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Quantifying Sunk Costs and Learning Effects in R&D Persistence

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Abstract

This paper analyzes and quantifies the fundamental factors that are likely to cause persistence in performing R&D activities: the existence of sunk costs associated with R&D activities and the process of learning that characterizes this type of activity. We estimate our model with Spanish manufacturing firms for the period 1991-2014. By decomposing the effects of sunk costs and learning effects, we find that both are important determinants of R&D persistence, and that failing to allow for learning systematically overestimates sunk cost effects. Both large firms and SMEs benefit from direct and indirect (via productivity) effects of R&D experience, but in large firms this is more likely to be manifest through productivity improvements while in smaller firms the effect is more skewed towards a direct effect on R&D likelihood. Further, our results suggest that whereas the impact of sunk costs in R&D persistence is greater for large firms than for SMEs, the scope for direct learning from continuous R&D engagement is greater for SMEs than for larger firms.

Keywords: R&D persistence, sunk costs; learning effects.
JEL: O32, L60

1. Introduction

Persistence in R&D is highly desirable for firms. It is related to greater productivity growth (Verspagen, 1995; Lööf *et al*., 2012), higher profitability (Cefis and Ciccarelli, 2005), and to an increased level of innovation (Beneito *et al*., 2015). This has potential policy implications at both national and EU level: for example, the Spanish Strategy for Science and Technology and Innovation 2013-2020 recognizes that boosting Spanish performance in R&D and innovation entails "promoting the stability and sustainability over time of such investments", and the European Union's 'Horizon 2020' includes the promotion of innovative firms as a priority objective. Despite the political interest and the existence of previous work that has explored the determinants of the innovative persistence of firms, we know little about the factors that lead firms to carry out innovative activities – and in particular R&D – in a persistent fashion.

From a theoretical point of view, the two fundamental factors that are likely to cause persistence in performing R&D activities are the existence of sunk costs associated to carrying out R&D activities and the processes of learning that characterize this type of activity. Regarding the existence of sunk costs associated with R&D activities, it is necessary to take into account that when firms decide to perform R&D activities they have to incur initial costs associated with the establishment of an R&D department, purchase of specific assets and recruitment and/or training of specialized personnel. These sunk costs represent both barriers to entry and exit of R&D activities and, therefore, are liable to cause persistence.

Both the evolutionary theory approach (Nelson and Winter, 1982) and the path-dependent technological change approach (Ruttan, 1997) recognize the existence of learning processes when firms perform R&D activities in a continuous manner. By investing in R&D firms develop capabilities, which incrementally give the firm a stock of knowledge and experience that can be used to develop new innovations. Therefore, the process of conducting R&D activities is characterized by increasing dynamic returns that materialize in learning and economies of scope in the production of innovations (Cohen and Levinthal, 1989).

Whether firms' persistence in R&D is due to the existence of sunk costs or to a process of learning is highly relevant both from the economic and the political perspective, as it raises completely different implications. Sunk costs, insofar as they imply the existence of exit barriers, may force firms that in the absence of these sunk cost would quit R&D activities to continue performing them, thus distorting the efficient allocation of resources within the firm. However, if firms' persistence in R&D is linked to learning processes that increase the efficiency of the innovative activity (Beneito *et al*., 2015), it would be necessary to take measures that encourage the continuous engagement in R&D activities. Furthermore, if persistence in innovation is desirable as a means to increase firms' innovation returns, it is pertinent to know what prevents firms from continuous engagement in R&D. Therefore, it is extremely interesting to try to quantify the extent to which the persistence in carrying out R&D activities is linked to the existence of sunk costs or learning effects.

To the best of our knowledge, the only work that tries to differentiate between sunk costs and learning as determinants of the persistence in the realization of R&D is Máñez *et al.* (2015). Using econometric models of duration, they obtain empirical evidence suggesting that both sunk costs and learning effects are important determinants of R&D persistence. However, their methodology does not permit quantification of the importance of these two factors. In order to quantify the role of sunk costs and learning effects to explain firms' persistent engagement in R&D, in this paper we integrate in a single econometric framework the dynamic autoregressive models, which analyze the role of sunk costs, with the duration model proposed by Mañez *et al*. (2015) to capture possible learning effects related to the continuous engagement in R&D. To achieve this, we adapt and extend the model proposed by Timoshenko (2015) to analyze the role of sunk cost and learning effects in firms' export decisions. Our model adds to the autoregressive structure of Mañez *et al*. (2009) or Peters (2009) a function of the number of years that the firm has been continuously engaged in R&D (*R&D age*) to capture possible learning effects. The comparison of the results of the estimations with and without learning effects allows us to measure which part of the persistence in R&D engagement may be attributed to the existence of sunk cost and which to possible learning effects.

Nevertheless, proper quantification of the effects of sunk costs and learning on R&D persistence requires acknowledgement of the possible indirect effect of R&D experience (proxied by R&D age) on the likelihood of performing R&D that accrue through its enhancing effects on productivity. Therefore, we consider that R&D experience may affect the probability of R&D engagement both directly and indirectly. By direct effects we mean those stemming from the inherent learning associated to continuous R&D engagement. By indirect effects we mean those that accrue to the probability of performing R&D through increased productivity. Further, given that both sunk costs and learning effect are more likely to happen for in-house (make) R&D than for external (bought) R&D, we will focus our analysis on in-house R&D. Therefore, hereafter unless otherwise stated when referring to R&D we mean in-house R&D.

To carry out our empirical analysis, we use a representative sample of Spanish manufacturing firms for the period 1991–2014, drawn from the Survey of Business Strategies (ESEE, henceforth). This annual survey does not include firms with less than 10 employees and classifies as SMEs those firms with less than 200 workers, and as large firms those with more than 200 workers. Thus, given the sampling procedure of this survey, we consider as SMEs those firms having between 10 and 200 employees.

The contribution of this paper to the literature on innovation persistence is at least threefold. First, this is the first attempt to disentangle and quantify the importance of sunk costs and learning effects as determinants of persistence in R&D. Second, we distinguish between the direct effects of R&D experience inherent to continuous R&D engagement, and the indirect effects that accrue to the likelihood of R&D engagement through enhanced productivity. Third, we analyze whether the role played by sunk costs and learning effects differs between large firms and SMEs. In the case of Spain this is especially relevant as SMEs represent about 95% of the total number of firms.

To anticipate our results, they are consistent with the previous literature in suggesting that both sunk costs and learning effects are crucial drivers of R&D persistence. However, our results suggest that, after accounting for possible indirect effects of R&D experience on the likelihood of performing R&D, a non-negligible part of the observed state-dependence, traditionally attributed to the presence of sunk costs associated R&D engagement, could be attributable to direct learning effects in R&D activities (Rosenberg, 1976; Nelson and Winter 1982). Further, it is interesting to remark that both large firms and SMEs benefit from direct and indirect (via productivity) effects of R&D experience, but in large firms this is more likely to be manifest through productivity improvements while in smaller firms the effect is more skewed towards a direct effect on R&D likelihood.

The rest of the paper is organized as follows. Section 2 summarizes the literature on innovation and R&D persistence. Section 3 describes the data and provides some descriptive statistics. Section 4 presents the empirical model. Section 5 reports the results and, finally, Section 6 concludes.

2. Literature Review

There is an enormous empirical literature indicating that R&D is a key input for firm-level product and process innovation[1]. For this reason alone there is cause to be interested in the determinants of R&D and of its persistence. However, persistence in R&D is worth looking at in its own right, regardless of whether it is an effective proxy for innovation. There are two reasons for this. First, R&D performance is itself productivity enhancing at the firm level (Verspagen, 1995; Lööf *et al*., 2012), and so increasing the number of R&D performers and its persistence is a desirable objective at the country level. Second, as Arqué-Castells (2013) points out, many public policies on innovation, such as tax credits and direct public subsidies, are actually directed to measurable innovation inputs such as R&D. Therefore identifying the nature and causes of R&D persistence is of economic and policy interest.

[1] See, for example, the references in Roper *et al*. (2008). Of course, R&D is neither a necessary nor sufficient condition for innovation at the firm level. However, the weight of empirical evidence of the links between the two strongly suggests that the association is more than mere correlation.

The causes of persistence in both innovation inputs and outputs is still relatively under-researched, both theoretically and empirically (Ganter and Hecker, 2013). Theoretically, there are two principal explanations for persistence in innovation[2]. The first is the sunk cost argument. Here, investment in the R&D activities that underlie (technological) innovation require a considerable and continuous outlay on capital equipment, specialized and skilled labour, and on information such as horizon-scanning and new market opportunities. These costs are typically unrecoverable and thus are sunk costs. These sunk costs provide a platform for future R&D activity for innovators as well as a potential entry barrier into R&D activity for non-innovators, leading to persistence in both innovation and non-innovation activity (Mañez *et al.* 2009; Sutton 1991). The second key explanation for persistence involves learning effects. Investing in R&D activities can be characterized as a process of knowledge accumulation and learning, in which the firm builds on its previous stock of knowledge and thus generates the new knowledge on which future innovations are based. Since the firm's knowledge base is cumulative, the process of conducting R&D activities is characterized by increasing dynamic returns that materialize in learning and economies of scope in the production of innovations, and is a source of future firm capability (Cohen and Levinthal, 1989; Nelson and Winter, 1982).

Empirically, it is important to determine whether any perceived persistence in innovation is real or spurious. Observed persistence could arise simply from individual firm heterogeneity, in which firms possess certain characteristics which make them more prone to performing innovation. If these characteristics themselves persist through time, the result can be a perception of persistence which is not actually 'true state dependence' (Arqué-Castells, 2013). While early empirical studies were unable to differentiate between these causes (e.g. Cefis and Orsenigo, 2001), more recent work has shed light both on the existence of true persistence and on its underlying drivers. For example, Raymond *et al*. (2010) conclude that in Dutch manufacturing there is true persistence in the probability of innovating in high-tech industries and spurious persistence in the low-tech sector. The emphasis therefore shifts to the determinants of persistence.

Much of the empirical work analyzing the determinants of innovation persistence has focused on the persistence in the achievement of innovation outputs such as patents or product innovations, and cover a wide range of countries (*inter alia* Geroski *et al*. 1997; Crépon and Duguet, 1997; Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001; Cabagnols, 2006; Roper and Hewitt-Dundas, 2008; Peters, 2009; Ganter and Hecker, 2013; Fontana and Vezzulli, 2016). The choice of innovation measure may influence the findings on whether there is persistence and on its determinants. For example, studies of patents typically find relatively low rates of

[2] A third potential explanation for persistence – financial constraints – has received rather less attention in the theoretical and empirical literature (Ganter and Hecker, 2013; Hall, 2002).

persistence (e.g. Malerba *et al*. 1997; Malerba and Orsenigo, 1999; Cefis 2003), while studies concentrating on (product) innovations or productivity are somewhat mixed, but on balance do tend to find evidence of true persistence (Roper and Hewitt-Dundas, 2008; Raymond *et al.*, 2010; Ganter and Hecker, 2013; Hecker and Ganter, 2014; Triguero *et al*., 2014). Arqué-Castells (2013) suggests this may in part reflect different underlying mechanisms determining persistence. For example, persistence in patenting need not be particularly strong at the firm level for the firm to remain an innovation leader, as patenting often involves winning patent races. By contrast, measures of innovation based on product innovation measures are less demanding indicators, and may better reflect learning effects and dynamic returns to scale.

In the case of R&D, the most likely reason for persistence *a priori* would appear to be sunk costs resulting in entry barriers which favour incumbents and deter entrants to R&D activity (Sutton 1991). Unsurprisingly, empirical research on R&D persistence has tended to focus on the sunk cost argument, with correspondingly little emphasis on possible learning effects in R&D. Several studies have analyzed innovative persistence from the perspective of the R&D investment, generally finding evidence of true persistence. On the one hand, both Mañez *et al.* (2009) and Peters (2009) specifically analyze the drivers of firms' persistence in R&D engagement. On the other hand, Artés (2009), Arqué-Castells (2013) and Garcia-Quevedo *et al.* (2014) for Spanish manufacturing firms, Piva and Vivarelli (2007, 2009) for Italian manufacturing firms, Raymond *et al.* (2010) for Dutch manufacturing firms and Woerter (2014) for Swiss firms explicitly recognize the existence of persistence on firms' decision of engaging in R&D activities. However, most of these studies use first order autoregressive dynamic models to analyze the role of sunk costs in the decision to carry out R&D, and they do not pay much attention to the role that intrinsic learning processes to the continuous realization of R&D activities can play as explanatory factor of the persistence of firms in R&D engagement. By contrast, Máñez *et al.* (2015) obtain empirical evidence suggesting that both sunk costs and learning effects are important determinants of R&D persistence: however, their methodology does not permit quantification of the importance of these two factors.

While it is natural to conceive of R&D persistence as being the preserve of larger firms, there is good reason to consider the issue with regard to SMEs. First, there is considerable evidence that official statistics systematically underestimate the extent of R&D carried out by SMEs, at least in part because of their tendency to concentrate on development rather than on fundamental research (Kleinknecht, 1987; Roper, 1999). Second, many governments have a policy objective of increasing SME competitiveness, often via innovation and internationalisation, and so the issue of persistence in R&D and innovation among smaller firms becomes of interest. Theoretically, there are reasons to believe the drivers of persistence may differ between smaller and lager firms. To the extent that small firms have more difficulty making the necessary investments for R&D, the associated sunk costs are more likely to provide a barrier to R&D entry for small than large firms. With respect to learning effects, theory provides rather more ambiguous lessons. SMEs may typically be further from the technology frontier than large firms, suggesting that they may have more to learn from persistence in R&D activity. But they may also lack the absorptive capacity to successfully turn the opportunities for learning into future innovation or productivity, implying that the relative importance of both sunk costs and learning with respect to SMEs versus large firms is an empirical issue. The one piece of research which explicitly compares the drivers of R&D persistence among large and small firms (Máñez *et al.,* 2015) indicates that sunk costs and learning may be present in both sets of firms, but sheds no light on the relative size of these effects in either case.

To summarise, the literature to date suggests that R&D persistence is a real phenomenon, that both sunk costs and learning effects may be at work, and that the drivers of persistence may differ between large and small firms. However, there is less clarity on the relative importance of sunk costs versus learning effects, or in precisely how the drivers of R&D persistence differ among firms of different sizes.

3. Data and R&D patterns

The data are drawn from the Spanish Survey of Business Strategies (ESEE, henceforth) for the period 1991–2014. This is an annual survey sponsored by the Spanish Ministry of Industry and carried out since 1990 that is representative of Spanish manufacturing firms classified by industry and size categories. It provides exhaustive information at the firm level. In particular, the ESEE provides information about firms' strategies, e.g., decisions firms take regarding R&D strategies.[3]

The sampling procedure of the ESEE is the following. Firms with less than 10 employees were excluded from the survey. Firms with 10–200 employees (SMEs) were randomly sampled, representing around 5% of the population in 1990. All firms with more than 200 employees (large firms) were requested to participate, obtaining a participation rate around 70% in 1990. Important efforts have been made to minimize attrition and to annually incorporate new firms with the same sampling criteria as in the base year, so that the sample of firms remains representative over time. From the ESEE survey we sample out those firms' observations that

[3] We do not use the year 1990 as the ESEE fails to supply information for some of the variables involved in the empirical analysis. Please check the web page of the ESEE in Fundación SEPI for further information: http://www.fundacionsepi.es/esee/en/epresentacion.asp.

fail to supply relevant information about all variables involved in our analysis. After cleansing the data, we end up with a sample of 29,795 observations corresponding to 2,692 firms.[4]

The ESEE provides information both about whether the firm invest in in-house R&D, and in case it invests how much it does. In particular, the question we use to determine firm's R&D status is: "Indicate if during this year, the firm has internally undertaken R&D activity." (in-house R&D). As for the question on the quantity the firm invests in internal R&D, it is as follows: "Indicate the total expenditure in internal R&D that the firm has carried out this year". Recall that to simplify exposition, unless otherwise stated along the paper when we refer to R&D we mean internal R&D.

Looking at the distribution of firms performing/not performing R&D in the data (see Table 1), we observe that 47.70% of the firms never undertake R&D, 12.93% undertake R&D every year they are in the sample, and 39.38% are switchers (i.e. they change from undertaking to non-undertaking R&D or vice versa at least once). Comparing for size groups, the percentage of firms that always undertake R&D is more than five times higher for large firms than for SMEs (31.16% and 5.87%, respectively). Conversely, the percentage of firms that never perform R&D is substantially higher for SMEs than for large firms (whilst 61.15% of SMEs never perform R&D, for large firms this percentage is 12.92%). As for switchers, whereas 55.98% of large firms are switchers (the highest percentage among large firms), this percentage for SMEs is 32.97%. The ratio in-house R&D expenditure (in percentage) over sales is 1.60% for the firms that perform in-house R&D. Furthermore, this ratio is higher for SMEs (1.95%) than for large firms (1.35%)

As explained in detail in Section 4.2.3, the only group of firms that contribute to the identification of the sunk costs and learning effects in our estimation exercise are the switchers. Therefore, we circumscribe the rest of this section to the analysis of this group of firms. Thus, Table 2 shows both for the full sample of switchers and by sizegroup the percentage of firms with *j* number of R&D spells.[5] Most of firms show either one or two R&D spells: 62.2% (51.2%) of SMEs (large firms) have a unique R&D spell; and, 28.9% (39.3%) have two R&D spells. Furthermore, the maximum number of R&D spells observed is five (both one SME and one large firm show five R&D spells)

With the aim of gaining insight on the issue of R&D persistence, we display in Figure 1 the Kaplan-Meier survivor function corresponding to large firms and SMEs. The Kaplan-Meier

[4] Further, since when using Blundell *et al.* (1999, 2002) method to control for unobserved heterogeneity in the estimation of the dynamic equation of the decision to engage in R&D, we use a 4 years pre-sample period and we lag explanatory variables one period, we require firms to be at least 6 years in the sample to be considered in estimation.

[5] Spell is defined as an episode of continuous engagement in R&D.

(empirical) survivor functions shows the percentage of R&D spells that continue in operation after a given number of years of uninterrupted R&D engagement. It is interesting to note that the survivor function for SMEs is always below that of large firms, indicating that SMEs R&D spells are shorter than those of their larger counterparts. Thus, whereas the mean (median) duration of R&D spells for SMEs is 4.23 (2), for large firms it is 6.63 (4) years. Furthermore, we can observe that for large firms and SMEs, the percentage of firms that cease undertaking R&D decreases as firms age in R&D activities (the Kaplan-Meier survivor function gets flatter as duration in R&D lengthens). This should be interpreted as evidence of negative duration dependence, that Mañez *et al*. (2015) link to learning processes arising from continuous engagement in R&D.[6]

Figure 2 shows how R&D expenditure in logs (and deflated to obtain real values) changes with R&D age. More specifically, the figure shows the growth of real R&D expenditure relative to the first year performing R&D. Thus, each point in the lines shows the ratio of the average real log R&D expenditure for firms with R&D age t (for t = 1,..,15) to the average real log R&D expenditure for firms in their first year performing R&D. In this figure, we can observe an increasing trend of R&D expenditure both for SMEs and large firms. The result is that after 15 years of continuous R&D performance, average R&D expenditure for large firms and SMEs is 12.9% and 8% higher, respectively, than the first year performing R&D. This increase in R&D expenditure is consistent with a process of learning, although it is possible that part of this growth in R&D activities could be due by a process of selection of the more efficient firms into performing R&D.

Figure 3 shows the evolution of in-house R&D intensity (defined as the ratio of in-house R&D expenditure over sales) with respect to R&D age. Two observational facts are worth to mention about this figure. On the one hand, regardless of R&D age, R&D intensity of R&D performing SMEs firms is higher than R&D intensity of R&D performing large firms. On the other hand, although we do not observe a clear pattern on the evolution of R&D intensity with respect to R&D age, it seems that for SMEs shows a slightly decreasing trend up to 9 years of continuous R&D performing and then an increasing trend. For large firms, the slightly decreasing extends up to 10 years of R&D age, and then this decreasing trend is reversed.

4. Empirical Model and Estimation Issues.

In this section we adapt and extend for the case of R&D the model proposed by Timoshenko (2015) to analyze the role of sunk costs and learning effects in firms' export decisions.

[6] In the terminology of duration models, negative duration dependence implies that the longer the spell, the lower the hazard of ending it at a given R&D survival time j.

4.1 Age dependence of R&D profits

Let $\pi_{it}(z_{it}, A_{it}, p_t)$ represent the increment to expected profits for firm i associated to engaging in R&D in period t (in comparison to a situation in which the firm does not perform R&D), assuming that the profit-maximizing level of R&D expenditure is always chosen. It is assumed that the extra profits associated to perform R&D are a function of productivity (z_{it}), a vector of market-level variables (p_t) that the firm takes as exogenous (such as market demand evolution or interest rates), and R&D experience (A_{it}). The novelty with respect to others models that analyze the firm dynamic decision of undertaking R&D is the inclusion of R&D experience as a determinant of the extra profits associated to engaging in R&D. We assume $\pi_{it}()$ to be an increasing function of R&D experience (A_{it}) on the grounds of previous empirical studies that relate persistent R&D engagement to a larger production of innovations that could result in larger demand and/or markups (Beneito *et al*., 2015) with the consequent positive effect in profits; or, directly to higher profitability such as it is the case of Cefis and Ciccarelli (2005). In both cases, the theoretical arguments linking persistent engagement in R&D and profits are the processes of learning-by-doing, learning-to-learn and increasing dynamic returns that characterize R&D activities. We will refer to this assumption as the "age dependence assumption" or "learning assumption".[7]

More specifically, we assume that *R&D experience,* A_{it}, is a discrete variable that measures the duration of firm i last period of consecutive years of R&D engagement immediately before arriving to period t, (i.e., the duration of the most recent R&D spell immediately before period t). $A_{i,t} = n$ implies that firm i performed R&D continuously between $t - n$ and $t - 1$. Further, as Timoshenko (2015) we assume full depreciation of R&D experience once a firm stops performing R&D.[8] Therefore, if firm i did not perform R&D in period $t - 1$, regardless of its previous R&D experience before period $t\text{-}1$, $A_{i,t} = 0$. Further, let productivity z_{it} follow an exogenous Markov process of the form $\mathrm{z}_{it} = \rho \mathrm{z}_{it-1} + \nu_{it}$.

Knowing its productivity and given its previous R&D experience, firm i decides in every period t whether engaging or not in R&D. If the firm i decides to perform R&D in period t its extra profits associated to perform R&D are given by $\pi(z_{it}, p_t, A_{it})$ if the firm performed R&D in period $t\text{-}1$ and $\pi(z_{it}, p_t, A_{it}) - f_e$ if the firm was not engaged in R&D in period t - 1. Where, f_e are the sunk entry costs in which firms have to incur to start performing R&D. These initial sunk

[7] Timoshenko (2015) uses the same terminology to refer to the export experience dependence of the extra profits associated with export performance.

[8] We will relax the assumption of full depreciation of R&D experience once a firm quits performing R&D in our empirical exercise.

costs are associated with the establishment of a department of R&D, purchase of specific assets and recruitment and/or training of specialized personnel.

4.2 A dynamic model of the R&D decision in presence of learning effects

4.2.1 Empirical model

In the presence of age-dependence, the persistence in R&D that previous literature has associated to the existence of sunk costs (Mañez *et al.,* 2009; Peters, 2009; Arque-Castells, 2013) could be also attributed to accumulation of R&D experience, and so to a process of learning. In what follows, we present a model of R&D decision in presence of learning effects that closely follows that developed by Timoshenko (2015) to model export participation.

Let be y_{it} the R&D decision of firm i in period t (with y_{it} = 1 if firm i engages in R&D and zero if it does not). Firms' decision on whether engaging or not in R&D results from maximizing the present discounted value of profits in the following Bellman equation:[9]

$$V(\mathrm{z}_{it}, \mathrm{A}_{it}, \mathrm{Y}_{it-1}) = \max_{\mathrm{Y}_{it}\in\{0,1\}} \{\pi(\mathrm{z}_{it}, \mathrm{A}_{it}) - f_e(1-\mathrm{Y}_{it-1}) + \delta E_{\mathrm{z}_{it+1}} V(\mathrm{z}_{it+1}, \mathrm{A}_{it+1}, \mathrm{Y}_{it}), \delta E_{\mathrm{z}_{it+1}} V(\mathrm{z}_{it+1}, 0, \mathrm{Y}_{it})\} \qquad (1)$$

where the discount factor is denoted by δ.

If we omit experience effects (i.e. if we omit A_{it}), equation (1) is the typical R&D decision problem considering sunk costs and uncertainty (see for example Mañez, 2009 or Peters, 2009). The policy function corresponding to this problem is described by two productivity thresholds: the entry threshold (z_H) and the exit threshold (z_L) with $z_L < z_H$.

$$y_{it} = \begin{cases} 1 \text{ if } z_{it} \geq z_H - (z_H - z_L)Y_{it-1} \\ 0 \text{ otherwise} \end{cases} \qquad (2)$$

Equation (2) implies that firm i will perform R&D in t if its productivity is above a given productivity threshold that depends on whether the firm was engaged in R&D or not in period t -1. If firm i did not perform R&D in period t – 1, it will only perform R&D in period t if $z_{it} > z_H$. However if firm i was engaged in R&D in period t -1, to continue performing R&D in t, its productivity has just to be higher than the lower productivity threshold z_L ($z_{it} > z_L$). Therefore, the existence of sunk costs produces a wedge between entry and exit productivity, this difference (z_H –z_L) is usually known as "hysteresis band". This wedge implies that the probability of performing R&D in period t depends on whether or not the firm performed R&D in in period *t-1*. Thus, firms that performed R&D in the previous period are more likely to

[9] We omit p_t from $\pi()$ as it is a vector of market level variables exogenous to the firm.

continue performing R&D than firms that were not engaged in R&D. Therefore, the existence of sunk costs itself is enough to cause R&D persistence. It is interesting to note that in this setup the higher the sunk R&D starting up costs, the larger is the hysteresis band and, hence, the more the expected R&D persistence. However, if sunk R&D costs are equal to zero then $z_H = z_L$ and the probability of engaging in R&D becomes independent of previous R&D history.

Introducing the probability of learning in this setup (such as in equation (1)) crucially affects the role played by sunk costs to explain R&D persistence. Proposition 1 in Timoshenko (2015), in a similar setup but related to the export decision, describes the properties of the thresholds of participation in a given activity when the profits associated with the performance of such activity depends both on sunk costs and experience performing the activity.

This proposition is based on the three following properties: i) $z_L(A_{it})$ is decreasing in A_{it} ; ii) if $f_e = 0, z_H = z_L(0)$; and, iii) if $f_e > 0, z_H > z_L(0)$. Since, now the exit threshold depends on A_{it}, the hysteresis band $[z_H - z_L(A_{it})]$ depends on previous R&D experience. Thus, it is assumed that the longer the spell of uninterrupted R&D, the more intense the learning (caught in the model by a lower $z_L(A_{it})$) and the wider the hysteresis band. From the point of view of R&D persistence, this assumption implies that the longer the R&D spell, the higher is the probability that the firm continues engaged in R&D.

After considering the possibility of learning, the R&D participation in equation (2) can be rewritten (adding and subtracting $z_L(0)$ from the coefficient of Y_{it-1}) as:

$$y_{it} = \begin{cases} 1 \text{ if } z_{it} \geq z_H - ([z_H - z_L(0)] + [z_L(0) - z_L(A_{it})])Y_{it-1} \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

If firm i did not invest in R&D in period t -1 ($Y_{it-1} = 0$) then the operating productivity threshold is $z_{it} > z_H$. However, if firm i invested in R&D in period t *-1* ($Y_{i,t-1} = 1$) then the binding productivity threshold is lower, and firm i will perform R&D as long as $z_{it} > z_L(A_{it})$. Therefore, firms with longer R&D experience (higher scope for learning) are more likely to continue undertaking R&D.

Interestingly, if f_e =0 (sunk R&D starting-up costs are zero) by Proposition 1 in Timoshenko (2015), $z_H = z_L(0)$, and then the coefficient of Y_{it-1} in equation (3) becomes $z_L(0) - z_L(A_{i,t})$. Thus, the productivity threshold if firm i was engaged in R&D in period t -1 is $z_{f_e=0} = z_L(A_{it})$. For any $A_{it} \geq 1, z_L(A_{it}) < z_H$, then $z_{f_e=0} < z_H$. This implies that once one considers the possibility of learning, even in the absence of sunk R&D costs, previous R&D experience has a positive impact on the probability of continuing engaged in R&D (as learning has a positive effect on profits). It should be noted that in this setup, it is assumed that once a firm decides to cease R&D activities, experience fully depreciates and when deciding to restart performing R&D in the future it will need a better productivity shock.

Therefore, equation (3) shows that the dependence of current R&D status on previous period R&D status is a sign of state dependence, but not necessarily of sunk costs, as state dependence could be the result of learning, sunk costs or both.

4.2.2 Estimating equation

From equation (3), following Timoshenko (2015), it is possible to develop an empirical model of R&D participation. The main interest here lies on decomposing state dependence in its sunk costs and learning components. Let us decompose the expression in front of Y_{it-1} in equation (3) into its two elements $[z_H - z_L(0)]$ and $[z_L(0) - z_L(A_{it})]$. Further, let us call the first elements β_{sc}. In the absence of entry sunk costs by Proposition 1 in Timoshenko (2015) $z_H = z_L(0)$ and, thus $\beta_{sc} = 0$. In the presence of sunk R&D costs $z_H > z_L(0)$ and so $\beta_{sc} > 0$. We will refer to β_{sc} as the sunk cost component of R&D state dependence. The second element of the expression in front of of y_{it-1}, $[z_L(0) - z_L(A_{it})]$, catches the effect of R&D age on the probability of performing R&D (i.e. how the R&D continuation threshold decreases with R&D experience). After this decomposition, equation (3) can be rewritten as:

$$Y_{it} = \begin{cases} 1 \ \text{ if } (z_{it} - z_H) + \beta_{SC} Y_{it-1} + [z_L(0) - z_L(A_{it})] Y_{it-1} \geq 0 \\ 0 \ \text{ otherwise} \qquad \ldots. \end{cases} \tag{4}$$

Finally, if as in Timoshenko (2015) we assume a logarithmic parametrization of the age effect, $\beta_a \ln(A_{it} + 1)$, and that $(z_{it} - z_H)$ may be parametrized as $\alpha + \gamma X_{it}$, our estimation equation is given by:

$$Y_{i,t} = \begin{cases} 1 \ \text{ if } \alpha + \beta_{SC} Y_{it-1} + \beta_a \log(A_{it} + 1) + \gamma X_{it} + \epsilon_{it} \geq 0 \\ 0 \ \text{ otherwise} \qquad \ldots. \end{cases} \tag{5}$$

where ϵ_{it} is the error term (its structure is detailed later in the next section); and, X_{it} includes a vector of observed firm characteristics that may affect $(z_{it} - z_H)$ and so firms' R&D engagement decisions.

The logarithmic functional assumed for the R&D age allows to separate the state dependence effect into its two components. Thus, for example, in equation (5) the effect of one-year R&D experience is given by $\beta_{SC} + \beta_a \log(2)$.

4.2.3 Estimation issues

In order to isolate the structural state-dependence parameters in equation (5), we use an econometric framework that controls for other competing sources of persistence in R&D

decisions, such as firm heterogeneity, or serial correlation in exogenous shocks. Most of this task is accomplished by including observable firm characteristics (X_{it}) -already included in equation (5)-, but we will also include industry dummies (s_i) and year effects (μ_t) in equation (5). Time effects aim to capture macro-level changes in market conditions that are common across firms, such as the business cycle, credit-market conditions, overall changes in demand and other time-varying factors. Industry dummies control for unobservable characteristics of markets where firms compete such as the use of technology or firm-specific behavior by industry.

Furthermore, it is important to recall that the theoretical model above assumes full depreciation of sunk costs and R&D experience once a firm ceases performing R&D. However, it is reasonable to assume that this depreciation does not happen all in one period but gradually as the firm continues without performing R&D. To account for the possibility of lower sunk startup costs and lower learning depreciation (in our setup we cannot distinguish between both effects) for firms that restart R&D activities after *j* years without performing them, we include in estimation the set of variables $\tilde{Y}_{it-j}$which take value 1 if the last time a firm performed R&D was in year $t-j$ (in estimation we assume $j \leq 3$).

Yet, there may be firm unobserved factors affecting causing persistence such as product attributes, managerial skills or R&D personnel ability. For this reason, we assume that ϵ_{it} in equation (5) has two components, a permanent firm specific effect (α_i) and a transitory component (u_{it}), then $\epsilon_{it} = \alpha_i + u_{it}$. Hence, we allow for two sources of serial correlation in ϵ_{it}. This is an important issue since, whether or not u_{it} are independent across *t,* ϵ_{it} will be always serially correlated because of α_i

Therefore, after including observable firm characteristics, industry dummies, time effects, the possibility of lower sunk cost when restarting R&D activities and the unobserved heterogeneity component, equation (5) becomes:

$$Y_{i,t} = \begin{cases} 1 \text{ if } \alpha + \beta_{SC} Y_{it-1} + \beta_a \log(A_{it}+1) + \gamma X_{it-1} + \delta_j \tilde{Y}_{it-j} + \mu_t + s_i + \epsilon_{it} \geq 0 \\ 0 \text{ otherwise} \qquad \qquad .... \end{cases} \qquad (6)$$

In equation (6) to avoid simultaneity problems we lag one period the observable firm characteristics included in X_{it}.

Finally, as we aim to analyze whether the relative importance of sunk costs and learning effects in explaining R&D persistence differs between SMEs and large firms, we consider a version of equation of (6) in which we interact the sunk R&D costs variable and the experience effects variable by the dummy variable d_L, that takes value 1 for large firms (firms with more than 200 workers in the ESEE) and zero otherwise. After accounting for differences between SMEs and large firms, equation (6) can be rewritten as:

$$Y_{i,t} = \begin{cases} \alpha + \beta_{SC} Y_{it-1} + \beta_{SC}^{L} Y_{it-1} d_L + \beta_a \log(A_{it}+1) + \beta_a^{L} \log(A_{it}+1)\, d_L + \beta_l d_L + \\ +\delta_j \tilde{Y}_{it-j} + \gamma X_{it-1} + \mu_t + s_i + \epsilon_{it} \geq 0 \\ 0 \ \text{ otherwise} \end{cases} \tag{7}$$

For the sake of robustness, in the estimation of the dynamic panel data discrete choice models of the decision to perform R&D of equations (6) and (7), we control for correlated unobserved firms' heterogeneity using two alternative approaches proposed by Blundell *et al.* (1999, 2002) and Wooldridge (2005). Both approaches stand to making assumptions about the distribution of the unobserved effects (α_i) conditional on observed covariates and adopting a conditional maximum likelihood approach (Chamberlain, 1982).

Following Blundell *et al*. (1999, 2002), we may model the distribution of α_i as:

$$\alpha_i = \delta_0 + \delta_1\, \bar{q}_i + e_{it} \tag{8}$$

where $\bar{q}_i$ is a vector including both the pre-sample mean of the dependent variable and the pre-sample mean of all remaining regressors. Blundell *et al*. (1999) suggests that the firms' permanent effects might be captured by the entry pre-sample mean of the dependent variable, which should act as a sufficient statistic for unobserved firm heterogeneity Nevertheless, Blundell *et al*. (2002) suggest that, given that in some cases not all the permanent effects might be captured by the pre-sample means of the dependent variable, it might be convenient, when available, also include pre-sample means of all remaining regressor. Finally, e_{it} represents the error term which is assumed to be independent of the of the pre-sample means of the dependent variable, the pre-sample means of the rest of explanatory variables, the explanatory variables and the idiosyncratic error term of the main equation. As we use as presample period 1991-1994 and the explanatory variables in in equation (6) are lagged one period, when following this approach, we carry out estimation for the period 1996-2014. [10]

Wooldridge (2005) approach models the distribution of $\alpha_i$as:

$$\alpha_o = \delta_0 + \delta_1 \bar{q}_i + \delta_2 Y_{io} + e_{it} \tag{9}$$

where $\bar{q}_i$ is a vector including Mundlak-Chamberlain means (Chamberlain, 1980; Mundlak, 1978). Thus, it includes the within-means of all the exogenous control variables. Y_{i0} represent the initial conditions and e_{it} is the error term which is assumed to be independent of the initial conditions, the explanatory variables, and the idiosyncratic error term in our main estimation

[10] Experimenting with different pre-sample periods gave qualitatively similar results.

equation.[11] We cannot include the within mean of the R&D Age variable as this variable is predetermined, its value in t depends both on past and future realizations of the R&D decision variable. Semykina (2018) suggests that, once time means of the exogenous control variables ($\bar{q}_i$) are included, the effects of the corresponding time-varying covariates are estimated based on their deviations from the individual time means. Therefore, this makes Mundlak-Chamberlain method analogous to fixed effects estimations of linear models. When using this estimation method, as Y_{i0} refers to the value of the dependent variable in 1991 and the explanatory variables in equation (6) are lagged one period, we carry out estimation for the period 1993-2014.

Assuming that the strategies proposed above play their role to capture individual unobserved effects, proper identification of the parameters of interest in our model requires a careful examination on the type of information that within firm variation conveys for three types of firms: firms that never invest in R&D; firms that always in invest in R&D; and, switchers, i.e. firms that invest in R&D some periods but do not do it other periods. Firms that never invest in R&D do not show any variation in the R&D spell length variable and, therefore, they do not contribute to the identification of the coefficients of this variable. As for firms that always invest in R&D, R&D experience and firm age change at a constant rate every year. Hence, within firm variation of these two variables is collinear, and so it will not be possible to separately identify the coefficient associated to these two variables. This implies that one cannot be sure about whether the coefficient of the R&D experience variable is actually capturing learning or different stages in the firms' life cycle. Thus, identification of the R&D age and the firm's age coefficients should rely on switchers. For these firms, the R&D age variable

[11] We have also experimented using Semykina (2018) to model the unobserved individual effects. According to this approach, one can assume that that the unobserved individual effects is function only of those covariates that theoretically are more likely to be correlated with the unobserved individual effects. As a first possibility, we have considered that the individual effects are only correlated to firms internal and external financial constraints variables. In this sense, their within-means could be considered as measures of firms' financial stability, and so they could be considered as proxies for unobserved firm-specific characteristics. As a second possibility, we have considered that the individual effect is mainly related to management quality and so we assume that the unobserved individual effect is only correlated to the two labour qualification variables included as explanatory variables. Result for the main variables of interest are quite similar to those using the two estimation approaches described above. These results are available upon request.

both shows within firm variation and its variation is not collinear to the variation of the firms' age variable. Therefore, we carry out all our estimation using just the sample of switchers.[12]

Nevertheless, even if we carry out our estimations only with the sample of switchers, there is an additional element that we should consider in the identification of the R&D age parameter. It is that selection on age could be still at work, so, for example we will only observe R&D ages higher than fifteen years for firms older than 15 years. To account for this issue, in Appendix D, we show the estimates of our variables of interest when splitting our sample on quartiles according to firms' age.

4.3. Indirect effects of R&D experience on the likelihood of R&D engagement

Unlike Timoshenko (2015), we propose that proper quantification of the effects of sunk costs and learning on R&D persistence in equations (6) and (7) requires acknowledgement of the possible indirect effect of R&D experience (proxied by R&D age) on the likelihood of performing R&D that accrue through its enhancing effects on productivity. Therefore, we consider that R&D experience may affect the probability of R&D engagement both directly and indirectly. By direct effects we mean those stemming from the inherent learning associated to continuous R&D engagement. By indirect effects we mean those that accrue to the probability of performing R&D through increased productivity

Exploring the indirect effects of R&D experience on the likelihood of performing R&D implies both to recognise which is the link between firms' R&D experience and productivity; and, the link between productivity and R&D engagement.

There are, at least, three strands in the literature supporting a positive relationship between R&D and firms' productivity. The first is based on the well-known R&D capital stock model of Griliches (1979, 1980) that analyses the relationship between R&D investments and productivity growth (see Griliches, 2000, for a survey). The second strand in the literature rendering theoretical support to the relationship between R&D and productivity growth is the active learning model (Ericson and Pakes, 1995; Pakes and Ericson, 1998). According to this model, R&D investments contribute to improve firms' productivity over time. Finally,

[12] In any case, it should be noted that even after restricting estimation to the subsample of switchers, the R&D spell length variable could be correlated with the error term ($E[A, \epsilon|X \neq 0]$) because those firms affected by negative shocks are likely to quit R&D more often and have shorter R&D spells and the other way around. Nevertheless, to address such endogeneity issue is difficult when information on credible exogenous sources of variation in R&D spells is not available. We are grateful to an anonymous referee on his/her suggestions about the relevance of each type of firms on the identification of the parameters of interest in our estimation.

endogenous growth theory is the third strand of the literature stressing the importance of R&D for productivity growth (Romer, 1990; Aghion and Howitt, 1992). More specifically on the effect of R&D experience on productivity, results in Beneito *et al*. (2014) suggest first, that R&D experience has a positive impact both in the number and the quality of the innovations; and, then, that these innovations have a positive effect on productivity.

As for the positive link between productivity and likelihood of performing R&D, the usual argument is a process of self-selection of the more productive firms into performing R&D (only the more productive firms can afford the sunk costs associated with R&D activities, see Sutton, 1991; Manez *et al*., 2009).

Accounting for the potential role of R&D experience in forging future firms' productivity involves departing from Timoshenko (2015) assumption of an exogenous Markov process for the law of motion of productivity, and considering an endogenous Markov process in which past R&D experience is explicitly allowed to affect current productivity (see DeLoecker, 2013 or Doraszelski and Jaumandreu, 2013 for similar strategies for exports and R&D, respectively).[13] The consideration of this endogenous Markov process makes it possible to analyse the existence of positive returns of R&D experience on productivity. In the next paragraphs we briefly sketch how to estimate total factor productivity under the assumption of and endogenous Markov process for the law of motion of productivity. For a more detailed explanation see Appendix B.

To estimate TFP, we assume that firms produce using a Cobb-Douglas technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + z_{it} + \eta_{it} \qquad (10)$$

where $y_{it}$is the natural log of production of firm i at time t, $l_{it}$is the natural log of labour measured as the number of effective hours worked), m_{it} is the log of intermediate materials, and $k_{it}$is the log of capital (adjusted for for capital utilization).[14] As for the unobservables, z_{it} is productivity (not observed by the econometrician but observable or predictable by the firm) and η_{it} is a standard *i.i.d.* error term that is neither observable nor predictable by the firm. Further, we assume that capital is a state variable, whereas labour and materials are variable non-dynamic inputs that can be adjusted whenever the firm faces a productivity shock.

We follow Wooldridge (2009) to get consistent estimates of input elasticities and estimates of TFP residuals. According to Wooldridge (2009), the semiparametric *control function* approaches proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) can

[13] Timoshenko assumes an AR1 process for the law of motion of productivity. She estimates a value added production function using Levinsohn and Petrin (2003) algorithm.

[14] Production, intermediate materials and capital have been deflated using individual firms' price deflators.

be reconsidered as consisting of two equations that can be jointly estimated by GMM using the appropriate instruments. The first equation deals with the problem of endogeneity of labour and materials. The second equation tackles the issue of the law of motion of productivity.

In the first equation, to solve the problem of endogeneity of labour and materials, we follow Levinshon and Petrin (2003) strategy and proxy for firm productivity inverting the demand of intermediate materials.[15] In this way, unobserved productivity can be written as a function of observables. In the second equation, to proxy for *unobserved* firm productivity, we assume that productivity evolves according to an endogenous Markov process:

$$z_{it} = f(z_{it-1}, R\&D\ Age_{it-1}) + \nu_{it} \tag{11}$$

where $f(\cdot)$ is an unknown function that relates productivity in t to productivity in *t-1* and to past R&D experience (measured by R&D age), and ν_{it} is an innovation term by definition uncorrelated with k_{it}. This endogenous Markov process allows past R&D experience explicitly affects current productivity.

The estimation of the production of the production function (10) for each of the 20 industries of the ESEE provides both estimates of the input elasticities at industry level, and firm specific estimates as a residual. Estimates of the input elasticities are shown in Table B1 in Appendix B.

Finally, it should be noted that in our estimation strategy, direct effects of R&D experience on R&D persistence are measured by the estimated coefficient of R&D age in equations (6) and (7). Empirical support for the existence of indirect effects will require: first, to show that R&D experience has a positive impact on productivity; and second, a positive and significant estimate of our productivity measure (included as explanatory variable) in equations (6) and (7).

5. Estimation results

Table 3 and 4 present the estimation results of our dynamic model for the decision to engage in R&D (equations 6 and 7). Table 3 shows the results corresponding to the estimation in which unobserved effects (α_i) are modelled following Wooldridge (2005) approach (*WO* estimation); and, Table 4 displays the results corresponding to the estimation using Blundell (1999, 2002) approach to model unobserved heterogeneity (*BL* estimation).

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[15] To invert the demand of materials, we rely on the assumptions that this function is strictly monotonic in unobserved productivity and that productivity is the only unobservable in the function (*scalar unobservable assumption*).

As for the set of variables included to catch the role of firms' observable characteristics we include the usual variables in this type of analyses such as size (*log(Capital stock)*), productivity (*log(TFP)*) and age (*log(Age)*. It is important, to recall that the inclusion of the productivity variable is a key element to capture possible indirect effects of R&D experience that accrue to the probability of R&D engagement through enhanced productivity.

We also include two variables capturing firm ownership structure, namely, foreign capital participation *(Foreign capital*) and whether the firm is a limited liability corporation (*Limited liability*). Foreign capital is included not as a measure of internationalisation per se, but because of the well-established tendency for foreign-owned establishments to have systematically different R&D and innovation tendencies from indigenously-owned firms (Love *et al*. 2009). As for the limited liability control, most companies do indeed have limited liability structure – but not all, hence the need for the control. Furthermore, we consider measures of both internal and external financial constraints (*cash-flow de*v and *long-run cost dev,* respectively), a set of variables proxying for industrial structure (*N. of competitors 0-10, N. of competitors 10-25, N. of competitors>25* and *Market share*), a set of variables proxying for firm's labour qualification (*High Skill Labour* and *Med-Skill Labour*) and two dummy variables capturing demand evolution (*Expansive demand* and *Recessive demand*).[16] Finally, we include an R&D appropriability variable (*Appropriability*) to account for the tendency for sectors to vary systematically in their capacity for firms to capture the benefits of R&D investment. In estimation, to avoid simultaneity problems we lag one period all variables except the ownership structure variables as they are usually time invariant. Table A1 in the Appendix provides detailed information about these variables, Table A3 supplies descriptive statistics and correlations.[17]

5.1 Sunk costs and direct effect of R&D experience

Column 1 of Tables 3 and 4 shows the estimation results corresponding to a dynamic autoregressive model of R&D engagement, in which firms' R&D decision in year t depends on the R&D decision in period t - 1 and on a vector of control variables (Model 1). This first estimation does not include any variable capturing possible R&D age effects. The estimate of the one-period lagged R&D decision is quite stable regardless of the method used to model

[16] The expansive and recessive variables are subjective, but there is no readily available objective measures at the firm level.

[17] Nominal variables are deflated using industry specific deflators according to the 20 sectors of the NACE. Rev. 2 classification.

individual unobserved heterogeneity and ranges between 1.820 and 1.940 in *WO* and *BL* estimations, respectively. This estimated coefficient is interpreted usually as arising uniquely from sunk costs.

Columns 2 and 3 of Tables 3 and 4 present the estimation results obtained when including in estimation R&D age to capture direct effects of R&D experience. In column (2), $g(A_{i,t})$ is parametrized as a quadratic function (Model 2) and in column 3 as a logarithmic function (Model 3). In column 2, the positive and significant estimate for the linear term of the $R\&DAge_{it}$ (that ranges between 0.137 in *BL* and 0.155 *WO*) and, the negative and significant sign of the quadratic term ($(R\&DAge_{i.t})^2$) suggest that the probability of performing R&D increases with R&D age at decreasing rate. A possible interpretation in terms of learning would imply that direct learning effects associated with continuous R&D engagement are more intense in the first years performing R&D. The positive and significant estimate for $log(R\&D\ Age_{i,t})$ in column 3 offers additional support for the existence of direct learning effects associated to the continuous engagement in R&D activities. This estimated coefficient remains quite stable regardless of the method used to capture unobserved individual effects (it is 0.304 and 0.246 in the *WO* and *BL* estimations, respectively).

Nonetheless the specific functional form assumed for $g(A_{i,t})$, the consideration of R&D age effects results in a reduction of the estimated sunk-cost parameter. In the quadratic specification it is 1.540 and 1.658 in *WO* and *BL*, respectively; and, in the log specification it ranges from 1.482 to 1.650 (in *WO* and *BL*, respectively). Our preferred specification is the one that assumes a logarithmic specification for $g(A_{it})$. As was shown in section 4, it permits the decomposition of state dependence into the effects of sunk costs and learning. Using this specification for R&D experience, we can observe that the estimate of the true effect of sunk costs in *WO* and *BL* are about a 18.5% and 15% lower, respectively, when one considers direct learning effects (column 3) than when no R&D experience effects are considered (column 1). Therefore, our results suggest that omitting the direct R&D experience mechanism leads to an overestimate of the effect of sunk costs.[18]

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[18] Timoshenko (2015) shows that assuming a log specification for the number of years continuously performing R&D allows separating the state dependence effect into its two components. However, assuming a semiparametric specification (including $Y_{i,t-1}$ and a set of dummies d_j= for j=2,..,J, taking value 1 if firms' R&D experience is equal to J years) does not allow this separate identification. Under the semiparametric specification, the estimate of Y_{it-1} includes both the sunk-cost effect and the effect of one-year experience in R&D. See the estimation results from this semiparametric specification in Table C1 in the Appendix C. As expected, the estimated sunk costs parameters associated to Y_{it-1} are larger than those obtained when we assume a log specification for R&D experience: around 1.73 *versus* 1.48 in *WO* estimation, and around 1.74 *versus* 1.65 in the *BL* estimation.

Column 4 of Tables 3 and 4 presents the result of an estimation that allows for differences in sunk costs between large firms and SMEs but does not control for the existence of possible direct R&D experience effects (i.e. it does not include any function of R&D age). In comparison to the estimation in column 1, we include as additional regressors the dummy variable d_L (it takes value 1 for large firms) and an interaction term between lagged R&D participation and this dummy variable ($Y_{i,t-1}*d_L$). The estimated coefficient of this interaction term is positive and significant (the estimated coefficients in *BL* and *WO* are 0.256 and 0.323, respectively). According to the traditional models of sunk costs, this should be interpreted as evidence of larger sunk costs effects for large firms. Mañez *et al.* (2009) find the same result in a similar estimation in which they also allow sunk costs to differ depending on the technological intensity of the industry in which firms operate.

Finally, column 5 of Tables 3 and 4 shows the estimates of equation (7) in which we allow both sunk costs and direct effects of R&D experience to differ between large firms and SMEs. For this estimation, we widen the estimation in column 4 to include the variables $log(R\&D\ Age_{i.t})$ and $log(R\&D\ Age_{i.t})*d_L$. The positive and significant estimate for the variable $Y_{i,t-1}*d_L$ in column 5 suggests that for large firms the true effect of sunk costs is larger than for SMEs. Further, this estimated coefficient is not much different in *WO* and *BL* (0.468 and 0.415, respectively). However, the negative and significant estimate for $log(R\&D\ Age_{i.t})*d_L$ indicates that the scope for direct learning effects when performing R&D seems to be lower for large firms than for SMEs. The estimated coefficient for $log(R\&D\ Age_{i.t})*d_L$ is quite similar regardless of the approach we follow to model the unobserved individual effect (it is -0.159 in *WO* and -0.146 in *BL*).

Furthermore, knowing that in this model the effect of one-year R&D experience in firm's latent utility of engaging in R&D in period t is given by $\beta_{SC} + \beta_a \log(2)$, allows us to calculate which part of this effect should be attributed to sunk costs and which to the direct effect of R&D experience. For the SMEs, the total effect one-year experience in R&D can be attributed to sunk costs ranges between 84.1% and 87.9% (in *WO* and *BL*, respectively). For the large firms the relative importance of sunk cost is even larger, and ranges between 92.8% and 94.8% (in *WO* and *BL*, respectively).

Following Mañez *et al.* (2009), we can argue that the higher sunk R&D costs faced by large firms could be due to the fact that part of the entry costs into R&D involve both exogenous and endogenous sunk costs. According to Sutton (1991), the minimal level of investments that an entrant to an industry must incur may be considered as an exogenous sunk cost. Astebro

(2004) translating this argument to R&D investments points out that the initial engagement in R&D requires a minimum setup cost related both to indivisibilities and to a minimum efficient scale to operate an R&D lab. Hence, up to some extent entry costs into R&D may be considered exogenous and independent of firm size in a given industry. Nevertheless, above this minimum setup level, R&D investments should also be considered as strategic actions aimed to maximize firm's profit through increased market share and/or lower production costs. This type of outlays is referred as endogenous R&D costs (Dasgupta and Stiglitz, 1980; Sutton, 1991). Therefore, following Sutton (1991) one can consider that a fraction of both endogenous and exogenous R&D costs is sunk.

Furthermore, in industries in which competition is through escalation in R&D investment (associated with endogenous sunk costs), SMEs need to maintain higher levels of R&D intensity to be able to compete with high R&D investments by large firms. As the intensity of this escalation mechanism increases, SMEs are less likely to be able to maintain high enough levels of R&D due to eroded profits. This can force SMEs to abandon a highly intensive R&D strategy. Thus, escalation in R&D investments may generate industries with a dual market structure where a group of large firms engaged in R&D coexist with a fringe of SMEs with reduced or no R&D expenditures (Sutton, 1991). This could explain our results suggesting that sunk R&D costs may be higher for large firms as these firms incur high endogenous R&D expenditures.

Both large and small firms benefit from the direct effects of R&D experience. Nevertheless, our results suggest that direct effects of R&D experience are bigger for SMEs than for large firms. This is very likely related to the fact that SMEs start from a lower level of knowledge about the processes of doing R&D on a continuing basis, and so learn and catch-up rapidly: they learn about the process of performing R&D.

Interestingly, the positive, significant coefficient of $\tilde{y}_{it-2}$, and the non-significant coefficient of $\tilde{y}_{it-3}$, both in WO and BL estimations, suggest a rapid depreciation of R&D experience. Firms that are two years without performing R&D are more likely to restart performing R&D that firms that have never performed R&D before, but this is not so for firms that have been three or more years without performing R&D.

5.2 Indirect effects of R&D experience

Testing for the existence of indirect effects of R&D experience on the likelihood of R&D engagement requires first to check whether R&D experience has productivity enhancement effects; and, second, whether more productive firms are more likely to engage in R&D. In what follows, we explain in detail the method followed to test the first condition. Verification of the second condition just implies to check whether the estimate of productivity in equations (6) and (7) is positive and significant.

If we consider the recursive nature of the endogenous Markov process described by equation (11), we can parametrize firm's productivity (z_{it}) in (12) as a function of the log of R&D age (*log(R&D age$_{it}$)*), and the initial condition value for productivity (z_{i0}). In addition, we control for other factors that may influence the evolution of firm's productivity including a vector of observed firm characteristics (X_{it-1}), year dummies (λ_t), industry dummies (λ_s) and firm level fixed effects (α_i). Thus, we estimate the following specification for the Markov process in (11):[19]

$$z_{it} = \delta_0 + \delta_1 \log(R\&D\ Age_{it-1}) + z_{i0} + \beta X_{it-1} + \lambda_t + \lambda_s + \alpha_i + \epsilon_{it} \qquad (12)$$

In the fixed effect panel data estimation of equation (12), the initial condition value of productivity (z_{i0}) and α_i collapse into a unique firm fixed effect. We interpret positive and significant estimates for (δ_1) as evidence of positive returns of R&D experience in terms of productivity. In estimation, we proxy R&D experience by the log of R&D Age.[20]

We show the results corresponding to the estimation of equation (12) in Table 5. The positive and significant estimate of *log(R&D Age$_{it-1}$)* in our baseline specification, column (1), suggest the existence of positive returns to R&D experience in terms of productivity. In column (2), we wide our baseline specification to allow possible differential effects of R&D experience for large firms and SMEs. In this estimation the estimated coefficient for *log(R&D Age$_{it-1}$)* should be interpreted as measuring the effect of R&D experience on TFP for SMEs, and the estimated coefficient for *log(R&D Age$_{it-1}$)*d_L* as measuring the differential effect associated to large firms. Thus, the estimates corresponding to these variables in Table 5 suggest positive effects of R&D experience on TFP both for SMEs and large firms, but also suggest that the returns of R&D experience in terms of productivity are larger for large firms than for SMEs. This may be related to the fact that larger firms are in a better position to capture the productivity benefits of repeated and lengthy R&D activity because they have the absorptive capacity and mechanisms in place to capture and absorb such productivity effects, while smaller firms are less able to absorb these effects.

At this point, it is necessary to recall that the test of the indirect effects of R&D experience on R&D persistence requires not only evidence of a positive effect of R&D experience on productivity, but also a positive effect of productivity on the likelihood of R&D engagement. The positive and significant estimates of productivity in columns 3 and 5 of Tables 3 (*WO*

[19] Mañez et al (2020) follow a similar approach for export and import age.

[20] As in all estimations, our measure of R&D Age is the number of years continuous R&D engagement plus one. We use this transformation to avoid excluding from estimation firms with no R&D experience

estimation) and 4 (*BL* estimation), in which we allow both for sunk costs and direct learning effects of R&D experience, suggest that the second condition for indirect effects is also fulfilled. Therefore, our estimations suggest the existence of positive indirect effects of R&D experience on the likelihood of R&D engagement via productivity

Further, the fact that in the estimation of equation (12) (see column 2 of Table 5) the effects of R&D experience on productivity are larger for large firms than for SMEs indicates that the indirect effects of R&D experience on the probability of performing R&D are more intense for large firms than for SMEs.

All in all, our results on direct and indirect effects of R&D experience suggest that that large firms and SMEs learn in different ways from their history of R&D engagement. Both large and small firms benefit from the direct and indirect (via productivity) effects of R&D experience, but in large firms this is more likely to be manifest through productivity improvements while in smaller firms the effect is more skewed towards a direct effect on R&D likelihood. SMEs appear to learn a lot from doing R&D not because they start from a lower level of productivity but because they start from a lower level of knowledge about the processes of doing R&D on a continuing basis, and so learn and catch-up rapidly: they learn about the process of performing R&D. By contrast, many large firms are more used to perform R&D, and therefore have less to learn directly from the process of repeatedly doing R&D in terms of future R&D. Instead, large firms get more of a boost to productivity from their R&D activity. This may be because larger firms are in a better position to capture the productivity benefits of repeated and lengthy R&D activity because they have the absorptive capacity and mechanisms in place to capture and absorb such productivity effects, while smaller firms are less able to absorb these effects.

5.3. Control variables and initial conditions

The main results on the control variable suggest that larger and older firms, with a higher proportion of high and medium-skilled workers are more likely to perform R&D.[21] Furthermore, firms that declare to have a significant market share in its main market, and facing a low to medium number of competitors in its main market are also more prone to engage in R&D.[22] As for the possible role of financial constraints, our results suggest that R&D investments are mainly financed using own-funds: whereas firms with larger cash-flow are more likely to perform R&D, firms' borrowing costs do not seem to affect the probability of performing R&D. Furthermore, the *BL* estimations suggest that firms facing an expansive demand are more likely

[21] The estimate corresponding to the *High Skilled Workers*$_{it-1}$ variable is significant in all estimations expect in those of columns 2,3 and 5 of Table 3 (*WO* estimation).

[22] In all estimations, the variables *N. of competitors 0-10* and *N. of competitors 10-25* are positive and significant.

to perform R&D what could interpreted as evidence in favor of demand-pull innovation. Nevertheless, this result is not confirmed by WO estimations.

As for the effects of the variables included in the estimation to capture unobserved heterogeneity it is worth remarking on two results. First, the estimate of initial condition Y_{i0} (capturing whether the firm performed R&D the first time it is observed in the sample) is negative and significant in all WO estimations (see Table 3). One could expect that the estimate of the initial condition should be positive if it were catching the existence of unobserved permanent effects that affect the probability of performing R&D.[23] However, in our sample of switchers firms ought to change R&D status at least once along the sample which can help to explain the negative sign. Furthermore, the estimate of Y_{ipre} (the pre-sample mean of the dependent variable) in the BL estimations, that could be catching a similar unobserved individual effect is non-significant once we consider the possibility of direct learning effects in our estimations (see columns 2, 3, and 5 of Table 4).

Second, the estimate of the within-sample mean of the age variable is positive and significant in WO estimations (see Table 3) as it is the pre-sample mean of the age variable in most of the BL estimations (see Table 4). This could be signaling the existence of an unobserved permanent fixed effect caught by firm age that affects the probability of exporting. This is unsurprising, given that firm age is associated with the ability to survive and is often related to efficiency.

5.4 Quantifying the relative importance of sunk costs and direct learning effects

With the aim of quantifying the relative importance of sunk costs and learning effects on the likelihood of performing R&D, we estimate how the probability of R&D engagement evolves with R&D age for three different scenarios: under scenario 1, we set sunk costs equal to zero and allow only for direct learning effects (i.e. $\beta_{sc} = 0$ and $\beta_a = \beta_a$); under scenario 2, we set direct learning effects to zero and allow for sunk cost effects (i.e. $\beta_{sc} = \beta_{sc}$ and $\beta_a = 0$); and, under scenario 3, we allow both for sunk costs and learning effects (i.e. $\beta_{sc} = \beta_{sc}$ and $\beta_a = \beta_a$).[24]

[23] In fact, this is the case in an estimation in which we consider the full sample of firms and not just the sample of switchers. In the estimation of equations (6) and (7) with the full sample the estimate of Y_{i0} ranges from 0.342 to 0.573. The results of these estimations are available upon request.

[24] To obtain these probabilities, we estimate equation (9) substituting the industry dummies by a set of three dummies capturing the technological regime of the industry in which the firm operates (High-tech, med-tech and low-tech. See Table A2 in Appendix A for the classification of the ESEE industries according to technological regime). We use the Wooldridge (2005) approach to proxy for unobserved heterogeneity. In particular, the estimated probabilities analysed in this section correspond to firms

Figures 4 and 5 show the predicted probabilities of engaging in R&D for each of these three scenarios for SMEs and large firms, respectively. Under scenario 2, in which we set direct learning effects to zero, the predicted probability of R&D engagement does not change with R&D age. In scenarios 1 and 3, the predicted probability of performing R&D is an increasing function of R&D age. Further, as one would expect the predicted probability of R&D engagement under scenario 3, in which we allow for sunk costs and learning effect is higher than under the two scenarios in which we allow just for one effect (except for the first period of engagement in R&D in which R&D experience is 0 and the predicted probabilities under scenarios 2 and 3 are identical).

The predicted probabilities confirm three results already suggested by our estimates of equation (7). First, the sunk cost effect is higher for large firms than for SMEs: in the absence of learning effects, the predicted probability of R&D engagement in period t for a large firm undertaking R&D in period t-1 is 0.738 and for a SME it is 0.505 (see *Only sunk cost* lines in Figures 4 and 5). Second, learning effects are more intense for SMEs than for large firms, as suggested by the higher rate of growth of the predicted probability of R&D engagement for SMEs than for large firms when bypassing sunk costs effects (see *Only learning* lines in Figures 4 and 5). Thus, for example, when accounting only for learning effects the increase in the predicted probability of R&D engagement after 15 years undertaking R&D is 0.283 for SMEs and 0.158 for large firms. Finally, when accounting both for sunk costs and learning effects and regardless of firm R&D age, the predicted probability of R&D engagement is larger for large firms than for SMEs (*Learning+sunk costs* lines in Figures 4 and 5), with this difference mainly explained by the sunk cost effects.

Calculus of the ratios between the predicted probabilities under the three scenarios defined above allow a sharper quantification of sunk costs and R&D effects. Hence, we calculate the ratio of the predicted probability under scenario 1 to that under scenario 2 (learning to sunk cost ratio); the ratio of the predicted probability under scenario 1 to that under scenario 3 (learning-to-both ratio); and, the ratio of the predicted probability under scenario 2 to that under scenario 3 (sunk costs-to-both ratio). These three ratios are displayed in Figures 6 and 7 for SMEs and large firms, respectively.

The learning-to sunk costs ratio is useful to gain insight on the relative importance of sunk costs and direct learning effects. Since sunk costs effects do not depend on R&D age, the evolution of the learning-to-sunk costs ratio is necessarily increasing in R&D age. Notwithstanding, both for SMEs and large firms, even after 25 years of R&D experience the sunk costs effect is larger than the direct learning effect. Further, the difference between the sunk

belonging to med-tech industries, the tech sector that represents a larger proportion of firms in our sample (47.59%). Probabilities are evaluated at means of the explanatory variables.

cost effect and the learning effect is greater for large firms than for SMEs. Thus, for SMEs with 5 years of R&D experience the predicted probability of R&D engagement when accounting for direct learning effects costs but not for sunk costs effects (scenario 1) is 47.2% of the predicted probability when accounting for sunk costs effects but not for direct learning effects (scenario 2). If R&D experience is 15 years this percentage is 75%, and if R&D experience is 25 year it is 89.4%. For large firms, the corresponding percentages are much smaller: 29.2%, 39.1% and 43.1% for R&D ages 5, 15 and 25 years, respectively

Both the sunk costs-to-both ratio and the learning-to-both ratio offer relevant information on the relative importance of direct learning effects and sunk costs effects on the probability of engaging in R&D. Since the sunk costs effect does not change with R&D age and the direct learning effect increases with R&D age, the learning-to-both ratio is increasing with R&D age both for large firms and SMEs. However, it increases much slowly for large firms than for SMEs. Hence, for SMEs the predicted probability of R&D engagement after 5, 15 and 25 of R&D experience when accounting just for learning (scenario 1) is 32.8%, 44.9% and 51.1%, respectively, of that when accounting both for direct learning and sunk costs effects (scenario 3). Nevertheless, for large firms, these percentages are much smaller 25.8%, 32.5% and 36% respectively. The sunk-to-both ratio, the other side of the coin, stays much higher for large firms than for SMEs and decreases at a lower rate: while for large firms with 25 years of R&D experience the predicted probability of engaging in R&D when accounting just for sunk costs is 81.6% of that when accounting for both sunk cost and direct learning effects, for SMEs it is 57.1%.

All in all, our prediction exercise suggests that, both for large firms and SMEs, the sunk costs effect is more important than the direct learning effect in the determination of R&D persistence for quite a wide range of R&D ages. Furthermore, the superior effect of sunk costs is noticeably larger in the case of large firms.

6. Concluding remarks

This paper highlights the extent to which persistence in R&D activities is linked to the existence of sunk costs and learning effects, as there is evidence that the persistence of R&D investment by firms is an important factor in achieving greater productivity growth and profitability. We have attempted to unravel and quantify the importance of sunk costs and effects of learning as determinants of persistence in R&D, and whether the importance of these two factors differs among SMEs and large firms. In addition, we differentiate between the direct and indirect (via productivity) effects of R&D experience.

Our findings are consistent with the literature which identifies sunk costs as a key factor explaining firms' persistence of R&D activities. Crucially, however, our results show that a non-negligible part of the observed state dependence in R&D activities could be associated with the processes of learning that characterize continuous engagement in R&D activities. Furthermore, our results suggest that whereas sunk R&D costs are larger for large firms, the scope of direct learning associated to the continuous undertaking of R&D activities is greater for SMEs than for large firms. Our results also suggest that large and small firms learn in different ways from their previous R&D engagement. SMEs appear to benefit principally from a direct learning effect related to R&D activity. They start from a lower level of knowledge about the processes of doing R&D on a continuing basis, and so learn and catch-up rapidly: they learn about the process of performing R&D. Larger firms are more used to perform R&D, and therefore have less to learn about the process of 'doing R&D'. However, their greater absorptive capacity puts them in a better position than SMEs to obtain a productivity boost from their R&D activity.

There is often an implicit assumption that since R&D is predominantly an activity performed by large firms, and because small firms often have difficulty making the necessary investments for R&D, that public policy should be concentrated on the former (as long as the social returns to R&D outweigh the private returns). Given that initiating R&D activities is costly, and that a percentage of the investment is likely to be irrecoverable in the event of exit, this is understandable. However, if at least part of the public policy commitment to R&D and innovation is concerned with generating 'dynamic returns to scale', and assuming that encouraging persistence in R&D activities is one way of achieving this, our results do suggest some lessons for policy. The participation of companies in R&D activities is in part a self-sustaining process. The present analysis suggests that measures to stimulate R&D policies can not only affect companies' current R&D activities but can also induce a lasting effect over time in promoting future R&D commitments. Given that the direct learning effect of continuous R&D is greater for small than for large firms, this may suggest that consideration of innovation support for small firms might allow for this possible positive effect, and that policy should favour measures addressed to ease continuous engagement in R&D activities once firms start performing R&D.

The precise nature of any appropriate policy support is inevitably context specific. Spain provides a combination of R&D tax credits and direct public subsidy for R&D activities (Arqué-Castells 2013; Busom *et al*. 2014). R&D subsidies are heavily skewed towards persistent R&D performers, with 84% of subsidies during the period 1998-2009 going to firms performing R&D in the previous period (Arqué-Castells 2013). In a study of the effect of subsidies versus tax credits in Spain, Arqué-Castells (2013) concludes that subsidies are more likely to reach young firms and those with no previous history of R&D activity, while tax credits assist R&D-performing firms to persist with, or increase their level of, R&D activity – regardless of firm size. Busom *et al*. (2014) agree that subsidies can work in inducing Spanish firms to enter R&D, but can also generate long-lasting persistence effects if the subsidy shares are large enough – possibly up to 50% in the case of SMEs, but lower (around 30%) in the case of larger firms. To the extent that the policy objective is both to increase the proportion of SMEs performing R&D and to encourage persistence in R&D with its associated learning effects, this appears to suggest that direct public subsidies may have an important role to play, although the extent of such subsidies required to produce a permanent effect on R&D behaviour may be substantial. Note, however, that our analysis says nothing about the relative size or distribution of social versus private returns to R&D with respect to large and small firms, and so we cannot say definitively that any policy shift towards R&D support for smaller firms would be socially desirable.

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TABLES

Table 1: Firm classification according to R&D pattern over time

	All firms		SMEs		Large firms	
	Number	%	Number	%	Number	%
Non- R&D	1284	47.70	1187	61.15	97	12.92
Always R&D	348	12.93	114	5.87	234	31.16
Switchers	1060	39.38	640	32.97	420	55.92
Total	2692		1941		751	

Table 2. Number of R&D spell for R&D switchers

	All firms		SMEs		Large firms	
Number of Spells	Number	%	Number	%	Number	%
1	613	57.83	398	62.19	215	51.19
2	350	33.02	185	28.91	165	39.29
3	76	7.17	44	6.88	32	7.62
4	19	1.79	12	1.88	7	1.67
5	2	0.19	1	0.16	1	0.24
Total N of firms	1060		640		420	
Total N of R&D spells	1627		953		674	

Table 3: Determinants of R&D engagement. Switchers. Wooldridge estimation method

Explanatory variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Y_{it-1}	1.820***	1.540***	1.482***	1.694***	1.315***
	(0.0375)	(0.0492)	(0.0566)	(0.0444)	(0.0726)
R&D Age$_{it}$		0.155***			
		(0.0184)			
(R&D Age$_{it}$*)*^{2}		-0.00671***			
		(0.000978)			
log(R&D Age$_{it}$*)*			0.304***		0.359***
			(0.0382)		(0.0522)
$Y_{it-1}*d_L$				0.323***	0.468***
				(0.0610)	(0.111)
log(R&D Age$_{it}$*)*$*d_L$					-0.159**
					(0.0668)
log(TFP$_{it-1}$)	0.207***	0.177***	0.178***	0.195***	0.172***
	(0.0652)	(0.0623)	(0.0620)	(0.0653)	(0.0622)
Foreign capital	-0.0515	-0.0694	-0.0600	-0.0654	-0.0697
	(0.0755)	(0.0750)	(0.0749)	(0.0763)	(0.0755)
Limited liability	0.0972	0.0790	0.0902	0.0894	0.0791
	(0.0868)	(0.0855)	(0.0855)	(0.0871)	(0.0858)
log(Capital Stock$_{it-1}$*)*	0.0777***	0.0624**	0.0611**	0.0734**	0.0595**
	(0.0294)	(0.0291)	(0.0291)	(0.0294)	(0.0292)
log(Age$_{it-1}$*)*	0.117*	0.176***	0.170***	0.132**	0.187***
	(0.0661)	(0.0643)	(0.0643)	(0.0661)	(0.0645)
High Skilled Labour$_{it-1}$	0.00663*	0.00603	0.00604	0.00681*	0.00622
	(0.00391)	(0.00386)	(0.00386)	(0.00392)	(0.00387)
Med Skilled Labour$_{it-1}$	0.00545**	0.00476**	0.00450*	0.00538**	0.00465**
	(0.00235)	(0.00233)	(0.00233)	(0.00234)	(0.00233)
N. of competitors 0-10	0.190***	0.177***	0.178***	0.190***	0.177***
	(0.0568)	(0.0560)	(0.0560)	(0.0567)	(0.0559)
N. of competitors 10-25	0.141**	0.120*	0.125*	0.144**	0.128*
	(0.0680)	(0.0672)	(0.0670)	(0.0678)	(0.0670)
N. of competitors>25	0.122	0.0955	0.0986	0.122	0.0987
	(0.0824)	(0.0813)	(0.0812)	(0.0821)	(0.0810)
Cash Flow Dev$_{it-1}$	0.115*	0.111*	0.113*	0.117*	0.114*
	(0.0601)	(0.0596)	(0.0595)	(0.0609)	(0.0603)
Long Run Cost Dev$_{it-1}$	0.0147	0.0110	0.0109	0.0147	0.0127
	(0.0139)	(0.0136)	(0.0136)	(0.0139)	(0.0137)
Appropriability$_{it-1}$	-0.00988	-0.0108	-0.00978	-0.00939	-0.0106
	(0.0182)	(0.0180)	(0.0180)	(0.0181)	(0.0180)
Market Share$_{it-1}$	0.134***	0.129***	0.126***	0.133***	0.125***
	(0.0364)	(0.0346)	(0.0344)	(0.0365)	(0.0345)
Espansive demand$_{it-1}$	0.0414	0.0444	0.0457	0.0432	0.0468
	(0.0392)	(0.0389)	(0.0388)	(0.0393)	(0.0388)
Recessive demand$_{it-1}$	-0.00716	-0.0151	-0.0169	-0.00586	-0.0163
	(0.0409)	(0.0405)	(0.0405)	(0.0409)	(0.0405)
$\tilde{y}_{it-2}$	0.211***	0.271***	0.273***	0.219***	0.277***
	(0.0557)	(0.0553)	(0.0553)	(0.0556)	(0.0552)
$\tilde{y}_{it-3}$	0.0154	0.0606	0.0611	0.0204	0.0625
	(0.0685)	(0.0675)	(0.0675)	(0.0684)	(0.0674)
d_L				-0.0718	-0.0561
				(0.0628)	(0.0568)

Table 3 (cont'd): Determinants of R&D engagement. Switchers. Wooldridge estimation method.

Initial Conditions	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Y_{it0}	-0.133***	-0.151***	-0.149***	-0.140***	-0.153***
	(0.0369)	(0.0329)	(0.0326)	(0.0370)	(0.0329)
$log(TFP)_{imean}$	-0.0322	-0.0352	-0.0332	-0.0289	-0.0315
	(0.0517)	(0.0503)	(0.0502)	(0.0515)	(0.0501)
Foreign capital$_{imean}$	-0.0323	-0.0103	-0.0218	-0.0265	-0.0156
	(0.0907)	(0.0872)	(0.0868)	(0.0918)	(0.0878)
Limited liability$_{imean}$	-0.0778	-0.0635	-0.0751	-0.0647	-0.0616
	(0.0953)	(0.0920)	(0.0918)	(0.0956)	(0.0922)
$log(Capital\ Stock_{it-1})_{imean}$	-0.00925	0.00103	0.00159	-0.0163	-0.00500
	(0.0323)	(0.0313)	(0.0313)	(0.0330)	(0.0320)
$log(Age)_{imean}$	0.124	0.178**	0.172**	0.140*	0.191**
	(0.0768)	(0.0740)	(0.0739)	(0.0768)	(0.0741)
High Skilled Labour$_{imean}$	-0.00429	-0.00379	-0.00367	-0.00349	-0.00332
	(0.00517)	(0.00489)	(0.00487)	(0.00519)	(0.00489)
Med Skilled Labour$_{imean}$	0.00525	0.00448	0.00478	0.00531	0.00455
	(0.00393)	(0.00364)	(0.00362)	(0.00394)	(0.00364)
N. of competitors 0-10$_{imean}$	-0.195**	-0.192**	-0.190**	-0.190**	-0.184**
	(0.0885)	(0.0822)	(0.0818)	(0.0886)	(0.0821)
N. of competitors 10-25$_{imean}$	-0.0268	-0.0107	-0.0132	-0.0291	-0.0144
	(0.116)	(0.107)	(0.106)	(0.116)	(0.106)
N. of competitors>25$_{imean}$	-0.0944	-0.0596	-0.0637	-0.0800	-0.0541
	(0.145)	(0.133)	(0.132)	(0.144)	(0.133)
Cash Flow Dev$_{imean}$	0.0713	0.0591	0.0579	0.0759	0.0625
	(0.0721)	(0.0632)	(0.0627)	(0.0727)	(0.0634)
Long Run Cost Dev$_{imean}$	-0.0946**	-0.0855**	-0.0813**	-0.0729	-0.0677*
	(0.0440)	(0.0399)	(0.0396)	(0.0457)	(0.0411)
Appropriability$_{imean}$	-0.0443	-0.0336	-0.0335	-0.0409	-0.0298
	(0.0675)	(0.0620)	(0.0617)	(0.0674)	(0.0617)
Market Share$_{imean}$	0.211**	0.185**	0.182**	0.203**	0.184**
	(0.0945)	(0.0859)	(0.0853)	(0.0949)	(0.0859)
Espansive demand$_{imean}$	0.0782	0.0735	0.0831	0.0755	0.0848
	(0.101)	(0.0920)	(0.0914)	(0.101)	(0.0918)
Recessive demand$_{imean}$	-2.498***	-2.427***	-2.277***	-2.311***	-2.158***
	(0.235)	(0.212)	(0.212)	(0.255)	(0.229)
Constant	-2.465***	-2.408***	-2.263***	-2.142***	-2.135***
	(0.234)	(0.212)	(0.211)	(0.230)	(0.228)
Observations	12,433	12,433	12,433	12,433	12,433
Number of firms	1,060	1,060	1,060	1,060	1,060

Notes:

1. Industry and year fixed effects included.
2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Determinants of R&D engagement. Switchers. Blundell estimation method.

Explanatory variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Y_{it-1}	1.940***	1.658***	1.650***	1.839***	1.502***
	(0.0522)	(0.0687)	(0.0772)	(0.0611)	(0.0983)
R&D Age_{it}		0.137***			
		(0.0216)			
(R&D $Age_{it})^2$		-0.00613***			
		(0.00111)			
log(R&D Age_{it}*)*			0.246***		0.297***
			(0.0482)		(0.0646)
$Y_{it-1}*d_L$				0.256***	0.415***
				(0.0779)	(0.154)
log(R&D $Age_{it})*d_L$					-0.146*
					(0.0834)
log(TFP_{it-1})	0.221***	0.201***	0.198***	0.216***	0.193***
	(0.0766)	(0.0731)	(0.0716)	(0.0771)	(0.0721)
Foreign capital	-0.0994	-0.106	-0.0934	-0.110	-0.0986
	(0.0717)	(0.0688)	(0.0675)	(0.0724)	(0.0680)
Limited liability	0.0235	0.00642	0.0151	0.0190	0.00835
	(0.0816)	(0.0774)	(0.0759)	(0.0820)	(0.0763)
log(Capital $Stock_{it-1}$*)*	0.106***	0.101***	0.0946***	0.103***	0.0941***
	(0.0298)	(0.0285)	(0.0281)	(0.0303)	(0.0287)
log(Age_{it-1}*)*	0.163	0.186*	0.210**	0.164	0.210**
	(0.108)	(0.104)	(0.103)	(0.108)	(0.103)
High Skilled $Labour_{it-1}$	0.00803**	0.00781**	0.00775**	0.00831**	0.00791**
	(0.00372)	(0.00357)	(0.00352)	(0.00374)	(0.00353)
Med Skilled $Labour_{it-1}$	0.00703***	0.00660***	0.00628***	0.00687***	0.00623***
	(0.00235)	(0.00229)	(0.00226)	(0.00235)	(0.00226)
N. of competitors 0-10	0.107*	0.104*	0.104*	0.108*	0.104*
	(0.0624)	(0.0605)	(0.0597)	(0.0625)	(0.0598)
N. of competitors 10-25	0.178**	0.169**	0.175**	0.180**	0.176**
	(0.0749)	(0.0725)	(0.0714)	(0.0749)	(0.0715)
N. of competitors>25	0.0627	0.0491	0.0499	0.0659	0.0516
	(0.0923)	(0.0892)	(0.0880)	(0.0922)	(0.0880)
Cash Flow Dev_{it-1}	0.178*	0.169*	0.178*	0.178*	0.177*
	(0.0957)	(0.0950)	(0.0956)	(0.0967)	(0.0965)
Long Run Cost Dev_{it-1}	0.0136	0.0145	0.0141	0.0139	0.0142
	(0.0214)	(0.0212)	(0.0210)	(0.0215)	(0.0210)
$Appropriability_{it-1}$	-0.00435	-0.00400	-0.00254	-0.00412	-0.00295
	(0.0217)	(0.0214)	(0.0213)	(0.0215)	(0.0212)
Market $Share_{it-1}$	0.132***	0.128***	0.123***	0.130***	0.122***
	(0.0489)	(0.0473)	(0.0466)	(0.0490)	(0.0467)
Espansive $demand_{it-1}$	0.0805*	0.0807*	0.0829*	0.0803*	0.0843*
	(0.0462)	(0.0453)	(0.0448)	(0.0464)	(0.0450)
Recessive $demand_{it-1}$	0.00239	-0.00616	-0.00518	0.000950	-0.00610
	(0.0484)	(0.0476)	(0.0472)	(0.0485)	(0.0472)
$\tilde{y}_{it-2}$	0.243***	0.300***	0.306***	0.251***	0.310***
	(0.0710)	(0.0716)	(0.0713)	(0.0710)	(0.0713)
$\tilde{y}_{it-3}$	0.0670	0.104	0.105	0.0703	0.107
	(0.0817)	(0.0810)	(0.0807)	(0.0817)	(0.0807)
d_L				-0.0968	-0.0686
				(0.0809)	(0.0745)
Leftcensor	0.176***	0.0784	0.0598	0.174***	0.0638
	(0.0595)	(0.0608)	(0.0597)	(0.0599)	(0.0602)

Table 4 (cont'd): Determinants of R&D engagement. Switchers. Blundell estimation method

Initial Conditions	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Y_{ipre}	-0.158**	-0.0262	0.0727	-0.165**	0.0569
	(0.0715)	(0.183)	(0.203)	(0.0718)	(0.204)
R&D Age$_{ipre}$		-0.105			
		(0.104)			
Log(R&D Age)$_{ipre}$			-0.300		-0.283
			(0.221)		(0.222)
log(TFP)$_{ipre}$	0.00977	0.00465	0.00666	0.0132	0.00861
	(0.0487)	(0.0462)	(0.0454)	(0.0487)	(0.0455)
Foreign capital$_{ipre}$	-0.0398	-0.0241	-0.0370	-0.0312	-0.0302
	(0.0813)	(0.0763)	(0.0744)	(0.0822)	(0.0751)
Limited liability$_{ipre}$	0.0165	0.0289	0.0154	0.0248	0.0222
	(0.0967)	(0.0909)	(0.0888)	(0.0970)	(0.0891)
log(Capital Stock$_{it-1}$*)*$_{ipre}$	-0.0363	-0.0346	-0.0288	-0.0362	-0.0301
	(0.0291)	(0.0275)	(0.0270)	(0.0295)	(0.0272)
log(Age)$_{ipre}$	0.120	0.137*	0.153**	0.123	0.154**
	(0.0764)	(0.0732)	(0.0718)	(0.0765)	(0.0719)
High Skilled Labour$_{ipre}$	-0.00851	-0.00847	-0.00800	-0.00807	-0.00782
	(0.00547)	(0.00518)	(0.00506)	(0.00548)	(0.00507)
Med Skilled Labour$_{ipre}$	0.00229	0.00174	0.00172	0.00257	0.00174
	(0.00395)	(0.00368)	(0.00357)	(0.00397)	(0.00360)
N. of competitors 0-10$_{ipre}$	-0.246***	-0.229***	-0.218***	-0.245***	-0.216**
	(0.0927)	(0.0866)	(0.0841)	(0.0930)	(0.0844)
N. of competitors 10-25$_{ipre}$	-0.257**	-0.214**	-0.203**	-0.256**	-0.205**
	(0.109)	(0.102)	(0.0993)	(0.109)	(0.0997)
N. of competitors>25$_{ipre}$	-0.0896	-0.0774	-0.0818	-0.0873	-0.0835
	(0.125)	(0.116)	(0.113)	(0.125)	(0.113)
Cash Flow Dev$_{ipre}$	-0.180	-0.197*	-0.203*	-0.187	-0.205*
	(0.126)	(0.117)	(0.114)	(0.127)	(0.115)
Long Run Cost Dev$_{ipre}$	-0.0255	-0.0240	-0.0215	-0.0227	-0.0196
	(0.0212)	(0.0196)	(0.0189)	(0.0223)	(0.0199)
Appropriability$_{i,pre}$	-0.0766	-0.0683	-0.0677	-0.0774	-0.0683
	(0.0611)	(0.0573)	(0.0559)	(0.0611)	(0.0560)
Market Share$_{ipre}$	0.105	0.0798	0.0685	0.105	0.0704
	(0.0705)	(0.0660)	(0.0641)	(0.0707)	(0.0643)
Espansive demand$_{ipre}$	0.102	0.0983	0.102	0.106	0.103
	(0.0799)	(0.0741)	(0.0720)	(0.0802)	(0.0722)
Recessive demand$_{ipre}$	-0.0296	-0.0249	-0.0331	-0.0334	-0.0325
	(0.0861)	(0.0799)	(0.0776)	(0.0866)	(0.0779)
Constant	-2.416***	-2.331***	-2.256***	-2.345***	-2.212***
	(0.310)	(0.308)	(0.286)	(0.332)	(0.305)
Observations	8,511	8,511	8,511	8,511	8,511
Number of firms	998	998	988	998	998

Notes:

3. Industry and year fixed effects included.
4. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Total factor productivity and firm R&D experience

	(1)	(2)
log(R&D Age$_{it-1}$)	0.0132***	0.0062*
	(0.0024)	(0.0033)
*log(R&D Age$_{it-1}$)*d$_L$*		0.0238***
		(0.0047)
log(Capital Stock$_{it-1}$)	0.0315***	0.0306***
	(0.0032)	(0.0032)
log(Age$_{it-1}$)	0.0104*	0.0112*
	(0.0061)	(0.0064)
Constant	1.892***	1.894***
	(0.104)	(0.103)
Observations	12,433	12,433
Number of ordinal	1,060	1,060
R-squared	0.752	0.754

Figures

Figure 1: Kaplan-Meier survival estimate for SMEs and large firms

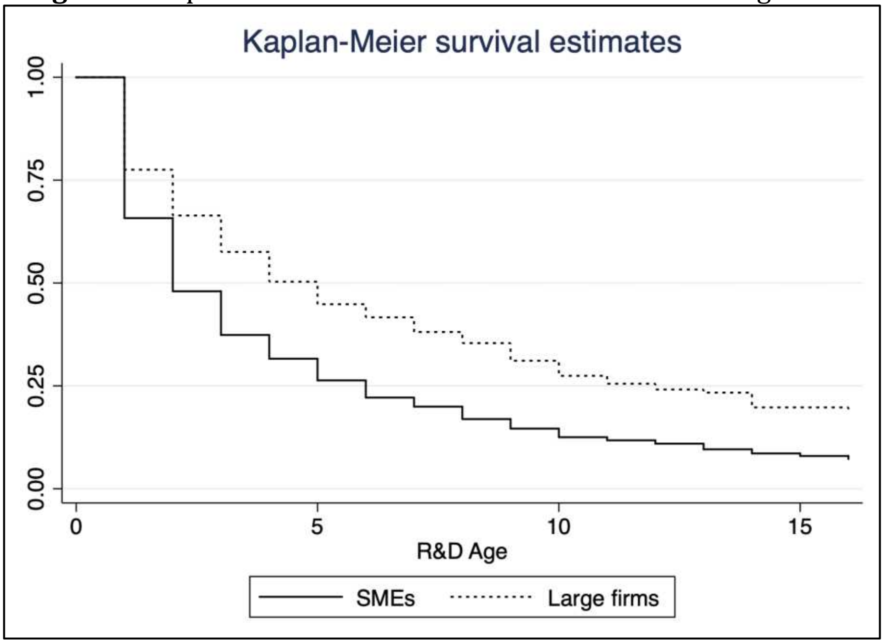


Figure 2. Average log-R&D expenditure of surviving firms. Switchers.

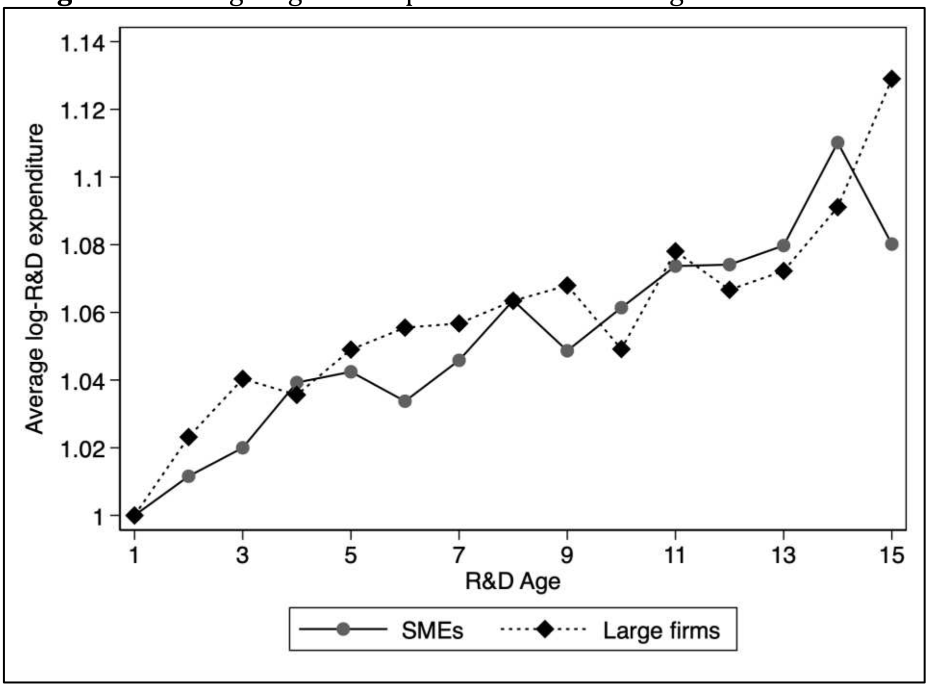


Figure 3. Average of in-house R&D intensity (in %) by R&D Age. Switchers.

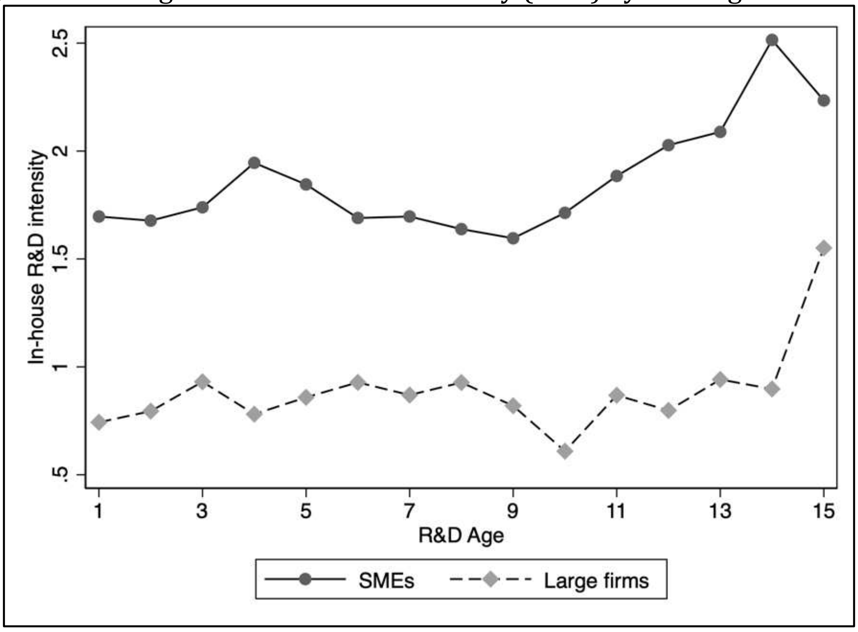


Figure 4: Predicted probability of engaging in R&D. SMEs

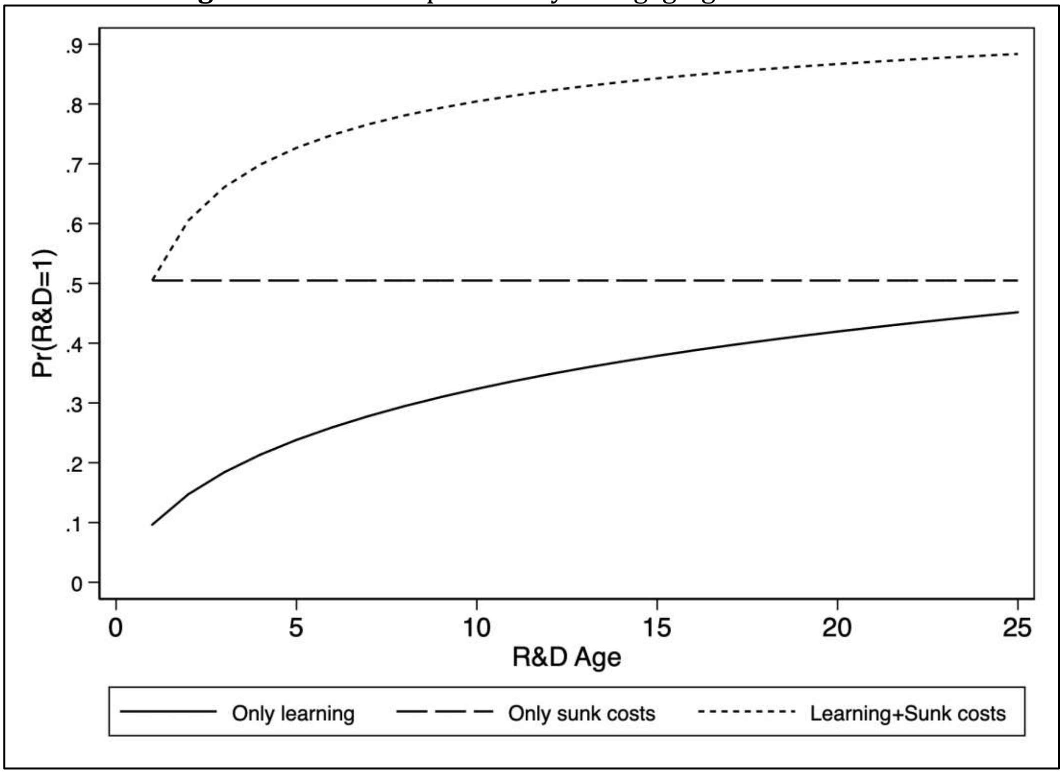


Figure 5: Predicted probability of engaging in R&D. Large firms

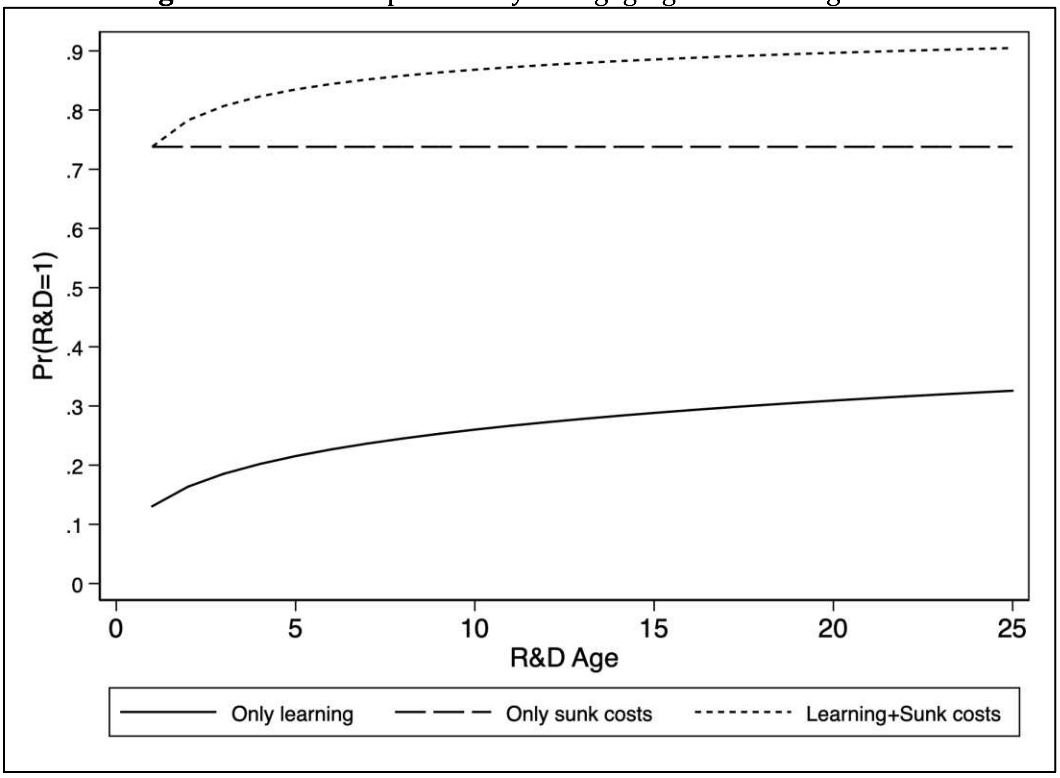


Figure 6: Relative probability of engaging in R&D. Sunk costs and learning. SMEs

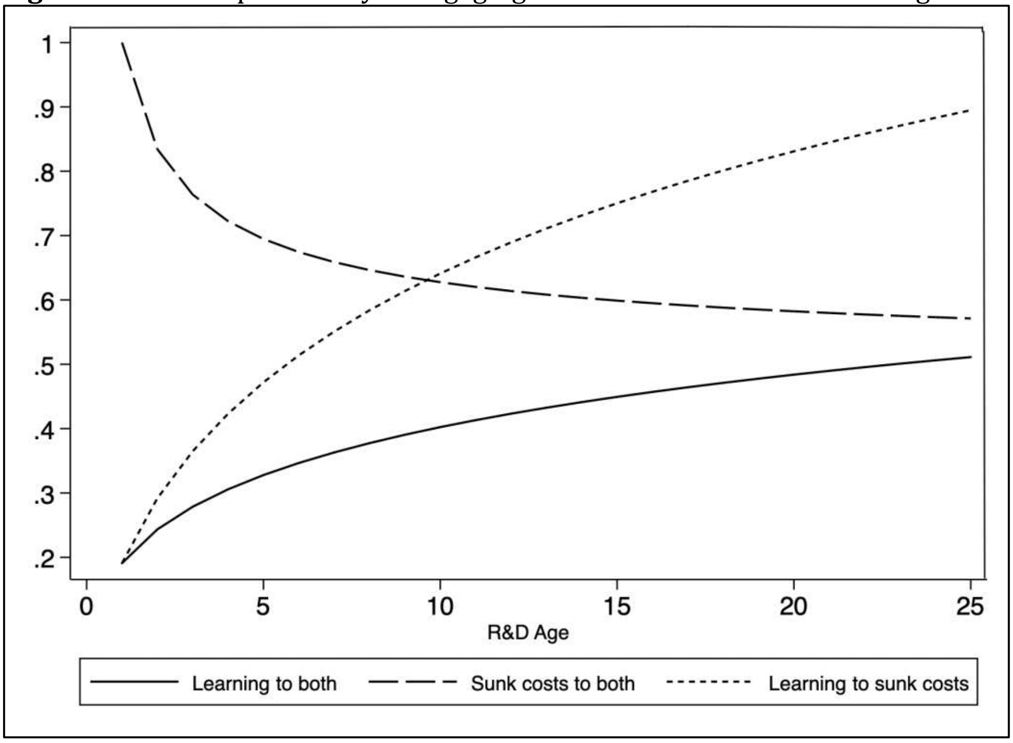
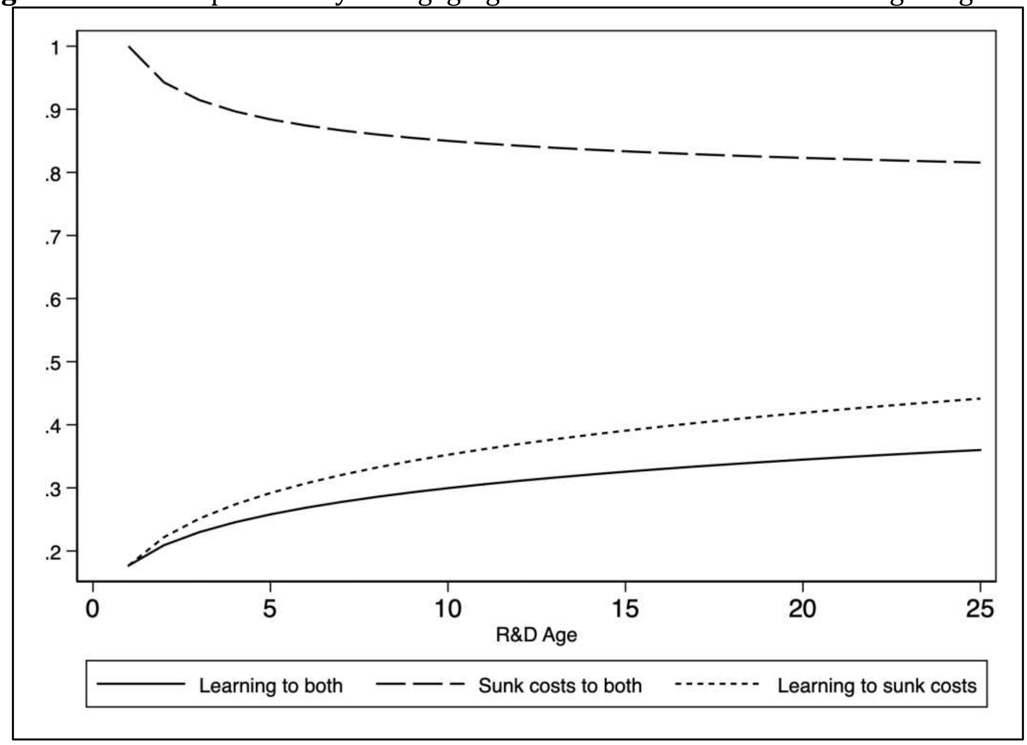


Figure 7: Relative probability of engaging in R&D. Sunk costs and learning. Large firms



Appendix A: Variable definition and ESEE industries

Table A1: Definitions of the explanatory variables

Variable	Definition
Y_{it-1}	Dummy that takes value 1 if the firm performs R&D in $t-1$ and 0 otherwise
R&D Age	Discrete variable that captures the number of years a firm has been consecutively performing R&D.
(R&D)^2	R&D age squared.
log(R&D age)	Logarithm of R&D age
d_L	Dummy variable for size that takes value one if firm is large and 0 if it is an SME
$Y_{i,t-1}*d_L$	Interaction between $Y_{i,t-1}$ and d_L
log(R&D age) * d_L	Interaction between the log of *R&D* age and d_L
ln(TFP)	Logarithm of productivity or TFP (Total Factor Productivity). See Appendix B for calculation method.
Limited liability	Dummy variable that takes value 1 if the firm is a Limited Liability Corporation) and 0 otherwise.
Foreign capital	Dummy variable that takes value 1 if there is foreign participation in the capital of the firm
ln(Capital_stock)	Logarithm of Capital Stock.
ln(Age)	Logarithm of the age of the firm
High skill labour	Proportion of graduates and engineers in the firm's labour force
Med skill labour	Proportion of technical engineers, experts and quality assistants in the firm labour force
N. of competitors 0-10	Dummy variable taking value 1 if the firm asserts to have less (or equal to) 10 competitors with significant market share in its main market.
N. of competitors 10-25	Dummy variable taking value 1 if the firm asserts to have more than 10 and less than 25 (or equal to) competitors with significant market share in its main market.
N. of competitors>25	Dummy variable taking value 1 if the firm asserts to have more than 25 (or equal to) competitors with significant market share in its main market.
Atomistic market	Reference category for the previous ones in estimation. Dummy variable taking value 1 if the firm asserts to be in a market where no firm has significant market share.

Table A1: Definitions of the explanatory variables (cont'd)

Market share	Dummy taking value 1 if the firm declares to have a significant market share in its main market
Appropriabiity	Ratio of the total number of patents over the total number of firms that assert to have achieved innovations in the firms' industry (20 industries of the two-digit NACE-93 classification) (in %).
Cash flow dev	Deviation of firms' cash-flow with respect the industry-year average cash-flow. Positive values of this variable imply that firm's cash-flow is larger than the corresponding year-industry-average.
Long run cost dev	Deviation of firms' cost of new long-term debt with respect to the industry-year average cost of new long-term debt (see Beneito *et al*. 2014 for further details). Positive values of this variable imply that firm's cost of new long-term debt is higher than the corresponding industry-year average.
Stable demand	Reference category. Dummy variable taking value 1 if the firm declares a stable demand.
Expansive demand	Dummy variable taking value 1 if the firm declares an expansive demand
Recessive demand	Dummy variable taking value 1 if the firm declares a recessive demand
$\tilde{y}_{it-2}$	Dummy variable taking value 1 if the last time the firm performed R&D was in t - 2
$\tilde{y}_{it-3}$	Dummy variable taking value 1 if the last time the firm performed R&D was in t - 3
Leftcensor	Dummy that takes value 1 for firms already engaged in R&D the first year they are in the sample (left-censored R&D spells)

Table A2. Industry classification according to technological intensity

Low technology industries
Meat products
Food and tobacco
Beverages
Textile and clothing
Leather, fur and footwear
Timber
Paper
Printing products
Furniture
Other manufacturing industries
Medium technology industries
Plastic and rubber products
Non-metallic minerals
Ferrous and non-ferrous metals
Metallic products
Industry and agricultural machinery
Electric materials and accessories
Motors and vehicles
Other transport equipment
High technology industries
Chemicals
Electronics and data processing

Table A3. Descriptive statistics (*N*=12,433)*

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Y_{it-1}	1.00														
2	*log(R&D Age*$_{it}$*)*	0.89	1.00													
3	*log(TFP*$_{it-1}$*)*	0.06	0.06	1.00												
4	*Foreign capital*	0.13	0.15	0.07	1.00											
5	*Limited liability*	0.12	0.12	0.05	0.20	1.00										
6	*log(Capital Stock*$_{it-1}$*)*	0.24	0.28	0.16	0.39	0.32	1.00									
7	*log(Age*$_{it-1}$*)*	0.10	0.13	0.11	0.15	0.24	0.39	1.00								
8	*High Skilled Labour*$_{i}$	0.11	0.13	0.04	0.14	0.07	0.15	0.14	1.00							
9	*Med Skilled Labout*$_{it-}$	0.13	0.14	0.06	0.09	0.03	0.08	0.01	0.29	1.00						
10	*N. of competitors 0-1*	0.08	0.08	0.12	0.15	0.07	0.21	0.13	0.09	0.05	1.00					
11	*N. of competitors 10-*	0.01	0.01	-0.05	-0.06	-0.02	-0.06	-0.02	-0.04	-0.04	-0.50	1.00				
12	*N. of competitors>25*	-0.04	-0.04	-0.03	-0.05	-0.05	-0.10	-0.05	-0.02	0.01	-0.35	-0.11	1.00			
13	*Cash Flow Dev*$_{it-1}$	0.00	0.00	0.00	-0.01	0.03	0.04	0.01	0.00	0.00	0.02	-0.01	-0.03	1.00		
14	*Long Run Cost Dev*$_{it-1}$	-0.07	-0.07	-0.08	-0.07	-0.09	-0.18	-0.09	-0.01	-0.02	-0.04	0.02	0.04	-0.01	1.00	
15	*Appropriability*$_{it-1}$	0.03	0.02	-0.06	0.03	-0.03	-0.04	0.01	0.06	0.03	0.01	-0.01	0.01	-0.02	0.02	1.00
16	*Market share*$_{it-1}$	0.14	0.14	0.09	0.19	0.18	0.30	0.15	0.08	0.02	0.39	-0.05	-0.15	0.04	-0.07	-0.00
17	*Expansive demand*$_{it-1}$	0.03	0.01	-0.00	0.04	0.05	0.01	-0.07	-0.01	-0.03	0.01	0.01	-0.00	0.04	-0.01	-0.02
18	*Recessive demand*$_{it-1}$	0.00	0.02	-0.02	-0.04	-0.04	-0.01	0.06	-0.01	-0.02	-0.02	-0.01	0.02	-0.05	0.02	0.03
19	d_L	0.21	0.25	0.10	0.36	0.26	0.71	0.30	0.06	0.04	0.15	-0.04	-0.11	0.01	-0.21	-0.04
20	$\tilde{y}_{i.t-2}$	-0.26	-0.23	-0.00	-0.02	-0.01	-0.04	-0.02	-0.01	0.00	0.01	-0.03	0.02	0.01	0.01	0.00
21	$\tilde{y}_{it-3}$	-0.23	-0.20	-0.00	-0.02	-0.02	-0.04	-0.03	-0.01	-0.01	-0.02	0.01	-0.00	-0.00	0.01	-0.00
22	*Leftcensor*	0.45	0.49	0.05	0.17	0.10	0.23	0.09	0.11	0.10	0.08	-0.01	-0.03	-0.00	-0.05	0.03
	Mean	0.45	0.68	5.75	0.26	0.72	15.62	3.22	5.74	7.13	0.61	0.14	0.08	0.03	-0.08	0.65
	S.D.	0.50	0.87	1.58	0.44	0.45	2.06	0.81	6.95	8.78	0.49	0.35	0.27	0.25	1.12	0.90
	Minimum	0.00	0.00	1.05	0.00	0.00	2.48	0.00	0.00	0.00	0.00	0.00	0.00	-11.06	-14.46	0.00
	Maximum	1.00	3.14	11.85	1.00	1.00	21.34	5.19	77.60	100.00	1.00	1.00	1.00	4.68	26.00	18.64

* Estimation sample when using Wooldridge (2005) approach to model unobserved heterogeneity

Table A3 (cont'd). Descriptive statistics (*N*=12,433)

		16	17	18	19	20	21	22
1	Y_{it-1}							
2	*log(R&D Age$_{it}$)*							
3	*log(TFP$_{it-1}$)*							
4	*Foreign capital*							
5	*Limited liability*							
6	*log(Capital Stock$_{it-1}$)*							
7	*log(Age$_{it-1}$)*							
8	*High Skilled Labour$_{i}$*							
9	*Med Skilled Labout$_{it-}$*							
10	*N. of competitors 0-1*							
11	*N. of competitors 10-*							
12	*N. of competitors>25*							
13	*Cash Flow Dev$_{it-1}$*							
14	*Long Run Cost Dev$_{it-1}$*							
15	*Appropriability$_{it-1}$*							
16	*Market share$_{it-1}$*	1.00						
17	*Expansive demand$_{it-1}$*	0.08	1.00					
18	*Recessive demand$_{it-1}$*	-0.05	-0.34	1.00				
19	d_L	0.26	0.05	-0.04	1.00			
20	$\tilde{y}_{it-2}$	0.01	0.01	0.01	-0.03	1.00		
21	$\tilde{y}_{it-3}$	-0.01	-0.01	0.01	-0.04	-0.08	1.00	
22	*Leftcensor*	0.10	-0.01	0.01	0.23	0.01	-0.04	1.00
	Mean	0.52	0.27	0.26	0.39	0.08	0.06	0.43
	S.D.	0.50	0.44	0.44	0.49	0.27	0.23	0.50
	Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Appendix B: Productivity estimation

We assume that firms produce using a Cobb-Douglas technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + z_{it} + \eta_{it} \tag{B.1}$$

where $y_{it}$is the natural log of production of firm i at time t, $l_{it}$is the natural log of labour measured as the number of effective hours worked), m_{it} is the log of intermediate materials, and $k_{it}$is the log of capital (adjusted for capital utilization). As for the unobservables, z_{it} is productivity (not observed by the econometrician but observable or predictable by the firm) and η_{it} is a standard *i.i.d.* error term that is neither observable nor predictable by the firm. Further, we assume that capital is a state variable, whereas labour and materials are variable non-dynamic inputs that can be adjusted whenever the firm faces a productivity shock.

We follow Wooldridge (2009) to get consistent estimates of input elasticities and estimates of TFP residuals. According to Wooldridge (2009), the semiparametric *control function* approaches proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) can be reconsidered as consisting of two equations that can be jointly estimated by GMM using the appropriate instruments. The first equation deals with the problem of endogeneity of labour and materials. The second equation tackles the issue of the law of motion of productivity.

To solve the problem of endogeneity of labour and materials, we follow Levinsohn and Petrin (2003) and use the demand of materials to proxy for "unobserved" productivity. This demand of materials function, $m_{it}(\cdot)$ is assumed to have a unique unobservable among its arguments (*scalar unobservable assumption)* and to be strictly monotonic on unobserved productivity. Hence, given that in equilibrium the demand of materials only depends on state variables, we can write this demand as $m_{it} = m_t(k_{it}, z_{it})$. Under the *scalar unobservable* and the *monotonicity assumption*, the demand of materials can be inverted to generate, $z_{it} = m_{it}^{-1}(k_{it}, m_{it}) = h_t(k_{it}, m_{it})$. Then substituting into the production function (B.1) we get our first estimation equation.

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + h_t(k_{it}, m_{it}) + \eta_{it} \tag{B.2}$$

Since $h_t(\cdot)$ is proxied by a third degree polynomial in its arguments, β_0, β_m and β_k are not identified from equation (B.2). Olley and Pakes (1996) and Levinsohn and Petrin (2003) get identification of these parameters adding a second equation in the GMM system that deals with the law of motion of productivity:

$$z_{it} = f(z_{it-1}) + \nu_{it} \tag{B.3}$$

where $f(\cdot)$ is a function that relates productivity in t to productivity in t-1, and $\nu_{it}$is an innovation term uncorrelated by definition with k_{it}.

Nevertheless, this exogenous Markov process, also assumed in Timoshenko (2015), does not consider the possibility of past R&D experience to affect productivity, and so it precludes the identification of a possible indirect effect of R&D experience on the likelihood of performing R&D channeled through increased productivity. In order, to explicitly allow past R&D experience to affect current productivity, we consider a more general (endogenous Markov process) in which R&D experience enters the Markov process (see Doraszelski and Jaumandreu, 2013 and DeLoecker, 2007, 2013 for similar approaches for R&D and exports, respectively):

$$z_{it} = f(z_{it-1}, R\&D\ Age_{it-1}) + \nu_{it} \tag{B.4}$$

Using that $z_{it} = h_t(k_{it}, m_{it})$ we can rewrite equation (B.4) as

$$z_{it} = f(z_{it-1}, R\&D\ Age_{it-1}) + \nu_{it} = f(h_t(k_{it-1}, m_{it-1}), R\&D\ Age_{it-1}) + \nu_{it} =$$
$$g_t(k_{it-1}, m_{it-1}, R\&D\ Age_{it-1}) + \nu_{it} \tag{B.5}$$

Finally plugging equation (B.5) in the production function (B.1), we get our second estimation equation:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + g_t(k_{it-1}, m_{it-1}, R\&D\ Age_{it-1}) + \xi_{it} \tag{B.6}$$

where $g_t(\cdot)$ is an unknown function proxied by a third degree polynomial in its arguments and $\xi_{it} = \eta_{it} + \nu_{it}$ is a composed error term.

Wooldridge (2009) proposes to estimate jointly (B.2) and (B.6) by GMM using the appropriate instruments for each equation. The production function is estimated for each of the twenty sectors of the ESEE, and firm specific productivity is estimated as a residual . The industry specific input elasticities are shown in Table B1 of this appendix.

Table B1: Estimated industry specific input elasticities from Cobb-Douglas production function

	Labour		Materials		Capital	
1. Meat products	0.152***	(0.007)	0.542***	(0.057)	0.036*	(0.020)
2. Food and tobacco	0.161***	(0.004)	0.300**	(0.121)	0.102***	(0.018)
3. Beverages	0.178***	(0.015)	0.495***	(0.133)	0.100**	(0.051)
4. Textiles and clothing	0.328***	(0.005)	0.459***	(0.110)	0.093***	(0.025)
5. Leather, fur and footwear	0.236***	(0.009)	0.507***	(0.078)	0.039*	(0.022)
6. Timber	0.295***	(0.011)	0.493***	(0.109)	0.068*	(0.035)
7. Paper	0.292***	(0.012)	0.488***	(0.140)	0.038*	(0.021)
8. Printing products	0.288***	(0.010)	0.494***	(0.106)	0.040*	(0.021)
9. Chemical	0.157***	(0.005)	0.649***	(0.126)	0.046*	(0.025)
10.Plastic and rubber products	0.251***	(0.008)	0.486***	(0.109)	0.111***	(0.031)
11. Non-metallic minerals	0.277***	(0.006)	0.589***	(0.088)	0.074**	(0.032)
12. Ferrous and non-ferrous metal	0.175***	(0.009)	0.616***	(0.114)	0.074**	(0.032)
13 Metallic products	0.284***	(0.006)	0.546***	(0.085)	0.045*	(0.025)
14. Ind. and agric. machinery	0.205***	(0.007)	0.531***	(0.060)	0.058***	(0.020)
15. Electronics and data process.	0.331***	(0.013)	0.568***	(0.099)	0.029*	(0.017)
16. Electrical mat. and access.	0.330***	(0.009)	0.529***	(0.086)	0.028	(0.022)
17. Motors and vehicles	0.192***	(0.009)	0.645***	(0.079)	0.037*	(0.021)
18. Other transport equipment	0.195***	(0.012)	0.640***	(0.106)	0.029*	(0.018)
19. Furniture	0.347***	(0.010)	0.542***	(0.129)	0.039*	(0.022)
20. Other manufact. industries	0.286***	(0.010)	0.709***	(0.127)	0.053*	(0.028)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix C: Non-parametric learning experience estimation

Table C1: Determinants of R&D engagement. Switchers. Non-parametric learning function

Explanatory variables	*Woldridge Init. Cond.*	*Blundell Init. Cond.*
Y_{it-1}	1.731***	1.742***
	(0.0604)	(0.0677)
$d_2= Y_{it-1}\, Y_{it-2}$	0.187**	0.164*
	(0.0830)	(0.0911)
$d_3=Y_{it-1}\, Y_{it-2}\, Y_{it-3}$	0.175*	0.172*
	(0.0991)	(0.010)
$d_4= Y_{it-1}\, Y_{it-2}\, Y_{it-3}\, Y_{it-4}$	0.0811	0.0846
	(0.0835)	(0.0909)
$log(TFP_{it-1})$	0.178**	0.200***
	(0.0751)	(0.0727)
Foreign capital	-0.149	-0.101
	(0.0919)	(0.0685)
Limited liability	0.0419	0.0121
	(0.107)	(0.0772)
$log(Capital\ Stock_{it-1})$	0.0858**	0.0961***
	(0.0398)	(0.0284)
$log(Age_{it-1})$	0.212*	0.178*
	(0.123)	(0.104)
High Skilled Labour$_{it-1}$	0.00829*	0.00772**
	(0.00448)	(0.00357)
Med Skilled Labour$_{it-1}$	0.00501*	0.00638***
	(0.00267)	(0.00228)
N. of competitors 0-10	0.178***	0.103*
	(0.0685)	(0.0603)
N. of competitors 10-25	0.180**	0.173**
	(0.0822)	(0.0723)
N. of competitors>25	0.129	0.0497
	(0.101)	(0.0890)
Cash Flow Dev$_{it-1}$	0.155**	0.174*
	(0.0690)	(0.0955)
Long Run Cost Dev$_{it-1}$	0.0225	0.0134
	(0.0202)	(0.0212)
Appropriability$_{it-1}$	-0.00970	-0.00323
	(0.0213)	(0.0214)
Market Share$_{it-1}$	0.138**	0.125***
	(0.0549)	(0.0471)
Espansive demand$_{it-1}$	0.0359	0.0841*
	(0.0461)	(0.0452)
Recessive demand$_{it-1}$	-0.0246	-0.00406
	(0.0485)	(0.0475)
$\tilde{y}_{it-2}$	0.312***	0.306***
	(0.0629)	(0.0710)
$\tilde{y}_{it-3}$	0.0611	0.106
	(0.0751)	(0.0808)
Leftcensor		0.0890
		(0.0571)

Table C1 (cont'ed): Determinants of R&D engagement. Switchers. Non-parametric learning function

Initial Conditions			
Wooldridge Inital Cond.		*Blundell Initial. Cond*	
Y_{it0}	-0.143***	$Y_{i,pre}$	-0.184***
	(0.0390)		(0.0665)
log(TFP)$_{i,mean}$	-0.0195	*log(TFP)*$_{i,pre}$	0.00519
	(0.0588)		(0.0461)
Foreign capital$_{i,mean}$	0.0689	*Foreign capital*$_{i,pre}$	-0.0336
	(0.108)		(0.0759)
Limited liability$_{i,mean}$	-0.0103	*Limited liability*$_{i,pre}$	0.0241
	(0.118)		(0.0905)
log(Capital Stock$_{it-1}$*)*$_{i,mean}$	-0.0202	*log(Capital Stock*$_{it-1}$*)*$_{i,pre}$	-0.0298
	(0.0422)		(0.0273)
log(Age)$_{i,mean}$	0.210*	*log(Age)*$_{i,pre}$	0.129*
	(0.123)		(0.0726)
High Skilled Labour$_{i,mean}$	-0.00918	*High Skilled Labour*$_{i,pre}$	-0.00850*
	(0.00597)		(0.00516)
Med Skilled Labour$_{i,mean}$	0.00576	*Med Skilled Labour*$_{i,pre}$	0.00203
	(0.00448)		(0.00365)
N. of competitors 0-10$_{i,mean}$	-0.223**	*N. of competitors 0-10*$_{i,pre}$	-0.225***
	(0.111)		(0.0860)
N. of competitors 10-25$_{i,mean}$	-0.0191	*N. of competitors 10-25*$_{i,pre}$	-0.213**
	(0.135)		(0.101)
N. of competitors>25$_{i,mean}$	-0.108	*N. of competitors>25*$_{i,pre}$	-0.0791
	(0.168)		(0.115)
Cash Flow Dev$_{i,mean}$	0.0375	*Cash Flow Dev*$_{i,pre}$	-0.190
	(0.0706)		(0.116)
Long Run Cost Dev$_{i,mean}$	-0.104**	*Long Run Cost Dev*$_{i,pre}$	-0.0247
	(0.0490)		(0.0194)
Appropriability$_{i,mean}$	-0.0203	*Appropriability*$_{i,pre}$	-0.0690
	(0.0815)		(0.0571)
Market Share$_{imean}$	-0.0311	*Market Share*$_{ipre}$	0.0821
	(0.0853)		(0.0654)
Espansive demand$_{imean}$	0.257**	*Espansive demand*$_{ipre}$	0.0946
	(0.106)		(0.0738)
Recessive demand$_{imean}$	0.00908	*Recessive demand*$_{ipre}$	-0.0301
	(0.118)		(0.0795)
Constant	-2.714***	Constant	-2.304***
	(0.260)		(0.291)
Observations	12,433		8,511
Number of firms	1.060		998

Notes:

1. Industry and year fixed effects included.
2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix D: Firm age robustness analysis

In this appendix, with the aim of checking the robustness of our estimation results to different firms' ages, we estimate equation (7), using Wooldridge (2005) approach to model unobserved heterogeneity, dividing the sample in four quartiles according to firm's age distribution. Results of these estimations for the main variables of interest (Y_{it-1}, $log(R\&D\ Age_{it})$, TFP_{it-1} and $log(Age_{it-1})$) are shown in Figure D1. In this figure, we show along with the point estimates of these variables, the 90% and 95% confidence intervals (thick and thin lines respectively). In this figure, we refer to the estimates corresponding to first, second, third and fourth age quartiles as *WO1*, *WO2*, *WO3* and *WO4*, respectively.

For the full sample, the point estimate of Y_{it-1}, traditionally associated to sunk costs, is 1.482 (see column 3 of Table 3). In panel A of Figure D1, it is possible to observe that the estimated coefficient of Y_{it-1}, which range from 1.17 to 1.70, increases as we move to higher age quartiles. Hence, this suggests that the importance of sunk costs is increasing in firm age. In any case, estimates for the full sample do not differ much from the estimates for the different age quartiles.

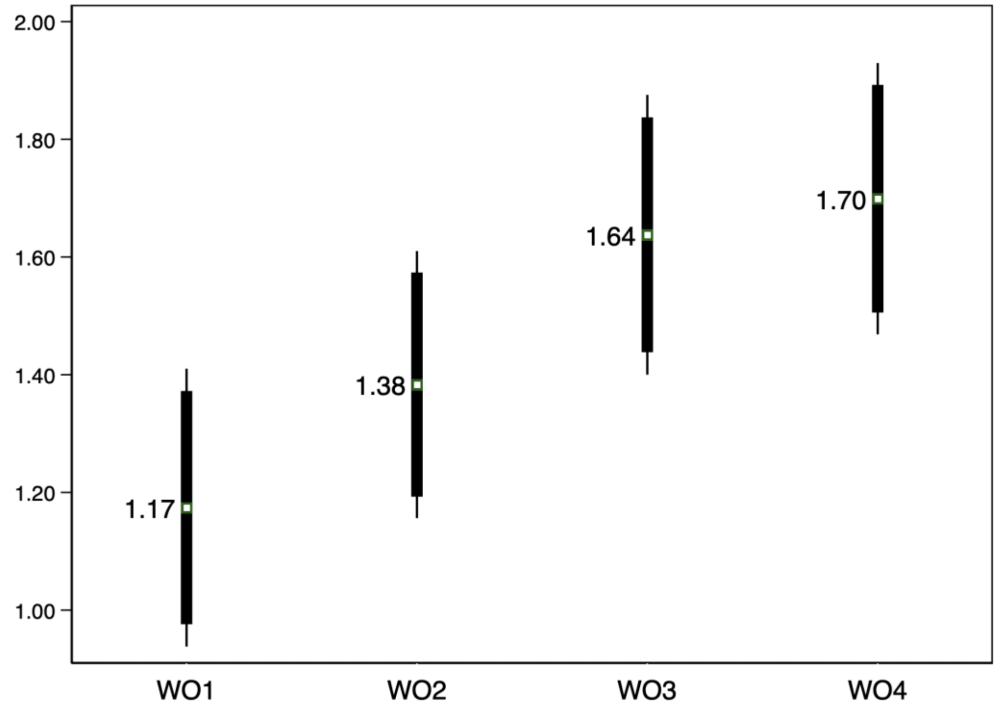
The estimated coefficient of the variable associated to direct learning effects, *log(R&D Age)*, for the full sample is 0.304 (see column 3 of Table 3). As shown in panel B of Figure D1, in the estimations by firms' age quartiles it ranges from 0.27 (for the fourth quartile) to 0.40 (for the second quartile).

The estimates of the coefficient for TFP, which in the full sample is 0.178 (see third column of Table 3), show an increasing pattern as we move from quartile 1 to quartile 4 of the firms' age distribution (see panel C of Figure D1). The TFP estimate in the first quartile is non-significantly different from zero, and estimates for the second, third and fourth quartile are 0.21, 0.28 and 0.32, respectively (the estimates corresponding to the second and third quartiles are significant only at 10% level).

Finally, once we split our estimation sample in quartiles according to firms' age, the estimate for the age variables is only significant at 10% level for age quartiles first and third.

Figure D1. Estimates by firms' age group

(A) Y_{it-1} Estimates



(B) log (R&G Age_{it}) estimates

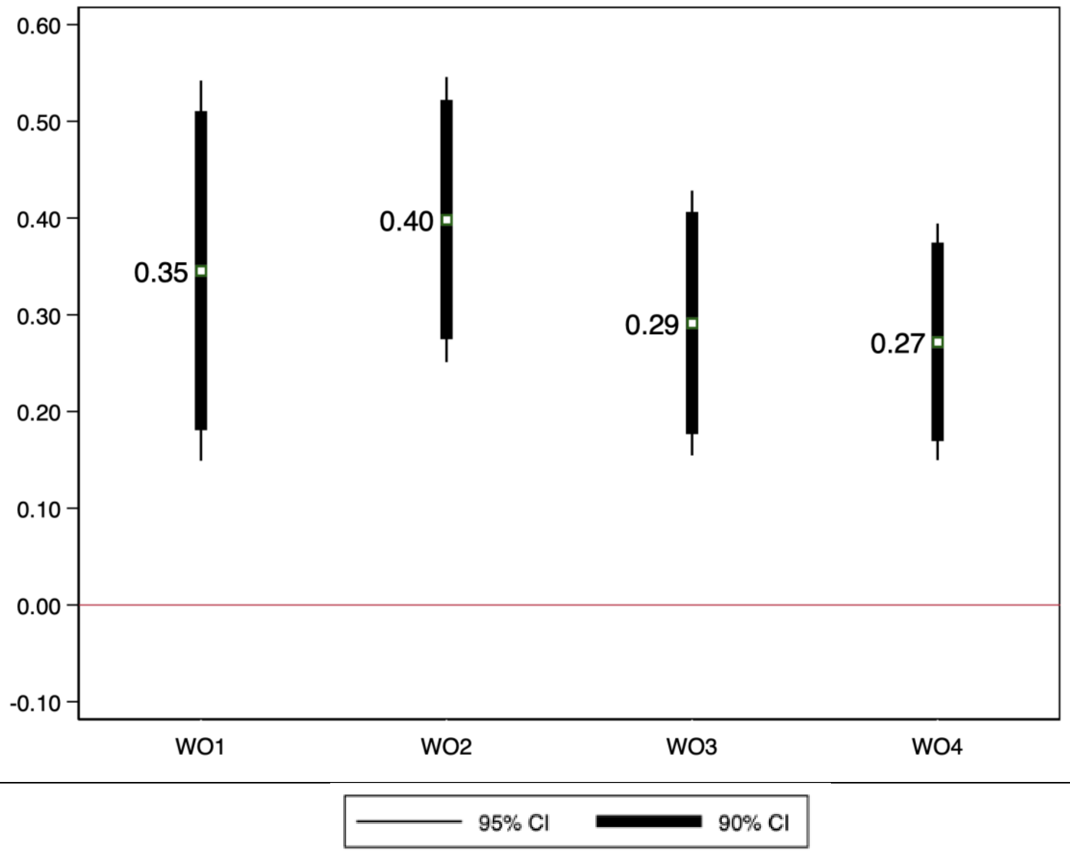
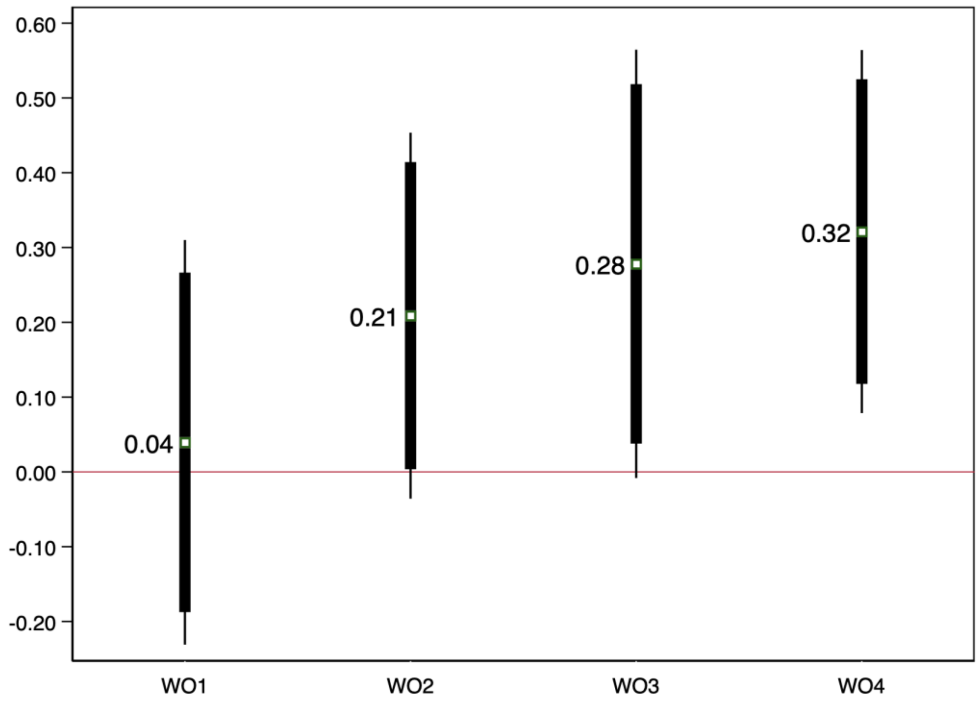
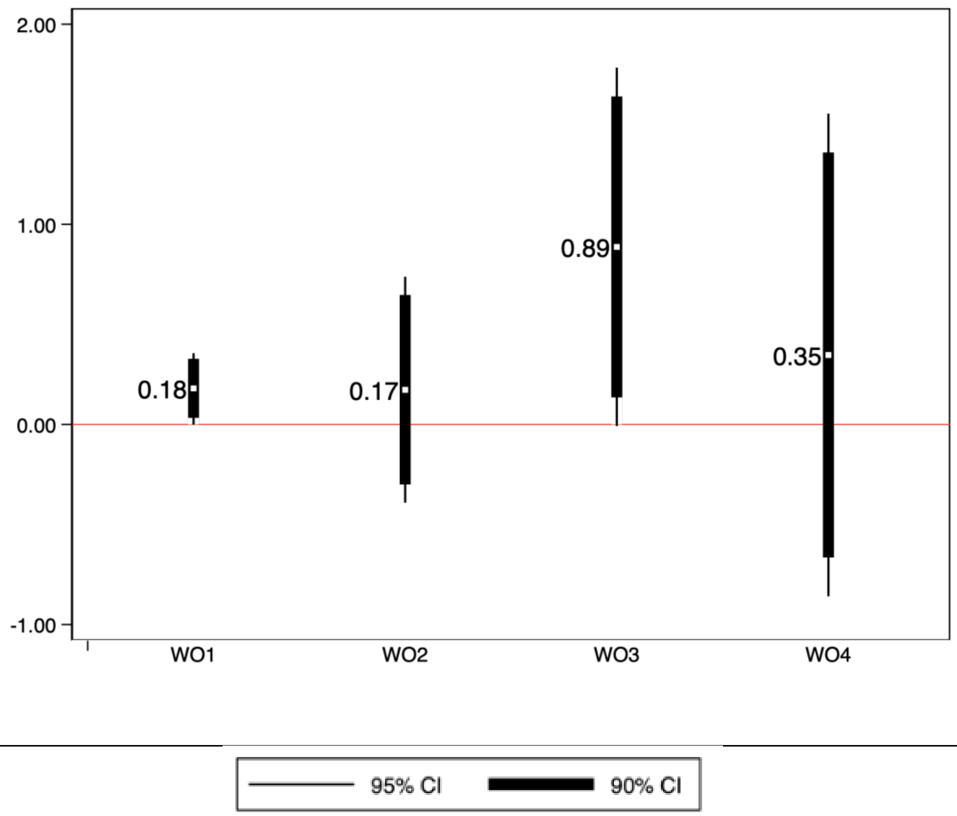


Figure D1 (cont'ed). Estimates by firms' age group

(C) TFP_{it-1} estimates



(D) *log (age$_{it-1}$)* estimates



Note: WO1, WO2, WO3 and WO4 correspond to the estimations of the first quartile, second quartile, third quartile and fourth quartile of the firms' age distribution, respectively.