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'Indigenous' innovation with heterogeneous risk and new firm survival in a transitioning Chinese economy

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ABSTRACT

This paper explores how heterogenous risk drives the firm innovation–survival relationship using a large sample of new entrepreneurial firms in China. Results show that innovation increases the probability of survival, although the impact on firm survival is conditioned by the timing of the innovation, the characteristics associated with the innovation strategy, along with the level of risk embodied in the innovation process. Cautious innovators are found to survive longer and contribute to a higher social welfare via gains in firm efficiency. In contrast, risky innovators are less likely to survive, are less efficient, and are only sometimes compensated for their risk in terms of higher profits. Results therefore show that other factors besides higher payoffs force some firms to engage in riskier innovation strategies.

1. Introduction

Firm entry and exit are important aspects of the evolution of industries (Caves, 1998; Tybout, 2000). In the Schumpeterian tradition, models of industry evolution predict that the process of market selection will penalize firms with a lower 'environmental fit' leading to early exit (Nelson and Winter, 1982). The firm will carry out innovation in an attempt to modify its 'environmental' competencies in order to increase its efficiency, capture more market share and survive longer. In models of 'active learning' (Nelson and Winter, 1982; Ericson and Pakes, 1995), a firm will reduce its probability of failure only if it is able to appropriate gains related to the new opportunities created by the innovative search process, otherwise the unproductive investment will increase the probability of failure.

The firm-learning and industry-dynamic models are all originally developed in advanced market economies in which market entry and exit is determined by economic efficiency. These models assume away the institutional environment, and predict a one-to-one relationship between productivity and survival (Baldwin, 1995). Transitioning economies however, by definition, undergo substantial changes in their political, economic and legal institutions, which present new opportunities and challenges to innovative activities not present in advanced market economies.

In China, as well as in other transitioning economies, the risk of engaging in innovative activities is comparatively higher than in advanced market economies, due to widespread intellectual property theft, unlawful abrogation of legal contracts and unfair competitive practices, the shortage of venture capital, poor institutional protection, and insufficient market demand (Zhou, 2008). The presence of these institutional barriers increase the fixed costs associated with innovation. As a result of the poor institutional and legal frameworks, Chinese innovative firms must depend heavily on state intervention and protectionism in order to survive.

In general, the impact of innovation on firm survival in transitioning economy contexts is not well-understood. How do certain characteristics – i.e. public subsidies, FDI, global competition – influence the innovation–survival relationship? How do various dimensions of risk – leverage, diversification, market and location – impact the innovation–survival relationship? In an attempt to answer these questions, the current paper explores the innovation–survival relationship using a sample of nearly 200,000

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new entrepreneurial firms in Chinese manufacturing during the 1998–2007 period.

In addition, the scope of the empirical analysis extends beyond measuring only the innovation–survival relationship. Following Fernandes and Paunov (2014), a dynamic framework is used to estimate the impact of innovation on firm profits and efficiency, respectively. This framework, although far from a rigorous welfare analysis, is capable of discerning between the private returns to innovation and the social returns to innovation that extend beyond the firm.

The outline of this paper is as follows. The subsequent section gives an overview of the survival literature. Section 3 introduces the hazard model. Section 4 provides information on the data source and variable development. Section 5 presents the empirical results, and Section 6 concludes.

2. Firm innovation and survival: a review

A number of recent studies focusing on different country contexts has emerged in the literature linking the innovation activities of the firm to its survival. The majority of these studies find that innovation, in general, tends to reduce the risk of business failure (Perez et al., 2004; Cefis and Marsili, 2006, 2011). At the same time, some studies highlight the fact that not all types of innovation result in a higher probability of survival (Buddelmeyer et al., 2010; Zhang and Mohnen, 2013; Fernandes and Paunov, 2014).

Rather, the type of innovation – e.g. product or process, radical or incremental – is found to have important implications on the innovation–survival relationship. Banbury and Mitchell (1995), for instance, find that incremental innovation does not effect firm failure in the U.S. cardiac pacemaker industry. For Australian firms, Buddelmeyer et al. (2010) find that a more radical innovation strategy may increase the risk of firm exit.

Astebro and Michela (2005) further suggest that firm survival is not only contingent on the *type* of innovation but also on the innovation strategy, or more precisely, *how* firms carry out innovation. In other words, the innovation–survival relationship is, at least in part, conditioned by the level of risk embodied in how innovation is carried out by the firm. Offering some support for this view, Zhang and Mohnen (2013) find in their study of Chinese manufacturing firms that R&D and new innovation sales both exhibit an inverted-U relationship with long-term survival.

In advanced market-based economies, firms pursue more risky innovation strategies in the hopes of receiving a higher payoff. In less developed country contexts, however, riskier innovation does not necessarily result in higher potential rewards. In their study of firm survival in Chile, Fernandes and Paunov (2014) find that risky innovators are only sometimes compensated for their risk in terms of higher payoffs. The authors argue that pursuing a risky innovation strategy is irrational, and suggest that other factors besides higher payoffs force some firms to engage in risky innovation. Such factors that are common in transitioning economies include market failures, information asymmetries, bankruptcy risks and agency conflicts.

3. Model specification

Hazard analysis describes the probability of survival for a business in a time span t, conditional that it survived up to $t-1$ periods (Δt), and given firm characteristics. The general hazard function represents the probability of failure of a firm during $t+\Delta t$ conditioned on the fact that the firm survives up to the time t. The hazard function is expressed as:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t <= T < t + \Delta t | T >= t)}{\Delta t} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \quad (1)$$

where $f(t)$ is the density function, $F(t)$ is the distribution function and $S(t)$ is the survival function. The survival function is $S(t) = exp(-\Lambda(t))$ and $\Lambda(t) = \int_0^t h(u)du$ is the cumulative hazard function.

A key drawback of the typical hazard models like Cox or discrete-time hazard is that they are subject to the proportionality assumption, which is unlikely to hold true when examining multiple cohorts. One way to deal with this shortcoming is to include a time-scaling factor using accelerated time failure (AFT) models. Using an AFT model relaxes the proportionality assumption and takes into account the fact that the relationship between innovation and survival varies over time. One main shortcoming of the conventional AFT approach, however, is that it does not control for unobserved firm heterogeneity. To address this issue, a frailty term is added (referred to as FAFT) to include random effects. In a FAFT model, the survivor function at time t, $S(t|\mathbf{x}_i, \alpha)$, are assumed to be of the following form

$$S(t|\mathbf{x}_i, \alpha) = S_0\left(\frac{t}{\psi_i}\right) \quad (2)$$

where $S_0(t)$ is the baseline survival model associated with a set of time-varying covariates, $\mathbf{x}_i$, and random effects α. The scaling factor ψ_i is expressed as follows,

$$\psi_i(\mathbf{x}_i, \alpha) = \exp(\eta_i) = \exp(w + \boldsymbol{\beta}'\boldsymbol{X_i}) \quad (3)$$

where $\alpha = \exp(w)$ is assumed to have a gamma distribution with distribution function $G(\alpha)$, and η_i is the linear component of the model. Thus, conditionally on α, the AFT model is assumed to hold, and the term α represents the frailty term with the mean of the distribution set to the value unity.

The model is fit using maximum likelihood. The likelihood function with left-truncated and right-censored observations is given in general form as:

$$L = \prod_{i=1}^{g} \int_0^\infty \left\{ \prod_{j=1}^{N} h(T_i)^{c_i} \left(\frac{S(T_i)}{S(E_i)}\right) \right\} dG(\alpha) \quad (4)$$

where E_i takes into account the left truncation, giving the first time a firm enters into the panel; c_i takes into account right censoring and take the value of 1 for firms that fail and 0 for firms that are still active at the end of observation time.

An appropriate underlying distribution must be chosen to estimate the hazard function. The log–logistic distribution provides a good starting place as it has a flexible form that allows for monotonous functional forms, and other shapes as well. The hazard function with a log–logistic distribution is:

$$h(t|\mathbf{x}_i, \alpha) = \frac{\psi_i^{1/\lambda}\, t^{(1/\lambda - 1)}}{\lambda[1 + (\psi_i t)^{1/\lambda}]} \quad (5)$$

The shape of the function is determined by λ. For $\lambda >= 1$, the functional form is decreasing monotonously and $0 < \lambda < 1$ has a bell-shaped form. To obtain the survival probabilities, the hazard model in Eq. (6) can be equivalently expressed as a log linear model for the random variable T_i by writing

$$\log(T) = \alpha + \mu + \boldsymbol{\beta}'\boldsymbol{X} + \sigma\epsilon \quad (6)$$

where μ, σ are unknown location and scale parameters, and ϵ has a distribution that determines T. Written in this way a positive coefficient represents a longer survival spell.

4. Data and variable development

This analysis utilizes the Annual Report of Industrial Enterprise Statistics compiled by the State Statistical Bureau of China for the years 1998–2007. Included in the data are all firms with an annual turnover over 5 million Renminbi (approximately \$600,000), accounting for 90% of industrial output in China. An extensive set of firm characteristics are included in the database, including information on firm production, sales revenues, employment, geographic location, industry affiliation, new product or process sales, sources of finance, and so forth.[1]

Numerical IDs are assigned to each firm using the firm's name, industry, address, etc. to link firms over time. When possible, firms are tracked as their boundaries or ownership structure change. On occasion, restructuring, merger, or acquisition results in new IDs being assigned to firms. The fraction of firms in a year that can be linked to a firm in the previous year ranges from 84.5% in the years 1998–1999 up to 92.2% in the final two years (2006–2007). Overall, 95.9% of all year-to-year matches are constructed using firm IDs, and 4.1% using other information on the firm. See Brandt et al. (2012) for further treatment of the data.

The sample is restricted to new firms where the majority shareholder is designated as a private, non-state-owned entity. The analysis focuses on entrepreneurial firms because their survival is based more on achieving competitive competency in the market, unlike for instance, state-owned enterprises whose survival may rest more on political connections or policy directives than on competitiveness. A clear benefit of focusing on new firms, aside from guiding policy, is that they are less constrained by previous decisions, i.e. past capital installments, that may influence the firm's innovation activities, thereby reducing concerns of endogeneity.

4.1. Variable development

4.1.1. Performance indicators

Firm entry, exit and duration are determined based on the firm's unique numerical ID. An important issue to consider is how to properly interpret firm exit, distinguishing financial distress and closure from that of other reasons for firm exit such as merger or acquisition or falling below the minimum sales threshold of \$600,000. Exit in this study is defined as firm closure. This claim is asserted for two reasons.

First, the panel data was carefully constructed in such a way that, when possible firms received a new firm ID if they go through restructuring, merger or acquisition, thereby reducing the risk that firms exit the survey due to merger or acquisition. Second, due to the measurement procedures of the China Statistical Bureau, the sales threshold barrier is not strictly enforced. Over the time period of analysis, 5% of privately owned firms reported sales below the five million RMB sales threshold.

The entry year of the firm is identified for the first year, t, that the firm is observed but not in any years prior to t. The exit year of the firm is defined as the last year, t, that the firm reported information but not in the year $t + 1$, $t + 2, \ldots, 2007$. The duration of a firm is defined by counting the number of years the firm is in operation, excluding its initial year of operation. All firms that entered and exited the survey in the same year are removed from the sample to reduce noise in the data from firms that are likely hovering around the sales threshold.

In addition to firm duration, profit rates and productivity are also used as proxies to measure firm performance beyond basic survival. The firm's profit rates is calculated as the ratio of firm profits (total plant sales minus materials costs, electricity costs, expenditures on wages, etc.) to plant sales.

While labor productivity is generally the most widely used measure of firm productivity, it does not take into account capital intensity. This is a key disadvantage, especially, in the case of China where the share of labor earnings in GDP accounts for less than one half of Chinese manufacturing. Instead, estimates of the firm's total factory productivity (TFP) are obtained following the three-step approach developed in Olley and Pakes (1996). TFP is the difference between the growth rate of output and the weighted average of the input factors' growth rate, and assumes the contribution from technological progress. Before the TFP estimates can be obtained, other variables like value added and the real capital stock must first be developed. The real value added (VA) is constructed by separately deflating output, net of goods purchased for resale and indirect taxes, and material inputs, where the input deflators are calculated using the output deflators and information from China's 2002 National Input–Output (IO) table.

Next, the real capital stock for 1998 is developed using the perpetual inventory method, assuming a depreciation rate of 9% and deflating annual investment using the Brandt–Rawski deflator. Following 1998, the observed change in the firm's nominal capital stock at original purchase prices is used as the estimate for the nominal fixed investment using the same rate of depreciation and deflator to roll the real capital stock estimates forward.

After constructing the firm's VA and real capital stock, the TFP estimates are obtained as follows. In the first step, consider a simple Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + u_{it} \tag{7}$$

where y_{it} is logged value added for firm i in period t. The coefficients l_{it}, k_{it} and a_{it} represent the log of labour, capital and age of firm i in year t. $u_{it} = \Omega_{it} + \eta_{it}$, where Ω_{it} is the productivity shock observed by the firm's decision makers and η_{it} is the unobserved errors.

In the second step, the investment equation is inverted nonparametrically to proxy for unobserved productivity that controls for the non-random sample selection that results from differing exit probabilities of small and large low-productivity firms. In many cases this step is problematic due to a high number of zero investments, but in the high-growth Chinese context only 1% of firms suffer from negative real investment. In the third step, TFP estimates are obtained by estimating the non-linear equations using the OLS method.

4.1.2. Innovation measure: new product and process sales

The main variable of interest is the firm's revenue from new product and process sales, which is used as a measure of innovation output, and is calculated as the ratio of new product and process sales to the firm's total revenue observed in year t. Most existing studies rely on innovation inputs such as R&D spending and patents, or a count variable for number of new products introduced to the firm. A key disadvantage with these measures of innovation is that they do not account for how successful the firm is at innovation, in terms of bringing the new product or process to market.

While the innovation proxy used in the current analysis offers some advantages over existing alternatives, it is important to mention one of its limitations is that it does not necessarily serve as a good indicator for the depth of innovation. This limitation does not impede the objectives of the current study since Chinese firms are expected to be carrying out 'minor' innovations that are incremental in nature. Studying the process of incremental innovation remains important for transitioning economies, since the cumulative effects of minor innovations are thought to be key drivers of productivity gains (Puga and Trefler, 2010).

Table 1 reveals that 17% of the almost 200,000 firms successfully introduced new products or processes during the 1998–2006 time period. On average, less than 5% of innovative firms exited the sample compared to more than 28% of non-innovative firms. The innovation rate is highest in the pharmaceuticals industry and lowest in the ferrous metal smelting and rolling processing industries.

[1] All relevant variables are deflated using a price index developed by Brandt et al. (2012).

Table 1
Descriptive statistics by industry.

		Firms (#)	Exit (%)	Innovators (%)	Innovators exit (%)	Non innovators exit (%)	High subsidy-led innovation (%)	Low subsidy-led innovation (%)	Unsubsidized innovation (%)
Whole sample:		195,427	13.85	17.02	5.17	28.16	0.20	0.39	6.99
2-Digit CIC industry classification:									
13	Agro-food processing	14,035	13.54	13.57	3.46	34.05	0.14	0.17	5.86
14	Food manufacturing	4,729	12.80	18.41	5.42	28.69	0.30	0.27	8.54
15	Beverage manufacturing	2,979	14.93	17.05	8.47	35.08	0.18	0.19	7.44
17	Textiles	20,170	12.38	12.90	4.36	28.07	0.08	0.37	4.93
18	Textiles, garments, shoes, hat manufacturing	9,562	15.27	11.19	2.79	26.54	0.02	0.58	4.78
19	Leather, fur, feather products	4,655	14.73	17.01	2.98	28.88	0.05	0.69	7.25
20	Wood processing - wood, bamboo, rattan, brown, grass products	6,977	13.78	12.12	3.91	25.90	0.13	0.13	4.91
21	Furniture making	2,767	12.82	17.07	4.15	27.29	0.02	0.55	6.90
22	Paper, paper products	5,434	12.96	10.59	3.47	31.87	0.15	0.10	3.95
23	Printing, record medium reproduction	2,949	10.88	12.05	2.58	30.85	0.10	0.16	4.81
24	Education and sports goods	2,230	12.30	15.85	4.07	26.08	0.04	0.71	5.95
26	Chemical materials and products	15,057	14.87	16.43	4.86	21.26	0.27	0.30	6.98
27	Pharmaceutical manufacturing	3,435	11.49	31.32	9.99	18.47	0.68	0.50	14.80
28	Chemical fiber	1,290	11.42	10.69	4.19	18.97	0.10	0.35	3.92
29	Rubber products	2,278	10.66	15.06	5.19	24.53	0.17	0.21	6.90
30	Plastic products	10,440	10.64	13.68	3.65	24.40	0.20	0.33	6.05
31	Nonmetallic mineral products	16,245	13.65	15.09	3.70	33.45	0.17	0.22	7.09
32	Ferrous metal smelting and rolling processing	6,460	15.81	10.36	3.34	36.02	0.09	0.10	4.66
33	Nonferrous metal smelting and rolling processing	5,016	21.57	14.18	5.34	28.38	0.19	0.35	5.77
34	Metallic mineral products	12,927	10.55	13.25	3.43	25.19	0.10	0.39	5.61
35	General equipment manufacturing	17,130	8.33	18.31	4.91	20.51	0.15	0.61	8.31
36	Special equipment manufacturing	8,553	10.10	20.90	6.51	21.33	0.34	0.47	10.36
37	Transportation equipment	8,432	11.44	21.19	6.40	23.79	0.23	0.50	9.08
39	Electrical machinery and equipment manufacturing	12,075	10.81	20.80	6.43	22.10	0.29	0.64	9.11
40	Communications equipment, computers and other electronic equipment	5,189	13.99	27.71	7.36	17.08	1.25	0.81	13.55
41	Instruments, meters, cultural and office machinery	2,390	12.41	31.11	10.46	16.15	1.21	1.23	18.30
42	Artwork and other manufacturing	4,429	12.46	14.68	2.57	27.16	0.08	0.61	5.53

Notes: 2-Digit industries are based on the China Industrial Classification (CIC) system. Values are based on averages calculated across the sample period 1998–2006. The variable definitions and summary statistics are provided in the Appendix Table A.1.

Fig. 1 reveals the regional concentration of innovation among 333 Chinese cities. The figure shows a high level of innovation clustering, especially along the coast in the Yangtze River Delta and the Pearl River Delta, both well known for their high-tech innovation centers. Smaller clusters farther north along the coast can also be spotted in and around Beijing and Tianjin. In contrast, innovation clusters in the interior of the country are noticeably absent.

Fig. 2 shows the Kaplan–Meier estimator, plotting the grouped survival probabilities separately for innovative and non-innovative firms. The figure reveals that innovative firms have higher survival probabilities for each year of duration. For the 1998 cohort, approximately 75% of innovative firms survived the entire 9-year time span, compared to only 55% of non-innovative firms. It is important to note that the gap in the survival probability increases over time, suggesting that the proportionality assumption is not satisfied. This finding offers some support that AFT modeling is an appropriate estimation strategy.

4.2. Dimensions of innovation risk

Four dimensions of innovation risk are considered in the empirical analysis. Emanating from the portfolio theory of finance, the first two dimensions of risk include firm's leverage (debt-to-assets ratio) and revenue diversification. While a healthy level of debt can provide innovative firms the necessary liquidity to carry out innovation, becoming over-leveraged puts the firm in danger of default, especially if innovation sales are not sufficient to pay off creditors. Innovative firms that accumulated a debt-to-assets ratio above [below] 50% prior to introducing a new innovation are classified as high [low] risk debt-led innovators.

The second dimension is diversification risk. Firms with a higher proportion of its revenue stemming from new product or process sales face increased risk because the ability of new innovations to raise revenues is less certain than those of more established products (Fernandes and Paunov, 2014). Firms are distinguished as having a higher diversification risk versus a lower diversification risk if the proportion of the firm's new innovation sales accounts for more than 50% of total revenue.

The two additional risk dimensions – market risk and location risk – respectively take into account uncertainty operating at the industry and regional level. Market risk arises due to challenges associated with introducing new products or processes into the market. Firms that introduce a new product or process in industries with a higher [lower] sales volatility are exposed to greater [less] risk as the demand for the product may fluctuate widely.

The location of the firm also influences the amount of risk embodied in the innovation process. Firms that are located in more geographically concentrated areas may benefit from spatial externalities like knowledge spillovers, thereby reducing innovation risk. At the same time, innovative firms in concentrated areas may simultaneously expose themselves to higher risk of failure by co-locating nearby with competing firms in the same industry. It is expected though that this additional risk is eclipsed by the positive externalities. Firms attempting to innovate in more isolated

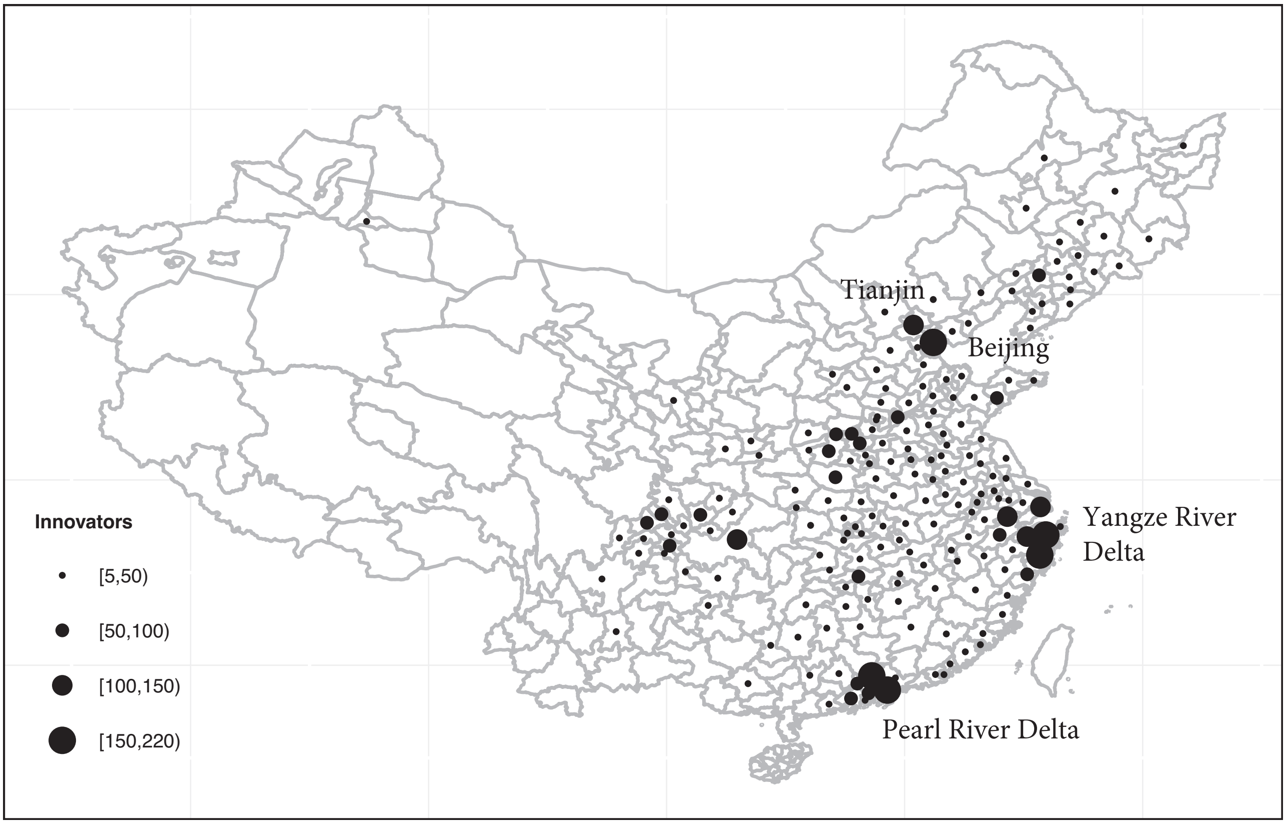

Fig. 1. Number of innovative startups, 1998–2007.

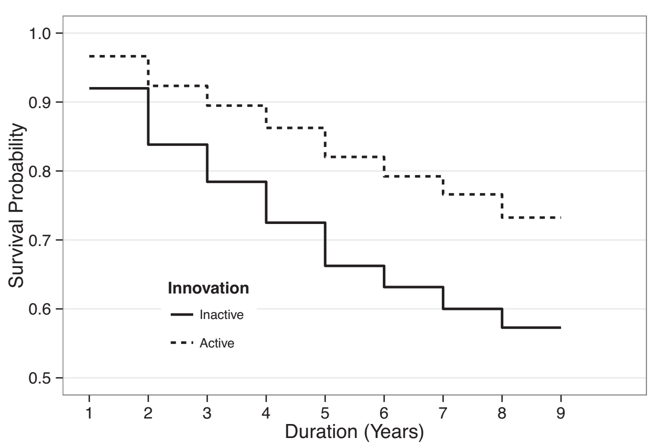

Fig. 2. Survival probability for firms with positive innovation sales (active) and without innovation sales (inactive), 1998–2007.

[concentrated] regions are therefore considered to be more [less] risky.

4.3. Control variables

The survival of new firms is related to various factors, including firm-specific characteristics, the intensity of market competition, and macroeconomic conditions. In line with the literature, the following firm level controls are included: current size and its square, initial size at which the firm started operations, and time-varying sales growth and capital intensity. The following time-varying industry and region controls are also included: industry sales growth, industry entry rate, a proxy for spatial agglomeration as measured by the Ellison & Glaeser (EG) index (Ellison and Glaeser, 1997),[2] industry average innovation and industry average subsidies.

Controlling for firm size and size squared addresses nonlinearities in the survival–size relationship, while including initial firm size takes into account the initial conditions of the firm, which tend to have persistent effects on firm survival (Mata and Portugal, 1994; Geroski et al., 2010).

The firm's sales growth is included to avoid capturing the 'desperate innovator effects – poor performing firms that switch products as a desperate measure to avoid imminent closure. This control is especially important in this study of risk on the innovation–survival relationship (Fernandes and Paunov, 2014). Controlling for capital intensity ensures that the effects of product innovation are not being picked up by capital accumulation related to process innovation.

5. Results on the effects of innovation on firm survival

Table 2 reveals the estimates from the baseline FAFT models with random effects.[3] Columns (1)–(3) report results using the log–logistic distribution while Columns (4)–(6) report results from the weibull distribution. Consistent with the existing literature, the

[2] The EG index can be written as $\gamma_i = G_i - (1-\sum_r x_r^2)H_i/(1-\sum_r x_r^2)(1-H_i)$, where $G_i = \sum(x_r - x_i)^2$ represents the spatial Gini coefficient, x_r is the share of total employment of all industries in city r, and x_i is the share of employment for city r in industry i, and H_i is the Herfindahl index.

[3] To add random effects, it is assumed that those effects are orthogonal to firm characteristics, a condition not easily satisfied for non experimental data. Alternative model specifications that are more flexible than the FAFT – e.g. linear exit probability model, logit, and discrete-time hazard models – were also estimated as robustness checks to account for unobserved heterogeneity. All robustness checks confirm original findings irrespective of the model estimation strategy.

Table 2
Results for innovation and firm survival.

	Frailty accelerated failure time models for firm survival (FAFT): Duration					
	Log–logistic			Weibull		
	(1)	(2)	(3)	(4)	(5)	(6)
Firm innovation intensity	0.006*** (0.0004)	0.012*** (0.0004)	0.006*** (0.0004)	0.009*** (0.0004)	0.013*** (0.0004)	0.005*** (0.0004)
Firm initial innovation		−0.128*** (0.004)	−0.090*** (0.004)		−0.142*** (0.004)	−0.096*** (0.003)
Firm size			0.095*** (0.003)			0.122*** (0.003)
Firm size^2			−0.0003 (0.0003)			−0.002*** (0.0003)
Firm initial size			−0.030*** (0.0004)			−0.027*** (0.0004)
Firm sales growth			0.020*** (0.0005)			0.020*** (0.001)
Firm capital intensity			0.028*** (0.0005)			0.037*** (0.001)
Industry revenue growth			−0.014*** (0.003)			−0.017*** (0.003)
Industry entry rate			−0.224*** (0.014)			−0.238*** (0.015)
Industry average innovation			−0.028* (0.016)			−0.032* (0.017)
EG index			0.150*** (0.030)			0.229*** (0.031)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	603,406	601,115	598,944	603,406	601,115	598,944
Log likelihood	−815,254	−814,840	−795,313	−762,101	−761,605	−738,493

Notes: $^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$. *t* statistics in parentheses. Robust standard errors were used obtaining these *t* statistics. The accelerated failure time models take into account right censoring, left truncation and do not assume the proportionality assumption – they have a time-scaling factor that increases (decreases the probability of failure when the value is greater (lesser) than 1. Columns (1)–(3) are estimated using the log–log distribution and Columns (4)–(6) are estimated using the Weibull distribution. The dependent variable is the duration period of the firm. The coefficients are presented as survival probabilities and represent the conditional probability of competing a survival spell. The variable definitions and summary statistics are provided in the Appendix Table A.1.

coefficient on innovation is positive and statistically significant at the .001 confidence level in all six models. Since the log likelihood values suggest that the weibull model provides the best fit to the data, the remaining discussion will be confined to Columns (4)–(6).

Column (4) shows that a one percentage increase in innovation intensity increases the probability of firm survival by a factor of 1.06.[4] Coinciding with previous findings (Mata and Portugal, 1994; Geroski et al., 2010), column (5) shows a negative and statistically significant coefficient on the firm's initial innovation intensity.

One interpretation of this finding is that attempting to introduce a new product or process in the same year that the firm enters the market are unsure of the market needs due to their lack of prior production experience. As a result, the resources utilized to carry out the innovative search will tend to be less efficiently allocated, thereby increasing the firm's survival risk. Note that the increase in the size of the coefficient on current innovation intensity doubles in size from 0.06 to 0.12. This finding indicates that of the firms that innovate in their initial year and are able to survive, their returns on subsequent investments will be higher as a result of the extra year of innovation experience.

Column (6) adds firm and industry controls to the model. In general, findings reflect results from existing studies (Dunne et al., 1989; Disney et al., 2003; Fernandes and Paunov, 2014). Larger firms tend to have a higher probability of survival, although the size effect is non-linear. More capital intensive firms tend to survive longer. Regarding the industry controls, firms have a higher probability of survival in industries with low sales growth, low entry rates and a higher EG index, respectively. Firms located within industries that have a higher industry average innovation are less likely to survive, an indication that the conditions in faster-paced industries are more unstable and may create higher turnover (Audretsch, 1991).

5.1. Comparing the effects of innovation on firm survival to profits and productivity

The effects of innovation extend beyond influencing survival, and are expected to also affect both the profits and the productivity of the firm. Table 3 estimates the effect of innovation on firm profits and productivity, respectively, using a fixed effect (FE) panel estimator as well as a dynamic panel model estimated in first differences.[5] The dynamic panel model takes into account possible dynamics and is estimated using the instrumental variables estimation method developed by Anderson and Hsiao (1982).

Column (1) re-reports the firm survival results from Table 2 above. Columns (2)–(5) show the results from the FE and dynamic analysis on firm profits and productivity, respectively. In each column, the findings reveal that the coefficient on innovation is positive and statistically significant for both firm profits and productivity. The positive increase in profits reflect the private gains from innovation, i.e. the ability of the firm to capture innovation

[4] Recall from Eq. 6 that $log(T)=\alpha+\mu+\beta'X+\sigma\epsilon$, which is equivalently expressed as $T=e^{\beta'X}e^{\epsilon}$. When some covariate, X_k is changed by some amount δ, the ratio of the survival time is: $T(X_k+\delta)/T(X_k)=e^{[X_k-(X_k+\delta)]}\beta_k=e^{\beta_k\delta}$. When δ is one unit, this expression simplifies to: $T(X_k+1)/T(X_k)=e^{\beta_k}$, where e^{β_k} is known as the time ratio, which can be interpreted similar to the log odds in logistic regression or as the hazard ratio in a PH model.

[5] In each subsequent model, the same set of control variables are included as in Table 2. One additional variable, firm exit (1 = yes, 0 = no), is added in the FE and dynamic models to control for the effect of attrition in the sample.

Table 3
Comparing the effects of innovation on firm survival to profits and productivity.

	FAFT with random effects	Fixed-effects estimator		Dynamic estimation first differences	
	Duration (1)	Profits (2)	TFP (3)	Profits (4)	TFP (5)
Innovation intensity	0.005***	0.247***	0.083***	0.084***	0.022***
	(0.0004)	(0.01)	(0.01)	(0.01)	(0.00)
Firm and industry controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects		Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes				
Region fixed effects	Yes				
Observations	598,944	450,328	450,328	450,328	450,328

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. *t* statistics in parentheses. Robust standard errors were used obtaining these *t* statistics. Column (1) report the results from the FAFT model. Columns (2)–(3) report the results from the fixed effects panel data estimator for firm profits and TFP, respectively. Columns (4)–(5) report the results from the dynamic estimations using first differences for firm profits and TFP, respectively. The Anderson–Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for underidentification and the Cragg–Donald Wald F statistic test for weak identification test. All models include the full set of firm and industry controls from Table 2. Columns (2)–(5) include an additional dummy variable for firm exit to account for possible attrition effects. All variable definitions and summary statistics are provided in the Appendix Table A.1.

Table 4
Moderating effects of State-Intervention on Innovation and Firm Survival, Profits and Productivity

	FAFT with random effects	Dynamic estimation first differences		FAFT with random effects	Dynamic estimation first differences	
	Duration (1)	Profits (2)	TFP (3)	Duration (4)	Profits (5)	TFP (6)
High subsidy-led innovation	0.060***	0.457***	0.082**			
	(0.005)	(0.044)	(0.025)			
Low subsidy-led innovation	0.035*	−0.118***	−0.005			
	(0.018)	(0.034)	(0.017)			
Unsubsidized innovation	−0.036***	0.015	0.031***			
	(0.002)	(0.009)	(0.004)			
Innovation in industry with high state protectionism				0.112***	0.055***	0.020*
				(0.003)	(0.016)	(0.009)
Innovation in industry with low state protectionism				0.120***	0.152***	−0.002
				(0.003)	(0.013)	(0.007)
Firm and industry controls	Yes	Yes	Yes	Yes	Yes	
Firm fixed effects		Yes	Yes		Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes			Yes		
Region fixed effects	Yes			Yes		
Observations	598,944	450,328	450,328	598,944	450,328	450,328

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. *t* statistics in parentheses. Robust standard errors were used obtaining these *t* statistics. Columns (1) and (4) report the results from the FAFT model. Columns (2)–(3) and (5)–(6) report the results from the dynamic estimations using first differences for firm profits and TFP, respectively. The Anderson–Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for underidentification and the Cragg–Donald Wald *F* statistic test for weak identification test. All models include the full set of firm and industry controls from Table 2. The dynamic models also include an additional dummy variable for firm exit to account for possible attrition effects. All variable definitions and summary statistics are provided in the Appendix Table A.1.

rents, whereas the positive increase in productivity reflects efficiency gains that extend beyond the firm and are expected to benefit society (Fernandes and Paunov, 2014).

5.2. Results on the effects of innovation with Chinese characteristics on firm survival, profits and productivity

Tables 4 and 5 show how several main innovation characteristics influence firm survival, profits, and productivity, respectively. Columns (1)–(3) in Table 4 reveal the role of state-led innovation, i.e. firms that became innovators after receiving production subsidies, on firm survival, productivity and profits. Innovative firms that initially received comparatively more subsidies are associated with a longer survival spell, higher profits, and larger productivity gains compared to their less subsidized and unsubsidized counterparts. Based on a *t*-test (*p-value <0.05*), the coefficients are statistically different from one another[6]. Innovative firms who initially received fewer subsidies increase their survival chances relative to unsubsidized innovators, but tend to be less profitable and less efficient.

Columns (4)–(6) show the returns to innovation in industries that are more (less) protected by the state. Firms that carry out innovation in industries that are less protected by the state are associated with higher profits, but lower efficiency, and tend to survive as long as innovative firms in more protected industries. The results from the *t*-test (*p*-value = 0.243), however, show that the coefficients are not statistically different for innovator firms in more versus less protected industries.

While previous empirical findings from within China suggest that state-subsidized innovation leads to positive results (Guan

[6] Unless otherwise stated, the difference between the coefficients of interest are statistically significant based on a t-test (*p-value <0.05*).

Table 5
Moderating effects of China's opening-up strategy on innovation and firm survival, profits and productivity.

	FAFT with random effects	Dynamic estimation first differences		FAFT with random effects	Dynamic estimation first differences	
	Duration (1)	Profits (2)	TFP (3)	Duration (4)	Profits (5)	TFP (6)
FDI-led innovation	0.120*** (0.002)	0.264*** (0.061)	0.127** (0.041)			
Non FDI innovation	0.056*** (0.006)	0.079** (0.025)	0.009 (0.013)			
Innovation in industry with high global competition				−0.026*** (0.004)	0.131 (0.220)	0.484*** (0.063)
Innovation in industry with low global competition				0.130*** (0.003)	0.109*** (0.024)	−0.005 (0.013)
Firm and industry controls	Yes	Yes	Yes	Yes	Yes	
Firm fixed effects		Yes	Yes		Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	598,944	450,328	450,328	598,944	450,328	450,328

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. *t* statistics in parentheses. Robust standard errors were used obtaining these *t* statistics. Columns (1) and (4) report the results from the FAFT model. Columns (2)–(3) and (5)–(6) report the results from the dynamic estimations using first differences for firm profits and TFP, respectively. The Anderson–Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for underidentification and the Cragg–Donald Wald F statistic test for weak identification test. All models include the full set of firm and industry controls from Table 2. The dynamic models also include an additional dummy variable for firm exit to account for possible attrition effects. All variable definitions and summary statistics are provided in the Appendix Table A.1.

Table 6
Moderating effects of firm-level risk on innovation and firm survival, profits and productivity.

	FAFT with random effects	Dynamic estimation first differences		FAFT with random effects	Dynamic estimation first differences	
	Duration (1)	Profits (2)	TFP (3)	Duration (4)	Profits (5)	TFP (6)
Higher debt-led innovation	0.302 (0.305)	−0.286*** (0.050)	−0.188 (0.127)			
Lower debt-led innovation	0.100*** (0.002)	0.015** (0.005)	0.114*** (0.010)			
Innovation accounting for more than 50% of revenues				−0.059*** (0.005)	0.029** (0.010)	0.050* (0.021)
Innovation Accounting for less than 50% of revenues				0.166*** (0.002)	0.009 (0.010)	0.257*** (0.019)
Firm and industry controls	Yes	Yes	Yes	Yes	Yes	
Firm fixed effects		Yes	Yes		Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	598,944	450,328	450,328	598,944	450,328	450,328

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. *t* statistics in parentheses. Robust standard errors were used obtaining these t statistics. Columns (1) and (4) report the results from the FAFT model. Columns (2)–(3) and (5)–(6) report the results from the dynamic estimations using first differences for firm profits and TFP, respectively. The Anderson–Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for underidentification and the Cragg–Donald Wald F statistic test for weak identification test. All models include the full set of firm and industry controls from Table 2. The dynamic models also include an additional dummy variable for firm exit to account for possible attrition effects. All variable definitions and summary statistics are provided in the Appendix Table A.1.

et al., 2009), in theory, firms with unfettered access to state finance are insulated from outside competition, and are thereby deprived of the incentives to be efficient innovators. As it turns out, both the empirical findings and theoretical expectations may be too simple, failing to take into account the complex, non-linear relationship between state support programs and innovation.

Table 5 reveals how China's opening up strategy moderates firm survival, profits and productivity, respectively. In Columns (1)–(3), firms that carry out innovation after attracting FDI tend to survive longer, earn higher profits and enjoy higher efficiency gains compared to firms that carried out innovation without FDI.

In spite of claims that Chinese firms are over-reliant on FDI (Young and Lan, 1997), the findings here suggest that expanding access to FDI increases both the social welfare via firm efficiency gains, as well as the private benefits accrued to the firm via higher profits. This finding coincides with the assertions in Nahm and Steinfeld (2014), who argue that access to foreign capital enables Chinese firms to re-create new products at a cheaper cost and in a more efficient manner.

In Columns (4)–(6), firms that introduce new innovations in more globally competitive industries are less likely to survive and are less profitable, but enjoy higher efficiency gains relative to their counterpart firms in less globally competitive industries. One interpretation of this finding is that the higher exposure to global competition erodes away the private gains from innovation, although that same competition drives firms to become more efficient innovators.

5.3. *Results on the effects of innovation with heterogeneous risk on firm survival, profits and productivity*

Table 6 presents the results on the two firm-level dimensions of risk. In Columns (1)–(3), firms that accumulated higher levels of debt prior to innovation experience a higher risk of failure, are

Table 7
Moderating effects of environmental risk on innovation and firm survival, profits and productivity.

	FAFT with random effects	Dynamic estimation first differences		FAFT with random effects	Dynamic estimation first differences	
	Duration (1)	Profits (2)	TFP (3)	Duration (4)	Profits (5)	TFP (6)
Innovation in industry with larger sales volatility	0.035	0.138***	−0.006			
	(0.026)	(0.034)	(0.068)			
Innovation in industry with smaller sales volatility	0.080***	0.115***	0.038***			
	(0.002)	(0.011)	(0.006)			
Innovation in industry with lower EG index value				0.064	−0.075	0.086
				(0.002)	(0.090)	(0.184)
Innovation in industry with higher EG index value				0.117***	0.018	0.090***
				(0.002)	(0.013)	(0.024)
Firm and industry controls	Yes	Yes	Yes	Yes	Yes	
Firm fixed effects		Yes	Yes		Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	598,944	450,328	450,328	598,944	450,328	450,328

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. *t* statistics in parentheses. Robust standard errors were used obtaining these t statistics. Columns (1) and (4) report the results from the FAFT model. Columns (2)–(3) and (5)–(6) report the results from the dynamic estimations using first differences for firm profits and TFP, respectively. The Anderson–Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for underidentification and the Cragg–Donald Wald F statistic test for weak identification test. All models include the full set of firm and industry controls from Table 2. The dynamic models also include an additional dummy variable for firm exit to account for possible attrition effects. All variable definitions and summary statistics are provided in the Appendix Table A.1.

less profitable and are less efficient relative to firms with lower debt levels. The results indicate that over-leveraged firms fail to be compensated in spite of taking on higher survival risk. The negative and statistically significant coefficient in Column (3) further reveals that more risky, i.e. higher debt-led, innovators experience a loss in efficiency.

In Columns (4)–(6), innovative firms that have higher diversification risk, i.e. innovation sales that account for more than 50% of firm revenues, are less likely to survive relative to their counterpart firms with lower diversification risk. This result confirms the finding in Zhang and Mohnen (2013). More diversification risk tends to generate higher profits, but come at the expense of efficiency. Innovative firms with higher diversification risk are therefore, found to be only partially compensated for their higher survival risk. The positive and statistically significant coefficient in Column (6), on the other hand, reveals that innovative firms with lower diversification risk enjoy a larger efficiency gain.

Table 7 presents the results on the market and regional dimensions of risk. In Columns (1)–(3), firms that innovate in industries with more market volatility are less likely to survive and are less efficient, but are as profitable as firms that innovate in industries with less market volatility.[7] The positive and statistically significant coefficient in Column (3) further indicates that innovation carried out in less volatile industries improves firm efficiency. In Columns (4)–(6), firms that innovate in more isolated regions, i.e. regions with a lower EG index, are less likely to survive, are less profitable, and are less efficient than spatially concentrated firms.

6. Conclusion

Innovation risk is higher in China compared to more advanced market economies, posing significant barriers to innovation. At the same time, state support and access to foreign capital present new opportunities that may help to mitigate certain risk factors, thereby facilitating the innovation process. Throughout this paper, I explored how the presence of these opportunities as well as certain risk factors moderate the effects of indigenous innovation on firm survival and subsequent performance.

Based on the partial welfare analysis, the results suggest that more cautious innovators increase their chances of survival and contribute more to social welfare via larger gains in firm efficiency. In contrast, more risky innovators are less likely to survive, are less efficient, and are only sometimes compensated for their risk in terms of higher profits. A similar relationship between innovation risk and firm performance is also found in the case of Chile (Fernandes and Paunov, 2014), providing some confirmation that factors other than higher payoffs force some firms in transitioning economies to engage in riskier innovation strategies. Common factors include market failures, asymmetric information, bankruptcy risks and agency conflicts.

Policy interventions are therefore necessary to help correct such market failures and other distortions that arise during economic transition in order to minimize innovation risk and promote a higher social welfare. The analysis shows, however, that the effects of public subsidies on survival and subsequent performance of innovative firms are complex and non-linear.

State-led innovators, for instance, are associated with higher rates of survival, higher profits, and larger efficiency gains, but only for innovative firms who initially received comparatively larger amounts of public subsidies. In contrast, innovative firms who initially received fewer subsidies ended up becoming less profitable and less efficient than their unsubsidized counterparts.

It is important to note that these findings are intended only to reveal the potential difficulties that can arise in transitioning economies as policy makers attempt to mitigate market failures and other undesirable factors in the economy. Future research is ultimately required to more closely examine the causal impacts of public programs that aim to encourage the type of innovation that is beneficial to both the firm and to society at large.

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[7] The results of the t-test for firm profits (p-value = 0.45) is not statistically significant.

Lien, and participants at the Chinese Economy: Past, Current, and Future Conference hosted by Tsinghua University. All errors and omissions are the responsibility of the author.

Appendix A.

See Table A.1.

Table A.1
Variable definitions and summary statistics.

Statistic	Definition	Mean	St. dev.
Duration	Length of the firm's survival spell, in years	5.16	2.13
TFP	Logged total factor productivity of firm i in year t. TFP is constructed using the Olley and Pakes (1996) method.	3.04	1.11
Profits	Logarithm of the ratio of firm profits (total plant sales minus materials costs, electricity costs, expenditures on wages, etc.) to plant sales	.13	.25
Firm exit	Variable equals 1 if the firm is observed in year t but not year $t+1$, and 0 otherwise	0.09	0.29
Firm innovation intensity	Logarithm of the ratio of new product and process revenue to total firm revenue observed in year t that it did not produce in year $t-1$ nor in any previous sample year leading up to $t-1$	0.002	0.01
Firm initial innovation	Logarithm of the ratio of new product and process revenue to total firm revenue recorded in the firm's initial year of operations	0.0001	0.002
Firm size	Logarithm number of employees	4.63	1.05
Firm size^2	Logarithm number of employees squared	22.53	10.11
Firm initial size	Logarithm number of employees recorded in firm's initial year of operations	3.88	1.83
Firm sales growth	Logarithm of the difference in firm sales between year t and year $t-1$.	0.005	1.02
Firm capital intensity	Logarithm of the ratio of capital to the total number of workers in the firm. Capital is constructed as defined in Brandt et al. (2012).	4.89	1.04
Industry sales growth	Logarithm of the difference in real sales of each 3-digit Chinese Industry Classification (CIC) between year t and year $t-1$.	0.13	0.45
Industry entry rate	Logarithm of the ratio of the number of new plants that operate in year t but not in year $t-1$ to the total number of plants in each 3-digit CIC for year t.	0.16	0.21
EG index	The EG index, developed by Ellison and Glaeser (1997) is calculated at the 3-digit CIC as: $\gamma_i = \frac{G_i-(1-\sum_r x_r^2)H_i}{(1-\sum_r x_r^2)(1-H_i)}$ where G_i is the spatial Gini coefficient, x_r is the share of total employment of all industries in region r, and x_s is the share of employment for region r in industry i. H_i is the Herfindahl index.	0.016	0.01
Industry average innovation	Logarithm of average share of firms with positive new product or process sales in each 3-digit CIC and year.	0.25	0.12
High [low] subsidy-led (unsubsidized) innovation	Variable equals 2 if firm i received state subsidies that account for more than 25% of its revenues in year $t-1$, prior to reporting its first new product and process sales in year t; Variable equals 1 if firm i received state subsidies that account to at most 25% of its revenues in year $t-1$, prior to reporting its first new product and process sales in year t; and 0 if firm i received zero subsidies in year $t-1$, prior to reporting its first new product and process sales in year t otherwise.	0.002 [0.004] (0.069)	0.045 [0.062] (0.254)
Innovation in industry with high [low] state protectionism	Variable equals 1 if the firm reports positive new product and process sales in year t and the size-weighted average state subsidies allocated to its 3-digit CIC industry is above [below] the median value across all 3-digit CIC industries, and 0 otherwise	0.031 [0.047]	0.173 [0.212]
High [low] FDI-led innovation	Variable equals 1 if firm i received foreign direct investments totaling more than [less than or equal to] 25% of its total revenue, in year $t-1$, prior to reporting its first new product and process sales in year t, and 0 otherwise.	0.005 [0.080]	0.07 [0.271]
Innovation in industry with high [low] liberalization	Variable equals 1 if the firm reports positive new product and process sales in year t and the size-weighted average exports in its 3-digit CIC industry is above [below] the median value across all 3-digit CIC industries, and 0 otherwise	0.008 [0.072]	0.086 [0.39]
High [low] debt-led innovation	Variable equals 1 if the firm reports positive new product and process sales in year t and its debt-to-assets ratio (leverage) is more than [less than or equal to] 50% of the firm's total revenues.	0.0007 [0.08]	0.0003 [0.05]
Innovation accounting for more [less] than 50% of revenues	Variable equals 1 if the firm reports positive new product and process sales in year t and these account for more than [less than or equal to] 50% of the firm's total revenues.	0.019 [0.11]	0.138 [0.32]
Innovation in industry with larger [smaller] sales volatility	Variable equals 1 if the firm reports positive new product and process sales in year t and has a standard deviation of real sales during the period 1998–2007 that is below [above] the median value across all 3-digit CIC industries, and 0 otherwise.	0.04 [0.03]	0.20 [0.18]
Innovation in industry with high [low] EG index value	Variable equals 1 if the firm reports positive new product and process sales in year t and operates within a 3-digit CIC industry that has a high [low] EG index value above (below).15, and 0 otherwise.	0.19 [0.09]	0.39 [0.29]

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