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REGULAR ARTICLE

Exploring the innovative effort: duration models and heterogeneity

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Abstract

Perseverance in R&D effort is the first fundamental step towards any kind of innovation. We investigate the beginning of the innovation story, rather than its end, through duration models. Among the drivers of our unconventional IO approach, we focus on heterogeneity, path dependence and market power, measured as elasticity of firm-specific demand. The Schumpeterian hypothesis emerges at the firm level. Heterogeneity at the industry level reveals Schumpeterian and Arrovian patterns, as well as U-shaped and inverted U-shaped patterns. We suggest considering the entire supply chain from a holistic perspective when evaluating mergers and innovation policies that support small firms by reducing their financial uncertainty and improving their institutional environment.

Keywords R& D effort · Duration models · Market power · Accumulated knowledge · Heterogeneity in panel data · Uncertainty · Financing

JEL Classification C23 · C41 · D22 · G32 · L10 · O30

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1 Introduction

Some innovations come about by chance, but most require perseverance, experiments, laboratory tests. Our intuition is that the probability of realising innovations and making them exploitable by the socio-technological system is causally related to the duration of R&D investments. Simply put, the duration of R&D effort, the primary input, underpins the innovative output. Our research question, therefore, concerns the incentives that stimulate and the barriers that hinder the survival of R&D investments. This is a relevant question, as the propensity and possibility of firms to continuously invest in R&D is crucial for maximising profits and increasing the likelihood of innovation. Besides, actual R&D investments are less than optimal (Jones and Williams, 1998), persistent R&D plays a central role for sustainable green innovations (Sarpong et al., 2023), and it is the increase in research effort that makes growth possible despite the decrease in research productivity (Bloom et al., 2020).

Our approach differs from the standard IO method, which is based on the intensive margin measured by how much the firm invests in R&D (input in levels), and number of patents, new products, new processes (the output). The standard IO method based on output may be biased towards successful innovations and is not necessarily fully correlated with R&D efforts. The R&D duration analysis captures this dimension and the potential of failed investments, thus complementing, rather than replacing, the existing IO approach. The amount of R&D investment used as input by the standard IO method is not necessarily meaningful, because even after a breakthrough has been made, a company must continue to invest in R&D, as it may take a long time to convert innovation into economic results (Coad and Rao, 2008). It is the experience of doing R&D at any given time that drives the innovation process by making firms progressively better (Geroski, 2005).

Rephrasing Mansfield et al. (1977), the innovation process is the product of some conditional probabilities: the probability that the R&D investment will be made on an ongoing basis; the probability that, in the event of technical success, the resulting product or process will be commercialised; and finally the probability that, in the event of commercialisation, the project will yield a satisfactory return on investment. As the process leading to innovative outputs follows several uncertain steps, but starts with the continuous implementation of R&D (the input) in the first instance, we provide empirical evidence on the determinants of this crucial first move.

Standard IO method also presents an empirical problem related to the variety of proxies used to quantify innovation (see Table 1 in Del Monte and Papagni (2003)). Outcomes like patents, new products, new processes are used, but these proxies are rather noisy (an example is the discussion on patents by Griliches (1990)). The evaluation of the results is complex, Coad and Rao (2008); Del Monte and Papagni (2003) use principal components analysis to create a synthetic measure of innovation containing input (R&D expenditure) and output (patents), and Neves et al. (2021) propose a meta-analysis. Instead, by focusing on the duration of the R&D effort (which represents the pedestal of innovation input), our research question partly overcomes the aforementioned measurement difficulties. The duration of the R&D investment is well defined, as we can take advantage of panel data from a rich survey that asks companies each year for the amount they spend on R&D, market research, product design and testing, excluding software development costs and expenditure on education and training of workers.

A number of determinants of R&D duration must be considered as they play a joint role in explaining why some companies are continuously involved in R&D effort while others exhibit intermittent investment behaviour. The process of converting an idea into a set of successful procedures/products is subject to interruptions caused by the uncertainty of the economic environment (Bloom, 2006), thus macroeconomic and firm-specific uncertainty are relevant elements. The process is also costly, so financial aspects, complementarity with other investments, institutional factors and exposure to international markets may play a role. The causal effect of past R&D activities on the R&D duration, due to the path-dependent nature of innovation (from the seminal contribution of Atkinson and Stiglitz (1969)) can be identified provided that unit-specific characteristics, both measurable and non-measurable, are controlled for. Measurable characteristics, such as age, ownership type, size and technological conditions are included as explanatory variables and analysed in their role of expose to the risk of R&D investment disruption. The role of unobservable heterogeneity is investigated at both the company and industry level. At the firm level we compare different models for continuous and discrete duration data, some of which are better suited to handle unobservable individual effects. The analysis conducted at company level is complemented by the heterogeneous panel-based analysis at industry level in which we emphasize sectorial disaggregation.

Considering the heterogeneity at the firm and industry level, a key aspect we want to assess is the role of market power on R&D effort. At the company level, to our knowledge, there is a lack of analysis regarding the role of market power, and its various measures, in the context of innovation duration models and controlling for other important determinants. An advantage of R&D duration analysis is that it delineates a causal effect of market power better than R&D output analysis does: R&D effort does not contribute with certainty to an increase, even temporary, in market power as patents or new leading products might do. In fact, the R&D project could fail, or be oriented toward a subset of potential products or be radical in nature and not serve any existing market. Even if the R&D effort were driven by the desire to achieve greater market power, this achievement is only a future potentiality that cannot empirically generate endogeneity due to simultaneity. Furthermore, the increase in market power depends on how the company manages to influence consumer preferences, something that is more related to advertising (once the discovery has been made) rather than R&D per se. As outlined by Griffith and Van Reenen (2022), theory can predict both positive and negative effects of competition on innovation, and empirical evidence is also mixed. Observable indicators of market competition are endogenous outcomes of more primitive objects, such as elasticities of substitution (consumer preferences).

In an attempt to provide robust empirical evidence, we propose a new direct survey-based measure of firm-specific elasticity of demand and discuss its role with respect to the standard firm-level accounting measure (the Lerner index based on the price–cost margin) and the industry-level concentration ratio (measured by the Herfindahl-Hirschman index and the number of firms). We also distinguish the effects of market power and firm size, which represents an important point as there is much research on the link between firm size and innovation (Cohen and Klepper, 1996a, b; Corsino et al., 2011; Plehn-Dujowich, 2009; Yin and Zuscovitch, 1998). Finally, we check robustness of our results to the possible endogeneity of the alternative market power measures and other explanatory variables.

At the industry level, what is important is to compare the aggregate and sector-disaggregated role of market power on R&D. This dual analysis delivers a landscape in which one may identify the possible emergence of feedback effects across sectors as well as along supply chains as a consequence of mergers and acquisitions, in terms of the resulting technological progress, in the long run.

The rest of this article is organised as follows: Sect. 2 theoretically motivates the relevance of investigating continuity of R&D effort through the duration analysis. Section 3 describes the empirical specifications of the R&D duration models. It also presents the sample, an unbalanced longitudinal panel of Italian companies. Section 4 reports the results and reflects on their interpretation. Section 5 highlights why Italy is an interesting case for our analysis and provides implications for innovation policy and antitrust policy, and suggestions for further research.

2 Duration of R&D effort

Theoretically, uniformly smoothing R&D efforts over the entire horizon is convenient in terms of the resulting discounted profit performance. The rationale for this statement is presented in Appendix A1.1. Empirically, in our data, it is striking that discontinuities in the R&D effort, controlling for the stock of accumulated knowledge and size, produce an average reduction in profits of around 10%. Despite the importance of continuous R&D efforts, few empirical studies have directly investigated this issue through duration models.

Usually random effect probit models and dynamic first-order autoregressive specifications are applied to R&D and innovative output, see Table 1 in Le Bas and Scellato (2014) and references therein. The discrete-time proportional hazard models are used by Máñez et al. (2015); Triguero et al. (2014) for Spanish manufacturing firms; Triguero et al. (2014) find a positive relationship between previous innovative experience and the probability of survival in innovation; Máñez et al. (2015) compares SMEs (between 10 and 200 employees) and large companies (more than 200 employees), and find more persistent R&D activities in SMEs operating in high-tech industries.

The richest literature is instead concerned with a parallel topic to our research question, namely whether innovation is positively associated with firm survival (the state of the art is Ugur and Vivarelli (2021)). Interestingly, Zhang and Mohnen (2022) find that R&D has a greater marginal effect on firm survival than (product) innovation output. Related to this field, the role of persistent innovation is stressed in Cefis and Ciccarelli (2005) who find that the difference in profitability between innovators (defined as firms that apply for a patent) and non-innovators is greater when comparison is made between persistent innovators and non-innovators. Similar results are in Bartoloni and Baussola (2009) who define innovators as firms that introduced either process and/or product innovations. Artés (2009) uses a random effect model inside a two-stage selection procedure and argues that market structure affects long-run R&D decisions (whether to conduct R&D or not) but does not affect short-run ones (how much to invest once the firm decides to be innovative).

Notwithstanding the difficulties embodied in a production-function framework, innovation input and output are also found to be positively associated with productivity, both at the aggregated level (Geroski, 1989) and at the firm level (Parisi et al., 2006). A more comprehensive approach is carried on by Crépon et al. (1998), who move from some "stylised facts" and build an empirical model that encompasses the whole innovation process: the decision to undertake research activity, the magnitude of such effort, the output of the innovative process and the impact on firm's productivity. Particularly relevant to our paper is the result that innovative output is positively affected by R&D intensity and, in turn, positively affects productivity. Other examples studying productivity benefits from R&D in a sophisticated framework are Doraszelski and Jaumandreu (2013); Mairesse and Robin (2009); Masso and Vahter (2008); Polder et al. (2009); Van Leeuwen and Klomp (2006).

Our duration model thus aims to describe the behaviour of firm-level R&D efforts in a dynamic and uncertain environment. We assume that firms striving to invest in R&D seek to maximise their profits, devote resources to it, are subject to constraints, have a history of transition before entering the current investment state (there is path dependence) and have specific individual, regional and sectoral characteristics (there are initial conditions that determine the different probabilities of being in the state we observe in the data).

The triggers for discontinuing R&D (competing risks) arrive randomly in the time interval from t_i to $t_i + \Delta t_i$ (or in the time interval $[t_i, t_i + 1)$ when time is discrete, see Sect. 3.2) with probability $\theta_{1i}(t)$; examples are a macroeconomic shock common to all firms, and firm-specific adverse events. Whenever a shock arrives, company i decides whether to interrupt or to continue R&D; the probability of stopping R&D is $\theta_{2i}(t)$ and depends on a set of constraints and incentives, as well as on the type of R&D and the firm, i.e. the factors suitable for considering that companies decide on the duration of R&D not only directly, but also indirectly through other decisions. Once R&D is stopped, a company may also decide to start R&D again, therefore we have multiple spells i.e. transition periods from R&D expenditure to R&D expenditure.

We estimate the conditional probability $\lambda_i(t|x_{it}, \nu_i) = \theta_{1i}(t)\theta_{2i}(t)$ of stopping R&D effort given that company i was still investing in t_i; in words, we explain the hazard rate of R&D effort as a function of measurable time-varying and time-invariant explanatory variables (condensed into x'_{it_i} for each company i at time t_i) and unobservable time-invariant explanatory variables capturing unmeasurable heterogeneity (the term ν_i). Note that the temporal observations may differ between i in the unbalanced panel; when unambiguous, we will use the simpler notation t and x'_{it}. The set x'_{it} for the hazard rates includes, as time-varying covariates, financial constrains (with a supposed positive effect), planned investments in physical capital and software (which should have a negative and positive effect, respectively), international competition (with a supposed negative effect), macroeconomic and firm-specific uncertainty (with positive effects), and, as time-invariant covariates, technological opportunities, age and group-membership (which should have negative effect on the hazard ratio), family-type ownership (whose role is a priori ambiguous) and geographical localization (in less developed areas, the hazard ratio should be higher).[1] In view of their relevance, the explanatory variables market power and persistence included in x'_{it} are discussed in the following two subsections.

The term v_i captures firm-specific factors such as organisational capabilities (Dosi et al., 2000), managerial capabilities, technological opportunities (Dosi, 1997), appropriability, unobservable type of R&D. These factors may not be captured by the measurable covariates and their omission would generate biased estimates in panel data, as we will discuss in Sect. 3.5.

2.1 Market power

One of the most crucial variables inside x'_{it} is market power. It is of particular interest to investigate its role within firm-level duration models, as well as to comparatively explore the role of market power on R&D intensity at a disaggregated level for as many sectors as possible, in order to provide as complete a picture as possible. Indeed, the effect of market power is ambiguous in both theoretical models and empirical studies and therefore requires analyses at the individual and sectoral level.

Schumpeter (1943), and the literature that sprung from his work, argue that firms with greater market power have a higher incentive to innovate because they can better appropriate the returns of their R&D investment: intense market competition would imply lower post-entry rents (Hall, 2011), whereas low competitive pressure would reduce the risks associated with an innovative race. In fact, were the race lost, a firm would still enjoy oligopolistic profits. On the other hand, many authors support Arrow (1962)'s thesis, that competition positively affects the innovative effort, as a firm that successfully introduces a new product in the market could then become monopolist ("escape-competition effect", Coscollá-Girona et al. (2015)). Conversely, firms that already enjoy market power do not need to innovate to stay in business. Moreover, a monopolist that innovates basically replaces itself as the monopolist in the market. This is the so called "replacement effect" put forward in Arrow as opposed to the "competitive effect" underlying the Schumpeterian hypothesis. An exhaustive account of the related theoretical debate is e.g. in (Tirole (1988) pp. 390–396) and Reinganum (1989), and is also incorporated in advanced IO textbooks as Martin (2001).

From the perspective of the duration model at the firm level, our idea is that market power incentives to invest in long-term projects, encourages continued investment and changes sensitivity to research failures, thus enabling companies to continue to invest in R&D even without success. We test alternative measures of market

[1] Further details are in Sect. A1.2 of the Appendix.

power in models controlling for other determinants which certainly include firm size. Although the literature has analysed innovative outcomes (product and process innovations), the same identified size-related reasons could also stimulate R&D effort. For example, the escape competition theory might be more appropriate for large firms, as they can exploit economies of scale, effectively protect their discoveries (conditions of appropriability), be better able to withstand uncertainty, be less financially constrained, make rational R&D planning decisions and have a greater "absorptive capacity", i.e. the ability to receive, process and utilise information from their environment (Geroski, 2005).

Indeed, the original positions adopted by Schumpeter and Arrow referred (or were taken to refer) to the impact of industry structure on innovation, whereas a significant part of the theoretical debate based on dynamic innovation races (stemming from Loury (1979); Lee and Wilde (1980)) has focused on the different degree of market power associated with Cournot and Bertrand Behavior for a given industry structure (see Delbono and Denicolò (1990, 1991)). In connection with this stream of literature, it is worth stressing that, in discussing the impact of competition on innovation incentives, the focus has been on the level of individual and aggregate R&D investments, i.e. R&D inputs. This also characterizes the empirical analysis of our paper, as we focus on R&D efforts that are inputs rather than outputs (the latter bring actual innovations of any kind).

Although the aforementioned literature looks at monotone relationships between innovation and market power or concentration, the empirical and theoretical analysis carried out by Aghion et al. (2005) (see also Aghion et al. (2015)) singles out a concave and single peaked one. This finding points at the existence of a specific industry structure maximising aggregate R&D effort, a critical feature which should systematically attract the attention of antitrust authorities evaluating a merger proposal which might foster or compromise the pace of technological progress of an entire industry in the long run, as the debate about the Dow-Dupont case has illustrated (see Federico et al. (2017, 2018); Denicolò and Polo (2018)). This is an aspect on which we shall specifically dwell upon after the discussion concerning duration and market power, showing indeed the arising of both monotone and non-monotone aggregate R&D curves, either U or inverted U-shaped, if we allow for heterogeneity in the industries.

In this respect, the ensuing debate initiated by Gilbert (2006) and then developed by Cohen (2010); Shapiro (2012); Whinston (2012) is of paramount importance. All these contributions discuss under a new light the emergence of a variety of patterns between innovation and competition or market structure, to emphasise the need of focussing on the policy implications concerning mergers. In particular, Shapiro (2012) proposes a reconciliation between the Schumpeterian and Arrovian positions through a few essential principles (*contestability*, *appropriability* and *synergies*), and stresses that merger policy need not depend on a specific shape of the relationship between innovation at the industry level and a specific measure of competition or concentration. Indeed, recent theoretical research (Marshall and Parra, 2019; Delbono and Lambertini, 2022) illustrates the possibility of generating virtually any effect of competition on innovation (either monotone or not) from a single model, by focussing on the technological and demand parameters that may affect this relationship. Possibly, but not necessarily, this obtains by changing also the numerosity and size of firms in the industry. More precisely, this is the case in Marshall and Parra (2019) whereas it is not in Delbono and Lambertini (2022) on which we base our sectorial disaggregated analysis presented in Sect. 4.1.

2.2 Innovation persistence

Since the well-know discussion of the *economics of QWERTY* (David, 1985), a stream of literature has tried to determine whether innovation persistence is "true" or "spurious". Spurious persistence refers to continuity in R&D effort due to unobserved time-invariant firm characteristics. It is an artefact of the inability to control for the individual heterogeneity, the v_i term of the conditional hazard $\lambda_i(t|x_{it}, v_i)$. Models can incorporate some correction accounting for spurious persistence, which is found to explain a significant part of the innovative process in standard IO methods (see, among others, Antonelli et al. (2013); Hecker and Ganter (2014); Lhuillery (2014); Peters (2009); Triguero and Córcoles (2013); Woerter (2014)).

Conversely, true persistence refers to the path-dependence nature of innovation which results from the causal effect of past on present innovative activities, i.e. the manifestation of state dependence independently of unobserved individual effects. In our case, it is the effect of inter-temporal spillovers between subsequent R&D efforts, that we capture through specific covariates inside x'_{it} of the conditional hazard $\lambda_i(t|x_{it}, v_i)$. Among the mechanisms that may explain true persistence, three major accounts can be told apart. First, technological knowledge is an economic good characterized by cumulability and non-exhaustibility, and represents at the same time an input and an output of the knowledge-generating process (Antonelli et al., 2012). Hence, firms that have generated new technological knowledge can rely upon such output to generate new, additional knowledge at a lower cost. Dynamic increasing returns are likely to shape innovative activities: the larger the cumulated size of innovation, the larger is the positive effect on costs ("learning-to-learn" and "learning-by-doing" effects). Malerba and Orsenigo (1995) propose the concept of cumulativeness at the firm level, according to which "firms continuously active in a certain technological domain accumulate knowledge and expertise".

A second stream holds that firms need to successfully profit from their innovation so to be able to innovate again. According to this view, commercial success increases the probability of future innovation because it allows for the reallocation of profits to new research projects ("success-breads-success" effect). Firms that successfully innovate are hence more likely to follow on innovations because of higher permanent market power (Le Bas and Scellato, 2014). We control for this effect by introducing market power into our set of explanatory variables. Hence, the innovative base at the company level is an important explanatory variable in a model aimed at understanding the role of market power on R&D duration.

Thirdly, it is worth mentioning the "sunk-costs" effect theory, according to which innovative activities are characterized by high set up costs for research facilities and the training of personnel, and by long-term commitments in terms of investment. Once research has started, the opportunity cost of interrupting it is quite high. This implies that research and development activities generate high entry and exit barriers as well (Antonelli et al., 2012).

All these arguments can be seen as complementary, rather than mutually exclusive, in explaining innovation persistence (Ruttan, 1997). They generate inter-temporal externalities and temporal spillovers. In brief, in Dosi (1988) "what the firm can hope to do technologically in the future is narrowly constrained by what it has been capable of doing in the past".[2]

3 The empirical framework

3.1 The data

The sample results from merging the Survey on Industrial and Service Firms, annually conducted by the Bank of Italy since 1984, and the Company Accounts Data Service (CADS), collected since 1982. Together they constitute an optimal database in terms of quality and continuity of the available information and representativeness of the Italian entrepreneurial population. Of particular interest are the questions on competitiveness and those on current (in the t-period), past (in the $t-1$-period) and prospective (the respondents' expectation in t for the future $t+1$) investments and sales.[3] The sample includes manufacturing, energy and mining industries, private non-financial services and construction, as well as companies with ten or more employees (both SMEs and large firms). We therefore extend the landscape of large manufacturing firms investigated by, e.g., Piva and Vivarelli (2007); Arrighetti et al. (2014).

The R&D investments over employees, $I^{\mathrm{R\&D}}_{it}/Em_{it}$, is at the core of our empirical analysis on R&D input duration.[4] It is worth stressing that the numerator is derived from the answer to a specific survey question by the Bank of Italy, and, as such, it represents the gross expenditure on R&D, market research, design and test products, while it excludes any costs for software development and expenditure on education and training of workers. Both the purchased services from an external company and the one developed in house are included, thus our measure could capture, in the words of Gilbert (2006), the numerous, scattered and varied sources of invention. Moreover, our measure is able to capture the innovation undertaken by small

[2] Differently from the Reinganum (1983) "memory-less" model in which each firm's probability of discovery is a function only of its current investment in R&D, Doraszelski (2003) considers that the success rate depends on both current and cumulative R&D expenditures.

[3] Details are, for example, in Bank of Italy (2008). The survey stimulated the design, in 2013, of the Federal Reserve Bank of Atlanta's Survey of Business Uncertainty (Altig et al., 2022).

[4] We normalize R&D spending by the total number of employees to avoid confounding the R&D impact with the size effect (Crépon et al., 1998) Alternative ways to normalize R&D, such as sales (used, e.g., by Lunn and Martín (1986); Levin et al. (1985)) or value-added that depends less than sales on the firm position along the value chain, produce robust results.

firms which relies more on the acquisition of external technologies (Bontempi and Mairesse, 2015; Conte and Vivarelli, 2005).[5]

To estimate the firm-level R&D duration models we exploit the 1996–2012 sub-period, while the pre-estimation 1984–1995 period is used to derive the instrument set for potentially endogenous explanatory variables (see Sect. 3.5.4).[6] For the industry-level analysis, we use the entire 1984–2012 period in order to maximise the number of observations available for each sector (see Sect. 4.1). Table 1 compares, over the estimating 1996–2012 period, the full sample of 3634 firms with the 1949 firms that performed R&D in at least one year and were considered in the duration analysis. The working sample is still representative of firms' characteristics as they were distributed in the full sample. Characteristics that are positively (negatively) correlated with R&D investment, and thus over- (under-) represented in the working sample, are controlled for in all estimated models, and the Heckman (1979) two-step estimator is implemented to avoid selection bias in the duration equations. Details on the sectorial distribution over the period 1984–2021 are in Table 7 in Appendix A1.2.

3.2 Measuring duration

Our variable of interest is the duration of firm's innovative effort, or its "innovative spell". Such spell is calculated for each firm in our sample as the number of years it reports positive $I^{\mathrm{R\&D}}_{it}/Em_{it}$. Our dependent variable is then represented by the probability that a firm interrupts R&D investment in the year t_i, given that it has invested in the period $(t_i - s; t_i - 1)$, $s > 0$. A distinguishing feature of duration data is that some observations may be right-censored: some spells may be incomplete and their true length unknown (this happens, for instance, when we register firms innovating in the last observed year, 2012, and we do not know whether they did the same in 2013 or not).[7] Let $T_i^\star$ be a random variable measuring the firm's innovative spell length, and let c_i be the censoring time (i.e. the time beyond which we do not observe the firm's behaviour), measured from the time origin of the spell. Then, the random variable that will be observed is $T_i = \min(T_i^\star, c_i)$. An indicator variable d_i is also observed, and it is equal to 1 if $T_i = T_i^\star$, 0 if $T_i = c_i$. Suppose the random

[5] Arrighetti et al. (2014) use internally produced and acquired externally intangible expenses, but he derives the values from the company's balance sheet, combining information also on advertisement expenditures. Doms et al. (1995) use, as a measure for innovation, the number of advanced technologies without distinguishing between technologies developed or just employed by the firm. As shown in Banbury and Mitchell (1995), many firms are able to survive in the market by keeping up with the technological forefront of the industry, either by being the first to market with incremental innovation or by quickly adopting competitors' products that are successful.

[6] The robustness checks over the entire 1984–2012 period confirm our findings.

[7] Right-censoring can be random (companies drop out of the sample before 2012 for various reasons and with varying censoring times) and fixed (companies have not stopped R&D spending in 2012). We performed some sensitivity analysis in various extreme-case scenarios to test the assumption that censoring times are non-informative. For example, we replicated our analyses on the balanced sub-sample where company exits are absent so they do not represent a confounding factor in the analysis of the mechanisms that lead to different R&D spells. The results are robust and available upon request.

variable T_i has continuous probability distribution $f(t_i)$, where t_i is realisation of T_i. The cumulative probability (failure function) is

$$F(t_i) = \int_0^{t_i} f(s)\mathrm{d}s = \Pr(T_i < t_i). \tag{1}$$

The survival function describes the probability that the innovative spell is at least of length t_i:

$$S(t_i) = 1 - F(t_i) = \Pr(T_i \geq t_i). \tag{2}$$

The probability that a spell that has lasted until time t_i will end in the next short time interval (Δt_i) is given by the hazard function

$$\begin{aligned} \lambda_i(t) = \lim_{\Delta t_i \to 0} \frac{\Pr(t_i \leq T_i < t_i + \Delta t_i | T_i \geq t_i)}{\Delta t_i} = \lim_{\Delta t_i \to 0} \frac{F(t_i + \Delta t_i) - F(t_i)}{\Delta t_i S(t_i)} = \\ = \frac{f(t_i)}{S(t_i)} \end{aligned} \tag{3}$$

where $f(t_i) = \mathrm{d}F(t_i)/\mathrm{d}t_i$. Roughly speaking, $\lambda_i(t)$ is the rate at which each spell i will be completed at duration t_i, given that it has lasted until t_i, and it represents the rate of change (and the derivative of the negative logarithm) of the survival function. All probabilities may be computed using the hazard function; for example, $F(t_i) = 1 - \exp\left(-\int_0^{t_i} \lambda_i(s)\mathrm{d}s\right)$ and $S(t_i) = \exp\left(-\int_0^{t_i} \lambda_i(s)\mathrm{d}s\right)$.

Actually our survival times are banded into discrete intervals of time, all intervals are of equal unit length (a year) so that $\Delta t_i = 1$, and there are $I = 1, 2, \dots, I_i$ grouping points defining the $I_i + 1$ intervals at which investment in R&D could be interrupted, $[0, 1), [1, 2), \dots, [I_i - 1, I_i), [I_i, \infty)$.[8] The time-aggregate hazard function can be written as $\lambda_i(t) = \Pr(T_i \in [t_i, t_i + 1) | T_i \geq t_i) = \Pr(t_i \leq T_i < t_i + 1 | T_i \geq t_i) = \frac{f(t_i)}{S(t_i)}$ to represent the probability that R&D spending will stop between time t_i and time $t_i + 1$, given that the company i is still investing until the beginning of interval $[t_i, t_i + 1)$, with $S(t_i) = \prod_{\tau=0}^{t_i - 1}(1 - \lambda_i(\tau))$.

Table 2 reports the functions of survival and hazard, estimated by the Kaplan and Meier (1958) and the Nelson (1972)-Aalen (1978) estimators respectively. The survival function is less-than-proportionally decreasing in time: at the end of the considered period, only about 16% of firms are still spending in R&D, but most of exits take place at the very beginning, with 49% of firms ceasing investment within the first 4 years. Alternatively, in terms of hazard rates (spell exit rates), the probability of interrupting innovative activity is higher in the first four years, but then decreases once the innovation activity has lasted for a certain period (the only exception to this pattern is related with the 2008/09 crisis, 13–14 in the table). Companies

[8] The modelling of duration can be unbalanced because there are $I_i + 1$ firm-specific non-overlapping intervals. Of course, the last interval is right censored when it includes 2012 (which delimits the end of our "tracking" period).

Table 1 Firm-level descriptive statistics

		Full sample (N=3,634)		Working sample (N=1,949)	
		Frequency	Percent	Frequency	Percent
Geogr. Area	North-West	939	25.84	594	30.48
	North-East	692	19.04	446	22.88
	Centre	815	22.43	451	23.14
	South	1,188	32.69	458	23.50
Tech. Index	High	141	3.88	103	5.28
	Medium-High	752	20.69	553	28.37
	Medium-Low	890	24.49	476	24.42
	Low	1,070	29.44	621	31.86
	Mining/Services	781	21.49	196	10.06
Dummy Variables	Group	1,508	41.50	977	50.13
	Listed	62	1.71	49	2.51
	Family	704	19.37	531	27.24
	Exporter	2,592	71.33	1,628	83.53
% revenues from export	Mean	0.26		0.33	
	Median	0.14		0.28	
	Std. Dev	0.29		0.30	
Size	10–99	1,900	52.28	785	40.28
	100–249	881	24.24	556	28.53
	250–500	401	11.03	284	14.57
	over 500	452	12.44	324	16.62
n. employees	Mean	350.05		465.14	
	Median	94		133	
	Std. Dev	1718.57		2243.77	
Age	0–1	1	0.03	–	–
	2–5	137	3.77	54	2.77
	6–10	322	8.86	126	6.46
	11–30	1,580	43.48	752	38.58
	31–50	1,010	27.79	629	32.27
	Over 50	584	16.07	388	19.91
years	Mean	33.46		37.13	
	Median	28		31	
	Std. Dev	26.06		27.06	
$I_{it}^{\mathrm{R\&D}}/Em_{it}$	Mean		1.15		3.56
	Median		0		1.21
	Std. Dev		4.69		7.72
	Between		72.08		74.86
	Within		27.77		24.74
	Time effect		0.15		0.40

Note: $I_{it}^{\mathrm{R\&D}}/Em_{it} \geq 0$ in full sample and > 0 in working sample. Panel observations over the period 1996–2012 are used for $I_{it}^{\mathrm{R\&D}}/Em_{it}$ which is measured in thousands of euros per employee; the total vari-

Table 1 (continued)

ability is decomposed into the percent components due to firms (between), firm-specific changes over time (within), and the factor common to all firms (time effect). The other descriptive statistics are at the firm level as they relate to relatively time-invariant variables. High Tech.: 1-Aerospace, 2-Computer, 3-Pharma, 18-Elec. machinery & Electronics, 21-Communic./Software/R&D. Medium-High Tech.: 9-Scient. instr., 10-Motor vehicles & Transport eq., 11-Chemicals, 17-Non-el. mach., 18-Elec. machinery & Electronics. Medium-Low Tech.: 4-Rubber/Plastic, 5-Shipbuilding, 6-Petroleum refining, 13-Non-fer. metal, 12-Fer. metal, 15-Non-met. min., 16-Fabr. metal. Low Tech.: 7-Paper/Printing, 8-Textile/Clothing/Leather, 19-Food/Tobacco, 20-Wood. Mining includes Coal/Gas/Oil Extraction, and Electric/Gas/Water Production and Distribution; Services include Wholesale and Retail/Transport/Real Estate, Renting and other Business Activities/Insurance/Buildings/Hotels

Table 2 Spell description; survival and hazard functions

	All Spells		No left-censoring	
	Survival	Hazard	Survival	Hazard
1	0.7927	0.2073	0.7751	0.2249
2	0.6563	0.1721	0.6258	0.1926
3	0.5669	0.1362	0.5161	0.1754
4	0.4857	0.1433	0.4192	0.1878
5	0.4299	0.1148	0.3606	0.1399
6	0.3797	0.1167	0.2995	0.1693
7	0.3423	0.0986	0.2542	0.1512
8	0.3081	0.1000	0.2219	0.1273
9	0.2778	0.0982	0.1951	0.1206
10	0.2480	0.1075	0.1666	0.1463
11	0.2232	0.1000	0.1453	0.1277
12	0.2119	0.0505	0.1369	0.0580
13	0.1786	0.1571	0.1112	0.1875
14	0.1593	0.1081	0.0941	0.1538
Num. of Spells	2,603		1,450	
Avg. Num. of Spells by Firm	1.336		1.237	
Avg. Spell Duration	2.589		2.403	
Num. of Firms	1,949		1,172	
Time at Risk	6,967		3,278	

experienced multiple spells meaning that they interrupted and restarted R&D spending several times (5 at maximum). The more frequently innovation is interrupted and restarted, the greater the number of spells and the lower their average duration, in our case just over two and a half years (2.59).[9]

In the last two columns of Table 2 we deal with left censoring which occurs when we do not observe the starting date of the R&D spell (this concerns the spells of

[9] Duration estimators are more accurate for short spells, because inference about very long durations is based on fewer observations (Kiefer, 1988).

firms reporting positive R&D investment in 1996, the first year of our estimating sample; the length of the innovative spell could be greater than what is observed).[10] As pointed out in Iceland (1997), omitting left-censored cases could lead to serious selection bias because one might exclude from the analysis firms that present the longest innovative spells. In fact, whereas firms that invest in R&D discontinuously (i.e. have several short spells) may be expected to re-enter the data set, firms that continuously engage in innovative activity would be ignored, leading to a downward bias in estimation of the survival function. Several methods can mitigate the problem (Stevens, 1995; Iceland, 1997; Carter and Signorino, 2013). To retain all available information, we follow Stevens (1995) suggesting to include left-censored spells in the analysis and add a dummy variable indicating whether the observed spell is left-censored or not.

3.3 Measuring market power

As emerged from the cellophane case (Stocking and Mueller, 1995), *measuring* market power is a non-trivial issue. What we can do, indeed, is to comparatively discuss alternative possibilities in the empirical analyses at company-level (in Sect. 4) and industry-level (in Sect. 4.1). The standard two proxies in the empirical IO literature are the firm-level Learner index measuring the price–cost margin, PCM, and the industry-level concentration ratio as the number of firms within each sector and the Herfindahl-Hirschman index.[11]

The price–cost margin is defined by (see Domowitz et al. (1986); Bontempi et al. (2010); Aghion et al. (2005)):

$$PCM_{it} = \frac{\text{Sales}_{it} + \Delta\text{Inventories}_{it} - \text{Payroll}_{it} - \text{Materials}_{it}}{\text{Sales}_{it}}.$$

where Δ is the change.[12] This measure is widely used in spite of its drawbacks. As reported in Coscollá-Girona et al. (2015); Domowitz et al. (1986), increased PCMs (or high degrees of concentration) are not necessarily symptoms of lack of competition. Boone (2000) points out that there is no simple relationship between product market competition and market structure if firm's cost efficiency levels are

[10] Innovative spells are likely to be left-truncated too, as firms might have experienced innovative spells that ended before 1996. Hence, the analysis is conditional upon firm survival up to 1996, and firm engaging in R&D investment in 1996 or later (delayed-entry). Fortunately, as shown by Bhattacharjee et al. (2009), delayed-entry does not jeopardise estimation as long as the correct entry time is considered. Our results are robust to changes in the starting years a firm reports positive R&D investment, i.e. it becomes at risk of discontinuing innovative activity; for example we checked 1984 instead of 1996.

[11] Examples of innovation studies that employ the PCM are Aghion et al. (2005); Antonelli et al. (2012); Audretsch (1995); Greenhalgh and Rogers (2006); studies based on concentration measures are, among others, Acs and Audretsch (1988); Audretsch (1991); Banbury and Mitchell (1995); Blundell et al. (1999); Cefis and Ciccarelli (2005); Duguet and Monjon (2004); Geroski et al. (2010); Lhuillery (2014); López-García and Puente (2006); Máñez et al. (2015). Market shares established arbitrarily, such as a set of dummy variables capturing some range on the number of competitors in the main product market, are used, e.g., in Woerter (2014).

[12] Results are robust to the inclusion/exclusion of the financial cost of capital, as in Aghion et al. (2005).

asymmetric. For instance, enhanced competition may raise the market shares of the most efficient firms at the expense of inefficient ones, increasing the concentration index ("reallocation effect", Boone (2008)); or concentration may rise as the most inefficient firms exit the market because of more intense competition ("selection effect", Boone (2008)). The latter case may also lead to an increase in the average PCM. In like manner, if less competitive pressure leads to higher costs due to inefficiency or absence of cost-reducing innovations, the PCM will decrease (Coscollá-Girona et al., 2015). Furthermore, as pointed out by Domowitz et al. (1986), PCMs are sensitive to demand fluctuations. A limitation of PCM that plagues the empirical works is that it is conceptually difficult as it includes wages of R&D employees in the payroll amount being deducted. If R&D is cut, it has a quasi-automatic effect on the PCM, unless employees are taking over other tasks within the firm or the data allows to separate R&D employees' wages from the total payroll. Another drawback of PCM is the high correlation with cash flow (41%) which we used to capture internal funds and financial constraints on innovation. In general, measures mainly based on the level of sales risk to generate empirically an obvious correlation with an input such as the amount of R&D expenditure or an output such as patents.

To be coherent with Delbono and Lambertini (2022) and the analysis disaggregated at the industry level, the second measure we use is $share_{jt}$, given by the total number of firms investing in R&D within each industry $j = 1, \dots, 23$ in each year t, divided by the total number of firms within each industry in each year. Compared with concentration measures that simply consider the largest firms in an industry, $share_{jt}$ takes into account the number of R&D producers inside each industry, not just the largest ones, reflecting the changes in the industrial diffusion of innovation activity.[13]

An important contribution of this study is the use of a third, and new, measure of market power, given by the implied demand elasticity obtained from qualitative data. In the 1996 and 2007 surveys firms were asked the following question (Bank of Italy, 2008):

> Consider the following hypothetical experiment: suppose your firm raises today the price of the goods produced by 10 percent. What would be the percent change in the value of sales, assuming that your firm's competitors leave their prices unchanged, and holding everything else constant?

Such a question directly refers to the firm price elasticity of demand, as all other variables can shift the demand curve faced by the firm are to be held constant in the thought experiment. The fact that Italian companies are small-sized, unlisted and typically operate in well-defined industries makes us to expect that the respondents have a clear idea when answering the survey question on demand elasticity.[14]

[13] Results are robust to the use of the Herfindahl-Hirschman index.

[14] In the 2007 survey firms declared that the leading product, or main product line, represents on average the 72% (80% at the median) of their total turnover. We suppose a price rise that causes a loss of sales could indicate a diversion to competitors or price sensitivity on the part of consumers (e.g., a monopoly but facing consumers who do not really need that good and hence buy less when the price increases).

The answers given in the two surveys show small differences, due to rounding and non-significant variations in elasticity.[15] This allows to assume that elasticity is a constant characteristics of our companies, thus not affected by endogeneity problems in our duration models (see Sect. 3.5.4). Hence, we can use the individual averages as an estimate of the firm-specific elasticity. Table 3 shows that mean operator does not change the statistical properties of the distribution. Descriptive statistics given in Table 3 are consistent with some firms having market power. The mean value of η is −1.36, and the great majority of firms, about 87%, show an implied elasticity greater than 1 in absolute value.

Table 4 reports some descriptive statistics about the relationship between the implied demand elasticity, R&D, PCM, firm's size and age. Additional qualitative analyses of the companies across elasticity classes confirm the capacity of our new measure to condense the market structure and degree of competition (see the Appendix, Sect. A1.3).

Low elasticity classes, in absolute values, are characterised by high R&D, high PCM, large size and high age companies. Firm's size is positively correlated with PCM (8%), share (14%), cash flow (7%), while it is not correlated with elasticity. This last point is important as, in our estimates, we aim at differentiating between firms size and market power.[16]

3.4 Measuring persistence

To capture the factors that determine the true persistence and cumulativeness of the R&D effort, we include four drivers: the lagged values of the logarithm of innovative stock (ln *RD*)[17] the number of previous spells in which the firm has continuously invested in R&D (*Spell Number*); the elapsed duration of previous spell (*Time*); and a dummy equal to 1 if the spell is left-censored (*Left Cens.*). As companies contribute to multiple spells (in Sect. 3.2), the inclusion of the previous event and its length among the time-varying explanatory variables helps to correct for the dependence between the occurrence of one event and the hazard of subsequent events.

[15] The overall distribution is quite similar across years, the regression of one answer on the other provides an estimate not statistically different from one with the R^2 higher than 92%.

[16] Firm size is proxied by the (logarithm of) total number of employees at year ends. It is worth noting that employment data refer to the whole labour force of the firm, because information disaggregated by organisational functions are not available.

[17] The stock measure, *RD*, is computed using the permanent inventory method: given the flow measure $I_{it}^{\mathrm{R\&D}}$, we have $RD_{it}; = I_{it}^{\mathrm{R\&D}} + (1-\delta)RD_{it-1}$, with δ representing the depreciation rate (equal to 30%). A comparison between the intangible assets obtained as capitalized R&D expenses and the stocks of intangibles reported in the companies' balance sheets is given in Bontempi and Mairesse (2015) where it is stressed that it is mandatory for firms to report R&D spending. The assumption that the firm's stock of knowledge depends on past flows of innovative activity is also in Blundell et al. (1999).

Table 3 Implied Elasticity

Variable	Mean	Min	25th P	Median	75th P	Max	Std. Dev	Skew	Kurt
$-\eta$	−1.35	−2.00	−1.50	−1.30	−1.10	0	0.36	−0.28	3.23
Avg. $-\eta$	−1.36	−2.00	−1.50	−1.30	−1.10	0	0.34	−0.30	3.23

Table 4 R&D, PCM, Size and Age across Elasticity Classes

$-\eta$ Class	$I_{it}^{\text{R\&D}}/Em_{it}$			PCM_{it}			Em_{it}			Age_{it}		
	Mean	50^{th} P	90^{th} P	Mean	50^{th} P	90^{th} P	Mean	50^{th} P	90^{th} P	Mean	50^{th} P	90^{th} P
Highly El	2.806	1.142	7.186	0.076	0.078	0.160	649	166	862	41	36	74
Elastic	2.971	1.162	7.124	0.085	0.085	0.173	503	196	1006	44	39	85
Unitary El	4.042	1.354	12.683	0.063	0.094	0.198	409	150	966	42	36	96
Inelastic	5.031	1.568	12.035	0.102	0.101	0.198	568	204	1254	45	41	75
Total	3.144	1.204	7.586	0.083	0.084	0.172	554	186	1,000	43	38	82

Note: Elasticity is grouped into four categories: Highly El. if $|\eta| \geq 1.5$ (33.77%); Elastic if $1 < |\eta| < 1.5$ (53.16%); Unitary El. if $|\eta| = 1$ (4.06%); Inelastic if $|\eta| < 1$ (9.01%)

3.5 Modelling duration

The next steps concern the specification of how the hazard depends on observed and unobserved explanatory variables (the shape of the hazard), the role of ignoring unobserved heterogeneity, and how to model the distribution of v_i. As discussed above, we have many theories that suggest potential covariates rather than a specific functional form of the duration model (the true form is unknown a priori). Henceforth, we prefer to use reduced form approaches, as it is common in the literature on duration analysis (Heckman and Singer, 1984a).[18] The comparison of qualitative results, obtained from alternative specifications of the hazard shape and treatments of heterogeneity, represents a sensitivity analysis on the model space, ensuring the transparency of our results and providing useful insights.

3.5.1 The Cox model

We use the semi-parametric (Cox, 1972) model as starting point for our analysis because it is quite flexible and does not require any assumption about the functional form of the hazard. Each i^{th} firm faces a hazard function which is common to all firms (the "baseline" hazard, λ_0 which is a function of t alone) and is then modified by the set of explanatory variables x'_{it}. The relationship between the individual risk and the vector x'_{it} depends upon the estimated coefficient vector β. The Cox model

[18] Rust (1994) notes that the validity of a structural model depends on its correct specification, and many assumptions make the structural model an abstract and approximate representation of reality.

assumes that the individual risk equals the product of the "baseline" risk and the function $\psi(\mathbf{x}, \beta) = \exp(\mathbf{x}'\beta)$:

$$\lambda_i(t|\mathbf{x};\beta) = \lambda_0(t)\psi(x_{it}, \beta) = \lambda_0(t)\exp(x_{it}'\beta). \tag{4}$$

In other words, the shape of the hazard function is the same for all firms, and variations in x_{it}' just shift the function. This allows for a direct interpretation of the estimated coefficients because for the k^{th} covariate $(k = 1, 2, \ldots, K)$

$$\beta_k = \frac{\partial \ln \psi(\mathbf{x}, \beta)}{\partial x_k} \tag{5}$$

represents the constant proportional effect of an increase in the relative variable on the conditional probability of exiting the innovative state. This approach provides estimation of β without requiring estimation of λ_0.

The Cox model suffers from four potential drawbacks. First, it implies a continuous-time specification, thus assuming the absence of ties. Even if the behavioural process generating the exit rates were to occur in continuous time, our data are nevertheless recorded in grouped form (the year). From Table 2, the ratio of the length of the intervals used for grouping to the average spell length is not small (equal to 0.386), suggesting that a discrete time specification would be more appropriate. Indeed, if ties occur infrequently, it is possible to account for them with the Efron (1977) method. But when ties are frequent, there is no way to avoid asymptotic bias in both the estimated coefficients and the corresponding covariance matrix. Second, the Cox model is not robust to neglected covariates, specifically unobserved heterogeneity (or frailty in biostatistics); failing to control for firm capabilities (technological opportunities, appropriability conditions, etc.) could lead to spurious association between e.g. R&D effort and market power, and spurious persistence.[19] Third, it is impossible to obtain any information about the shape of the hazard function λ_0, which is actually important to ascertain if there is negative (positive) duration dependence. Finally, the Cox model in Equation (4) assumes Proportional Hazards (PH). This means that the effect of any explanatory variable on the hazard is assumed to be constant over duration time. It is straightforward that, should the PH assumption fail, estimated covariate effects would be biased. The PH assumption may fail to hold for two reasons: (1) because the effect of explanatory variables is intrinsically non-proportional; (2) because unobserved individual heterogeneity is not accounted for and makes the effect depend on duration time, even if the underlying process is of the proportional hazards form (Lancaster and Nickell, 1980; Brenton et al., 2010). Estimated results for the Cox model are in the Appendix A1.4, Table 11; in Table 12 the PH assumption is strongly reject.

[19] Rephrasing Heckman and Singer (1984a), if the weakest companies are the first to stop R&D spending, only the strongest firms continue to invest. This generate a bias toward negative duration dependence (the hazard rate will appear to fall over time), which we will return to later.

3.5.2 The Cloglog model

The *Cloglog* model assumes a complementary log-log form for the hazard, and overcomes many limitations that affect the Cox model. In fact, as well as giving a discrete time representation of an underlying continuous time proportional hazards model, it also controls for unobserved heterogeneity and gives information about the duration dependence of the hazard. The conditional likelihood of the data (a sample of N firms where independence over i is assumed) is

$$
\begin{aligned}
L &= \prod_{i=1}^{N}\left\{ f(t_i|x_{it_i};\beta)^{d_i}[1-F(t_i|x_{it_i};\beta)]^{1-d_i} \right\} = \prod_{i=1}^{N}\left\{ f(t_i|x_{it_i};\beta)^{d_i}[S(t_i|x_{it_i};\beta)]^{1-d_i} \right\} = \\
&= \prod_{i=1}^{N}\left\{ \lambda_i(t_i|x_{it_i};\beta)^{d_i} S(t_i|x_{it_i};\beta) \right\} = \prod_{i=1}^{N}\left\{ [1-S(t_i|x_{it_i};\beta)]^{d_i} S(t_i|x_{it_i};\beta) \right\} = \\
&= \prod_{i=1}^{N}\left\{ \left[1-\exp\left(-\int_{t_i}^{t_i+1}\lambda_i(s|x_{is};\beta)\mathrm{d}s\right)\right]^{d_i} \prod_{\tau=0}^{t_i-1}(1-\lambda_i(\tau|x_{i\tau};\beta)) \right\} = \\
&= \prod_{i=1}^{N}\left\{ \left[1-\exp\left(-\exp(x'_{it_i}\beta)\int_{t_i}^{t_i+1}\lambda_0(s)\mathrm{d}s\right)\right]^{d_i} \prod_{\tau=0}^{t_i-1}(1-\lambda_i(\tau|x_{i\tau};\beta)) \right\} = \\
&= \prod_{i=1}^{N}\left\{ \left[1-\exp\left(-\exp(x'_{it_i}\beta+\gamma(t_i))\right)\right]^{d_i} \prod_{\tau=0}^{t_i-1}\left[\exp\left(-\exp(x'_{i\tau}\beta+\gamma(\tau))\right)\right] \right\}
\end{aligned} \tag{6}
$$

where $d_i = 1$ if the interval is not right-censored and 0 otherwise. The first term corresponds to completed spells and represents the conditional probability that T_i falls into the $[t_i, t_i + 1)$ interval. If a firm i is censored (exits the sample) at some point inside the interval, we do not know whether it would have invested during the interval or not, and we must censor it (the first term equals 1). The second term is the probability that a spell lasts at least until the interval $[t_i - 1, t_i)$. The last three rows are the discrete-time variant of a continuous-time PH model (Kalbfleisch and Prentice, 2002; Kiefer, 1988; Meyer, 1990). If $t_i \in [t_i, t_i + 1)$, $\gamma(t_i) = \ln\left(\int_{t_i}^{t_i+1}\lambda_0(s)\mathrm{d}s\right)$, and the time-varying covariates in x'_{it_i} are assumed to be constant within each interval (but may vary between time intervals). The baseline hazard function $\gamma(t_i) = [\gamma(0)\gamma(1)\ldots\gamma(I_i - 1)]'$ is a polynomial in time that allows for a flexible definition of duration dependence; usually it is chosen by the researcher. In the present work, the highest order polynomial that resulted significant was the first, as we include appropriate covariates to capture the duration dependence of the hazard (see Sect. 3.4).

Without loss of generality, we can write the log-likelihood as

$$
\ln L = \sum_{i=1}^{N} d_i \ln\left[1-\exp\left(-\exp(x'_{it}\beta+\gamma(t))\right)\right] - \sum_{i=1}^{N}\sum_{\tau=0}^{t-1}\left(\exp(x'_{i\tau}\beta+\gamma(\tau))\right) \tag{7}
$$

where the expression for the interval hazard rate $\lambda_i(t|x_{it}'\beta) = 1 - \exp\left(-\exp(x_{it}'\beta + \gamma(t)\right)$ can be seen as a form of generalized linear model with particular link the complementary log-log transformation, $\ln\left[-\ln(1-\lambda_i(t|x_{it};\beta))\right] = x_{it}'\beta + \gamma(t)$ (Allison, 1982; Jenkins, 1995).

Since in each discrete-time interval the spell either ends or it does not, a binary choice model can be used for the probability of interrupting R&D in each period (Jenkins, 1995; Kiefer, 1988; Han and Hausman, 1990; Meyer, 1990; Lancaster, 1990; Sueyoshi, 1995). In the log-likelihood

$$\ln L = \sum_{i=1}^{N} d_i \ln\left[1 - S(t_i|x_{it};\beta)\right] + \sum_{i=1}^{N} \ln\left[S(t_i|x_{it};\beta)\right] \tag{8}$$

$1 - S(t_i|x_{it};\beta) = F(t_i|x_{it};\beta)$ is either the logit or probit model, rather than the complementary log-log model. For example, a logistic hazard model with interval-specific intercepts may be consistent with an underlying continuous time model in which the within-interval durations follow a loglogistic distribution (Sueyoshi, 1995). The log-likelihood is

$$\ln L = \sum_{i=1}^{N} d_i \ln\left(\frac{\lambda_i(t|x_{it};\beta)}{1-\lambda_i(t|x_{it};\beta)}\right) + \sum_{i=1}^{N}\sum_{\tau=0}^{t_i-1} \ln(1-\lambda_i(\tau|x_{i\tau};\beta)) \tag{9}$$

where $\dfrac{\lambda_i(t|x_{it};\beta)}{1-\lambda_i(t|x_{it};\beta)} = \left(\dfrac{\lambda_0(t)}{1-\lambda_0(t)}\right)\exp(x_{it}'\beta)$.

It follows that $\ln\left(\dfrac{\lambda_i(t|x_{it};\beta)}{1-\lambda_i(t|x_{it};\beta)}\right) = \mathrm{logit}[\lambda_i(t|x_{it};\beta)] = \delta(t) + \exp(x_{it}'\beta)$, where $\delta(t) = \mathrm{logit}[\lambda_0(t)]$ can be a polynomial in time as the $\gamma(t)$ in the *Cloglog* model. The *Cloglog* and logistic hazard models yield similar results for relatively small hazard rates: $\mathrm{logit}[\lambda_i(t|x_{it};\beta)] = \ln\left(\dfrac{\lambda_i(t|x_{it};\beta)}{1-\lambda_i(t|x_{it};\beta)}\right) = \ln(\lambda_i(t|x_{it};\beta))$ $-\ln(1-\lambda_i(t|x_{it};\beta)) \approx \ln(\lambda_i(t|x_{it};\beta))$ for small $\lambda_i(t|x_{it};\beta)$.

Hence, Eq. (9) can be rewritten as the log-likelihood function of a binary dependent variable $y_{it} = 1$ if spell i ends in interval t, and 0 otherwise:

$$\ln L = \sum_{i=1}^{N}\sum_{\tau=0}^{t}\left[y_{i\tau}\ln\lambda_i(\tau|x_{it};\beta) + (1-y_{i\tau})\ln(1-\lambda_i(\tau|x_{it};\beta))\right] \tag{10}$$

where the functional form for $\lambda_i(t|x_{it};\beta)$ can be a complementary log-log model or a logistic model. Considering the R&D investment a continuous process measured in grouped form, we prefer the model with the *Cloglog* link. In general, duration data are much more informative than binary data (Rust, 1994; Van den Berg, 2001) as they preserve information about the differences in time in which each company stopped R&D spending and multiple spells; on the other side, the logistic model is not a PH model.

As argued in Sect. 2, many studies highlight the importance of unobserved heterogeneity (let denote it by v_i) in explaining the persistence of innovation. If unobserved heterogeneity is indeed important, ignoring it will lead to over- (under-) estimation of the degree of negative (positive) duration dependence (Lancaster, 1979; Kiefer, 1988). This is a selection effect: if duration dependence is negative, individuals with high values of v will stop R&D faster, *ceteris paribus*. Furthermore, the proportionate effect β_k of a given regressor x_k on the hazard rate will no longer be constant and independent of survival time, and β_k will be biased (Lancaster, 1979). Heterogeneity enters the underlying continuous hazard function multiplicatively:

$$\lambda_i(t|x_{it};\beta, v_i) = \lambda_0(t)\exp(x'_{it}\beta)v_i, \tag{11}$$

hence, the *Cloglog* model becomes:

$$\lambda_i(t|x_{it};\beta, v_i) = 1 - \exp[-\exp(x'_{it}\beta + \gamma(t) + u_i)] \tag{12}$$

where $u_i \equiv \ln v_i$ and v_i is a random variable taking on positive values, with mean normalised to one and finite variance σ^2. In multi-spell data we do not require that v_i is distributed independently of x_{it}Honoré (1993).[20]

Estimation of model (12) requires an expression for the density function that does not condition upon the unobserved effects. It is hence convenient to specify a distribution for v to “integrate out” the unobserved effect (i.e., one works with the function $\lambda_i(t|x_{it};\beta, \sigma^2)$ rather than $\lambda_i(t|x_{it};\beta, v_i)$). We compared two assumptions, the first one that the heterogeneity v_i is normally distributed, and the second one with Gamma-distributed frailty (Meyer, 1990). The two distributions either require numerical quadrature techniques or provide closed form expressions for the hazard function with frailty which, in the end, is summarised by few key parameters.

The *Cloglog* framework also allows for the incorporation of unobserved heterogeneity non-parametrically by assuming that there are several types of firm spell (“mass points” in Heckman and Singer (1984b)). This implies that each spell has probabilities associated with the different mass point, allowing for different intercepts of the hazard function. For a model with $n = 1, \dots, M$ mass points m_n with probabilities p_{m_n}, the hazard in Eq. (12) becomes:

$$\lambda_i(t|x_{it};\beta, m) = 1 - \exp[-\exp(m_n + x'_{it}\beta + \gamma(t))]. \tag{13}$$

Normalising the first mass point to zero, the intercept for type-1 firms is β_0 (corresponding to the first element of x'_{it} which is $\equiv 1$), that for type-2 firms is $\beta_0 + m_2$ and so on. The log-likelihood is $\ln L = \sum_{i=1}^{N}\sum_{n=1}^{M} p_{m_n} \ln L_n$ where $\ln L_n = d_i \ln\left[1 - S_n(t_i|x_{it};\beta, m_n)\right] + \ln\left[S_n(t_i|x_{it};\beta, m_n)\right]$.

Estimated results for the *Cloglog* models with normally-distributed frailty, gamma distributed frailty, and mass -points frailty are in the Appendix A1.4, Tables 13, 15, 16. The PH assumption, in Table 14, is not rejected.

[20] As a robustness check for the possible correlation between unobservables and covariates, and to conserve parameters, we consider the correlated random effects model with the Mundlak (1978)-type specification of Chamberlain (1980).

3.5.3 The probit model

Discrete-time survival analysis often employs logit models as an alternative to semi-parametrical approaches as the *Cloglog*, to relax the PH assumption. However, because the considered event (interruption of innovative effort) occurs quite frequently, and many spells last longer than 1 year, the logit assumption of event independence would be invalid, leading to biased estimates (Banbury and Mitchell, 1995). Hence, we prefer to use a random effects probit model (Antonelli et al., 2013; Hecker and Ganter, 2014; Lhuillery, 2014; Peters, 2009; Triguero and Córcoles, 2013; Triguero et al., 2014).

The expressions in the likelihood function are given by

$$\begin{aligned} f(y_{it}|x_{it};\beta, v_i,) &= \Phi\left(\frac{x_{it}'\beta + \bar{x}_i'\pi}{\sqrt{1+\sigma_\upsilon^2}}\right) \qquad \text{if } y_{it} = 1, \\ &= 1 - \Phi\left(\frac{x_{it}'\beta + \bar{x}_i'\pi}{\sqrt{1+\sigma_\upsilon^2}}\right) \quad \text{if } y_{it} = 0 \end{aligned} \tag{14}$$

where Φ denotes the cumulative density function of the standard normal distribution. We added to model specification the individual averages of time-varying explanatory variables so to estimate the Chamberlain (1980) correlated random effects probit model in the Mundlak (1978) version. Hence, unobserved heterogeneity v_i is assumed to be normally distributed with mean $\bar{x}_i'\pi$, and σ_υ^2 is the variance of the error in $v_i = \bar{x}_i'\pi + \upsilon_i$.

Estimated results are in the Appendix A1.4, Table 17.

3.5.4 Discussion on endogeneity

The hazard rate framework allows for a "less-affected-by-endogeneity" investigation of the role of market structure and other controls on R&D effort. Indeed, companies are not certain that their investments will be successful and will definitely bring, for example, greater market power, generating simultaneity. We are not investigating long-run equilibria and perfect markets, but rather situations characterized by imperfections, such as sunk costs, uncertainty and its "wait and see" effect, which produce rigidities in immediately implementing R&D investments and being successful. In other words, we estimate the duration of R&D expenditure, which is an "ex-ante" input indicator and, for this reason, makes the endogeneity problem less relevant than when considering "ex-post" innovative output indicators.[21].

To confirm our assumption, we proceed with two identification strategies that, although different, produce robust results. Both strategies are based on the vector

[21] As an example, we might expect a feedback between a patent and firm sales (Piva and Vivarelli, 2007)). However, even patents themselves have an indirect and short-lived effect: Coad and Rao (2008) show that patents positively affect company profits through sales growth, i.e. they typically do not increase profit margins but, instead, improve corporate profits by increasing sales at constant profit margins.

partition $x'_{it} = (x'_{0i}, x'_{1it}, x'_{2it})$. The term x'_{0i} contains time-invariant measurable firm- and industry-level characteristics which, together with the duration model that accounts for unobservable individual effects, Eq. (12), and the Mundlak (1978)'s approach, allow for controlling the endogeneity due to the omission of stable drivers of innovation. The term x'_{1it} contains exogenous time-varying covariates like the firm-specific shocks and the macroeconomic (common to all the companies) uncertainty. The term x'_{2it} contains *potentially* non exogenous time-varying explanatory variables like cash flow, debt, size, PCM and share, revenues from export, and accumulated stock of knowledge.[22] Firms that continuously invest in R&D *could* obtain higher profits and greater availability of cash flow to internally finance the innovative expenses, a higher demand associated with decreasing prices (e.g., due to process innovation) and/or increasing market share (e.g., due to product innovation), and have a higher stock of cumulated R&D. However, we can reasonably assume that there are lags between an initial effort in R&D and the uncertain and delayed outcomes. Also, it should be emphasised that, compared to the PCM, which is also affected by measurement and collinearity problems, the elasticity of demand has proven to be quite stable over our sample period and can therefore be included in the x'_{0i} term: consumer preferences are not directly influenced by companies, even if they spend a lot on advertising (see Sect. 3.3).

Our first identification strategy is supported by Nickell (1996) who uses lagged market power, and Hall et al. (1999) who, through bivariate causality regressions, show that sales growth clearly led to R&D growth in all the countries studied. Additionally, although innovation and standard measures of market power could be simultaneously determined, the evidence from the literature testing endogeneity is ambiguous (Gilbert, 2006). Hence, we use the vector $x'_{it} = (x'_{0i}, x'_{1it}, x'_{2it-1})$ and assume that the values before the start of the spell, x'_{2it-1}, do not depend on the occurrence of exit in $[t, t+1)$ or in some later intervals. This corresponds to the weak exogeneity assumption in dynamic regression models or predictability (Ridder and Tunali, 1999) which implies that the observable values of the covariates for the hazard at time t are given just before t.

The second identification strategy is based on two-stage regressions (Chan, 2016) in which, in the first stage, we regress the possible endogenous explanatory variables x'_{2it} on the included exogenous variables and the scores of the appropriate lags of the transformed endogenous variables (the instruments, s'_{it}): $x'_{2it} = x'_{0i}\gamma_0 + x'_{1it}\gamma_1 + s'_{it}\gamma_2 + \epsilon_{it}$. In the second stage we use the reduced-form

[22] According to the classification by Kalbfleisch and Prentice (2002), x'_{1it} contains "external" covariates whose complete time path from entry to the state t can be used in estimating conditional hazards. As these variables have paths determined independently of whether or not a particular firm has interrupted R&D, they are exogenous. The variables in x'_{2it} are not exactly "internal" covariates whose path is meaningfully defined only up to the time of exit, whereas after the state t their presumably unknown future has no behavioural interpretation. In fact, variables like debt, profits and market power, despite not external to each company and possibly related to R&D, have paths that are still defined after t as they also depend on other choices and investments of the firm. These variables could be exogenous in a spirit similar to the Granger (1969)'s non-causality.

residuals, $\hat{\epsilon}_{it} = x'_{2it} - x'_{0i}\hat{\gamma}_0 - x'_{1it}\hat{\gamma}_1 - s'_{it}\hat{\gamma}_2$, as additional variables in the estimation of the duration models,[23]

To avoid the problem of over-fitting due to the use of many instruments, we use the Bontempi and Mammi (2015)'s procedure to extract the components that account for 90% of the variability of the set of instruments. We assume that $\mathbf{z}$ is the p-columns GMM-Lev style instrument matrix (Arellano and Bover, 1995), composed of the 14 to 24 lags in the pre-estimation period 1984–1995 of x'_{2it} transformed into first differences to avoid correlations with unobserved heterogeneity. We extract p ordered eigenvalues $\lambda_1, \lambda_2, ..., \lambda_p \geq 0$ from the covariance/correlation matrix of $\mathbf{z}$, and find the corresponding eigenvectors $e_1, e_2, \dots, e_p$. The instruments are the scores obtained from the principal component analysis $\mathbf{s}_w = \mathbf{z}e_w$ for $w = 1, 2, \dots, p$. Writing $\mathbf{z} = [z_1 \dots z_r \dots z_p]$ with z_r being the r^{th} column of the instrument matrix, the score s_w corresponding to the w^{th} component is $s_w = e_{w1}z_1 + \cdots + e_{wr}z_r + \cdots + e_{wp}z_p$, where e_{wr} is the r^{th} element of the principal component e_w. The first step uses $w = 5$, i.e. the first five components extracted from the variable-specific lags for cash flow, PCM and share; the lags of all variables together for R&D stock, debt, export earnings and size.[24] The identification based on the lagged explanatory variables resembles that proposed by Macher et al. (2021) assuming that R&D expenditures do not spillover from one period to future periods. Since we use lags computed in the pre-sample period, 1984–1995, we can suppose that positive temporal spillovers, if present, are nonetheless decreasing over time and have disappeared once long lags (14 to 24) are taken into account, thus not invalidating our instruments.

4 Results

In Table 5 we compare the estimates of our duration models, along the columns, using the same specification which is our preferred choice. It includes elasticity of demand $-\eta$, size, the EPU index of macroeconomic uncertainty and the firm-specific uncertainty (the discrepancy between actual and planned investments), cumulativeness and left-censoring, and the set of control variables. We consider the fourth column of Table 5, the *Cloglog* model with "mass points", as the most reliable empirical specification for our data, the other estimates being reported as robustness checks.[25] The results are discussed along the following points.

[23] The regression-based approach also offers a Hausman (1978)-type test for endogeneity. Apart *PCM* the estimated parameters are robust and close to those based on the use of lagged explanatory variables, particularly for our favourite model with mass points for unobserved heterogeneity.

[24] We verified the components extracted from both the lags of each specific variable taken alone and from the lags of all the variables taken together. The selected instruments are based on the Fisher (1966)'s criteria.

[25] Our choice derives from the models' comparison, tests and robustness checks reported in the Appendix A1.4.

Persistence of R&D. The true persistence of the innovation process, linked to cumulativeness, irreversibility and increasing returns on innovation investment, learning-by-doing and learning-to-learn effects, is globally captured by the logarithm of the R&D stock and the variables *Spell Number, Time*. There is evidence of persistence in R&D investments: the coefficient for the lagged stock of accumulated knowledge is negative and significant. The coefficient of *Time* is also negative (significant in Cox and Probit models), suggesting that the longer a firm has continuously invested in R&D, the more likely it is to continue investing (negative duration dependence). This is coherent with our expectations, and confirms the results of Acs et al. (2008); Hecker and Ganter (2014); Máñez et al. (2015); Triguero et al. (2014) who found significant R&D temporal spillovers in Cox/Probit models. The coefficient of the number of previous spells is significant (and negative) in the continuous Cox and discrete log-logistic models under the assumption of normally distributed frailty. Firms that have shown a discontinuous attitude towards innovation, but have had several innovation spells, are less likely to stop investment again. In contrast, the frailty models take into account the possibility of unobserved differences between firms, e.g. that some companies have high hazards (many spells) while others have low hazards (few spells). Controlling for unobserved heterogeneity eliminates what might otherwise be interpreted as a causal effect of each spell on the hazard of subsequent R&D spells. When the models are estimated by adding the Heckman-type selection to check the unbiasedness of the results, only the lagged accumulated knowledge stock becomes non-statistically significant, while the other parameters are robust. The inverse Mills ratio correcting for selection bias appears to be collinear with the R&D stock, an expected outcome, but quite interesting to see confirmed in the data.

Left-Censoring. The dummy variable *Left Cens.* is negatively associated with firms discontinuing their innovative activity in all the duration models we estimated. As discussed in Sect. 3.2, this precaution mitigates the bias in estimation due to left-censoring. The negative and significant coefficient confirms the preliminary hypothesis that left-censored spells are likely to be the longest. The exclusion of such spells would have hence resulted in a severe overestimation of the hazard function.

Market Power and size. The parameter of *PCM*, the standard measure of market power, is negative and significant only in our favourite model, the *Cloglog* with frailty captured by mass points when instrumented with the two-stage regressions. It also assumes a value aligned with that of elasticity $-\eta$. However, as outlined in Sect. 3.3, price cost margin suffers from multicollinearity with cash flow and size, two variables adversely affected by the inclusion of *PCM* in our models. The industry-level concentration index, *share*, is also negative and significant in the *Cloglog* model with mass-points frailty, although it suffers from a correlation problem with firm size.[26] Our measure of the implied demand elasticity, $-\eta$, always shows negative coefficients, which are significant in our preferred duration models. This corroborates the Schumpeterian hypothesis of a positive relationship between market

[26] It provides, instead, robust estimates in the industry-level models of Sect. 4.1.

Table 5 Comparison of Estimating Methods

	Cox Frailty: No	*Cloglog* Frailty: Normal	*Cloglog* Frailty: Gamma	*Cloglog* Frailty: Mass Points	*Probit* Frailty: Normal
Cumulativeness					
$\ln RD_{t-1}$	−0.083***	−0.069***	−0.091***	−0.088***	−0.009
	(0.0288)	(0.0230)	(0.0300)	(0.0267)	(0.0220)
$N.Spells_{t-1}$	−1.307***	0.113	−0.062	−0.020	0.048
	(0.1964)	(0.0996)	(0.0788)	(0.1046)	(0.0745)
$Time_{t-1}$	−0.581***	−0.149***	−0.019	0.009	−0.078***
	(0.0568)	(0.0273)	(0.0287)	(0.0307)	(0.0192)
Left Censoring					
Left Cens	−0.165	−0.460**	−0.932***	−1.026***	−0.219**
	(0.1410)	(0.1896)	(0.1809)	(0.2306)	(0.0875)
Market Power					
$-\eta$	−0.116	−0.248	−0.535***	−0.596***	−0.129
	(0.1339)	(0.1778)	(0.1272)	(0.1646)	(0.1168)
$\ln Size_{t-1}$	−0.056	−0.153**	−0.202**	−0.216***	−0.064
	(0.0650)	(0.0595)	(0.0915)	(0.0735)	(0.2262)
Financing					
CF_{t-1}	−0.036	−0.648	−2.364***	−2.645***	−0.278
	(0.7776)	(1.0068)	(0.7561)	(0.8544)	(0.6342)
D_{t-1}	−0.251	0.460*	1.013***	1.074***	0.079
	(0.2664)	(0.2764)	(0.3279)	(0.3393)	(0.3202)
Technological Opportunities					
HT	0.249	0.004	−0.674	−0.914	0.253
	(0.5306)	(0.5974)	(2.1696)	(0.7446)	(0.2556)
MHT	0.875**	0.492	−0.289	−0.317	0.429**
	(0.4018)	(0.3774)	(0.3690)	(0.5222)	(0.1783)
MLT	0.934**	0.630*	0.187	0.152	0.491***
	(0.3942)	(0.3473)	(0.3742)	(0.5383)	(0.1875)
Planned Investments					
IM_{t-1}	−0.098	−0.356	−5.111**	−5.810**	−2.683*
	(1.0265)	(1.3667)	(2.2278)	(2.2617)	(1.4242)
IS_{t-1}	−1.403	−0.482	−1.412	−4.388	9.700
	(6.1174)	(10.1697)	(7.8273)	(9.5700)	(8.7979)
ΔIM_{t-1}	−2.772***	−3.406*	−0.957	−0.934	−1.376
	(1.0308)	(1.7830)	(2.5643)	(2.0550)	(1.2684)
ΔIS_{t-1}	10.716	6.977	9.438	11.225	6.595
	(10.1001)	(7.5413)	(10.3832)	(8.8211)	(7.1297)
International Competition					
Exp_{t-1}	−0.024	−0.269	−0.587**	−0.680***	0.533
	(0.1883)	(0.2098)	(0.2451)	(0.2270)	(0.3335)
Uncertainty					
EPU	−0.013***	−0.001	0.003**	0.003	−0.001

Table 5 (continued)

	Cox Frailty: No	*Cloglog* Frailty: Normal	*Cloglog* Frailty: Gamma	*Cloglog* Frailty: Mass Points	*Probit* Frailty: Normal
	(0.0016)	(0.0012)	(0.0015)	(0.0020)	(0.0012)
Other Measurable Individual Characteristics					
ln Age	0.012	−0.065	0.060	0.105	−0.041
	(0.0744)	(0.1100)	(0.1498)	(0.1330)	(0.0679)
Group	0.085	0.150	0.212	0.191	0.138*
	(0.1131)	(0.1081)	(0.1350)	(0.1291)	(0.0786)
Family	0.110	0.040	−0.039	−0.056	0.026
	(0.1080)	(0.1318)	(0.1369)	(0.1506)	(0.0694)
Centre	0.239*	0.351***	0.489***	0.555***	0.204***
	(0.1286)	(0.1167)	(0.1244)	(0.1326)	(0.0731)
South	0.594***	0.515***	0.659***	0.771***	0.309***
	(0.1288)	(0.1382)	(0.1645)	(0.1292)	(0.0957)
L-Likelihood	−1766.958	−1043.627	−671.154	−670.143	−1028.847
Heterogeneity‡	No	Yes	Yes	Yes	Yes
A.I.C	3577.916	2135.255	1390.308	1374.285	2123.693
B.I.C	3685.510	2280.761	1535.813	1477.352	2323.764
Obs	983	3174	3174	3174	3174

Note: Bootstrapped standard errors in parentheses. Efron (1977) method used to handle tied failures in Cox model. Significance of the coefficients: * for p<.10, ** for p<.0.05, and *** for p<.01. (‡) The presence of heterogeneity is tested for in Tables 13, 15, 16, 17 of the Appendix

power and innovation, and also the "success-breads-success" effect hypothesis that explain firmsâ€™ innovation duration. Another positive feature of elasticity, $-\eta$, is the absence of correlation with financing and firm size. In particular, size presents negative and significant coefficients. Consistent with the observation by Hall (2011), we argue that larger firms can diversify their activities and are therefore more likely to persist in R&D investment.

Financing. We find that the firm's cash flow has a negative and significant effect on the probability of discontinuing R&D investment, supporting the hypothesis that firms with internal funds are better able to sustain the expenses connected with research and development activities. Overall, the negative sign of cash flow (*CF*) and the positive one for debt (*D*) tend to signal the presence of liquidity constraints due to agency costs and asymmetric information particularly relevant in the R&D case (Bontempi, 2016).

Technological Opportunities. In line with the findings of Coscollá-Girona et al. (2015); Crépon et al. (1998); Duguet and Monjon (2004); Hecker and Ganter (2014); Huang (2008); Máñez et al. (2015); Peters (2009); Triguero and Córcoles (2013); Triguero et al. (2014), technological opportunities, proxied by the dummy variables *HT*, *MHT* and *MLT*, have positive coefficients for medium-high and medium-low technology classes. The dummy *HT* is negative, although not significant, in the

Cloglog models. In general, we observe that sectoral dummies, as well as other individual characteristics, are relevant in the Cox and probit models only. The non-significance of the dummy *HT* may depend on the fact that high-technology firms represent about 5% of the working sample; moreover, Italian firms are inclined to engage in R&D activities even in sectors that can be defined as low R&D, and this aspect will be further investigated at a more disaggregated level in Sect. 4.1.

Planned Investments. Although seldom significant, the variables considering firms' planned investment in physical capital (machinery, *IM*) and software (*IS*) provide some information on the relationship between the different types of investment. While *IM* tends to show a negative coefficient, suggesting a kind of complementary effect with R&D effort, the coefficient of software investment is either not statistically significant or is positive, suggesting substitutability between innovative effort and IT acquisition. The difference between planned and actual investments in software, ΔIS, tends to have a positive and statistically significant parameter in the specifications containing *PCM* and *share*. This suggests that the probability of maintaining an R&D effort is negatively affected by unexpected deviations from investment plans. This effect of firm-specific uncertainty is in line with the result obtained for the variable *EPU*, which controls for uncertainty at the macroeconomic level (discussed below).

International Competition. The intensity for export earnings, *Exp*, controls for the firm's exposure to international competition, thus adding further information to that captured by elasticity (see the Table 9 in the Appendix on the location of major competitors). The coefficient is negative and generally significant.[27] The literature (Antonelli et al., 2012; Coscollá-Girona et al., 2015; Hecker and Ganter, 2014; Máñez et al., 2015; Triguero and Córcoles, 2013; Peters, 2009; Masso and Vahter, 2008) finds a positive and strong relationship between exports and R&D. Lööf et al. (2015) point out that the openness of business sectors increases the likelihood that a firm accesses more information, exploits spillovers and thus increases its knowledge stock (the "learning-by-exporting" effect).

Uncertainty. All models were estimated with time-dummies as an alternative to the uncertainty index, *EPU* (we present the two cases for the specification with elasticity in Appendix A1.4). The coefficients of the time effects are jointly significant and negative in all specifications, capturing the 2008–2009 crisis. The same effect is more efficiently estimated by the *EPU* index, which also upholds the sunk cost theory and strengthens the dynamic link between current and past R&D activity.

Other Measurable Individual Characteristics. Individual characteristics such as age and ownership type (family and group) turn out to be insignificant in most of the specifications considered, apart from the Cox and probit models. If significant, group membership and the effect of ownership, captured by the dummies *Group* and *Family*, have a positive effect on the hazard rate. The dummies for the geographical area (*Centre, South*), taking Northern Italy as reference, represent the differences in

[27] Alternatively, we used a dummy for "large exporters", where a large exporter is defined as a firm whose ratio of export revenue to total revenue is above the 75^{th} percentile of the distribution). The estimated coefficients are coherent with those reported here.

institutional quality at the regional level. The coefficients are positive and significant, and the estimate of *South* is the highest.

Comparison of the effects. The estimated coefficient are like non-standardised regression coefficients, as they depend on the metric of each independent variable (unless it is a dummy variable). We can rely on exponentiated coefficients (always positive) that can be interpreted as hazard ratios. Making the computation for the *Cloglog* model with "mass points' of Table 5, the hazard ratio for the dummy *South* tells us that firms operating in Southern Italy have a 116% higher innovation hazard than firms located in Northern Italy. Debt increases the hazard by 193% while internal funds, learning-by-exporting and accumulated knowledge reduce the hazard by 93%, 49% and 8%, respectively. The hazard for companies with inelastic demand (greater market power) is 45% lower than the hazard for companies with highly elastic demand. The hazard for large firms is 19% lower than for small firms.

4.1 Industry structure and aggregate investment

As innovation regimes vary dramatically across industries and there is significant firm-level heterogeneity within industries, a criticism of previous studies that have investigated the relationship between market power and industry R&D is to postulate an inverted-U pattern looking only at aggregated data (Aghion et al., 2005). Before delving into the results, a few words should be spent to illustrate the empirical context. Estimating heterogeneity by sector requires a long time span, so we exploit the unbalanced panel of 3,971 firms over the 1984–2012 period covering twenty-two groups of four-digit SIC codes (311 firms covering seventeen industries in the 1973–1994 period were used by Aghion et al. (2005)). We have twenty manufacturing industries, one Mining/electrical/gas/water industry (prod.& distr.), and one service industry (Communication, Software, R&D). The resulting industry-level panel is an unbalanced panel of 588 observations per industry year (354 in Aghion et al. (2005)).[28]

When exploring industry-level data, and to be coherent with Aghion et al. (2005) who use patent activity but assert that their results are robust to the use of R&D expenditure, we revert to the standard IO method and measure innovation input by the total amount of R&D investment per employee within each sector j in each year t (the amount may be null). Concentration is measured by $share_{jt}$ as in Delbono and Lambertini (2022).[29] We estimate a quadratic function in which total R&D, at the aggregate level and by sector, is the dependent variable while the share of R&D performing firms within each sector and the square of the share are explanatory variables. The estimated results for the whole panel are displayed in the bottom left

[28] We do not observe enough firms in all industries in all years. For example, we have completely excluded the sectors of wholesale trade, transport, buildings, hotels, insurance and other business services.

[29] Once again, our results are robust to the use of Lerner's index (used by Aghion et al. (2005)) and Herfindahl-Hirschman index.

graph of Fig. 1. These results are robust to different estimation methods (GMM) and model's specification (inclusion of industry and year effects, and dynamics).

The inverted U-shaped relationship of Aghion et al. (2005) is confirmed by the Italian panel data at the aggregate level. The results show that competition is positive at the aggregate level, as industries with a higher level of competition should have higher R&D. When competition is relatively low, increased (additional) competition leads to a larger increase in R&D than when the competition is relatively high. Furthermore, we expect R&D to decrease with competition as industries become more and more competitive.

However, at the disaggregated by-industry level, we have heterogeneous patterns. Among the twenty-two industries, we have selected the most emblematic cases, visualised in Fig. 1 and estimated in Table 6. Differences can be seen between sectors, from inverted U-shaped relationships of R&D and competition to U-shaped relations, passing through linear relationships. While, for example, the Aerospace, Computer, Pharmaceutical, Shipbuilding, Petroleum and most Low Tech. industries such as Textile (sectors 1, 2, 3, 5, 6, 8) have an *inverted U-shaped* relationship, the relationship is *increasing-Arrovian* in the Ferrous and Non-ferrous metal (sectors 12, 13), it is *U-shaped* in Fabr. metal, Non elec. machinery, Low Tech. Food/Tobacco industries and Communication/Software/R&D services (sectors 16, 17, 19, 21), and it is *decreasing-Schumpeterian* in the High Tech. Elec. machinery (sector 18). Delbono and Lambertini (2022) assume that high R&D productivity is characterised by an Arrovian pattern for drastic innovations and an inverted U-shaped pattern for small innovations; the Schumpeterian pattern characterises low R&D productivity.[30] The estimated share corresponding to the maximum R&D is lower than the average effective share in Aerospace and Pharmaceutical, while it is higher than the average effective share in Shipbuilding and Petroleum and is in line with the average effective share in Computer and Textile. The estimated share corresponding to the minimum R&D is higher than the average effective share in Non-metal min., Fabr. metal and Non elec. machinery, while it is lower than the average effective share in Communication/Software/R&D services.

The above findings show that the same non-monotone pattern does emerge in very heterogeneous industries, and therefore any merger proposal could and possibly should be assessed ex ante through analogous exercises to ascertain the nature and form of aggregate innovation efforts prior to the merger. It is also worth stressing that a similar argument holds even if the pattern is monotone. More explicitly, let us assume that Schumpeter is right. A horizontal merger should be allowed if technical progress prevails over any consideration of the price effect. Yet, merging firms

[30] Although the inverted U-shaped at the aggregate level appears to be robust, the heterogeneous disaggregated relationships vary depending on the institutional framework and the ex-ante classification of the industries. Lee (2005) finds a positive concentration-R&D relationship for Korean manufacturing industries with low appropriability; in Negassi et al. (2019) the inverted U-shaped result does not hold for private sector industries on French data; in Peneder and Woerter (2014) the inverted U-shaped is steeper for creative firms than for adaptive firms on Swiss data; Macher et al. (2021) finds Mr. Schumpeter's result in the cement industry of the United States.

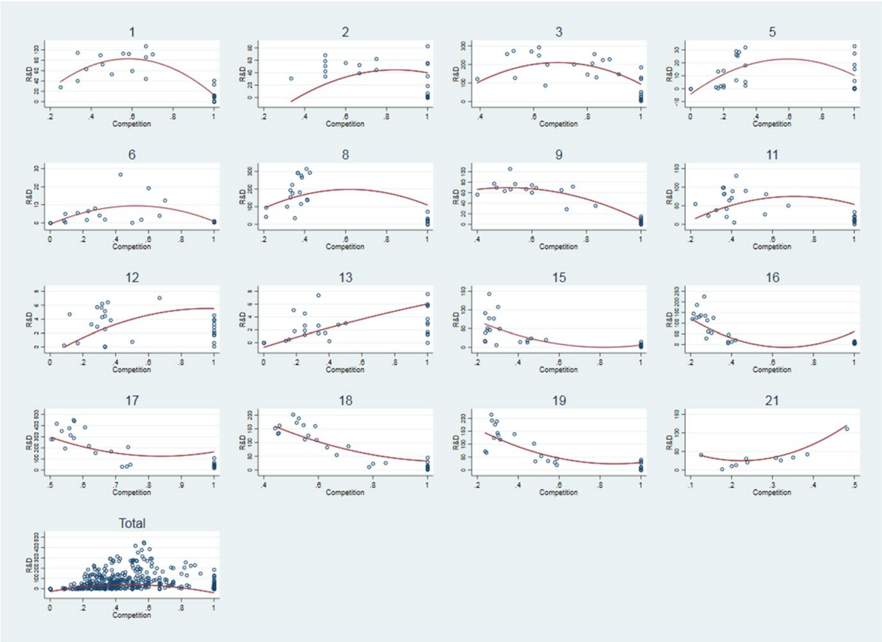

Fig. 1 Comparison between industries. The figure plots the estimated relationship between competition, on the x-axis, and R&D expenditure, on the y-axis. Each point represents an industry-year in the total plot, and a year in the by-industry plots. The overlaid estimated quadratic curves are reported in Table 6 for each industry. Industries: 1-Aerospace (Fabr. transport eq., HT); 2-Computer (Fabr. elect. eq.. HT); 3-Pharma (Chemicals, HT); 5-Shipbuilding (Fabr. transport eq., MLT); 6-Petroleum refining (MLT); 8-Textile/Clothing/Leather (LT); 9-Scient. instr. (Fabr. elect. eq., MHT); 11-Chemicals (MHT); 12-Fer. metal (Primary metals, MLT); 13-Non-fer. metal (Primary metals, MLT); 15-Non-met. min. (Minerals prod./glass/cement, MLT); 16-Fabr. metal (Fabr. metal/machinery/eq., MLT); 17-Non-el. mach. (Fabr. metal/machinery/eq., MHT); 18-Elec. machinery & Electronics (Fabr. elect. eq., HT/MHT); 19-Food/Tobacco (LT); 21-Communic./Software/R&D (HT)

should not get rid of any portion of their R&D plants to invoke the efficiency effect, as has been the case in the merger proposal designed by Dow and Dupont.

In this respect, a quick glance at Fig. 1 suggests a few additional considerations which help justifying the analysis of aggregate R&D curves at the sectoral level. Examine industries 1, 12 and 17, in which the related curves are, respectively, concave and single-peaked (1-Aerospace), concave and monotonically increasing (12-Primary metals) and U-shaped (17-Non-electrical machinery), and consider the impact of a horizontal merger in any of these sectors along the supply chain. For instance, if the merger takes place in the aerospace industry and, possibly, happens to drive the industry towards the peak of its own R&D curve - a fact that, in itself, may intuitively be brought forward to favour the merger proposal - the antitrust agency evaluating this merger proposal should also investigate its bearings on the technical progress characterising the two aforementioned industries operating upstream, in particular whether any of the firms in those

Table 6 By-industry disaggregated estimates

	$j=1$	$j=2$	$j=3$	$j=5$
$share_{jt}$	467.79***	330.29***	1667.17***	91.82***
	(120.655)	(35.62)	(491.366)	(26.991)
$share_{jt}^2$	−401.37***	−195.53***	−1209.23***	−77.32***
	(85.123)	(33.75)	(374.880)	(24.557)
$share^*$	0.58***	0.85***	0.69***	0.59***
	(0.031)	(0.086)	(0.062)	(0.037)
Obs	24	27	29	28
R^2	0.76	0.74	0.62	0.20
rmse	18.823	14.460	62.378	11.080
	$j=6$	$j=8$	$j=9$	$j=11$
$share_{jt}$	39.29**	757.19*	265.47*	359.14*
	(15.810)	(418.082)	(154.040)	(179.594)
$share_{jt}^2$	−37.63**	−611.46*	−259.30**	−253.49*
	(14.800)	(355.931)	(103.757)	(127.501)
$share^*$	0.52***	0.62***	0.51***	0.71***
	(0.015)	(0.040)	(0.095)	(0.067)
Obs	23	29	29	29
R^2	0.32	0.79	0.90	0.66
rmse	5.861	52.149	10.982	22.361
	$j=12$	$j=13$	$j=15$	$j=16$
$share_{jt}$	13.84*	8.13*	−301.89**	−847.12***
	(6.805)	(4.659)	(126.242)	(182.518)
$share_{jt}^2$	−7.17	−1.36	184.31*	641.37***
	(6.111)	(4.378)	(90.602)	(123.345)
$share^*$			0.82***	0.66***
			(0.067)	(0.025)
Obs	29	29	29	29
R^2	0.49	0.42	0.45	0.82
rmse	1.586	1.824	28.038	29.261
	$j=17$	$j=18$	$j=19$	$j=21$
$share_{jt}$	−2529.99**	−678.49**	−523.52***	−642.75***
	(1079.043)	(311.835)	(146.202)	(149.250)
$share_{jt}^2$	1509.68**	313.93	300.54**	1435.59***
	(666.545)	(201.269)	(116.226)	(207.222)
$share^*$	0.84***		0.87***	0.22***
	(0.047)		(0.123)	(0.022)
Obs	29	29	29	11
R^2	0.82	0.86	0.74	0.92
rmse	67.103	26.843	36.691	9.975

Note: Industries are: 1-Aerospace (Fabr. transport eq., HT); 2-Computer (Fabr. elect. eq.. HT); 3-Pharma (Chemicals, HT); 5-Shipbuilding (Fabr. transport eq.,MLT); 6-Petroleum refining (MLT); 8-Textile/Clothing/Leather (LT); 9-Scient. instr. (Fabr. elect. eq.,

Table 6 (continued) MHT); 11-Chemicals (MHT); 12-Fer. metal (Primary metals, MLT); 13-Non-fer. metal (Primary metals, MLT); 15-Non-met. min. (Minerals prod./glass/cement, MLT); 16-Fabr. metal (Fabr. metal/machinery/eq., MLT); 17-Non-el. mach. (Fabr.metal/machinery/eq., MHT); 18-Elec. machinery & Electronics (Fabr. elect. eq., HT/MHT); 19-Food/Tobacco (LT); 21-Communic./Software/R&D (HT). *share** is the share corresponding to either the maximum or the minimum of per-employee R&D. Robust standard errors in parentheses. Significance of the coefficients: * for p<.10, ** for p<.0.05, and *** for p<.01

sectors happens to belong to the same industrial group as one of the firms filing the merger proposal. In other words, a merger at any stage of the supply chain may systematically exert some relevant feedbacks along the entire supply chain, and this impact should be an integral part of the merger assessment. Similar considerations apply if one replaces industry 1 with 5 (Shipbuilding), industry 12 with 13 (Non-ferrous metals) and industry 17 with 18 (Electrical and electronic machinery).

All this is clearly connected with the long-standing discussion about the vertical externality affecting vertical relations along supply chains, and the related hold-up problem, pioneered by Williamson (1971) and later elaborated upon by Grout (1984); Rogerson (1992); MacLeod and Malcomson (1993), among others (a compact reconstruction of this debate can be found in Lambertini (2018)). Accordingly, the bearings of the intensity of competition (or industry structure) on R&D, both at the firm and industry level, should be reinterpreted theoretically as well as empirically, with the aim of providing a comprehensive assessment apt to put antitrust agencies in a position to take the most appropriate decisions concerning both vertical and horizontal mergers.

Last but not least, one should also consider that virtually any of the sectors whose R&D patterns appear in Figure 1 do operate at a global level, and their performance along many dimensions, including innovation, are shaped by international inter- and intraindustry trade as well as horizontal and vertical relations. The latter include mergers, supply and retail contracts, and the organization of R&D activities taking place along value chains in several forms, such as RJVs, possibly complemented by at least some degree of open innovation, whose relevance may in turn depend upon legal and institutional settings across countries. All of this prompts for a number of desirable extensions of the foregoing analysis, and indeed one has been recently probed by Tomàs-Porres et al. (2023). On the basis of a sample selected from the Spanish Technological Innovation Panel, this paper shows that persistence is reinforced by trade, the more so the larger is the relevant portion of the global economy in which a firm is actively involved. This seemingly suggests that the challenges posed by comparatively unfamiliar markets - so to speak - are a powerful incentive, a theme that would require further data, for example on the existence of innovation alliances.

5 Conclusions

This study explores the determinants of R&D effort duration on a panel of Italian firms. Previous literature (Malerba and Orsenigo, 1995, 1996) suggests that Italy can be included in the Schumpeter Mark I technology class, which represents a pattern of increasing innovation (creative destruction), in which the concentration of innovative activity is low, innovators are of small economic size, stability in the ranking of innovators is low and the entry of new innovators is high. This class characterises the "traditional" sectors (mechanical technology, tools and white electrical industry). Within this technology class interesting results emerge as market power, liquidity and institutional constraints, learning-by-exporting, and size play a larger role than accumulated knowledge. These results could be reversed if we considered a pattern of deepening innovation (creative accumulation), as in the US, which is related to the dominance of a few firms that are continuously innovative through the accumulation of technological and innovative capabilities over time. Based on the productivity gap between the EU and the US, Castellani et al. (2019); Ortega-Argilés and Vivarelli (2015) suggest that EU firms may have problems in organising R&D processes effectively and thus in learning from past R&D. Our results offer some insights to policy makers.

We underline that the market power-R&D link is highly firm- and industry-specific. The implications of our work concern both antitrust and innovation policy. With regard to the latter, persistence in R&D efforts should be encouraged, as R&D effort is a state-dependent process in which past experience is an incentive to continue the effort by producing positive time spillovers. Particularly important for small companies, which are less endowed with internal funds and market power, is the creation of a less uncertain financial support and institutional environment, less influenced by territorial divisions, so as to enable them to bear the sunk costs of R&D and to be more responsive in their investment decisions (less influenced by 'cautionary effects'). As far as antitrust policy is concerned, the suggestion is not to limit oneself to the assessment of the firms directly involved in the merger, but to broaden the analysis to the consideration of the repercussions that the proposed merger may have along the entire supply chain in which the firms operate. In the light of what has been said with regard to innovation policy, a merger could be advantageous for small companies if it enables them to overcome constraints on the continuity of the innovation effort.

Some questions are open for further research: first, more attention should be paid to the construction of valid measures for market power, as traditional ones (such as price–cost margin) are probably insufficient to describe competitive pressure. We believe that our measure, which takes into account a microeconomic concept such as elasticity of demand at the firm level, may be appropriate. If the data were collected annually, it would also be possible to explore long-run dynamics, perhaps in comparison with the SSNIP test (small but significant non transitory increase in price test) used to define markets in competition economics, before measuring market power in the defined market.

Secondly, an extension of our research could distinguish the event "R&D effort interruption" from acquisition. A firm that successfully innovates but is unable to fully appropriate the returns of its efforts (for example, because it does not have the resources to adequately advertise and distribute its products) could be acquired by a larger firm. To establish the continuity of the innovation effort, it would therefore be appropriate to consider that the R&D activity was not interrupted, but transferred to another company.

Finally, the analysis of R&D patterns at the industry level prompts further research, the nature of which should be both theoretical and empirical, regarding the repercussions of horizontal and vertical mergers on the R&D performance of industries and supply chains in the long run.

Appendix

The bearings of investment duration in a toy model

The rationale of investment duration can be grasped through the analysis of a duopoly game of R&D for process innovation which is a simplified version of Kamien and Zang (2000), in which technological spillovers flow from one firm to the other through absorptive capacity.

Firms 1 and 2 are Cournot players, facing a market demand for a homogeneous good $p_t = a - q_{1,t} - q_{2,t}$ over discrete time $t = 1, 2, ...T$. Firms use a constant return to scale production technology summarised by the cost function $C_{i,t} = c_{i,t}q_{i,t}$, with

$$c_{i,t} = c_0 - k_{i,t}\left(1 + \beta k_{j,t}\right) \tag{A.1}$$

In (A.1), c_0 is the common initial level of the marginal and average production cost; $k_{i,t}$ is the R&D effort of firm $i = 1, 2$; and parameter $\beta \in [0, 1]$ measures the intensity of knowledge spillover incoming from the rival firm, conditional upon firm i's absorptive capacity: if, in any given period, i does not invest, its absorptive capacity in that period vanishes completely, and $c_{i,t} = c_{i,t-1}$.

A minimalist assumption consists in adopting a time horizon consisting of three periods, so that $T = 3$ and $t = 1, 2, 3$. At every t, firms play a two-stage game where the first stage hosts the choice of k_{it} (if any), while the second describes market competition. Information is symmetric, complete and imperfect at each stage, while it is perfect between stages, in such a way that firms observe R&D choices before setting quantities. Across periods, firms use the same discount factor $\delta \in (0, 1)$.

The Cournot-Nash output levels can be easily obtained once and for all, and correspond to $q^*_{i,t} = \left(a - 2c_{i,t} + c_{j,t}\right)/3$. As far as R&D behaviour is concerned, we stipulate the following: each firm is endowed with the same amount of resources equal to $K > 0$, which has to be invested in full over the three periods, and the firm may decide to split it over several periods, knowing that the cost associated to every effort carried out at any t goes along a cost $\Gamma_{i,t} = bk^2_{i,t}$, because of decreasing returns to R&D. Hence, the firms has to jointly account for absorptive capacity and investment smoothing.

The individual profit function at the first stage of any period t is

$$\pi_{i,t} = \left(a - q^*_{i,t} - q^*_{j,t} - c_{i,t}\right)q^*_{i,t} - bk^2_{i,t} \tag{A.2}$$

for any $k_{i,t} \geq 0$.

Now suppose firm 1 goes for perfect smoothing, with $k_{i,t} = K/3$ for all t, while firm 2 chooses $k_{2,1} = k_{2,3} = K/2$ and $k_{2,2} = 0$. It is worth noting that this implies that firm 2 has no absorptive capacity in the second period, thereby receiving no spillover from firm 1, and transmits a higher spillover to the latter at $t = 1, 3$. As we are about to see, this discontinuity has significant bearings on firms' comparative performance.

The aforementioned investment plans deliver the following pairs of marginal costs:

$$c_{1,1} = c_0 - \frac{K}{3}\left(1 + \frac{\beta K}{2}\right); c_{2,1} = c_0 - \frac{K}{2}\left(1 + \frac{\beta K}{3}\right) \tag{A.3}$$

$$c_{1,2} = c_{1,1} - \frac{K}{3}; c_{2,2} = c_{2,1} \tag{A.4}$$

$$c_{1,3} = c_{1,2} - \frac{K}{3}\left(1 + \frac{\beta K}{2}\right); c_{2,3} = c_{2,2} - \frac{K}{2}\left(1 + \frac{\beta K}{3}\right) \tag{A.5}$$

Plugging these expressions into (A.2), one obtains the discounted individual profit flows of the two firms, defined as $\Pi_i = \pi_{i,1} + \delta\left(\pi_{i,2} + \delta\pi_{i,3}\right)$, over the whole time horizon:

$$\Pi_1 = \Big\{36\left(a - c_0\right)^2[1 + \delta(1 + \delta)] + 12X\left(a - c_0\right)[1 + \delta(5 + 6\delta) + X\beta(1 + \delta(1 + 2\delta))]$$
$$+X^2\left[(1 + X\beta)^2 + \delta\left((5 + X\beta)^2 + (3 + X\beta)^2\delta\right) - 36b(1 + \delta(1 + \delta))\right]\Big\}/324 \tag{A.6}$$

$$\Pi_2 = \Big\{36\left(a - c_0\right)^2[1 + \delta(1 + \delta)] + 12X\left(a - c_0\right)[2(2 + \delta(1 + 3\delta)) + X\beta(1 + \delta(1 + 2\delta))]$$
$$+X^2\left[(4 + X\beta)^2 + \delta\left((2 + X\beta)^2 + 4(3 + X\beta)^2\delta\right) - 81b\left(1 + \delta^2\right)\right]\Big\}/324 \tag{A.7}$$

Then, it easily ascertained that

$$sgn\left\{\Pi_1 - \Pi_2\right\} = \tag{A.8}$$

$$sgn\left\{3bX(5 + \delta(5\delta - 4)) + \left[12\left(a - c_0\right) + X(2X\beta + 7)\right]\delta - 12\left(a - c_0\right) - X(2X\beta + 5)\right\}$$

with $5 + \delta(5\delta - 4) > 0$ for all $\delta \in (0, 1)$, and

$$\left[12\left(a - c_0\right) + X(2X\beta + 7)\right]\delta - 12\left(a - c_0\right) - X(2X\beta + 5) \geq 0 \tag{A.9}$$

for all

$$\delta \in \left[\frac{12\left(a - c_0\right) + X(2X\beta + 5)}{2\left(a - c_0\right) + X(2X\beta + 7)}, 1\right) \tag{A.10}$$

Accordingly, we may conclude that any δ belonging to the above interval suffices to ensure $\Pi_1 > \Pi_2$, for any $b > 0$. Otherwise, the necessary and sufficient condition for $\Pi_1 > \Pi_2$ is

$$b > \frac{12\left(a - c_0\right) + X(2X\beta + 5) - \left[12\left(a - c_0\right) + X(2X\beta + 7)\right]\delta}{3X[5 + \delta(5\delta - 4)]} \equiv \widehat{b} \tag{A.11}$$

and one may quickly check that, provided it is positive, then $\widehat{b}$ is inside the interval where $\Pi_1, \Pi_2 > 0$. The foregoing discussion boils down to saying that, in this example, uniformly smoothing R&D efforts over the entire horizon is convenient in terms of the resulting discounted profit performance, provided decreasing returns to R&D activity are sufficiently relevant, namely, for all $b > \max\left\{0, \widehat{b}\right\}$.

An obvious extension of the above toy model and its results, so as to include product innovation, would consist in admitting the presence of product differentiation *à la* Singh and Vives (1984) as well as indexing choke prices as $a_{i,t}$. This would allow one to define the product-specific market size as $\sigma_{i,t} \equiv a_{i,t} - c_{i,t}$ and then assume that efforts $k_{i,t}$ affect $\sigma_{i,t}$ through the same mechanism as in (A.1), whereby process and product innovation have the same effect on gross profits (Futia, 1980).

Additional control variables in duration models

Financing. Hall et al. (1999) provides the important suggestion that liquidity constraints and credit rationing might play a role in fuelling the relationship between innovation and demand. To assess the demand-pull impact on R&D investment, therefore, we control for the availability of internal funds and the ability to raise external funds through bank credit. The variable CF_{it-1} is the cash flow net of dividends paid over sales. The variable D_{it-1} is the short- and long-term bank debt and financial debt to other financial institutions, divided by sales. We believe it is important that the two sources of finance are included in the duration models, both from the point of view of correctly specifying the capital structure of the firms (Bontempi, 2003), and for the institutional characteristics of the country under analysis (Munari et al., 2010).[31] Italy's national corporate governance is

[31] Only Triguero and Córcoles (2013) use firm leverage, defined as external funds relative to equity.

Table 7 Industry-level descriptive statistics

	HT	MHT	MLT	LT	MS	Total	$\frac{I_{it}^{R\&D}}{Em_{it}}$	Em_{it}	η_i	PCM_{it}	$share_{jt}$	$Hazard_{it}$
	%	%	%	%	%	%	$x_{j..}$	$x_{j..}$	$x_{j..}$	$x_{j..}$	$x_{j.}$ %	$x_{j..}$
1-Aerospace (Fabr. transp. eq.)	13.00					0.51	7.94	1503	−1.31	0.086	49.26	0.1392
2-Computer (Fabr. elect. eq.)	11.01					0.43	6.60	2902	−1.33	0.073	52.04	0.1332
3-Pharma (Chemicals)	41.06					1.62	8.96	693	−1.23	0.109	55.11	0.1459
21-Communic./Software/R&D	20.13					0.79	1.66	291	−1.12	0.055	14.92	0.1765
18-Elec. mach & El. (Fabr. el. eq.)	14.80	16.03				4.04	3.00	561	−1.38	0.085	41.45	0.1479
9-Scient. instr. (Fabr. el.. eq.)		5.86				1.26	3.01	424	−1.25	0.079	43.15	0.1456
10-Motor vehicles & Transport eq		13.19				2.84	3.65	2657	−1.49	0.069	39.92	0.1515
11-Chemicals		15.16				3.27	1.44	356	−1.29	0.089	32.16	0.1574
17-Non-el. mach. (Fabr. met./mach./eq.)		49.76				10.72	1.72	465	−1.42	0.073	43.88	0.1474
4-Rubber/Plastic			14.49			3.70	0.80	439	−1.53	0.075	32.43	0.1561
5-Shipbuilding (Fabr. transp. eq.)			3.37			0.86	1.29	862	−1.50	0.039	26.48	0.1430
6-Petroleum refining			1.96			0.50	0.72	258	−1.10	0.085	24.35	0.1822
13-Non-fer. metal (Primary metals)			3.12			0.80	0.34	416	−1.54	0.073	22.41	0.1570
12-Fer. metal (Primary metals)			4.19			1.07	0.30	958	−1.54	0.074	31.19	0.1651
15-Non-met. min. (Min./glass/cement)			26.43			6.76	0.49	255	−1.44	0.085	25.50	0.1559
16-Fabr. metal (Fabr. metal/mach./eq.)			45.10			11.53	0.55	171	−1.41	0.062	23.27	0.1563
14-Other manuf			1.35			0.35	0.63	185	−1.32	0.086	40.28	0.1509
7-Paper/Printing				12.38		3.73	0.98	333	−1.50	0.077	25.56	0.1563
8-Textile/Clothing/Leather				37.49		11.29	1.13	275	−1.36	0.062	30.55	0.1546
19-Food/Tobacco				34.60		10.42	0.70	247	−1.34	0.077	25.52	0.1567
20-Wood				15.53		4.67	0.68	186	−1.28	0.065	35.12	0.1503
22-Mining					14.45	2.72	0.39	325	−1.08	0.047	15.93	0.1683

Table 7 (continued)

	HT	MHT	MLT	LT	MS	Total	$\frac{I_{it}^{R\&D}}{Em_{it}}$	Em_{it}	η_i	PCM_{it}	$share_{jt}$	$Hazard_{it}$
	%	%	%	%	%	%	$x_{j..}$	$x_{j..}$	$x_{j..}$	$x_{j..}$	$x_{j.}$ %	$x_{j..}$
23-Services					85.55	16.11	0.11	466	−1.33	0.067	6.05	0.1758
Total	3.94	21.55	25.57	30.11	18.83	100	1.13	437	−1.38	0.071	27.32	0.1551

Note: Panel observations (3,971 firms over the 1984–2012 period with $I_{it}^{\mathrm{R\&D}}/Em_{it} \geq 0$) distributed according to NACE and OECD taxonomies. Mining includes Coal/Gas/Oil Extraction, and Electric/Gas/Water Production and Distribution; Services include Wholesale and Services Retail/Transport/Real Estate, Renting and other Business Activities/Insurance/Buildings/Hotels. % are the frequencies of each industry and technological class. $x_{j..} = (N_j T_{ji})^{-1} \sum_{i=1}^{N_j} \sum_{t=1}^{T_{ji}} x_{jit}$ where $j = 1, \dots, 23$ is industry, $i = 1, \dots, N_j$ is firm belonging to each industry j and $t = 1, \dots, T_{ji}$ is the number of periods available for each firm i inside each industry j. In column $Hazard_{it}$, $x_{j..}$ is the average of the hazard rates of each firm i inside each industry j estimated as in Sect. 3.2. $x_{j.}$% indicates the average over time of the by-industry percentage shares classified as "insider-dominated" and the corporate financial system as "continental". These characteristics entail less protection of outside investors (compared to "outsider-dominated" systems such as the UK and the US), strong and stable links between companies and banks, and less frequent changes in corporate control.

Technological Opportunities. The Eurostat NACE Rev.2 classification of economic activities (Eurostat, 2008) is used to classify our enterprises and their four-digit sectors along the rows of Table 7. Sectors are further grouped along the columns of Table 7 into High, Medium-High, Medium-Low, and Low Technology, and Mining/Services classes according to the criterion defined by OECD (1986). If the R&D/output ratio is above 4%, the sectors are High Technology (Aircraft, Computer and Office Equipment, Pharmaceuticals, Electronics). If the ratio is in the range 1–4%, the sectors are Medium-High Technology (Chemicals, Electric and Non-electric Machinery, Motor Vehicles). Otherwise, they are Medium-Low and Low Technology (Rubber/Plastics, Shipbuilding, Petroleum refining, Primary metals, Minerals prod./Glass/Cement, Fabr. metal/Machinery/Eq., Textiles, Food, Paper and Wood). Table 7 reports the frequencies for the unbalanced panel of 3,971 firms, over the 1984–2012 period, aggregated in the twenty-two units explored in Sect. 4.1. In the firm-level duration analysis of Sect. 4 we captured the technological opportunities by adding three dummy variables, *HT*, *MHT*, *MLT*.[32] These dummy variables would capture differences in the intensity of innovation effort, levels of specific technologies, differences in terms of market structure, opportunity and suitability of conditions, spillovers, and propensity to undertake R&D (Dosi, 1988, 1997; Vergauwen et al., 2007; Pavitt, 1984; Malerba and Orsenigo, 1996; Piva and Vivarelli, 2007). However, as Table 7 shows, the landscape is quite heterogeneous and difficult to be captured by a simple and unique approach. For example, Italy is characterised by R&D shares of the country's total R&D exceeding 6% not only in High Technology (e.g., 3-Pharma) and Medium-High Technology (e.g., 10-Motor vehicles, 17-Non-el. mach., 18-El. mach.), but also in Low Technology (e.g., 8-Textile/Clothing/Leather, 19-Food/Tobacco). Industry 3 has relatively inelastic demand and a high PCM; elasticity increases and PCM remains high in industries 17 and 18; elasticity is even higher, with a decrease in PCM in industry 10; industry 19 has a higher PCM than industries 8, 10 and 17 in the face of comparatively less elastic demand. The concentration of companies carrying out R&D is high in 3, 17, 18, 10 and decreases in 8 and, especially, 19; coherently, firms in industries 19 and 8 have comparatively higher average hazard rates. Indeed, the innovation process can be very different depending on the sector. In 3-Pharma most companies are continuously working on hundreds or thousands of drugs, hoping that

[32] We aggregated Medium-Low and Low Technology groups, and used Mining/Services, *MS*, as the benchmark.

one will work. We could assume the process can be very long. Maybe in 8-Textile and 19-Food innovation is defined quite differently, with the innovative change to produce a "new" product is less of a step change and more of a continuous development on a product; then the lag between R&D effort and the innovation output may be only a few years.

Planned Investments. The investments, planned in $t-1$ for the period t and divided by the sales surveyed in $t-1$, are IM_{it-1} and IS_{it-1}, respectively, where IM is the physical capital[33] and IS includes software/database/mineral exploitation[34] The discrepancies between actual investments in $t-1$ and planned investments in $t-2$ for the period $t-1$, divided by sales in $t-1$, are, respectively, ΔIM_{it-1} for physical capital and ΔIS_{it-1} for software. Planned investments in physical capital and software are included to capture complementary competences with R&D, if any (Brynjolfsson and Hitt, 2000), and possible long delays in realisation (Edquist and Henrekson, 2017). Since deviating is costly, the differences between planned and actual investments represent firm-specific shocks.

International Competition Our measures of market power may not reflect exposure to international competition and its stimulation of R&D effort. Moreover, foreign markets can facilitate technology spillovers (a recent review on the role of export on R&D is Maican et al. (2022)). Therefore, we add the degree of openness, measured by Exp_{it-1}, the lagged share of the firm's exports in its sales. This variable provides a basic indication of each firm's openness to foreign competition.

Uncertainty The Economic Policy Uncertainty index, *EPU*, taken from Baker et al. (2016), is introduced to capture the uncertainty and macroeconomic effects common to all firms. Alternatively, we use time-dummies to catch the business cycle and the economic downturn started in 2008–2009.[35] The theory of sunk costs underpins the possible role of uncertainty: as R&D investment entails flow adjustment costs (whereas stock adjustments are possible for physical capital), uncertainty causes firms to be less responsive in their decision-making (the "caution" effect), strengthening the dynamic link between current and past R&D activity (Bloom, 2006; Geroski et al., 2010).

Other Measurable Individual Characteristics As control variables for company-specific effects, we use the logarithm of firm age (ln *Age*), group-membership (*Group*), family type of ownership (*Family*), and geographical area,

[33] It includes machinery, equipment and vehicles, while excluding real estate and buildings.

[34] Software has been developed in house (development should be valued at an estimated price or, if not possible, at its production cost). Database expenditure refers to the database used in production for more than one year. Mineral exploitation includes test drilling, survey flights or other surveys, and transportation costs. *IS* also includes copyrighted entertainment, literary and artistic originals (films, sound recordings, manuscripts, models, etc.). Patents, marketing and advertising costs are excluded.

[35] Thus, we allow hazard rates to change autonomously with time.

captured by the two dummy variables for Central and Southern Italy, *Centre* and *South*, respectively (Northern Italy is used as a benchmark). The age of the firm, calculated on the basis of the year in which the firm was founded, would assess the competencies and experience accumulated over time by the companies. Companies belonging to an entrepreneurial group might have more opportunities to finance R&D projects and share the uncertainty involved in innovation activities (Belenzon and Berkovitz, 2010; Guzzini and Iacobucci, 2014). Being part of a group could represent the absence of financial constraints, as participation in an industrial group may allow the firm to access funds through the holding company (Angelini and Generale, 2008). In Cucculelli and Peruzzi (2020), family involvement in ownership, management and governance influences innovation. On the one hand, family-owned firms are expected to have long-term investment horizons: owners hold significant stakes and have reduced agency problems (as owners are usually also managers and have strong ties to the company because ownership is often passed down through generations), so they have greater incentives to ensure that the firm does not underinvest. On the other hand, family-owned firms may be more risk-adverse, as families invest a significant amount of their own wealth in the company (Munari et al., 2010), and Bianco et al. (2013) show that the investments of family firms are significantly more sensitive to uncertainty. Hecker and Ganter (2014) suggest also that family business whose management control and ownership passes to the next generation are likely to suffer from a certain degree of organisational inefficiency, as the pool of potential managerial talent is reduced. The geographical location of firms is important to capture the conditions that control occupational and geographical mobility and/or consumer readiness/resistance to change (Dosi, 1988). As reported in Jappelli et al. (2002), judicial institutions (as measured by the length of civil trials and the number of pending lawsuits) are less efficient in Southern Italy, making the enforcement of contracts uncertain and more costly for firms. Inefficient courts depress market performance and the availability of loans, which in turn reflects negatively on the propensity to engage in risky projects (such as research and development).

Qualitative aspects across elasticity classes

In Tables 8, 9 and 10 we make use of the qualitative information available from the annual surveys to delve into the characteristics of the companies in the various elasticity classes.

Table 8 Market Structure across Elasticity Classes

$-\eta$ Class	Position in 1996$^{(a)}$			Position in 2006$^{(b)}$			Market share of firm$^{(c)}$			Market share of competitor$^{(c)}$		
	First	Four	Ten	Weak	Equal	Strong	< 30%	30–49%	≥ 50%	< 30%	30–49%	≥ 50%
Highly El	33.00	45.00	22.00	11.37	51.81	36.82	85.34	11.75	2.91	68.88	26.24	4.88
Elastic	30.78	39.85	29.37	9.40	46.54	44.06	81.68	11.59	6.74	75.59	21.30	3.12
Unitary El	75.00	15.00	10.00	7.86	51.43	40.71	92.23	0.97	6.80	94.29	4.76	0.95
Inelastic	18.31	33.80	47.89	6.74	51.40	41.85	82.28	12.03	5.70	69.31	20.00	10.69
Total	32.49	40.24	27.28	9.79	49.04	41.17	83.32	11.32	5.36	73.43	22.20	4.37

Note: Elasticity is grouped into four categories: (1) Highly El. if $|\eta| \geq 1.5$, (2) Elastic if $1 < |\eta| < 1.5$, (3) Unitary El. if $|\eta| = 1$, and (4) Inelastic if $|\eta| < 1$. $^{(a)}$ Frequencies from 1996 survey: "Could you say whether your enterprise, by market share on the domestic market, is the first enterprise, or one of the first four enterprises, or one of the first ten enterprises?". $^{(b)}$ Frequencies from 2006 survey: "How would you describe your present overall position in relation to your main competitors?". $^{(c)}$ Frequencies from 2007 survey (also available in 1996, very close to those of 2007): market shares refer to the combined Italian/foreign market; the competitor is the leading competitor (the market shares of the second and third competitors are less than 30%)

Table 9 Location of Main Competitors across Elasticity Classes

$-\eta$ Class	Leading Competitor[(a)]					Second Competitor[(a)]					Third Competitor[(a)]				
	SR	OR	EU	UC	W	SR	OR	EU	UC	W	SR	OR	EU	UC	W
Highly El	28.3	35.6	29.8	1.1	5.3	11.3	30.3	36.1	9.5	12.8	14.3	26.5	25.2	6.1	28
Elastic	38.6	36.7	19	3.2	2.66	7.3	35.9	38.3	4.8	13.7	16.3	26.2	27.1	4	26.3
Unitary El	31.3	25.9	34.7	8.2	0	6.9	7.6	48.3	14.5	22.8	8	14.5	22.5	13	42
Inelastic	33.3	41.4	20.5	2.3	2.6	12.6	32.6	44.9	2.6	7.4	17.5	28.3	27	11.1	16.1
Total	34.2	36.4	23.5	2.6	3.4	9.2	32.6	38.5	6.6	13.1	15.4	26.1	26.3	5.8	26.4

Note: Elasticity is grouped into four categories: (1) Highly El. if $|\eta| \geq 1.5$, (2) Elastic if $1 < |\eta| < 1.5$, (3) Unitary El. if $|\eta| = 1$, and (4) Inelastic if $|\eta| < 1$. [(a)] Frequencies from the surveys in 1996/2007: "Please give the location of your three main competitors". SR = Same Region of Italy; OR = Other region of Italy; EU = EU countries on 31-12-2003 and other European countries; UC = USA or Canada; W = China or India or Rest of the World

The inelastic class consists of companies with a strong position and a high market share, while the highly elastic class contains companies with market shares below the 30%.

The elasticity is high in absolute values when the competitors are located in the same region or in Europe or China/India. If we consider the third competitor, located in the USA/Canada, we observe a decrease in elasticity.

Classes with a low elasticity, in absolute values, are characterised by a high advertising intensity (given by the ratio of advertising expenditure to sales) and the importance of promotional activities and trademark, while they attach no or little importance to technological content and product innovations, the organisation of production to contain costs, and product quality. In Strickland and Weiss (1976) the price elasticity of a firm's demand curve is lower in more concentrated industries, and advertising is expected to increase with concentration. Assuming there is a direct link between elasticity and advertising, we can confirm the stability of the elasticity over time. If it is possible for firms to spend on advertising to differentiate themselves and create barriers to entry, advertising may serve as a signal of product quality or R&D effort, and both R&D and advertising are strategic investments if the cost efficiency due to the R&D process induces a greater advertising effort to expand market sakes (Cabral, 2000). However, simultaneous-equations bias is not an important factor in estimating the concentration-advertising relationship (Strickland and Weiss, 1976).

Table 10 Advertising and Factors of competition across elasticity classes

$-\eta$ Class	Types of $R\&D_{it}^{(a)}$			$ADV_{it}/Sales_{it}$			Product Innov. Imp.[b]			Org. Prod. Imp.[b]		
	Product	Process	Both	Mean	50^{th} P	90^{th} P	No	Fairly	Very	No	Fairly	Very
Highly El	12.78	9.05	55.94	0.001	0.000	0.000	13.95	44.44	41.62	22.05	49.18	28.77
Elastic	20.71	6.93	63.32	0.006	0.000	0.017	15.92	36.32	47.76	29.21	46.71	24.08
Unitary El	14.91	0.88	69.30	0.014	0.000	0.027	5.76	56.12	38.13	22.30	39.57	38.13
Inelastic	32.94	6.75	48.02	0.007	0.000	0.010	26.30	29.86	43.84	29.08	55.49	15.43
Total	32.57	7.38	60.05	0.005	0.000	0.008	15.85	39.29	44.87	26.38	48.12	25.50

Note: Elasticity is grouped into four categories: (1) Highly El. if $|\eta| \geq 1.5$, (2) Elastic if $1 < |\eta| < 1.5$, (3) Unitary El. if $|\eta| = 1$, and (4) Inelastic if $|\eta| < 1$. [a] Frequencies from the surveys in 2010/2011. [b] Frequencies from 2007 survey: "What weight does the firm attribute to the following factors in its competition policy?" We present the Technology Content/Product Innovation, and Organizing Production to Contain Costs (offshoring, outsourcing, etc.). The other possible factors of competition are: Product Quality (not important in Inelastic and extremely important in Highly Elastic); Promotion/Trademark/Advertising/Distribution Network (not important in Highly El. and extremely important in Unitary El. coherently with advertising expenses over sales); After-Sales Services (not important in Highly El. and Inelastic, and extremely important in Elastic/Unitary El.)

Robustness checks

Tables 11, 13, 15, 16, and 17 present four sets of alternative specifications for each duration model. The first set considers our measure of market power, the elasticity $-\eta$, in columns EL1-EL4 of each Table, and tests the robustness of results to the use of time dummies, macroeconomic uncertainty, firm-specific uncertainty, and the inclusion of size. The second set of specifications uses *PCM* (columns PCM5-PCM6 of each Table); in the third set of specifications (columns Share7-Share8 of each Table) we use *share* which is further investigated in Sect. 4.1 (results are robust to the use of the Herfindahl-Hirschman index and firm-level market share in terms of revenues; this last measure, as expected, is affected by the largest correlation with size). The last specification (in column Size9 of each Table) exploits firm size as an alternative proxy for market power. Operatively, we first exclude firm size from the estimated models for each alternative measure of market power and then introduce it as an additional control variable. This investigation is important because we might expect size and market power to be correlated. Our preferred model is EL4, discussed in Sect. 4 of the paper.

Table 11 Robustness checks for the Cox model with no frailty

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Cumulativeness									
$\ln RD_{t-1}$	−0.084***	−0.095***	−0.089***	−0.083***	−0.076***	−0.097***	−0.078***	−0.099***	−0.097***
	(0.0222)	(0.0196)	(0.0202)	(0.0288)	(0.0192)	(0.0162)	(0.0200)	(0.0172)	(0.0154)
$N.Spells_{t-1}$	−1.448***	−1.354***	−1.302***	−1.307***	−1.324***	−1.321***	−1.316***	−1.313***	−1.321***
	(0.1970)	(0.2182)	(0.1879)	(0.1964)	(0.1683)	(0.1790)	(0.1693)	(0.1844)	(0.1816)
$Time_{t-1}$	−0.601***	−0.608***	−0.578***	−0.581***	−0.616***	−0.609***	−0.612***	−0.606***	−0.609***
	(0.0463)	(0.0538)	(0.0473)	(0.0568)	(0.0476)	(0.0376)	(0.0363)	(0.0377)	(0.0411)
Left Censoring									
Left Cens	−0.186	−0.079	−0.164	−0.165	−0.124	−0.106	−0.145	−0.123	−0.107
	(0.1367)	(0.1211)	(0.1181)	(0.1410)	(0.1205)	(0.1209)	(0.1311)	(0.1107)	(0.1169)
Market Power									
$-\eta$	−0.076	−0.072	−0.117	−0.116					
	(0.1354)	(0.1434)	(0.1277)	(0.1339)					
PCM_{t-1}					0.138	0.058			
					(0.5346)	(0.5200)			
$share_{t-1}$							1.628***	1.589***	
							(0.5685)	(0.5591)	
$\ln Size_{t-1}$				−0.056		0.173***		0.173***	0.174***
				(0.0650)		(0.0403)		(0.0487)	(0.0400)
Financing									
CF_{t-1}	−0.297	−0.304	−0.065	−0.036	−0.405	−0.414	−0.314	−0.354	−0.389
	(0.6654)	(0.6250)	(0.7787)	(0.7776)	(0.7090)	(0.5094)	(0.4992)	(0.6021)	(0.5265)
D_{t-1}	−0.339	−0.313	−0.236	−0.251	−0.100	−0.072	−0.098	−0.064	−0.075
	(0.2243)	(0.2746)	(0.2801)	(0.2664)	(0.2018)	(0.2225)	(0.1888)	(0.2068)	(0.1939)

Table 11 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Technological Opportunities									
HT	0.250	0.371	0.253	0.249	0.389	0.405	−0.222	−0.198	0.400
	(0.5521)	(0.4930)	(0.5847)	(0.5306)	(0.3696)	(0.3816)	(0.4547)	(0.4184)	(0.3022)
MHT	0.634	0.890**	0.890**	0.875**	0.851***	0.922***	0.335	0.417	0.922***
	(0.4223)	(0.4061)	(0.4089)	(0.4018)	(0.2150)	(0.2945)	(0.3809)	(0.3638)	(0.2362)
MLT	0.690*	0.944**	0.947**	0.934**	0.891***	0.962***	0.611**	0.689**	0.961***
	(0.4068)	(0.3769)	(0.3855)	(0.3942)	(0.1955)	(0.2689)	(0.3099)	(0.3100)	(0.2115)
Planned Investments									
IM_{t-1}	0.962	1.109	−0.152	−0.098	0.680	0.332	0.659	0.301	0.330
	(1.0822)	(0.9698)	(1.1941)	(1.0265)	(0.6990)	(0.6383)	(0.7656)	(0.6805)	(0.7090)
IS_{t-1}	−2.052	−1.136	−1.365	−1.403	−0.332	−0.292	−0.467	−0.423	−0.288
	(5.8972)	(4.9970)	(10.8490)	(6.1174)	(1.1794)	(3.1102)	(5.7145)	(4.4598)	(2.5305)
ΔIM_{t-1}			−2.808**	−2.772***	−2.850***	−2.896***	−2.861***	−2.922***	−2.889***
			(1.2707)	(1.0308)	(0.8379)	(0.9352)	(0.9894)	(0.9912)	(0.9227)
ΔIS_{t-1}			10.767	10.716	14.210***	14.435**	14.871***	15.033***	14.436***
			(10.6671)	(10.1001)	(4.5357)	(5.7834)	(5.5336)	(5.5892)	(5.0640)
International Competition									
Exp_{t-1}	0.070	−0.041	−0.036	−0.024	−0.227*	−0.260	−0.281*	−0.311*	−0.262
	(0.1851)	(0.1509)	(0.2323)	(0.1883)	(0.1353)	(0.1694)	(0.1468)	(0.1718)	(0.1596)
Uncertainty									
EPU		−0.013***	−0.013***	−0.013***	−0.014***	−0.013***	−0.015***	−0.014***	−0.013***
		(0.0016)	(0.0017)	(0.0016)	(0.0010)	(0.0011)	(0.0012)	(0.0012)	(0.0012)
Time dummies	Yes	No	No	No	No	No	No	No	No

Table 11 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Other Measurable Individual Characteristics									
ln Age	−0.147*	−0.074	0.002	0.012	−0.038	−0.060	−0.039	−0.062	−0.060
	(0.0881)	(0.0674)	(0.0699)	(0.0744)	(0.0758)	(0.0714)	(0.0895)	(0.0663)	(0.0886)
Group	0.067	0.060	0.059	0.085	−0.005	−0.106	−0.002	−0.102	−0.106
	(0.1076)	(0.0995)	(0.1111)	(0.1131)	(0.0780)	(0.0900)	(0.0879)	(0.0774)	(0.0826)
Family	0.260**	0.149	0.127	0.110	0.196**	0.205**	0.194**	0.202**	0.206**
	(0.1116)	(0.1138)	(0.0995)	(0.1080)	(0.0908)	(0.0849)	(0.0946)	(0.0814)	(0.0887)
Centre	0.323***	0.219	0.242**	0.239*	0.284***	0.313***	0.292***	0.321***	0.313***
	(0.1207)	(0.1395)	(0.1141)	(0.1286)	(0.0979)	(0.0958)	(0.1023)	(0.0984)	(0.0975)
South	0.749***	0.530***	0.607***	0.594***	0.392***	0.450***	0.400***	0.456***	0.450***
	(0.1296)	(0.1242)	(0.1323)	(0.1288)	(0.0977)	(0.1033)	(0.1131)	(0.0991)	(0.0966)
L-Likelihood	−2051.379	−2104.884	−1767.301	−1766.958	−3081.429	−3075.109	−3078.448	−3072.194	−3075.122
A.I.C	4150.758	4247.768	3576.602	3577.916	6204.858	6194.217	6198.895	6188.389	6192.243
B.I.C	4270.896	4342.878	3679.304	3685.510	6319.052	6313.849	6313.089	6308.020	6306.437
Obs	1103	1103	983	983	1699	1699	1699	1699	1699

Note: Bootstrapped standard errors in parentheses. Efron (1977) method used to handle tied failures. Significance of the coefficients: * for p<.10, ** for p<.0.05, and *** for p<.01. This model does not control for unobserved heterogeneity

Table 12 Test of proportional hazard assumptions for the Cox model

Variables	Cox Models, as in Table 11								
	P-value for the Test of Schoenfeld Residuals.								
	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
$\ln RD_{t-1}$	(0.4384)	(0.4191)	(0.4710)	(0.9882)	(0.6723)	(0.7868)	(0.6775)	(0.8527)	(0.7772)
$N.Spells_{t-1}$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Time_{t-1}$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Left Cens	(0.6272)	(0.6151)	(0.9697)	(0.9467)	(0.9654)	(0.8484)	(0.8604)	(0.9200)	(0.8441)
$-\eta$	(0.0399)	(0.1363)	(0.1454)	(0.1721)					
PCM_{t-1}					(0.8833)	(0.9956)			
$share_{t-1}$							(0.8266)	(0.9052)	
$\ln Size_{t-1}$				(0.0456)		(0.0001)		(0.0020)	(0.0001)
CF_{t-1}	(0.2349)	(0.2329)	(0.2958)	(0.2488)	(0.3316)	(0.1596)	(0.1922)	(0.2339)	(0.1747)
D_{t-1}	(0.5468)	(0.2912)	(0.1899)	(0.2088)	(0.0525)	(0.1104)	(0.0372)	(0.0921)	(0.0672)
HT	(0.4019)	(0.5138)	(0.7175)	(0.6728)	(0.8536)	(0.7609)	(0.9785)	(0.8104)	(0.6996)
MHT	(0.3463)	(0.4575)	(0.4957)	(0.4525)	(0.8780)	(0.5822)	(0.9219)	(0.6855)	(0.4910)
MLT	(0.2828)	(0.3717)	(0.4200)	(0.3883)	(0.9127)	(0.6324)	(0.9524)	(0.7113)	(0.5406)
IM_{t-1}	(0.9335)	(0.9930)	(0.8819)	(0.9629)	(0.1834)	(0.3841)	(0.2398)	(0.4376)	(0.4322)
IS_{t-1}	(0.8509)	(0.8700)	(0.9163)	(0.8604)	(0.8413)	(0.9441)	(0.9663)	(0.9626)	(0.9318)
ΔIM_{t-1}			(0.8558)	(0.9404)	(0.7890)	(0.6494)	(0.7982)	(0.6531)	(0.6480)
ΔIS_{t-1}			(0.7934)	(0.7760)	(0.9176)	(0.9858)	(0.9552)	(0.9842)	(0.9859)
Exp_{t-1}	(0.6384)	(0.2389)	(0.4004)	(0.3323)	(0.0255)	(0.1816)	(0.0363)	(0.1631)	(0.1560)
EPU		(0.0001)	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln Age	(0.8886)	(0.2734)	(0.8944)	(0.7097)	(0.5625)	(0.8968)	(0.6954)	(0.9983)	(0.9137)
Group	(0.5877)	(0.3400)	(0.2981)	(0.1156)	(0.0104)	(0.0010)	(0.0186)	(0.0001)	(0.0003)
Family	(0.0562)	(0.0662)	(0.0542)	(0.0384)	(0.0118)	(0.0072)	(0.0152)	(0.0047)	(0.0100)
Centre	(0.5748)	(0.3856)	(0.3154)	(0.3790)	(0.5708)	(0.2655)	(0.5442)	(0.2611)	(0.2748)
South	(0.0675)	(0.7588)	(0.7882)	(0.9678)	(0.7520)	(0.7261)	(0.7191)	(0.8250)	(0.7096)
Global Test	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		

Note: The PH tests, based on the Schoenfeld residuals (Hess and Persson, 2012), strongly reject the PH assumption. In Model EL1, there are deviations from the PH assumptions in 2009 and 2010

Table 13 Robustness checks for the *Cloglog* model with normally-distributed frailty

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Cumulativeness									
$\ln RD_{t-1}$	−0.092***	−0.090***	−0.078***	−0.069***	−0.067***	−0.075***	−0.067***	−0.075***	−0.075***
	(0.0180)	(0.0193)	(0.0217)	(0.0230)	(0.0187)	(0.0187)	(0.0183)	(0.0191)	(0.0169)
$N.Spells_{t-1}$	0.107	0.101	0.121	0.113	−0.012	0.013	−0.001	0.021	0.015
	(0.1114)	(0.1161)	(0.1037)	(0.0996)	(0.0989)	(0.1117)	(0.0962)	(0.0868)	(0.1162)
$Time_{t-1}$	−0.145***	−0.143***	−0.147***	−0.149***	−0.122***	−0.125***	−0.122***	−0.124***	−0.125***
	(0.0260)	(0.0311)	(0.0360)	(0.0273)	(0.0268)	(0.0297)	(0.0237)	(0.0263)	(0.0286)
Left Censoring									
Left Cens	−0.448***	−0.446**	−0.446***	−0.460**	−0.497***	−0.465***	−0.494***	−0.465***	−0.461***
	(0.1424)	(0.1753)	(0.1563)	(0.1896)	(0.1123)	(0.1421)	(0.1451)	(0.1203)	(0.1337)
Market Power									
$-\eta$	−0.239*	−0.232*	−0.246	−0.248					
	(0.1357)	(0.1372)	(0.1688)	(0.1778)					
PCM_{t-1}					−0.651	−0.697			
					(0.5287)	(0.4699)			
$share_{t-1}$							0.732	0.649	
							(0.6948)	(0.5518)	
$\ln Size_{t-1}$				−0.153**		0.102*		0.094*	0.097*
				(0.0595)		(0.0599)		(0.0550)	(0.0513)
Financing									
CF_{t-1}	−1.162	−1.274*	−0.720	−0.648	−0.768	−0.761	−1.105	−1.118*	−1.123
	(0.9352)	(0.6825)	(0.8366)	(1.0068)	(0.8439)	(0.7560)	(0.8829)	(0.6131)	(0.7793)
D_{t-1}	0.388	0.381*	0.497**	0.460*	0.255	0.276	0.280	0.300	0.291
	(0.2415)	(0.2004)	(0.2233)	(0.2764)	(0.2141)	(0.2068)	(0.2166)	(0.2248)	(0.2313)

Table 13 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Technological Opportunities									
HT	0.480	0.465	0.109	0.004	0.097	0.142	−0.150	−0.079	0.165
	(0.4423)	(0.4744)	(0.5269)	(0.5974)	(0.3461)	(0.3380)	(0.4572)	(0.4713)	(0.3422)
MHT	0.782***	0.773*	0.597*	0.492	0.688**	0.746***	0.457	0.536	0.742***
	(0.3007)	(0.4279)	(0.3424)	(0.3774)	(0.2736)	(0.2590)	(0.3623)	(0.3529)	(0.2369)
MLT	0.881***	0.879**	0.733**	0.630*	0.833***	0.896***	0.709**	0.781***	0.895***
	(0.2837)	(0.4087)	(0.3443)	(0.3473)	(0.2533)	(0.2480)	(0.3140)	(0.2865)	(0.2150)
Planned Investments									
IM_{t-1}	1.248	1.250	−0.474	−0.356	−0.381	−0.531	−0.324	−0.460	−0.479
	(1.1342)	(0.9987)	(1.2368)	(1.3667)	(0.5701)	(0.7001)	(0.8486)	(0.6597)	(0.8761)
IS_{t-1}	−0.579	−0.526	−0.490	−0.482	0.346	0.361	0.246	0.265	0.319
	(5.3124)	(10.8431)	(10.0470)	(10.1697)	(3.7864)	(3.1542)	(3.1240)	(2.9857)	(4.0406)
ΔIM_{t-1}			−3.348*	−3.406*	−0.783	−0.746	−0.780	−0.743	−0.736
			(1.7409)	(1.7830)	(0.8911)	(0.7438)	(0.9991)	(0.8863)	(0.7477)
ΔIS_{t-1}			7.716	6.977	9.042*	9.358**	8.918*	9.209**	9.271*
			(9.5417)	(7.5413)	(5.1362)	(4.2695)	(4.6754)	(4.3456)	(4.8525)
International Competition									
Exp_{t-1}	−0.295	−0.283	−0.319*	−0.269	−0.517***	−0.541***	−0.525***	−0.545***	−0.531***
	(0.2019)	(0.2116)	(0.1937)	(0.2098)	(0.1459)	(0.1532)	(0.1915)	(0.1707)	(0.1698)
Uncertainty									
EPU		−0.002	−0.001	−0.001	−0.002**	−0.002**	−0.003**	−0.003**	−0.002*
		(0.0017)	(0.0016)	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0014)
Time dummies	Yes	No	No	No	No	No	No	No	No

Table 13 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Other Measurable Individual Characteristics									
ln Age	−0.103	−0.098	−0.095	−0.065	−0.069	−0.087	−0.079	−0.095	−0.095
	(0.0691)	(0.0815)	(0.1019)	(0.1100)	(0.0925)	(0.0833)	(0.0766)	(0.0815)	(0.0824)
Group	0.131	0.128	0.064	0.150	0.052	−0.017	0.059	−0.005	−0.007
	(0.1041)	(0.1056)	(0.0964)	(0.1081)	(0.0791)	(0.1201)	(0.0921)	(0.0993)	(0.1039)
Family	0.021	0.018	0.055	0.040	0.229**	0.222**	0.221***	0.215**	0.220**
	(0.1093)	(0.0885)	(0.1166)	(0.1318)	(0.1025)	(0.1031)	(0.0789)	(0.1009)	(0.0975)
Centre	0.324***	0.307**	0.379***	0.351***	0.363***	0.389***	0.367***	0.390***	0.386***
	(0.1250)	(0.1307)	(0.1219)	(0.1167)	(0.1107)	(0.1080)	(0.1084)	(0.0915)	(0.1085)
South	0.574***	0.530***	0.559***	0.515***	0.437***	0.477***	0.451***	0.488***	0.484***
	(0.1316)	(0.1457)	(0.1351)	(0.1382)	(0.1391)	(0.1077)	(0.1251)	(0.1116)	(0.1204)
L-Likelihood	−1177.516	−1205.221	−1046.253	−1043.627	−1661.323	−1659.171	−1662.006	−1660.188	−1660.703
ρ	0.018	0.011	0.000	0.000	0.089	0.071	0.092	0.075	0.072
σ_ρ	0.173	0.133	0.007	0.004	0.401	0.355	0.407	0.366	0.358
A.I.C	2405.031	2452.443	2138.505	2135.255	3368.646	3366.341	3370.012	3368.376	3367.405
B.I.C	2558.127	2582.200	2277.948	2280.761	3518.756	3522.979	3520.123	3525.013	3517.516
Obs	3374	3565	3174	3174	5047	5047	5047	5047	5047

Note: Bootstrapped standard errors in parentheses. Significance of the coefficients: * for $p<.10$, ** for $p<.0.05$, and *** for $p<.01$. Parameter ρ represents the fraction of variance due to unobserved heterogeneity, and σ_ρ is the panel-level standard deviation

Table 14 Test of proportional hazard assumptions for the *Cloglog* model

Variables	*Cloglog* models, as in Table 13								
	P-value for the Hypothesis $\xi_k = 0$.								
	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
$\ln RD_{t-1}$	(0.1669)	(0.1155)	(0.1867)	(0.3376)	(0.0404)	(0.0286)	(0.0954)	(0.0783)	(0.0637)
$N.Spells_{t-1}$	(0.6184)	(0.5007)	(0.4862)	(0.5047)	(0.8232)	(0.8391)	(0.9181)	(0.9317)	(0.9038)
$-\eta$	(0.6257)	(0.6475)	(0.6130)	(0.6798)					
PCM_{t-1}					(0.3279)	(0.2699)			
$share_{t-1}$							(0.3500)	(0.5158)	
$\ln Size_{t-1}$				(0.8482)		(0.5692)		(0.5360)	(0.5053)
CF_{t-1}	(0.2417)	(0.3924)	(0.4528)	(0.4310)	(0.3845)	(0.3717)	(0.5753)	(0.4453)	(0.5019)
D_{t-1}	(0.4329)	(0.5368)	(0.6799)	(0.7383)	(0.7694)	(0.7869)	(0.7075)	(0.8044)	(0.7384)
IM_{t-1}	(0.3439)	(0.3094)	(0.5877)	(0.6621)	(0.6044)	(0.5867)	(0.5753)	(0.5431)	(0.5847)
IS_{t-1}	(0.9716)	(0.9928)	(0.8704)	(0.8475)	(0.5211)	(0.6313)	(0.5826)	(0.5407)	(0.5945)
ΔIM_{t-1}			(0.3682)	(0.3383)	(0.3402)	(0.2128)	(0.2565)	(0.2790)	(0.3406)
ΔIS_{t-1}			(0.8949)	(0.8081)	(0.9102)	(0.9597)	(0.8686)	(0.9297)	(0.9411)
Exp_{t-1}	(0.2227)	(0.1793)	(0.3324)	(0.1931)	(0.8593)	(0.9676)	(0.9595)	(0.8221)	(0.9414)
EPU	(0.9111)	(0.9781)	(0.9226)	(0.9640)	(0.8113)	(0.8830)	(0.8157)	(0.8749)	(0.8588)
ln Age	(0.9768)	(0.9234)	(0.8449)	(0.9126)	(0.9248)	(0.9551)	(0.9359)	(0.9538)	(0.9464)
Global Test	(0.1967)	(0.5851)	(0.9691)	(0.9755)	(0.9518)	(0.9493)	(0.8888)	(0.5737)	(0.7341)

Note: The PH assumption in the *Cloglog* model with unobserved heterogeneity is tested by allowing the explanatory variables to vary over time (McCall, 1994; Hess and Persson, 2012), i.e. we test the hypothesis $\xi_k = 0, \forall k = 1, \dots, K$, where ξ_k is the coefficient of the interaction term $(x_k \cdot t)$. McCall (1994) report that this test is robust to the assumed distribution of heterogeneity (here we use normally-distributed frailty). Results do not reject the PH assumption

Table 15 Robustness checks for the *Cloglog* model with gamma-distributed frailty

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Cumulativeness									
$\ln RD_{t-1}$	−0.130***	−0.109***	−0.100***	−0.091***	−0.093***	−0.098***	−0.092***	−0.097***	−0.098***
	(0.0209)	(0.0176)	(0.0221)	(0.0300)	(0.0204)	(0.0198)	(0.0158)	(0.0189)	(0.0203)
$N.Spells_{t-1}$	−0.161	−0.093	−0.042	−0.062	−0.022	−0.009	−0.034	−0.021	−0.009
	(0.1054)	(0.1056)	(0.1061)	(0.0788)	(0.0897)	(0.0874)	(0.0685)	(0.0714)	(0.0960)
$Time_{t-1}$	−0.054*	−0.019	−0.022	−0.019	−0.034	−0.038	−0.035	−0.039	−0.038
	(0.0290)	(0.0277)	(0.0329)	(0.0287)	(0.0227)	(0.0285)	(0.0214)	(0.0238)	(0.0254)
Left Censoring									
Left Cens	−0.957***	−0.948***	−0.892***	−0.932***	−0.637***	−0.609***	−0.636***	−0.606***	−0.609***
	(0.1495)	(0.1806)	(0.1798)	(0.1809)	(0.1620)	(0.1336)	(0.1118)	(0.1259)	(0.1636)
Market Power									
$-\eta$	−0.670***	−0.596***	−0.526***	−0.535***					
	(0.1457)	(0.1890)	(0.1907)	(0.1272)					
PCM_{t-1}					0.086	0.040			
					(0.4451)	(0.5040)			
$share_{t-1}$							−0.835	−0.887	
							(0.6584)	(0.6956)	
$\ln Size_{t-1}$				−0.202**		0.081		0.085*	0.081*
				(0.0915)		(0.0612)		(0.0457)	(0.0469)
Financing									
CF_{t-1}	−3.127***	−2.936***	−2.387***	−2.364***	−2.140***	−2.092***	−2.103***	−2.076***	−2.073***
	(0.7934)	(0.8156)	(0.8107)	(0.7561)	(0.7402)	(0.8004)	(0.7110)	(0.6456)	(0.7686)
D_{t-1}	0.911***	0.805***	1.051***	1.013***	0.626***	0.641***	0.613***	0.629***	0.641***
	(0.2796)	(0.2918)	(0.2718)	(0.3279)	(0.1729)	(0.2336)	(0.2297)	(0.2003)	(0.1967)

Table 15 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Technological Opportunities									
HT	−0.057	−0.184	−0.538	−0.674	−0.312	−0.288	−0.026	0.021	−0.289
	(0.6177)	(1.8272)	(2.4583)	(2.1696)	(0.3764)	(0.3793)	(0.5158)	(1.7084)	(0.3206)
MHT	0.458	0.109	−0.169	−0.289	0.181	0.220	0.444	0.501*	0.221
	(0.4427)	(0.3706)	(0.3810)	(0.3690)	(0.2561)	(0.2106)	(0.3903)	(0.2882)	(0.2393)
MLT	0.829**	0.474	0.301	0.187	0.492**	0.531***	0.636*	0.686***	0.531**
	(0.4112)	(0.3713)	(0.3793)	(0.3742)	(0.2292)	(0.1726)	(0.3373)	(0.2078)	(0.2201)
Planned Investments									
IM_{t-1}	−3.605**	−3.489***	−5.183**	−5.111**	−2.815***	−3.017***	−2.833***	−3.040***	−3.019***
	(1.6338)	(1.3313)	(2.2902)	(2.2278)	(0.9337)	(1.0749)	(0.9792)	(1.0325)	(0.9821)
IS_{t-1}	−0.247	−0.561	−1.690	−1.412	0.456	0.468	0.540	0.554	0.470
	(7.7650)	(6.9875)	(10.9957)	(7.8273)	(2.4613)	(5.3681)	(5.1717)	(3.9975)	(3.6867)
ΔIM_{t-1}			−0.888	−0.957	−0.527	−0.481	−0.521	−0.471	−0.482
			(2.3044)	(2.5643)	(0.7732)	(1.0715)	(1.1672)	(0.8704)	(1.1144)
ΔIS_{t-1}			10.111	9.438	11.938***	12.157***	11.956**	12.184***	12.162***
			(7.8518)	(10.3832)	(4.4326)	(4.4913)	(5.1972)	(4.5931)	(4.0586)
International Competition									
Exp_{t-1}	−0.585**	−0.580***	−0.651***	−0.587**	−0.694***	−0.711***	−0.673***	−0.690***	−0.712***
	(0.2355)	(0.2240)	(0.2376)	(0.2451)	(0.1808)	(0.1677)	(0.1723)	(0.1511)	(0.1522)
Uncertainty									
EPU		0.002	0.003**	0.003**	0.002	0.002	0.002	0.002	0.002
		(0.0014)	(0.0014)	(0.0015)	(0.0012)	(0.0010)	(0.0012)	(0.0013)	(0.0010)
Time dummies	Yes	No	No	No	No	No	No	No	No

Table 15 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Other Measurable Individual Characteristics									
ln Age	0.080	0.068	0.027	0.060	−0.061	−0.074	−0.059	−0.073	−0.074
	(0.1072)	(0.1044)	(0.1085)	(0.1498)	(0.0812)	(0.0904)	(0.0769)	(0.0911)	(0.0801)
Group	0.129	0.118	0.106	0.212	0.101	0.048	0.098	0.044	0.048
	(0.1176)	(0.1056)	(0.1214)	(0.1350)	(0.0988)	(0.1011)	(0.1070)	(0.0927)	(0.1076)
Family	−0.115	−0.094	−0.019	−0.039	0.096	0.086	0.102	0.092	0.086
	(0.0998)	(0.1160)	(0.1393)	(0.1369)	(0.0916)	(0.0957)	(0.0893)	(0.0854)	(0.1004)
Centre	0.600***	0.534***	0.519***	0.489***	0.365***	0.387***	0.360***	0.382***	0.387***
	(0.1495)	(0.1270)	(0.1576)	(0.1244)	(0.1155)	(0.1381)	(0.1199)	(0.1140)	(0.1305)
South	0.833***	0.753***	0.711***	0.659***	0.569***	0.599***	0.564***	0.595***	0.598***
	(0.1714)	(0.1546)	(0.1271)	(0.1645)	(0.1304)	(0.1187)	(0.1152)	(0.1270)	(0.1324)
L-Likelihood	−714.576	−748.842	−673.045	−671.154	−1128.531	−1127.752	−1128.072	−1127.215	−1127.754
χ^2 Test	925.928	912.774	746.415	744.947	1066.917	1063.663	1069.293	1066.880	1066.756
χ^2 p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A.I.C	1481.152	1539.685	1392.090	1390.308	2303.062	2303.503	2302.143	2302.431	2301.507
B.I.C	1641.804	1669.442	1531.533	1535.813	2453.172	2460.140	2452.254	2459.068	2451.618
Obs	3565	3565	3174	3174	5047	5047	5047	5047	5047

Note: Bootstrapped standard errors in parentheses. Significance of the coefficients: * for p<.10, ** for p<.0.05, and *** for p<.01. The reported χ^2 test and p-value check for the presence of unobserved heterogeneity

Table 16 Robustness checks for the *Cloglog* model with mass-points frailty

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Cumulativeness									
$\ln RD_{t-1}$	−0.111***	−0.108**	−0.097**	−0.088***	−0.094***	−0.100***	−0.093***	−0.099***	−0.100***
	(0.0312)	(0.0484)	(0.0469)	(0.0267)	(0.0180)	(0.0206)	(0.0186)	(0.0180)	(0.0214)
$N.Spells_{t-1}$	−0.078	−0.044	−0.009	−0.020	−0.022	−0.010	−0.034	−0.023***	−0.010
	(0.1340)	(0.1277)	(0.0835)	(0.1046)	(0.0859)	(0.0857)	(0.0832)	(0.0061)	(0.0860)
$Time_{t-1}$	−0.025	0.020	0.008	0.009	−0.012	−0.016	−0.014	−0.019	−0.016
	(0.0397)	(0.0634)	(0.0377)	(0.0307)	(0.0239)	(0.0221)	(0.0204)	(0.0353)	(0.0223)
Left Censoring									
Left Cens	−1.019***	−1.066***	−0.994***	−1.026***	−0.696***	−0.672***	−0.688***	−0.662***	−0.672***
	(0.2440)	(0.1980)	(0.1804)	(0.2306)	(0.1404)	(0.1381)	(0.1405)	(0.1657)	(0.1233)
Market Power									
$-\eta$	−0.675***	−0.687***	−0.587***	−0.596***					
	(0.1840)	(0.2089)	(0.2118)	(0.1646)					
PCM_{t-1}					0.093	0.044			
					(0.5833)	(0.5408)			
$share_{t-1}$							−0.838	−0.896***	
							(0.7756)	(0.2233)	
$\ln Size_{t-1}$				−0.216***		0.085		0.088	0.085
				(0.0735)		(0.0602)		(0.0656)	(0.0564)
Financing									
CF_{t-1}	−3.015***	−3.159***	−2.633***	−2.645***	−2.296***	−2.253***	−2.247***	−2.224	−2.232***
	(0.9706)	(0.8887)	(0.9718)	(0.8544)	(0.7910)	(0.7809)	(0.4764)	(1.4445)	(0.8504)
D_{t-1}	0.779***	0.823***	1.138***	1.074***	0.667***	0.680***	0.648***	0.661**	0.680***
	(0.2278)	(0.3130)	(0.4146)	(0.3393)	(0.2235)	(0.1841)	(0.2237)	(0.2888)	(0.2418)

Table 16 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Technological Opportunities									
HT	−0.300	−0.205	−0.745	−0.914	−0.339	−0.318	−0.053	−0.008	−0.319
	(0.8541)	(0.5804)	(2.2278)	(0.7446)	(0.5013)	(0.3735)	(0.4666)	(0.4425)	(0.4491)
MHT	0.383	0.141	−0.179	−0.317	0.215	0.252	0.474	0.531***	0.252
	(0.3932)	(0.3121)	(0.3962)	(0.5222)	(0.2815)	(0.2502)	(0.3711)	(0.1885)	(0.2814)
MLT	0.689*	0.512*	0.281	0.152	0.531**	0.570**	0.670**	0.720***	0.570**
	(0.3529)	(0.3109)	(0.3622)	(0.5383)	(0.2659)	(0.2318)	(0.2792)	(0.1293)	(0.2623)
Planned Investments									
IM_{t-1}	−4.634*	−4.391**	−6.026***	−5.810**	−3.281***	−3.454***	−3.248***	−3.424***	−3.457***
	(2.5852)	(1.8007)	(2.2400)	(2.2617)	(1.1039)	(1.0844)	(1.0449)	(0.6097)	(1.1714)
IS_{t-1}	−0.399	−0.664	−4.991	−4.388	0.499	0.510	0.579	0.593	0.513
	(5.5787)	(9.2941)	(14.6690)	(9.5700)	(5.3994)	(4.4341)	(6.8738)	(0.8342)	(8.6673)
ΔIM_{t-1}			−0.862	−0.934	−0.479	−0.449	−0.473	−0.441	−0.449
			(1.9205)	(2.0550)	(0.7027)	(1.2335)	(1.1479)	(1.1254)	(1.1285)
ΔIS_{t-1}			12.154	11.255	12.857**	13.029***	12.784***	12.947***	13.025***
			(10.3698)	(8.8211)	(5.1584)	(3.6895)	(4.8058)	(0.8687)	(4.4640)
International Competition									
Exp_{t-1}	−0.817***	−0.713***	−0.751***	−0.680***	−0.725***	−0.747***	−0.703***	−0.723***	−0.748***
	(0.2137)	(0.2457)	(0.2432)	(0.2270)	(0.1645)	(0.1717)	(0.1664)	(0.1447)	(0.2011)
Uncertainty									
EPU		0.002	0.003	0.003	0.001	0.002	0.002	0.002	0.002
		(0.0041)	(0.0020)	(0.0017)	(0.0011)	(0.0012)	(0.0014)	(0.0013)	(0.0013)
Time dummies	Yes	No	No	No	No	No	No		

Table 16 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Other Measurable Individual Characteristics									
ln Age	0.135	0.108	0.057	0.105	−0.050	−0.066	−0.048	−0.066	−0.066
	(0.0998)	(0.2047)	(0.1311)	(0.1330)	(0.0820)	(0.0960)	(0.0910)	(0.0833)	(0.0710)
Group	0.076	0.120	0.090	0.191	0.103	0.048	0.101	0.044**	0.048
	(0.1726)	(0.1224)	(0.1160)	(0.1291)	(0.1105)	(0.0977)	(0.0796)	(0.0220)	(0.1097)
Family	−0.170	−0.119	−0.043	−0.056	0.104	0.090	0.109	0.096	0.090
	(0.1294)	(0.1321)	(0.1435)	(0.1506)	(0.1105)	(0.0973)	(0.0909)	(0.0807)	(0.1057)
Centre	0.748***	0.650***	0.599***	0.555***	0.408***	0.428***	0.398***	0.419***	0.428***
	(0.2153)	(0.1303)	(0.1105)	(0.1326)	(0.0992)	(0.1269)	(0.1160)	(0.1546)	(0.1300)
South	0.989***	0.888***	0.826***	0.771***	0.637***	0.664***	0.624***	0.653***	0.664***
	(0.1996)	(0.1321)	(0.1595)	(0.1292)	(0.1085)	(0.1242)	(0.1213)	(0.2135)	(0.1184)
L-likekihood	−713.357	−747.191	−672.013	−670.143	−1128.055	−1127.316	−1127.646	−1126.831	−1127.318
*m*2	3.276***	3.005***	2.823***	2.925***	2.410***	2.455**	2.433**	2.500**	2.458**
*m*2 se	0.569	0.577	0.577	0.580	0.873	0.970	1.011	1.152	0.973
A.I.C	1480.713	1538.383	1392.026	1390.286	2304.110	2304.632	2303.291	2303.661	2302.637
B.I.C	1647.544	1674.319	1537.532	1541.854	2460.748	2467.796	2459.928	2466.825	2459.274
Obs	3565	3565	3174	3174	5047	5047	5047	5047	5047

Note: Bootstrapped standard errors in parentheses. Significance of the coefficients: * for $p<.10$, ** for $p<.0.05$, and *** for $p<.01$. $m2$ represents the estimated second mass point and its corresponding standard error. If $m2$ is significant, there is unobserved heterogeneity. Estimates of the third mass point are not significant, and the results under the assumption of three mass points are not statistically different from those with two mass points

Table 17 Robustness checks for the random effects probit model with normally-distributed frailty

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Cumulativeness									
$\ln RD_{t-1}$	−0.004	−0.009	−0.011	−0.009	0.009	0.006	0.005	0.003	0.007
	(0.0165)	(0.0200)	(0.0222)	(0.0220)	(0.0179)	(0.0185)	(0.0163)	(0.0197)	(0.0230)
$N.Spells_{t-1}$	0.021	0.020	0.049	0.048	−0.035	−0.030	−0.029	−0.026	−0.029
	(0.0611)	(0.0705)	(0.0711)	(0.0745)	(0.0613)	(0.0607)	(0.0608)	(0.0719)	(0.0624)
$Time_{t-1}$	−0.077***	−0.070***	−0.077***	−0.078***	−0.063***	−0.063***	−0.055***	−0.055***	−0.062***
	(0.0162)	(0.0163)	(0.0161)	(0.0192)	(0.0139)	(0.0125)	(0.0162)	(0.0182)	(0.0168)
Left Censoring									
Left Cens	−0.237***	−0.235**	−0.214**	−0.219**	−0.269***	−0.254***	−0.281***	−0.267***	−0.251***
	(0.0821)	(0.0960)	(0.0970)	(0.0875)	(0.0741)	(0.0692)	(0.0843)	(0.0997)	(0.0783)
Market Power									
$-\eta$	−0.119	−0.117	−0.128	−0.129					
	(0.0763)	(0.0814)	(0.0989)	(0.1168)					
PCM_{t-1}					−0.427	−0.424			
					(0.5014)	(0.3215)			
$share_{t-1}$							1.657***	1.569***	
							(0.5320)	(0.5158)	
$\ln Size_{t-1}$				−0.064		0.033		0.034	0.034
				(0.2262)		(0.1760)		(0.1852)	(0.1932)
Financing									
CF_{t-1}	−0.311	−0.453	−0.251	−0.278	−0.349	−0.317	−0.398	−0.357	−0.359
	(0.6013)	(0.7624)	(0.7697)	(0.6342)	(0.5057)	(0.5077)	(0.5476)	(0.5193)	(0.5442)
D_{t-1}	0.297	0.210	0.083	0.079	−0.005	0.016	0.054	0.072	0.054
	(0.2999)	(0.2397)	(0.3368)	(0.3202)	(0.2375)	(0.2593)	(0.2619)	(0.2407)	(0.2396)

Table 17 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Technological Opportunities									
HT	0.433	0.403	0.287	0.253	0.232	0.283	0.453*	0.528*	0.301
	(0.3298)	(0.2711)	(0.3692)	(0.2556)	(0.2226)	(0.1820)	(0.2568)	(0.3111)	(0.2364)
MHT	0.460*	0.429**	0.461*	0.429**	0.481***	0.536***	0.692***	0.762***	0.534***
	(0.2641)	(0.2182)	(0.2361)	(0.1783)	(0.1546)	(0.1808)	(0.2317)	(0.2658)	(0.1626)
MLT	0.499**	0.474**	0.519**	0.491***	0.543***	0.598***	0.652***	0.715***	0.599***
	(0.2493)	(0.2255)	(0.2352)	(0.1875)	(0.1601)	(0.1688)	(0.1862)	(0.2047)	(0.1464)
Planned Investments									
IM_{t-1}	−0.342	−0.386	−2.677**	−2.683*	−1.478**	−1.565**	−1.446*	−1.533	−1.539**
	(1.2087)	(1.0289)	(1.2961)	(1.4242)	(0.6503)	(0.6951)	(0.8515)	(0.9487)	(0.7769)
IS_{t-1}	7.453	7.625	9.911	9.700	5.306	5.485	5.608*	5.788	5.644
	(8.2075)	(7.5619)	(10.2203)	(8.7979)	(5.1307)	(4.1823)	(3.2763)	(4.1694)	(4.5091)
ΔIM_{t-1}			−1.407	−1.376	0.059	0.030	0.073	0.048	0.029
			(1.0214)	(1.2684)	(0.6927)	(0.7387)	(0.6864)	(0.6729)	(0.5233)
ΔIS_{t-1}			6.676	6.595	6.584	6.598	6.286**	6.338	6.481*
			(6.3455)	(7.1297)	(4.0976)	(4.1325)	(2.9437)	(4.3892)	(3.6942)
International Competition									
Exp_{t-1}	0.401	0.423	0.545	0.533	0.372	0.398	0.416*	0.439	0.397
	(0.3265)	(0.3867)	(0.4331)	(0.3335)	(0.2728)	(0.2757)	(0.2268)	(0.2806)	(0.3252)
Uncertainty									
EPU		−0.001	−0.001	−0.001	−0.002**	−0.002**	−0.003***	−0.003***	−0.002**
		(0.0012)	(0.0010)	(0.0012)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Time dummies	Yes	No	No	No	No	No	No		

Table 17 (continued)

	EL1	EL2	EL3	EL4	PCM5	PCM6	Share7	Share8	Size9
Other Measurable Individual Characteristics									
ln Age	−0.074	−0.067	−0.054	−0.041	−0.031	−0.050	−0.040	−0.058	−0.053
	(0.0636)	(0.0579)	(0.0560)	(0.0679)	(0.0519)	(0.0437)	(0.0404)	(0.0493)	(0.0550)
Group	0.151**	0.140***	0.103*	0.138*	0.094	0.037	0.092*	0.038	0.041
	(0.0696)	(0.0506)	(0.0624)	(0.0786)	(0.0615)	(0.0638)	(0.0543)	(0.0681)	(0.0604)
Family	0.024	0.014	0.033	0.026	0.140***	0.139***	0.146**	0.145**	0.137**
	(0.0710)	(0.0720)	(0.0823)	(0.0694)	(0.0519)	(0.0533)	(0.0583)	(0.0578)	(0.0587)
Centre	0.199**	0.183**	0.214**	0.204***	0.228***	0.248***	0.229***	0.247***	0.246***
	(0.0866)	(0.0787)	(0.0861)	(0.0731)	(0.0546)	(0.0634)	(0.0761)	(0.0611)	(0.0633)
South	0.355***	0.322***	0.324***	0.309***	0.249***	0.283***	0.259***	0.291***	0.283***
	(0.0866)	(0.0926)	(0.0851)	(0.0957)	(0.0597)	(0.0723)	(0.0780)	(0.0701)	(0.0751)
L-likelihood	−1156.987	−1188.148	−1030.016	−1028.847	−1638.585	−1634.272	−1633.432	−1629.555	−1635.500
ρ	0.048	0.035	0.000	0.000	0.077	0.075	0.081	0.079	0.076
σ_ρ	0.224	0.189	0.006	0.006	0.289	0.285	0.296	0.293	0.286
A.I.C	2375.975	2430.296	2122.033	2123.693	3341.169	3336.543	3330.865	3327.111	3335.000
B.I.C	2565.814	2597.127	2309.978	2323.764	3550.019	3558.446	3539.714	3549.013	3543.850
Obs	3374	3565	3174	3174	5047	5047	5047	5047	5047

Note: Bootstrapped standard errors in parentheses. Significance of the coefficients: * for p<.10, ** for p<.0.05, and *** for p<.01. Parameter ρ represents the fraction of variance due to unobserved heterogeneity, and σ_ρ is the panel-level standard deviation. Cross-correlated random effects significant for $\ln RD_{t-1}$, $share_{t-1}$, IM_{t-1}, ΔIM_{t-1}, Exp_{t-1}

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