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

Anthony Howell*

School of Economics, Peking University, No. 5 Yiheyuan Road, Haidian District, Beijing, PR China

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

* Corresponding author.
E-mail address: tonyjhowell@pku.edu.cn

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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