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

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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.

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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 knowledge production lines; (iii) normalised average value of the knowledge production line, which depends on gross profits, the cost of innovation, the discount rate for R&D projects and the rate of creative destruction in the industry; and (iv) a firm-value function that depends on the number of knowledge production lines, output and the normalised average value of the knowledge production line. The fifth component represents a digression from Aghion et al. (2014) and consists of equating the firm value in (iv) with a market-based value, which we assume to follow a Wiener process until the firm exits the market due to liquidation (McDonald and Siegel, 1985). As we demonstrate in Appendix A, the model specifies survival time as follows:

$$E\,[t] \cong \frac{2}{2\mu - \sigma^2}\left[\ln(k) + \ln\left(\frac{Y_t}{V_0}\right) + ln\frac{\pi - \zeta w z_i^{\eta}}{\rho + x - z_i}\right] \quad (1)$$

Here, *E[t]* is expected survival time, which increases with the number of innovation lines (k), the ratio of output to initial firm value (Y_t/V_0) and gross profits (π). However, the relationship between survival time and innovation intensity is non-linear: survival time increases with the linear term (z_i) in the denominator, but decreases with the non-linear term (z_i^{η}) in the numerator.[1] In Appendix A, we demonstrate that the extremum in the relationship between innovation intensity and survival time is a local maximum, where the marginal cost of investment in innovation is equal to the normalised value of the knowledge production line. After that point, a further increase in innovation intensity diminishes firm value (and survival time) as it adds to the cost of innovation more than it adds to firm value.

The model allows for two further predictions. First, survival time increases with higher gross profits, π, at each level of innovation intensity.[2] Stated differently, R&D intensity and gross profits are complements in that R&D-active firms with higher gross profits enjoy longer survival times compared to competitors with the same level of R&D intensity but lower levels of gross profits. Hence, and to the extent that profits and market concentration are correlated positively, the model allows for predicting that R&D-active firms would survive longer if they are located in more concentrated industries. Second, higher discount rates (ρ) for R&D projects or higher rates of creative destruction in the industry (x) reduce firm survival provided that $(\rho + x) > z_i$.[3] Higher discount rates reduce survival time due to their negative effect on the normalised value of the knowledge production line, which is adjusted for expected future risks.[4] Survival time also decreases with the rate of creative destruction because the latter accelerates the rate at which the firm's own innovative technology becomes obsolete (Aghion et al., 2014).

Hence, our testable hypotheses can be stated as follows:

H1. The effect of R&D investment on survival is subject to diminishing scale effects, whereby survival time increases with R&D intensity at decreasing rates and eventually falls as R&D intensity exceeds an optimum level.

H2. R&D intensity and market concentration are complements in that a given level of R&D intensity is associated with longer survival times when R&D-active firms are in more concentrated industries.

H3. Survival time is negatively related to the rate of creative destruction in the industry and the discount rate, provided that the sum of the two is larger than the firm's innovation intensity.

To test for **H1**, we approximate innovation intensity (z_i) with a second-order polynomial of *R&D intensity* (*RD_int*), *defined as ratio of firm's total R&D to turnover,* such that $z_i \approx aRD\_int^2 + bRD\_int$.[5] Given the logarithmic functional form in (9), we also use the Taylor approximation of $\ln(RD\_int + 1) \approx RD\_int$ if *0 < RD_int < 1*. The R&D intensity of more than ninety percent of firms in the dataset satisfies this condition. We check whether the results are sensitive to different values for the maximum level of R&D intensity by estimating the model with five different cut-off points, including top R&D intensity less than one and top R&D intensity below the 98th, 97th, 95th, and 75th percentiles of the R&D intensity distribution.

To test for **H2**, we use market concentration as a proxy for unobserved profits. This approximation is justified on the basis of theoretical and empirical findings that firm profit and market concentration are correlated positively in different industries (Bain, 1951; Peltzman, 1977; Tirole, 1988; Berger 1995; Slade 2004).

Finally, to test for **H3** we measure the creative destruction rate in the industry by the median of R&D intensity at 3-digit SIC level. Given that the discount rate for each firm is not known, we use the business lending premium as a proxy. The latter reflects the risk premium on lending to private corporations compared to the risk-free Treasury bill interest rate.

Table 1 below provides a summary of the main covariates of interest and a range of firm-, industry- and macro-level variables controlled for. The choice of each covariate and its expected effect on survival are informed by the relevant literature indicated in the last column.

Covariates (1) and (2) enable us to test if the relationship between R&D intensity and firm survival is subject to increasing or diminishing scale effects. So far, only two working papers have tested for non-linear relationship between R&D intensity and survival (Sharapov et al., 2011; Zhang and Mohnen, 2013). However, both studies lack a theoretical model that provides an optimising foundation for the relationship. In addition, they report conflicting findings: whereas the former report an inverted-U relationship between R&D intensity and *hazard rates* in UK data, which is the opposite of what we predict, the latter reports an inverted-U relationship between R&D intensity and *survival rates* for Chinese start-ups, which is in line with our prediction. Finally, the findings in both studies require further robustness checks before they can be upheld.

Covariate 3 allows for testing whether R&D intensity and market concentration are complements or substitutes. To the best of our knowledge, this is the first study that addresses this issue. As indicated above, we predict complementary effects as both R&D intensity and market concentration have an 'escape competition effect' (Aghion et al., 2014).

We control for covariates four and five to test if survival time is negatively related to creative destruction and the premium on busi-

[1] Of the remaining variables, σ is the volatility and μ is the drift parameter in the Wiener process. In line with existing empirical findings, we assume that $\sigma < \sqrt{2\mu}$ (see Appendix A).

[2] See Appendix A.

[3] See Appendix A.

[4] In Schumpeterian models of innovation, higher discount rates are conducive to lower innovation intensity (Aghion et al., 2014). This adverse effect on innovation intensity may be an additional channel through which higher discount rates reduce survival time. However, our focus here is on the survival effects of the discount rate through firm value, holding the innovation intensity constant (see Appendix A).

[5] R&D intensity is a common input measure of innovation as it reflects the proportion of output devoted to innovation (Aghion et al., 2005, 2014). For approximation of the innovation input with a polynomial function of R&D intensity, see Lokshin et al. (2008). For other applications of the polynomial functions to other inputs, see Fuss et al. (1978) and Basant and Fikkert (1996).

[6] Pavitt1 consists of firms in science-based industries such as chemicals, office machinery, precision, medical and optical instruments industries, ICT. Pavitt2 includes specialized suppliers of technology–mechanical engineering industries, manufacturers of electrical machinery, equipment, etc. Pavitt3 includes scale-intensive industries such as pulp and paper, transport vehicles, mineral oil refining industries. Pavitt4 includes industries dominated by technology suppliers, e.g., textiles & clothing, food & drink, fabricated metals. Finally, Pavitt5 consists of unclassified industries.

Table 1
Covariates and expected effects on firm survival.[6]

Covariate	Description and (expected effect)	Related literature
Covariates of main interest		
1. R&D intensity	Logarithm of R&D expenditures as proportion of turnover (+)	Mahmood (2000), Esteve-Pérez et al. (2004), Børing (2015) and Ericson and Pakes (1995)
2. R&D int. sq.	Squared logarithm of R&D intensity (−)	Aghion et al. (2001, 2014), Ericson and Pakes (1995), Sharapov et al. (2011) and Zhang and Mohnen (2013)
3. (R&D int.)*(HI)	Product of R&D intensity and HI (+)	Aghion et al. (2001, 2014), Ericson and Pakes (1995)
4. Median R&D intensity in industry	Proxy for creative destruction. The median R&D intensity is at 3-digit industry level (−)	Schumpeter (1942), Aghion et al. (2001, 2014), Audretsch (1991) and Audretsch (1995)
5. Lending premium	Business lending rate minus government bond rate, obtained from Bank of England data (−)	Holmes et al. (2010) and Liu (2004)
6 & 7. Herf. Index (HI) and its square	Herfindahl-Hirschman index (HI) calculated at 3-digit industry level (+ /−; −/ +)	McCloughan and Stone (1998), Baldwin and Rafiquzzaman (1995), Wagner (1994) and Fernandes and Paunov (2015)
Other firm-level covariates		
8. Firm growth relative to industry	Growth of firm's deflated turnover minus 3-digit industry median growth (+)	Cefis and Marsili (2005), Mata et al. (1995) and Agarwal (1997)
9. Fast growth in last 3 years before exit	Dummy variable = 1 if the firm grows faster than 3-digit industry median growth for three consecutive years before exit (−)	New. Reviewer recommendation to test for overstrained growth strategy
10. Age	Logarithm of firm age in years (+)	Hopenhayn (1992), Ericson and Pakes (1995), (Geroski, 1995), Cefis and Marsili (2005), Doms et al. (1995) and Disney et al. (2003)
11. Age squared	Squared logarithm of age (−)	Ericson and Pakes (1995), Cefis and Marsili (2005) and Evans (1987)
12. Size	Logarithm of employees headcount (+)	Hopenhayn (1992), Ericson and Pakes (1995), (Geroski, 1995), Cefis and Marsili (2005), Doms et al. (1995) and Disney et al. (2003)
13. Size squared	Squared logarithm of employees (−)	Bhattacharjee et al. (2009) and Cefis and Marsili (2005)
14. Local unit	Indicates number of live local unit in multi-plant firm (+ /−)	Audretsch (1995) and Fernandes and Paunov (2015)
15. Labour productivity	Deflated turnover per employee (+)	Audretsch (1991), Ericson and Pakes (1995) and Griliches and Regev (1995)
16. Civil R&D	Dummy variable indicating that firm is engaged in civil R&D only; firms engaged in defence R&D are excluded (+ /−)	New. To test if survival rates differ between firms engaged in civil and defence R&D
17. UK-owned	Dummy variable indicating that the firm is UK-owned (+ /−)	Sharapov et al. (2011)
Industry covariates		
18. Pavitt technology classes[a]	Four dummy variables for 4 Pavitt classes–excluded category is Pavitt class dominated by technology suppliers (+ /−)	Pavitt (1984), Agarwal and Audretsch (2001) and Cefis and Marsili (2005)
19. Industry dummies	2-digit industry dummies	Usual practice to control for industry effects
Macroeconomic factors		
20. Crisis year	Dummy equal 1 for the Asian crisis year of 1998; dot.com bubble crisis of 2001; and the recent financial crisis in 2008 (−)	Not tested before; but Bhattacharjee et al. (2009) report higher hazard rates in periods of volatility
21. Effective exchange rate	Average effective exchange rate defined against a basket currencies–an increases indicates appreciation (−)	Bhattacharjee et al. (2009) and Goudie and Meeks (1991)

[a] Pavitt technology classes are from Pavitt (1984), as revised slightly by Bogliacino and Pianta (2010).

ness lending. We measure creative destruction with the median (rather than mean) of R&D intensity in the industry because R&D intensity is known to be highly skewed. Both Audretsch (1991) and Audretsch (1995) report that industry-level R&D intensity has a negative effect of survival time. Similarly, both Holmes et al. (2010) and Liu (2004) also report a negative relationship between interest rates and firm survival. The contribution here is to demonstrate that these covariates are integral to the formal survival model we propose.

Covariates six and seven enable us to test for the direct effect of market concentration on survival. McCloughan and Stone (1998) and Baldwin and Rafiquzzaman (1995) find a significant positive relationship between market concentration and firm survival. However, Mata and Portugal (1994) and Wagner (1994) report insignificant effects. The aim here is to verify whether market concentration affects survival after controlling for its interaction with R&D intensity.

Covariate eight measures the difference between firm growth and the median growth in the 3-digit SIC industry level. As such, it reduces heterogeneity in firm growth by correcting for industry fixed effects. On the other hand, the covariate nine controls for the fast growth in the last 3 years before exit in form of a dummy variable that is equal to 1 if the firm grows faster than the 3-digit industry median for three consecutive years before exit. It is intended to verify if fast growth over a sustained period before exit may be a sign of an overstained growth strategy.[7]

We control for a wide range of other variables tested widely in the literature. The firm-specific covariates include age and size,

[7] We thank one of our anonymous reviewers for drawing our attention to the need for reducing heterogeneity in the firm-specific growth variable, and to test for the presence of overstrained growth before exit. We are solely responsible for any error or omission in implementing reviewers' recommendations.

domestic ownership, number of plants (local units), and whether the firm is engaged in civil R&D as opposed to those engaged in defence-only or civil and defence R&D. We also control for non-linearity in age and size to verify if firms experience a reversal in fortunes once they are beyond an 'optimal' age or size. In addition to industry dummies, we control for Pavitt technology classes to test if the technology type matters for survival after controlling for R&D intensity (see Agarwal and Audretsch, 2001; Cefis et al., 2005). To take account of the macro-economic environment, we use the effective exchange rate as a measure of international competitiveness and the years of financial crisis as indicators of downswings.

4. Data and methodology

Our dataset is constructed by merging two UK firm-level databases: the Business Structure Database (BSD) and the Business Expenditure on Research and Development (BERD).[8] BSD consists of annual snapshots from the Interdepartmental Business Register (IDBR), which includes all firms registered for VAT and/or PAYE (pay-as-you-earn) purposes. It provides firm-level demographic information, together with unique firm identifiers (*entref*) and local-unit (plant) identifiers (*luref*) (ONS, 2016).

In BSD, firm exit is recorded as the year in which the firm disappears due to mergers, acquisitions, liquidation or bankruptcy. If the firm disappears due to mergers or acquisitions, its *entref* disappears but its *luref* remains the same. On the other hand, if the firm disappears due to liquidation or bankruptcy, both *entref* and *luref* disappear from the Register. Therefore, it was possible to differentiate between exits due to corporate market control and liquidation/bankruptcy. We identified the former by checking if the firm's local-unit reference survived its enterprise reference. If this condition holds, the firm is excluded from the analysis. Hence, the survival analysis here is based on firm exits due to liquidation or bankruptcy.

Due to recording errors, some firms remain in the IDBR for several years with zero employment and turnover. We have corrected for such anomalies by constructing our own exit year, which is the earliest of the death year recorded by the ONS or the first year when the firm employment and turnover are zero for 3 consecutive years. The number of firms affected by this correction was 147. Another anomaly in the BSD concerns incorrectly recorded birth years. Firms that appeared in the first Business Register in 1973 were given a birth year of 1973 despite the fact that most of them had existed before 1973. After excluding the firms with incorrect birth years, the number of remaining firms is 39,846.

BERD consists of repeated annual surveys with stratified sampling of firms known to be R&D-active.[9] The most R&D-intensive 400 firms receive a long questionnaire, with detailed questions on R&D types and sources of funding. Other firms receive a short questionnaire with questions on total, intramural and extramural R&D only. Missing data is imputed using other sources such as R&D Tax Credit returns or Annual Business Surveys (ONS, 2015).

We merged BERD with BSD, using the unique enterprise identifier (*entref*).[10] We omitted 1773 firms with anomaly *entrefs*, obtaining a merged set of 38,113 firms born in 1974 or after. We checked the distribution of R&D intensity for skewness.[11] We have established that the 99th percentile for R&D intensity is several times the turnover. To minimise the effect of such suspicious outliers, we excluded firm/year observations in the top 1% of the R&D intensity distribution. Hence, our estimation sample consists of 37,930 firms with 185,094 firm/year observations.[12]

The annual entry and exit rates, together with associated changes in employment and total R&D expenditures are reported in a *Data in Brief* article.[13] Results indicate that: (i) overall exit rate (1.9%) is smaller than the entry rate (4%); (ii) total number of jobs created by entrants is greater than job destruction due to exits; and (iii) total R&D investment by entrants is higher than that of exiters. However, after the onset of the financial crisis, exit rates have been higher or equal to entry rates; and net employment and R&D expenditures have been negative for at least two years.

We also checked the correlations between entry and exit rates at 2-digit industry level, with and without correction for industry fixed effects (Dunne et al., 1988; Disney et al., 2003). The results indicate that both uncorrected and corrected entry and exit rates are highly and positively correlated only contemporaneously. Stated differently, periods of high (low) entry are also periods of high (low) exit – irrespective of whether industry-specific technological conditions are taken into account. This finding points out to absence of a 'sorting effect' in UK firm dynamics, whereby the lower-quality of the marginal entrant in the period of above-average entry increases the exit rate in the subsequent period (Disney et al., 2003).

Given these data characteristics, we follow a sequential estimation strategy. First, we provide nonparametric survival time estimates, using the Kaplan-Meier estimator:

$$S(t) = \prod_{j<t} \frac{N_j - D_i}{N_j} \tag{2}$$

where t is time, N_j is the number of firms at risk at time j, and D_j is the number of failures ('exits') at time j. The non-parametric estimates compare firm/year categories based on R&D intensity and market concentration (Herfindahl index) quartiles. We verify the equality of the non-parametric survival estimates using Wilcoxon, Tarone-Ware, Peto-Peto and Logrank tests.

Second, we estimate a Cox proportional hazard model, where the distribution of the initial hazard is non-parametric and the baseline hazard function $h_0(t)$ for the j^{th} firm shifts proportionately with each covariate in $\mathbf{X}$. Another property of the model is that the hazard ratio for different firms is time-invariant. We reject the Cox model because it fails the Schoenfeld (1982) residuals tests of the proportionality assumption. We have also tested for time-invariant effects, which we had to reject as the interactions of the covariates with time came out statistically significant.

As a result, we turn to parametric models, where survival can be estimated in proportional hazard (PH) or accelerated failure time (AFT) metrics:

$$h(t_j) = h_0(t)\, exp(\mathbf{X}_j \beta) \tag{3-PH}$$

[8] The standard disclaimer applies: the use of these data does not imply the endorsement of the data owner or the UK Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

[9] The stratified sample consists of about 400 R&D-intensive firms (sampled 1:1); size-band2 firms (with 100–399 employees) sampled 1:5 and size-band3 firms (with 0–99 employees) sampled at a rate of 1:20. Firms covered in BERD account for about 80% of the business R&D expenditures in the UK (ONS, 2012).

[10] It must be noted that the time dimension of our data (1998–2012) corresponds to the rise of the Internet. As such, our findings may be reflecting period-specific dynamics in innovation. This is an issue worth investigating by using two comparable samples over different periods, but this is beyond the scope of this paper.

[11] High level of skewness in R&D intensity is a well-known feature, predicted by both stochastic and Schumpeterian models of R&D investment (Klette et al., 2004; Aghion et al., 2014). Fig. A1 in the Appendix A presents the kernel density plot for R&D intensity in our sample.

[12] We conduct a range of sensitivity checks to establish if parameter estimates are sensitive to the level of top R&D intensity excluded from the analysis – see Tables A2 and A3 in the Appendix A.

[13] See *Data in Brief*, xx(x), xxx (details to be completed after approval by *Data in Brief* editors.)

$$logt_j = \mathbf{X}_i\beta + z_j \quad \text{(3-AFT)}$$

In Eq. (3-PH), $h(t_j)$ is the hazard rate of j^{th} firm; $h_0(t)$ is the baseline hazard rate whose distribution depends on ancillary parameter(s) to be estimated; $\mathbf{X}_j$ is a vector of covariates that affect the hazard rate; and β is a vector of coefficients to be estimated. In Eq. (3-AFT), $logt_j$ is logarithm of survival time of j^{th} firm; $\mathbf{X}_j$ and β are as defined above; and z_j is the error term with a density function *f(t)*.

We estimate four non-nested models with different ancillary parameters: exponential, Weibull, Gompertz, and log-normal. We have chosen the optimal model using the minimum Akaike (AIC) and Schwartz (Bayesian) information criteria (*BIC*), and the fit level in the Cox-Snell residuals plots. Both sets of criteria favoured the *log-normal* model.[14]

We estimate the model using covariates in Table 1 with and without controlling for left truncation and frailty (unobserved heterogeneity). Left truncation occurs because we do not observe some firms before the start of the analysis time in 1998 even though such firm may have existed in the past. To address this issue, we estimated the model with firms born in 2001 and thereafter to verify if the results are sensitive to controlling for left truncation. We also estimated the model with unshared frailty to verify if the variance of the frailty coefficient (θ) is statistically different than zero. If the variance of the frailty coefficient approaches zero, i.e., if heterogeneity among survivors is insignificant, the model with frailty reduces to a survival model without frailty regardless of the frailty distribution (Box-Steffensmeier and Bradford, 2004). The significance of the frailty variance (θ) is tested with likelihood-ratio tests, where the null hypothesis is zero variance. For frailty, we choose the flexible gamma distribution.[15]

The log-normal model is suitable for right-censored data, where subjects may be still alive at the end of the analysis period. This is ensured by defining the initial time, the end of the analysis time and the failure (exit) event. In addition, it is appropriate for data exhibiting delayed entry, gaps, time-varying covariates, or multiple failures (Blossfeld et al., 1989; Cleves et al., 2008). Finally, parameter estimates are elasticities of the survival time with respect to covariates if the latter are expressed in logarithms or semi-elasticities if they are expressed in levels (Cefis et al., 2005).

4.1. Results

First, we present non-parametric estimations of the survival function (Fig. 1). In summary, non-parametric results indicate the following: firms with above-median R&D intensity (in the 3rd and 4th quartiles) have lower survival rates than those with below-median R&D intensity (in the 1st and 2nd quartiles); and firms in the bottom quartile of the market concentration have lower survival rates compared to the rest. In addition, the survival rate of the firms in the top quartile of the market concentration remains higher than all other quartiles as time increases. The *Log-rank*, *Wilcoxon*, *Tarone-Ware* and *Peto-Peto* tests indicate that the differences between survival rates are significant in both cases.

However, one should not read too much into non-parametric estimates as they are not conditioned on firm, industry and macroeconomic indicators that affect survival. Therefore, we turn to parametric estimations based on summary statistics in Table A1 in Appendix A, reported for the full sample and for surviving and exiting firms separately. One evident pattern in Table A1 is that the distribution of R&D intensity is strongly skewed to the right – with skewness measures of 6.7, 7.7 and 5.2 for the full sample, survivors and exiters respectively. This is in line with the empirical patterns reported in the literature (Klette et al., 2004; Aghion et al., 2014). Secondly, mean R&D intensity is larger among exiters (0.30) compared to survivors (0.16) or full sample (0.20). This is interesting because it indicates that higher levels of R&D investment do not necessarily ensure survival. Third, exiting firms: (i) are smaller with mean employment of 69 compared to survivors (130) or full sample (113); (ii) have lower real turnover per employee with mean of £201 thousand in 2010 prices compared to survivors (£214 thousand) or full sample (£210 thousand); and (iii) grow slower than the industry median growth (by −3%), whereas the growth differential is positive for survivors (4%) and the full sample (2%).

Results from the log-normal estimation are in Table 2. Column 1 reports results from the baseline sample, which includes all firms born after 1973, excluding top 1% of the R&D intensity distribution. Results in column 2 are for firms born in 2001 or after, with a view to verify if coefficient estimates are sensitive to left truncation. Columns 3 and 4 replicate the estimations in (1) and (2) by taking account of frailty at the firm level.

The likelihood ratio test for frailty (Gutierrez, 2002) does not reject the null hypothesis that the frailty coefficient's variance (θ) is zero. Hence, there is no systematic difference between the estimates with and without frailty. Furthermore, levels of multicollinearity (VIF values) are below the commonly agreed upper limit of 10.[16] Finally, the sign, significance and magnitude of the estimates are largely consistent across estimations/samples, with the exception of the Herfindahl index and its square. Given these findings, our inference will be based on the baseline estimation in Column 1 (Table 2), preferred on the basis of favourable log-likelihood, AIC and BIC values.

However, we will qualify our inference in two ways. First, we will compare the sign and significance of each estimate in column 1 with the rest in Table 2. We will infer that the finding in column 1 is upheld: (a) strongly if similarity across Table 2 is 75% or more; (b) moderately if similarity is between 50%–74%; and (c) upheld weakly if similarity is less than 50%. Then we will take into account the results from 10 sensitivity checks reported in Tables A2 and A3 in Appendix A. In Table A2, we check if the results remain robust to 6 different cut-off points for top R&D intensity. In Table A3, we check if the results remain robust to 4 step-wise estimations. We conclude that the estimated parameter in the baseline model is: (a) strongly-robust, if it is consistent with all sensitivity checks in Tables A2 and A3; (b) medium-robust, if it is consistent with 60% or more of the sensitivity checks; and (c) weakly-robust, if it is consistent with less than 60% of the findings. To facilitate the comparison, Table 3 below reports the signs and significance of the coefficient estimates from model 1 in Table 2, together with their consistency across Table 2 and their robustness to sensitivity checks in Tables A2 and A3 in Appendix A.

Starting with the first two covariates of main interests (R&D intensity and its square), we conclude that there is strong evidence that the relationship between R&D intensity and survival time is subject to decreasing scale effects and this finding is strongly-robust to sensitivity checks. This is in line with the prediction of

[14] See Fig. A2 in the Appendix A, where the hazard function for the lognormal model follows the 45° line very closely, except for large values of time. However, those of other parametric models (exponential, Weibull and Gompertz) deviate from the 45° line significantly and the deviation increases with time.

[15] The choice is informed by findings indicating that the distribution of heterogeneity among survivors converges to a gamma distribution rapidly (Abbring and van Den Berg, 2007: 145).

[16] The major contributors to mean VIF values are age and age-squared. When we estimate the models without these covariates, the VIF value is around 4. Furthermore, the magnitude, signs and significance of the estimates remain in line with those in Table 2. These results are not reported here, but are available on request. The correlation matrix for the covariates is presented in Table A4 in the Appendix A.

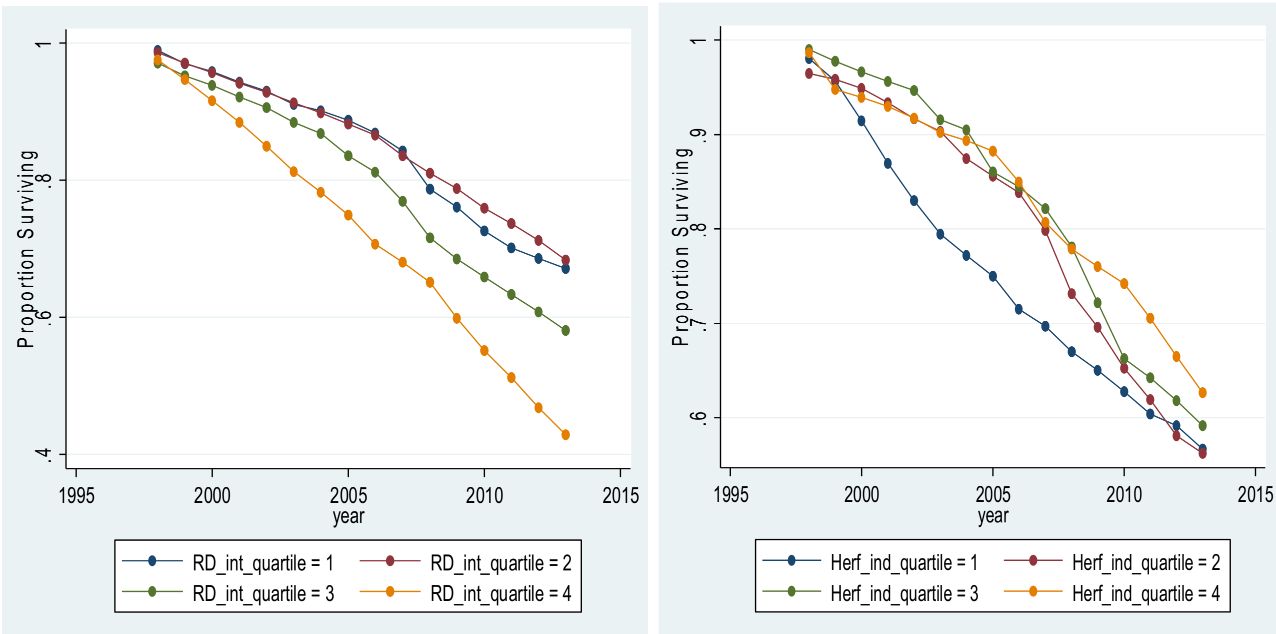

Fig. 1. Non-parametric survival functions. Survival rates by R&D intensity quartiles Survival rates by Herfindahl index quartiles.

the theoretical model we constructed and lends strong support for **Hypothesis 1**.[17]

We also find that market concentration and R&D intensity might be complements: a given level of R&D intensity is associated with longer survival times if firms are located in more concentrated industries. Both R&D intensity and market concentration enable R&D-active firms in concentrated markets to increase the normalised value of the knowledge production line and survive longer than other firms with similar R&D intensity but lower market power. However, the complementary is only weakly-robust to sensitivity checks. An examination of Table A2 in Appendix A indicates that this result is highly sensitive to the level of top R&D intensity excluded from the analysis. Indeed, the effect disappears when the cut-off point for top R&D intensity is at the 97th percentile or less. Hence, we conclude that the support to **Hypothesis 2** is sensitive to skewness in the R&D intensity distribution. Despite this caveat, we think that the finding is novel enough to warrant further research.

The negative relationship between survival time and industry-level R&D intensity and lending premium is highly consistent across estimations and highly robust to sensitivity checks.[18] Our findings are also consistent with previous work (Audretsch, 1991; Audretsch et al., 1995 on the effect of industry-level R&D intensity; and Holmes et al., 2010 and Liu, 2004 on the effect of interest rates). Hence, we conclude that there is strong support for **Hypothesis 3**; and that the proposed model is versatile enough to explain empirical patterns reported elsewhere.

The sign/significance consistency of the Herfindahl index and its square is low across Table 2; with a level of robustness to sensitivity checks at 70%. We interpret this as weak evidence in support of a non-linear relationship between market concentration and survival time. The ambiguity in the effect of market concentration is in line with the existing literature. Whilst Mata and Portugal (1994) and Wagner (1994) report insignificant or ambiguous effects, McCloughan and Stone (1998), Baldwin and Rafiquzzaman (1995) and Helmers and Rogers (2010) find significant positive effects. In addition, they resonate with an early observation in Geroski (1991) who concludes that particular *market niches* are more likely to be important to new entrants.

The positive and significant coefficients on age and size reflect strong consistency within Table 2 and strong robustness to sensitivity checks. They are also consistent with both theoretical and empirical findings, which indicate that new entrants have shorter survival time, but those that survive have longer survival times (Erikson and Pakes, 1995; Klette et al., 2004; Aghion et al., 2014; Cefis et al., 2005; and Evans, 1987 among others).

However, controlling for non-linearities in the effects of age and size has been an exception rather than the rule, e.g. Bhattacharjee et al. (2009) and Cefis and Marsili (2005). This issue has not been emphasised in literature reviews (Geroski, 1995). Our findings indicate absence of a non-linear relationship between age and survival. This is in contrast to 'liability of adolescence' or 'honeymoon effect' hypotheses that, respectively, posit *U-shaped* and *inverted-U* shaped relationships between age and survival (Fichman and Levinthal (1991). However, we find strong support for an inverted-U relationship between size and survival. This is in line with evidence on size distribution and survival among Portuguese firms (Cabral et al., 2003); and suggests that a large size beyond an efficient scale may be a hazard factor in firm dynamics.

We report that the relationship between the number of plants (local units) and firm survival is insignificant in the preferred model (1). However, this finding is not supported by findings in the rest of Table 2 and in sensitivity checks in Tables A3 and A4 in Appendix A. The positive relationship is in line with Audretsch (1995), who report that multi-plant firms have lower hazard rates because they can diversify risks and/or restructure in the face of adverse shocks. Hence, we conclude that our finding from the preferred model should be treated with caution.

We also report that labour productivity (deflated turnover per employee) and firm growth relative to 3-digit industry median growth have positive effects on survival time. These findings are

[17] As an anonymous reviewer has pointed out, the scale effect may be specific to new innovation dynamics during the rise of the Internet. This argument can be tested by comparing results from two comparable datasets before and after late 1990s. This is beyond the scope of this paper, but we strongly recommend testing for R&D scale effects with both recent and older data.

[18] In the Appendix A, we demonstrate that the negative effects of the discount rate (ρ) and the rate of creative destruction (x) on survival depends on the following condition: $(\rho + x) > z$ where z is innovation intensity. This condition is satisfied in the data, with median values as follows: $\rho = 0.10$; $x = 0.03$ and *R&D intensity* = 0.04.

Table 2
R&D intensity, market concentration and firm survival.

Dep. variable: time to exit	(1#)	(2)	(3)	(4)
Covariates of main interest				
Log (Total RD intensity + 1)	0.326***	0.292***	0.368***	0.298***
	(0.0591)	(0.0773)	(0.0633)	(0.0774)
Log² (Total R&D intensity + 1)	−0.166***	−0.176***	−0.185***	−0.177***
	(0.0301)	(0.0396)	(0.0348)	(0.0397)
*Log (Total R&D intensity + 1)*HI*	0.411**	0.959***	0.377*	0.918***
	(0.168)	(0.235)	(0.179)	(0.234)
Herfindahl index (HI)	−0.540***	0.273	−0.195	−0.0474
	(0.144)	(0.189)	(0.137)	(0.183)
Herfindahl index²	0.762***	−0.490*	0.338	−0.248
	(0.218)	(0.263)	(0.223)	(0.267)
Median R&D int. in industry	−0.317***	−0.813***	−0.405***	−0.708***
	(0.0784)	(0.0987)	(0.0826)	(0.100)
Lending premium	−1.654***	1.471***	−1.738***	1.447***
	(0.0479)	(0.0877)	(0.0474)	(0.0882)
Other firm-level covariates				
Firm growth relative to	0.0319***	0.0293***	0.0331***	0.0308***
industry growth	(0.00494)	(0.00640)	(0.00501)	(0.00645)
Fast growth over 3 years	−1.074***	−0.703***	−1.102***	−0.716***
before exit	(0.0379)	(0.0389)	(0.0386)	(0.0393)
Log (Age)	0.537***	2.669***	0.528***	2.662***
	(0.0561)	(0.0902)	(0.0568)	(0.0928)
Log² (Age)	−0.0175	−0.502***	−0.0172	−0.500***
	(0.0136)	(0.0248)	(0.0138)	(0.0257)
Log (Employment)	0.232***	0.217***	0.232***	0.209***
	(0.0163)	(0.0251)	(0.0157)	(0.0247)
Log² (Employment)	−0.0251***	−0.0290***	−0.0255***	−0.0283***
	(0.00235)	(0.00455)	(0.00230)	(0.00447)
Log (Live local units + 1)	0.0263	0.0879***	0.0418**	0.0978***
	(0.0185)	(0.0283)	(0.0184)	(0.0287)
Log (Def. turnover/employee)	0.0988***	0.0720***	0.100***	0.0696***
	(0.00806)	(0.0107)	(0.00778)	(0.0107)
Firm engages in civil R&D only	0.0548***	0.101***	0.0347***	0.0867***
	(0.00999)	(0.0153)	(0.0105)	(0.0156)
Firm is UK-owned	0.0755***	0.0304	0.0702***	0.0153
	(0.0213)	(0.0450)	(0.0215)	(0.0456)
Other industry-level covariates				
Pavitt technology class 1	0.0312	−0.118	0.0617**	0.110***
	(0.0947)	(0.143)	(0.0245)	(0.0320)
Pavitt technology class 2	0.176***	0.138*	0.0932***	0.0695**
	(0.0615)	(0.0766)	(0.0232)	(0.0290)
Pavitt technology class 3	0.0583	0.170*	−0.00126	0.00630
	(0.0594)	(0.0887)	(0.0304)	(0.0486)
Pavitt technology class 5	0.105	0.0666	0.0627*	0.0632*
	(0.0706)	(0.0782)	(0.0321)	(0.0383)
Other macro-level covariates				
Average eff. exchange rate	−0.0553***	−0.0300***	−0.0556***	−0.0297***
	(0.000695)	(0.00105)	(0.000686)	(0.00105)
Crisis dummy	−0.135***	−0.597***	−0.132***	−0.591***
	(0.00918)	(0.0297)	(0.00934)	(0.0300)
Constant	4.843***	0.705***	4.849***	0.408**
	(0.252)	(0.265)	(0.104)	(0.163)
Observations	168626	38949	168306	38949
Number of subjects (firms)	36821	12416	36798	12416
Log likelihood	−28684.7	−9243.8	−28970.7	−9399.4
AIC	57585.4	18697.6	57991.4	18850.7
BIC	58669.2	19597.5	58242.3	19073.6
σ	0.685***	0.578***	0.692***	0.583***
θ			1.430E-08	7.79e-09
VIF#	7.46	6.19	7.46	6.19
2-digit industry dummies	Yes	Yes	No	No

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Top 1% of R&D intensity is excluded from all estimations. 1# = All firms born in 1974 or after (preferred model); 2 = Firms born in 2001 and after; 3 = Model (1) with frailty; 4 = Model (2) with frailty.

strongly consistent across estimations and sensitivity checks. The positive relationship between survival and firm growth is in line with empirical findings reported in previous studies (Doms et al., 1995; Mata et al., 1995; Agarwal, 1997; Cefis et al., 2005). The added value of our finding is that the positive effect of growth on survival holds even after correcting for industry fixed effects. The positive relationship between labour productivity and survival is also in line with Olley and Pakes (1992), who demonstrate that low productivity is a major cause of exit. It is also in line with the 'shadow of death' argument in Griliches and Regev (1995), who report from Israeli data that exiting firms are significantly less productive.[19]

However, our findings also indicate that aggressive growth strategies may reduce survival time (we thank an anonymous

[19] This is indeed what we observe in the UK data too—with lower real turnover per employee among exiters compared to survivors and the full sample (see, summary statistics in Table A1 in the Appendix A).

Table 3
Consistency of parameter estimates: Baseline model versus different estimations and sensitivity checks.

	Sign and significance in baseline model in Table 2	% of similarity in Table 2	Consistency with 10 sensitivity checks (in Tables A3 and A4)	Robustness to sensitivity checks
Log (Total RD int. + 1)	+***	100%	100%	Strongly-robust
Log² (Total R&D int. + 1)	−***	100%	100%	Strongly-robust
*Log (Total R&D intensity + 1)*HI*	+***	100%	40%	Weakly-robust
Herfindahl index (HI)	−***	25%	70%	Medium-robust
Herfindahl index²	+***	50%	70%	Medium-robust
Median R&D intensity in industry	−***	100%	80%	Strongly-Robust
Lending premium	−***	100%	100%	Strongly-robust
Firm growth relative to industry growth	+***	100%	100%	Strongly-robust
Fast growth over last 3 years before exit	−***	100%	100%	Strongly-robust
Log (Age)	+***	100%	80%	Strongly-robust
Log² (Age)	Insignificant	50%	80%	Strongly-robust
Log (Employment)	+***	100%	100%	Strongly-robust
Log² (Employment)	−***	100%	100%	Strongly-robust
Log (Live local units + 1)	Insignificant	25%	10%	Weakly-robust
Log (Def. turnover/employee)	+***	100%	100%	Strongly-robust
Firm engages in civil R&D only	+***	100%	80%	Strongly-Robust
Firm is UK-owned	+***	50%	90%	Strongly-Robust
Pavitt technology class1	Insignificant	50%	80%	Strongly-Robust
Pavitt technology class2	+***	100%	100%	Strongly-robust
Pavitt technology class3	Insignificant	25%	80%	Strongly-robust
Pavitt technology class5	Insignificant	25%	80%	Strongly-robust
Average eff. exchange rate	−***	100%	100%	Strongly-robust
Crisis dummy	−***	100%	100%	Strongly-robust

Comparing the finding from baseline model in column 1 of Table 2 with the rest of Table 2 and sensitivity checks in Tables A3 and A4 in Appendix A. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Firms and firm characteristics after the turning points.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Linear R&D coefficient	0.439	0.52	0.721	0.763	5.854	0.38	0.326
Quadratic R&D coefficient	−0.288	−0.388	−0.675	−0.768	−33.79	−0.228	−0.166
R&D*Herfindahl index#	0.409	0	0	0	0	0	0.411
Median Herf. index in sample	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Turning point [log (RD +1)]	0.80	0.67	0.53	0.50	0.09	0.83	1.06
Turning point (R&D intensity)	1.24	0.95	0.71	0.64	0.09	1.30	1.88
Total firms above turning point	3441	4260	5323	5731	18,297	337	2485
Total firms in sample	36,699	36,553	36,244	36,201	32,014	11,644	36,821
% of firms above turning point	9.38	11.65	14.69	15.83	57.15	2.89	6.75
Mean employment above turning point	23	27	30	31	51	97	22
Mean employment in sample	114	115	117	117	135	162	113
Mean R&D int. above turning point	3.06	2.58	2.12	1.98	0.57	3.32	3.16
Mean R&D intensity in sample	0.16	0.13	0.11	0.10	0.04	0.07	0.20

Samples vary by cut-off points for top R&D intensity percentiles and sector composition. (1): top 2% cut-off, all sectors; (2): top 3% cut-off, all sectors; (3): top 5% cut-off, all sectors; (4): cut-off at R&D intensity of 1 or more, all sectors; (5): top 25% cut-off, all sectors; (6): top 1% cut-off, manufacturing firms only; (7): top 1% cut-off, baseline sample. #: a value of 0 indicates that the coefficient estimate is insignificant.

reviewer for pointing to this possibility). Specifically, we find that firms that grow faster than the industry median for three consecutive years before exit have shorter survival times. This finding is compatible with case-study evidence indicating that aggressive growth strategies may be detrimental to firm performance in the absence of appropriate growth management strategies. The latter should be in place to address fast-growth challenges such as training, customer support, increased management delegation, and investment in enhanced organisational structures (Greening et al., 1996; Oliva et al., 2003). The fast-growth firms are similar to others in terms of R&D intensity and productivity, but they are much smaller – with mean employment of 16 against 114 in the rest of companies.[20] Hence, we cautiously suggest that the negative relationship between fast growth and survival in our data may be reflecting overstrained ambitions for increased market shares.

Two other firm characteristics that may be specific to UK firms are found to have positive effects on survival: UK ownership (with medium support) and engagement in civil R&D only (with strong evidential support). Both coefficient estimates are strongly-robust to sensitivity checks. Longer survival among UK-owned firms is in line with Sharapov et al. (2011). This may be due to better local knowledge of UK-owned firms and/or aggressive relocation strategies of the foreign-owned firms, who relocate to other countries in the face of adverse market conditions in the UK. Furthermore, longer survival among firms engaged in civil R&D may be due to absolute and relative decline in UK defence expenditures. Since late 1980s, defence-related R&D expenditures in the UK fell from £5 bn in 1989 to £2 bn in 2012 in constant prices (ONS, 2014). In addition, the difference between civil and defence R&D expenditures has widened in favour of the former, from £10 bn in to £22 bn over the same period (ONS, 2014). We conjecture that some of the firms engaged in defence-related R&D may have exited due to reduced government subsidies for defence-related R&D

[20] Fast-growing firms are also smaller when size is measured with deflated turnover, with a mean of £5.2 m against £24.2 m for other firms.

We also find that firms specialised in the supply of technology (Firms in Pavitt class 2 that includes mechanical engineering, manufacturing of electrical equipment, renting of machinery, etc.) have longer survival times relative to other technology classes. This finding is in line with Agarwal and Audretsch (2001) and Cefis and Marsili (2005) and it indicates that the nature of the technology in the industry matters. We conjecture that Pavitt2 firms may be enjoying specific market niches, but this issue requires further investigation.

Finally, our findings indicate that the macroeconomic environment has a significant effect on firm survival. In addition to the negative effect of the lending premium discussed above, we find that the onset of a financial crisis and currency appreciation tend to reduce survival time. These findings are supported by strong evidence and remain highly consistent across various sensitivity checks. They are also in line with those reported in few studies (Bhattacharjee et al., 2009; Goudie et al., 1991). The evidence we report here can go some way towards bridging the evidence gap, which led earlier reviewers to conclude that the empirical work controlling for macroeconomic conditions leaves the "impression that . . . hazard rates are rather insensitive to the observed variation in the macro environment" (Caves, 1998).

4.2. Turning points for R&D intensity

Three issues arise in the context of quadratic specifications: (i) whether the linear and quadratic terms are jointly significant; (ii) whether the turning point occurs within the sample range for R&D intensity; and (iii) the number of firms above the turning point and their characteristics. We have addressed issue (i) by conducting likelihood ratio tests of joint significance for the linear and non-linear terms, all of which indicate joint significance in all reported estimates. To address issues (ii) and (iii), we calculated the levels of R&D intensity that constitute the turning point for the inverted-U curve,[21] and some descriptive statistics that provide information about the firms with R&D intensity above the turning point (Table 4). Columns 1–6 report evidence related to the same samples in Table A3 in Appendix A. Column 7 reports evidence related to the preferred model (column 1) in Table 2 above.

The percentage of firms with R&D intensity above the turning point is not trivial – it ranges between 2.9% and 57%. Hence, the scale effect in the relationship between R&D intensity and firm survival is not an aberration caused by an arbitrary cut-off point for the top R&D intensity. As expected, the mean R&D intensity above the turning point is always much larger than the mean R&D intensity in the sample (cf. last two rows of Table 4). We observe that firms above the turning point are smaller in terms of employment. Given that we already control for size (firm employment) in the estimations, we conclude that the downward-sloping relationship between R&D intensity and survival time after the turning points is driven by diminishing scale effects rather than size.

5. Conclusions

In this paper, we set out with the observation that empirical findings on the relationship between input or output measures of innovation and firm survival are varied and often conflicting. We also observed that this is in contrast to largely convergent findings on the relationship between survival and a wide range of firm-, industry- or macro-level factors. Hence, we argued that the variation in the evidence base may be due to lack of control in existing models for scale effects in the relationship between R&D intensity and survival and possible complementarity/substitution effects in the relationship between R&D intensity and market concentration.

To test these arguments, we proposed a theoretical model informed by Schumpeterian perspectives on competition, innovation and growth. The proposed model predicts an inverted-U pattern in the relationship between R&D intensity and firm survival. It also implies that R&D intensity and market concentration are complements; and creative destruction (proxied by industry-level R&D intensity) and the discount rate (proxied by business lending premium) are negatively associated with survival time.

We have tested these predictions using UK data for 37,930 firms from 1998 to 2012. The diminishing scale effect is strongly consistent across different samples and estimations with and without frailty. We have also found medium evidential support for the prediction that innovation and market concentration are complements. However, this finding is only weakly-robust to skewness in the R&D intensity. Finally, we report that the model's predictions concerning the negative effects of creative destruction and the discount rate are supported by UK evidence. These findings contribute to existing knowledge by highlighting the importance of controlling for: (i) scale effects in R&D intensity; (ii) complementarity between the latter and market concentration; and (iii) the roles of creative destruction and discount rate. The evidence with respect to direct effects of market concentration remains inconclusive.

Secondly, we find that firm growth above the industry median over a sustained period before exit is associated with shorter survival time. We interpret this as a reflection of overstrained growth strategies, whereby smaller firms that focus on growth as a means of enhancing market share face a higher risk of exit, perhaps due to a gap between their growth ambitions and growth management capacity.

Thirdly, our findings concerning the effects of a wide range of firm-, industry- and macro-level covariates such as age, size, and productivity, firm growth relative to the industry, technology class, crisis years, and international competitiveness are all consistent across estimations and in line with the existing literature.

One implication of our findings for future research is that it is necessary to control for scale effects in the relationship between R&D intensity and survival. This can be done with new datasets and as replications of the existing studies, which tend to adopt a linear specification for the relationship between R&D intensity and survival. Controlling for scale effects is advisable because it allows researchers to establish whether the relationship between R&D intensity and firm survival is monotonic or subject to increasing or decreasing scale effects; and whether the scale effects vary between industries or over time.

Another implication is that controlling for complementarity or substitution between R&D intensity and market power is justified on both theoretical and empirical grounds. Although our findings lend only moderate support for complementarity between R&D intensity and market concentration, we are of the view that controlling for complementarity/substitution between R&D intensity and a better measure of market power is a fruitful avenue for future research. We suggest that market power indices based on profit margins, corrected for efficiency as suggested by Boone (2008a,b), can be used by researchers drawing on publicly available financial data for listed and unlisted firms. This line of research can shed additional light on whether the survival effects of R&D investment are mediated through market power (escape-competition effect) or increased efficiency (competition effect).

In terms of policy and practice, our findings indicate that there may be an 'optimal' level of R&D investment for maximising survival time, but the optimal level is likely to differ depending on the

[21] The turning points are calculated as follows. Let $\frac{\partial E[t]}{\partial RD_{int}} = \beta_1 + 2\beta_2 RD\_int + \beta_3\overline{HI} = 0$, where RD_int is total R&D intensity and $\overline{HI}$ is median Herfindahl index in the sample. Then the turning point for R&D intensity is given by: $RD\_int = \left(\beta_1 + \beta_3\overline{HI}\right) / \left(-2\beta_2\right)$.

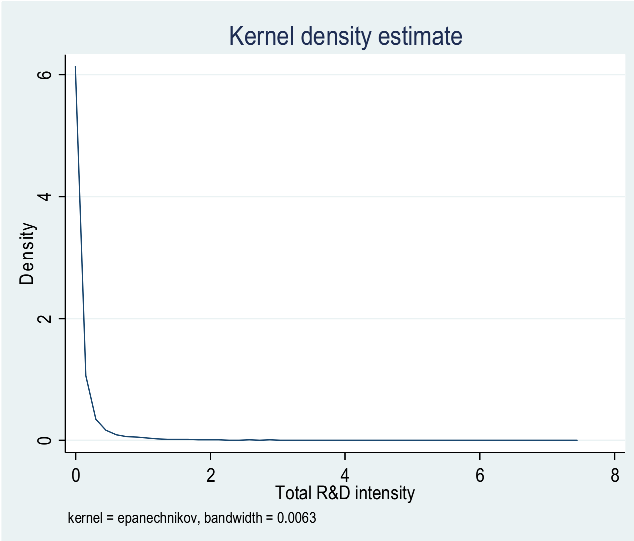

Fig. A1. Kernel density plot for R&D intensity in the estimation sample.
Note: The level of R&D intensity skewness in the sample is very high (+6.70). The number of observations with zero R&D intensity is 2459 (1.33% of the total). The number of observations with R&D intensity greater than 1 is 9769 (or 5.3% of the total). Mean value of R&D intensity is 0.20.

level of creative destruction in the industry, the level of product-market competition, and the extent of skewness in the distribution of R&D intensity. Such variations, however, are part and parcel of the 'active learning' process that shapes the decisions of both firm managers and policy-makers aiming to maximise the returns on R&D investment.

Appendix A. A survival model with R&D scale effects.

Drawing on Aghion et al. (2014), we begin with a firm that combines a number of scientists (S_i) with a stock of knowledge (k) and generates a Poisson count of innovation flows (Z_i) in accordance with a Cobb-Douglas production function with constant returns to scale Eq. (A1)(.)

$$Z_i = \left(\frac{S_i}{\zeta}\right)^{\frac{1}{\eta}} k_i^{1-\frac{1}{\eta}} \tag{A1}$$

Here, ζ is scaling factor, $1/\eta < 1$ and denotes the elasticity of innovation flows with respect to scientists, and k is the number of knowledge production lines (knowledge stock). The latter increases to $k+1$ when R&D investment is successful; but also decreases to k-kx when creative destruction occurs at the rate of x. From Eq. (A1), the total and average cost functions are:

$$C(z_i, k) = \zeta w k z_i^{\eta} \quad (\text{Total cos tofknowledgeproduction}) \tag{A2.1}$$

$$C(z_i) = \zeta w z_i^{\eta} \quad (\text{Average cost ofknowlegdeproduction per innovation line})$$

The total and average costs increase with wage rate (w) and innovation intensity (z_i), defined as $z_i = Z_i/k$. Finally, the average normalized value of the knowledge production line is determined endogenously by firm and industry characteristics in accordance with Eq. (A3):

$$v = \frac{\pi - \zeta w z_i^{\eta}}{\rho + x - z_i} = \frac{\pi_A}{\rho + x - z_i} \tag{A3}$$

In Eq. (A3), π is gross profit per innovation line, π_A is gross profits adjusted for cost of innovation, ρ is discount rate, and x is the rate of creative destruction in the industry.[22] The firm chooses its innovation intensity (z_i) to maximise the average value per knowledge production line (v). The latter increases with gross profits, but decreases with the discount rate (ρ) and with the rate of creative destruction in the industry (x).[23] The effect of innovation intensity on normalised value is non-linear: v increases through the linear term in the denominator (z_i), but decreases with the non-linear term in the numerator (z_i^{η}).

Denoting firm output at time t with Y_t and the knowledge production lines with k, Aghion et al. (2014) derive the balanced-path value $V_t(k)$of the firm as:

$$V_t(k) = kY_t v \tag{A4}$$

We utilize the model to evaluate the effect of R&D intensity on firm survival. To do this, we depart from Aghion et al. (2014), where the firm exits when it loses all of its knowledge production lines due to creative destruction. Instead, we hypothesize that the firm exits when its market value is zero.

The use of firm value for modelling survival time requires that the market prices the firm's R&D investment correctly. Some studies report that returns on R&D-intensive stocks are not higher than those of non-R&D-intensive firms (Chan et al., 1999). However, a larger body of work reports that the effect of R&D intensity on the firm's stock-market value is positive and strong, even though the coefficients fluctuate over time (Hall, 2006; Chauvin et al., 1993; Ehie and Olibe, 2010). Given these findings, we assume that the firm's market value can be taken as *approximately equal* to firm value in Eq. (A4).

Assuming that the firm's market value follows a Wiener process until liquidation (McDonald and Siegel, 1985), we can write the log-normally distributed value of the firm as a function of time as follows:

$$V_t(k) = kY_t v \cong V_0 e^{\left[\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma\sqrt{t}N(0,1)\right]} \tag{A5}$$

Here, V_0 is the firm's initial value, μ and σ are drift and volatility parameters respectively, t is time to exit (liquidation), and *N(0, 1)* is the standard normal distribution with mean 0 and a variance of 1. Taking logarithms across and noting that the expected value of the standard-normal variable is zero, we obtain Eq. (A6):

$$E[V_t(k)] = E[\ln(k) + \ln Y_t + \ln v] \cong E[\ln Vo] + \left(\mu - \frac{\sigma^2}{2}\right) E[t] \tag{A6}$$

Given that the initial (V_0) is constant and that the expected values of k, Y_t and v are equal to their equilibrium values; we can write:

$$\ln(k) + \ln Y_t + \ln v \cong \ln Vo + \left(\mu - \frac{\sigma^2}{2}\right) E[t] \tag{A7}$$

From Eq. (A7), we can derive the expected value of survival time as:

$$E[t] \cong \frac{2}{2\mu - \sigma^2}[\ln(k) + \ln Y_t - \ln Vo + \ln v] \tag{A8}$$

Replacing v with its equivalent in (3), we obtain:

$$E[t] \cong \frac{2}{2\mu - \sigma^2}\left[\ln(k) + \ln\left(\frac{Y_t}{V_0}\right) + \ln\frac{\pi - \zeta w z_i^{\eta}}{\rho + x - z_i}\right] \tag{A9}$$

[22] Optimising behaviour requires that adjusted gross profit is strictly positive – i.e., $\pi - \zeta w z_i^{n} = \pi_A > 0$. Otherwise, the firm is better off shutting down the knowledge production line(s) with zero or negative value.

[23] A higher discount rate reflects a higher opportunity cost for a given level of innovation intensity (z_i), and the rate of creative destruction in the industry renders the firm's technology obsolete.

Table A1
Summary statistics[a].

Full sample

Variable	N	Mean	Min.	Max.	Skew.
R&D intensity (RD_int)	185,094	0.20	*	*	6.70
RD_int - squared	185,094	0.39	*	*	11.94
*R&D_int * HI*	185,094	0.02	0	4.37	14.05
Herfindahl index (HI)	185,094	0.10	0.01	1	3.09
HI-squared	185,094	0.02	5.7E-5	1	7.66
Relative growth	172,477	0.02	−9.57	11.76	0.40
Fast growth dummy	172477	0.01	0.00	1.00	13.54
Age	185,094	14.27	*	*	0.47
Age -squared	185,094	277.78	*	*	1.43
Employment (Emp)	185,094	113.36	*	*	68.55
Emp- squared	185,094	128E+4	*	*	118.55
Live local units	185,094	1.92	*	*	168.11
Productivity	184,893	210.26	*	*	127.90
Civil R&D only	185,094	0.42	*	*	0.34
UK-owned	185,094	0.88	*	*	−2.37
Median R&D intensity in industry	172,477	0.08	0	2.87	2.07
Pavitt class 1	185,094	0.36	0	1	0.60
Pavitt class 2	185,094	0.22	0	1	1.38
Pavitt class 3	185,094	0.09	0	1	2.80
Pavitt class 4	185,094	0.27	0	1	1.03
Pavitt class 5	185,094	0.06	0	1	3.55
Effective exch. rate	185,094	92.47	79.99	103.67	−0.30
Crisis dummy	185,094	0.15	0	1	1.93
Lending premium	185,094	0.12	−0.034	0.383	0.67
Number of firms	37,930				

Survivors

Variable	N	Mean	Min.	Max.	Skew.
R&D intensity (RD_int)	134,626	0.16	*	*	7.68
RD_int - squared	134,626	0.29	*	*	14.22
*R&D_int * HI*	134,626	0.02	0	4.37	15.09
Herfindahl index (HI)	134,626	0.10	0.01	1	3.07
HI-squared	134,626	0.02	5.7E-5	1	7.45
Relative growth	128,791	0.04	−7.33	11.76	0.84
Fast growth dummy	128791	0.00	0.00	0.00	.
Age	134,626	15.65	*	*	0.33
Age -squared	134,626	319.68	*	*	1.23
Employment (Emp)	134,626	130.07	*	*	61.51
Emp- squared	134,626	166E+4	*	*	103.73
Live local units	134,626	2.19	*	*	145.65
Productivity	134,544	213.78	*	*	142.79
Civil R&D only	134,626	0.43	*	*	0.29
UK-owned	134,626	0.87	*	*	−2.24
Median R&D intensity in industry	128,791	0.07	0	2.87	2.40
Pavitt class 1	134,626	0.32	0	1	0.76
Pavitt class 2	134,626	0.22	0	1	1.32
Pavitt class 3	134,626	0.10	0	1	2.68
Pavitt class 4	134,626	0.29	0	1	0.93
Pavitt class 5	134,626	0.06	0	1	3.54
Effective exch. rate	134,626	90.82	79.99	103.67	0.05
Crisis dummy	134,626	0.13	0	1	2.17
Lending premium	134,626	0.11	−0.034	0.38	0.74
Number of firms	24,412				

Exiters

Variable	N	Mean	Min.	Max.	Skew.
R&D intensity (RD_int)	50,468	0.30	*	*	5.19
RD_int - squared	50,468	0.68	*	*	8.89
*R&D_int*HI*	50,468	0.03	0	3.57	11.99
Herfindahl index (HI)	50,468	0.09	0.01	1	3.15
HI-squared	50,468	0.02	5.7E – 5	1	8.29
Relative growth	43,686	−0.03	−9.57	9.11	−0.09
Fast growth dummy	43686	0.02	0.00	1.00	6.65
Age	50,468	10.61	*	*	0.82
Age -squared	50,468	166.03	*	*	2.15
Employment (Emp)	50,468	68.81	*	*	95.65
Emp- squared	50,468	26E + 04	*	*	222.4
Live local units	50,468	1.19	*	*	33.78
Productivity	50,349	200.84	*	*	85.75
Civil R&D only	50,468	0.38	*	*	0.49
UK-owned	50,468	0.91	*	*	−2.81

Table A1 (*Continued*)

Exiters					
Variable	N	Mean	Min.	Max.	Skew.
Median R&D intensity in industry	43,686	0.11	0	2.16	1.42
Pavitt class 1	50,468	0.45	0	1	0.21
Pavitt class 2	50,468	0.19	0	1	1.57
Pavitt class 3	50,468	0.08	0	1	3.17
Pavitt class 4	50,468	0.22	0	1	1.36
Pavitt class 5	50,468	0.06	0	1	3.57
Effective exch. rate	50,468	96.86	79.99	103.67	−1.53
Crisis dummy	50,468	0.21	0	1	1.45
Lending premium	50,468	0.14	−0.034	0.38	0.46
Number of firms	13,518				

[a] Minimum and maximum values are suppressed to comply with non-disclosure requirements of the data hosts, UK Data Service. Firms born after 1973, excluding top 1% of R&D intensity distribution. All covariates are as described in Table 1. Pavitt technology classes are as described in note 5.

Eq. (A9) informs the three hypotheses spelled out in the main text. However, the validity of those hypotheses hinges on three assumptions.

First, the elasticity of innovation flow with respect to scientists is positive but less than 1, i.e.:

$$0 < 1/\eta < 1 \tag{A10}$$

This assumption implies that innovation flows are produced not by scientists (S_i) only, but by combining the scientist input with an existing stock of knowledge (k)We argue that this assumption holds because otherwise the elasticity of innovation flow with respect to knowledge capital (k) is zero or negative (i.e., $1 - 1/\eta \leq 0$). This scenario, however, is unrealistic given the extensive evidence that knowledge capital measured as R&D capital stock has a positive effect on productivity−see Griliches (1979) on theoretical and measurement issues, and Hall et al. (2010) and Ugur et al. (2015) for reviews.

Secondly, profits adjusted for innovation cost must be positive – i.e.:

$$\pi - \zeta w z_i^{\eta} = \pi_A > 0 \tag{A11}$$

We argue that this assumption also holds because otherwise the firm is better-off shutting down the knowledge production lines that generates loss or no profits.

Finally, the volatility parameter (σ) in the Wiener process is small relative to the drift parameter (μ). Specifically:

$$\sigma < \sqrt{2\mu} \tag{A12}$$

This assumption is compatible with existing evidence, which indicates that the volatility parameter is usually around one-tenth of the drift parameter in a large number of stock markets including the UK (Casas et al., 2008).

Provided that these assumptions are satisfied, it can be established that the turning point for the survival time as a function of innovation intensity is a local maximum, which indicates a diminishing scale effect in the relationship between survival and innovation intensity.

To demonstrate this, first take the first-order partial derivative with respect to innovation intensity (z_i) and set equal to zero, to obtain:

$$\frac{\partial E[t]}{\partial z_i} \cong \frac{2}{2\mu - \sigma^2}\,\frac{\rho + x - z_i}{\pi - \zeta w z_i^{\eta}}\,\frac{\left[-\eta\zeta w z_i^{\eta-1}(\rho + x - z_i) + \left(\pi - \zeta w z_i^{\eta}\right)\right]}{(\rho + x - z_i)^2}$$

$$= \frac{2}{2\mu - \sigma^2}\left[\frac{(\rho + x - z_i)\left[-\eta\zeta w z_i^{\eta-1}(\rho + x - z_i) + \left(\pi - \zeta w z_i^{\eta}\right)\right]}{\left(\pi - \zeta w z_i^{\eta}\right)(\rho + x - z_i)^2}\right]$$

$$= \frac{2}{\left(2\mu - \sigma^2\right)}\left[\frac{-\eta\zeta w z_i^{\eta-1}(\rho + x - z_i)^2 + \left(\pi - \zeta w z_i^{\eta}\right)(\rho + x - z_i)}{\left(\pi - \zeta w z_i^{\eta}\right)(\rho + x - z_i)^2}\right]$$

$$= \frac{2}{2\mu - \sigma^2}\left[\frac{1}{\rho + x - z_i} - \frac{\eta\zeta w z_i^{\eta-1}}{\pi - \zeta w z_i^{\eta}}\right] = 0 \tag{A13}$$

Recalling that $\sigma < \sqrt{2\mu}$, the first term is positive – i.e., $\frac{2}{2\mu - \sigma^2} > 0$. Also, recalling that adjusted profits are positive (i.e., $\eta\zeta w z_i^{\eta-1} > 0$), the first-order condition for observing an extremum in survival time is given in Eq. (A14):

$$\frac{1}{\rho + x - z_i} - \frac{\eta\zeta w z_i^{\eta-1}}{\pi - \zeta w z_i^{\eta}} = 0 \text{ or } \frac{1}{\rho + x - z_i} = \frac{\eta\zeta w z_i^{\eta-1}}{\pi - \zeta w z_i^{\eta}} \tag{A14}$$

Multiplying both sides with $\pi - \zeta w z_i^{\eta}$ and recalling that $v = \frac{\pi - \zeta w z_i^{\eta}}{\rho + x - z_i}$, we obtain:

$$\eta\zeta w z_i^{\eta-1} = \frac{\pi - \zeta w z_i^{\eta}}{\rho + x - z_i} = v \tag{A15}$$

Stated explicitly, Eq. (A15) indicates that the extremum for survival time as a function of innovation intensity occurs when the marginal cost innovation intensity (left-hand side) is equal to the normalised value of the knowledge production line (right-hand side). This is compatible with optimising firm behaviour.

Whether the turning point is a local maximum depends on the second-order condition, which can be stated as follows.

$$\frac{\partial^2 E[t]}{\partial {z_i}^2} \cong \frac{2}{\left(2\mu - \sigma^2\right)}\left[\frac{1}{(\rho + x - z_i)^2} - \frac{\eta(\eta - 1)\zeta w z_i^{\eta-2}\left(\pi - \zeta w z_i^{\eta}\right) + \eta\zeta w z_i^{\eta-1}\eta\zeta w z_i^{\eta-1}}{\left(\pi - \zeta w z_i^{\eta}\right)^2}\right] < 0 \tag{A16}$$

Noting that $\pi - \zeta w z_i^{\eta} = \pi_A$ from Eq. (A3) and $\eta\zeta w z_i^{\eta-1} = v$ from the first-order condition in Eq. (A15), we obtain:

$$\frac{\partial^2 E[t]}{\partial {z_i}^2} \cong \frac{2}{\left(2\mu - \sigma^2\right)}\left[\frac{1}{(\rho + x - z_i)^2} - \frac{\eta(\eta - 1)v^{-2}\pi_A + v^2}{\pi_A^2}\right] < 0 \tag{A17}$$

Recalling that $\sigma < \sqrt{2\mu}$ and $\pi_A > 0$ from Eqs. (A12) and (A11), the second-order condition for a local maximum boils down to:

$$\frac{\partial^2 E[t]}{\partial {z_i}^2} \cong \frac{1}{(\rho + x - z_i)^2} - \frac{\eta(\eta - 1)v^{-2}\pi_A + v^2}{\pi_A^2} < 0. \tag{A18.1}$$

Multiplying both sides of the inequality with π_A^2, we obtain:

$$\frac{\pi_A^2}{(\rho + x - z_i)^2} - \left[\eta(\eta - 1)v^{-2}\pi_A + v^2\right] < 0 \tag{A18.2}$$

Table A2
Sensitivity checks for different cut-off points of R&D intensity.

Dep. variable: time to exit	(1)	(2)	(3)	(4)	(5)	(6)
Log(Total RD intensity + 1)	0.439***	0.520***	0.721***	0.763***	5.854***	0.380**
	(0.0762)	(0.0988)	(0.138)	(0.143)	(0.667)	(0.162)
Log^2 (Total R&D intensity + 1)	−0.288***	−0.388***	−0.675***	−0.768***	−33.79***	−0.228**
	(0.0529)	(0.0917)	(0.188)	(0.204)	(4.597)	(0.0896)
*Log(Total R&D intensity + 1)*HI*	0.409*	0.326	0.00604	−0.0451	−1.239	0.400
	(0.213)	(0.278)	(0.379)	(0.393)	(1.545)	(0.547)
Herfindahl index (HI)	−0.527***	−0.519***	−0.501***	−0.498***	0.0181	−0.487
	(0.146)	(0.149)	(0.152)	(0.152)	(0.172)	(0.334)
Herfindahl index^2	0.748***	0.741***	0.731***	0.732***	0.0705	0.883
	(0.219)	(0.221)	(0.223)	(0.224)	(0.265)	(0.701)
Median R&D int. in industry	−0.342***	−0.387***	−0.481***	−0.482***	−0.611***	1.498***
	(0.0799)	(0.0824)	(0.0882)	(0.0897)	(0.136)	(0.491)
Lending premium	−1.662***	−1.659***	−1.664***	−1.663***	−1.805***	−2.476***
	(0.0483)	(0.0489)	(0.0500)	(0.0501)	(0.0621)	(0.0906)
Firm growth relative to	0.0331***	0.0355***	0.0416***	0.0428***	0.0570***	0.0535***
Industry growth	(0.00511)	(0.00531)	(0.00561)	(0.00566)	(0.00776)	(0.0110)
Fast growth over 3 years	−1.081***	−1.103***	−1.128***	−1.128***	−1.412***	−1.420***
Before exit	(0.0383)	(0.0390)	(0.0400)	(0.0401)	(0.0554)	(0.113)
Log (Age)	0.534***	0.531***	0.532***	0.532***	0.450***	0.337***
	(0.0565)	(0.0571)	(0.0581)	(0.0582)	(0.0738)	(0.129)
Log^2 (Age)	−0.0162	−0.0149	−0.0137	−0.0133	0.00642	0.0205
	(0.0137)	(0.0138)	(0.0140)	(0.0140)	(0.0172)	(0.0283)
Log (Employment)	0.228***	0.227***	0.224***	0.222***	0.202***	0.178***
	(0.0164)	(0.0166)	(0.0168)	(0.0168)	(0.0189)	(0.0307)
Log^2 (Employment)	−0.0246***	−0.0244***	−0.0240***	−0.0239***	−0.0208***	−0.0166***
	(0.00236)	(0.00238)	(0.00240)	(0.00240)	(0.00268)	(0.00385)
Log (Live local units + 1)	0.0262	0.0270	0.0264	0.0260	0.0364*	0.00317
	(0.0186)	(0.0188)	(0.0190)	(0.0190)	(0.0216)	(0.0332)
Log (Def. turnover/employee)	0.0997***	0.0999***	0.100***	0.100***	0.120***	0.124***
	(0.00821)	(0.00838)	(0.00864)	(0.00867)	(0.0100)	(0.0169)
Firm engages in civil R&D only	0.0551***	0.0549***	0.0560***	0.0562***	0.0492***	−0.00788
	(0.0101)	(0.0102)	(0.0104)	(0.0104)	(0.0126)	(0.0169)
Firm is UK-owned	0.0746***	0.0732***	0.0728***	0.0733***	0.0563**	0.00985
	(0.0214)	(0.0215)	(0.0217)	(0.0217)	(0.0244)	(0.0296)
Pavitt technology class 1	0.0301	0.0282	0.0313	0.0308	0.0171	−0.0683
	(0.0952)	(0.0957)	(0.0967)	(0.0968)	(0.0301)	(0.123)
Pavitt technology class 2	0.175***	0.172***	0.173***	0.173***	0.0613**	0.159*
	(0.0617)	(0.0621)	(0.0626)	(0.0627)	(0.0264)	(0.0820)
Pavitt technology class 3	0.0564	0.0536	0.0597	0.0595	−0.0232	0.0234
	(0.0596)	(0.0600)	(0.0606)	(0.0606)	(0.0328)	(0.0663)
Pavitt technology class 5	0.104	0.105	0.101	0.102	0.0515	0.210
	(0.0708)	(0.0712)	(0.0717)	(0.0719)	(0.0363)	(0.223)
Average eff. exchange rate	−0.0554***	−0.0557***	−0.0559***	−0.0559***	−0.0607***	−0.0656***
	(0.000701)	(0.000709)	(0.000722)	(0.000724)	(0.000868)	(0.00147)
Crisis dummy	−0.134***	−0.134***	−0.138***	−0.138***	−0.139***	−0.0430***
	(0.00925)	(0.00938)	(0.00962)	(0.00965)	(0.0124)	(0.0145)
Constant	4.850***	4.873***	4.903***	4.898***	5.237***	6.015***
	(0.253)	(0.253)	(0.261)	(0.261)	(0.128)	(0.237)
Observations	167279	165733	162542	162140	130482	61296
Number of subjects (firms)	36699	36553	36244	36201	32014	11644
Log likelihood	−28489.2	−28232.3	−27624.6	−27550.2	−21296.2	−10259.6
AIC	57194.3	56680.6	55465.2	55316.4	42642.3	20615.2
BIC	58277.3	57762.5	56545.1	56396.0	42886.8	21048.3
VIF	7.52	7.62	7.73	7.73	7.96	9.91
σ	0.687***	0.689***	0.691***	0.691***	0.724***	0.698***
2-digit industry dummies	Yes	Yes	Yes	Yes	No	Yes

Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Models 1–6 are based on full sample of firms born in 1974 and after, excluding the following R&D intensities: (1) = top 2% cut-off; (2) = top 3% cut-off; (3) = top 5% cut-off; (4) = cut-off at R&D intensity at 1 or more; (5) top 25% cut-off; (6) = manufacturing firms born in 1974 or after, excluding top 1% of R&D intensity distribution.

Noting that $\frac{\pi_A^2}{(\rho+x-z_i)^2} = \upsilon^2$, the second-order condition boils down to:

$$\eta(\eta-1)\upsilon^{-2}\pi_A > 0. \tag{A18.3}$$

Noting that $1/\eta<1$, and hence $\eta > 1$; $\eta(\eta-1) > 0$. Also, $\pi_A > 0$ and υ^{-2} is a positive fraction. Hence, the second-order condition for a local maximum is satisfied; and the relationship between innovation intensity and survival time follows an *inverted-U* pattern.[24] This result informs **Hypothesis 1** of the paper.

The model also informs **Hypothesis 2** of the paper, which indicates that gross profits and R&D intensity have complementary

[24] Note that the model can yield other results if the restrictions on elasticity coefficients and adjusted profits are relaxed. If $1/\eta > 0$ (i.e., if the elasticity of knowledge capital is negative), the model yields a U-shaped relationship between innovation and survival. The relationship is indeterminate if $1/\eta = 0$ (i.e., if the elasticity of knowledge capital is zero). On the other hand, the model yields a U-shaped relationship between innovation intensity and survival if $\pi_A < 0$ and the relationship is indeterminate if $\pi_A = 0$. However, we rule out these outcomes for reasons indicated above.

Table A3
Robustness checks – stepwise estimations.

Dep. Var.: Time to exit	(1)	(2)	(3)	(4)
Log (R&D intensity + 1)	0.253***	0.476***	0.354***	0.338***
	(0.0796)	(0.0838)	(0.0591)	(0.0593)
Log (R&D intensity + 1) sq.	−0.0979**	−0.207***	−0.172***	−0.169***
	(0.0381)	(0.0416)	(0.0301)	(0.0302)
*Log(Total R&D intensity + 1)*HI*	1.282***	1.352***	0.271	0.371**
	(0.250)	(0.250)	(0.165)	(0.165)
Herfindahl index (HI)	0.890***	0.995***	−0.193	−0.399***
	(0.193)	(0.193)	(0.137)	(0.141)
Herfindahl index²	−0.903***	−1.055***	0.336	0.459**
	(0.299)	(0.299)	(0.223)	(0.226)
Firm growth relative to median	0.0310***	0.0371***	0.0321***	0.0325***
Industry growth	(0.00713)	(0.00721)	(0.00497)	(0.00496)
Fast growth for 3 years	−1.835***	−1.830***	−1.102***	−1.093***
before exit	(0.0607)	(0.0605)	(0.0385)	(0.0382)
Log (Age)	−1.389***	−1.369***	0.529***	0.530***
	(0.0816)	(0.0814)	(0.0567)	(0.0565)
Log² (Age)	0.368***	0.364***	−0.0177	−0.0170
	(0.0204)	(0.0203)	(0.0137)	(0.0137)
Log (Employment)	0.312***	0.305***	0.233***	0.227***
	(0.0233)	(0.0236)	(0.0157)	(0.0160)
Log² (Employment)	−0.0320***	−0.0310***	−0.0256***	−0.0246***
	(0.00345)	(0.00345)	(0.00230)	(0.00231)
Log (Live local units + 1)	−0.0464*	−0.0540**	0.0414**	0.0355*
	(0.0275)	(0.0275)	(0.0184)	(0.0184)
Log (Def. turnover/employee)	0.196***	0.200***	0.100***	0.0985***
	(0.0117)	(0.0118)	(0.00776)	(0.00794)
Civil R&D only	−0.0822***	−0.0822***	0.0349***	0.0468***
	(0.0150)	(0.0151)	(0.0105)	(0.0103)
Firm is UK-owned	0.131***	0.125***	0.0702***	0.0732***
	(0.0323)	(0.0322)	(0.0215)	(0.0214)
Median R&D intensity in		−0.288***	−0.397***	−0.299***
Industry		(0.112)	(0.0822)	(0.0844)
Pavitt technology class 1		−0.0313	0.0616**	0.134***
		(0.0360)	(0.0244)	(0.0313)
Pavitt technology class 2		0.131***	0.0937***	0.153***
		(0.0350)	(0.0231)	(0.0304)
Pavitt technology class 3		−0.0714	−0.000965	0.0407
		(0.0458)	(0.0304)	(0.0345)
Pavitt technology class 5		0.0593	0.0633**	0.110**
		(0.0492)	(0.0321)	(0.0545)
Average eff. exchange rate			−0.0555***	−0.0556***
			(0.000684)	(0.000684)
Crisis dummy			−0.131***	−0.126***
			(0.00931)	(0.00925)
Lending premium			−1.738***	−1.734***
			(0.0473)	(0.0474)
Constant	0.512***	0.483***	4.842***	4.992***
	(0.105)	(0.107)	(0.104)	(0.172)
Industry dummies	None	None	None	1-digit
–				
Sigma	0.952***	0.948***	0.692***	0.689***
Observations	168843	168626	168626	168626
AIC	69353.4	69142.5	58095.6	57971.2
BIC	69524.0	69363.3	58346.5	58402.8
VIF	9.91	8.19	7.46	7.46
Number of subjects	36836	36821	36821	36821
Log likelihood	−34659.7	−34549.3	−29022.8	−28942.6

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All firms born in 1974 or after, excluding top 1% of R&D intensity. 1: with firm covariates only; 2: Model (1) + industry covariates; 3: Model (2) + Macro covariates; 4: Model (3) + 1-digit industry dummies.

effects on survival. To demonstrate that this is the case, we take the second derivative of Eq. (A13) with respect to gross profits (π).

$$\frac{\partial^2 E[t]}{\partial z_i \partial \pi} = \frac{2}{2\mu - \sigma^2}\left[\frac{1}{\left(\pi - \zeta w z_i^{\eta}\right)^2}\right] > 0 \tag{A19}$$

The second derivative is positive since the denominator is a squared term and $2/2\mu - \sigma^2 > 0$, as indicated above. Hence, holding the level of innovation intensity constant, an increase in gross profits is associated with an increase in survival time.

We can also show that the model informs **Hypothesis 3**, which posits that higher discount rates and rates of creative destruction in the industry reduce the normalised value of the knowledge production line and hence survival time. To demonstrate the negative relationship with survival time, we take the derivatives of Eq. (A9) with respect the discount rate (ρ) and the rate of creative destruction (x), bearing in mind that $2/2\mu - \sigma^2 > 0$.

$$\frac{\partial E[t]}{\partial \rho} = \frac{2}{2\mu - \sigma^2}\left[\frac{(\rho + x - z_i)}{\left(\pi - \zeta w z_i^{\eta}\right)} \frac{-1\left(\pi - \zeta w z_i^{\eta}\right)}{(\rho + x - z_i)^2}\right]$$
$$= \frac{2}{2\mu - \sigma^2}\frac{-1}{(\rho + x - z_i)} < 0 \text{ if } \quad (\rho + x) > z_i\,. \tag{A20.1}$$

Table A4
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. Total R&D int.	1.000																							
2. Total R&D int. sq.	0.904	1.000																						
3. Interaction 1*4	0.735	0.665	1.000																					
4. Herfindahl index	−0.014	−0.003	0.177	1.000																				
5. Herf. ind. sq.	−0.023	−0.010	0.128	0.892	1.000																			
6. Relative growth	−0.169	−0.137	−0.131	−0.004	−0.004	1.000																		
7. Fast growth	0.009	0.006	0.005	0.002	0.002	−0.004	1.000																	
8. Age	−0.163	−0.083	−0.117	−0.007	0.002	−0.020	−0.048	1.000																
9. Age squared	−0.140	−0.071	−0.099	0.000	0.003	−0.020	−0.040	0.964	1.000															
10. Employment	−0.023	−0.011	−0.013	0.047	0.037	0.005	−0.007	0.067	0.065	1.000														
11. Empl. sq.	−0.003	−0.002	−0.001	0.024	0.019	−0.001	−0.001	0.010	0.009	0.869	1.000													
12. Local units	−0.012	−0.006	−0.008	0.025	0.021	0.001	−0.003	0.029	0.027	0.532	0.513	1.000												
13. Deflated turnover	−0.010	−0.004	−0.007	0.011	0.005	0.016	0.000	0.008	0.007	0.000	0.000	0.000	1.000											
14. Civil R&D firm	−0.079	−0.030	−0.028	0.106	0.071	0.018	−0.015	0.120	0.110	0.060	0.013	0.029	0.000	1.000										
15. UK-owned firm	0.055	0.026	0.038	0.001	0.000	−0.006	0.020	−0.126	−0.108	−0.061	0.001	−0.011	−0.029	−0.088	1.000									
16. Med. Ind. R&D int.	0.372	0.179	0.285	−0.046	−0.059	0.004	0.029	−0.268	−0.240	−0.038	−0.003	−0.015	−0.014	−0.253	0.082	1.000								
17. Pavitt class 1	0.263	0.120	0.181	−0.063	−0.069	0.007	0.019	−0.195	−0.179	−0.020	0.009	−0.003	−0.014	−0.187	0.041	0.689	1.000							
18. Pavitt class 2	−0.059	−0.030	−0.066	−0.113	−0.072	−0.002	0.001	0.002	0.000	−0.010	−0.004	−0.008	−0.006	−0.163	0.023	−0.184	−0.381	1.000						
19. Pavitt class 3	−0.064	−0.028	−0.029	0.131	0.107	0.003	−0.011	0.081	0.067	0.021	−0.002	0.001	0.009	0.103	−0.079	−0.165	−0.234	−0.172	1.000					
20. Pavitt class 4	−0.166	−0.073	−0.116	−0.014	−0.017	−0.007	−0.013	0.174	0.168	0.006	−0.004	0.003	0.014	0.229	−0.036	−0.400	−0.448	−0.330	−0.202	1.000				
21. Pavitt class 5	−0.028	−0.016	0.010	0.180	0.158	−0.001	0.000	−0.042	−0.040	0.021	0.000	0.011	0.000	0.094	0.043	−0.090	−0.190	−0.140	−0.086	−0.164	1.000			
22. Av. Eff. Exch. Rate	0.001	−0.005	−0.029	−0.088	−0.052	−0.006	0.028	−0.167	−0.189	0.020	0.004	0.008	−0.008	0.149	−0.014	−0.003	0.064	−0.037	0.015	−0.034	−0.018	1.000		
23. Crisis dummy	0.019	0.012	0.004	−0.008	−0.004	0.004	0.000	−0.061	−0.066	0.008	0.003	0.001	−0.003	−0.053	−0.020	0.049	0.042	−0.016	0.010	−0.022	−0.025	0.131	1.000	
24. Lending premium	0.034	0.017	0.006	−0.028	−0.012	0.008	−0.013	−0.083	−0.085	0.015	0.006	0.000	−0.002	−0.078	−0.032	0.104	0.053	−0.015	0.012	−0.036	−0.027	0.064	0.761	1.000

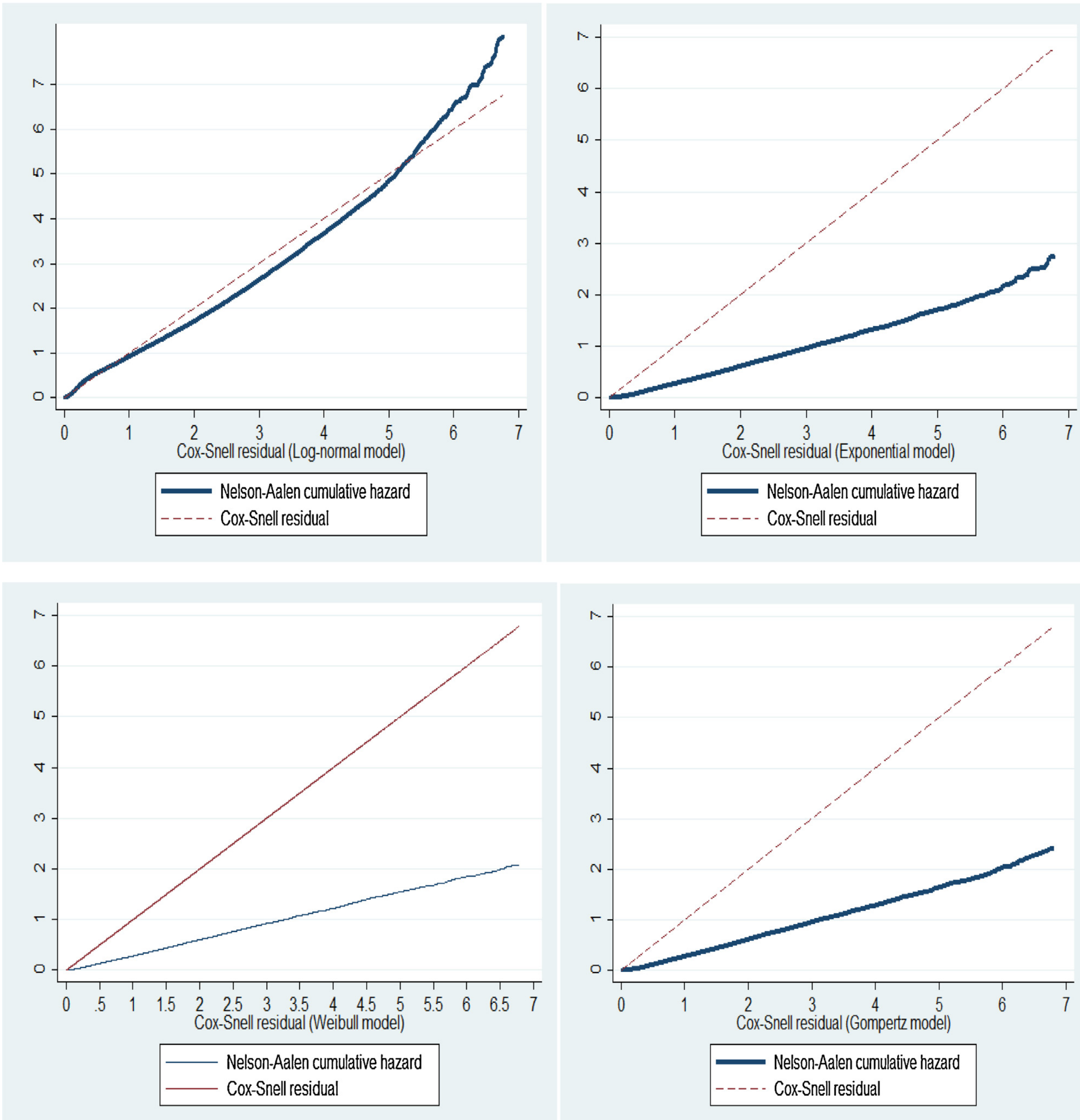

Fig. A2. Cox-Snell residual plots for log-normal and comparator models.
Note: The Cox-Snell residuals are conditional on the covariate vector. The Nelson-Aalen cumulative hazard function is compared with the diagonal line. If the hazard function follows the 45° line, the model fits the data well. Only the log-normal model (top-left corner) satisfies this condition. Deviations from the 45° line at large values of time are to be expected (Cleves et al., 2008).

Similarly,

$$\frac{\partial E[t]}{\partial x} = \frac{2}{2\mu-\sigma^2}\left[\frac{(\rho+x-z_i)}{\left(\pi-\zeta w z_i^{\eta}\right)}\frac{-1\left(\pi-\zeta w z_i^{\eta}\right)}{(\rho+x-z_i)^2}\right]$$

$$= \frac{2}{2\mu-\sigma^2}\frac{-1}{(\rho+x-z_i)} < 0 \text{ if } \quad (\rho+x) > z_i\,. \tag{A20.2}$$

Results in Eqs. (A20.1) and (A20.2) indicate that an increase in the discount rate or in the rate of creative destruction is associated with a reduction in survival time – provided that the firm's innovation intensity is less than the sum of two rates.

Finally, it can also be shown that an increase in the discount rate or in the rate of creative destruction is associated with a reduction in the normalised value of the production line. From Eq. (A3), we can write:

$$\frac{\partial v}{\partial \rho} = \frac{-1\left(\pi-\zeta w z_i^{\eta}\right)}{(\rho+x-z_i)^2} = -\frac{\left(\pi-\zeta w z_i^{\eta}\right)}{(\rho+x-z_i)^2} < 0 \text{ if } \quad \pi-\zeta w z_i^{\eta} > 0 \tag{A21.1}$$

$$\frac{\partial v}{\partial x} = \frac{-1\left(\pi-\zeta w z_i^{\eta}\right)}{(\rho+x-z_i)^2} = -\frac{\left(\pi-\zeta w z_i^{\eta}\right)}{(\rho+x-z_i)^2} < 0 \text{ if } \quad \pi-\zeta w z_i^{\eta} > 0 \tag{A21.2}$$

Results in Eqs. (A21.1) and (A21.2) indicate that an increase in the discount rate or the rate of creative destruction is associated with a decrease in the normalised value of the knowledge production line – provided that the adjusted profits are positive.

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