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Innovation and survival of new firms in Chinese manufacturing, 2000-2006

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INNOVATION AND SURVIVAL OF NEW FIRMS IN CHINESE MANUFACTURING, 2000-2006

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Abstract

Using a large dataset of over 100,000 Chinese firms created between 2000 and 2006, we explore whether there is a link between innovation effort (R&D) or innovation output (the share of innovative sales) and the firm's duration of survival. We estimate a complementary log log model with time-varying explanatory variables controlling for individual heterogeneity. We find that innovative firms tend to survive longer, more so because of R&D than because of introducing new products. There seems to be an inverted-U relationship between R&D or innovation output and long-term survival, suggesting that too much R&D or product innovation can cause firms to die, perhaps because of excessive risk. Survival has a cyclical behavior, and it varies across provinces. It also varies with ownership. State-owned firms have a higher hazard rate than privately-owned firms, which have a higher hazard rate than foreign-owned firms.

Key words: firm survival, complementary log-log duration models, China, innovation

JEL codes: L25, O38

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Introduction

Following up on Schumpeter's (1942) assertion that innovation is important for firms' survival, many empirical papers have explored the relationship between the probability of survival and the existence of innovative activities. The commonly held view is that innovation improves the firm's competitiveness and therefore its survival (see section 2 for a review of the literature).

Most of these studies are based on existing firms that are heterogeneous with respect to their pre-sample history, which could determine their chances of survival. Our paper is restricted to firms newly created between 2000 and 2006 and examines what happens to these "start-ups" subsequent to entry depending on whether or not they perform some innovation activities.[1] It identifies the difference in survival due to innovation activities by conditioning on firm size, ownership and sector specific characteristics.

[1] Some of these "start-up" firms may be the result of a merger, acquisition or re-organization, in which case there was a prior experience. Unfortunately, the data that we have do not allow us to trace back the possible history of these apparently new firms.

Our research attempts to disentangle the impact of innovation efforts (R&D) and innovation output (in the sense of new products successfully introduced on the market). We also explore the nonlinear effect of innovation input and output intensities on survival (by including square terms that allow for U-shaped or inverse-U-shaped effects of innovation on survival). The different starting dates of new firm creation allow us to control for the effects of economic fluctuations on survival. We use a large dataset of over 100,000 firms in Chinese manufacturing that enables us to examine differences between innovation and survival across industries.

The paper is organized as follows. Section 2 reviews the existing empirical evidence regarding innovation and survival. Section 3 presents the data and illustrates them by means of some descriptive statistics. Section 4 discusses some econometric issues regarding the estimation of survival models with discrete panel data. Section 5 presents and interprets the estimation results, and section 6 concludes

2. Literature Review

Various innovation indicators have been used in the empirical literature almost all confirming the positive role of innovation on firm survival.

The first studies have related survival to the presence of R&D activities. Using panel data on publicly traded firms in the US manufacturing sector from 1976-1983, Hall (1987) finds that the intensity of R&D expenditure increases the survival probability, and that this effect is stronger for firms that do not patent than for firms that do. In a study of Spanish manufacturing firms, Pérez, Llopis and Llopis (2004) confirm that firms that invest in R&D activities experience a 57% lower exit risk than firms that do not, and that this effect is enhanced by the international orientation of the firms. Fontana and Nesta (2009) report a positive non-linear relationship between the firm's R&D effort or its product innovation record and the probability of surviving.

A second group of studies has examined the link between survival and innovation output indicators. Christensen, Suárez and Utterback (1998) find that firms that innovate in products with new market segments in the disk drive industry have a significantly higher probability of survival than firms that enter established market segments with better performing new components. Banbury and Mitchell (1995) obtain a positive relationship between survival and the number of new products introduced in the market. Greenstein and Wade (1998) find that firms producing older computer models have a lower chance of surviving in the market. According to Baldwin and Gu (2004) process innovation is associated with higher plant survival rates in Canadian manufacturing while product innovation is related to lower survival rates. Cefis and Marsili (2005) also concluded that process innovation has a direct and positive effect on firm survival, while product innovation influences survival only in combination with process innovation.

A third collection of studies linked firms' survival to their use of intellectual property rights. Helmert and Rogers (2008) analyzed the survival of the complete cohort of more than 162,000 limited companies incorporated in Britain in 2001 over the subsequent five-year period. Their results indicated that IP activity was associated with a higher probability of survival. In contrast, using a panel of almost 300,000 Australian companies, Buddelmeyer, Jensen and Webster (2010) show that the degree of uncertainty embodied in different innovation proxies shapes the pattern of company survival. Radical innovation investments (new-to-world), measured by IP applications, are associated with lower survival rates; whereas past successful radical innovations, as proxied by the stock of patents, and incremental innovation investment (new-to-company), measured by trademark applications, are associated with higher company survival rates.

Survival has also been shown to depend on certain firm or market characteristics. Audretsch and Mahmood (1994) conclude on the basis of 12000 newly established plants in U.S. manufacturing in 1976 that the presence of scale economies, a high technology environment, and a relatively small initial start-up size tend to elevate the risk of failure confronting new business. In addition to the usual variables representing firm- and industry-specific features that impact firms' survival, Lin and Huang (2008) distinguish two Schumpeterian technological regimes: creative destruction (the entrepreneurial regime) and creative accumulation (the routinized regime). After controlling for age, size, entry barriers, capital intensity, the profit margin, the concentration ratio, the profit-cost ratio and entry rates, their empirical results show that new firms are more likely to survive under the entrepreneurial regime. Moreover, this effect is larger within the younger cohorts of firms than within the older ones. Cefis and Marsili (2006) show that the positive and significant effect of innovation on the probability of survival in Dutch manufacturing increases over time and is conditional on firm age and size. The paper observes that small and young firms are the most exposed to the risk of exit, as earlier studies have found, but also those that benefit most from innovation to survive in the market, especially in the longer term. Fernandez and Paunov (2012) find that risky innovators, in the sense of innovating in a single product, are more likely to die. Doms, Dunne and Roberts (1995) find that capital-intensive plants and plants employing advanced technology in U.S. manufacturing have higher growth rates and are less likely to fail.

3. Data and Descriptive Statistics

3.1 Data

Our primary data has been compiled by the National Bureau of Statistics of China. It includes over 100,000 firms in each year over the period 1999 to 2006, and it has two characteristics that make it particularly suitable for the analysis of new firm survival. First, it is a yearly census of all state-owned and all non-state-owned firms with sales higher than 5 million RMB (Yuan). Second, it has a longitudinal dimension, i.e., individual firms are identified by an identification code (ID) that allows them to be followed over time. A firm is identified as a new firm when it has a new ID. Similarly, a firm is defined as dead when its ID disappears.[2] In other words, a firm is considered to

[2] Again we have no way of knowing whether firms that disappear from our sample actually survive but under a different name following a reorganization or merger.

have started in year t if it has no ID from 1999 to $t-1$, to have died in year t if it has no ID from year $t+1$ to 2006, and otherwise its exit date is considered to be a right censored observation.[3] To reduce the unobservable heterogeneity caused by regional disparities, this study focuses on the most dynamic provinces of China in terms of new firm formation rates. As figure 1 shows, in 9 provinces (Zhejiang, Shanghai, Tianjin, Jiangsu, Beijing, Guangdong, Shandong, Fujian and Liaoning) on average more than 0.5 firms were created per ten thousand persons over the period 2000-2006. We shall restrict ourselves to those 9 provinces for the rest of our analysis.

[3] We have eliminated any case of re-entry (around 2% of all observations). This can only happen when a firm is dropped from the sample in a particular year because it no longer has the minimum size to be included in the census.

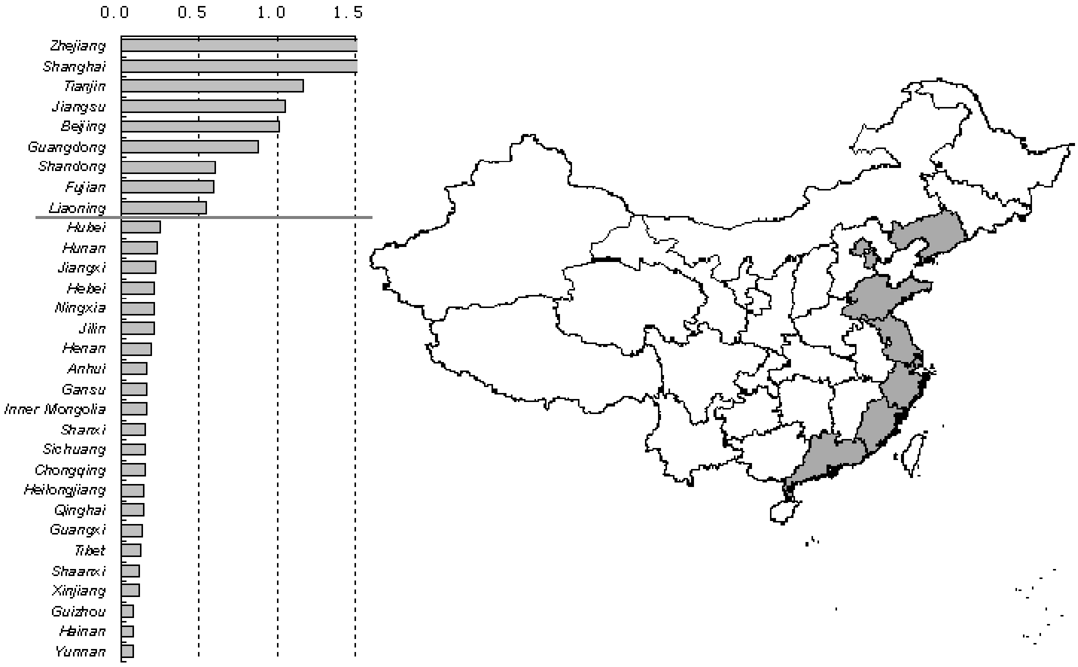

Figure 1 Most dynamic regions in China in terms of firm formation rates (number of new firms/10 000 people): average over 2000-2006

Table 1 informs us about the number of survivors over the years for each cohort of firms born between 2000 and 2006. Table 2 reproduces the same information in terms of the percentages of the total number of firms surviving over time among those created each year. For instance, the 25,794 figure in the cell of line 2 and column 2 indicates that of the 30 603 firms newly created in 2001, 84.29% survive two years after their creation. The increase in 2004 in the number of new firms is, according to officials at the National Bureau of Statistics, to a large extent caused by an extended coverage of the census.[4]

Table 1 Number of survivors after x years in the most dynamic provinces of China

Start year	1	2	3	4	5	6	7
2000	19,310	13,431	11,575	10,067	7,755	7,088	6,501
2001	30,603	25,794	21,889	16,462	15,100	13,868	

[4] Small-scale private limited liability corporations and small-scale other limited liability corporations seem to be included in the census year 2004.

2002	23,137	19,439	14,834	13,530	12,356		
2003	29,193	21,883	19,880	18,115			
2004	91,621	69,222	61,735				
2005	24,628	21,680					
2006	36,757						

An interesting question is what makes some firms survive longer than others? According to Schumpeter's theory of creative destruction, some products get kicked out of the market by the appearance of new products with superior quality, new functionalities or lower prices, and as a consequence some of the firms producing old products can no longer survive. Conversely, firms that come up with new products should be able to better resist the waves of creative destruction. One question will be whether this is indeed the case. The second question will be whether it is the current innovation that matters for survival or whether the protection due to innovation lasts for some time. We distinguish two measures of innovation: the R&D intensity (measured by the executed R&D over sales ratio) and the new product intensity (measured by the share of output in a given year that is due to products new to the firm).[5] Another question that we shall investigate is whether it is R&D or product innovation that is more relevant for survival. It may well be that product innovation protects a firm temporarily from competition, but that R&D as an investment in future product innovations is more relevant for long-term survival. But it can also be argued that increasing R&D leads other firms to increase their own R&D and thereby increases competition and the danger of bankruptcy, whereas product innovation discourages entry and increases exit of competitors.

Another reason for comparing the R&D and innovation output data is the absence of R&D data for 1999, 2000 and 2004. For 2004 the R&D expenditure figures were constructed in the following way: if the firm existed in that year, but not in the year before and the year after, its R&D is put equal to zero; if it started to exist in that year R&D takes the same value as in the following year; if it stopped to exist in that year it takes the value of the R&D in the preceding year; and if it existed before and after it

[5] A product is new, according to the National Bureau of Statistics, if it is produced by a new technology, has a new design, or has enhanced qualities and increased functionalities in comparison to the old product regarding structure, material and production technology. It includes products newly introduced on the national or the provincial market [translation by the authors].

takes the mean value of the years just before and just after. For 2000 we extrapolated the R&D using the value of 2001. For innovation output we constructed the data in a similar way for 2004; for 2000 we had the data. Even if R&D is more relevant than innovation output, it might be more affected by these measurement errors, although innovation output measured by the share of sales due to new products is itself probably more subjective and less systematically recorded than R&D.

Table 2 Survival rates after x years in the most dynamic provinces of China

Start year	1	2	3	4	5	6	7
2000	100.00%	69.55%	59.94%	52.13%	40.16%	36.71%	33.67%
2001	100.00%	84.29%	71.53%	53.79%	49.34%	45.32%	
2002	100.00%	84.02%	64.11%	58.48%	53.40%		
2003	100.00%	74.96%	68.10%	62.05%			
2004	100.00%	75.55%	67.38%				
2005	100.00%	88.03%					
2006	100.00%						

Table 3 gives the number of new firms by province over our sample period and the number of them that do not innovate (neither by way of R&D expenditure nor by way of new products), the number of R&D performers and the number of firms that manufacture products new to the firm. The provinces with the largest number of startups are in decreasing order of importance Zhejiang, Jiangsu, Guangdong and Shandong. At the bottom of the scale are the cities of Beijing and Tianjin. There is more heterogeneity across provinces in product innovation than in R&D performance. The ranking in the number of R&D performing firms across provinces is similar to the ranking in the number of startups across provinces, but the ratio of product innovators to startups is much more variable across provinces than the ratio of R&D performers to startups. For instance, Guangdong ranks second in product innovators and Beijing and Tianjin have a greater number of product innovators than Fujian and Shanghai. It will thus be important to account for some regional heterogeneity.

Table 3 Counts of new firms and their innovativeness, by province, 2000-2006

	Number of new firms	… without R&D and new products		… with R&D		… with new products	
		nb	%	nb	%	nb	%
Beijing	8,207	5,938	72.4	1,828	22.3	1,660	20.2
Fujian	14,014	11,995	85.6	1,702	12.1	535	3.8
Guangdong	44,153	36,472	82.6	5,477	12.4	3,798	8.6
Jiangsu	52,471	45,819	87.3	5,545	10.6	1,988	3.8
Liaoning	15,820	13,728	86.8	1,362	8.6	1,148	7.3
Shandong	38,467	32,915	85.6	4,168	10.8	2,181	5.7
Shanghai	16,541	14,299	86.4	1,826	11.0	801	4.8
Tianjin	7,638	5,634	73.8	877	11.5	1,483	19.4
Zhejiang	57,973	44,769	77.2	8,069	13.9	8,517	14.7

Table 4 reports the average survival rates over the period 2000-2006 per province, where survival rates are measured as the number of survivors divided by the total number of new entrants in the start year, and depending on whether there was R&D, new to the market product innovation, or no innovation at all. It shows first of all that, in all provinces, innovators have a higher survival rate than non-innovators, and second that, in general, new product innovators have a higher survival rate than R&D performers.

Table 4 New firm survival rates in the most dynamic provinces of China, 2000-2006

Provinces	Survival rates of			
	All firms	… without R&D and new products	… with R&D	… with new products
Beijing	0.477	0.403	0.701	0.716
Fujian	0.661	0.636	0.776	0.797
Guangdong	0.585	0.544	0.733	0.797
Jiangsu	0.492	0.456	0.721	0.653
Liaoning	0.606	0.589	0.709	0.709
Shandong	0.588	0.561	0.709	0.728
Shanghai	0.546	0.508	0.774	0.778
Tianjin	0.355	0.284	0.596	0.538
Zhejiang	0.597	0.528	0.766	0.868

3.2 Survival spell statistics

To get a feeling of the possible effect of innovation on firm survival we follow the average R&D (in % of total sales) and the average share of output due to new products over the complete cohorts of firms born during 2000-2006 (tables 5 and 6). Although there are some differences among individual start-years, the results indicate that firms that innovate in their start year (be they R&D performers or product innovators) tend to survive longer. For example, among the firms born in 2000, those living up to 2006 had on average a 0.19% R&D intensity in the first year of their life, whereas those disappearing one year after their birth had only a 0.10% R&D intensity.

Table 5 Average R&D intensity in the start year for firms that survive more than x years

Start year	1	2	3	4	5	6	7
2000	0.10%	0.15%	0.16%	0.17%	0.19%	0.18%	0.19%
2001	0.11%	0.11%	0.11%	0.12%	0.12%	0.12%	
2002	0.14%	0.14%	0.15%	0.15%	0.15%		
2003	0.13%	0.13%	0.14%	0.14%			
2004	0.17%	0.22%	0.22%				
2005	0.13%	0.12%					
2006	0.13%						

Table 6 Average share of output due to new products in the start year for firms that survive more than x years

Start year	1	2	3	4	5	6	7
2000	2.69%	2.95%	3.05%	3.18%	3.27%	3.27%	3.20%
2001	2.11%	2.24%	2.34%	2.50%	2.58%	2.62%	
2002	1.82%	1.87%	1.96%	2.01%	2.06%		
2003	1.86%	2.04%	2.09%	2.09%			
2004	2.48%	3.28%	3.28%				
2005	4.05%	3.98%					
2006	3.95%						

Table 7 Estimated average lifespan of new firms in the most dynamic provinces of China, 2000-2006

	Non-innovators	New products only	R&D only	R&D and new products
All firms	2.75	3.47	3.8	4.07
High tech	2.57	3.17	3.61	3.76
Medium tech	2.72	3.46	3.82	4.13
Low tech	2.8	3.55	3.84	4.26

Another way to see the importance of initial R&D or product innovation on survival is to compare the average life-span for non-innovators (having neither R&D nor new products), and innovators of three kinds, those that perform R&D but have no new products, those that have new products but no R&D, and those that are innovative in the two dimensions. The average life-span for innovators is persistently higher than for non-innovators (table 7). Moreover it is higher for R&D performers than for product innovators, and even higher for firms that do both. Because of the right-censoring we do not know how much longer they survive, but given the information within our sample period, we can say that the firms with both R&D and product innovation survive at least one and a half year longer than non-innovators. This pattern is also visualized in figure 2 where the Kaplan-Meier survival rates are plotted for the four types of firms. In all three sectors, there is a clear monotonic ordering of the survival rate curves. The survival curve for firms with R&D and product innovation is always above the one for firms with R&D only, followed by the one with product innovation only and then by the one for non-innovators.

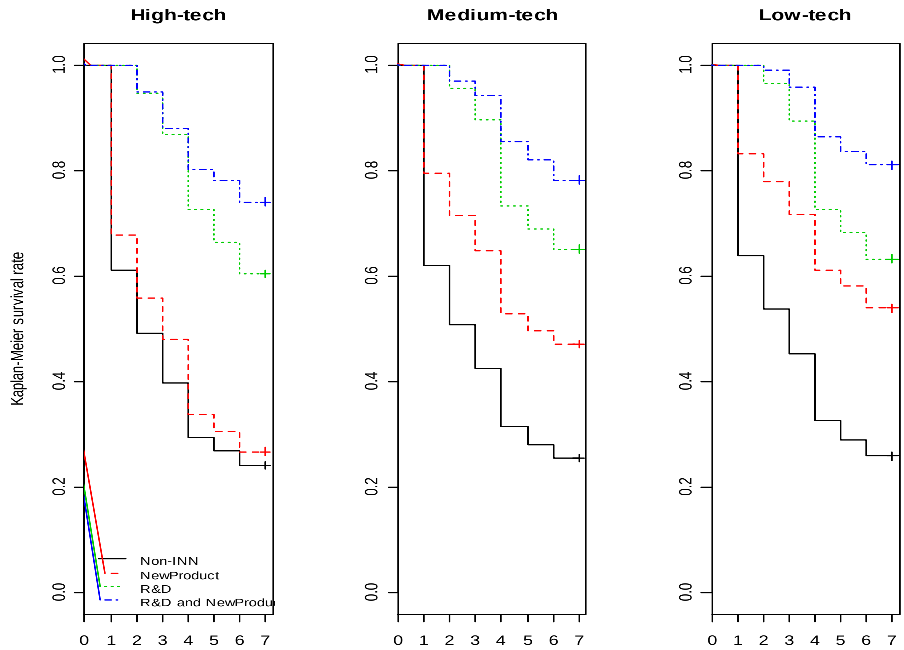

Figure 2 Shape of survival rates depending on the type of innovativeness across technology levels

3.3 Control variables

The descriptive evidence and the non-parametric Kaplan-Meir product limit estimates reveal that there are significant differences in the survival of new firms depending on whether and how they are innovative. We shall explore this innovation dependence by controlling for other factors that could influence the hazard (or the survival) rate and by experimenting with different econometric specifications.

At the firm level, we control for the initial firm size (*entrysize*), measured as the number of employees in the first year of the firm's existence compared to the average employment of the largest firms that make up 50% of the total industry shipment. We take the initial rather than the time-varying contemporaneous firm size to minimize the possibility of an endogeneity bias (see section 3.2). We expect larger firms to have the financial means and to take advantage of scale economies to establish themselves more quickly on the market and to resist the pressure of competition. We control for the ownership status. State-owned (*state-owned*) firms are likely to be less dynamic than privately owned firms, and firms from Hong-Kong, Macao, Taiwan and other foreign countries (*HMTF*) might benefit from connections, complementarities with mother companies and more financial resources to face the wind of competition. Our main interest centers on the influence of innovation. To try and separate out the effects of R&D and product innovations, we interact the R&D intensity (*rdt*), measured by the R&D to sales ratio, with the presence or absence of product innovation (*DN0 and DN1*). And likewise we interact the product innovation intensity (*npt*), measured by the fraction of output due to new products, with the presence or not of R&D (*DR0 and DR1*). If R&D matters even in the absence of product innovation or vice versa, then we could clearly identify whether it is R&D or product innovation that is most relevant for firm survival. We expect the intensity of product innovation to favor survival in the short run and the intensity of R&D to increase long-term survival. We also allow for the fact that the relationship between innovation and survival is nonlinear by adding square terms.

Besides firm-level effects, we also want to control for industry specificities. Instead of including 4-digit industry dummies, we have decided to characterize the sector influence by a number of structural characteristics that might differ from industry to industry. The proportion of product innovators (*toin*) in the total number of firms in the industry serves the opportunity of innovating. Firms in highly innovative environments benefit from spillovers emanating from other firms and from academic research. Audretsch (1991) argues that firms in highly innovative environments face a higher risk of exit. We think that this would rather be the case for small firms. Therefore we consider the proportion of innovators among the firms with less than 300 employees in the industry (*smin*) to represent the competition among innovators, and we expect this variable to have a negative effect. The four-firm concentration ratio (*CR4*), measured by the market share of the 4 largest firms in the industry, captures the monopoly power that is expected to increase the hazard rate because in highly concentrated industries the incumbents are more likely to retaliate effectively against newcomers (Geroski et al, 2007). A higher entry rate (*entryrate*), measured as the proportion of new entries to the total number firms in an industry, is expected to capture lower entry barriers and hence have a positive effect on the hazard rate (Geroski et al., 2007). A high price-cost margin (*pricecost*), measured by the value of shipment net of wage and material costs divided by the value of shipment, indicates the extent to which an establishment could operate at a suboptimal level of scale without being driven out of market (Audretsch and Mahmood, 1995). A growing industry (*growth*), measured by the annual rate of growth of employment in the industry, offers more possibilities for long survival. And finally, we control for four barriers to entry, the capital intensity (*capital*), measured by the capital-labor ratio, which is associated to greater scale economies (White 1982), the advertisement to sales ratio (*advertise*) representing additional costs especially detrimental to small firms, the average wage rate (*wage*), reflecting labor-related sunk costs (Audretsch and Mahmood 1995), and the scale economies measured by the minimum efficient scale (*MES*). All of these measures are expected to have a negative influence on the hazard rate.

We also control for regional effects, as the regulatory environment, the geographical position and the infrastructure may make it easier to do business and survive longer in some provinces than in others. And, last but not least, we control for cyclical effects by constructing dummies for the age of the firm interacted with its year of birth. In other words, we construct year dummies that affect differently firms of different ages so as to allow the cyclical effects to be modulated by learning by doing.

In appendix 1 we list all the variables together with their measurement and abbreviations.

Table 8 Descriptive statistics

	Variable	Definition	High–Tech		Medium–Tech		Low–Tech	
			mean	SD	mean	SD	mean	SD
firm	rdt	R&D intensity (in %)	0.84	3.87	0.14	1.15	0.05	0.59
	NP0	% of non-product innovators	76.34		87.61		91.98	
	NP1	% of product innovators	23.66		12.39		8.02	
	npt	New product intensity (in %)	8.75	25.04	3.07	14.55	1.72	10.96
	DR0	% of non-R&D performers	62.79		81.58		87.81	
	DR1	% of R&D performers	37.21		18.42		12.19	
	entrysize	nb of employees in 1st year/aver. nb of empl. in largest firms	0.13	0.27	0.17	0.31	0.20	0.33
	ownership	% of Hongkong, Macao, Taiwan, & foreign control firms	51.70		68.87		66.01	
	ownership	% of state-owned firms	7.02		10.42		7.60	
	ownership	% of other ownership firms	41.03		20.65		26.33	
sector SIC-4	toin	% of firms in an industry that are product innovators	18.51	6.70	9.43	5.14	5.40	2.83
	smin	% of small firms in an industry that are product innovators	15.16	6.15	7.14	3.91	4.38	2.67
	CR4	Four-firm concentration ratio (in %)	22.33	13.37	15.66	10.77	11.36	8.54
	entryrate	Entry rate (in %)	25.97	15.17	27.02	14.18	27.37	13.39
	pricecost	Price-cost margin (in %)	16.43	3.99	15.50	3.10	15.19	3.32
	growth	Industry growth (in %)	7.76	6.39	4.54	5.69	4.12	8.20
	capital	Capital intensity (in thousand Yuan)	4.92	2.00	5.04	2.11	4.10	2.18
	advertise	Advertisement expenses intensity (in %)	0.48	0.96	0.16	0.48	0.26	0.57
	wage	Average wage per employee (in thousand Yuan)	19.42	8.18	15.18	5.10	12.06	3.03
	MES	Minimum efficiency scale (in thousand Yuan)	0.60	0.21	0.64	0.16	0.68	0.15

As expected, R&D intensity, new product innovation intensity and the frequencies of R&D and new products are higher in the high-tech than in the medium-tech sectors and are the lowest in the low-tech sectors. The initial size, on the contrary, is highest in low-tech sectors and lowest in high-tech sectors. More than half of the firms are controlled by Hong Kong, Macao, Taiwan and other foreign countries. Between 7% and 10% of the firms are state-owned. At the industry level, again the total innovation ratio and the innovation ratio among small firms are highest in the high-tech sectors and lowest in the low-tech sector, and so are the four-firm concentration ratio and the wage rate. The ranking is in the reverse order regarding the minimum efficient scale and the entry rate, but the differences across the three groups of industries are not so big. There is less of a clear pattern with respect to technology regarding the other variables. It is noticeable that the advertisement to sales ratio is substantially higher in the high-tech industries, getting close to 50%.

We did some data cleaning. When new products or R&D intensity were negative, we replaced them by 0. When employment was less than 10, we replaced it by the mean in the sample. If R&D was bigger than sales, we replace it by sales, and if sales of new products was more than output, we replaced it by output.

4. Econometric considerations

Most of the studies on firm survival use the Cox proportional hazard (PH) model, whereby specific covariates determine differences across firms with respect to the baseline hazard model that depends only on time (Audretsch and Mahmood 1995; Agarwal and Audretsch 2001; Cefis and Marsili 2005; Buddenmeyer et al. 2006; Strotmann 2007). However, the Cox partial likelihood method by Cox is based on the assumption of a continuous survival time and on an exact ordering of firms with respect to their failure time, whereas with annual data we are only able to observe failure times at discrete intervals, that is, we only know which firms exit the market from year to year without being able to distinctly order their failure times within each period. In other words, we have non-genuine tied observations, i.e. a certain number of firms exit in a particular year, but we can’t observe the exact time at which they exit. Even the Breslow (1974) and Efron (1977) approximations, and other so-called exact methods developed to deal with tied data, have been shown to lead to biased estimates when the true model is in fact the Cox PH model (Scheike and Sun 2007).

4.1 Complementary log-log model

We therefore applied a discrete time model to explore the relationship between innovation and new firm survival. Suppose T_i is the discrete survival time variable of firm i=1, …, N. The discrete-time hazard rate h_{ij} is defined as:

$$h_{ij} = \Pr(T_i = j | T_i \geq j) \tag{1}$$

From year 1 to the end of year *j* (years are indexed by k), a firm spell is either completed (c_i=1) or right censored (c_i=0). The contribution for a censored spell is given by the discrete time survivor function:

$$\Pr(T_i > j) = S_i(j) = \prod_{k=1}^{j}(1-h_{ik}), \tag{2}$$

and the likelihood contribution of each completed spell is given by the discrete time density function:

$$\Pr(T_i = j) = f_i(j) = \frac{h_{ij}}{1-h_{ij}}\prod_{k=1}^{j}(1-h_{ik}). \tag{3}$$

Using (2) and (3), the log likelihood of the whole sample is:

$$\begin{aligned} \log L &= \log\{\prod_{i=1}^{N}[\Pr(T_i = j)]^{c_i}[\Pr(T_i > j)]^{1-c_i}\} = \log\{\prod_{i=1}^{N}[(\frac{h_{ij}}{1-h_{ij}})^{c_i}\prod_{k=1}^{j}(1-h_{ik})]\} \\ &= \sum_{i=1}^{N} c_i \log(\frac{h_{ij}}{1-h_{ij}}) + \sum_{i=1}^{N}\sum_{k=1}^{j}\log(1-h_{ik})] \end{aligned} \tag{4}$$

We can rewrite (4) as the log likelihood of a new binary variable y_{ik} taking value 1 for spell *i* when it ends at year *k* and 0 otherwise. In other words, for firms that never exit, $y_{ik} = 0$ in all years, and for those that exit during the sample period, $y_{ik} = 1$ at the year of exit and 0 otherwise:

$$\log L = \sum_{i=1}^{N}\sum_{k=1}^{j}[y_{ik}\log h_{ik} + (1-y_{ik})\log(1-h_{ik})] \ . \tag{5}$$

The discrete time duration model can then be estimated by binary variable methods, and time-varying covariates can be incorporated (Jenkins 2005). To complete the specification of the log-likelihood, the functional form of h_{ik} should be specified. Following Prentice and Gloeckler (1978), we assume the hazard rate h_{ik} to be distributed as a *complementary log-log (*or *cloglog)* function, as it has the convenient property that it represents the discrete time representation of an underlying continuous time proportional hazard model:

$$h(x_{ik}) = 1 - \exp[-\exp(\beta_0 + x_{ik}'\beta + \gamma_k)]. \tag{6}$$

By specifying a dummy variable to represent each year, we model the baseline hazard rate γ_k as a step function that describes the evolution of the baseline hazard between censored intervals. Furthermore, this non-parametric specification of the baseline hazard allows us to have a flexible pattern of duration dependence. The x_{ik} is a vector of time-varying covariates. Some of them are firm specific and others are industry specific.

4.2 Unobserved heterogeneity specification

Model (6) is based on the assumption that it includes all possible sources of individual variation of the hazard rate. In addition to adding control variables we have also coped with heterogeneity by estimating the model separately on industry groups, by taking only new firms, by having only new product innovations, and by taking only the 9 most dynamic provinces of China. But there are several determinants of firm survival that cannot be included due to restrictions in the data set. For example, information on entrepreneurs as well as possible public innovation assistance, which are the key factors to start-ups' survival, are not available in our case. As Heckman and Singer (1984) proved, the lack of control for unobserved heterogeneity would severely bias the estimated hazards towards negative duration dependence.

It is a commonly held view that the choice of frailty distribution is not important if the baseline hazard is non-parametrically specified (Meyer, 1990; Han and Hausman, 1990; Manton et al., 1986). The non-parametric approach to specifying frailty distribution is developed by Heckman and Singer (1984). The essential idea of non-parametric approach is that one fits an arbitrary frailty distribution by a set of parameters, including a set of "mass points" and the probabilities of an individual being located at each mass point. There is a discrete (multinomial) rather than a continuous mixing distribution.

Suppose that there are two different types of individuals in our data set so that each individual has certain probabilities associated to the different "mass-points". This implies different intercepts for the hazard function, one for each different type. The hazard model (6) becomes

$$h_{\mathrm{type}}(x_{ik}) = 1 - \exp[-\exp(\mathrm{m}_{\mathrm{type}} + \beta_0 + x_{ik}'\beta + \gamma_k)] \tag{7}$$

Assuming that the mass-point for type1 is normalized to zero, then the hazard rate function (7) becomes

$$h_{\text{type1}}(x_{ik}) = 1 - \exp[-\exp(\beta_0 + x_{ik}'\beta + \gamma_k)] \qquad \text{for type1}$$

$$h_{\text{type2}}(x_{ik}) = 1 - \exp[-\exp(\mathrm{m}_{\text{type2}} + \beta_0 + x_{ik}'\beta + \gamma_k)] \qquad \text{for type2} \tag{8}$$

If $\mathrm{m}_{\text{type2}}>0$, then type2 firms are fast losers relatively to type1 firms, other things being equal.

The likelihood of firm *i* with spell length of *j* years is the probability weighted sum of the contributions arising from type1 or a type2 firm, i.e.

$$L_i = \pi L_{i1} + (1-\pi) L_{i2} \tag{9}$$

where

$$L_{i1} = \left(\frac{h_{ij1}}{1-h_{ij1}}\right)^{c_i} \prod_{k=1}^{j} (1-h_{ik1}) \qquad L_{i2} = \left(\frac{h_{ij2}}{1-h_{ij2}}\right)^{c_i} \prod_{k=1}^{j} (1-h_{ik2}) \tag{10}$$

π is the probability of belonging to type1, and c_i is the censoring indicator.

Alternatively, the unobserved heterogeneity can be treated parametrically by assuming a Gamma or a Gaussian distribution.[6] We have compared the models with different heterogeneity specifications within the nonparametric baseline specification (see appendix table 1). The different frailty specifications provide similar results with regard to the sign and significance of the covariates, but differences in the magnitude of the coefficients.

4.3 Endogeneity bias

To explain as much as possible new firm survival, we have opted for using a range of time-varying covariates. The potential problem with time-varying covariates is that they might be endogenous with respect to the dependent variable. Our firm-level innovation proxies, R&D intensity and new product intensity, may be endogenous to the decision to exit the market, since a firm that knows that it is about to "die" may be less likely to innovate. In another context, this has been referred to in the literature as the "shadow of death" (Griliches and Regev 1995). A positive observed relationship between innovation and death would underestimate the true effect of innovation on survival and a negative relation would overestimate the true effect.

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[6] Strotmann (2007) used the gamma frailty distribution.

To assess the potentiality endogeneity of R&D and/or innovation, we use their initial values instead of their contemporaneous values in each year, thereby ignoring their changes over time. Dropping the time-varying portion of these covariates takes away that part of their variance that is most likely to be tainted by reverse causality. We can consider that the initial value of the covariate serves as an instrument for the future contemporaneous observations. It could be argued that the initial size could be affected by the perceived probability of success, but we consider this unlikely. The estimated results with initial values for the covariates are robust compared to the model with time-varying variables (see appendix table 2). For firms that are both R&D performing and product innovative we notice a slightly higher coefficient for the contemporaneous value than for the initial value of R&D or innovation intensity. For firms that do R&D but are not innovative or that come up with new products without doing any R&D, the hazard rate is more sensitive to the initial value than to the contemporaneous value of R&D or product innovation intensity. Hence although there is a potential endogeneity bias, it is not of very large and does not change the sign of the relationships.[7]

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[7] To some extent, the initial firm size and the initial R&D and innovation intensities capture the firm specific effects, since the initial value of those variables does not vary over time, only across firms. This way of capturing unobserved individual heterogeneity forces, however, the individual effects to be proportional to the initial values of size, R&D and innovation.

5. Empirical results

We have thus estimated the complementary log-log duration model with non-parametric frailty, and time-varying R&D and new product intensities. We have estimated the model separately for three groups of industries (the high-tech, medium-tech, and low-tech industries). The results are tabulated in table 9 and tables 9a to 9c. In tables 9a to 9c we give details of the cyclical, regional and ownership influences on the hazard rate, that, for lack of space, are not included in table 9. The coefficients correspond to the β's in equation (6). They have the same interpretation as in the continuous PH models, i.e. they indicate by how much the hazard rate changes in percentages as the explanatory variable increases by one unit (for the units, see table 8). The hazard rates tabulated in the column next to the coefficients express the new hazard rates in proportion to the baseline hazard rate at the beginning of each period after a marginal change in the explanatory variables.[8]

There is evidence of a nonlinear relationship between innovation activity and new firm survival: the first-order coefficients of R&D intensity and new product intensity are

[8] The hazard rates are obtained by exponentiating the corresponding coefficient divided by hundred if the variable is not expressed in percentages.

negative; the second-order coefficients are positive for R&D intensity and zero for new product intensity. Beyond a certain threshold, the risk associated with innovation activity could have a negative impact on new firm survival. Below the threshold, the intensity of R&D or product innovation has marginally a higher impact on firm survival (or conversely on the hazard rate) in medium-tech industries than in high- and low-tech industries. The decrease in the hazard rate following a marginal increase in R&D intensity might be lower in high-tech industries because there R&D is riskier being typically geared at satisfying new demands instead of merely improving on existing demands. Furthermore, new firms in high-tech industries are likely to operate in a more competitive environment that leads to a higher risk of exit. In low-tech industries, the higher effect on the hazard rate of a marginal increase in innovation compared to the medium-tech industry may reflect lower rates of return to innovative efforts there compared to medium-tech industries.

We have interacted R&D intensity with the presence or not of product innovation and likewise product innovation intensity with the presence or not of R&D activities. It turns out that R&D efforts for non-product innovators have a stronger impact on survival than R&D efforts for product innovators, especially in medium- and low-tech industries. Thus it seems that it is the innovation effort more than the innovation success that influences firm survival. Survival results more from long-term innovation efforts than from short-term product introductions on the market. In all three industry groups, the results indicate that product innovation has a stronger effect on survival if it is accompanied with own R&D. This result confirms the superior importance of R&D over product innovation. It could also be interpreted as showing that product innovation with own R&D efforts has a stronger impact on firm survival than product innovation through copying, licensing or benefiting from spillovers. Another explanation for the higher effect of R&D over product innovation on firm survival is that a firm that executes R&D does not only aim at producing a new product, but also at introducing process innovations in order to raise productivity and lower cost, which leads to a higher possibility of survival. It is especially important for new firms to catch up with the average level of efficiency as quickly as possible to avoid being "kicked out" of the market.

Firms that start larger have a lower hazard rate than firms that start with a smaller size: a one percentage point increase in the number of employees compared to the largest firms in the industry at the start decreases the hazard rate by 1.1% in high-tech industries and by 0.7 % in medium- and low-tech industries.

Regarding the industry-specific control variables, there is more variation across industries. The proportion of product innovators among all firms in an industry decreases the hazard rate in medium- and low-tech industries whereas the proportion of product innovators among the small firms (less than 300 employees) increases the hazard rate everywhere. In China the threat of competition comes from innovation in small firms (contrary to Audretsch's (1991) finding that the regime with small firms innovating promotes survival). As in other studies, the survival rate is negatively influenced by the extent of scale economies (MSE), the four-firm concentration ratio characterizing the industry structure, and in high-tech industries, a decrease in the rate of new entrants. The explanation thus seems to be that incumbents are better able to control the market. The price-cost margin at the industry level is not significantly related to firms' survival. Industry growth increases the hazard rate in high-tech industries but lowers it in medium- and low-tech industries. A higher capital intensity or wage rate at the sector level decreases the hazard rate whenever the effect is statistically significant. A higher advertisement to sales ratio in the industry decreases the hazard rate in high-tech industries but reflects competitive pressure in medium- and low-tech industries.

As can be seen from table 9a, the baseline hazard has been increasing till 2004 and decreasing afterwards: for firms appearing in 2000, the hazard rate increased in the first 4 years, for those that began in 2001 it increased in the first three years, for those with start year 2002 it increase for the first two years, and so on. This pattern is pervasive across all industry groups. This pattern is even more clearly visible in figure 3. The baseline hazard rate follows the same pattern but with different starting years. The cyclical effect does not seem to play out very differently for firms of different ages.

There is clearly a regional pattern. In almost all provinces the hazard rate is lower than in Beijing with the exception of Tianjin for medium- and low-tech and Jiangsu for low-tech. The regional dummies probably capture industry-specific effects at a finer level of detail than the three categories that we have considered, reflecting industry-specific technologies, product lifecycles and market structures.

Finally, state-owned firms die faster than private firms under Chinese control, a reflection of the privatization of the Chinese economy, but firms owned by foreigners tend to survive longer than Chinese privately held firms. We do not observe the phenomenon of lower survival rate for foreign-owned firms that Bernard and Sjöholm (2003) uncovered for Indonesian firms.

There are around 72% of type I firms and 28% of type II firms, the fast losers with a positive intercept for the baseline hazard function (2.554 for firms in the high-tech industry) and hence a higher hazard rate than those of type I.

Table 9 Complementary log-log model with non-parametric frailty

Variables		high-tech			medium-tech			low-tech		
		coef	hazard rate	p-value	Coef	hazard rate	p-value	coef	hazard rate	p-value
firm	rdt*DN0	-0.078	0.925	0.000	-0.136	0.873	0.000	-0.107	0.899	0.000
	rdt*DN1	-0.079	0.924	0.000	-0.109	0.897	0.000	-0.081	0.922	0.047
	$(rdt)^2$*DN0	0.001	1.001	0.000	0.002	1.002	0.000	0.001	1.001	0.006
	$(rdt)^2$*DN1	0.001	1.001	0.000	0.001	1.001	0.000	0.001	1.001	0.415
	npt*DR0	-0.024	0.976	0.001	-0.033	0.967	0.000	-0.032	0.969	0.000
	npt*DR1	-0.039	0.962	0.000	-0.055	0.946	0.000	-0.045	0.956	0.000
	$(npt)^2$*DR0	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000
	$(npt)^2$*DR1	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000
	Entrysize	-1.086	0.989	0.000	-0.681	0.993	0.000	-0.732	0.992	0.000
	ownership dummy	included			included			included		
sector	toin	-0.002	0.998	0.570	-0.011	0.990	0.000	-0.058	0.944	0.000
	smin	0.044	1.045	0.000	0.009	1.010	0.013	0.033	1.033	0.000
	CR4	0.015	1.015	0.000	0.007	1.007	0.000	0.000	1.000	0.178
	entryrate	-0.007	0.993	0.018	0.001	1.001	0.478	0.000	1.000	0.000
	pricecost	-0.001	0.999	0.889	-0.001	0.999	0.767	0.000	1.000	0.000
	growth	0.014	1.014	0.000	-0.006	0.994	0.000	-0.018	0.982	0.000
	capital	-0.038	0.962	0.001	0.002	1.002	0.465	-0.009	0.991	0.000
	advertise	-0.045	0.956	0.059	0.082	1.086	0.000	0.159	1.172	0.000
	wage	-0.037	0.963	0.000	-0.027	0.974	0.000	-0.078	0.925	0.000
	MES	0.005	1.005	0.954	0.505	1.656	0.000	0.689	1.993	0.000
region	province dummy	included			included			Included		

cyclical	startyear*age dummy	included		included		Included	
constant		-1.613	0.001	-2.400	0.000	-1.121	0.000
M2 constant		2.554	0.000	2.674	0.000	3.073	0.000
logitp2 constant		-0.954	0.000	-0.934	0.000	-0.977	0.000
Prob. Type 1		0.722	0.000	0.718	0.000	0.727	0.000
Prob. Type 2		0.278	0.000	0.282	0.000	0.273	0.000
Number of firm-year observations		n=43,325		n=354,045		n=243,248	
Log-likelihood		-15215		-122078		-86,256	

Table 9a Complementary log-log model with non-parametric frailty: cyclical effects										
variables		high-tech			medium-tech			low-tech		
		coef	hazard rate	p-value	coef	hazard rate	p-value	coef	hazard rate	p-value
cyclical	2000*age1	-0.006	0.994	0.987	0.558	1.748	0.000	-0.343	0.710	0.000
	2000*age2	-0.063	0.939	0.880	0.352	1.422	0.032	-0.390	0.677	0.000
	2000*age3	0.131	1.140	0.757	0.462	1.588	0.005	-0.081	0.923	0.091
	2000*age4	0.793	2.209	0.060	1.251	3.493	0.000	0.693	1.999	0.000
	2000*age5	0.160	1.174	0.724	0.384	1.469	0.027	-0.106	0.900	0.110
	2000*age6+7	-0.505	0.603	0.248	-0.223	0.800	0.196	-0.408	0.665	0.000
	2001*age1	-0.673	0.510	0.100	-0.406	0.666	0.011	-1.532	0.216	0.000
	2001*age2	-0.440	0.644	0.285	0.011	1.011	0.944	-0.810	0.445	0.000
	2001*age3	0.412	1.509	0.320	1.032	2.805	0.000	0.542	1.719	0.000
	2001*age4	0.066	1.068	0.880	0.239	1.270	0.160	-0.294	0.746	0.000
	2001*age5+6	-0.814	0.443	0.057	-0.181	0.835	0.281	-0.638	0.529	0.000
	2002*age1	-0.601	0.548	0.143	-0.288	0.750	0.071	-1.384	0.251	0.000
	2002*age2	-0.006	0.994	0.988	0.562	1.755	0.000	-0.039	0.962	0.425
	2002*age3	-0.325	0.723	0.454	0.050	1.051	0.766	-0.374	0.688	0.000
	2002*age4+5	-0.513	0.599	0.223	-0.325	0.722	0.053	-0.589	0.555	0.000
	2003*age1	-0.082	0.921	0.840	0.295	1.344	0.061	-0.509	0.601	0.000
	2003*age2	-0.388	0.678	0.360	-0.274	0.760	0.094	-0.789	0.454	0.000
	2003*age3+4	-0.502	0.605	0.231	-0.562	0.570	0.001	-0.771	0.463	0.000
	2004*age1	0.262	1.299	0.523	0.293	1.340	0.066	-0.630	0.533	0.000
	2004*age2+3	-0.581	0.559	0.155	-0.519	0.595	0.001	-1.073	0.342	0.000
	2005*age1+2	-1.144	0.319	0.005	-1.153	0.316	0.000	-1.886	0.152	0.000

Table 9b Complementary log-log model with non-parametric frailty: regional effects										
variables		high-tech			medium-tech			low-tech		
		coef	hazard rate	p-value	coef	hazard rate	p-value	coef	hazard rate	p-value
region	Beijing	drop			drop			Drop		
	Fujian	-0.807	0.446	0.000	-0.931	0.394	0.000	-0.900	0.406	0.000
	Guangdong	-0.686	0.504	0.000	-0.594	0.552	0.000	-0.368	0.692	0.000
	Jiangsu	-0.305	0.737	0.000	-0.024	0.976	0.537	0.072	1.075	0.010
	Liaoning	-0.260	0.771	0.021	-0.413	0.662	0.000	-0.330	0.719	0.000
	Shandong	-0.477	0.620	0.000	-0.444	0.642	0.000	-0.261	0.770	0.000
	Shanghai	-0.509	0.601	0.000	-0.374	0.688	0.000	-0.119	0.888	0.007
	Tianjin	-0.272	0.762	0.024	0.308	1.361	0.000	0.503	1.653	0.000
	Zhejiang	-0.728	0.483	0.000	-0.493	0.611	0.000	-0.422	0.656	0.000

Table 9c Complementary log-log model with non-parametric frailty: ownership effects										
variables		high-tech			medium-tech			low-tech		
		coef	hazard rate	p-value	coef	hazard rate	p-value	coef	hazard rate	p-value
Ownership	other	drop			drop			drop		
	HMTF	-0.608	0.544	0.000	-0.473	0.623	0.000	-0.406	0.666	0.000
	State owned	0.374	1.454	0.000	0.496	1.642	0.000	0.496	1.642	0.000

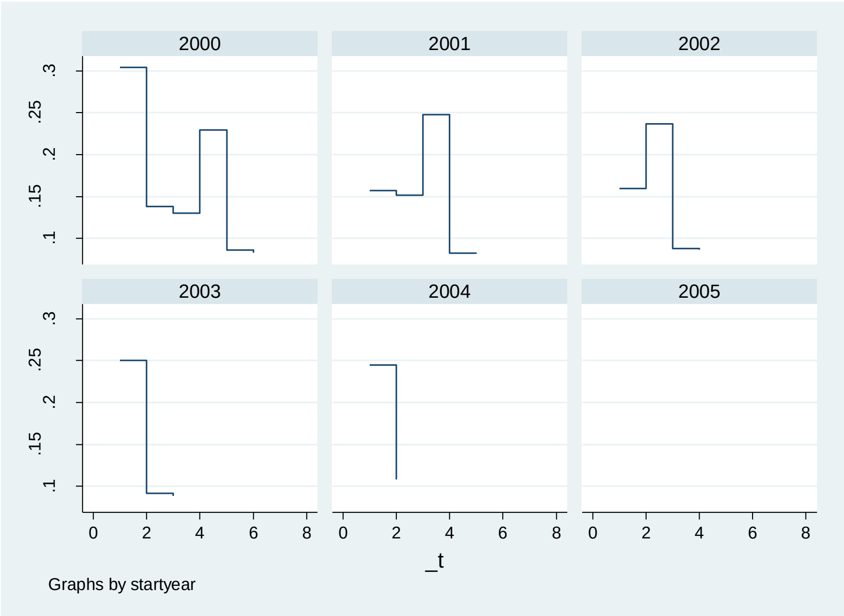

Figure 3 Baseline hazard rate of new firm started in 2000-2005

6. Conclusion

Using a large dataset of over 100,000 Chinese firms created between 2000 and 2006, we explore whether there is a link between innovation effort (R&D) or innovation output (the share of innovative sales) and the firm's duration of survival. We estimate a complementary log log model with time-varying explanatory variables controlling for individual heterogeneity.

We obtain the following findings regarding the determinants of firm survival in China. First, innovation decreases the hazard rate of firm disappearance, both ex ante (i.e. in the form of R&D as a measure of innovation efforts) and ex post (i.e. in the form of new product sales as a measure of innovation success). Disappearance could mean bankruptcy or absorption by another firm. The data do not allow us to go beyond the conclusion that firms cease to exist. Between the two sides of innovation, the input and the output side, R&D seems to matter more for survival than the success brought about from product innovations. Second, there seems to be an inverted-U relationship between R&D or innovation output and long-term survival, suggesting that too much R&D or product innovation can cause firms to die, perhaps because of excessive risk. Third, survival has a cyclical behavior, and it varies across provinces for reasons that we intend to investigate in another paper. Finally, it varies with ownership. State-owned firms have a higher hazard rate than privately owned firms, which have a higher hazard rate than foreign-owned firms. This ownership behavior reflects the ongoing privatization and liberalization of the Chinese economy.

Promoting innovation, and even more so R&D efforts, is one way of keeping firms alive longer. Avoiding firm closures may be an indirect way of avoiding worker layoffs. But there is also an optimal level of R&D and/or innovation beyond which the hazard rate of firm closure increases. This could possibly be due to higher levels of risk or decreasing returns. It might be interesting to find out what this optimal innovativeness is in different industries. This would require an analysis at a finer level of detail than the three industry groupings we have considered in this paper. We leave this for future work.

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Appendix A: Technology-Industry Classification

Chinese GB/T 4754-2002	GB/T 4754-2002 Code
Low Technology industries	
Processing of Food from Agricultural Products	13
Manufacture of Foods	14
Manufacture of Beverages	15
Manufacture of Tobacco	16
Manufacture of Textiles	17
Manufacture of Wearing Apparel and Other Fiber Products	18
Manufacture of Leather, Fur, Down and Related Products	19
Manufacture of Furniture	21
Manufacture of Paper and Paper Products	22
Printing, Reproduction of Recording Media	23
Manufacture of Culture, Education and Sport Products	24
Manufacture of Artwork and Other Manufacturing	42
Manufacture of recycling	43
Medium Technology industries	
Processing of Petroleum, Coking	25,excluding 253
Manufacture of Raw Chemical Materials and Chemical Product, excluding Fine Chemical Product	26,excluding 2665
Manufacture of Chemical Fibers	28
Manufacture of Rubber	29
Manufacture of Plastics	30
Manufacture of Non-metallic Mineral Products	31
Smelting and Pressing of Ferrous Metals	32
Smelting and Pressing of Non-ferrous Metals	33
Manufacture of Metal Products	34
Manufacture of General Purpose Machinery	35
Manufacture of Special Purpose Machinery, excluding Medicine Machinery	36,excluding 368
Manufacture of Transport Equipment ,excluding aircraft and spacecraft	37,excluding 376

Manufacture of Electrical Machinery and Equipment	38
High Technology industries	
Processing of Nuclear Fuel	253
Manufacture of Fine Chemical Product	2665
Manufacture of Medicine and Pharmaceuticals	27
Manufacture of Medicine Machinery	368
Manufacture of Aircraft and Spacecraft	376
Manufacture of Electronic and Communication Equipment	40
Manufacture of Precision Instruments and Office Machinery	41

Note: The classification used here is in line with the high-tech industry classification compiled by the National Bureau of Statistics (NBS) of China and the technology industry classification compiled by the OECD.

Appendix B: Variable definitions

level	variable	definition	Measurement
firm	rdt	R&D intensity	R&D divided by shipments (in %)
	npt	new product intensity	new product output divided by total output (in %)
	DN0	non-product innovator dummy	non-product innovator 1, else 0
	DN1	product innovator dummy	product innovator 1, else 0
	DR0	non-R&D performer dummy	non-R&D performer 1, else 0
	DR1	R&D performer dummy	R&D performer 1, else 0
	entrysize	firm size in initial year	employment/mean employment of the largest plants in the industry that account for one-half of the industry value of shipments in initial year
	HMTF	Hong Kong, Macao, Taiwan and Foreign firm dummy	HMTF firm in initial year 1, else 0
	state	state owned dummy	state-owned firm in initial year 1, else 0
	other	other ownership firm dummy	other ownership in initial year 1,else 0
sector SIC-4	toin	total innovation ratio	number of innovators/total number of firms (in %)
	smin	small innovation ratio	number of innovators/total number of firms (for firms with < 300 employees) (in %)
	CR4	four-firm concentration ratio	total market share of the 4 largest firms in the industry (in %)
	entryrate	entry rate	number of entry firms divided by total number of firms (in %)
	pricecost	price-cost margin	value of shipments minus labor and material costs/value of shipments (in %)
	growth	industry growth	average rate of growth of employment in the industry from start-up year to observed year (in %)
	capital	capital intensity	capital per employee (in thousand Yuan)

	advertise	advertisement intensity	advertisement expenses divided by shipments (in %)
	wage	average wage per employee	total wages divided by number of employees (in thousand Yuan)
	MSE	minimum efficiency scale	mean shipment of the largest plants in the industry accounting for one-half of the industry value of shipment (in thousand Yuan)

Appendix table 1

Estimation results based on different unobserved heterogeneity specifications

Medium-tech industries

Variables	Non-parametric		Gaussian		Gamma	
	coef	p-val	coef	p-val	coef	p-val
rdt*DN0	-0.078	0.000	-0.136	0.000	-0.169	0.010
rdt*DN1	-0.079	0.000	-0.163	0.000	-0.261	0.002
$(rdt)^2$*DN0	0.001	0.000	0.002	0.000	0.004	0.000
$(rdt)^2$*DN1	0.001	0.000	0.002	0.000	0.004	0.018
npt*DR0	-0.024	0.001	-0.044	0.000	-0.084	0.000
npt*DR1	-0.039	0.000	-0.074	0.000	-0.195	0.000
$(npt)^2$*DR0	0.000	0.000	0.000	0.000	0.001	0.000
$(npt)^2$*DR1	0.000	0.000	0.001	0.000	0.002	0.000
entrysize	-1.086	0.989	-1.142	0.989	-1.742	0.998
ownership dummy	included		included		included	
toin	-0.002	0.570	-0.019	0.000	-0.055	0.000
smin	0.044	0.000	0.020	0.000	0.077	0.000
CR4	0.015	0.000	0.010	0.000	0.023	0.000
entryrate	-0.007	0.018	-0.008	0.000	-0.015	0.000
pricecost	-0.001	0.889	-0.007	0.000	0.005	0.637
growth	0.014	0.000	-0.002	0.490	-0.021	0.000
capital	-0.038	0.001	0.006	0.152	-0.001	0.969
advertise	-0.045	0.059	0.134	0.000	0.371	0.000
wage	-0.037	0.000	-0.045	0.000	-0.084	0.000
MES	0.005	0.954	0.577	0.000	1.319	0.000
province dummy	included		included		included	
start year* age dummy	included		included		included	
Number of firm-year observations	n=354,045					
Likelihood-ratio test for individual effect	significant		significant		Significant	

Appendix table 2 "Testing" for endogeneity

Variables		High-tech				Medium-tech				Low-tech			
		contemporaneous		initial		contemporaneous		initial		contemporaneous		initial	
		Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Firm	rdt*DN0	-0.080	0.000			-0.141	0.000			-0.105	0.000		
	rdt*DN1	-0.069	0.000			-0.110	0.000			-0.052	0.141		
	$(rdt)^2$*DN0	0.001	0.000			0.002	0.000			0.001	0.001		
	$(rdt)^2$*DN1	0.001	0.000			0.001	0.000			0.000	0.390		
	rdt0*DN0			-0.129	0.000			-0.211	0.000			-0.187	0.000
	rdt0*DN1			-0.046	0.002			-0.032	0.070			0.037	0.180
	$(rdt0)^2$*DN0			0.001	0.000			0.002	0.000			0.002	0.000
	$(rdt0)^2$*DN1			0.001	0.002			0.000	0.238			-0.001	0.272
	npt*DR0	-0.019	0.001			-0.025	0.000			-0.017	0.000		
	npt*DR1	-0.031	0.000			-0.042	0.000			-0.032	0.000		
	$(npt)^2$*DR0	0.000	0.000			0.000	0.000			0.000	0.000		
	$(npt)^2$*DR1	0.000	0.000			0.000	0.000			0.000	0.000		
	npt0*DR0			-0.032	0.000			-0.020	0.000			-0.008	0.008
	npt0*DR1			-0.018	0.000			-0.027	0.000			-0.009	0.152
	$(npt0)^2$*DR0			0.000	0.000			0.000	0.000			0.000	0.196
	$(npt0)^2$*DR1			0.000	0.011			0.000	0.000			0.000	0.946
	entrysize	-0.935	0.000	-0.994	0.000	-0.580	0.000	-0.594	0.000	-0.524	0.000	-0.624	0.000
	ownership dummy	included		included		included		included		included		included	
sector	toin	0.003	0.009	0.003	0.383	-0.008	0.000	-0.008	0.000	-0.064	0.000	-0.049	0.000
	smin	0.029	0.037	0.029	0.000	0.005	0.054	0.005	0.089	-0.048	0.000	0.031	0.000

	CR4	0.010	0.013	0.011	0.000	0.005	0.000	0.005	0.000	0.002	0.001	0.001	0.187
	entryrate	0.001	0.006	0.001	0.555	0.005	0.000	0.005	0.000	0.007	0.000	0.004	0.000
	pricecost	0.005	0.012	0.005	0.199	0.000	0.944	0.000	0.934	-0.004	0.057	-0.002	0.491
	growth	0.013	0.017	0.013	0.000	-0.005	0.000	-0.005	0.000	-0.009	0.000	-0.010	0.000
	capital	-0.033	-0.017	-0.032	0.000	-0.002	0.336	-0.002	0.359	0.012	0.000	-0.012	0.000
	advertise	-0.033	0.002	-0.031	0.082	0.050	0.000	0.051	0.000	0.188	0.000	0.094	0.000
	wage	-0.027	-0.022	-0.028	0.000	-0.015	0.000	-0.015	0.000	-0.084	0.000	-0.042	0.000
	MES	0.059	0.199	0.061	0.394	0.398	0.000	0.403	0.000	0.401	0.000	0.547	0.000
region	province dummy	included		included		Included		included		included		included	
cyclical	Start year*age dummy	included		included		included		included		included		included	
Number of firm-year observations		n=43,325		n=43,325		n=354,045		n=354,045		n=243,248		n=243,248	
Log-likelihood		-15,250		-15,292		-122,239		-122,355		-86,406		-86,435	

N.B. rdt(0)=R&D intensity in period t(0), npt(0)=new product intensity in period t(0), t(0) being the initial year