Firm Dynamics of Hi-Tech Start-ups: Does Innovation Matter?

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Abstract

Innovation plays a vital role in corporate issues since it brings potentially appreciable profits and shores up their statuses in certain fields, although it may also harness firms, especially smaller ones, with high survival risks. This concern brings forth our research topic: could innovation diminish firms' risk of failure? Our paper concentrates on hi-tech start-ups and complements existing firm dynamic studies by adopting a comprehensive annual survey dataset from a science park located in Beijing. Using a novel discrete-time proportional hazards model, and thanks to extensive data available, we can take a deeper investigation into this topic. Our research complies with most of the previous studies that show that the benefit from innovativeness outweighs the cost and we solidify our conclusions by considering a few distinctive features existing in China's economy.

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Introduction

Firm dynamics have long concerned economists. Whether in developed or developing countries, the exit and entry of firms to the market are an essential part of industrial development (Tybout, 2000) (*41*). Recent years have seen a burgeoning increase in the number of start-ups in China, leading to one of the world's largest pools of unlisted companies. These fledgeling companies, however, have fairly high rates of exit from the market. This brings to the following question: What are the factors that assist new businesses or lead to their exit from the market? There are numerous studies about how innovation influences the dynamics of companies, but few have discussed this topic in regard to start-ups. Innovativeness, on one side, is one of the most important factors to measure a start-up's potentiality. However, start-ups bear more associated risks in engaging in research and development due to the limited resources compared with large companies. Hence, in this paper, we delve into whether innovation activities have impacts on the survival of start-ups and, if they do, are the impacts positive or negative.

We refer to a survey that includes a series of start-ups operating at a science park supported by the government located in northwest Beijing named Zhongguancun. Known as China's Silicon Valley, Zhongguancun is the earliest Science & Technology Zone plan launched by the Chinese government, which collocates some of China's most advanced hi-tech companies. By using an exclusive and extensive annual corporate survey dataset, we discuss the innovativeness through two indexes derived from the survey. The first one is the number of patent applications, which is a fairly typical proxy in previous innovation studies. In addition, we employ another indicator standing for innovation abilities, measured by the proportion of sales of new products to total sales. When combining these two variables, we can explore to which extent innovativeness, assessed either by input or output of innovation activities, influences the risk of exit. The survey dataset provides uninterrupted descriptions of each firm as long as they operate at the science park. This feature helps us to control the possible heterogeneity problems.

Following previous studies on corporate survival, we adopt the complementary log-log model, put forward by Prentice and Gloeckler (1978) (*37*) in order to fit our data structure and solve the heterogeneity problems. This model helps to solve two major concerns with the data: discrete survival times and right censoring. Furthermore, we also exploit other attributes shown in the survey as control variables to avert biased estimation due to heterogeneous corporate characteristics. These attributes are some of the most typical features distinguishing companies in China such as the ownership, industry, and exportation, among others. We find that innovativeness has a significant positive impact on lessening the risk of exit, measured either by the number of patents or the sales ratio of new products. This result leads to the conclusion that the benefits to innovate overweigh the negative impacts it brings to a start-up. In other words, though a start-up has to bear the risk of running out of money, in general, innovation activities are an efficient way to diminish the risk of exit. Moreover, we attempt to find the mechanism behind this finding, showing that innovativeness mainly promotes total factor productivity and average productivity per labor unit hired for start-ups.

This paper complements existing studies in four aspects. The cornerstone of our paper is that it is the first one to use a specific Chinese start-up survey dataset to discuss firm dynamics. The comprehensive dataset covers more characteristics of companies compared to other large scaled corporate surveys. Second, we employ a novel hazard survival model favoring right censoring, and solve potential heterogeneity problems thanks to a broad selection of variables provided by the survey dataset. Furthermore, we ponder the mechanism behind the finding as well as discuss financial constraints, which is a major concern in the Chinese financial system. Moreover, the source of a patent and the destination of its application are investigated, helping us to dig into the distinctiveness of a patent, further exploring the quality of the innovativeness and its impact.

This paper is structured as below: the second part reviews previous studies regarding the relationship between innovation and the survival of companies. In the third part, we introduce our dataset. The fourth part evaluates existing models we have on the table about firm survival. In the fifth part, we conduct a battery of robustness tests to solidify our test results. The last part concludes.

Literature Review

The prevailing perspective is that innovation can enhance the chance for firms to survive, often attributed to the benefits brought by innovation activities. Innovation can reduce the costs of production (Cohen and Klepper, 1996 (*13*)) and strengthen firms' dynamic capabilities, including distinctive processes, asset positions, and evolution paths (David J. Teece et al., 1997 (*40*)). It can also help firms deal better with government's regulations (Porter and Van der Linde, 1995 (*36*)) and improve their potential and realized absorptive capacities (Zahra and George, 2002 (*44*)). Thus, when the benefits brought by the research and development activities override the cost, better fiscal performance is expected and longer survive in the market is more likely. There are a large number of studies that substantiate this point. Arrighetti and Vivarelli (1999) (*3*) use an Italian small-firm dataset and find that innovation is related to a superior postentry performance. J.L. Calvo (2006) (*8*) concludes that innovation activity, either measured by process or product, is a strong positive factor in the firm's survival and its employment growth based on a sample of Spanish manufacturing firms. Cefis and Marsili (2005, 2006, 2012) (*9*) (*10*) (*11*) conclude that a positive connection exists between innovation premiums and life expectancy shown by adopting observations of manufacturing firms in the Netherlands. By considering patent portfolios in a group of French firms, Colombelli et al. (2013) (*14*) shows that innovation enhances the survival likelihood of firms. Results in Helmers and Rogers (2010) (*25*) indicate that intellectual property activity, measured as patenting and trade-marking, is associated with a considerably lower probability of exit by using a British dataset. Wagner and Cockburn (2010) (*43*) find that in Internet-related firms that made an initial public offering on the NASDAQ, patenting is positively associated with survival. Esteve-Perez and Manez-Castillejo (2006) (*21*) test a number of hypotheses mainly drawn from the Resource-Based Theory of the Firm and establish that firms with more assets concentrating on research and development enjoy better survival prospects. Fernandes and Paunov (2015) (*22*) use plant-product data for Chile and find that innovating plants have a lower exit hazard.

However, there are a few circumstances in which the risk of innovation activities could beat the benefits brought by the process. Cader and Leatherman (2011) (*7*) found omitted observations or missing data in previous studies using US data, resulting in erroneous conclusions, and technology-intensive firms were more likely to fail within the first five years. Ari Hyytinen et al. (2015) (*27*) adopt an different view using ex-ante measures and, find that a startup's innovativeness is negatively associated with its subsequent survival in Finland. Another interesting finding is from Buddelmeyer et al. (2010) (*6*) that although radical innovation, captured by the stock of granted patents, enhances survival prospects, firms are more likely to fail after investing in radical innovation, as measured by submitted applications. These studies capture some flaws in precursors and found the different conclusions. In a word, most of the previous research suggests that there exists a positive relationship between innovation and the chance to survive. Nevertheless, considering the aspects brought forth by the later papers, we have to be more cautious about data accuracy and heterogeneous problems.

Our dataset has two major specific characteristics that must be considered. One is that it only includes hi-tech companies, and the other is that our research is based in China, where the government plays an essential role in the development of the science park, and handouts from the government cannot be ignored. Start-ups are usually more proactiveness and competitive aggressiveness (Lumpkin and Dess, 1996 (*33*)). Theoretically, Dahlqvist and Wiklund

(2012) (*18*) think that a new venture, which is based on a novel business idea, may eventually outperform its competitors in the same field. Starters are also more flexible toward rapid changes happen in the market (Klepper and Simons, 1997 (*30*)). Therefore, we may assume the same positive association shown in Rosenbusch et al. (2011) (*39*) that the relationship between innovativeness and small business performance is stronger for younger firms and can be seen in our dataset. Another point of interest is China's subsidy policy. Government subsidies have a positive certification effect on the acquisition of bank loans (L. Li et al., 2018 (*32*)). Additionally, the subsidies can even boost the innovation itself. According to Dang and Motohash (2015) (*19*), patent subsidy programs increase patent counts by more than 20%. Zhang et al. (2014) (*45*) illustrates that government subsidies, in the long and short-terms, have significant positive effects on the financial performance of energy manufacturing companies.

Due to the hypotheses mentioned above, the next step for us is to see what economic models economists have on the table for the firm survival research. In earlier studies, we could find some traditional methods are adopted, such as OLS (J.L. Calvo, 2006 (*8*)) and Log-logistic models (Mahmood, 2000 (*34*)). The Cox Model, which was first introduced by Cox (1972) (*16*) is popular in firm survival research thanks to its convenient estimation of the effects of plant characteristics on survival using a proportional shifter of the baseline hazard function with no requirements on that function's shape (Agarwal and Audretsch, 2001 (*1*); M.Y. Chen, 2002 (*12*); Disney et al., 2003 (*20*); Girma, Gorg, and Strobl, 2007 (*24*)). Another similar discrete time survival model often employed is the complementary log-log model (Musso and Schiavo, 2008 (*35*); Bayus and Agarwal, 2007 (*4*); Agarwal et al., 2002 (*2*)).

Data description

We use a comprehensive and exclusive firm-level dataset, which includes comprehensive information on small and micro-enterprises. These companies are hi-tech start-ups subsidized by the government and located in Zhongguancun Science & Technology Zone. The dataset covers the period from 2007 to 2013, and the number of firms in the survey each year exceeds 9,000. The frequency and ratio of each year are presented in Table 1 below.

Year	Stay Sample	Exit Sample	Total Number	Exit Rate (%)	Percent
2007	12,932	1,399	13,303	9.76	17.52
2008	11,501	2,013	13,513	14.90	17.79
2009	10,534	926	11,455	8.08	15.08
2010	9,394	914	10,307	8.87	13.57
2011	8,534	772	9,306	8.30	12.25
2012	7,387	1,629	9,016	18.07	11.87
2013	7,110	1,941	9,051	21.45	11.92
Total	67,392	9,594	75,951	12.46 (ave.)	100.00

Table 1: Firm Stay and Exit Statistical Description

The firm sample in our dataset covers six main industries including service, software, and wholesale. In addition, this dataset allows us to get access to other information like the ownership of the firms, whether certificated as hi-tech and the certification time, financial condition, human resource condition, import and export trade, new products, R&D, and patent applications.

The status of a firm and its spell duration

In our model, the hazard rate is used to measure firm dynamics. To determine the hazard rate of the firms, we have to define their status, which is a binary variable: survival or exit. There are a few reasons that lead a firm to exit: mergers, acquisitions, bankruptcy, and so forth. However, thanks to the characteristics of our samples, we can track the information of firms as long as they are still located in the science park. Thus, it is much easier to define the status of the companies and their spell durations, compared to most previous studies (e.g. Fontana et al., 2009 (*23*); Ugur et al., 2015 (*42*); Buddelmeyer et al., 2006 (*5*)). In this paper, we define the status of exit when a company stops reporting. We show the exit rate for each year in Table 1. The average exit rate in our sample is 12.46%, which is lower than the average exit rate in China, where for the state-owned and private firms, it is 15.8% and 13.8%, respectively, from 2007 to 2012 (Hsieh and Song, 2015 (*26*)).

The innovativeness of firms

The firms innovation abilities are the major concern in this study. Herein, we use two approaches to measure a firm's ability to innovate. First, we consider firms' new products, which are the outcome of a firm's innovation activities. Using the fraction of sales of the new product to total sales, we measure how the innovative output influences the survival of the start-ups. Additionally, we take patent application into account, so that we can measure the input of innovation activities' impacts on the chance of surviving. Here, we use the number of applications for patents from the survey as the indicator, and we follow J Dang and K Motohashi, 2015 (*19*) using the improved logarithm form to process the number[1].

Other control variables

From our comprehensive survey data, we can draw a number of other variables to include into our analysis to avoid biased estimations. According to the findings of previous studies, we choose those factors that might influence firms' dynamic processes. For our main regressions, we first consider sales growth, which is calculated as the difference in sales between year t and year $t-1$ divided by the total sales in year $t-1$. Capital intensity is also taken into consideration, presented as fixed investment per capita for each company. Additionally, firm subsidies are a factor that cannot be ignored that affects the growth of a firm. Thus, we use the proportion of the subsidy accounting for the total asset as the index. Other variables include firm size and

[1] in detail: log(Applications of patents) = log (number of applications in year t + 1/3);

age, measured by the number of employees and the years since the first operation, respectively. In Table 2[2], we present the statistical description of all variables and calculate the difference between the state-owned enterprises (SOE) and privately-owned enterprises (POE) group and the POE and foreign-owned enterprises (FOE) group, which are presented by $DIFF1$ and $DIFF2$, respectively.

Variable	Mean				SOE	POE	DIFF1	FOE	DIFF2
Exit	0.106	1	0	-1	0.072	0.107	-0.035***	0.133	-0.030***
New product	8305	1088	9122	8034.453***	15000	5984	9120.713***	25000	-1.9e+04***
New sale	12008	1430	13000	1.2e+04***	30000	9259	2.1e+04***	30000	-2.0e+04***
Grant ratio	0.651	0.0550	0.718	0.663***	2.866	0.541	2.324***	0.897	-0.345***
New sale ratio	0.159	0.154	0.160	0.00500	0.163	0.160	0.003	0.142	0.019***
LogPan	-0.818	-1.016	-0.795	0.221***	-0.530	-0.827	0.297***	-0.854	0.033***
Valid patent	1.738	2.195	1.729	-0.467	1.983	1.687	0.296	1.999	-0.304
Paper	-1.019	-1.068	-1.014	0.054***	-0.694	-1.026	0.332***	-1.044	0.019***
Trademark	-0.939	-1.044	-0.928	0.116***	-0.895	-0.943	0.047***	-0.946	0.00700
ZScore	2.787	1.014	2.978	1.964***	3.553	2.992	0.561	0.463	2.575***
Sale growth	0.797	0.875	0.792	-0.0830	0.428	0.827	-0.399***	0.584	0.252***
K Intensity	2.816	2.643	2.834	0.191***	3.575	2.750	0.825***	3.197	-0.449***
Subsidy	0.004	0.00200	0.00500	0.003***	0.004	0.004	-0.001*	0.005	0
Size	2.583	1.600	2.697	1.097***	3.551	2.491	1.060***	2.736	-0.203***
Age	2.077	1.804	2.108	0.304***	2.517	2.066	0.450***	2.064	0.002
Profit rate	-1.417	-3.396	-1.227	2.169***	-0.443	-1.358	0.915***	-2.229	0.878***

Table 2: Variables Description

In our robustness tests, we introduce additional variables in order to solidify our analysis. First, we classify the scale of firms according to the registration information of the companies: micro, small, and large. Then, we introduce a few other indicators relevant to innovativeness, including the proportion of hi-tech labors over total staff, the number of trademarks the company

[2] $Exit$ is the exit rate. $Newproduct$ is the output of new products. $Newsale$ is the sales volume of new products. $Grantratio$ is the ratio of successful applications; $Newsaleratio$ is the ratio of the sales of new products; $LogPan$ is the logarithm form of patent number; $Validpatent$ is the ratio of valid patent number to to total number of patent application; $Paper$ and $Trademark$ are the numbers of papers and trademarks in the logarithm form; $ZScore$ is $1.2*((currentassetcurrentdebt)/totalasset)+1.4*(investrevenue/totalasset)+3.3*profitrate+0.999*(totalsale/totalasset)+0.6*(totalequity/totalliablity)$; $KIntensity$ is Capital Intensity

applied for, and the number of publications. Another benefit of our dataset is that we include the source information of every patent. We can distinguish whether the patent is developed by the company itself or acquired from domestic or foreign companies. The information on companies applying for patents outside of China is also provided. From the survey, we also consider the financial characteristics of firms, comprised of the Return on Assets (ROA), Total Factor Productivity (TFP), and productivity per capita.

Kaplan-Meier Survival Analysis

From our statistical summary, a basic trend showing a higher survival rate for more innovative firms can be seen. The Kaplan-Meier estimation is a fundamental method in survival analysis (Kaplan and Meier, 1958 (*29*)). It has become a basic and important method of dealing with differing survival times, especially when the right censoring problem exists (Rich et al., 2010 (*38*)). Another necessity of using the Kaplan-Meier survival analysis is because the hazard models we use are in a linear form (Lee JW et al., 2006 (*31*)); thus, non-linear survival curves may lead to biased estimation. We portray the Kaplan-Meier curves for firms from 2007 to 2013 in Figure 1.

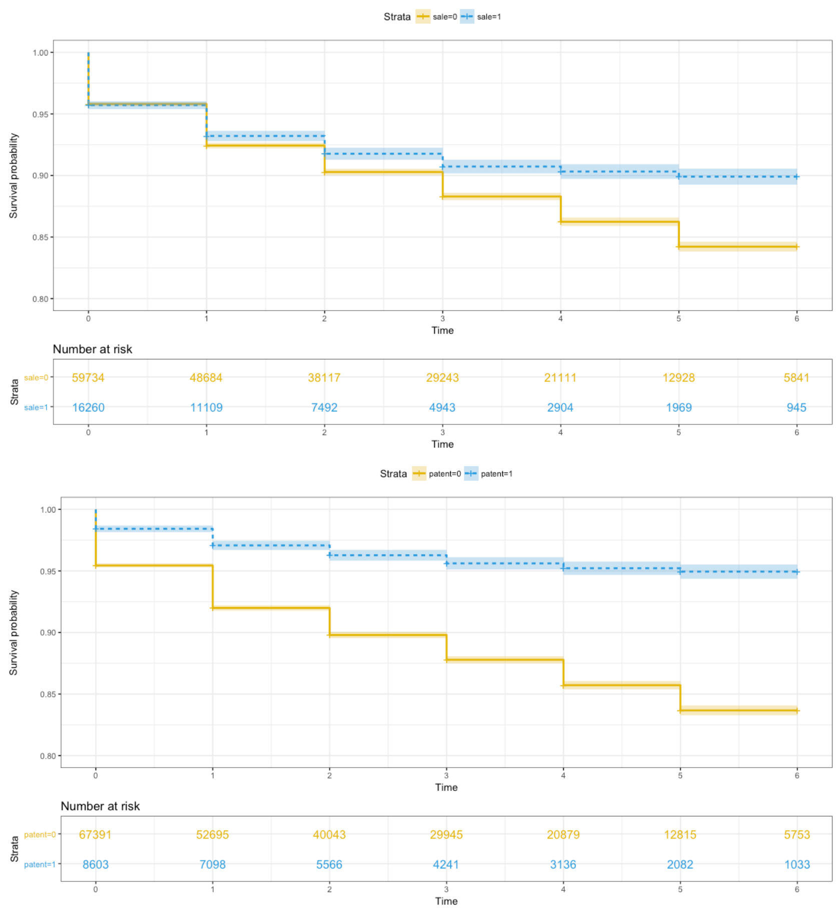

Figure 1: Kaplan-Meier Survival Curves

The survival curves above represent the survival probabilities of innovative and less innovative firms, measured by whether they have new products that sold (top) or patents (bottom) in six years. Results show that the survival probabilities of more innovative firms are always higher than less innovative firms for the firms in our time range. This provides the foundation for our analysis using hazard models.

Model Specification

To identify the impacts of innovativeness, which consist of both the input and output effort in our study, we consider how factors including innovation abilities and other control variables influence the hazard rate for the survival of start-ups. To begin with, we have to take a few points into account, which may violate the assumptions of conventional models and require us to figure out proper methods to solve them. First, the probability to exit is conditional, which means survival rates fluctuate with time. Second is a typical problem that exists in survival research. Due to the limitation of observations, in the end year, we cannot track if the company continues to operate or exit, which leads to the uncertainty.

First, we extend the proportional hazards model to discrete time, defining the survivor function at time t_j as the probability the survival time T is at least t_j.

$$S(t_j) = S_j = Pr(T \geq t_j) = \sum_{k=j}^{\infty} f_j \tag{1}$$

where T is a discrete random varibale taking value t_j with probability:

$$f_j = f(t_j) = Pr(T = t_j) \tag{2}$$

Then, we construct the conditional probability of firms to exit λ_j at the hazard time t_j, the point in time at which the company survives.

$$\lambda(t_j) = \lambda_j = Pr\{T = t_j | T \geq t_j\} = \frac{f_j}{S_j} \tag{3}$$

We realize that the survival function at time t_j can be reconstructed as the hazard rate at all prior time points in time $t_1, \ldots, t_{j-1}$:

$$S_j = (1 - \lambda_1)(1 - \lambda_2) \ldots (1 - \lambda_{j-1}) \tag{4}$$

In a word, this equation implies that if a firm survives to t_j, it has to survive to t_1, and given that the firm survives to t_1, it can survive to t_2, and so on, until the firm survives to t_{j-1}.

Then, we need to proceed with the model in terms of the conditional probability. The first one is based on a logit model, which was put forward by Cox (1972) (*15*). The hazard rate is under the condition, which is represented by a series of covariate values $\mathbf{x}_i$,giving us the hazard of a company at time j: $\lambda(t_j|\mathbf{x}_i)$. The conditional hazard rate satisfies the logit form as below:

$$\frac{\lambda(t_j|\mathbf{x}_i)}{1-\lambda(t_j|\mathbf{x}_i)} = \frac{\lambda_0(t_j)}{1-\lambda_0(t_j)} exp(\mathbf{x}b) \tag{5}$$

Here $\lambda_0(t_j)$ is the baseline hazard at time t_j, which is a hypothetical situation where the characteristics vector $\mathbf{x}$ is 0, changing only with the varying of time intervals. Additionally, $exp(\mathbf{x}b)$ is the relative risk relevant to the covariate values $\mathbf{x}_i$. Accordingly, we can rewrite as:

$$logit \lambda_0(t_j|\mathbf{x}_i) = \alpha_j + \mathbf{x}b \tag{6}$$

where α_j equals $\lambda_0(t_j)$, the logit form of the baseline hazard. The Cox model treats time as a discrete factor by introducing one parameter α_j for each possible time of the exit of an observation at t_j. This model does not suit our dataset mainly because the companies need to be placed in an order based on their exit times, although it does not require survival time to be a continuous variable. As we mentioned previously, our dataset is based on annual surveys; hence, the survival times of companies are distributed into one-year intervals, so it is not probable for us to identify the accurate exit order. As a result, the estimation of the Cox model could be biased (Cox and Oaks, 1984) (*17*).

Another alternative extension of the proportional hazard model regarding discrete time observation is through the complementary log-log method. In this model, we start with the survival function, which can be written as:

$$S(t_j|\mathbf{x}_i) = S_0(t_j)exp(\mathbf{x}b) \tag{7}$$

Here, $S(t_j|\mathbf{x}_i)$ stands for the probability that a firm with covariate values **x** survives to time t_j, while $S_0(t_j)$ is the baseline survival function. Since we already know that $S_j = (1-\lambda_1)(1-\lambda_2)\ldots(1-\lambda_{j-1})$, we can rewrite the function with a similar relationship for the complement of the hazard function:

$$1 - \lambda(t_j|\mathbf{x}_i) = [1 - \lambda_0(t_j)]^{exp(\mathbf{X}b)} \tag{8}$$

From that, we adopt the complementary log-log method to transform the right-hand side to a linear function, giving a new function:

$$log(-log(1 - \lambda(t_j|\mathbf{x}_i))) = \alpha_j + \mathbf{x}b \tag{9}$$

where α_j equals $log(-log(1-\lambda_0(t_j)$ is the complementary log-log (cloglog) transformation of the baseline hazard. The cloglog model can be fitted to our discrete survival data by generating pseudo-observations as before and fitting a generalized linear model with a binomial error structure and complementary log-log link. However, only under non-informative censoring is there no difference between adopting the binomial likelihood and the discrete-time survival likelihood for the logit and complementary log-log links. Because right-censoring is one of our major considerations to improve accuracy, the best strategy for us here is to follow the cloglog model. Another vital reason why the cloglog link is better than the Cox (logit) is that in our dataset, time is discrete, but we only observe it in a grouped form. In particular, results based on the cloglog link would be more robust to the choice of categories.

Empirical Findings

In Table 3, we present the results of our main regressions, and the three different methods are explicated. First, we observed that in all three regressions, innovation, no matter if measured by product or patent application, does reduce the risk of exit. For the regression considering product innovation as the main variable, the cloglog model shows the maximum value of the log-likelihood. When the year and industry are controlled, the coefficient on product innovation is significantly negative. This means that the higher the ratio of new products accounting for total sales, the less risk a company has to bear. Thus, innovativeness does count toward the survival of a firm. Additionally, capital intensity, subsidies from the government, and firm size all play an essential role in firms' survival. The higher capital intensity means more active firms participate in investment., Like innovativeness, showing dichotomy in profitability, investment plays a positive part in reducing the risk of exit. Subsidies, contributing to firms' growth is intuitive since it is a direct capital injection. Another variable, sales growth, is significant but has small regression coefficients, which likely means that sales may not be the key factor in determining survival. Another interesting finding is that the coefficients on firm age and its squared form do not show any significant level in our regressions. This leads to a conclusion that the length of years does affect hi-tech start-ups' subsistence.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	Probit	Logit	Cloglog	Probit	Logit	Cloglog
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation	-0.076***	-0.159***	-0.147***			
	(0.019)	(0.037)	(0.034)			
Patent Application				-0.067***	-0.156***	-0.151***
				(0.018)	(0.040)	(0.038)
Sales Growth	-0.004***	-0.007***	-0.006***	-0.004*	-0.008*	-0.008*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)	(0.004)
Capital Intensity	-0.026***	-0.050***	-0.046***	-0.022***	-0.041***	-0.037***
	(0.002)	(0.005)	(0.005)	(0.006)	(0.011)	(0.010)
Subsidy	-2.909***	-6.102***	-5.900***	-3.031***	-6.369***	-6.169***
	(0.555)	(1.393)	(1.382)	(0.842)	(2.006)	(1.950)
Firm Size	-0.301***	-0.495***	-0.436***	-0.300***	-0.489***	-0.426***
	(0.021)	(0.036)	(0.034)	(0.023)	(0.047)	(0.042)
Firm Size^2	0.006	-0.015*	-0.022***	0.006	-0.014	-0.021**
	(0.004)	(0.008)	(0.007)	(0.005)	(0.011)	(0.010)
Firm Age	-0.163	-0.198	-0.148	-0.127	-0.111	-0.057
	(0.127)	(0.223)	(0.203)	(0.167)	(0.327)	(0.288)
Firm Age^2	0.023	0.017	0.007	0.013	-0.007	-0.017
	(0.031)	(0.054)	(0.049)	(0.040)	(0.078)	(0.069)
Constant	-0.926***	-1.780***	-1.951***	-1.006***	-1.971***	-2.142***
	(0.142)	(0.239)	(0.215)	(0.182)	(0.356)	(0.318)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Observations	41,555	41,555	41,555	42,957	42,957	42,957
Log-likelihood	-9,119	-9,122	-9,104	-9,895	-9,850	-9,804

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 3: Baseline Results on Innovation and Firm Exit

Since the samples in our dataset are all start-ups in the science park, we are able to test whether the scale of firms shows some importance in how innovativeness diminishes the risk of exiting. We adopt the classification method according to the definition in the survey. For each innovation activities proxy, we create three regressions according to firm scales: micro, small, and large. Table 4 shows the regression results. For our main regression variables, the trend is clear: with the increase of firm scale, every unit of input of innovation activities contributes more to the reducing of risk to exit.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	Micro	Small	Large	Micro	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation	-0.216*	-0.346***	-0.484**			
	(0.128)	(0.086)	(0.222)			
Patent Application				-0.029***	-0.156***	-0.217***
				(0.003)	(0.049)	(0.077)
Sales Growth	-0.007*	-0.006	-0.015	-0.009***	-0.006	-0.008
	(0.004)	(0.007)	(0.037)	(0.001)	(0.007)	(0.034)
Capital Intensity	-0.029*	-0.049***	-0.119**	-0.022***	-0.041***	-0.096*
	(0.016)	(0.015)	(0.050)	(0.004)	(0.015)	(0.056)
Subsidy	3.588	-6.780***	-7.781*	1.674	-7.301***	-8.587*
	(3.961)	(2.514)	(4.267)	(1.277)	(2.561)	(4.556)
Firm Size	-0.347*	-1.137***	-0.742	-0.348***	-1.147***	-0.844
	(0.206)	(0.410)	(1.097)	(0.027)	(0.403)	(1.103)
Firm Size^2	-0.080	0.107	0.028	-0.051**	0.110	0.044
	(0.153)	(0.083)	(0.103)	(0.021)	(0.081)	(0.113)
Firm Age	-0.405	0.097	-0.148	-0.311***	0.175	-1.212
	(0.555)	(0.425)	(0.301)	(0.098)	(0.418)	(1.093)
Firm Age^2	0.070	-0.047	0.140	0.047*	-0.075	0.093
	(0.135)	(0.101)	(0.254)	(0.027)	(0.100)	(0.262)
Constant	-1.544***	-1.325**	-2.250	-1.638***	-1.495**	0.109
	(0.578)	(0.664)	(2.682)	(0.092)	(0.655)	(2.886)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Observations	7,092	22,175	12,288	8,059	22,589	14,934
Log-likelihood	-2,838	-5,237	-1,016	-3,335	-5,420	--1,098

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 4: Results on Innovation and Firm Exit across Firm Size

Another important firm characteristic we look into is ownership. Due to the complicated market structure in China, different ownerships lead to large differences from operation to management. Thus, we assume ownership could also be a critical factor influencing the extent that innovativeness lessens the risk of exit. According to the question set in the survey, we classify the companies into three categories: state-owned, privately-owned and foreign-owned. In our dataset, SOE makes up the smallest part of all observations while POE accounts for over 86% of all the firms. What is noticeable in the regression results is that the coefficients of SOEs are much larger than the other two, especially reflected by the term for the number of patents. This could be explained by the complex rules SOEs have to obey, leading to more barriers to innovation, so that every unit of innovation contributes more to the survival of SOEs.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	SOE	POE	FOE	SOE	POE	FOE
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation	-0.978**	-0.312***	-0.305*			
	(0.491)	(0.071)	(0.183)			
Patent Application				-0.217***	-0.155***	-0.112**
				(0.013)	(0.041)	(0.057)
Sales Growth	-0.563*	-0.006	-0.014	-0.551***	-0.007	-0.014
	(0.288)	(0.004)	(0.029)	(0.013)	(0.004)	(0.029)
Capital Intensity	0.012	-0.053***	0.000	-0.014	-0.044***	0.029
	(0.074)	(0.011)	(0.044)	(0.012)	(0.010)	(0.044)
Subsidy	-71.647*	-7.383***	2.929*	-25.010*	-8.036***	1.748
	(41.081)	(2.263)	(1.548)	(14.822)	(2.293)	(1.152)
Firm Size	0.315	-0.435***	-0.416***	0.330***	-0.447***	-0.307***
	(0.462)	(0.048)	(0.115)	(0.043)	(0.045)	(0.069)
Firm Size^2	-0.170*	-0.021*	-0.020	-0.178***	-0.018	-0.037
	(0.089)	(0.011)	(0.030)	(0.014)	(0.011)	(0.024)
Firm Age	-0.075	-0.168	1.682	-0.884***	-0.083	0.786
	(3.590)	(0.320)	(1.101)	(0.257)	(0.306)	(1.716)
Firm Age^2	0.019	0.013	-0.445*	0.187***	-0.014	-0.354
	(0.687)	(0.077)	(0.250)	(0.059)	(0.074)	(0.421)
Constant	-2.542	-1.931***	-3.712***	-1.836***	-2.096***	-1.879
	(3.242)	(0.346)	(1.369)	(0.241)	(0.335)	(1.757)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Observations	1,365	36,638	4,240	1,403	37,881	4,991
Log-likelihood	-229.1	-8201.5	-831.8	-249.7	-8817.2	-947.4

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 5: Results on Innovation and Firm Exit across Ownership

Robustness Tests

In the preceding section, we mentioned a few concerns that might cause biased estimations. In this part, we propose a number of robustness tests to solidify our conclusions. This involves a series of firm's internal characteristics and external operational environments, which may exert influence on the firm's financial condition.

Changing regression methods: In our previous analysis, we mentioned that through improving the survival function, we could obtain less biased estimations. If that is the case, then changing the model will not affect the significance level. Whereas the cloglog model is the uniquely appropriate one for grouped data from the continuous proportional hazards model of Kalbfleisch and Prentice (1980) (*28*), in practice, the model with a logit link (Cox) is used more frequently, because the logistic regression is better known, and software for this model is more widely available.

In Table 6, we adopt three different methods to test the trend. Column 1 and 4 present the regression results from the Cox proportional hazard models. Column 2 and 5 explicate the results from general OLS models while considering firm-level fixed effects. And last, column 3 and 6 give the results from continuous-time parametric survival models, where the distribution of the hazard function is assumed as a Weibull distribution. We control the heterogeneity in the models by set firm-level random effects with the assumption that they are uncorrelated with other explanatory variables. From the results, even though fewer significant log-likelihood values could be observed, we still find a significantly negative correlation between innovativeness and hazard rate. Therefore, these tests indicate using other less accurate regression models can still capture the trend existing in start-ups.

	Alternative Models for Firm Death					
	Cox:	OLS with Fixed Effects:	Weibull with Unobserved Heterogeneity:	Cox:	OLS with Fixed Effects:	Weibull with Unobserved Heterogeneity:
:	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation	-0.139*	-0.007**	-0.174**			
	(0.080)	(0.003)	(0.085)			
Patent Application				-0.010**	-0.002***	-0.167***
				(0.004)	(0.001)	(0.038)
Sales Growth	-0.007*	-0.001	-0.006	-0.041***	-0.001***	-0.012***
	(0.004)	(0.000)	(0.004)	(0.010)	(0.000)	(0.004)
Capital Intensity	-0.050***	-0.003**	-0.050***	-0.554***	-0.002***	-0.026**
	(0.010)	(0.001)	(0.011)	(0.039)	(0.001)	(0.010)
Subsidy	-6.422***	-0.168*	-6.728***	-6.742***	-0.175***	-8.617***
	(1.951)	(0.068)	(1.856)	(1.958)	(0.038)	(1.882)
Firm Size	-0.531***	-0.061***	-0.534***	-0.009	-0.064***	-0.543***
	(0.042)	(0.013)	(0.045)	(0.010)	(0.003)	(0.042)
Firm Size^2	-0.014	-0.006***	-0.013	-0.051	-0.006***	-0.013
	(0.010)	(0.001)	(0.010)	(0.276)	(0.000)	(0.010)
Firm Age	-0.144	-0.063**	0.051	-0.025	-0.059***	-0.192
	(0.288)	(0.023)	(0.316)	(0.067)	(0.019)	(0.307)
Firm Age^2	0.000	0.012*	-0.046	0.010**	0.011***	0.141*
	(0.070)	(0.005)	(0.076)	(0.004)	(0.004)	(0.077)
Constant		0.214***			0.213***	
		(0.041)			(0.023)	
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Firm Fixed Effect		YES			YES	
Observations	41,555	41,555	41,555	42,957	42,957	42,957
R-squared		0.059			0.061	
Log-likelihood	-24,094		-12,348	-26,333		-13,360

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 6: Results on Innovation and Firm Exit using Different Methods

Alternative innovativeness measurements: Patents are a conventional symbol reflecting the innovation ability of a firm. In this paper, we proposed our own method: the sales of new products thanks to our comprehensive dataset. Here, we continue to make a more detailed exploration of the relationship between innovation and firms' dynamics. There are two major caveats in our analysis that come from adopting those two innovativeness proxies. First, can these two indicators accurately reflect the innovation abilities of firms? If we use other measurements, will the results change? Second, since both the patent application and sales of new products represent the outcome of investment in innovation activities, does the effort in research and development also have positive impacts on firm survival?

We use two groups of other indicators that stand for the efforts and outcome of the innovation activities of a firm. The first group includes R&D expenditures and the numbers of researchers and scientists. This is the first step needed for firms to innovate and reflects their investment in research and development. The second group consists of the number of trademarks applying for and publications.

	Discrete Time Hazard Models for Firm Death with Random Effects				
	Innovation Input			Innovation Output	
	(1)	(2)	(3)	(4)	(6)
R&D Expenditure /Total Expenditure	-0.369**				
	(0.187)				
Researchers/ Total Employees		-0.301***			
		(0.076)			
Scientists/ Total Employees			-0.364***		
			(0.047)		
Trademarks				-0.082*	
				(0.048)	
Publication					-0.023***
					(0.007)
Sales Growth	-0.007*	-0.007*	-0.007*	-0.008*	-0.005***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
Capital Intensity	-0.015	-0.013	-0.015	-0.039***	-0.023***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.001)
Subsidy	-4.263**	-4.241**	-3.568**	-6.227***	-3.065***
	(1.749)	(1.745)	(1.701)	(1.955)	(0.072)
Firm Size	-0.324***	-0.314***	-0.308***	-0.426***	-0.300***
	(0.044)	(0.044)	(0.043)	(0.042)	(0.004)
Firm Size^2	-0.042***	-0.044***	-0.046***	-0.024**	-0.005***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.001)
Firm Age	-0.035	-0.023	-0.041	-0.059	-0.126***
	(0.315)	(0.315)	(0.308)	(0.288)	(0.039)
Firm Age^2	-0.010	-0.013	-0.012	-0.016	0.013
	(0.076)	(0.076)	(0.074)	(0.069)	(0.010)
Constant	-2.793***	-2.806***	-2.215***	-2.065***	-0.960***
	(0.366)	(0.366)	(0.331)	(0.319)	(0.043)
Year Dummies	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES
Observations	41,555	41,555	41,555	42,957	42,957
Log-likelihood	-9,216	-9,209	-9,777	-9,811	-9,803

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 7: Results on Innovation and Firm Exit using Alternative Innovativeness Measurements

Table 7 shows the regression results of all five new indicators in which we use the cloglog models. The larger the coefficients of these five variables are, the higher the innovation abilities. We find the signs of coefficients of all new proxies in these two groups are significantly negative, which confirm our assumption again. This leads to a derivative conclusion that innovativeness, no matter in which form, could reduce the risk of exit for start-ups. More importantly, investment in innovation activities, no matter in what stage, could help firms to survive.

Exportation and patent sources: Next, we discuss whether the characteristics of firms influence the impacts of the innovation activities, reducing the risk of exit. Three factors are considered here, including whether the firm is export-oriented, the source of the patents, and the locations of firms applying for the patents. First, for exports, we divide the firms into two groups: those with export activities and those without. For innovation measured by patents or new products, the two groups both show significant levels. Nonetheless, the export-oriented firms show a higher coefficient. This indicates innovativeness plays an essential role in the survival of export-oriented firms. The results imply that compared with non-export companies, a one unit increase in patent applications or new products sales ratio, the export-oriented firms will benefit 76.92% and 49.67% more, respectively, in reducing the risk of exit. That may be attributed to the fact that intellectual property in China is not strictly protected; thus, a firm with a new product or patent faces fewer plagiarism problems abroad, which means fewer competitors.

When it comes to the source of patents, we distinguish between companies according to whether they purchase patents directly oversea. What is astonishing is that for those who purchase patents overseas, the coefficients on innovativeness are much larger. In other words, those passive companies face higher risks of being non-innovative. This is affirmed in the sales of new products test. The coefficient on new product sales for purchasing companies is around 3.8 times as much as those that only produce patents themselves or get them domestically. This also reflects that the patent quality in China is not satisfying enough. At last, we look at where those start-ups apply for patents. Here, we divide the participants into two groups: those that only apply for patents in Mainland China and others that apply overseas as well. A large gap is also obvious between these two groups. The group with overseas patent applications is more sensitive to innovativeness improvement. We explain this phenomenon by the higher requirements for patent applications overseas. A one unit increase in innovation abilities in terms of patent numbers requires more effort in the group applying for patents overseas.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	Export		Foreign-Tech		Foreign-Apply	
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation*Export	-0.552**					
	(0.270)					
Product Innovation*Non-Export	-0.312***					
	(0.069)					
Patent Application*Export		-0.226***				
		(0.081)				
Patent Application* Non-Export		-0.151***				
		(0.051)				
Product Innovation*purchased			-0.692***			
			(0.052)			
Product Innovation*Non-purchased			-0.320***			
			(0.016)			
Patent Application* purchased				-0.572***		
				(0.004)		
Patent Application* Non-purchased				-0.149***		
				(0.003)		
Product Innovation*oversea					-0.570***	
					(0.219)	
Product Innovation*Non-oversea					-0.301***	
					(0.070)	
Patent Application*oversea						-0.215***
						(0.040)
Patent Application* Non-oversea						-0.127**
						(0.057)
Sales Growth	-0.006	-0.010***	-0.006***	-0.008***	-0.006	-0.010***
	(0.004)	(0.002)	(0.001)	(0.000)	(0.004)	(0.002)
Capital Intensity	-0.046***	-0.022	-0.046***	-0.037***	-0.046***	-0.022
	(0.010)	(0.014)	(0.003)	(0.000)	(0.010)	(0.014)
Subsidy	-5.543***	-8.166***	-5.536***	-6.172***	-5.529***	-8.197***
	(1.928)	(1.557)	(0.263)	(0.017)	(1.929)	(1.565)
Firm Size	-0.425***	-0.389***	-0.424***	-0.427***	-0.426***	-0.389***
	(0.045)	(0.106)	(0.021)	(0.002)	(0.045)	(0.107)
Firm Size^2	-0.022**	-0.030	-0.022***	-0.021***	-0.022**	-0.029
	(0.010)	(0.019)	(0.005)	(0.001)	(0.010)	(0.019)
Firm Age	-0.142	-0.725***	-0.141	-0.053***	-0.136	-0.726***
	(0.301)	(0.133)	(0.109)	(0.004)	(0.301)	(0.128)
Firm Age^2	0.009	-0.003	0.009	0.018***	0.007	-0.003
	(0.072)	(0.030)	(0.029)	(0.001)	(0.072)	(0.029)
Constant	-1.982***	-0.155	-1.982***	-2.143***	-1.986***	-0.129
	(0.328)	(0.185)	(0.101)	(0.005)	(0.328)	(0.171)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Wald Test	0.038	0.518	0.000	0.000	0.023	0.069
Observations	41,555	49,492	41,494	42,957	41,555	49,492
Log-likelihood	-9113.3	-10345.8	-9112.2	-9803.1	-9113.3	-10346.7

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 8: Results on Innovation and Firm Exit across Oversea

The mechanism: Since we have discussed to which extent innovativeness can pare down the risk of exit, it is necessary to explore the mechanism behind it. We consider three factors that might be triggered by the increment of innovation: Return on Assets (ROA), Total Factor Productivity (TFP), and Labor Productivity per Person employed ($Productivity$). We adopt a System-GMM model to test if the mechanism is logical, where the lagged form of each dependent variable is also taken into consideration. We present our regression results in Table 9. Columns 1-3 examine how new products work, and columns 4-6 are about patents. For our two innovativeness proxies, there is no doubt from the results of the regressions that innovation activities prompt all of the dependent variables, which are closely related with corporate operations.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	ROA	TFP	Productivity	ROA	TFP	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
L. ROA	0.146			0.149		
	(0.185)			(0.184)		
L. TFP		0.488***			0.504***	
		(0.173)			(0.181)	
L. Productivity			0.508***			0.517***
			(0.152)			(0.158)
Product Innovation	0.467***	0.131***	0.111***			
	(0.093)	(0.035)	(0.033)			
Patent Application				1.242***	0.335***	0.290***
				(0.253)	(0.096)	(0.092)
Capital Intensity	-0.080***	-0.006	0.131***	-0.155***	-0.025	0.112***
	(0.023)	(0.017)	(0.022)	(0.030)	(0.023)	(0.018)
Subsidy	2.842**	0.556	0.393	2.508**	0.500	0.328
	(1.158)	(0.375)	(0.288)	(1.175)	(0.410)	(0.314)
Firm Size	0.475***	-0.397***	0.051	0.223***	-0.459***	-0.010
	(0.068)	(0.070)	(0.037)	(0.067)	(0.091)	(0.025)
Firm Age	0.307	0.194***	0.048	0.369*	0.207***	0.060
	(0.202)	(0.062)	(0.061)	(0.207)	(0.069)	(0.067)
Constant	-3.043***	2.318***	2.054***	-0.770	2.729***	2.453***
	(0.791)	(0.625)	(0.526)	(0.688)	(0.774)	(0.667)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Observations	48,069	46,188	48,009	48,069	46,188	48,009
AR (2)	0.871	0.892	0.370	0.440	0.370	0.452
Hansen Test	0.773	0.838	0.813	0.829	0.926	0.925

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 9: Results on Mechanism Test

The efficiency of firms' operations: In our previous regressions, notwithstanding, we controlled year and industry dummies in order to solve heterogeneity problems, but firm-level heterogeneity might still be a caveat to the accuracy of our regression results. Hence, we take a further step to consider the efficiency of firms' operations by considering the profitability of new products, success rate of patent applications, and risks facing the firms whole industry.

After taking these variables into account, we get new results shown in Table 10. Column 1 and 2 examine the proportions of sales of new products to total sales. We divide our observations into two groups: ones whose new products make up no less than 50% of total sales and the other with less than 50%. So here we can generate a dummy variable: $Less50\%Revenue$ and $More50\%Revenue$, which is then timed with our former variables, either $ProductInnovation$ or $PatentApplication$. The results show that the profitability does not influence the significance level. However, it is fairly noticeable that in a firm whose new products are less successful, innovation cuts down the risk of exit even more. This affirms that marginal effects on the impacts of innovativeness in terms of new product development exist. In other words, for start-ups, a one-unit input in innovation development is more rewarding in earlier stages.

Another group of dummy variables are set up based on the percent of patent applications granted: $HighGrant$ means the rate is no less than 50%, and $LowGrant$ stands for a rate lower than 50%. We use the same method to measure the effect of grant rate and innovation. Impressively, only the high grant rate group displays significant levels in the regression results. This finding points out that the quality of innovation outweighs the quantity. Only high-quality innovation, in terms of patents granted, can promote the survival of start-ups.

Furthermore, another concern here is the risk itself. Samples in our survey cover many different industries, and different volatility levels exist in different industries. Hence, we introduce dummy variables representing the level of volatility in an industry: $HighVol$ means the industry bears high volatility and vice versa. The results indicate that being in a high-risk or lower risk industry does not affect the significance of the coefficients of innovation interaction terms. However, innovativeness in less volatile industries is more effective at diminishing the risk of exit. This is reflected in both new products and patents.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation*Less50% Revenue	-1.346***					
	(0.414)					
Product Innovation* More50% Revenue	-0.307***					
	(0.067)					
Patent Application* Less50% Revenue		-0.114***				
		(0.039)				
Patent Application* More50% Revenue		-0.082*				
		(0.046)				
Product Innovation*High Grant			-0.318***			
			(0.068)			
Product Innovation* Low Grant			-0.555			
			(0.379)			
Patent Application* High Grant				-0.140***		
				(0.043)		
Patent Application* Low Grant				-0.216		
				(0.140)		
Product Innovation*Low Vol					-0.217***	
					(0.024)	
Product Innovation*High Vol					-0.146***	
					(0.029)	
Patent Application* Low Vol						-0.086**
						(0.036)
Patent Application* Low Vol						-0.057**
						(0.026)
Sales Growth	-0.006	-0.008*	-0.006	-0.008*	-0.008***	-0.008***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)
Capital Intensity	-0.046***	-0.038***	-0.046***	-0.037***	-0.040***	-0.038***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.002)	(0.003)
Subsidy	-5.296***	-6.176***	-5.526***	-6.170***	-5.940*	-6.221*
	(1.914)	(1.953)	(1.928)	(1.951)	(3.464)	(3.534)
Firm Size	-0.421***	-0.428***	-0.424***	-0.427***	-0.412***	-0.426***
	(0.045)	(0.042)	(0.045)	(0.042)	(0.013)	(0.014)
Firm Size^2	-0.022**	-0.022**	-0.022**	-0.021**	-0.027***	-0.024***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)
Firm Age	-0.131	-0.038	-0.141	-0.057	-0.040	-0.045
	(0.301)	(0.288)	(0.301)	(0.288)	(0.082)	(0.083)
Firm Age^2	0.007	-0.021	0.009	-0.017	-0.016	-0.019
	(0.072)	(0.069)	(0.072)	(0.069)	(0.018)	(0.018)
Constant	-2.003***	-2.117***	-1.981***	-2.129***	-2.027***	-2.069***
	(0.329)	(0.319)	(0.328)	(0.319)	(0.104)	(0.087)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Wald Test	0.000	0.443	0.536	0.623	0.000	0.059
Observations	41,555	42,954	41,555	42,957	41,555	42,954
Log-likelihood	-9109.9	-9805.0	-9113.5	-9803.4	9796.5	-9807.2

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 10: Robustness Test on the efficiency of firms' operation

Financial constraints: Finally, we have another look at the financial characteristics of firms. Here, we take a very crucial problem in China into account: financial constraints. We set two dummy variables: $Non - FC$, which represents that the company does not face strong financial constraints and FC, which indicates the reverse condition. By timing these two dummies with our innovation proxies, we get new interaction terms in our regression models. To specify this concern, we divide our observations into three categories again: SOE, POE, and FOE. From Table 11, significant levels can be found in most of the interaction coefficients, except SOE with financial constraints. First, SOEs in China face more budget constraints in research and development and second, financial constraints deepen this trend. Thus, the role of innovativeness is much less important than other factors. Another eye-catching finding is that in non-financially-constrained companies, innovation is more effective in reducing the risk of exit. That is obvious since a company with less financial constraint can have more resources to put into innovation and development.

	Discrete Time Hazard Models for Firm Death with Random Effects					
	SOE	POE	FOE	SOE	POE	FOE
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation* Non-FC	-0.827**	-0.460***	-0.346*			
	(0.364)	(0.101)	(0.195)			
Product Innovation* FC	-0.535*	-0.177*	-0.260*			
	(0.325)	(0.091)	(0.153)			
Patent Application* Non-FC				-0.312**	-0.171***	-0.255***
				(0.143)	(0.037)	(0.062)
Patent Application* FC				-0.124	-0.091***	-0.177***
				(0.326)	(0.031)	(0.036)
Sales Growth	-0.574**	-0.006	-0.014	-0.575***	-0.009***	-0.014
	(0.274)	(0.004)	(0.019)	(0.185)	(0.001)	(0.023)
Capital Intensity	0.012	-0.053***	0.000	-0.012	-0.036***	0.013
	(0.072)	(0.011)	(0.030)	(0.072)	(0.010)	(0.076)
Subsidy	-723.722	-7.256***	2.926*	-703.833	-8.311*	6.423***
	(474.839)	(2.256)	(1.659)	(438.959)	(4.408)	(1.286)
Firm Size	0.306	-0.434***	-0.415***	0.371	-0.369***	-0.669***
	(0.374)	(0.048)	(0.003)	(0.488)	(0.022)	(0.150)
Firm Size^2	-0.170**	-0.021*	-0.020***	-0.180	-0.036***	0.044
	(0.086)	(0.011)	(0.003)	(0.111)	(0.009)	(0.029)
Firm Age	-0.122	-0.163	1.697***	-0.801	-0.470***	2.308
	(1.264)	(0.320)	(0.008)	(0.734)	(0.154)	(1.732)
Firm Age^2	0.024	0.011	0.449***	0.171	0.015	0.816*
	(0.287)	(0.077)	(0.011)	(0.185)	(0.039)	(0.427)
Constant	-2.448*	-1.934***	-3.725***	-1.984*	-1.238***	-3.755**
	(1.307)	(0.346)	(0.235)	(1.013)	(0.125)	(1.863)
Year Dummies	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Wald Test	0.000	0.000	0.075	0.088	0.000	0.000
Observations	1,365	36,638	4,240	1,403	37,881	4,991
Log-likelihood	-229.7	-8199.0	-831.8	-246.4	-8817.3	-879.6

Robust standard errors in parentheses. Significant at *10%, **5%, ***1% confidence levels. The specifications have a binary dependent variable that is equal to 1 in the year of exit for plants that exit and 0 otherwise. The table shows marginal effects. For dummy variables, the marginal effect is the change in the probability of exit associated with a change in the variable from 0 to 1, and for continuous variables, the marginal effect is the marginal change in the probability of exit associated with a change in the variable evaluated at the means of other variables. The regressors are defined in Table A1.

Table 11: Finanical Constraints Robustness Test

Conclusions

Firms face uncertainties when innovating, which is particularly common in start-ups while huge profits could be foreseen due to the success of innovation or low efficiency of innovativeness leading to bankruptcy. In this paper, we test which situation exists in China through an exclusive dataset consisting of hi-tech start-ups in a science park located in Beijing. We investigate whether innovation can reduce the risk to exit and if so, to which extent can innovation help the firm to avoid exiting. Measured by two indicators, the number of patents and the fraction of sales of new products, innovativeness in our paper is presented by efforts and outcomes.

We adopt a novel discrete-time proportional hazards model, the complementary log-log model, which helps us to solve the concerns about discrete survival times and right censoring. Assessed by both, our results show innovation diminishes the hazard rate for the firms to exit the market when other firm-level control variables are also taken into account. A one percent increase in the new product sale ratio or a gain of one patent application leads to a 0.147 and 0.151 unit reduction in hazard rate, respectively. A series of robustness tests were conducted to solidify our conclusions. Furthermore, we seek to uncover the mechanism behind the results in order to have a full understanding of how innovativeness operates in start-ups in which ROA, TFP, and productivity all play vital roles.

These findings raise a few policy implications for the government as well as for the start-ups. First, firms should be encouraged to innovate since both small and large firms benefit from new products and patent applications. Innovation favors firms at the micro level by reducing the risk of exit and at the macro level, to some extent, by helping industries upgrade. Second, the reducing effect is even more obvious in a more dynamic market. In our research, these start-ups that involve exports or acquiring activities get more reduction in the risk of exit from innovation. Thus, it is strategically reasonable for the government to make the market more open. Third, there is still a huge gap between state-owned and private companies benefiting from commercial activities, which is reflected here as the risk of exit. Hence, a fairer stage for competition should be made for both SOEs and POEs. At last, we find that financial constraint is still a problem that cannot be ignored. Financially constrained firms confront restrictions of development even though they tend to innovate. More efforts should be put toward relieving this problem, which has been prevalent in China's industries for many years.

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