>
<td>0.000313</td>
<td>0.618</td>
<td>0.999</td>
</tr>
<tr>
<td>Product</td>
<td>-0.922</td>
<td>0.420</td>
<td>4.823**</td>
<td>0.398</td>
</tr>
<tr>
<td>B2B2C</td>
<td>-0.302</td>
<td>0.493</td>
<td>0.375</td>
<td>0.739</td>
</tr>
<tr>
<td>InterestRate</td>
<td>-0.245</td>
<td>0.223</td>
<td>1.205</td>
<td>0.783</td>
</tr>
</tbody>
</table>

Note: Likelihood ratio statistic = 23.60, significant at the .01 level. Significance levels for the explanatory variables in this table are given by: \( * \) \( p < .10 \), \( ** \) \( p < .05 \), \( *** \) \( p < .01 \).
capital involved and impacts the sector creates on the economy, it is important to examine the survival of Internet firms. Even though influences of the factors might not be the same were the Internet more mature, analysis still can reveal their relative strength for predicting failure. Second, the results of our econometric models may not apply to B2B firms. We will continue to collect more data and incorporate other B2B firms into our future analysis. For that, we need to have cases involving the failure of publicly-held B2B Internet firms. Third, because we only have publicly-traded Internet firms in our sample, our results may not be generalizable to privately-held Internet firms. While it is very difficult to collect financial data on private firms to perform semi-parametric analyses, we plan to collect more duration data to test for differences in the duration patterns of the two types of firms.

References


