Research Policy 45 (2016) 1474–1492

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Inverted-U relationship between R&D intensity and survival: Evidence on scale and complementarity effects in UK data☆

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ARTICLE INFO

Article history:
Received 15 August 2015
Received in revised form 15 April 2016
Accepted 21 April 2016
Available online 10 May 2016

JEL classification:
C41
D21
D22
L1
03

Keywords:
R&D
Innovation
Firm dynamics
Survival analysis

ABSTRACT

Existing evidence on the relationship between R&D intensity and firm survival is varied and often conflicting. We argue that this may be due to overlooking R&D scale effects and complementarity between R&D intensity and market concentration. Drawing on Schumpeterian models of competition and innovation, we address these issues by developing a formal model of firm survival and using a panel dataset of 37,930 of R&D-active UK firms over 1998–2012. We report the following findings: (i) the relationship between R&D intensity and firm survival follows an inverted-U pattern that reflects diminishing scale effects; (ii) R&D intensity and market concentration are complements in that R&D-active firms have longer survival time if they are in more concentrated industries; and (iii) creative destruction as proxied by median R&D intensity in the industry and the premium on business lending have negative effects on firm survival. Other findings concerning age, size, productivity, relative growth, Pavitt technology classes and the macroeconomic environment are in line with the existing literature. The results are strongly or moderately robust to different samples, stepwise estimations, and controls for frailty and left truncation.

1. Introduction

Existing work has so far identified a wide range of consistent empirical patterns on firm entry and exit, of which the following are cited most often: (i) contemporaneous entry and exit rates are highly and positively correlated; (ii) firm size and age are correlated positively with survival; (iii) small firms that survive tend to grow faster than larger firms; and (iv) younger firms have a higher probability of exiting, but those that survive tend to grow faster than older firms (Geroski, 1995; Klette et al., 2004).

In contrast, findings on the relationship between innovation and survival are varied and often conflicting. This is the case with respect to both input measures such as investment in research and development (R&D) and output measures such as patents, trademarks or product/process innovations. To understand the causes of heterogeneity, we propose and test a Schumpeterian model of knowledge production, firm value and survival. The model yields three testable hypotheses: (i) the effect of R&D intensity on firm survival is subject to diminishing returns, whereby survival time increases at diminishing rates and eventually falls as R&D intensity exceeds an optimal level; (ii) R&D intensity and market concentration are complements in that a given level of R&D intensity is associated with longer firm survival in more concentrated industries; and (iii) higher levels of R&D intensity in the industry and higher premiums on business lending are associated with shorter survival time.

The article is organised as follows. Section 2 provides a brief review of the related literature. In Section 3, we propose a survival model informed by Schumpeterian models of competition, innovation and firm performance. In Section 4, we discuss our data and estimation methodology. In Section 5, we estimate our model with a lognormal duration estimator chosen on the basis of Akaike and Bayesian information criteria and Cox-Snell residuals. We conclude by summarising the main findings and their implications for future research.

☆ Research for this paper has been funded by ESRC under grant reference no ES/K004824/1. We thank our funders for their generous support. We also thank the participants of the workshop held on 4 June 2015 for their engagement and comments. The views expressed here are those of the authors, who are responsible for any errors or omissions.

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http://dx.doi.org/10.1016/j.respol.2016.04.007
0048-7333/

2. Related literature

Theoretically, investment in R&D can enhance a firm's survival as a result of productivity gains (Griliches, 1979) and/or increased market power (Aghion et al., 2014). However, R&D investment entails risks and is a major source of stochastic productivity shocks that generate both entry and exit (see, for example, Jovanovic, 1982, 1994; Hopenhayn, 1992; Ericson and Pakes, 1995). Secondly, the productivity of R&D projects tends to diminish with size, particularly when firms are closer to the technology frontier (Pammolli et al., 2011; DiMasi and Grabowski, 2012). Furthermore, there is evidence that the patents-to-R&D ratio tends to fall as R&D intensity increases (Kortum, 1993). Finally, Czarnitzki and Toole (2013) report that larger R&D projects are usually observed in highly concentrated industries and this may be due to higher market uncertainty associated with larger projects.

Given such complexities in the relationship between R&D intensity and firm performance, it is not surprising to observe varied and often conflicting findings on the relationship between R&D intensity and survival. Heterogeneity is evident irrespective of whether the explanatory variable is an *output* or *input* measure of innovation. Some studies using an *output* measure (e.g., patent count, trademarks, number of product or process innovations) report a positive and significant relationship between innovation and firm survival among US firms (Audretsch, 1991), Dutch manufacturing firms (Cefis et al., 2005, 2006), and UK firms (Helmers et al., 2010).

However, several studies also report insignificant or even negative effects. Audretsch (1995) use the same dataset as Audretsch (1991) and report that small-firm innovation rate has no effect on survival when firm characteristics such as age and size are controlled for. Similarly, Giovannetti et al. (2011) report that product or process innovation has no effect on survival among Italian firms. Using Australian data, Jensen et al. (2006) and Buddelmeyer et al. (2010) report interesting findings: whereas patent applications as a measure of high-risk innovation are associated with lower survival rates, trademark applications as a measure low-risk innovation lead to higher survival rates.

Conflicting findings have been reported with respect to survival-effects of R&D intensity too. Of these, Esteve-Pérez et al. (2004) and Esteve-Pérez and Mañez-Castillejo (2008) estimate Cox proportional hazard (CPH) and parametric survival models and report a positive effect in Spanish firm data. A similar finding is reported by Li et al. (2010), who estimate a CPH model with data on 870 software companies and report that the firm's R&D capital expenditures on labs and equipment are associated with lower hazard rates.

In contrast, a number of studies report mixed, insignificant or negative effects. Mahmood (2000) estimates a log-logistic model of survival with US data on start-up companies from 1976 to 1986. Splitting the sample by industry and technology level, he reports 17 estimations in total – 8 for low-tech, 6 for medium-tech, and 3 for high-tech industries. He finds that R&D intensity have insignificant effects in 11 out of 17 estimations. Of the six significant effects, four are positive and two are negative; and the estimates are consistently smaller in magnitude as one moves from low-tech through medium-tech to high tech industries.

A similar set of findings is reported by Børing (2015), who estimates a competing-hazard model with Norwegian firm data. The R&D intensity, measured as share of R&D personnel in total employment, is insignificant among energy, materials, services and scale-intensive industries, and positive only in the science-based industry and specialised suppliers of technology. When all firms are pooled together, R&D intensity increases hazard rates, i.e. it reduces survival time. Finally, a negative relationship between survival and R&D expenditures is reported in Wilbon (2002), who estimates a logit regression with data on high-tech US firms that went public in 1992.

Two working papers report non-linear effects. Sharapov et al. (2011) estimate a CPH model using UK data for manufacturing firms and report an inverted-U relationship between R&D intensity (R&D/turnover ratio) and *hazard rates*, although this relationship was not robust across samples. In contrast, Zhang and Mohnen (2013) report an inverted-U relationship between R&D intensity (R&D/sales ratio) and *survival rates* of Chinese start-ups.

It can be argued that heterogeneous findings may be due to different samples and estimation methods. Nevertheless, such differences do not seem to have generated varied and often conflicting findings on survival effects of other firm-, industry- or macro-level factors. For example, survival is reported to increase with age and size, albeit the relationship may be non-linear in some cases (Geroski, 1995; Klette et al., 2004). Productivity or growth are also reported to have usually positive effects on survival (Cefis et al., 2005; Mata et al., 1995; Agarwal, 1997). There is also consistency in reported effects of industry-level factors such as industry technology class (Pavitt, 1984), entry rates, and industry growth; as well as macro-economic indicators such as currency appreciation, lending rates or economic crisis periods (for a review, see Manjón-Antolín and Arauzo-Carod, 2008).

Therefore, we argue that the heterogeneity in the evidence base may be a symptom of model misspecification. One potential source of specification bias is the absence of control for R&D scale effects, which may matter for several reasons. First, the riskiness of R&D investments may increase with R&D intensity (Ericson and Pakes, 1995; Czarnitzki and Toole, 2013). Secondly, R&D investment may not generate commercially successful innovation outcomes and/or the firm may fail to diversify its revenue streams at the same pace as its investment in innovation (Fernandes and Paunov, 2015). Third, a given level of own R&D intensity may have different effects on firm survival depending on R&D intensity in the firm's industry (Schumpeter, 1942; Audretsch et al., 2000; Fritsch et al., 2006; Aghion et al., 2014).

Model specification bias could also arise from the absence of control for complementarity or substitution between R&D intensity and market structure. Such control is justified given the insights from the industrial organisation literature on innovation. As indicated by Gilbert (2006), a given level of market concentration induces different levels of innovation inputs or outputs – depending on the initial level of concentration. Also, a given level of competition may induce different levels of R&D investments depending on creative destruction in the industry (Aghion et al., 2005, 2009, 2014). Given these insights, it is necessary to control not only for direct effects of R&D intensity and market concentration separately, but also for their interactive effects.

3. Model of R&D intensity and survival

Drawing on Schumpeterian models of competition, innovation and growth, we propose a survival model that takes account of R&D scale effects, complementarity/substitution between R&D intensity and market concentration, creative destruction in the industry, and the risk premium on business lending. The model shares the Schumpeterian view that: (a) R&D investments are motivated by the prospects of innovation rents; and (b) growth is a function of creative destruction that involves the replacement of old technologies by new innovations (Aghion et al., 2014).

The model has five main pillars, four of which are standard components in Aghion et al. (2014): (i) a knowledge production function with two inputs (number of scientists and knowledge stock) and constant returns to scale; (ii) a cost function for knowledge production, with costs increasing in the wage rate and the number of