Economic Modelling 75 (2018) 458–468

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Does innovation facilitate firm survival? Evidence from Chinese high-tech firms

Dongyang Zhang [a], Wenping Zheng [b,*], Lutao Ning [c]

[a] School of Economics, Capital University of Economics and Business, China
[b] School of International Trade and Economics, University of International Business and Economics, China
[c] School of Business and Management, Queen Mary, University of London, UK

ARTICLE INFO

JEL classification:
O30
O31
L11
C41

Keywords:
Innovation
Patents
Survival
High-tech firms
China

ABSTRACT

The impact of innovation mechanisms on firm survival remains inconclusive in the existing literature, especially when we consider the case of a rapidly growing emerging economy. Using a unique firm-level dataset of 14,065 Chinese high-tech start-ups from 2007 to 2013, we employ a discrete time hazard model to study the impact of differences in internal and external innovation mechanisms, specifically, innovation efficiency and spillover effect derived from trade, on the likelihood of firms' survival as these factors are currently less understood. Bigger and older technology-intensive firms tend to have lower probability of exit. Our results suggest that innovation as measured by patents, innovation efficiency and firms' import and export activities can increase the survival rate of Chinese high-tech firms. This implies that policy makers should focus on promoting both internal and external innovation mechanisms to improve the survival of indigenous high-tech firms.

1. Introduction

Firm exit and entry are crucial determinants of industrial upgrading and economic growth (e.g. Tybout, 2000). In a reasonably efficient market, Ericson and Pakes (1995) find that competition ensures that superior firms experience both a higher probability of surviving and better performance. Nevertheless, there is an ongoing debate on the underlying factors that lie behind firms' survival (firm size, Geroski, 1995; firm age, Klette and Kortum, 2004; He and Yang, 2016). While innovation is a typical measurement of superior firms, previous findings regarding its impact on firms' survival rates through innovation activities remain mixed and inconclusive (see Fig. 1).

Innovative firms (e.g. firms with R&D investments-innovation input, new products or patents-innovation output) can enhance their survival chances as a result of greater efficiency, productivity and profits and of an increase in their market power (Griliches, 1979; Aghion et al., 2014). Recent evidence shows that innovation can help firms survive longer in the market (Cefis and Marslli, 2011). However, the inherent uncertainties and commercialisation risks involved might increase the probability of innovation failure. The existence of information asymmetry might cause uncertainties in the market and cause innovative firms to suffer from financial constraints. Outside lenders may refuse to finance innovative projects if firms' resources are concentrated mostly on intangible investments. As the “pecking order” theory suggests, innovation activities affect relative costs, and firms can only bear a small amount of outside financing. In an environment in which there are financial constraints affecting innovative activities and/or projects, firms may stop financing innovative projects, thereby hampering their performance and making them more likely to exit the market (Feldman and Kelley, 2006).

With respect to the output measurement of innovation, such as new products, patents or inventions, and trade-marks, the output of innovation in the production and marketisation processes also presents survival risks. When introducing new products, a firm that is introducing these new products can be recognized as producing both a signal and an innovation output. Meanwhile, there are a great number of sunk costs in both product and process innovation. Firms have to cover these sunk costs with sales of the new product, or the probability of exit will increase. In addition, the new products might lose their advantage in the market due to potential copying by competitors, and the originally innovating firms can then not increase their market power as a result of introducing new products. Ericson and Pakes (1995) further propose a model to prove that innovation can help firms gain success in the market.

* Corresponding author.
E-mail addresses: zhangdongyang@cueb.edu.cn, zhdyruc@gmail.com (D. Zhang), wenpingzheng@uibe.edu.cn (W. Zheng), l.ning@qmul.ac.uk (L. Ning).

https://doi.org/10.1016/j.econmod.2018.07.030
Received 31 January 2018; Received in revised form 29 July 2018; Accepted 29 July 2018
Available online 11 August 2018
0264-9993/

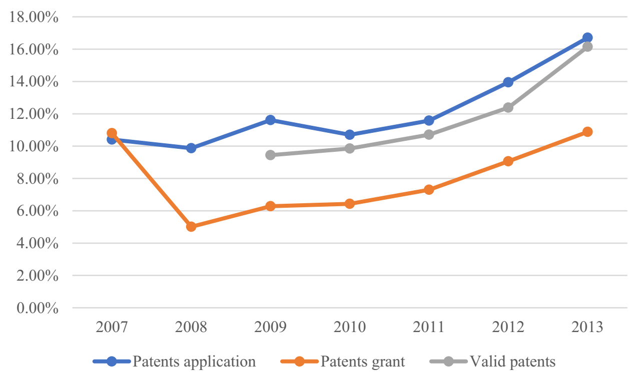

Fig. 1. Firm information summarized by patents.

However, they point out that firm death rates may increase if the new products are not accepted by the market. Thus innovation failure might decrease the survival rate. Some findings highlight that not all the innovation activities can reduce the failure rate significantly (Fernandes and Paunov, 2015; Howell, 2015; Nemlioglu and Mallick, 2017).

Given these complexities in the influence of firms' innovative activities on survival or death as discussed above, there is a need to focus on several of the included findings. For example, regarding input measures such as the quantity of investment in research and development, Li et al. (2010) reported that the R&D input of firms can significantly decrease firm death rates. Zhang and Mohnen (2013)also demonstrate that the relationship between R&D or new products and survival rates shows an inverted U-curve. In contrast, several studies have demonstrated some mixed, insignificant or even negative effects on survival performance when they measure innovation by means of different innovation proxies (Mahmood, 2000; Wilbon, 2002; Børing, 2015). Some evidence uses output measures, and their findings show that firm survival duration is positively and significantly associated with innovation (e.g. patents, trademarks, new products or new processes) (Audretsch, 1991; Helmers and Rogers, 2010). Using the alternative approach, there is some evidence to show that not all output of innovation has a significant effect on firm survival. Regarding product and process innovation, Giovannetti et al. (2011) show that the output of innovation does not affect firm survival in the case of Italian firms. Similarly, Fernandes and Paunov (2015) find that new products can increase the likelihood of firm survival under certain conditions. Finally, based on a firm-level database of Australian firms, Jensen et al. (2008) and Buddelmeyer et al. (2009) suggest patent and trademark applications have a disparate effect on firm survival because the underlying risks associated with the innovation that companies undertake are different.

In an attempt to provide further understanding of these issues, this paper examines how innovative activities affect the survival rates in Chinese high-tech start-ups. Our study further focuses on the impact of the differences in innovation efficiency and spillover effect derived from trade on this relationship as internal and external environmental factors that have often been neglected in previous studies. Previous literature has long argued that external cooperation can be substituted for internal innovative activities and increase innovation efficiency. Innovation efficiency refers to the efficient output of innovation activities, such as new products and granted patents (Haupt et al., 2007),d that occurs because innovative cooperation decreases transaction cost and spills over specialized knowledge, if available (Pisano, 1990; Luh et al., 2016), allowing firms to save time and decrease innovation costs, while innovation activities can be more efficient (Veugelers and Cassiman, 1999). These innovation efficiencies (such as the number of granted patents) can result in an increase in firms' market power through the selling of new products or improved productivity. Moreover, in the emerging market context, where internal R&D capability is weak, international trade provides major knowledge spillovers as it allows domestic firms to come into contact with external innovations, advanced knowledge and the technologies needed for innovation to occur (Ning et al., 2016). This is because trade brings firms into contact with international best practices or standards and enables "learning by doing" through interactions with multinational firms as affiliates in their supply chain or through labour mobility (Chaudhuri and Biswas, 2016). Firms can get advantages from the spillovers generated by investments in innovation by their trade partners, particularly in developing countries. These firms can build on their accumulation of external sources of knowledge to innovate (Luh et al., 2016) so that they can benefit from an improved capability to meet varieties of demand in both domestic and international markets.

The effects of innovation on the likelihood of firm survival have not so far been fully discussed, especially in an emerging market context, such as in the case of China, and related studies are rather few. In the process of China's economic transition, market power and the market system have been gradually introduced, and market-oriented institutions have experienced rapid growth. To compete with their competitors and gain success in domestic and international markets, firms try to understand the market system well and address market power. Firms develop their own core competences through innovation (Eriksson et al., 2014) and increase their probabilities of survival (Howell, 2015). Meanwhile, Chinese firms' innovation activities face challenges caused by market failure, unfair competitive practices and institutional uncertainties (He and Yang, 2016). This is particularly the case for high-tech-intensive firms, SMEs and start-ups (Hall, 2002).

By employing a rich dataset of 14,065 Chinese high-tech firms located in the Zhongguancun (ZGC) district of Beijing and their innovation proxies during the period from 2007 to 2013, this study makes several contributions to the hitherto inconclusive literature on the issues of firm survival and innovation performance. First, our dataset allows for the construction of objective and more detailed firm-level time-varying variables. By controlling for several firm performance variables, we use innovation performance to explain Chinese firms' survival. Second, we adopt several measures of innovation along several dimensions, such as patents, inventions, trademarks and scientific publications, and thus extend the literature on the different effects of the measurement of innovation on firms' performance (Chen, 2002; Dang and Motohashi, 2015). Third, since our sample is from Chinese high-tech industries, we extend the work of Fernandes and Paunov (2015) into the world's largest transition and emerging economy. Our work differs from theirs in that we focus on the heterogeneities of the knowledge spillover effect rather than the risks involved in the relationship between innovation and firm survival, as is studied in Fernandes and Paunov (2015), because in the emerging market context indigenous innovation capability is weak and knowledge spillover plays a far more important role in innovation (Ning et al., 2016). Fourth, we further introduce the efficient output of innovation, as measured by granted patents, into our regression model and investigate the effects of innovation efficiency on firm survival rates. Finally, our paper uses a more rigorous regression-complementary log-log (cloglog) approach, instead of using a Cox hazard model, so that we can better cope with unobserved firm heterogeneity and correct for omitted variable biases.

Our main findings suggest that patents can, in general, significantly reduce Chinese high-tech firms' exit probabilities. Time-varying industry and year-fixed effects are obtained in our baseline results. In addition, some mechanisms significantly reduce the probability of exit rates through innovation. We also show that import and export activities can better help firms survive in the market through the innovation spillover effect. Using proxies for innovation, we find that scientific publications are not significantly associated with firm survival, as they can not be translated into firm growth. Trademarks have a significant intangible impact on firm survival. In addition, relatively small firms are relatively more efficient in innovation activities and tend to survive in the market.

We organize this paper as follows: Section 2 shows our methodology, baseline regression model and variable definitions. In section 3, we introduce our data and discuss descriptive statistics in detail. Section 4 shows our main regression results and findings. Section 5 shows various tests for robustness. We conclude with policy implications in Section 6.

2. Estimation strategy

A hazard model designed for survival duration, which is measured by the length between the entrance and exit of a firm, can correctly identify the effect of innovation on firm survival (Kiefer, 1988; Klein and Moeschberger, 1987; Fernandes and Paunov, 2015). A hazard model is often more suitable for the investigation of firm survival because the duration information is incomplete. The hazard rate is defined as the conditional probability of a firm completing survival status (exiting) after t periods, with the condition that it has survived for t-1 periods and all firm-level characteristics are controlled. There are several advantages of using the hazard model to identify the impact of innovation on survival. First, hazard models can evaluate the conditional probability of an event rather than the unconditional probability (e.g., *OLS* and *Probit* models). Hazard models can control for both the data on firms exiting at year t and the information on firms surviving until the t-1 period. Second, hazard models relax the condition of constant survival rates during the sample period since they use the information of firms' survival duration rather than exit event timings. Third, hazard models focus on the issue of the right-censoring of observations.[1] Furthermore, hazard models can better overcome the inefficiencies of linear models, such as *OLS*, because the predicted exit probabilities may lie outside the interval of [0,1] and the corresponding variances might not follow the non-negative rule. Following the work of Fernandes and Paunov (2015), we set a firm survival event i to be complete ($c_i = 1$) or right censored/incomplete ($c_i = 0$). In addition, the length that a firm survives (i.e. the duration to a failure event) T can be used to define the survivor function S, which is the probability of a firm surviving no less than g years:

$$S_i(g) = Pr(T_i > g) = \prod_{k=1}^{g}(1 - h_{ik}), \tag{1}$$

where $T_i = min\{T_i^*, C_i^*\}$, T_i^* is the latent failure time and C_i^* is the latent censoring time for the survival event. The survival event, which is exiting in g years with the condition of surviving for g-1 years, is defined as

$$\begin{aligned} h_i(g) &= Pr\left(g-1 < T_j \le g \middle| T_j > g-1\right) \\ &= Pr\left(g-1 < T_j \le g\right) / Pr\left(T_j > g-1\right), \end{aligned} \tag{2}$$

When y_{jg} is a binary variable, which is valued 1 if firm exit event i occurs in year g and 0 otherwise, equation (3) shows the log-likelihood function as follows:

$$\log L = \sum_{i=1}^{I} \sum_{k=1}^{g} \left[y_{jg} \log h_{ig} + \left(1 - y_{ig}\right) \log\left(1 - h_{ig}\right)\right], \tag{3}$$

where the contribution to the log likelihood of a right-censored firm survival event i is the function of discrete time survivor, equation (1), and that of a completed firm survival event i in interval g is the discrete time density function, the probability of ending in g years. Equation (3) assumes that standard regression models for binary choice panel data can be estimated by employing discrete time hazard models following the work of Jenkins (1995).

In order to provide a full estimation, the log-likelihood function needs a function-form specification for the discrete time hazard rate h_{ig} that associates the exit probabilities with the controlled factors. In addition, we also take into account three functional forms. These include the complementary log-log (cloglog) model (Prentice and Gloeckler, 1978), the *Probit* and the *Logit* (Fernandes and Paunov, 2015), which allow for

Table 1a
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Initial size	76986	2.617	1.399	0	8.983
Age	75913	8.083	4.808	0	63.000
Size	76422	2.590	1.555	0	9.420
Sales growth	58186	−0.1666	2.518	−16.151	15.308
Labor productivity	75816	2.303	2.729	0	13.410
Capital intensity	75041	2.630	1.673	0	7.405
Multi-plant	76986	0.075	0.264	0	1
Patent Application	76986	0.118	0.323	0	1
Grant Patent	76986	0.079	0.270	0	1
Log(Patent Application)	76498	0.180	0.598	0	7.726
Log(Grant Patent)	75914	0.108	0.473	0	6.275
Log(Valid Patent)	49136	0.225	0.733	0	7.824

taking the unobserved individual heterogeneity into account in each case by firm-level random effects. For the cloglog model, we estimate the results by the equation shown as follows:

$$cloglog\left[1 - h_{ig}(X/v)\right] = \log\left(-\log\left[1 - h_g(X/v)\right]\right) = \beta_i X_{ig} + \varepsilon_{ig}, \tag{4}$$

where the vector X_{it} includes control variables of the determinants of firm survival that are consistent with existing empirical studies. We use the patent dummy variable as well as the logarithm of patent numbers to measure innovation activities. The number of patent counts of a firm is an import indicator with which to measure innovation activity, and it is usually characterised as an output of the knowledge production function (Griliches, 1990). Patents play a particularly effective role in high technology industries. Furthermore, previous evidence has shown that intensively cited patents are recognized as higher quality signals to the market (Arora et al., 2000), because they can result in higher market value and greater technological progress (Harhoff et al., 2003).

For robustness checks, we control for several variables. We first include time varying firm-level sales growth, *Sales Growth*$_{it}$, to act as a proxy for firms' growth opportunities (Fernandes and Paunov, 2015). Second, firm age may also have a significant influence on firms' survival or failure. To cope with the potential nonlinear impact of survival time on failure, we include the Age[2] variable in our regression model. Third, the logarithm of its total number of employees is used to measure firm size, Size$_{it}$, since the size of a firm may directly affect its growth performance. Usually, smaller firms may face tighter financial constraints and greater discrimination by financial institutions than larger firms, so they have a higher risk of death (Clementi and Hopenhayn, 2006). The firm's size[2] term is incorporated to control for the consideration of non-monotonicity.[2] We further control for the initial size of the firm in the coverage of the survey sample and measure it by the logarithm of the total number of employees in the opening year, its square term and a binary indicator for the status of whether it is a multi-plant firm or not (Disney et al., 2003; Bernard and Jensen, 2007). Additionally, labour productivity, measured by the logarithm of total sales per capita, is the most widely used indicator of a firm's operational and management capabilities. All data in this paper are deflated by deflators.[3] Lastly, firm

[1] It should be that at the end of our observation period some of the firms are still in operation. However, we can not observe enough information to confirm this.

[2] In China, due to the dominance of the planned economy before the 1980s, a number of older enterprises in China are mainly state-owned. Since the 1990s, China has started to push reforms in these state-owned enterprises (SOEs), and this is an essential part of China's economic transition. During this process, numerous SOEs have been privatised, merged or reorganised, resulting in large numbers of exits of older firms. Moreover, as older firms or larger firms may suffer from x-inefficiency, the squared terms of size and age are controlled for in our estimations (Liu and Li, 2015).

[3] Our data have been deflated by the deflators taken from the China Statistical Yearbook (various issues) published by the National Bureau of Statistics of China. We use the provincial capital goods deflator to deflate the capital variables and the gross domestic product (GDP) deflator to deflate the other variables.

Table 1b
Firm exit rates by year.

Year	2007	2008	2009	2010	2011	2012	2013	Total
Stay samples	12,932	11,501	10,534	9394	8534	7387	7110	67,392
Exit samples	1399	2013	926	914	772	1629	1941	9594
Total samples	14,331	13,514	11,460	10,308	9306	9016	9051	76,986
Exit rates	9.76%	14.90%	8.08%	8.87%	8.30%	18.07%	21.45%	12.46%

Table 1c
Firm information summarized by patents.

	2007	2008	2009	2010	2011	2012	2013	Total
(1) Patents application								
Non-innovative firms	12,839	12,180	10,130	9,205	8,228	7,758	7,539	67,879
Innovative firms	1,492	1,334	1,330	1,103	1,078	1,258	1,512	9,107
Total	14,331	13,514	11,460	10,308	9,306	9,016	9,051	76,986
Percentage	10.41%	9.87%	11.61%	10.70%	11.58%	13.95%	16.71%	11.83%
(2) Patents grant								
Non-innovative firms	12,783	12,837	10,740	9,645	8,627	8,199	8,066	70,897
Innovative firms	1,548	677	720	663	679	817	985	6,089
Total	14,331	13,514	11,460	10,308	9,306	9,016	9,051	76,986
Percentage	10.80%	5.01%	6.28%	6.43%	7.30%	9.06%	10.88%	7.91%
(3) Valid patents								
Non-innovative firms	0	0	10,378	9,293	8,309	7,900	7,589	43,469
Innovative firms	14,331	13,514	1,082	1,015	997	1,116	1,462	33,517
Total	14,331	13,514	11,460	10,308	9,306	9,016	9,051	76,986
Percentage	100%	100%	9.44%	9.85%	10.71%	12.38%	16.15%	43.54%

exit may vary across industries and years. We thus include industry fixed effects at the two-digit level, and we also control for yearly fixed effects to reduce the potential estimation bias from the missing information of unobservable factors at the industrial level or time-varying factors.

3. Data

3.1. Data management

We employ an unparallelled dataset focusing on Chinese high-tech manufacturing firms in the Zhongguancun (ZGC) district in Beijing.[4] The dataset includes their products, financing and innovation information collected by the Zhongguancun Statistical Yearbook of the ZGC Regulation Institution spanning the period from 2007 to 2013, with 76,000 total observations. The survey is a statistical census of ZGC firms (of more than ten employees), the detailed information in which is important for our deep research of firm survival. The database allows us to identify the survival period, enabling us to follow high-tech firms over time and identify the exit of a firm in year $t+1$ by checking whether it is in the survey in year $t+1$ and after. If the firm exits the survey in year t and not in t + 1, it does not survive. This database has an additional strength in that it includes various innovation indices of firms, which may help to demonstrate heterogeneity in terms of survival related to innovation outputs (Disney et al., 2003; Wang et al., 2017). In addition, we define the real survival status by rechecking the update status via the registration database maintained by the SAIC (State Administration for Industry and Commerce of the People's Republic of China). In that way, the definition of death or survival of a firm may be more accurate than the definition of exiting from the dataset that is used in most of the existing literature.[5]

[4] Zhongguancun is referred to as China's Silicon Valley. It is one of the top industrial clusters in China and is most famous for firms in the computer, semiconductor and telecommunications industries (Wang et al., 2017).

[5] However, we only have access to the registration database with records up to December 2015. If a firm exits after the year 2015, we cannot make an accurate judgement on its exit status. Since our estimation model can better help solve this problem, we present a detailed explanation in section 2.

We have deleted some observations of firms that have negative sales, i.e. negative total assets minus liquid assets, due to data availability. We also dropped the data of firms for which there were incomplete records. In order to control for the potential influence of outliers, variables are winsorised at the 1% level in each tail of the regressors, following the work of Guariglia and Liu (2014). We have in addition matched the addresses, telephone numbers and sector codes of different firms and dropped the ineffective data of firms with less than eight members (Brandt et al., 2014). Our resulting dataset therefore includes 14,065 firms, which comprise 57,725 firms' year level observations.

3.2. Statistical description

We report the descriptive statistics of key variables in Table 1a. On average, we find that 12% of firms introduced new patents, and that the share of granted new patents is 8%. Firm age is approximately 8.083 years. The initial size and firm size are 2.617 and 2.590, respectively, and there is a small gap between initial and firm size. Labour productivity and capital intensity perform well, with means of 2.303 and 2.630, respectively. However, the mean of sales is about −0.167 and changes sharply, which shows that the sales of the innovative firms bring shocks for all firms in our sample. Table 1b shows the information on firms' exit rates. To examine the dynamic system of industry, we first define the entry and exit of the firm. We assume that if firm_{it} is reported in the survey in year *t*, while not in year *t-1*, then the firm_{it} is considered as a new entrant. However, if the firm_{it} has information in year *t* but not in year *t*+1, then we recognize firm_{it} as a failure. The exit ratio is the number of failed firms divided by the total number of existing firms (He and Yang, 2016). The average yearly exit ratio of firms in the Chinese manufacturing sector is approximately 12.46%. Exit rates are becoming higher, and the exit rate was 21.45% in 2013. Meanwhile, the number of firms decreased sharply in the ZGC district from 14,331 in 2007 to 9051 in 2013. In addition, based on the firm innovation variables, the innovation indicators over time are shown by Table 1c. Based on the information of patent applications, granted patents and valid patents, we find that innovative firms are expanding in the ZGC district. In particular, the granted and valid rates of patents show that both the numbers of patents and the efficiency of innovation have been growing quickly in ZGC firms.

Table 2
Baseline results on innovation and firm exit: innovation proxied by patents application.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Clog-log	probit	logit	clog-log	probit	logit
Innovation dummy	−0.559***	−0.272***	−0.587***			
	(-7.71)	(-7.79)	(-7.81)			
Ln(innovation)				−0.384***	−0.162***	−0.399***
				(-7.30)	(-6.91)	(-7.35)
Initial size	0.009	0.007	0.022	0.010	0.008	0.023
	(0.25)	(0.31)	(0.54)	(0.28)	(0.39)	(0.57)
Initial size^2	0.014*	0.010**	0.016*	0.014*	0.009**	0.016*
	(1.87)	(2.17)	(1.91)	(1.86)	(2.09)	(1.90)
Age	−0.034***	−0.019***	−0.039***	−0.034***	−0.020***	−0.039***
	(-3.93)	(-4.25)	(-4.31)	(-3.95)	(-4.29)	(-4.33)
Age^2	0.001*	0.000**	0.001**	0.001*	0.000**	0.001**
	(1.92)	(2.05)	(2.15)	(1.94)	(2.12)	(2.19)
Size	−0.487***	−0.371***	−0.574***	−0.488***	−0.372***	−0.575***
	(-14.47)	(-20.79)	(-15.10)	(-14.46)	(-20.78)	(-15.08)
Size^2	−0.039***	0.001	−0.031***	−0.039***	0.001	−0.031***
	(-5.07)	(0.14)	(-3.72)	(-4.99)	(0.21)	(-3.66)
Sales growth	0.021***	0.020***	0.021***	0.021***	0.012***	0.021***
	(3.74)	(3.60)	(3.45)	(3.74)	(3.62)	(3.45)
Labor productivity	−0.104***	−0.060***	−0.112***	−0.105***	−0.061***	−0.113***
	(-15.43)	(-16.78)	(-15.35)	(-15.52)	(-16.97)	(-15.43)
Multi-plant	−0.226**	−0.116**	−0.248**	−0.232**	−0.122***	−0.255***
	(-2.45)	(-2.51)	(-2.54)	(-2.51)	(-2.62)	(-2.61)
Constant	−0.344	0.105	0.075	−0.346	0.105	0.070
	(-0.87)	(0.45)	(0.16)	(-0.88)	(0.44)	(0.15)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Log-likelihood	−17832	−17842	−17881	−17827	−17841	−17831
Number of id	14,065	14,065	14,065	14,064	14,064	14,064

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled in the regressions.

4. Empirical results of innovation on firm survival in high-tech firms

4.1. Baseline regression results

The empirical results of equation (4) are demonstrated in Table 2. In this result, we report the impact of innovation on firm survival hazard rates. All regression results are based on hazard model-cloglog with discrete time and random effects, with additional models, including the probit and the logit with firm random effects, also used to estimate our regressions. We use heteroscedastic robust standard errors to reinforce the significance of the estimated effects.

The results from the cloglog, the probit and logit models for the panel data show consistent significance for the relationship between firms' innovation proxies and their survival rates. Following the work of Fernandes and Paunov (2015), the Log-likelihood of each model is adopted to measure the innovation efficiency. The larger the value of Log-likelihood, the more efficient the model. Our results are consistent with their findings. The log-likelihood value of cloglog is largest among the three groups and suggests that the cloglog is the most reliable estimation method. The innovation dummy shows a significantly negative sign at the 1% level in columns 1–3. The marginal effect implies that firms with innovation output measured by patents can decrease their exit rates by 56% in the cloglog model. The regression results show that innovation significantly decreases the exit probability for Chinese firms. If we keep all the other variables unchanged, the marginal effect in Table 2 implies that a firm's innovation activities, as measured by the number of patent applications, decrease its exit probability. The logarithm of patent numbers also has a negative effect on the exit rate (at the 1% level) in columns 4–6. The marginal effect implies that firms with 1% increasing in innovation patents can decrease their exit rates by 38% in the cloglog model. These results are in conformance with the previous conclusion that innovation provides a motivation than can better help firm survival in developing countries (Fernandes and Paunov, 2015). Innovation can better help firms increase productivity, raise the value added of new products and further increase their competitive power in the market. Inefficient firms will be squeezed out from the market by fierce competition and resources reallocated to more efficient firms, thus increasing the survival rate of firms. Market forces thus have played a positive role in China's market development.

In regard to controlling for firm-specific elements in the regression, firms with higher sales growth have lower exit probability (Fernandes and Paunov, 2015), and labour productivity exerts a positive and substantial impact on firm survival (Liu and Li, 2015). Both coefficients of Size and Size^2 have significant signs. The firm Age is negatively associated with firm exit. These results are in accordance with the conclusion of previous studies that firms' exit rates decline with their age (e.g., Jovanovic, 1982; Clementi and Hopenhayn, 2006). Furthermore, the coefficients of Age^2 suggests that the relationship is positive and that there are significant non-linearities (Tsoukas, 2011; Liu and Li, 2015).

4.2. Innovation efficiency on firm survival regression results

To further explore the mechanism by which innovation motivates firm survival, we checked a series of efficiency assessments to verify and extend our main results. Previous literature has found that patent data is a good measurement of innovation, and patent performance as the output of innovation can contribute to firm growth, i.e. by producing new products and increasing TFP growth, particularly in the long-run (Griliches, 1990). In addition to considering patent applications, demonstrate that granted and valid patent numbers are good measurements of innovation efficiency, because patents that are granted and valid patents are those that have been approved by the market. This means these patents are efficient outputs of innovation and can help firms grow and gain market power (Lev, 2001). In addition, considering the difference between patent applications and granted patents, not all application patents can make an equal contribution to the firm, so the real contribution of innovation should be estimated through the granted and valid patents

Table 3
Baseline results on innovation and firm exit: innovation proxied by patents grant.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	clog-log	probit	logit	clog-log	probit	logit
Innovation dummy	−0.682***	−0.337***	−0.719***			
	(-6.57)	(-6.96)	(-6.71)			
Ln(innovation)				−0.448***	−0.201***	−0.468***
				(-6.05)	(-6.15)	(-6.13)
Initial size	0.008	0.005	0.0195	0.009	0.007	0.021
	(0.21)	(0.23)	(0.48)	(0.24)	(0.31)	(0.51)
Initial size^2	0.015*	0.010**	0.0167**	0.015*	0.010**	0.017*
	(1.92)	(2.27)	(1.98)	(1.89)	(2.18)	(1.95)
Age	−0.032***	−0.018***	−0.037***	−0.032***	−0.019***	−0.037***
	(-3.70)	(-4.00)	(-4.07)	(-3.71)	(-4.04)	(-4.09)
Age^2	0.001*	0.000*	0.001**	0.001*	0.000*	0.001**
	(1.75)	(1.87)	(1.99)	(1.77)	(1.92)	(2.01)
Size	−0.492***	−0.373***	−0.579***	−0.491***	−0.372***	−0.578***
	(-14.54)	(-20.90)	(-15.15)	(-14.47)	(-20.76)	(-15.07)
Size^2	−0.040***	0.001	−0.032***	−0.041***	0.000	−0.032***
	(-5.10)	(0.12)	(-3.76)	(-5.15)	(0.03)	(-3.83)
Sales growth	0.021***	0.012***	0.022***	0.021***	0.012***	0.022***
	(3.81)	(3.59)	(3.50)	(3.81)	(3.61)	(3.51)
Labor productivity	−0.107***	−0.061***	−0.115***	−0.108***	−0.062***	−0.115***
	(-15.81)	(-17.21)	(-15.72)	(-15.85)	(-17.31)	(-15.76)
Multi-plant	−0.232**	−0.117**	−0.252***	−0.237**	−0.120***	−0.257***
	(-2.51)	(-2.52)	(-2.58)	(-2.56)	(-2.59)	(-2.63)
Constant	−0.345	0.106	0.077	−0.347	0.105	0.076
	(-0.87)	(0.45)	(0.17)	(-0.87)	(0.44)	(0.17)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Log-likelihood	−17841	−17848	−17862	−17836	−17845	−17882
Number of id	14,065	14,065	14,065	14,064	14,064	14,064

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled in the regressions.

Table 4
Baseline results on innovation and firm exit: innovation proxied by valid patents.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	clog-log	probit	logit	clog-log	probit	logit
Innovation dummy	−0.671***	−0.331***	−0.705***			
	(-7.66)	(-7.86)	(-7.71)			
Ln(innovation)				−0.336***	−0.149***	−0.346***
				(-6.60)	(-6.57)	(-6.65)
Initial size	0.010	0.006	0.022	0.00	0.006	0.018
	(0.26)	(0.29)	(0.53)	(0.03)	(0.25)	(0.40)
Initial size^2	0.014*	0.010**	0.016*	0.017**	0.010**	0.018*
	(1.85)	(2.20)	(1.91)	(2.01)	(2.16)	(1.93)
Age	−0.033***	−0.019***	−0.038***	−0.029***	−0.016***	−0.033***
	(-3.74)	(-4.19)	(-4.13)	(-2.66)	(-2.85)	(-2.92)
Age^2	0.001*	0.000*	0.001**	0.001	0.000	0.001
	(1.83)	(2.11)	(2.10)	(1.23)	(1.34)	(1.41)
Size	−0.499***	−0.373***	−0.586***	−0.539***	−0.390***	−0.617***
	(-14.63)	(-20.90)	(-15.20)	(-14.26)	(-20.11)	(-16.44)
Size^2	−0.039***	0.001	−0.031***	−0.029***	0.004	−0.022**
	(-4.96)	(0.16)	(-3.64)	(-3.48)	(0.95)	(-2.46)
Sales growth	0.021***	0.011***	0.021***	0.020***	0.010***	0.019***
	(3.76)	(3.54)	(3.47)	(3.04)	(2.72)	(2.66)
Labor productivity	−0.107***	−0.061***	−0.115***	−0.103***	−0.058***	−0.108***
	(-15.67)	(-16.98)	(-15.57)	(-13.32)	(-14.44)	(-13.95)
Multi-plant	−0.232**	−0.118**	−0.252**	−0.228**	−0.121**	−0.250**
	(-2.51)	(-2.54)	(-2.58)	(-2.24)	(-2.36)	(-2.33)
Constant	0.313	0.422*	0.773	−1.676***	−0.671**	−1.445**
	(0.76)	(1.76)	(1.64)	(-3.09)	(-2.22)	(-2.47)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	45,463	45,463	45,463
Log-likelihood	−17832	−17841	−17881	−13510	−13524	−13849
Number of id	14,065	14,065	14,065	12,037	12,037	12,037

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled in the regressions.

Table 5
Regression results of characterization of innovation and firm death.

VARIABLES	(1)	(2)	(3)	(4)
	Clog-log	Clog-log	Clog-log	Clog-log
Patent Application × export	−0.613**			
	(-2.47)			
Patent Application × nonexport	−0.555***			
	(-7.40)			
Patent Application × import		−1.540***		
		(-3.42)		
Patent Application × nonimport		−0.522***		
		(-7.14)		
Grant patent × export			−0.698***	
			(-6.35)	
Grant patent × nonexport			−0.548*	
			(-1.86)	
Grant patent × import				−1.076**
				(-2.38)
Grant patent × nonimport				−0.657***
				(-6.19)
Constant	−0.344	−0.343	−0.345	−0.344
	(-0.87)	(-0.87)	(-0.87)	(-0.87)
Firm-level controls	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,725
Number of id	14,065	14,065	14,065	14,065

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled in the regressions. Firm-level controls are in those regressions, but not reported.

information (Haupt et al., 2007). To explore the linkage between innovation efficiency and firm survival, we first estimate our specification for using granted patents to measure innovation efficiency. Second, we use the valid patents information to exploit the influence of innovation efficiency on firm survival. Patents and inventions are outputs incorporating innovation, and granted and valid patents in particular are efficient outputs of firms' innovation activities.

Tables 3 and 4 present the results based on separating innovation proxies into dummies and real values corresponding to granted patents and valid patents. We find that new patents' efficiencies reduce Chinese firms' exit probabilities. The logarithm of patents is also statistically negative at the 1% significance level in Tables 3 and 4 The marginal effect implies that firms with granted patents can decrease their exit rates by 68%, and firms with a 1% increase in granted patents can decrease their exit rates by 45% in the cloglog model. Our findings contribute strong evidence to support previous theories that demonstrate that innovative firms can enhance firm productivity and increase their market power, thus increasing their survival rates (Griliches, 1979; Aghion et al., 2014). Granted and valid patents can directly improve the productivity of technologies by updating their products and management processes so they can compete with other competitors in the market to increase their market power. Therefore, innovative firms have a greater possibility of survival in the Chinese market.

4.3. *The effect of firms' export and import activities on the innovation-survival link*

We further explore what might drive the negative innovation-exit relationship, testing the validity and extension of our main results with a series of import and export tests. Knowledge spillovers have always performed as a crucial driving force of economic growth in theory (Jones, 2005). In general, the distribution of innovation activities is concentrated in a dozen developed nations (Eaton and Kortum, 1999). Moreover, foreign direct investment (FDI) can directly contribute to capital formation and facilitate the diffusion of new technologies to improve the efficiencies and qualities of local firms. Governments across the world actively seek to attract FDI, and through it, domestic producers can raise their productivity, shape market structure and increase their survival rate (Luh et al., 2016). Therefore, firms can benefit from the spillover effects of innovation through exports and imports.

Table 5 presents the regression results by investigating whether exports and imports can help firms innovate and increase the probability of firm survival. Columns 1–2 show that the marginal effect implies that firms that export can decrease their exit rates by 61% (compared to 56%

Table 6
Regression results on innovation and firm exit: innovation proxied by scientific publications.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	clog-log	probit	logit	clog-log	probit	logit
Panel A	Dependent variable: scientific publications					
Innovation dummy	−0.212	−0.094	−0.235			
	(-1.55)	(-1.41)	(-1.64)			
Ln(innovation)				−0.114	−0.034	−0.124
				(-1.37)	(-0.92)	(-1.45)
Constant	−0.346	0.111	0.079	−0.349	0.107	0.077
	(-0.87)	(0.47)	(0.17)	(-0.88)	(0.45)	(0.17)
Firm-level controls	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Number of id	14,065	14,065	14,065	14,064	14,064	14,064
Panel B	Dependent variable: scientific trademarks					
Innovation dummy	−0.426***	−0.206***	−0.446***			
	(-5.07)	(-4.94)	(-5.07)			
Ln(innovation)				−0.357***	−0.168***	−0.375***
Constant	−0.347	0.117	0.079	−0.350	0.109	0.076
	(-0.87)	(0.50)	(0.17)	(-0.88)	(0.46)	(0.17)
Firm-level controls	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Number of id	14,065	14,065	14,065	14,064	14,064	14,064

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled for in the regressions. Firm-level controls are in those regressions, but not reported.

Table 7
Regression results on innovation and firm exit: innovation proxied by invention application.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	clog-log	probit	logit	clog-log	probit	logit
Panel A	Dependent variable: invention application					
Innovation dummy	−0.562***	−0.270***	−0.589***			
	(-6.62)	(-6.65)	(-6.69)			
Ln(innovation)				−0.386***	−0.158***	−0.401***
				(-5.80)	(-5.36)	(-5.83)
Constant	−0.344	0.108	0.077	−0.348	0.107	0.072
	(-0.87)	(0.46)	(0.17)	(-0.88)	(0.45)	(0.16)
Firm-level controls	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Number of id	14,065	14,065	14,065	14,064	14,064	14,064
Panel B	Dependent variable: invention grant					
Innovation dummy	−0.685***	−0.317***	−0.714***			
	(-5.09)	(-5.13)	(-5.14)			
Ln(innovation)				−0.491***	−0.209***	−0.509***
				(-4.57)	(-4.46)	(-4.59)
Constant	−0.347	0.107	0.078	−0.349	0.105	0.076
	(-0.87)	(0.45)	(0.17)	(-0.88)	(0.44)	(0.17)
Firm-level controls	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Number of id	14,065	14,065	14,065	14,064	14,064	14,064
Panel C	Dependent variable: valid invention					
Innovation dummy	−0.585***	−0.285***	−0.613***			
	(-6.82)	(-6.83)	(-6.85)			
Ln(innovation)				−0.342***	−0.147***	−0.354***
				(-5.61)	(-5.34)	(-5.59)
Constant	−0.350	0.104	0.073	−0.351	0.104	0.073
	(-0.88)	(0.44)	(0.16)	(-0.88)	(0.44)	(0.16)
Firm-level controls	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Number of id	14,065	14,065	14,065	14,064	14,064	14,064

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled for in the regressions. Firm-level controls are in those regressions, but not reported.

for firms that do not export) by making patent applications. Firms without imports can decrease their exit rates by 52%, however, firms with imports exhibit three times the survival rate of firms that import. Columns 3–4 show similar results when we use the number of granted patents to measure innovation efficiency. The results show that exports and imports increase a firm's survival ratio because knowledge spillover contributes to the firms' innovation activities through the export and import processes. International trade enables information and foreign knowledge to be diffused through imports and exports, which can have positive impacts on import- or export-related spillovers on productivity (Bournakis et al., 2018). In addition, there is a cost-reducing effect in import or export activities, either because of the lower cost of inputs or because of scale effects on outputs (Kasahara and Lapham, 2013). Thus, domestic firms gain market power and have higher survival rates.

4.4. Alternative innovation measurements and firms' survival

To expand the ways in which measurements of innovation impact survival rates, we further introduce scientific publications and trademarks as indicators of innovation to investigate this relationship. Scientific publications and trademarks are also the outputs of innovation activities. They have social influence and can help firms gain market power to compete with their competitors. In particular, trademarks can help firms separate their products from those of their competitors. Therefore we further investigate whether or not publications and trademarks increase the survival rates of firms.

Panel A in Table 6 presents the relationship between innovation as measured by scientific publications and firm survival; we find that scientific publications cannot reduce Chinese firms' exit probabilities. This illustrates that scientific publications do not significantly incorporate this knowledge into production processes, and therefore, scientific publications are not efficient at raising the likelihood of survival. Moreover, panel B shows that trademarks can significantly increase the survival rates of firms. Fleisher and Sheila (2010) demonstrate that branding and quality certifications are signals to the market that the firm will supply products with the promised quality. Furthermore, they provide a barrier to effective competition from other competitors and increase specialisation in production.

5. Robustness tests

To ensure the robustness of baseline results, the additional checks in this section involve the estimation of alternative types of innovation and innovation efficiency indicators, such as inventions, valid patents and validated inventions. As invention is also an alternative output of innovation, it can improve firm efficiency and increase market share. In addition, inventions are susceptible to industrial applications, which provide them with higher margins that can enable them to reclaim front-end investments in innovation. By obtaining preferential market opportunities, inventions and efficiencies have a substantial influence on the death rate of firms (Paunov, 2016). Panel A–C in Table 7 present the estimates of using inventions as a measure of innovation. The coefficients

Table 8
Regression results on innovation and firm exit: firm size heterogeneity test.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	cloglog	probit	logit	cloglog	probit	logit
Innovation dummy	−0.492***	−0.376***	−0.564***			
	(-2.98)	(-4.49)	(-3.24)			
Innovation dummy×size	−0.025	0.035	−0.009			
	(-0.45)	(1.38)	(-0.15)			
Ln(innovation)				−0.664***	−0.380***	−0.719***
				(-5.36)	(-7.12)	(-5.70)
Ln(innovation)× size				−0.089***	−0.060***	−0.100***
				(2.63)	(4.81)	(2.97)
Constant	−0.3426	0.1044	0.0752	−0.3509	0.0971	0.0679
	(-0.87)	(0.44)	(0.17)	(-0.89)	(0.41)	(0.15)
Firm-level controls	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes
Observations	57,725	57,725	57,725	57,723	57,723	57,723
Number of id	14,065	14,065	14,065	14,064	14,064	14,064

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled for in the regressions. Firm-level controls are in those regressions, but not reported.

of innovation variables are also negative at the 1% significance level. These marginal effects imply that firms with invention applications, granted inventions and validated inventions can decrease their exit rates by 56%, 69% and 59% respectively in the cloglog model. Therefore, the regressions analyzed above demonstrate that our empirical results are robust. As expected, inventions significantly reduce exit rates. Moreover, more efficient inventions play an important role in increasing the likelihood of firms' survival. Our findings show that the negative and significant influence of innovation on firm exit is robust and duly unaffected by alternative measurement techniques.

Furthermore, we test how innovation interacting with firm size affects firm survival rates. Table 8 shows that the dummy variable of innovation interacting with firm size is not significant, but that the logarithm of patents interacting with firm size shows a negative and significant impact on firm survival (all models are tested at the 1% significance level). This test demonstrates that relatively large high-tech start-ups might be more flexible and more enthusiastic about innovating to compete and survive in the market.

6. Conclusions and policy implications

Employing unique panel data for Chinese high-tech start-ups' in the ZGC district and using the cloglog model with random effect, our results reaffirm that firm-level innovation plays a significant role in influencing firm survival. Our findings support the broader findings of previous studies of this relationship. In addition, we find that innovation efficiencies, through an internal innovation mechanism, significantly reduce exit probability. We further investigate how an external innovation mechanism – firms' import and export activities – affects the relationship between firm survival and innovation. The trade linkages of Chinese firms enable them to draw upon the large stock of knowledge capital of their trading partners to innovate and to enhance their domestic position. They thus play a significant role in a firm's survival. Firms with import and export statuses are efficiently affected by innovation with regard to the knowledge spillover effect. We also measure innovation along several different dimensions, including patents, inventions, scientific publications and trademarks, and our results suggest that the aforementioned output of innovation, with the exception of scientific publications, can decrease the failure rates of Chinese firms. Overall our results indicate that innovation is an important determinant of high-tech start-ups' survival in China.

The present study leads to the clear policy message that governments need to continue to promote innovation, removing barriers to innovation and fostering a favorable environment in which firms can innovate. At the same time, it is particularly important to encourage international trade to allow domestic knowledge-intensive firms to benefit from cross-border spillover effects, especially in the context of emerging markets. It is also important to facilitate the process by which these firms improve innovation efficiency through converting their innovation output into patents. These internal and external factors have been shown to be important for ensuring the survival of knowledge-intensive firms in China. Nevertheless, China's intellectual property rights protection is still weak and policy reforms are needed to strengthen and protect firms' innovation. The long-term survival of innovative firms will contribute to China's sustainable economic growth.

Nonetheless, this paper is not without limitation. First, future research could further analyse the different mechanisms associated with product types, industrial policies and firm-level interactions between innovation and survival probability. Second, future research could investigate the risk of the different heterogeneities for the link between innovation and the exit rate. Future research could use more fine-grained data that covers more geographical areas in China, when they become available, to pursue this research further.

Acknowledgements

We are grateful to the participants of the Economic Modelling Conference on The Challenges of Managing and Modelling Innovation and Growth in China. We are further indebted to Professor Sushanta Mallick and Professor Anthony Howell for their helpful remarks on earlier versions of this paper. The usual disclaimer applies. Zhang acknowledges financial support from The Ministry of Education of Humanities and Social Science Youth Project and the Beijing Municipal Social Science Foundation (Project NO: 17LJC008). Zheng acknowledges financial support from the National Natural Science Foundation of China (Project NO: 71572034).

Appendix

Appendix Table 1

Estimation models	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Fixed effects model		Random effects model	
Panel A	Dependent variable: patent application					
Innovation dummy	−0.0222***		−0.0192***		−0.0234***	
	(-7.77)		(-3.33)		(-4.88)	
Ln(innovation)		−0.0095***		−0.0107***		−0.0110***
		(-7.39)		(-3.21)		(-4.15)
R-squared	0.1197	0.1196	0.1522	0.1522		
Observations	57,817	57,815	57,817	57,815	57,817	57,815
Panel B	Dependent variable: patent grant					
Innovation dummy	−0.0242***		−0.0252***		−0.0273***	
	(-7.72)		(-3.70)		(-4.63)	
Ln(innovation)		−0.0096***		−0.0161***		−0.0125***
		(-6.96)		(-4.09)		(-3.89)
R-squared	0.1196	0.1195	0.1523	0.1523		
Observations	57,817	57,815	57,817	57,815	57,817	57,815
Panel C	Dependent variable: valid patent					
Innovation dummy	−0.0298***		−0.0359***		−0.0336***	
	(-9.34)		(-4.74)		(-6.27)	
Ln(innovation)		−0.0108***		−0.0217***		−0.0135***
		(-8.52)		(-5.61)		(-5.52)
R-squared	0.1281	0.1279	0.1477	0.1479		
Observations	45,546	45,546	45,546	45,546	45,546	45,546

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; t-statistics are shown in parentheses. The fixed effects of year and industry have been controlled for in the regressions; firm-level controls are also controlled in those regressions.

References

Aghion, P., Akcigit, U., Howitt, P., 2014. What do we learn from Schumpeterian growth theory?. In: Handbook of Economic Growth, vol. 2. Elsevier, pp. 515–563.
Arora, A., Fosfuri, A., Gambardella, A., 2000. Markets for technology and their implications for corporate strategy. Soc. Sci. Elec. Publ. 10 (2), 419–451.
Audretsch, D.B., 1991. New-firm survival and the technological regime. Rev. Econ. Stat. 441–450.
Bernard, A.B., Jensen, J.B., 2007. Firm structure, multinationals, and manufacturing plant deaths. Rev. Eco. Stat. 89 (2), 193–204.
Børing, P., 2015. The effects of firms' R&D and innovation activities on their survival: a competing risks analysis. Empir. Econ. 49 (3), 1045–1069.
Bournakis, I., Christopoulos, D., Mallick, S., 2018. Knowledge spillover and output per worker: an industry-level analysis for OECD countries. Econ. Inq. 56, 1028–1046.
Brandt, L., Van Biesebroeck, J., Zhang, Y., 2014. Challenges of working with the Chinese NBS firm-level data. China Econ. Rev. 30, 339–352.
Buddelmeyer, H., Jensen, P.H., Webster, E., 2009. Innovation and the determinants of company survival. Oxf. Econ. Pap. 62 (2), 261–285.
Cefis, E., Marsili, O., 2011. Born to flip. exit decisions of entrepreneurial firms in high-tech and low-tech industries. J. Evol. Econ. 21 (3), 2473–2498.
Chaudhuri, S., Biswas, A., 2016. Endogenous labour market imperfection, foreign direct investment and external terms-of-trade shocks in a developing economy. Econ. Modell. 59, 416–424.
Chen, M.Y., 2002. Survival duration of plants: evidence from the US petroleum refining industry. Int. J. Ind. Organ. 20 (4), 517–555.
Clementi, G.L., Hopenhayn, H.A., 2006. A theory of financing constraints and firm dynamics. Q. J. Econ. 121 (1), 229–265.
Dang, J., Motohashi, K., 2015. Patent statistics: a good indicator for innovation in china? patent subsidy program impacts on patent quality. China Econ. Rev. 35, 137–155.
Disney, R., Haskel, J., Heden, Y., 2003. Entry, exit and establishment survival in UK manufacturing. J. Ind. Econ. 51 (1), 91–112.
Eaton, J., Kortum, S., 1999. International technology diffusion: theory and measurement. Int. Econ. Rev. 40 (3), 537–570.
Ericson, R., Pakes, A., 1995. Markov-perfect industry dynamics: a framework for empirical work. Rev. Econ. Stud. 62 (1), 53–82.
Eriksson, T., Qin, Z., Wang, W., 2014. Firm-level innovation activity, employee turnover and hrm practices — evidence from chinese firms. China Econ. Rev. 30 (4), 583–597.
Feldman, M.P., Kelley, M.R., 2006. The ex-ante assessment of knowledge spillovers: government R&D policy, economic incentives and private firm behavior. Res. Pol. 35 (10), 1509–1521.
Fernandes, A.M., Paunov, C., 2015. The risks of innovation: are innovating firms less likely to die? Rev. Econ. Stat. 97 (3), 638–653.
Fleisher, C.S., Sheila, W., 2010. Competitive intelligence analysis failure: diagnosing individual level causes and implementing organisational level remedies. J. Strat. Market. 18 (7), 553–572.
Geroski, P.A., 1995. What do we know about entry? Int. J. Ind. Organ. 13 (4), 421–440.
Giovannetti, G., Ricchiuti, G., Velucchi, M., 2011. Size, innovation and internationalization: a survival analysis of Italian firms. Appl. Econ. 43 (12), 1511–1520.
Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. Bell J. Econ. 92–116.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey. J. Econ. Lit. 28 (4), 1661–1707.
Guariglia, A., Liu, P., 2014. To what extent do financing constraints affect Chinese firms' innovation activities? Int. Rev. Financ. Anal. 36, 223–240.
Hall, B.H., 2002. The financing of research and development. Oxf. Rev. Econ. Pol. 18 (1), 35–51.
Harhoff, D., Henkel, J., Hippel, E.V., 2003. Profiting from voluntary information spillovers: how users benefit by freely revealing their innovations. Res. Pol. 32 (10), 1753–1769.
Haupt, R., Kloyer, M., Lange, M., 2007. Patent indicators for the technology life cycle development. Res. Pol. 36 (3), 387–398.
He, Canfei, Yang, Rudai, 2016. Determinants of firm failure: empirical evidence from China. Growth Change 47 (1), 72–92.
Helmers, C., Rogers, M., 2010. Innovation and the survival of new firms in the UK. Rev. Ind. Organ. 36 (3), 227–248.
Howell, Anthony, 2015. 'Indigenous' innovation with heterogeneous risk and new firm survival in a transitioning Chinese economy. Res. Pol. 44 (10), 1866–1876.
Jenkins, S.P., 1995. Easy estimation methods for discrete-time duration models. Oxf. Bull. Econ. Stat. 57 (1), 129–136.
Jensen, P.H., Webster, E., Buddelmeyer, H., 2008. Innovation, technological conditions and new firm survival. Econ. Rec. 84 (267), 434–448.
Jones, D., 2005. Information and knowledge. Dublin Penny J. 1 (43), 344-344.
Jovanovic, B., 1982. Selection and the evolution of industry. Econometrica 649–670.
Kasahara, H., Lapham, B., 2013. Productivity and the decision to import and export: theory and evidence. J. Int. Econ. 89 (2), 297–316.
Kiefer, N.M., 1988. Economic duration data and hazard functions. J. Econ. Lit. 26 (2), 646–679.
Klein, J.P., Moeschberger, M.L., 1987. Survival Analysis: Techniques for Censored and Truncated Data. Springer, New York.
Klette, T.J., Kortum, S., 2004. Innovating firms and aggregate innovation. J. Polit. Econ. 112 (5), 986–1018.
Lev, B., 2001. Intangibles: Management Measurement, and Reporting. Brookings Institution Press, Washington, DC.
Li, S., Shang, J., Slaughter, S.A., 2010. Why do software firms fail? Capabilities, competitive actions, and firm survival in the software industry from 1995 to 2007. Inf. Syst. Res. 21 (3), 631–654.
Liu, X., Li, H., 2015. Financial constraints and the productivity–survival link: evidence from China's firm-level data. Ind. Corp. Change 26 (5), 763–779.
Luh, Y.H., Jiang, W.J., Huang, S.C., 2016. Trade-related spillovers and industrial competitiveness: exploring the linkages for OECD countries. Econ. Modell. 54, 309–325.

Mahmood, T., 2000. Survival of newly founded businesses: a log-logistic model approach. Small Bus. Econ. 14 (3), 223–237.
Nemlioglu, I., Mallick, S.K., 2017. Do managerial practices matter in innovation and firm performance relations? New evidence from the UK. Eur. Financ. Manag. 23 (5), 1016–1061.
Ning, L., Wang, F., Li, J., 2016. Urban innovation, regional externalities of foreign direct investment and industrial agglomeration: evidence from Chinese cities. Res. Pol. 45 (2016), 830–843.
Paunov, C., 2016. Corruption's asymmetric impacts on firm innovation. J. Dev. Econ. 118, 216–231.
Pisano, G., 1990. The R&D boundaries of the firm: an empirical analysis. Adm. Sci. Q. 35, 153–176.
Prentice, R.L., Gloeckler, L.A., 1978. Regression analysis of grouped survival data with application to breast cancer data. Biometrics 57–67.
Tsoukas, S., 2011. Firm survival and financial development: evidence from a panel of emerging Asian economies. J. Bank. Finance 35 (7), 1736–1752.
Tybout, J.R., 2000. Manufacturing firms in developing countries: how well do they do, and why? J. Econ. Lit. 38 (1), 11–44.
Veugelers, R., Cassiman, B., 1999. Make and buy in innovation strategies: evidence from belgian manufacturing firms. Res. Pol. 28 (1), 63–80.
Wang, Y., Li, J., Furman, J.L., 2017. Firm performance and state innovation funding: evidence from China's Innofund program. Res. Pol. 46 (6), 1142–1161.
Wilbon, A.D., 2002. Predicting survival of high-technology initial public offering firms. J. High Technol. Manag. Res. 13 (1), 127–141.
Zhang, M., Mohnen, P., 2013. Innovation and survival of new firms in chinese manufacturing, 2000-2006. Merit Working Papers 91 (6), 33–51.