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Cumulative versus Punctuated Patterns of R&D Learning, Productivity, and R&D Persistence

Juan A Mañez
Juan.A.Manez@uv.es
Universitat de Valencia and ERICES
ORCID: 0000-0003-1105-0815

James H Love
j.h.love@leeds.ac.uk
Leeds University Business School, University of Leeds
ORCID: 0000-0003-3478-685X

Ana Luiza Terra
Universitat de Valencia
terra.analuiza@gmail.com

Authors contribution:
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Cumulative versus Punctuated Patterns of R&D Learning, Productivity, and R&D Persistence

Abstract

This paper analyzes how R&D persistence is affected both by direct learning determinants and indirect determinants through enhanced productivity. Advancing previous research, we allow for three distinct forms of R&D experience through which learning occurs: the firm's current within-spell learning; learning derived from the firm's cumulative R&D experience; and the potential detrimental effect of punctuated learning, where a firm's cumulative R&D experience is divided into multiple R&D spells. Our findings suggest markedly different learning processes depending on firm size and technology. Small and large firms, and firms operating in low and med-tech sectors benefit from cumulative previous R&D but medium-sized and high-tech firms do not. However, a history of fragmented or intermittent R&D is negatively associated with R&D persistence for all firm sizes, but not for low-tech firms. While cumulative R&D experience improves productivity for all firms, there is evidence of an indirect (productivity) association of R&D experience on subsequent R&D persistence only for SMEs and low-tech firms.

Plain English Summary

This paper analyzes how R&D persistence is affected for three distinct forms of R&D experience: the firm's current within-spell learning; learning derived from the firm's cumulative R&D experience; and the potential detrimental effect of punctuated learning, where a firm's cumulative R&D experience is divided into multiple R&D spells. While SMEs are typically considered to be a homogeneous group, we find significant differences between them in the determinants of R&D persistence. For small firms, the length of the current R&D spell does not matter while cumulative previous R&D experience does matter. For medium-sized firms it is precisely the reverse, suggesting the need for differentiated policy responses within SMEs. Subsidies may be more effective for small firms which do not depend on lengthy recent R&D spells in order to achieve persistence in the future, while tax credits might be more efficient for medium-sized enterprises where recent continuous R&D activity is more important for persistence.

Keywords: R&D persistence, cumulative and punctuated learning, productivity.

JEL Codes: O31, O32, C41, L25

1. Introduction

In the context of the knowledge economy, innovation has gained significant recognition as a crucial factor for enhancing a company's performance and ensuring its survival and growth. Moreover, from a public policy standpoint, the importance of innovation lies in its contribution to sustaining economic growth and generating employment opportunities, ultimately fostering social development. This in turn has led to an interest in whether and how innovation policy can help solve societal grand challenges (Kuhlmann and Rip 2018; Laatsit et al., 2025). Since innovation is often underpinned by R&D activity, the determinants of R&D, and the frequency with which it is carried out, is of both theoretical and policy interest.

Our concern is with the role of R&D persistence. The evidence on whether R&D persistence matters for firm performance is somewhat mixed. Some empirical studies find that R&D persistence is an important positive contributor to performance. For example, Beneito et al. (2014) and Ipinnaiye et al. (2025) establish a positive relationship between R&D persistence and an increased level of product innovation, while Hendrickson et al. (2021) demonstrate that persistence in R&D is associated with the introduction of multiple and more novel types of product innovation. Furthermore, several authors have linked R&D persistence with increased profitability (Cefis and Ciccarelli, 2005) and greater productivity growth (Verspagen, 1995; Lööf et al., 2012). By contrast, Guarascio and Tamagni (2019) find that Spanish firms that display persistent R&D do not grow more and do not display more persistent sales growth. Despite the contested nature of the empirical literature, the determinants and effects of R&D persistence remain of academic and policy interest (e.g. NESTI, 2017).

The focus of this paper lies in conducting a comprehensive exploration of the learning process associated with performing R&D activities, acknowledging its close association with the pattern of R&D experience accumulation. We therefore examine three specific determinants in detail at the firm level. First, we examine the direct channel through which R&D experience is linked to learning processes and, in turn, to firms' continuity in R&D. Second, we analyse the indirect channel, whereby accumulated R&D experience may relate to subsequent R&D persistence through its association with higher productivity. Third, we consider how different patterns of prior R&D activity—whether continuous or punctuated—shape R&D persistence through both the direct and indirect channels. We define R&D persistence as the number of consecutive years during which a firm undertakes R&D activities. In contrast, a firm's R&D experience is measured as the total number of years it has previously invested in R&D, whether continuously or intermittently. This broader measure captures the cumulative learning that can arise both from sustained engagement and from more episodic R&D involvement. Accordingly, R&D experience reflects the stock of knowledge accumulated through a firm's historical pattern of R&D activity, irrespective of whether this learning occurred within a single uninterrupted spell or across multiple punctuated spells. R&D learning is the process that links experience and subsequent persistence.

The direct channel between R&D experience and R&D persistence arises from the learning processes associated with the cumulative performance of R&D activities. As firms make repeated investments in R&D, firms develop capabilities which gradually produce a stock of knowledge and experience that is crucial for firms to develop new innovations. Consequently, the cumulative investment in R&D activities leads to increasing dynamic returns to scale, yielding benefits in terms of learning and economies of scale in the production of innovations. This relationship underscores the importance of continuous and persistent investment in R&D for firms seeking to enhance their innovative capacities.

A common characteristic of empirical studies on R&D persistence is their association of learning effects with the cumulative investment in R&D, specifically tied to the continuous involvement in these activities. For example, in both Mañez et al. (2015) and Mañez and Love (2020), learning effects are modeled as a function of the number of years of uninterrupted R&D performance. In other words, these studies are exclusively focused on *within-spell* R&D learning. In common with such studies, our empirical analysis defines a firm as an 'innovator' if it performs R&D in a given year. However, there is no reason to assume that the learning benefits derived from accumulated R&D performance are exclusively tied to the experience gained during the current R&D spell. It is plausible that experience acquired in previous R&D spells can provide the firm with valuable knowledge in the event of reinitiating R&D activities. While certain knowledge may be specific to previous R&D projects or spells and may rapidly depreciate, more general knowledge obtained from previous R&D spells can contribute to the firm's absorptive capacity (Cohen and Levinthal, 1989). This accumulated knowledge can prove advantageous when resuming R&D to undertake new projects associated with subsequent R&D spells.

We acknowledge that firms derive learning benefits from their cumulative as well as recent experience, and this learning positively contributes to R&D persistence. However, we contend that continuous engagement in R&D activities leads to distinct learning outcomes compared to a pattern characterized by episodic R&D spells. Firms that exhibit episodic or punctuated R&D performance are less likely to develop the profound routine-based learning that is associated with continuous R&D engagement (Argote and Miron-Spektor 2011; Love and Mañez 2019). Consequently, one of the central aims of the paper is to distinguish between learning that arises from continuous R&D engagement and learning that reflects the accumulation of R&D experience—whether acquired through sustained or intermittent activity—in order to understand how each relates to firms' R&D performance. Additionally, we aim to test the hypothesis that punctuated R&D may have a detrimental effect on R&D persistence, potentially offsetting the beneficial impacts of accumulated learning-by-performing R&D.

In addition to the direct channel linking accumulated R&D experience to R&D persistence, accumulated R&D experience may also operate through an indirect channel that runs via productivity. Prior R&D experience can be associated with higher productivity, and greater productivity is, in turn, linked to a higher likelihood of maintaining R&D activities (Beneito et al., 2014). Consequently, we posit that R&D experience relates to R&D persistence both directly, through the learning embedded in sustained R&D engagement, and indirectly, through its association with enhanced productivity. We further assess whether this indirect channel varies depending on whether past R&D experience has been acquired continuously or through episodic patterns. The hypotheses are tested using data from 1992 to 2023 drawn from the Spanish Survey of Business Strategies (ESEE), a representative panel of Spanish manufacturing firms.

This paper therefore makes several contributions to the literature on R&D persistence. First, to examine the direct channel linking accumulated R&D experience to R&D persistence, and drawing on recent work on learning-by-exporting (Love and Mañez, 2019), we differentiate between three forms of R&D experience that facilitate learning in the context of R&D performance. These include within-spell R&D experience (related to continuous R&D performance) as examined by Mañez et al. (2015) and Mañez and Love (2020), learning derived from a firm's previous cumulative R&D experience (measured by the number of years of previous R&D experience at the start of the current R&D spell), and the potential adverse effects of punctuated learning, which occur when a firm's cumulative experience is fragmented across multiple spells. While there is a literature on the effects of R&D persistence on product innovation outcomes (see e.g. Ipinnaiye et al., 2025), the existence and effects of these three separate learning effects have not previously been considered in the theoretical or empirical literature. Second, we analyse the indirect channel through which cumulative R&D experience may be associated with R&D persistence via its correlation with higher productivity, and we assess whether episodic R&D activity shapes the relationship between cumulative R&D experience and productivity.

Finally, recognizing that the determinants of R&D persistence may vary between firms of different sizes and technological capacity, we conduct our analysis on both the full sample of firms and sub-samples comprising large, medium-sized and small firms, as well as low-, medium- and high-technology enterprises. This allows us to examine whether punctuated learning is more prevalent among SMEs and low-tech firms, and whether this potential higher prevalence hampers their ability to fully benefit from the learning effects stemming from cumulative R&D performance. There is some suggestion of this in the recent literature. For example, Antonioli and Montresor (2021) find that innovation persistence during crisis periods is lower for SMEs than for larger firms. Thus smaller firms are not merely less persistent on average but are differentially exposed to macroeconomic disruptions that interrupt R&D spells, a mechanism consistent with the punctuated-learning hypothesis.

The paper is structured into six sections. The subsequent section provides the theoretical framework and outlines the hypotheses to be tested. Section 3 offers details regarding the data used and presents descriptive statistics. In Section 4, the empirical model is introduced, along with a discussion of the relevant econometric considerations. The analysis of the results is provided in Section 5. Lastly, the final section is dedicated to a thorough discussion of the findings and concluding remarks.

2. Theory and hypothesis

In this section, we outline a set of hypotheses concerning the determinants of R&D persistence. We first consider the direct channel, which links the accumulation of R&D experience to firms' continuity in R&D and encompasses different forms of learning-by-performing R&D. We then examine the indirect channel, through which accumulated R&D experience may relate to R&D persistence via the enhanced productivity typically associated with previously accumulated R&D experience. Last, we incorporate additional factors that may influence R&D persistence, recognising that disregarding these determinants could bias the evaluation of our main hypotheses.

2.1 Direct channel of R&D experience: learning processes and R&D persistence

In our analysis of the direct channel of R&D experience, our objective is to test three interconnected hypotheses that stem from considering three distinct forms of R&D experience, through which learning by performing R&D occurs. These forms include: first, the firm's current *within-spell* learning; second, the learning derived from the firm's *cumulative* R&D experience (measured by the number of years of previous R&D experience before the current R&D spell); and finally, the potential detrimental influence of *punctuated* learning, which characterizes situations where a firm's cumulative R&D experience is divided into multiple R&D spells.

Several theories have been used to explain the learning process associated with R&D activities and its role in fostering R&D persistence. The first is technology-push theory, initially introduced by Mowery and Rosenberg (1979). This theory posits that R&D activities are an autonomous and self-sustaining process guided by its own set of developmental rules. The second theory, evolutionary theory, was developed by Nelson and Winter (1982) and Dosi (1988). It claims that the technological learning is a consequence of path-dependent trajectories, and that innovations are the result of the acquisition of specific competencies and of the events that enabled this accumulation. The third theory, path dependence of technical change, as described by Atkinson and Stiglitz (1969), emphasizes the role of practice in generating learning effects. This theory focusses on the experience of the innovator and the knowledge acquired by the individual as a driver that determines modernization. Common to these theories is the view that the knowledge base of the firm is cumulative, and that R&D activities are characterized by increasing and dynamic returns that are themselves potential sources of learning and of firm capability in the future (Mañez and Love, 2020). According to these models, firms learn from their experience and knowledge accumulation and so their abilities to survive and to keep performing R&D activities improve as both time and investments accumulate.

At the firm level, numerous studies have provided empirical evidence of the persistence of R&D investment and innovation, notably Geroski et al. (1997), Deschryvere (2014), Mañez et al. (2015), and Mañez and Love (2020). Examining innovation inputs, Peters (2009b) and Mañez et al. (2009) have estimated dynamic autoregressive models to analyze firms' decisions to invest in R&D, Peters (2009b) focusing on the German manufacturing and service industries, while Mañez et al. (2015) focused on the Spanish manufacturing industry. These studies demonstrate that past R&D experience plays a significant role in shaping future R&D investments. However, it is important to note that the primary aim of these papers is to capture the influence of sunk costs on firms' decisions regarding R&D investment.

In the context of studies specifically aimed at analyzing the determinants of firms' R&D persistence, the most comprehensive studies are Mañez et al. (2015) and Mañez and Love (2020). Mañez et al. (2015) focuses on Spanish manufacturing SMEs to assess the factors influencing R&D persistence. Their findings, obtained through the application of survival econometric techniques, indicate a significant association between R&D persistence and the accumulation of R&D capital and knowledge. They also observe a self-sustaining effect of engaging in R&D activities. Similarly, for the case of Spain, Mañez and Love (2020) estimate an econometric model that extends the autoregressive structure employed by Mañez et al. (2009) and Peters (2009b) by incorporating the number of years of continuous R&D engagement. Their objective is to quantify the impact of sunk costs and learning on firms' R&D persistence. The results suggest that while the influence of sunk costs on R&D persistence is more pronounced for large firms compared to SMEs, the learning effect resulting from continuous R&D engagement is more significant for SMEs than for large firms. In the context of other countries, Juliao-Rossi et al. (2020) examined Colombian manufacturing firms and found empirical evidence indicating a correlation between persistence and learning derived from interactions with external financial resources. Furthermore, the authors emphasize the importance of continuous investments in innovation to enhance the likelihood of persistently engaging in such activities. A noteworthy common feature among all the aforementioned papers is their explicit association of the learning process with uninterrupted engagement in R&D activities, specifically the number of consecutive years during which firms have undertaken R&D. In the context of survival econometric techniques (as is the case in this paper), each episode of continuous investment in R&D is referred to as an R&D spell. Therefore, previous papers have primarily focused on analyzing *within-spell* learning processes. This leads to our first hypothesis:

- H1a. R&D persistence is positively associated with the length of the current R&D spell.

However, it is important to recognize that if there are learning processes associated with the accumulation of R&D experience, they need not be limited solely to the experience gained during the current R&D spell (i.e., the ongoing episode of continuous R&D engagement). Learning processes may also arise from cumulative experience acquired in previous R&D spells, resulting in knowledge that proves valuable when a firm reinitiates R&D activities. Although certain knowledge may be specific to R&D projects undertaken during previous R&D spells and consequently subject to rapid depreciation, more general knowledge can enhance a firm's absorptive capacity (Cohen and Levinthal, 1989). This enhanced absorptive capacity can be particularly advantageous when a firm recommences R&D to undertake new projects in subsequent R&D spells.

By performing an activity repeatedly over time, a firm accumulates knowledge not just about the mechanics of the research process, but also learns how to organize and manage R&D activity in an effective manner (Andersson and Lööf, 2009). This allows the firm to develop routines and knowledge about how to organize the R&D process which remain relatively stable through time, which become embedded in the organizational memory, and which do not rapidly atrophy (Love and Mañez, 2019). Their accumulated knowledge thus results in a lower cost of subsequent re-entry into R&D, or of altering their R&D strategy. For example, Añón Higón (2023) finds that firms that outsourced R&D offshore in the past are more likely to continue doing so, but also more likely to switch to onshore outsourcing — a cross-spell dynamic that is structurally analogous to the concept of cumulative experience carrying over across interrupted R&D spells.

Therefore, we acknowledge that firms learn from their previous cumulative experience and this learning contributes positively to R&D persistence. Hence:

- H1b. R&D persistence is positively associated with the total years of cumulative previous R&D experience.

However, we also argue that, for any given cumulative R&D experience, uninterrupted performance of R&D activities has different learning outcomes from a pattern of punctuated R&D spells. Constant routines become easier to organize, manage and becoming assimilated within the firm when firms perform R&D continuously. Besides, unceasing activities avoids depreciation or atrophying of useful knowledge obtained by experience. By contrast, firms with episodic (punctuated) R&D investments are less likely to develop the deep routine-based learning associated to continuous R&D performance. In this regard, we expect that among firms with identical cumulative R&D experience (measured as the number of years of previous R&D performance) at the onset of the current R&D spell, those with a lower number of previous spells (i.e., firms that perform R&D in a more continuous fashion) will experience lengthier subsequent R&D spells.

A useful analogy here is with the learning-by-exporting literature, which acknowledges that learning from previous periods of exporting may be compromised by intermittent exporting for a number of reasons: "First, the firm it is unlikely to develop deeply embedded routine-based exporting learning; second, it has to keep re-learning what it has forgotten in periods of non-exporting because its bank of organizational memory is compromised; and third, the specific knowledge it has accumulated in the past may not be as useful the next time around when it has to re-enter exporting" (Love and Mañez 2019: 76).

A similar situation arises with punctuated R&D activity. Deep, routine-based learning derives from the continuous experience of repeating similar tasks (Argote and Miron-Spektor 2011). This is less likely to be achieved when the firm is infrequently involved in R&D activity, and therefore each new spell of R&D activity is less likely to deliver new learning. In addition, while some aspects of R&D activity always remain useful, inevitably there will be some depreciation or atrophying of useful knowledge where R&D

activity is intermittent, especially in situations where technology is fast moving and new techniques are constantly being developed, and where R&D is linked to particular products. This leads to delay and costs in re-learning knowledge that has been lost when R&D activity is re-started. This leads to our next hypothesis:

- H1c. R&D persistence is negatively associated with the number of previous R&D spells.

2.2. Indirect channel: R&D experience, productivity and R&D persistence

As noted in the introduction, we argue that cumulative R&D experience can shape R&D persistence through both direct and indirect channels. As described in the former section, when referring to the direct channel, we are specifically alluding to the outcomes that arise from the inherent learning processes linked to cumulative R&D experience (acquired either through uninterrupted R&D performance or through punctuated R&D spells). In contrast, the indirect channel captures the way in which cumulative R&D experience may contribute to a higher likelihood of continued R&D activity by operating through enhanced productivity.

To examine the indirect channel through which R&D experience may shape R&D persistence, two key links must be considered: the association between firms' R&D experience and productivity, and the relationship between productivity and the continuation of R&D activities.

The existing literature provides evidence supporting a positive association between R&D activities and firms' productivity through various research strands. Firstly, the well-established R&D capital stock model, proposed by Griliches (1979, 1980), explores the relationship between R&D investments and productivity growth (for a survey, refer to Griliches, 2000). Secondly, the active learning model, proposed by Ericson and Pakes (1995) and further developed by Pakes and Ericson (1998), offers theoretical support for the link between R&D investments and the enhancement of firms' productivity over time. Lastly, the third strand of literature, rooted in endogenous growth theory, emphasizes the crucial role of R&D in promoting productivity growth (Romer, 1990; Aghion and Howitt, 1992). Specifically concerning the impact of R&D experience on productivity, findings from Beneito et al. (2014) indicate a positive influence of R&D experience on both the quantity and quality of innovations, which subsequently contributes to enhanced productivity. Based on these considerations, we propose the following hypothesis:

- H2a: Cumulative R&D experience is positively linked to productivity

When examining the relationship between R&D experience and productivity, we explicitly acknowledge for the possibility that this association differs depending on whether experience is accumulated through uninterrupted R&D engagement or through a sequence of intermittent R&D spells. Consequently, we expect that the influence of cumulative R&D performance on productivity will be more substantial when it arises from continuous R&D engagement compared to when it stems from episodic R&D performance.

The rationale for this builds directly on the arguments developed for the direct channel, which distinguishes how continuous and punctuated R&D experience relate to firms' ability to sustain R&D over time. Firms that engage in R&D intermittently are less likely to develop stable, routine-based learning and may need to repeatedly relearn skills that erode during periods without R&D activity, as their organisational memory becomes weakened (Love and Mañez, 2019). These limitations can constrain the productivity gains typically associated with accumulated R&D experience. On this basis, we formulate the following hypothesis regarding the relationship between cumulative R&D experience and productivity:

- H2b: The positive association between cumulative R&D experience and productivity is stronger when experience derives from continuous R&D engagement rather than from punctuated R&D activity.

Regarding the positive relationship between productivity and the probability of continuous engagement in R&D, higher productivity is expected to be positively associated with R&D persistence because it strengthens firms' financial capacity, raises the expected returns to innovation, and reflects the accumulation of organisational capabilities that make continued R&D more attractive. More productive firms face fewer liquidity constraints and can more easily absorb the sunk and fixed costs of maintaining R&D programmes (Griliches, 1979; Wakelin, 2001), while dynamic models show that productivity gains from past R&D generate a "success-breeds-success" mechanism that increases the incentive to continue investing (Flaig & Stadler, 1994; Geroski et al., 1997). At the same time, productivity growth often signals the presence of established routines, specialised personnel, and learning accumulated through prior R&D, making interruptions particularly costly (Peters, 2009a; Mañez et al., 2015; Mañez & Love, 2020). Endogenous productivity frameworks likewise demonstrate that firms able to convert R&D into higher productivity are those most likely to sustain investment over time (Doraszelski & Jaumandreu, 2013; Raymond et al., 2015). Together, these insights suggest a self-reinforcing relationship in which greater productivity facilitates, motivates, and supports persistent engagement in R&D. Summing up, there seems to exist a self-selection process whereby more productive firms are inclined to undertake R&D initiatives.

- H2c: R&D persistence is positively associated with productivity.

Collectively, hypotheses H2a, H2b and H2c point to the existence of an indirect channel through which accumulated R&D experience may be linked to R&D persistence via enhanced productivity. Figure 1 provides a graphical summary of all the hypothesis described above, and the time structure assumed for the direct and indirect channels.

A key aspect of our identification strategy is the distinction in timing between the analyses of the direct and indirect channels. For the direct channel, we examine whether R&D experience accumulated up to $t–1$ is associated with R&D persistence in t. For the indirect channel, by contrast, we rely on R&D experience measured up to $t–2$ when analysing its association with productivity in $t–1$, and productivity in $t–1$ subsequently enters the analysis of persistence in t. This sequencing strengthens the temporal ordering between experience, productivity, and persistence, and thereby enhances the interpretability of the indirect channel. Thus, we consider that our assumptions regarding the temporal structure linking R&D experience and R&D persistence help to mitigate possible endogeneity concerns related to a two-way relationship between R&D persistence and productivity.

2.3 Other controls influencing persistence in R&D

In addition to the variables central to our hypotheses, we control for several factors commonly linked to firms' persistence in R&D. First, we include sunk costs, which play a well-established role in sustaining R&D engagement. Because R&D requires substantial set-up investments in specialised assets and skilled labour, firms face non-recoverable costs when entering or exiting these activities. Prior studies show that such sunk costs are closely associated with continued R&D participation (Peters, 2009b; Mañez-Castillejo et al., 2009; Arqué-Castells, 2013; Mañez & Love, 2020).

Second, we account for success-breeds-success mechanisms, whereby past innovative achievements reinforce firms' ability and incentives to maintain R&D activity. Evidence in Flaig and Stadler (1994), Geroski et al. (1997), Peters (2009a), Mañez et al. (2015) and Holl et al. (2023) highlights the relevance of these feedback dynamics.

Third, we incorporate demand conditions, following the demand-pull literature (Schmookler, 1962, 1966). Expanding demand relaxes financial constraints and encourages firms to sustain R&D investment, whereas recessive conditions intensify liquidity pressures and may prompt R&D reductions due to its uncertain returns.

Finally, we control for market structure, internal organisational changes, and the availability of R&D subsidies, all of which may influence the duration of R&D spells. Accounting for these factors helps avoid omitted-variable bias in our analysis of R&D persistence.

3. Data and descriptive statistics

3.1 Data

This study uses data from the Spanish Survey of Business Strategies (ESEE), an annual panel survey of Spanish manufacturing firms conducted since 1990. The survey covers firms with at least 10 employees and is representative by industry and size. The sampling design distinguishes between two groups: firms with more than 200 employees are all requested to participate, while those with 10–200 employees are randomly selected using a stratified and proportional sampling method. In the initial year, 2,188 firms were interviewed. Since then, efforts have been made to minimize attrition and preserve representativeness by incorporating new firms following the original sampling criteria.[1]

The ESEE is well suited for analysing firms' R&D persistence using survival methods. As a longitudinal panel, it provides detailed annual information on firm characteristics, enabling the analysis of R&D spell duration over time. It also allows identification of key outcomes, including firm exit, survey attrition, entry into and exit from R&D, and continued engagement over the period 1992–2023. The availability of this information is instrumental in conducting rigorous analyses of firms' persistence in R&D using survival analysis methods.[2]

The initial dataset (1992–2023) comprises an unbalanced panel of 56,223 firm-year observations for 7,063 firms. Of these, 3,728 firms (24,014 observations) never engage in R&D, while 3,325 firms (32,309 observations) undertake R&D at least once; the R&D survival analysis focuses on this latter group. The estimation sample is constructed by requiring firms to appear in the sample for at least two years and

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[1] See http://www.fundacionsepi.es/investigacion/esee/ *en/spresentacion.asp* for more details about the database. Important efforts have been made to minimize problems of attrition replacing firms that leave the sample with new firms, or firms of similar characteristics.

[2] It is necessary to point out a limitation of the ESEE. When trying to use the ESEE to analyse the evolution of aggregated R&D magnitudes, one should consider that from 2010 onwards we observe two compositional issues that could affect these R&D measures. Let us use as example average R&D expenditure evolution. First, the number of large firms in the sample falls substantially (from 407 in 2010 to a minimum of 197 in 2020) and, since large firms spend 10 to 20 times more on R&D than SMEs, their declining presence mechanically depresses the overall average (extensive margin). Second, even among the large firms that remain, average size declines significantly (from 776 to 563 employees between 1992 and 2020), which, given the well-established positive correlation between firm size and R&D expenditure, further reduces average spending independently of any behavioural change (intensive margin). These compositional shifts do not, however, affect the reliability of our estimates for three reasons: our duration analysis models the decision to perform R&D rather than its level; estimates are identified by within-firm variation over time rather than cross-sectional differences; and firms exiting the sample — whether through failure or attrition — are treated as right-censored, explicitly recognising that R&D persistence and firm survival are governed by different processes. Firm size controls and year fixed effects further absorb any residual correlation between sample composition and R&D behaviour.

excluding firms with missing information on key variables. Observations for 2023 are included only to identify whether R&D spells active in 2022 continue into 2023. The final sample consists of 14,516 firm-year observations corresponding to 2,536 firms.

As noted, the analysis focuses on firms that engage in R&D at least once. These firms may differ systematically from those that never innovate. However, these differences should not be interpreted as a source of selection bias in our estimations, but rather as the outcome of well-documented economic mechanisms related to selection into innovation and returns-to-innovation (Mañez et al., 2005). On the one hand, larger and more productive firms are more likely to engage in innovation activities, as they possess the resources and capabilities required to bear the associated fixed costs and risks (Cohen and Levinthal, 1990). On the other hand, innovation itself may enhance firm performance by increasing productivity, fostering growth, and raising input intensity through complementarities with capital, intermediate inputs, and skilled labour (Crépon et al., 1998). Therefore, the positive association between innovation, size, productivity, and resource use likely reflects a combination of ex ante selection into innovation and ex post performance effects.

To assess these differences, we estimate the following equation:

$$log(y_{it}) = \beta_0 + \beta_1 sample_{it} + \delta log(size_{it}) + \sum_{j=2}^{10} \gamma_i \, ind_j + \sum_{i=1992}^{2022} \lambda_t year_t + e_{it} \quad (1)$$

where $sample_{it}$ is a dummy variable taking value one for all observations corresponding to firms that exhibit at least one R&D spell during the period they are observed in the sample, and zero otherwise. The dependent variable (y_{it}) is alternately defined as firm age, output per worker, capital per worker, size (as measured by the number of employees), and intermediate materials per worker. As in the baseline specification, we control for firm size (except when size is the dependent variable), as well as industry and year fixed effects.

Table 1 reports the estimated differences (in percentage terms) between firms with and without innovation experience, computed from the estimated coefficient β_1 as $100(\exp(\beta_1 - 1))$. Results show that innovative firms are significantly larger, more productive, and more resource-intensive. For example, output per worker is 31.66%

higher, capital per worker 58.48% higher, and firm size nearly 198% larger (all p = 0.000). These differences are consistent with both selection into innovation and returns-to innovation mechanisms. Consequently, the observed differences reflect underlying economic processes rather than a source of bias that would invalidate the empirical analysis.

Before describing the estimation sample in detail, Table 2 reports transition probabilities between R&D and non-R&D states over 1992–2023 for all firms reporting R&D activity, providing an initial view of R&D persistence. The results indicate strong persistence in both states for the full sample. Around 88% of R&D-performing firms continue in the following year, while 11.66% exit R&D. Persistence in the non-R&D state is about 5 percentage points higher, with only around 6% of non-R&D firms entering R&D. These patterns suggest that while entry into R&D is relatively difficult, firms that engage in R&D tend to persist, although R&D exits remain more common than R&D entries.

To examine heterogeneity, we analyse transition probabilities by firm size and technological regime. Firms are classified as small (10–50 employees), medium (51–200), and large (over 200), and into low-, medium-, and high-tech industries following the OECD classification (Hatzichronoglou, 1997). The results reveal substantial heterogeneity. While R&D engagement shows strong state dependence, persistence and transition rates vary markedly across these dimensions.

R&D persistence increases with firm size. Small firms show the lowest continuity in R&D (64.4%) and the highest persistence in non-R&D (96.6%), suggesting difficulties in sustaining R&D. This asymmetry suggests that while small firms can occasionally initiate R&D projects, structural barriers hinder their ability to sustain them. Medium firms occupy an intermediate position (86.9% and 90.9%), while large firms show the highest R&D persistence (93.5%) and the lowest non-R&D persistence (85%), indicating more stable engagement.,

A similar pattern emerges across technological regimes, highlighting the role of knowledge intensity. Low-tech firms display the lowest R&D persistence (83.4%) and the highest non-R&D persistence (95.2%), indicating more episodic, project based activity. Medium-tech firms lie in between (89.2% and 92.9%), while high-tech firms exhibit the highest R&D persistence (93.4%) and the lowest non-R&D persistence (90.5%), suggesting that R&D is a core component of their competitiveness.

Taken together, these results indicate that R&D persistence increases with both firm size and technological intensity. Small and low-tech firms exhibit less continuous R&D, while large and high-tech firms display more stable, structurally embedded R&D strategies. Medium-sized and medium-tech firms occupy a transitional position characterized by moderate persistence. This supports the view that R&D follows cumulative and path-dependent dynamics: as firms grow and operate in more technology-intensive environments, R&D becomes progressively a more continuous activity embedded in firms' competitive strategies.

The estimation sample covers 1992–2022 and includes 14,516 observations for 2,536 firms, corresponding to 3,182 R&D spells. By size, it comprises 791 small firms (31.2%), 847 medium (33.4%), and 898 large (35.4%), with a similar distribution of spells: 1,017 (31.2%), 1,074 (33.7%), and 1,091 (34.3%), respectively. This balanced composition ensures robust representation across firm-size categories, allowing the analysis to capture the heterogeneity of R&D persistence patterns in the Spanish manufacturing sector.

By technological intensity, the sample is also balanced: low-tech firms account for 4,961 observations (34.2%), 1,046 firms (41.2%), and 1,332 spells (41.9%); medium-tech firms for 5,640 (38.8%), 913 (36%), and 1,176 (37%); and high-tech firms for 3,915 (27%), 577 (22.8%), and 674 (21.1%). This reflects the predominance of low- and medium-tech activities within Spanish manufacturing while maintaining substantial coverage of high-tech sectors where R&D engagement tends to be more continuous.

3.2 R&D investment experience, punctuated R&D, and heterogeneity

One of the hypotheses examined in this study is that learning effects may stem both from the accumulation of R&D experience within the current R&D spell and from previous cumulative R&D engagement, as well as from the way such experience is built in the presence of punctuated R&D activities. The following sections explore these relationships in greater depth, focusing on differences by firm size and technological regime.

3.2.1 Firm size

To examine the role of firm size, we estimate Kaplan–Meier survival functions (Figure 2), which report the proportion of R&D spells remaining active over time and capture the accumulation of experience within each spell. This can be interpreted as reflecting the process of experience accumulation, whereby longer spell durations correspond to higher levels of firm-specific R&D experience.

One-year continuation rates are 72.2% for small firms, 82.7% for medium firms, and 88.8% for large firms. Persistence declines over time, particularly in early years: after 5 (10) years, R&D survival falls to 31.12% (17.53%) for small firms, 49.97% (36.77%) for medium firms, and 66.91% (53.28%) for large firms. Across all groups, most exits occur within the first five years with substantially fewer exits in the subsequent five-year period (years 6–10).

In addition, survival functions progressively flatten over time, as the duration of continuous R&D investment increases, indicating that the probability of exit declines with spell length. This pattern is consistent with negative duration dependence: the longer firms sustain R&D activities, the lower their likelihood of exit. Overall, these findings support the hypothesis that accumulated R&D experience fosters learning and enhances persistence.

Figure 2 shows that the survival function for large firms lies above that of medium firms, which in turn lies above that of small firms, indicating that R&D persistence increases with firm size. Median spell duration is 3 years for small firms and 5 years for medium firms, while more than 50% of large firms remain in R&D after 12 years. Mean durations are 5.8, 11.3, and 14.7 years, respectively. A log-rank test rejects equality of survival functions across groups ($\chi^2 = 303.14$, $p = 0.000$).

Table 3 provides evidence on punctuated R&D spells. While most firms experience a single R&D spell, multiple spells occur in about 21% of small firms, and in nearly 19.8% and 16.7% of medium and large firms, respectively. These patterns indicate episodic R&D engagement, characterized by multiple interruptions and resumptions of R&D activities. In some cases, firms experience up to five distinct R&D spells over the period.

3.2.2 Technological regime

We next estimate Kaplan–Meier survival functions by technological regime (Figure 3). The results show clear differences across regimes. One-year continuation rates are 75.3% (low-tech), 84.3% (medium-tech), and 88.4% (high-tech). Persistence declines over time, but at different rates: after 5 (10) years, R&D survival falls to 39.6% (29.6%) for low-tech firms, 53.9% (40.0%) for medium-tech firms, and 65.6% (53.4%) for high-tech firms. This indicates that R&D activity is more short-lived and project-based in low-tech sectors, while it becomes more sustained as technological intensity increases.

Across all regimes, as in the firm size analysis, survival functions flatten over time, indicating negative duration dependence. This pattern is consistent with cumulative learning and capability accumulation over time. The ranking of survival curves shows that persistence increases with technological intensity, with high-tech firms consistently above medium-tech and low-tech firms. Median spell duration rises from 4 years (low-tech) to 6 years (med-tech) and over 11 years (high-tech), while mean durations are 8.4, 11.9, and 14.4 years. A log-rank test rejects equality of survival functions across regimes ($\chi^2 = 125.44$, $p = 0.000$), confirming significant heterogeneity in persistence.

Table 3 provides additional evidence on punctuated R&D. While most firms experience a single spell, a non-negligible share display punctuated R&D trajectories. Multiple spells occur in 20.6% of low-tech firms, 20.4% of medium-tech firms, and 16.7% of high-tech firms, indicating intermittent R&D engagement with episodes of cessations and re-entry. These patterns are more prevalent in lower-tech sectors, suggesting that discontinuity decreases with technological intensity as learning, absorptive capacity, and strategic commitment to innovation become stronger.

In summary, the descriptive evidence shows that both firm size and technological intensity play a central role in shaping R&D continuity. Small and low-tech firms exhibit more punctuated R&D patterns and a higher risk of interruption, likely reflecting structural and financial constraints that limit the accumulation of long-term capabilities. By contrast, large and high-tech firms display more sustained R&D engagement, suggesting the presence of more developed innovation systems and routines that embed R&D within their core strategies. Medium-sized and medium-tech firms occupy an intermediate position, alternating between periods of engagement and temporary withdrawal. Overall, these patterns point to an evolutionary process in which R&D

persistence strengthens with firm growth and technological sophistication, gradually transforming innovation into a more continuous and systematic activity.

4. Model specification

4.1 Empirical model and econometric issues

To examine the factors influencing firms' R&D persistence we employ duration techniques, which allow for the assessment of exit risk and its determinants over time while accounting for the occurrence and timing of exits. We measure R&D persistence by the length of continuous R&D, so that the duration of a spell of R&D captures persistence in R&D. We employ a multivariate analysis to assess the influence of several factors on the hazard risk associated with the termination of R&D spells. Specifically, we investigate how different patterns of learning and productivity effects impact the duration of these R&D spells, essentially elucidating their roles as determinants of R&D spell survival. Additionally, our analysis includes controls for various covariates that may potentially exert an influence on the duration of R&D spells, as well as factors related to unobserved heterogeneity within the dataset.

Given that the underlying transitions between performing R&D and not performing it, and vice versa, are continuous processes, but the available data are collected on a yearly basis, rendering it interval-censored, we opt to employ discrete-time proportional hazard models. In this framework, we treat the duration of R&D investment spells as a discrete variable (Jenkins, 2005). This modelling approach enables us to flexibly specify the baseline hazard function and account for unobserved heterogeneity within these spells. Furthermore, it allows us to investigate duration dependence, which can be understood as the influence of the length of survival time on R&D persistence.

We estimate the discrete time representation of the following underlying continuous time proportional hazard model

$$\theta(j, x_{ij}) = \theta_0(j). exp^{\beta_0 + x_{ij}\beta}. v_i \tag{2}$$

where j refers to a given duration year, i is the spell identifier, and x_{ij} a vector of spell, firm and industry characteristics (including among others total factor productivity). In this framework, $\theta(j, x_{ij})$ is the hazard function and $\theta_0(j)$ is the baseline hazard function (that is a function of number of years of continuous R&D performance). The proportional variation relative to the average firm is incorporated multiplicatively in the unobserved heterogeneity term (v_i). Further, we assume a gamma distribution for the frailty (unobserved heterogeneity) component, based on Meyer (1990).

Log linearizing the expression (2) we obtain:

$$log\theta(j, x_{ij}) = log\theta_0(j) + \beta_0 + x_{ij}\beta + \log(v_i) \quad (3)$$

Considering expression (3), we observe that after controlling for the covariates and unobserved heterogeneity, the baseline hazard $\theta_0(j)$ is the hazard that is associated to the passage of survival time which is common to all R&D spells.

The dependent variable of the survival model used in this study to analyze R&D persistence is a binary variable instead of a direct measure of continuous R&D investment years. The referred dependent variable takes value 1 for the survival period in which the firm stops investing in R&D and 0 for the periods in which it continues investing.

Two relevant issues warrant consideration when constructing this binary variable. Firstly, we must address the presence of right-censored R&D spells, which are those that continue beyond the last year of our sample period. For these right-censored spells, our binary dependent variable takes value 0 for all survival years. Secondly, our dataset permits the differentiation between R&D spells concluding due to a firm's cessation of R&D activities and those concluding due to firm failure. Treating R&D spells that terminate because of firm failure as completed spells (and changing the binary dependent variable to one in the last observed survival year) would erroneously imply that the factors governing R&D spell duration align with those influencing firm survival. To circumvent this issue, we categorize these spells as right-censored, thus explicitly acknowledging that the determinants of R&D persistence differ from those dictating firm survival.

A final consideration pertains to the use of data for the year 2023, which is exclusively employed to assess whether R&D spells that were ongoing in 2022 continued to operate in 2023. This data is also used to construct our censoring variable.

Consequently, the estimation period we examine spans 31 years, encompassing the period from 1992 to 2022.[3]

4.2 Independent variables

To evaluate the hypotheses introduced in Section 2, we construct a set of variables capturing the different dimensions of firms' R&D experience and a range of additional factors that may influence R&D persistence. Table 3 provides a schematic overview. Since the assessment of the indirect channel operating through productivity requires separate estimations, those variables are discussed in detail in the following section.

A central variable in the duration framework is *Log(Surv. Time)*, which represents the baseline hazard and captures within-spell learning: as firms remain engaged in an R&D spell, they accumulate tacit knowledge, strengthen routines, and amortize set-up costs. A negative coefficient signals negative duration dependence—namely, that longer spells are associated with a lower probability of termination—which corresponds to hypothesis H1a. This variable allows us to observe whether continued engagement in the current spell is systematically linked to greater persistence. Substantiating this hypothesis would indicate the presence of *within-spell* learning.

Hypothesis H1b focuses on cumulative R&D experience acquired prior to the current spell. To assess it, we include the variable *Previous R&D investment experience*, which measures the total number of years during which the firm performed R&D (either continuously or intermittently) before the spell under examination. A negative estimate implies that accumulated experience is associated with lower hazard rates and hence

[3] Note that a problem of endogeneity could arise if some of our covariates co-evolve with the duration of the R&D spell since the former may be pre-determined by the latter. To test for the presence of this potential source of bias we have carried out in Appendix B alternative estimations using the approach proposed in Geroski et al. (1997) (and followed also for example by Bianchini and Pellegrino, 2019). Thus, we set the value of the covariates at their value the first period of the spell and keep it constant throughout the spell. The main problem of this approach it that it does not allow us to test for the existence of a potential indirect association of past cumulative R&D experience on R&D persistence through enhanced productivity. For the sake of brevity, we present results for the full sample and for size groups. Results by technological regime are available under request.

greater persistence. The third form of experience, relevant for H1c, is captured by *Previous number of spells*, a count of the firm's previous R&D episodes. This variable reflects whether the learning derived from intermittent, punctuated R&D trajectories is weaker or more fragile than the learning generated through continuous R&D engagement. A positive coefficient would indicate that a history of fragmented spells is associated with shorter persistence in the current spell.[4]

To assess the potential indirect channel through productivity (H2c), we include a measure of firm productivity, *TFP*, which allows us to examine whether more productive firms are more likely to sustain R&D engagement.

Because the relationships of interest may be confounded by other sources of observed or unobserved heterogeneity, we introduce several additional controls, grouped into five broad categories: firms' commitment to R&D activities (sunk costs), success-breeds-success mechanisms, demand-pull conditions, market structure, and other firm-level characteristics.

We start describing the variables we use to proxy for firms' commitment to R&D activities. R&D investment involves substantial sunk costs related to establishing research infrastructures, mobilising specialised human capital, and maintaining internal capabilities. To reflect heterogeneity in commitment to R&D, we include three strategy dummies: *Only External*, *Only Internal*, and *Both*. These classify whether the firm outsources R&D, performs R&D exclusively in-house, or combines internal and external modes. The category *Only External* is omitted to avoid collinearity. Firms performing internal or combined R&D are expected to demonstrate greater persistence due to higher sunk costs and richer opportunities for organisational learning. *R&D intensity*, defined as the ratio of R&D expenditure to sales, further captures the degree of commitment. We also include *Log(R&D emp)* as a measure of the R&D workforce scale. Finally, both in the estimations for the full sample and for size groups, we undertake classification of industries into low-, medium-, and high-technology regimes following

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[4] Difficulties in retaining R&D personnel, particularly among small and medium-sized firms, may attenuate the learning effects associated with accumulated R&D experience. To the extent that part of this experience is embodied in workers, labour mobility may weaken the ability of the variable *Previous R&D investment experience* to accurately proxy the stock of accumulated R&D knowledge, potentially leading to weaker empirical support for H1b.

the OECD (Hatzichronoglou, 1997), as we expect the technological regime to affect the scale and complexity of R&D operations.

With respect to the success-breeds-success mechanisms, past innovation outcomes often reinforce the continuation of R&D activities. We capture this dynamic by including dummies for *Product innovation* and *Process innovation*, indicating whether the firm has introduced new products or processes. We also consider *Log(Approp)*, an indicator of the industry-level appropriability conditions, measured as the log ratio of total patents and utility models to the number of firms reporting innovations (Mañez et al., 2015). To incorporate financial considerations, we include the *Score E* index (Mañez & Vicente-Chirivella, 2021), which summarises internal and external financial health. High values of this index denote stronger financial health. Thus, a negative coefficient would indicate that financially stronger firms experience longer R&D spells.

Consistent with the demand-pull hypothesis (Schmookler, 1962, 1966), firms' expectations regarding demand conditions influence their R&D behaviour. To evaluate the impact of the evolution of firm's demand, we include the dummy *Drecessive*, equal to 1 when the firm experiences recessive demand. Thus, this variable distinguishes situations where a firm reports a declining or recessive demand from those where it reports either expansive or recessive demand conditions.[5] Recessive conditions may constrain liquidity and lead firms to deprioritise long-term investments such as R&D. We also include an *Exporter* dummy, recognising that export-oriented firms may face stronger innovation pressures due to international competition, which can foster R&D persistence.

The competitive environment can further shape the incentives to maintain R&D. We therefore include *Mshare*, a dummy indicating whether the firm reports holding a significant market share in its main market, and *Log(CR4)*, the log of the four-firm concentration ratio, to proxy market concentration.

[5] This proxy for firm-level demand conditions is closely correlated with the business cycle. For instance, 44.45% of firms reported facing declining demand during the Great Recession (2008–2013), compared to only 12.96% during the subsequent expansion (2014–2019). A similar pattern emerges around the COVID-19 shock: 39.53% of firms declared facing declining demand in 2020, whereas this share falls to 12.19% during the following expansion period (2021–2023).

In addition to the aforementioned controls, we include several other controls measures. We incorporate firm size (*Log(Employment)*), firm age (*Log(Age)*), and a dummy for receiving public R&D subsidies (*R&D Sub*), as public support may reduce financing constraints and encourage longer R&D engagement.[6] Year dummies capture business cycle conditions common across firms. Finally, organisational changes such as absorptions (*Absorption* dummy) and excisions (*Excision* dummy) may disrupt internal routines; hence, we include these dummies to identify firms experiencing structural adjustments during the spell.

Together, this set of variables provides a detailed framework for assessing both the direct and indirect channels through which R&D experience may influence R&D persistence, while controlling for a rich set of firm- and industry-level characteristics known to affect firms' innovation behaviour.

4.3 Indirect channel of cumulative R&D experience through productivity: TFP estimation

To assess the existence of indirect channel of R&D experience on R&D persistence it is necessary to first ascertain whether R&D experience is positively associated to productivity (H2a, H2b). Second, one should determine whether firms with higher productivity are more inclined to engage in R&D activities (H2c). The second condition simply entails verifying if the estimate of productivity in equation (3) is both negative and statistically significant. Here we elaborate on the methodology employed to evaluate the first condition i.e. H2a and H2b.

To account for the potential association between cumulative R&D experience and firms' productivity, we follow the productivity estimation approach proposed by Doraszelski and Jaumandreu (2013). This structural framework allows current productivity to evolve as a function of past productivity and firms' cumulative R&D experience, thereby providing a coherent way to analyse the role of accumulated R&D experience in shaping productivity dynamics. Accordingly, we estimate TFP using a Cobb–Douglas production function and implement the Wooldridge (2009) procedure,

[6] We carry out a detailed analysis of the role of R&D subsidies on R&D persistence in Appendix C.

which we adapt to incorporate an endogenous Markov process (equation 4) in which past cumulative R&D experience directly affects current productivity.[7]

$$\omega_{it} = f(\omega_{it-1}, R\&D\ Experience_{it-1}) + \nu_{it} \quad (4)$$

Similar approaches have been employed in the analysis of the effect of exports (DeLoecker, 2013) and R&D (Doraszelski and Jaumandreu, 2013) on productivity. Technical details of how to estimate total factor productivity under the assumption of an endogenous Markov process governing the law of motion of productivity are provided in Appendix A. Here we summarize the empirical model.

If we take into consideration the recursive nature of the endogenous Markov process in equation (4), it becomes possible to linearize the endogenous law of motion of productivity to parameterize the productivity of a firm (ω_{it}) as a function of the log of firm's R&D experience up to *t-1* ($\log(R\&D\ Experience_{it-1} + 1)$) and the initial condition value for productivity (ω_{i0}). $R\&D\ Experience_{it-1}$ is proxied for the logarithm of the cumulative (total) prior number of years in which the firm has been actively engaged in R&D, encompassing both continuous and episodic R&D spells. The rationale behind considering the total number of R&D engagement years before a specific period, rather than exclusively focusing on the years within a particular spell leading up to that period, is grounded in the expectation that the productivity-enhancing benefits of R&D experience extend beyond individual spells and have a lasting influence on future productivity. This suggests that R&D experience can be associated with higher productivity even when it has been accumulated through discontinuous rather than uninterrupted R&D activity.

Additionally, we control for other factors that might influence the firm's productivity evolution, such as a vector of observed firm characteristics (X_{it-1})

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[7] An alternative would be to adopt the standard three-equation CDM (Crépon et al., 1998) framework linking R&D investment, innovation outputs, and firm productivity. However, the approach of Doraszelski and Jaumandreu (2013) is better suited to our purposes, as it explicitly models productivity dynamics as a function of past productivity and cumulative R&D experience. By contrast, the CDM framework is primarily designed to analyse the relationship between innovation inputs, innovation outputs, and productivity.

(including firm age and size), year-specific dummy variables μ_t, industry-specific dummy variables (μ_s) and firm-level fixed effects (α_i). As a result, we estimate the following specification for the Markov process in equation (5).[8]

$$\omega_{it} = \delta_0 + \delta_1 log(R\&D\ Experience_{it-1} + 1) + \omega_{i0} + \beta X_{it-1} + \mu_t + \mu_s + \alpha_i + \epsilon_{it} \qquad (5)$$

In the fixed-effect panel data estimation of equation (5), the initial condition value of productivity (ω_{i0}) and α_i collapse into a single firm-specific fixed effect. Positive and statistically significant estimates for δ_1 are interpreted as evidence of the positive relationship between R&D experience and productivity and would support Hypothesis 2a.

The confirmation of the indirect channel of cumulative R&D experience on R&D persistence, both for firms that have accumulated R&D experience through continuous R&D performance and firms that have gained R&D experience through punctuated R&D spells, requires negative estimates for the coefficient associated to TFP in equation (3) as well as a positive estimate for $\log(R\&D\ Experience_{it-1} + 1)$ in equation (5).

Nonetheless, the formulation presented in equation (5) assumes a uniform relationship between R&D experience and productivity, regardless of whether it has been acquired through sustained, continuous R&D engagement or through a series of punctuated R&D spells. Given our theoretical expectation that the positive association of R&D experience with productivity is more pronounced when accumulated continuously in comparison to episodic, discontinuous spells, we broaden our analytical framework by introducing an expanded version of equation (5). This augmented specification facilitates an investigation into the different association of R&D experience to productivity contingent upon whether such experience has been garnered in a continuous or discontinuous manner.

$$\omega_{it} = \delta_0 + \delta_1 log(R\&D\ Experience_{it-1} + 1) + \delta_2 Disc_{it} +$$
$$\delta_3 log(R\&D\ Experience_{it-1} + 1) \times Disc_{it} + \omega_{i0} + \beta X_{it-1} + \mu_t + \mu_s + \alpha_i + \epsilon_{it} \qquad (6)$$

In equation (6), the variable $Disc_{it}$ is a dummy variable that takes on a value of 1 for observations corresponding to second and subsequent spells of a particular firm. A

[8] Mañez and Love (2020) use the same approach for R&D Age (measured as the number of years of within spell experience).

positive and statistically significant estimation for δ_1 suggests a positive association of uninterrupted R&D experience with productivity. Similarly, a positive and statistically significant estimation for $\delta_1 + \delta_3$ indicates that R&D experience gained through punctuated R&D spells also is positively associated with productivity (these two results would offer empirical support for Hypothesis 2a). In line with Hypothesis 2b, we expect that the influence of R&D experience on productivity will be stronger when it is acquired continuously compared to when it is obtained through a series of punctuated R&D spells. Therefore, we expect the estimate of δ_3 to be negative and statistically significant.

Finally, to confirm the hypothesis of an indirect channel for firms with an uninterrupted R&D experience, it is necessary to observe a positive and statistically significant estimate of δ_1 in equation (6), as well as a negative and significant estimate for the TFP variable in equation (3) (i.e. H2c). Likewise, to confirm the hypothesis for firms with R&D experience acquired through a series of punctuated R&D spells, it is required to observe a positive and significant estimate of $(\delta_1 + \delta_3)$ in equation (6), along with a negative and significant estimate for the TFP variable in equation (3).

5 . Results

The results from the estimation of the discrete-time proportional hazard model, introduced in Section 4 are presented in Tables 6 and 7. Table 6 provides the results for the entire sample of firms and across size groups. Table 7 provides separate estimates for low-, med- and high-tech firms.

For every estimation (entire sample, size groups and technological regimes), we reject the null hypothesis positing that the variance of the unobserved heterogeneity component equates to zero (see the bottom of Tables 6 to 7). This finding suggests the existence of unobserved heterogeneity, which may encompass factors such as managerial capabilities, attributes of a firm's R&D personnel, or organizational processes not accounted for in the accessible dataset. In the presence of such unobserved heterogeneity, the interpretation of hazard ratios within proportional hazard models becomes awkward, as outlined by Gutierrez (2002). Therefore, in Tables 6 and 7, we provide coefficients rather than hazard rates to accommodate this complexity in our analysis. These coefficients represent the impact of the covariates on the hazard of R&D

spell termination. Positive coefficients signify an increase in the hazard (corresponding to a diminished expected duration of the R&D spell), whereas negative coefficients denote a reduction in the hazard (indicating an increase in the expected duration of the R&D spells).

5.1 R&D persistence and learning

5.1.1. The role of firm size

The estimations presented in columns 1 to 4 of Table 6, corresponding respectively to the full sample, small (≤ 50 employees), medium (> 50 and ≤ 200), and large (> 200) firms, reveal marked asymmetries in the determinants of R&D persistence. Further, the estimation results allow an assessment of whether hypotheses H1a, H1b, and H1c are supported for each size category.

The coefficient of *Log(Surv. time)* is negative and statistically significant for the full sample as well as for medium and large firms, while it is not for small firms. This finding confirms H1a for medium and large firms but not for small ones, indicating that within-spell learning (associated to negative duration dependence) is a feature of firms with more formalized and continuous R&D activities. This pattern is consistent with the idea that larger firms possess greater absorptive capacity and more developed organizational routines that facilitate incremental learning over time. The absence of duration dependence among small firms suggests that their R&D efforts are subject to financial or managerial constraints that prevent sustained learning during a single spell.

The coefficient of *Previous R&D Investment Experience* is negative and statistically significant for small and large firms, but not for medium firms. Therefore, we find evidence supporting H1b for small and large firms, whereas no support is found for medium firms. This result suggest that cumulative R&D experience enhances persistence at both ends of the size distribution, although very likely through different channels. Among small firms, prior R&D engagement may compensate for structural disadvantages, such as limited funding or weaker R&D teams, by improving their ability to manage the R&D process. Among large firms, accumulated experience strengthens within-firm learning and may contribute to consolidate internal R&D infrastructures, promoting long-term persistence. The non-significance of the *Previous R&D Investment Experience* estimate observed for medium firms may reflect their intermediate position.

Although, they conduct R&D regularly, they lack the scale or internal capabilities to convert accumulated experience systematically into sustained R&D activities.[9]

The coefficient of *Previous number of spells* is positive and highly significant across all firm-size categories, confirming H1c. These results suggests that a history of punctuated or discontinuous R&D activity is associated with shorter subsequent spells, consistent with the notion that interruptions in R&D weaken organizational memory and affect negatively to learning trajectories. The robustness of this result across all groups highlights the importance of continuity in innovation activities as a key determinant of R&D persistence.

It is noteworthy to consider aggregated estimated coefficients for both *Previous R&D Investment Experience* and *Previous number of spells*. The results pertaining to both small, medium and large firms imply that a history of punctuated R&D episodes may reduce the anticipated duration of forthcoming R&D spells. However, for large and small firms the knowledge accrued from preceding years of R&D performance could partially offset this negative association, even when such experience was not acquired within the context of the current spell under examination. Thus, while fragmentation in R&D engagement tends to undermine persistence, the accumulation of prior experience for small and large firms mitigates this effect by reinforcing firms' knowledge bases and facilitating the reactivation of innovation capabilities.

Taken together, the results provide partial confirmation of the three hypotheses across firm sizes. H1a (within-spell learning) holds for medium and large firms but not for small firms; H1b (cumulative learning) is supported for small and large firms but not for medium size firms; and H1c (negative association of intermittent R&D engagement) is confirmed across all firm sizes. Overall, the findings reveal that the mechanisms underlying R&D persistence vary systematically with firm size. Small firms depend on

[9] The lack of statistical significance of the coefficient on *Previous R&D investment experience* for medium sized firms could be related to the mobility of R&D personnel across firms, which would reduce the ability of this variable to capture accumulated experience. However, if this mechanism were dominant, a similar pattern would be expected also for small firms. In contrast, the coefficient remains negative and statistically significant for small firms, suggesting that labour mobility alone is unlikely to fully account for the observed results.

prior experience to sustain R&D; medium firms rely primarily on learning processes embedded within ongoing projects; and large firms maintain persistence both through the within spell learning and past R&D experience that allow the consolidation of organizational routines. These results are consistent with the cumulative and path-dependent nature of R&D behaviour.

5.1.2 The role of technological intensity

The estimations reported in columns 1 to 3 of Table 7, which distinguish between low-, medium-, and high-technology firms, reveal substantial cross-regime differences in the factors shaping R&D persistence. These estimations will allow us to check whether persistence patterns align with the hypotheses that within-spell learning enhances continuity (H1a), cumulative R&D experience fosters persistence (H1b), and a history of episodic R&D engagement diminishes it (H1c).

For low-, medium- and high-tech firms alike, the coefficient of Log(Surv. time) is negative and statistically significant, confirming H1a across all three technological groups. These consistent results suggest that within-spell dynamic learning is a pervasive and general mechanism underlying R&D persistence, operating across the full spectrum of technological intensity. Regardless of their technological context, firms appear capable of consolidating routines and transforming accumulated within-spell knowledge into sustained R&D commitment. Overall, these findings point to a common learning-by-doing process that cuts across all sectors, reinforcing the view that exposure to ongoing R&D activity generates self-reinforcing dynamics that foster persistence irrespective of the technological environment in which firms operate.

Turning to cumulative experience, the coefficient of *Previous R&D Investment Experience* is negative and statistically significant for low- and medium-tech firms, but not for high-tech firms, providing partial support for H1b. In these sectors, cumulative experience operates alongside within-spell learning—captured by *Log(Surv. time)*—as a complementary mechanism sustaining R&D persistence. Prior R&D engagement appears to provide a stock of knowledge and organizational capabilities that facilitates continued participation in R&D activities. This suggests that, in low- and medium-technology environments, both accumulated experience and learning within ongoing R&D spells jointly contribute to reinforcing persistence. For high-tech firms, however, R&D persistence is already deeply rooted and previous accumulated experience seems to exert no effect on R&D persistence. Their persistence seems driven less by cumulative knowledge acquired previously to current R&D spell and more by the constant renewal of capabilities resulting from more continuous involvement in R&D activities.[10] Further, for firms operating in high-tech sectors prior R&D experience may have little impact on the length of subsequent R&D efforts due to the rapid obsolescence of R&D projects in these sectors.

The coefficient of *Previous number of spells* is positive and statistically significant for medium- and high-tech firms, but not significant for low-tech firms, providing support for H1c only in more technologically intensive environments. In medium- and high-tech sectors, firms with more punctuated R&D trajectories are less likely to sustain long-term innovation activities, suggesting that interruptions weaken persistence. By contrast, in low-tech sectors, episodic R&D engagement does not appear to systematically affect the duration of subsequent R&D spells. These findings are consistent with the view that continuity in research effort is particularly important for preserving absorptive capacity and maintaining learning-by-doing benefits in more technologically intensive contexts.

A joint consideration of *Previous R&D Investment Experience* and *Previous number of spells* provides further insight into the mechanisms underlying R&D persistence. For medium-tech firms, a punctuated R&D history tends to shorten subsequent spells, while the stock of knowledge accumulated through earlier engagements partly mitigates this effect. Thus, although interruptions weaken persistence, prior experience can offset this pattern by preserving organizational competences and lowering barriers to re-entry into R&D activities. For low-tech firms, however, the absence of a significant effect of episodic R&D history suggests that persistence is shaped primarily by accumulated experience and within-spell learning, rather than by the structure of past R&D trajectories. Among high-tech firms, this

[10] Longer observed duration of R&D spells for firms operating in high-tech sectors support the importance of with spell learning vs. experience acquired in previous spell. Thus, a large majority of high-tech firms experience a single R&D spell, and the median duration of the first R&D spell for low-, med, and high-tech firms is 4, 8 and 14 years, respectively.

compensatory mechanism also appears limited, as prior R&D experience does not significantly influence persistence; instead, continuity depends more strongly on sustained engagement in R&D activities, possibly reflecting the rapid obsolescence of knowledge in these sectors.

Our findings indicate that persistence mechanisms differ with technological intensity. In low-tech sectors, both within-spell learning and accumulated R&D experience sustain R&D engagement, with little evidence that the episodic structure of past R&D activity plays a systematic role. In medium-tech industries, persistence reflects the combined influence of within-spell learning, cumulative experience, and continuity in R&D trajectories. In high-tech settings, uninterrupted R&D engagement itself becomes the primary driver, with persistence relying mainly on learning processes within ongoing R&D spells. These differences reinforce the cumulative and path-dependent nature of R&D behaviour, where the balance between experience, continuity and learning adapts to the technological context in which the firm operates.

Taken together, our results demonstrate that both firm size and technological intensity shape R&D persistence through complementary yet distinct learning mechanisms. Persistence is cumulative and path-dependent but manifests differently across size and technological contexts. Small and low-tech firms both rely on the legacy of prior R&D experience, as accumulated knowledge may help offset more limited managerial and absorptive capacities. In low-tech sectors, this effect operates alongside learning processes within ongoing R&D spells, which also contribute to sustaining R&D persistence. Medium-sized and medium-tech firms, sustain persistence primarily through learning-by-doing within current R&D projects, although med-tech firms learning also profits from previous R&D experience. Large and high-tech firms, by contrast, exhibit persistence that is structurally embedded within their strategic and organizational functioning. For high-tech R&D persistence mainly stems from within spell learning processes, while for large firms it is also originated in previous R&D experience

Beyond these differences, the evidence points to a common underlying mechanism: the cumulative nature of learning in R&D. Firms that maintain continuous engagement consolidate knowledge, refine their innovation routines, and reduce uncertainty, thereby reinforcing their capacity to sustain future R&D. Conversely, interruptions in R&D trajectories, whether due to financial shocks, managerial turnover, or shifting priorities, tend to disrupt organizational memory and weaken the link between past and future R&D activities. This interplay between continuity, capability accumulation, and organizational adaptation underscores that R&D persistence is a manifestation of how firms internalize and institutionalize learning over time.[11]

5.2. The indirect channel linking R&D experience to R&D persistence

As outlined earlier, the exploration of an indirect channel linking R&D experience to R&D persistence necessitates the examination of two critical conditions. First, whether R&D experience exerts a productivity-enhancing influence. Second, whether more productive firms are more likely to sustain their R&D engagement.

If the association between cumulative R&D experience and productivity remains consistent, irrespective of whether it was acquired through continuous or episodic R&D engagement, the confirmation of the first condition hinges on whether the estimate for R&D experience is positive and significant in the estimation of equation (5) (i.e. H2a). However, if the association between R&D and productivity hinges on the pattern of R&D experience accumulation, then we ought to investigate whether the estimates for R&D experience in equation (6), corresponding to firms that have acquired their R&D experience continuously or intermittently, emerge as positive and statistically significant (i.e. H2b). A subsequent comparison of these estimates is necessary in this context.

To corroborate the second condition for the presence of an indirect channel, it suffices to verify whether the estimate for Total Factor Productivity (TFP) within equation (3) is negative and statistically significant (H2c).

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[11] An interesting issue, which cannot be addressed directly given the available data, is that digital R&D may depreciate faster than non-digital R&D. As an indirect approach, we exploit the fact that certain sectors have a higher propensity to engage in digital R&D and examine whether the direct channel of R&D experience varies with sectoral digital intensity. Specifically, we replicate the analysis classifying firms into low-, medium-, and high-digitalization sectors following the OECD taxonomy proposed by Calvino et al. (2018). The results are reported in Appendix D.

5.2.1. Analysis of the indirect channel across size groups

We begin by examining whether firm size conditions the indirect channel linking R&D experience to R&D persistence through productivity. Results are shown in Table 8 for the full sample of firms and the subsamples of small, medium and large firms. The positive and statistically significant estimates of *Log(R&D Experience+1)* $_{it-1}$ across all four samples implies the presence of favorable returns associated with accumulated R&D experience in terms of productivity, a result observed in both small, medium and large firms, confirming H2a. The estimates also suggest that the productivity advantages associated with R&D experience are more pronounced for large firms when compared with small and medium sized. This difference could be attributed to the larger firms' heightened capacity to capture and assimilate the productivity gains arising from extensive and recurrent R&D activities. Such firms exhibit superior absorptive capabilities and have established mechanisms to adeptly harness and deploy these productivity enhancements.

The estimation of equation (6) demonstrates potential variations in the association between R&D experience and productivity, contingent upon it has been acquired through continuous or punctuated R&D engagement (refer to columns 2, 4, 6 and 8 of Table 8). In the estimation of equation (6), the estimated coefficient of *Log(R&D experience*$_{it-1}$*+1)* should be interpreted as quantifying the association of R&D experience and TFP when R&D experience has been acquired through uninterrupted R&D engagement. On the other hand, the estimated coefficient of *Log(R&D experience*$_{it-1}$*+1)*$\times$ *Disc*$_{it}$ captures the differential association between R&D experience and TFP when R&D experience has been gained through punctuated R&D spells in comparison to experience acquired through continuous R&D engagement. Notably, for large firms, the association between R&D experience gained through punctuated activities and productivity is weaker than the association observed for continuous R&D engagement (for large firms, the estimate of *Log(R&D Experience*$_{it-1}$*+1)*$\times$*Disc*$_{it}$ is negative and significant).[12]

[12] Although, for large firms, the association between R&D experience and productivity is weaker when that experience has been accumulated through punctuated rather than continuous R&D engagement, it remains positive and statistically significant. In particular, the estimated coefficient $\delta_1 + \delta_3$ from equation (6) is 0.0298, with a p-value of 0.015, indicating that productivity is still positively related to R&D experience even when the latter stems from intermittent R&D activity.

Conversely, both for small and medium sized firms, continuous R&D engagement is not associated with productivity outcomes that differ significantly from those linked to punctuated R&D. Accordingly, while our findings lend empirical support to H2b for large firms, this association is not substantiated in the case either for small or medium firms. This discrepancy may be attributed to the fact that large firms frequently undertake more intricate R&D projects that necessitate sustained and continuous efforts to reap the rewards in terms of enhanced productivity. By contrast, SMEs appear to derive productivity benefits from previous R&D activity irrespective of whether it is accumulated through continuous or punctuated engagement.

Recall that establishing an indirect channel from R&D experience to R&D persistence requires two conditions: first, that accumulated R&D experience is positively associated with productivity; and second, that productivity is positively linked to the likelihood of sustaining R&D engagement (H2c). The negative and statistically significant estimates of TFP in columns 1, 2 and 3 of Tables 6 suggest that, for both the full sample of firms and the subsets of small and medium sized firms more productive firms tend to undergo lengthier R&D spells. However, it is noteworthy that productivity does not seem to be a discernible determinant of the likelihood of R&D spell termination among large firms (as evidenced by the non-significance of the estimate of the TFP variable in column 4 of Table 6).

Taking these findings into consideration, alongside the observed positive association between R&D experience and productivity (a trend evident in both small, medium and large firms, irrespective of the pattern of experience acquisition), points to the presence of a positive indirect association between R&D experience and R&D persistence within the context of small and medium sized firms.[13] However, this association is not observed for large firms. Consequently, these results provide empirical

[13] Recall that for small and medium-sized firms, the positive association between R&D experience and productivity does not vary according to whether this experience has been accumulated through continuous or punctuated R&D engagement. For large firms, by contrast, the association is stronger when experience stems from continuous R&D activity, although it remains positive and statistically significant even when the underlying experience has been acquired through intermittent R&D spells.

support for an indirect (productivity-related) channel in small and medium firms but do not indicate a corresponding association for large firms.

In summary, the evidence points to heterogeneous learning dynamics arising from R&D experience across firm sizes. While large, medium, and small firms all benefit from prior R&D engagement, they do so through distinct mechanisms. Medium and large firms appear to capitalize on within-spell learning, consolidating capabilities and knowledge as R&D projects progress, whereas small firms show no significant evidence of this process. This pattern is consistent with the view that larger firms possess more developed absorptive capacities and formalized routines that allow them to assimilate and refine knowledge more effectively over time. At the same time, both small and large firms display learning associated with the accumulation of experience across R&D spells, suggesting that repetition and cumulative exposure play a role in sustaining innovation efforts at the two ends of the firm-size spectrum.

Besides, for both large, medium and small firms, the accumulation of experience over a series of spells, as opposed to continuous engagement, leads to a diminution in the value of the accrued knowledge. This decline is attributed to the phenomenon of knowledge decay and the imperative to reacquire knowledge when recommencing R&D activities. Furthermore, a salient difference in the learning process emerges across firms' sizes, with the positive association between of R&D experience on productivity proving more pronounced for large firms. Additionally, while the pattern of R&D experience acquisition appears to have no significant correlation with the productivity returns of small and medium sized firms, uninterrupted R&D engagement yields higher productivity dividends for large firms. Lastly, a distinction emerges between the groups of small and medium firms and that of large firms concerning the association between productivity and the R&D persistence. Increased productivity augments the prospects of persistence for small and medium firms, whereas this association remains unobserved for large firms. Consequently, our empirical analysis suggests that an indirect channel linking accumulated R&D experience to R&D persistence through productivity operates only for small and medium firms.

In essence, our study unveils noteworthy dissimilarities in the learning dynamics and outcomes associated with R&D experience between SMEs and large firms. These findings enrich our comprehension of the intricate interplay between R&D experience, productivity, and R&D persistence, shedding light on the distinctive dynamics operating within firms of different sizes.

5.2.2. Assessing the indirect channel between R&D experience and persistence across technological regimes

The analysis of the indirect channel linking R&D experience and R&D persistence through productivity reveals significant heterogeneity across technological regimes. Columns 1 to 3 of Table 7 report the duration estimates for low-, medium-, and high-tech firms, while Table 9 documents how cumulative and continuous R&D engagement relate to productivity.

Across all technological regimes, cumulative R&D experience is found to enhance firm productivity, confirming H2a. The estimated coefficient of $Log(R\&D\ Experience + 1)_{t-1}$ in Table 9 is positive and significant for low-, med-, and high-tech firms, though its magnitude rises for higher technological intensity sectors (from 0.066 in low-tech to 0.135 in medium-tech and 0.110 in high-tech industries). This pattern suggests that although greater R&D experience is associated to higher productivity across technological sectors, the strength of this association is markedly higher for medium-tech and high-tech firms. For medium- and high-tech firms, R&D experience likely enhances their ability to exploit and integrate existing knowledge and accelerate technological upgrading. In contrast, for low-tech firms, R&D experience probably yields incremental rather than transformative productivity gains. Overall, the results confirm the relevant role of cumulative learning as a source of productivity growth but also indicate that its intensity varies with the technological opportunities available in each regime.

When examining whether punctuated R&D engagement penalizes the productivity gains from R&D experience (H2b), the results display marked contrasts across technological groups. For low-tech firms, the interaction term $Log(R\&D\ Experience{+}1)_{t-1} \times Disc_t$ in Table 9 is negative and significant, showing that discontinuous R&D efforts substantially weaken the productivity benefits of prior R&D experience. This implies that sustained engagement is necessary to preserve knowledge and prevent the depreciation of technological competences in these firms. By contrast, for medium-tech firms, the interaction term is non-significant, suggesting that productivity gains from

R&D experience do not differ between continuous and intermittent R&D trajectories. Finally, for high-tech firms, the interaction coefficient is again negative and significant, confirming that continuous R&D engagement strongly reinforces the productivity effects of accumulated experience. Thus, H2b holds for low- and high-tech firms, but not for medium-tech firms.[14]

Recall that establishing the indirect association between R&D experience and R&D persistence hinges on verifying two conditions: first, that R&D experience is positively associated with productivity, and second, that productivity constitutes a positive determinant of the probability to continue R&D activities (H2c). These two conditions jointly allow assessing whether productivity acts as a mediating channel through which accumulated R&D experience translates into sustained engagement in R&D activities. Estimation results from Table 7 reveal that the relationship between *TFP* and R&D persistence varies substantially across technological regimes. For low-tech firms, the estimate of *TFP* is negative and statistically significant, indicating that more productive firms are more likely to enjoy larger R&D spells. This finding implies that productivity improvements enable these firms to sustain their R&D activities over time. In contrast, for medium and high-tech firms, *TFP* is statistically insignificant, suggesting that productivity does not significantly influence the hazard of R&D spell termination. Very likely, for these firms R&D practices are part of a strategic commitment that goes beyond productivity. Consequently, H2c is supported for low-tech firms but not for med or high-tech firms.

When these findings are considered alongside the positive association between R&D experience and productivity (observed across all technological regimes, regardless of whether we account for the pattern of acquisition), they indicate the existence of a productivity-mediated link between R&D experience and R&D persistence only for low-

[14] For both low-tech and high-tech firms, the positive association between R&D experience and productivity is weaker when experience has been accumulated through discontinuous rather than continuous R&D engagement. Nevertheless, the association remains positive and statistically significant. In the estimation of equation (5), the combined coefficient $\delta_1 + \delta_3$ equals 0.017 for low-tech firms (p = 0.003) and 0.075 for high-tech firms (p = 0.007).

tech firms. In these industries, productivity gains derived from accumulated R&D experience appear to reinforce firms' ability to sustain innovation efforts over time, likely by enhancing the efficiency of incremental learning processes. By contrast, this indirect channel is not observed for medium- and high-tech firms, where productivity is not significantly associated with the likelihood of maintaining R&D engagement. For these firms, persistence seems to stem from structural and strategic commitments to innovation rather than from productivity improvements. Overall, the evidence suggests that the indirect productivity channel operates primarily in less technology-intensive settings, where productivity gains remain critical to the continuation of R&D activity.

Bringing these results together, the indirect effect of R&D experience on R&D persistence through productivity manifests differently across technological regimes. H2a holds across all regimes, confirming that cumulative R&D experience enhances productivity, though with stronger effects in technologically advanced sectors. H2b is supported for low- and high-tech firms, where continuity in R&D engagement amplifies productivity improvements, but not for medium-tech firms. H2c is validated for low-tech firms, where productivity supports R&D engagement, but we do not find evidence supporting it for med-tech or high-tech firms. The overall pattern thus reveals a dual dynamic: in low-tech sectors, productivity acts as an enabling mechanism linking R&D experience to persistence, whereas in med and high-tech industries, persistence becomes decoupled from productivity probably due to the incorporation of R&D activities into firms' strategic core (specially for high-tech firms). These findings highlight how technological intensity shapes the pathways through which learning and performance feed into sustained R&D engagement, consistent with the cumulative and path-dependent nature of innovation processes.

Overall, the results reveal a dual gradient in the operation of the productivity-mediated link between R&D experience and R&D persistence, shaped jointly by firm size and technological intensity. We find evidence in favour of the existence of the indirect link among small and medium firms and low-tech firms, where productivity serves as an enabling mechanism that transforms accumulated R&D experience into the capacity to sustain R&D activities over time. By contrast, in large and med- and high-technology firms, the indirect association becomes statistically non-significant. Very likely, because persistence is already embedded within long-term strategic routines and institutionalized research infrastructures, rendering productivity gains less relevant as a determinant of R&D continuation. Together, these findings underscore that the productivity channel linking R&D experience and persistence is not at work for all the firms but depends on firm size and technological regime.

6. Discussion and conclusions

Previous research has delved into the factors influencing the persistence of R&D activities, as evidenced by studies such as Mañez et al. (2015) and Mañez et al. (2020). While these investigations encompass the concept of learning-by-doing R&D as a determinant of R&D persistence, to the best of our knowledge, no prior study has undertaken an analysis of how distinct patterns of accumulation of R&D experience impact the process of learning through R&D engagement and subsequently influence the persistence in these activities. These existing analyses primarily focus on the effect of R&D experience accrued within the current R&D spell throughout its duration, neglecting to consider other potential learning dynamics. While there has been some previous analysis on the impact of continuous versus intermittent R&D on innovation outcomes, (e.g. Bartoloni & Baussola, 2018; Lööf & Johansson, 2014; Østergaard & Drejer, 2022; Ipinnaiye et al., 2025), none of these has comprehensively examined how previous R&D patterns are linked (both directly and indirectly via productivity) to subsequent R&D persistence.

Our primary contribution therefore lies in conducting a comprehensive exploration of the potential effects of learning by accumulating R&D experience on firms' persistence in R&D. To achieve this objective, we analyse both the direct channel which links R&D experience to continued R&D, as well as the indirect channel through which accumulated experience may be connected to R&D persistence via its association with higher productivity. We demonstrate that the accumulation of prior R&D experience may play a crucial role in extending the duration of future R&D spells. Nonetheless, it is important to note that this beneficial association may be partially offset when firms past experience has been acquired through episodic and intermittent learning stemming from a history of punctuated R&D performance. Consequently, our more noteworthy contribution is therefore the distinction we draw between within-spell learning, cumulative learning, and learning arising from punctuated R&D histories, and the assessment of how each is linked to R&D persistence. Furthermore, we investigate how these categories of R&D experience may give rise to different learning processes, each exerting varying influences on the persistence of R&D activities. In addition, to analyse the indirect channel which links R&D experience and R&D persistence through productivity, we adopt the approach proposed by Mañez and Love (2020), which posit the possibility that R&D experience is associated with higher productivity, and that greater productivity, in turn, is correlated with stronger R&D persistence.

Our analysis, based on data spanning the period from 1992 to 2023 for the Spanish manufacturing sector, provides empirical insights into both the direct and indirect channels described above. Table 10 summarizes the findings for each hypothesis both for all firms and separately for firms in different sizebands and technological categories.

Concerning the direct channel, we show how cumulative (prior R&D experience) and punctuated learning produce distinct patterns in the context of learning-by-performing R&D activities. Unlike previous research which typically finds that R&D persistence of any kind is positively associated with innovation outcomes (e.g. Cuervo-Cazurra et al., 2018; Ipinnaiye et al., 2025), our findings demonstrate considerable heterogeneity, differing between (and among) SMEs and large firms and across technological regimes. For example, in the case of SMEs, prior R&D experience is positively associated to the persistence in R&D activities among small firms, but not those of medium size. Nevertheless, when such R&D experience is accrued through a history characterized by intermittent spells of R&D engagement, as opposed to a continuous and uninterrupted process, the learning trajectory appears to be less intensive. Our results suggest that a portion of the knowledge acquired during each of the previous R&D spells tends to depreciate before the firm embarks on its subsequent R&D spell. Consequently, among firms that have amassed an equivalent level of cumulative R&D experience, those with a history of episodic R&D engagement tend to experience shorter R&D spells in the future, in contrast to their counterparts which have acquired experience through continuous engagement in R&D. This insight implies that, for SMEs, intermittent past experiences in R&D lead to recurrent episodes of intermittent R&D activities in the future. These findings not only shed light on the shorter R&D spells observed in SMEs compared to large firms but also extend our understanding beyond the conventional explanations centered on resource constraints faced by SMEs or the limited within-spell learning opportunities available to them.

Regarding the direct channel on large firms, our findings indicate that prior cumulative experience has a marginal influence on R&D persistence. Nevertheless, it is crucial to emphasize that this does not imply a lack of learning from previous cumulative R&D experience among large firms; rather, it simply points out the existence of different learning mechanisms at play for large firms and SMEs. This distinction becomes evident through our examination of descriptive statistics, as exemplified by the Kaplan-Meier survival function presented in Figure 2, which reveals that large firms enjoy greater R&D experience and are more likely to be engaged in R&D continuously than small or medium-sized firms. Consequently, most of their learning processes are encapsulated by the within-spell learning effect. It follows that larger firms, typically endowed with greater resources, may have already surpassed the barriers associated to performing R&D, and so they have less to learn from each additional year of R&D experience. Nevertheless, even for large firms (and high-tech firms) a history characterized by episodic R&D spells may compromise the advantages derived from continuous R&D performance.

The finding that firms with more interrupted R&D histories face a persistently higher hazard of stopping their current R&D spell, even after controlling for total accumulated experience (H1c), can be interpreted through two complementary theoretical frameworks that have attracted considerable attention in recent years. The first is organizational resilience. Following Duchek (2020)'s capability-based account of resilience, sustained R&D engagement builds three interlinked sub-capabilities: anticipation (identifying and preparing for potential threats before they materialize), coping (developing and implementing solutions during adverse events), and adaptation (learning from experience to reconfigure organizational capabilities after a shock). Each R&D interruption erodes all three: it depletes the firm's internal expertise, disrupts the tacit-knowledge stocks and coordination mechanisms built up during the preceding spell, and weakens the learning routines that underpin future adaptive capacity. A firm that has interrupted R&D multiple times has had to rebuild these capabilities from a lower base after each gap, and begins each new spell with shallower adaptive reserves than a firm with equivalent total experience accumulated in fewer, longer spells.

The digital transformation literature adds a further dimension by identifying a mechanism through which the punctuated-learning penalty may be attenuated. Vial (2019) defines digital transformation as a process that triggers significant changes to an entity's value creation paths through combinations of information, computing, communication, and connectivity technologies. At the organizational level, such infrastructure enables knowledge developed before an interruption to remain accessible and usable after it, because key elements of the knowledge base can be codified in systems that persist independently of the individuals who created them. The structural analogue to our model is clear: pre-interruption investments in digital infrastructure function as a latent asset that reduces re-entry costs when firms resume R&D after a gap.

With regard to the outcomes about the indirect channel relating R&D experience and R&D persistence through enhanced productivity, our analysis reveals distinctive patterns between large firms and SMEs. In the case of large firms, the productivity gains stemming from continuous involvement in R&D activities outweigh those associated with intermittent or episodic R&D efforts. Conversely, in the SME context, we do not find significant differences in the productivity benefits derived from continuous versus episodic R&D engagement. Nevertheless, it is worth noting that since productivity exerts a positive influence on R&D persistence exclusively for SMEs, we identify evidence of an indirect channel only for SMEs.

These size-differentiating results both confirm and extend recent empirical evidence on R&D persistence. For small firms, our finding that cumulative prior experience is the dominant persistence driver — not within-spell learning — is consistent with Ipinnaiye et al. (2025), who show using Irish data that persistent R&D is more strongly associated with innovation success in small firms than in larger ones. Our contribution is to identify the mechanism: it is the accumulated stock of prior cross-spell engagement, not the depth of any single episode, that sustains small-firm R&D commitment.

The medium-firm pattern is our most novel finding relative to a literature that has predominantly treated SMEs as homogeneous. For small firms, it is the historical stock of R&D engagement accumulated across spells that directly buffers persistence; within-spell duration adds nothing beyond that. For medium firms, the mechanism inverts: it is learning within the current spell that operates directly, while the cross-spell stock provides no additional direct premium — its contribution to persistence running entirely through the TFP channel. Medium firms are therefore protected against R&D exit by how deeply embedded they are in their ongoing R&D episode and by whether prior R&D has translated into productivity improvements, but not by the breadth of their R&D history per se. This size-contingent pattern is consistent with recent evidence on the anatomy of innovation persistence. Arroyabe and Schumann (2022) show that true state dependence accounts for roughly half of observed innovation persistence once time-constant firm-level heterogeneity is properly separated out. The implication is that the cross-spell experience stock, while undeniably present, does not necessarily generate an independent direct state-dependence mechanism over and above what a firm's productive characteristics already explain — a characterisation that fits H2a–H2c indirect channel we document for medium firms. At the R&D spell level, Bontempi et al. (2024) find, in duration models on Italian firms (1996–2012), that accumulated R&D knowledge significantly reduces the exit hazard, yet this effect co-exists with firm-level performance capacity as necessary conditioning factors; once unobserved firm heterogeneity is captured via frailty terms, spell-history count effects lose statistical significance. The parallel to our medium-firm results is clear: experience history reaches persistence through productive capacity rather than through a freestanding direct mechanism.

For large firms, all three direct-channel mechanisms operate simultaneously (H1a–H1c confirmed) while the indirect TFP channel is inoperative, consistent with large-firm R&D persistence as an institutionalised, self-sustaining process. Pigini et al. (2025) corroborate this with EU R&D Investment Scoreboard data: among the world's leading R&D investors, persistence in R&D intensity is primarily driven by time-constant firm-specific heterogeneity, with firms benchmarking to their own historical R&D targets rather than sector means — a pattern fully consistent with strategic-routine-based persistence that does not require productivity as a mediating signal.

The implications of our analysis have both managerial and policy relevance. Previous research has consistently suggested a positive association between R&D

persistence and improved firm performance. Consequently, firms ought to be inclined toward a sustained commitment to R&D activities. While it may appear strategically convenient for firms to discontinue R&D efforts following the completion of an R&D project, they must consider not only the sunk exit and re-entry costs but also the phenomenon of learning depreciation that may accompany a pattern of episodic R&D engagement. Punctuated learning could potentially undermine a firm's absorptive capacity, placing it at a disadvantage when compared to competitors that maintain continuous R&D initiatives. Nevertheless, our findings suggest that for small firms, even experience gained in previous R&D episodes may prove beneficial upon re-entering R&D activities. Thus, given the advantages, particularly in terms of learning intensity, associated with a strategy of sustained R&D engagement as opposed to episodic engagement, firms should carefully assess their resource availability before embarking on R&D activities in a continuous manner. They should also conduct a thorough cost-benefit analysis to ascertain whether it is more profitable to discontinue R&D activities after completing a research project or to maintain these activities, albeit potentially at a minimum level, to mitigate the risks of learning and knowledge depreciation.

The analysis also has policy implications. Assuming persistent R&D is a desirable objective for policy because of its beneficial effects on innovation and growth, the appropriate policy response depends very much on the size and sectors of the economy to be targeted. For example, while it is perhaps no surprise that large firms differ from SMEs in terms of the factors that influence R&D persistence, our results also demonstrate that while SMEs are typically considered to be a homogeneous group in policy terms, there are some significant differences between them in terms of the determinants of R&D persistence. For small firms, the length of the current R&D spell does not matter while cumulative previous R&D experience does matter. For medium-sized firms it is precisely the reverse, suggesting that suitable policy responses may have to be nuanced within the SME grouping.

What this means in practice is inevitably context specific. In the case of Spain, policy comprises a combination of R&D tax credits and direct public subsidy for R&D activities (Arqué-Castells 2013; Mañez and Love 2020). Evidence suggests that subsidies are more likely to reach younger (and therefore smaller) firms and those with no previous history of R&D activity, while tax credits tend to assist R&D-performing firms to persist with, or increase their level of, R&D activity regardless of size (Arqué-Castells 2013). This is consistent with the present empirical results, which suggest that R&D subsidies are positively associated with R&D persistence among small (and large) firms, but with no association among medium-sized enterprises. As discussed in detail in appendix C, the differential influence of R&D subsidies across firm sizes very likely reflects the heterogeneous constraints and capacities that shape firms' ability to sustain innovation.[15] For small firms, public support acts primarily as a mechanism that contributes to relieve liquidity constraints (Meuleman and De Maeseneire, 2012; Bellucci et al., 2019).[16] They may help them overcome severe financing and risk constraints that limit their ability to sustain continuous R&D efforts. By contrast, medium-sized firms appear less responsive to R&D subsidies in terms of sustaining long-term R&D engagement. This outcome can be understood by considering their intermediate resource position and limited policy alignment. Medium-sized firms often fall into a policy gap: too large to qualify for SME-targeted schemes yet too small to compete for large-scale strategic grants.

If the policy objective is to increase R&D persistence among SMEs, this may suggest some differentiation of policy between small and medium-sized enterprises, with subsidies possibly being more effective for small firms which do not depend on lengthy recent R&D spells in order to achieve persistence in the future, while tax credits might be more efficient for medium-sized enterprises where recent continuous R&D activity is more important for persistence. However, this may require a shift in policy: unsurprisingly, in Spain R&D subsidies are heavily skewed towards persistent (mainly large) R&D performers, with over 80% of subsidies in the first decade of this century going to firms performing R&D in the previous period (Arqué-Castells 2013). While shifting R&D subsidies towards smaller firms may improve their R&D persistence, this may involve a considerable fiscal outlay. For example, Busom *et al*. (2014) argue that subsidies generate long-lasting persistence effects, but only if the subsidy shares are

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[15] Further, in Appendix E we examine whether the estimation results for the direct and indirect channels of R&D are sensitive to replacing the R&D subsidy dummy with a measure of R&D subsidy persistence (the number of consecutive years during which firms have receive R&D subsidies).

[16] The mean of our financial score variable (Score E) is 4.86, 5.33 and 5.69 for small, medium and large firms. Recall that the higher the financial constraints index the lower the financial constraints stringency.

large enough. They estimate the required level of subsidy to be much higher for SMEs (up to 50%) compared with larger firms (around 30%).

One limitation of our study is that, given the duration-model framework adopted, we are not able to disentangle the respective roles of sunk costs and accumulated R&D experience as determinants of R&D persistence. Addressing this issue would require an alternative modelling strategy, such as that proposed by Mañez and Love (2020), which explicitly identifies the relative contributions of sunk costs and learning effects. A promising avenue for future research would be to extend this framework to analyse how, once separated from sunk cost effects, learning mechanisms may vary depending on the pattern of accumulation of R&D experience. This would further enhance our understanding of the mechanisms underlying R&D persistence.

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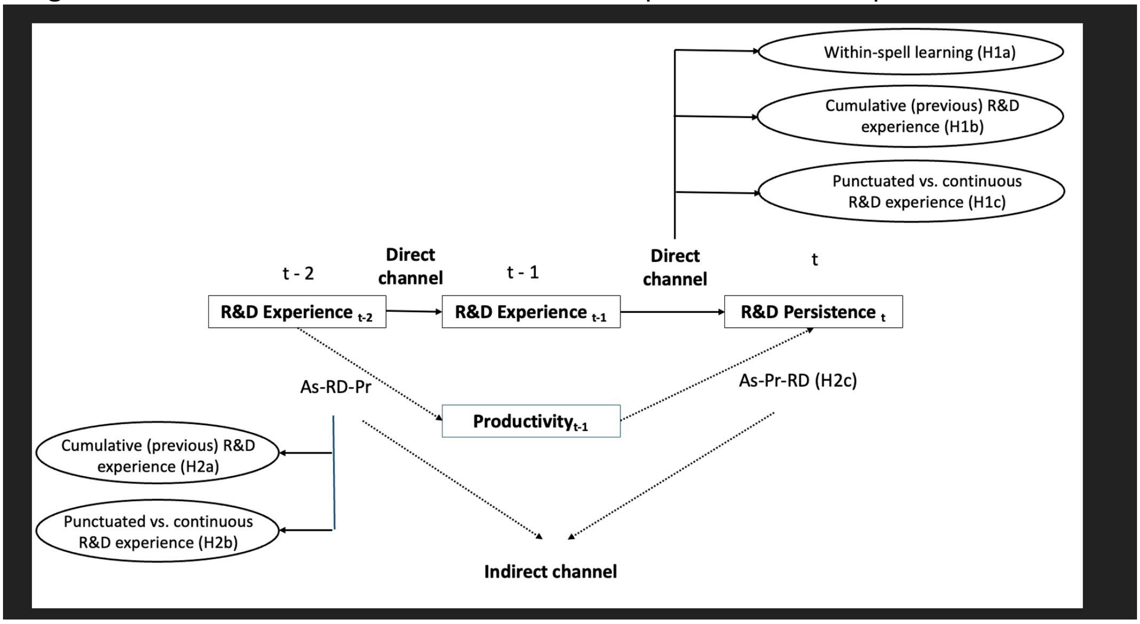
Figure 1: Direct and indirect channels of R&D experience on R&D persistence



As-RD-Pr: Association between R&D experience up to *t* -2 and productivity in *t-1*

As-Pr-RD: Association between productivity in *t* -1 and R&D persistence in *t*

Indirect channel: As-RD-Pr+ As-Pr-RD

Figure 2: Kaplan Meier survivor function by size group

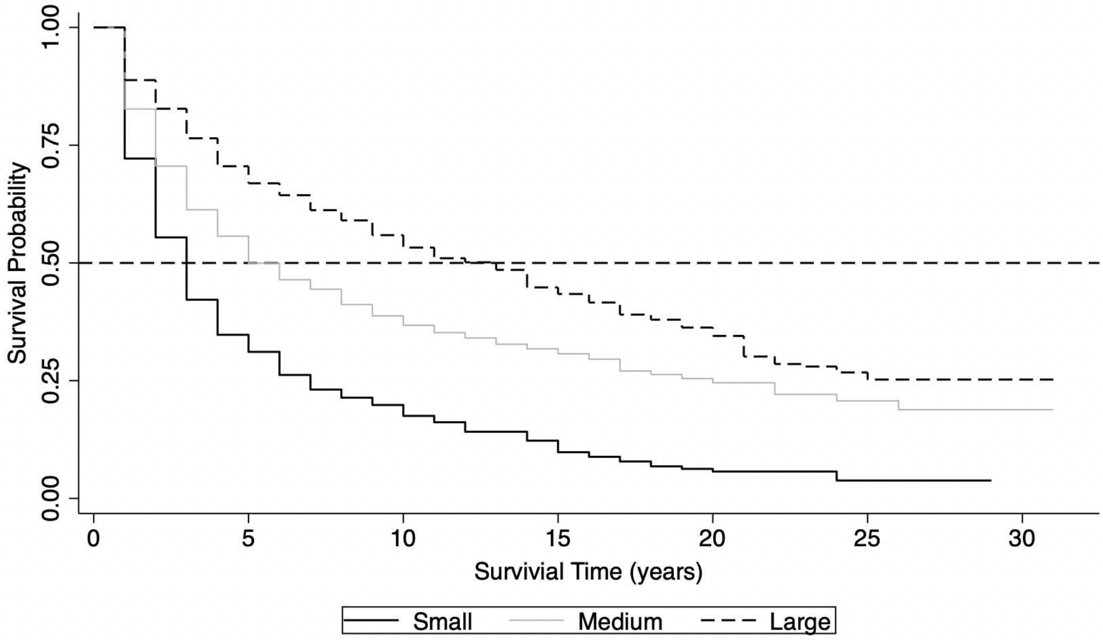


Figure 3: Kaplan Meier survivor function by technological regime

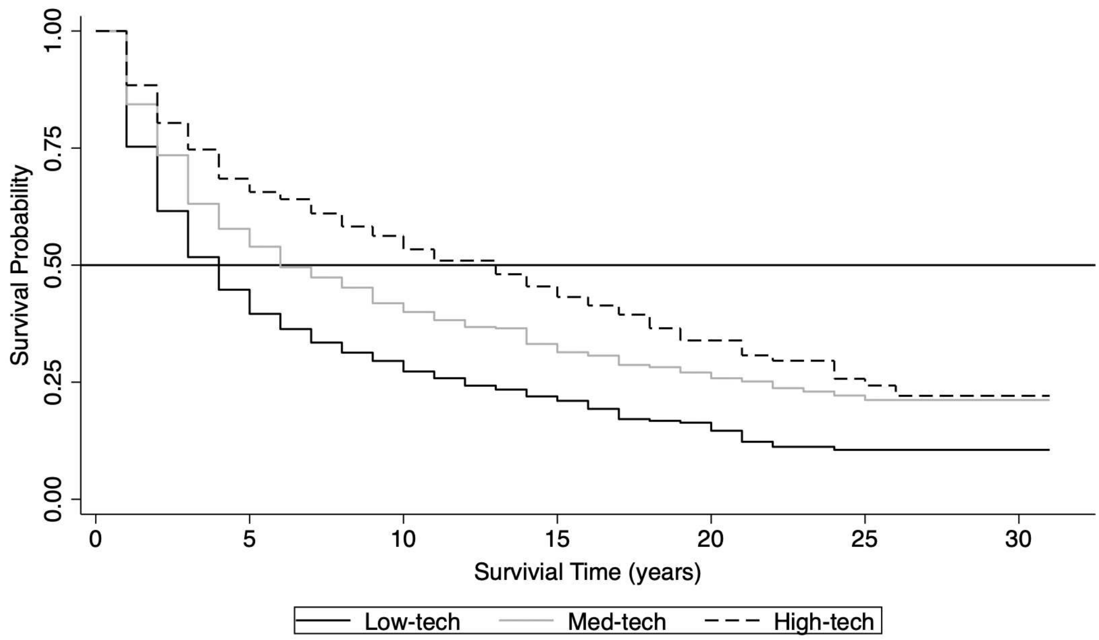


Table 1. Differences between firms with and without innovation experience

	Differences in %	p-value
Output per worker	31.66	0.000
Capital per worker	58.48	0.000
Intermediate materials per worker	45.45	0.000
Size	198.24	0.000
Age	13.59	0.000

Table 2 Transition probabilities between R&D investment states.

Status in t - 1	Status in t	
	No investment in R&D	Investment in R&D
All firms		
No investment in R&D	93.96	6.04
Investment in R&D	11.66	88.43
Size groups		
Small firms		
No investment in R&D	96.58	3.42
Investment in R&D	25.55	64.45
Medium firms		
No investment in R&D	90.89	9.11
Investment in R&D	13.08	86.92
Large firms		
No investment in R&D	84.97	15.03
Investment in R&D	6.49	93.51
Technological regimes		
Low-tech		
No investment in R&D	95.21	4.79
Investment in R&D	16.93	83.37
Medium-tech		
No investment in R&D	92.93	7.67
Investment in R&D	10.81	89.19
High-tech		
No investment in R&D	90.54	9.46
Investment in R&D	6.62	93.38

Table 3. Number of R&D spells by firm: size group and technological regime

			Size group					
	All firms		Small firms		Medium firms		Large firms	
N. of R&D spells	N. of firms	% of firms	N. of firms	% of firms	N. of firms	% of firms	N. of firms	% of firms
1	2,052	80.91	625	79.01	679	80.17	748	83.30
2	359	14.16	121	15.30	126	14.88	112	12.47
3	95	3.75	33	4.17	28	3.31	34	3.79
4	23	0.91	9	1.14	11	1.30	3	0.33
5	7	0.28	3	0.38	3	0.35	1	0.11
			Technological regime					
			Low-tech		Med-tech		High-tech	
N. of R&D spells			N. of firms	% of firms	N. of firms	% of firms	N. of firms	% of firms
1			820	79.39	727	79.63	505	83.30
2			176	16.83	127	13.91	56	12.47
3			41	3.92	42	4.60	12	3.79
4			7	0.67	14	1.53	2	0.33
5			2	0.19	3	0.33	2	0.11

Table 4. Variables description.

Variable	Description
Log(Surv. time)	Log of survival time (baseline hazard). From 1 to 25 (maximum spell duration)
Previous R&D investment experience	Number of (observed) previous years of R&D investment at the year of the start of the current spell
Previous number of spells	Number of (observed) previous R&D investment spells
Only Internal	Dummy = 1 if the firm declares to perform internal R&D; 0 otherwise
Only External	Dummy = 1 if the firm reports to be engaged just in external R&D; 0 otherwise
Both	Dummy = 1 if the firm declares to perform internal and external R&D; 0 otherwise
R&D intensity	R&D expenditures over firm sales
Low-tech regime	See Table 4
Med-tech regime	See Table 4
High-tech regime	See Table 4
Log(R&D emp)	Log of the number of employees engaged in R&D activities
TFP	Total factor productivity (see section 4.2)
Process innovation	Dummy that takes value 1 if the firm introduces a process innovation and 0 otherwise
Product innovation	Dummy that takes value 1 if the firm introduces a product innovation and 0 otherwise
Log(Approp)	The log of the ratio of the industry-year total number of patents and utility models over the total number of firms that assert to have achieved innovations (either product, process innovations or both)
Score E	Financial score that captures the availability funds (the higher the better the financial health of the firm). Includes both internal and external financial constraints components. See Mañez and Vicente-Chirivella (2021) for details on its calculation.
Drecessive	Dummy=1 if the firm declares a recessive demand (in contrast to situation a in which a firm declares an expansive or stable demand)
Exporter	Dummy = 1 if the firm declares to export a positive amount; 0 otherwise
Mshare	Dummy =1 if the firm declares a significant market share in its main market
Log(CR4)	Log of the market concentration ratio corresponding to the four largest firms operating in the market
Log(Employment)	Log of the number of employees
R&D Sub	Dummy = 1 if the firm receives R&D subsidies; 0 otherwise
Young	Dummy = 1 if the firm's age is equal or below 10 years; 0 otherwise
Year dummies	Dummy = 1 for the corresponding calendar year; 0 otherwise
Changes in firm structure	
Absorption	Dummy = 1 the year the firm has absorbed another firm; 0 otherwise
Excision	Dummy = 1 the year the firm has experienced one excision of a part of it; 0 otherwise

Table 5. Sector technological intensity classification (NACE-2009 two-digit industrial classification)

Technological intensity	Sector
Low	Meat industry; Beverages, Textiles and clothing; Leather and shoes; Wood; Paper industry; Printing and printing products; Non-metallic mineral products; Metallic products; Furniture, Other manufacturing goods
Medium	Food and tobacco; Rubber and plastic; Ferrous and non-ferrous metals; Industrial and agricultural machinery; Vehicles, cars, and motors
High	Other transport equipment; Chemical products; Office machines Electric and electronic machinery and material

Table 6. Determinants of the duration of R&D investment spells. All firms and by size groups.

	All firms (1)	**Small (2)**	**Medium (3)**	**Large (4)**
Log(Surv. time)	-0.232***	-0.0078	-0.407***	-0.287***
	(0.0592)	(0.141)	(0.125)	(0.0599)
Previous R&D investment exper.	-0.0472***	-0.0910***	0.00651	-0.0476*
	(0.0165)	(0.0319)	(0.0271)	(0.0262)
Previous number of spells	0.221***	0.178**	0.189**	0.272***
	(0.0638)	(0.090)	(0.0951)	(0.103)
TFP	-0.390***	-0.321*	-0.747***	-0.0991
	(0.101)	(0.178)	(0.163)	(0.162)
Only Internal	-0.159**	-0.207*	0.0446	-0.298**
	(0.0758)	(0.125)	(0.133)	(0.138)
Both	-0.579***	-0.782***	-0.390***	-0.526***
	(0.0853)	(0.151)	(0.148)	(0.146)
R&D Intensity	-3.189	3.226**	-3.945**	-6.318***
	(1.028)	(1.525)	(1.969)	(3.002)
Med-tech regime	-0.311***	-0.192	-0.340***	-0.385***
	(0.0672)	(0.118)	(0.115)	(0.109)
High-tech regime	-0.480***	-0.569***	-0.590***	-0.283*
	(0.0952)	(0.171)	(0.165)	(0.156)
Log(R&D emp)	-0.278***	-0.534***	-0.245***	-0.184***
	(0.0358)	(0.0900)	(0.0669)	(0.0493)
Process innovation	-0.143***	-0.0482	-0.190**	-0.213**
	(0.0549)	(0.0930)	(0.0953)	(0.0966)
Product innovation	-0.349***	-0.147	-0.450***	-0.415***
	(0.0601)	(0.102)	(0.106)	(0.105)
Log(Approp)	-0.0438	-0.0971	0.0239	-0.0183
	(0.0813)	(0.141)	(0.138)	(0.142)
Score E	-0.0565***	-0.0431	-0.0368	-0.0954***
	(0.0185)	(0.0326)	(0.0315)	(0.0313)
DRecessive	0.182***	0.520	0.0342	0.360***
	(0.0618)	(0.769)	(0.107)	(0.107)
Exporter	-0.336***	0.140	-0.262*	-0.348**
	(0.0741)	(0.106)	(0.135)	(0.169)
Mshare	-0.139**	-0.349***	-0.227**	-0.164
	(0.0665)	(0.110)	(0.110)	(0.113)
Log(CR4)	0.0202	-0.00526	0.0310	0.00605
	(0.0202)	(0.118)	(0.0344)	(0.0397)
Log(Employment)	-0.190***	0.00992	-0.214**	-0.665***
	(0.0298)	(0.0318)	(0.0927)	(0.132)
R&D Sub	-0.269***	-0.251**	-0.0595	-0.223***
	(0.0733)	(0.103)	(0.121)	(0.0752)
Log(Age)	-0.0324	0.0154	-0.0914	-0.0224
	(0.0399)	(0.128)	(0.0704)	(0.0649)
Absorption	-0.0665	-0.0315	-0.363	-0.00398
	(0.222)	(0.0706)	(0.460)	(0.284)
Excision	0.977***	0.465	0.361	1.186***
	(0.226)	(0.564)	(0.522)	(0.268)
Constant	0.457**	0.892	0.425	0.951*
	(0.206)	(0.655)	(0.524)	(0.557)
Unobserved heterogeneity: LR Test of Gamma Variance=0				
Chibar2(01)	12.7432	9.253	4.277	9.123
Prob≥chibar2	0.0009	0.001	0.019	0.005
Observations	14,516	3,036	4,426	7,054

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

Table 7. Determinants of the duration of R&D investment spells by technological intensity

	Low-tech (1)	**Med-tech (2)**	**High-tech (3)**
Log(Surv. time)	-0.288***	-0.284***	-0.223***
	(0.0916)	(0.0896)	(0.0811)
Previous R&D investment exper.	-0.0497**	-0.0475*	-0.0105
	(0.0252)	(0.0255)	(0.0307)
Previous number of spells	0.133	0.202**	0.354***
	(0.0959)	(0.0977)	(0.122)
TFP	-0.611***	-0.255	-0.0549
	(0.150)	(0.175)	(0.222)
Only Internal	-0.123	-0.0368	-0.579***
	(0.106)	(0.124)	(0.180)
Both	-0.574***	-0.405***	-0.889***
	(0.122)	(0.139)	(0.198)
R&D Intensity	0.709	-3.199	-1.867***
	(0.816)	(1.395)	(0.625)
Log(R&D emp)	-0.309***	-0.218***	-0.252***
	(0.0601)	(0.0568)	(0.0680)
Process innovation	-0.0700	-0.131	-0.394***
	(0.0799)	(0.0890)	(0.133)
Product innovation	-0.380***	-0.247***	-0.388***
	(0.0908)	(0.0951)	(0.138)
Log(Approp)	0.135	-0.342*	-0.0969
	(0.126)	(0.186)	(0.136)
Score E	-0.0583**	-0.0103	-0.129***
	(0.0273)	(0.0302)	(0.0418)
DRecessive	0.197**	0.101	0.319**
	(0.0883)	(0.104)	(0.145)
Exporter	-0.341***	-0.181	-0.531***
	(0.100)	(0.128)	(0.181)
Mshare	-0.243**	-0.135	0.0258
	(0.101)	(0.106)	(0.145)
Log(CR4)	0.0411	0.00694	-0.0373
	(0.0288)	(0.0336)	(0.0479)
Log(Employment)	-0.108**	-0.305***	-0.0501
	(0.0449)	(0.0476)	(0.0639)
R&D Sub	-0.153	-0.432***	-0.201
	(0.109)	(0.124)	(0.156)
Log(Age)	-0.0456	-0.00165	-0.114
	(0.0604)	(0.0615)	(0.0886)
Absorption	-0.0916	-0.150	0.0530
	(0.350)	(0.363)	(0.460)
Excision	-0.316	1.014***	1.556***
	(0.724)	(0.331)	(0.356)
Constant	0.117	0.0966	0.576
	(0.281)	(0.332)	(0.462)
Unobserved heterogeneity: LR Test of Gamma Variance=0			
Chibar2(01)	4.304	9.230	8.756
Prob≥chibar2	0.019	0.005	0.001
Observations	4,961	5,640	3,915

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

Table 8: Total factor productivity and firms' R&D experience: full sample and size groups

	All		Small		Medium		Large	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(R&D Experience+1)$_{t-1}$	0.091***	0.092***	0.084***	0.072***	0.072***	0.057***	0.101***	0.107***
	(0.004)	(0.005)	(0.011)	(0.011)	(0.008)	(0.010)	(0.005)	(0.006)
Disc$_t$		0.093***		0.043		0.029		0.183***
		(0.018)		(0.033)		(0.029)		(0.030)
Log(R&D Experience+1)$_{t-1}$×Disc$_t$		-0.032***		-0.014		0.019		-0.078***
		(0.008)		(0.015)		(0.013)		(0.012)
Log(Employment)$_{t-1}$	0.067***	0.067***	0.062***	0.054***	0.024	0.024*	0.093***	0.091***
	(0.008)	(0.007)	(0.018)	(0.016)	(0.015)	(0.015)	(0.010)	(0.010)
Log(Age)$_{t-1}$	-0.005	-0.005		0.040**	-0.010	-0.003	-0.009	-0.009
	(0.010)	(0.010)		(0.020)	(0.017)	(0.017)	(0.013)	(0.013)
Constant	3.630***	3.622***	3.874***	3.806***	4.046***	4.031***	3.297***	3.290***
	(0.046)	(0.045)	(0.065)	(0.065)	(0.081)	(0.078)	(0.070)	(0.069)
Observations	11,912	11,912	2,123	2,123	3,516	3,516	6,273	6,273
R-squared	0.984	0.984	0.985	0.985	0.982	0.983	0.985	0.985

Notes:

1. All estimations include year and industry effects
2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Total factor productivity and firms' R&D experience: technological regimes

	Low-tech		Med-tech		High-tech	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(R&D Experience+1)$_{t-1}$	0.066***	0.064***	0.135***	0.129***	0.110***	0.107***
	(0.007)	(0.008)	(0.007)	(0.005)	(0.008)	(0.009)
Disc$_t$		0.119***		0.062**		0.025
		(0.024)		(0.028)		(0.047)
Log(R&D Experience+1)$_{t-1}$×Disc$_t$		-0.050***		-0.016		-0.032*
		(0.011)		(0.012)		(0.018)
Log(Employment)$_{t-1}$	0.050***	0.047***	0.060***	0.061***	0.068***	0.069***
	(0.011)	(0.011)	(0.012)	(0.010)	(0.016)	(0.015)
Log(Age)$_{t-1}$	0.085***	0.091***		-0.025**	-0.027*	-0.025*
	(0.020)	(0.020)		(0.010)	(0.015)	(0.015)
Constant	3.727***	3.704***	3.533***	3.556***	3.612***	3.602***
	(0.077)	(0.078)	(0.066)	(0.059)	(0.092)	(0.089)
Observations	3,895	3,895	4,671	4,671	3,320	3,320
R-squared	0.993	0.993	0.983	0.983	0.942	0.942

Notes:

1. All estimations include year and industry effects
2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Summary of empirical results by hypothesis

Hypothesis	All firms	Small	Medium	Large	Low-tech	Med-tech	High-tech
H1a. R&D persistence is positively associated with the length of the current R&D spell	Yes	No	Yes	Yes	Yes	Yes	Yes
H1b. R&D persistence is positively associated with the total years of cumulative previous R&D experience	Yes	Yes	No	Yes	Yes	Yes	No
H1c. R&D persistence is negatively associated with the number of previous R&D spells.	Yes	Yes	Yes	Yes	No	Yes	Yes
H2a: Cumulative R&D experience is positively associated with productivity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2b: The positive association of cumulative R&D with productivity is more pronounced when it arises from continuous engagement in R&D as opposed to punctuated R&D engagement	Yes	No	No	Yes	Yes	No	Yes
H2c: R&D persistence is positively associated with productivity	Yes	Yes	Yes	No	Yes	No	No

Appendix A

Estimation of the effect of Cumulative R&D on Productivity

To estimate total factor productivity, we assume that firms produce using a Cobb-Douglas production technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \omega_{it} + \xi_{it} \tag{A1}$$

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 workers), m_{it} is the log of intermediate materials, and k_{it} is the log of capital (adjusted for capital utilization).[17] As for the unobservables, ω_{it} is productivity (not observed by the econometrician but observable or predictable by the firm) and ξ_{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.

To obtain reliable estimates of input elasticities and TFP residuals, we adopt the methodology suggested by Wooldridge (2009). Drawing from Wooldridge (2009), the semiparametric control function approaches originally proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) can be reformulated as a system of two equations that can be jointly estimated through generalized method of moments (GMM) using appropriate instrumental variables. The first equation addresses the issue of endogeneity related to labor and materials, while the second equation addresses the issue of the law of motion governing productivity. By employing this approach, we are able to address both endogeneity and productivity dynamics simultaneously in our estimation procedure.

To address the issue of endogeneity of labor and materials in the first equation, we adopt the approach proposed by Levinsohn and Petrin (2003). Thus, we use the inverted demand for intermediate materials as a proxy for firm productivity.[18] By doing so, the unobserved productivity can be expressed as a function of observables. Moving to the second equation, we assume that unobserved firm productivity follows an endogenous Markov

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

[18] 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).

process. This assumption allows us to capture the dynamics of productivity over time, taking into account the influence of cumulative R&D experience.

$$\omega_{it} = f(\omega_{it-1}, R\&D\ Experience_{it-1}) + \nu_{it} \qquad \text{(A2)}$$

where $f(\cdot)$ represents an unknown function that relates productivity in period t and productivity in the previous period (t - 1), as well as the impact of past cumulative R&D experience. Additionally, the term ν_{it} is an innovation term, by definition uncorrelated with k_{it}. This formulation of an endogenous Markov process permits the explicit influence of past R&D experience on current productivity, thereby allowing for a more comprehensive understanding of the relationship between cumulative R&D experience and productivity dynamics.

The estimation of the production function (equation A1) is conducted for each of the 10 industries in which Doraszelski and Jaumandreu (2013) group firms in the ESEE. This estimation process yields estimates of input elasticities at the industry level as well as firm-specific TFP estimates as a residual. The estimates of the input elasticities are presented in Table A1.

In estimating the production function presented in equation (A1), we include all firms in the sample that provide the necessary information, rather than solely focusing on the firms engaged in R&D that are included in our survival analysis. Limiting the analysis to observations solely from firms undertaking R&D would impede an industry-based TFP estimation due to the small sample size, which may undermine the reliability of the results obtained through the demanding estimation procedure. However, once the TFP measure is obtained, the subsequent analysis is restricted to the sample of firms that declare to be engaged in R&D. We include this TFP as a covariate in the estimation of equation (2).

R&D Experience is proxied for the logarithm of the cumulative (total) number of years in which the firm has been actively engaged in R&D, encompassing both continuous and episodic R&D spells.[19]

[19] In the estimation of productivity, we use log(R&D Experience$_{it-1}$+1) and not just log(R&D Experience$_{it}$) because in estimation we are using the full sample of R&D performers and firms that do not perform R&D.

Table A1: Estimated industry specific input elasticities from Cobb-Douglas production function

	Labour	Materials	Capital
1. Metal and metal products	0.270***	0.670***	0.087***
	(0.009)	(0.021)	(0.015)
2. Non-chemical materials	0.230***	0.685***	0.087***
	(0.013)	(0.037)	(0.021)
3. Chemical products	0.229***	0.668***	0.078***
	(0.009)	(0.029)	(0.017)
4. Agricultural and industrial machinery	0.238***	0.574***	0.061***
	(0.014)	(0.039)	(0.019)
5. Electrical goods	0.286***	0.601***	0.055**
	(0.014)	(0.043)	(0.025)
6. Transport equipment	0.214***	0.629***	0.066**
	(0.014)	(0.030)	(0.027)
7. Food, drinks and tobacco	0.155***	0.733***	0.079***
	(0.007)	(0.021)	(0.013)
8. Textile, leather and shoes	0.320***	0.451***	0.076***
	(0.009)	(0.050)	(0.016)
9. Timber and furniture	0.270***	0.563***	0.056***
	(0.011)	(0.042)	(0.016)
10. Paper and printing products	0.296***	0.569***	0.053***
	(0.013)	(0.042)	(0.016)

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

Appendix B

Dealing with a possible endogeneity issue

An endogeneity problem may arise if some of the covariates in equation (2) evolve alongside the duration of the R&D spell, given that these covariates might be predetermined by how long the spell lasts. To evaluate this potential bias, we present in this appendix an alternative set of estimations based on the approach proposed by Geroski et al. (1997), which has also been employed by, for instance, Bianchini and Pellegrino (2019). Specifically, we fix the values of the covariates at their initial levels during the first period of the spell and hold these values constant throughout the spell. The main drawback of this method is that it does not allow for testing a possible indirect effect of cumulative R&D experience on R&D persistence via enhanced productivity. In addition, this approach may be particularly problematic for long R&D spells, as it is unrealistic to assume that firm characteristic, as proxied by our covariates, remain unchanged over extended periods.

Despite these limitations, our results for the variables of interest closely resemble those reported in the main text, implying that any endogeneity bias is likely marginal, if present at all. Table B1 shows that, for the full sample, we confirm hypotheses H1a, H1b, and H1c. In line with Table 6, the estimated coefficients for *Log(Surv. Time)* and *Previous R&D Investment Experience* are negative and significant, whereas the coefficient for *Previous Number of Spells* is positive and significant. For the subsample of small firms (see column 2 of Table B1), these alternative estimations replicate the findings from Table 6, confirming H2a and H3a but not H1a: the coefficient for *Previous R&D Investment Experience* is negative and significant, while that for *Previous Number of Spells* is positive and significant; however, the coefficient of *Log(Survival Time)* is not significant. Furthermore, in the subsample of medium firms (column 3 of Table B1)—mirroring the results in Table 6—the estimates support H1a and H1c but not H1b. The coefficient for *Log(Surv. Time)* is negative and significant, that for *Previous Number of Spells* is positive and significant, and the coefficient for *Previous R&D Investment Experience* is not significant. Finally, for large firms (column 4 of Table B1), the evidence once more supports hypotheses H1a, H1b and H1c, mirroring the patterns reported in Table 6. Both *Log(Surv. Time)* and *Previous R&D Investment Experience* exhibit negative and statistically significant coefficients, while *Previous Number of Spells* displays a positive and significant association.

Table B1. Determinants of the duration of R&D investment spells. All firms and by sizegroups. Initial values

	All firms	**Small**	**Medium**	**Large**
	(1)	**(2)**	**(3)**	**(4)**
Log(Surv. time)	-0.205***	-0.0391	-0.260*	-0.366***
	(0.0759)	(0.165)	(0.154)	(0.0642)
Previous R&D investment exper.	-0.0435**	-0.0838**	0.0266	-0.0578**
	(0.0180)	(0.0330)	(0.0320)	(0.0280)
Previous number of spells	0.215***	0.129**	0.185*	0.266**
	(0.0715)	(0.063)	(0.00991)	(0.112)
TFP	-0.373***	-0.155	-0.983***	-0.179
	(0.113)	(0.230)	(0.230)	(0.174)
Only Internal	-0.186**	-0.421***	-0.0706	-0.0551
	(0.0883)	(0.147)	(0.172)	(0.147)
Both	-0.518***	-0.851***	-0.385*	-0.255
	(0.104)	(0.185)	(0.199)	(0.166)
R&D Intensity	-0.844	0.286	-3.533	-7.147**
	(0.801)	(0.878)	(2.242)	(3.637)
Med-tech regime	-0.342***	-0.210*	-0.343**	-0.360***
	(0.0751)	(0.122)	(0.138)	(0.118)
High-tech regime	-0.597***	-0.710***	-0.713***	-0.225
	(0.106)	(0.183)	(0.197)	(0.165)
Log(R&D emp)	-0.265***	-0.303***	-0.351***	-0.0231
	(0.0397)	(0.0946)	(0.0775)	(0.109)
Process innovation	0.00875	-0.00325	0.0952	-0.330***
	(0.0643)	(0.109)	(0.117)	(0.114)
Product innovation	-0.249***	-0.0736	-0.377***	-0.111
	(0.0679)	(0.118)	(0.124)	(0.169)
Log(Approp)	-0.0387	0.0690	0.0361	-0.0628*
	(0.0957)	(0.162)	(0.167)	(0.0330)
Score E	-0.0659***	-0.0563	-0.0638*	-0.0424
	(0.0210)	(0.0373)	(0.0383)	(0.117)
DRecessive	0.0616	0.0578	0.0272	-0.174***
	(0.0714)	(0.123)	(0.130)	(0.0513)
Exporter	-0.306***	-0.352***	-0.248	-0.0978
	(0.0853)	(0.122)	(0.161)	(0.189)
Mshare	-0.190***	-0.00808	-0.315***	0.276**
	(0.0668)	(0.119)	(0.115)	(0.140)
Log(CR4)	0.0299	0.00447	0.0560	-0.107**
	(0.0225)	(0.0344)	(0.0405)	(0.0482)
Log(Employment)	-0.258***	-0.377***	-0.335***	-0.0570
	(0.0322)	(0.107)	(0.114)	(0.0793)
R&D Sub	-0.0927	0.169	0.0552	-0.278**
	(0.0801)	(0.145)	(0.140)	(0.136)
Log(Age)	-0.0132	0.00217	-0.0477	-0.0371
	(0.0392)	(0.0690)	(0.0752)	(0.0596)
Absorption	-0.0992	0.359	-0.437	-0.0641
	(0.224)	(0.568)	(0.474)	(0.248)
Excision	1.035***	0.639	0.621	-0.421
	(0.231)	(0.663)	(0.543)	(0.457)
Constant	0.684***	1.066**	0.948	-0.429
	(0.231)	(0.449)	(0.654)	(0.568)
Unobserved heterogeneity: LR Test of Gamma Variance=0				
Chibar2(01)	9.253	10.368	4.292	9.077
Prob≥chibar2	0.001	0.001	0.019	0.001
Observations	14,516	3,036	4,426	7,054

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

Appendix C.

C.1 R&D subsidies and firm size

Our estimations uncover a nuanced relationship between public R&D support and firms' R&D persistence. The results indicate that R&D subsidies are positively associated with longer R&D spell durations among large and small firms, whereas no significant association emerges for medium-sized firms. This heterogeneity suggests that the persistence-enhancing role of public funding varies systematically with firm size. Accordingly, this appendix explores in greater depth the relationship between R&D subsidies and the duration of R&D spells across firm-size categories.

Table C1: Some statistics on R&D subsidies and R&D persistence

	Small	Medium	Large
Share of firm-year observations with positive R&D subsidy that correspond to each size group	13.96	26.74	59.30
Share of spells for which the firm was granted an R&D subsidy at least half of the years of the spell that correspond to each size group	25.66	33.55	40.79
Share of ending R&D spells for which the firms enjoyed R&D subsidies at least half of the years of the spell	18.32	21.91	20.04

Table C1 reveals relevant differences in access to R&D subsidies across firm sizes, as well as meaningful differences in how public support interacts with firms' R&D persistence. Large firms clearly dominate in participation, accounting for 59.3% of firm-year observations and 40.8% of R&D spells classified as subsidized, defined here as spells during which firms received public R&D support in at least half of the observed years of the spell. This could be a reflect of their stronger institutional capacity to apply for and manage public funds, underpinned by established R&D departments and administrative expertise.

Medium-sized firms display an intermediate level of participation, representing 26.7% of subsidized firm-year observations and 33.5% of subsidized spells. Interestingly, their relatively higher share of R&D spells ending after receiving a subsidy at least half of the years (22%) in comparison to both small and large firms suggests that, although they access funding more often than small firms, they are less sensitive to R&D subsidies when deciding whether to continue R&D. In other words, subsidies appear less decisive in shaping their R&D persistence

Small firms, which represent only around 14% of firm-year observations and 25.7% of subsidized spells, face persistent barriers to participation. Administrative complexity, limited human resources for managing funding applications, or stringent co-financing requirements could often restrict their access. Yet, once obtained, subsidies play a more relevant role in sustaining their R&D continuity than for medium size firms. The lower share of spell terminations for subsidized spells (18.3%) indicates that public support tends to exert a stronger stabilizing influence for small firms, reducing the hazard that firms quit R&D.

Taken together, our statistics point to a dual asymmetry: one in access and another in effectiveness. Large firms dominate in access and embed subsidies within established R&D systems, medium firms access funding but their R&D persistence exhibit lower dependence on it, and small firms remain underrepresented in subsidies participation but derive relevant persistence benefits from public support.

The differential influence of R&D subsidies across firm sizes very likely reflects the heterogeneous constraints and capacities that shape firms' ability to sustain innovation. For small firms, public support acts primarily as a mechanism that contributes to relieve liquidity constraints (Meuleman and De Maeseneire, 2012; Bellucci et al., 2019). They may help them overcome severe financing and risk constraints that limit their ability to sustain continuous R&D efforts. There exists empirical evidence showing that subsidies play a decisive role in enabling small firms to persist in innovation by compensating for limited internal resources and facilitating access to complementary private finance (Meuleman and De Maeseneire, 2012; Ziesemer, 2021). The signaling function of subsidies also improves the firm's perceived reliability with investors and may generating learning effects that sustain engagement in R&D beyond the duration of the subsidy.[20] In this sense, subsidies serve as a driver for continuous engagement, transforming short-term financial support into a mechanism for long-term learning and capability accumulation.

[20] Kleer (2010) frames subsidies as credible signals to private investors under asymmetric information and Ziesemer's (2021) review suggest that across OECD countries, subsidy schemes often complement rather than substitute R&D financing.

For large firms, R&D subsidies foster persistence through a different mechanism. These firms operate their own in-house R&D departments typically and face fewer financial constraints, yet public funding reinforces their strategic commitment to long-term innovation. Moreover, public support can act as a coordinating and signaling tool, which enhance reputational capital and attracts complementary private investment (Ziesemer, 2021). Subsidies do not only reduce costs but also help embed R&D continuity within firms' strategic and organizational routines. Petrin and Radicic (2023), using Spanish data point out that direct R&D subsidies are frequently designed to support risk-intensive technological projects and early-stage research, activities unlikely to yield short-term returns. Their analysis suggests that such funding helps firms with larger, formalised R&D systems to absorb more complex long-horizon investments and institutionalise research collaborations, thereby providing a form of strategic stability to innovation trajectories. In the same line, Herrera and Bravo-Ibarra (2010) find that Spanish larger and with existing in-house R&D departments firms are more likely to receive R&D subsidies what contributes to provide stability to internal research programs and strengthens R&D routines and internal capabilities. Taken together, these studies indicate that R&D subsidies, disproportionally concentrated among large firms function not only as financial incentives but as strategic instruments that stabilize ongoing research programmes, sustain collaboration, and consolidate the organizational routines underpinning long-term innovation.[21] Furthermore, cross-country evidence indicates direct R&D support are disproportionately concentrated among large R&D-performing firms, which suggests that public support may reinforce existing innovation capacities rather than primarily fostering new entrants into R&D (Appelt et al., 2020).[22]

By contrast, medium-sized firms appear less responsive to R&D subsidies in terms of sustaining long-term R&D engagement. This outcome can be understood by considering their intermediate resource position and limited policy alignment. Medium-sized firms often fall into a policy gap: too large to qualify for SME-targeted schemes yet too small to compete for

[21] The statistics shown in Table C.1 reinforce previous observed association between subsidies and firms size since R&D subsidies are disproportionally biased to large firms.

[22] The report also documents that business R&D is highly concentrated (both across firms and industries) and that tax incentives and direct funding tend to support firms that are already R&D performers, particularly larger or more established ones.

large-scale strategic grants. One underlying reason is organisational capacity: SMEs generally face pronounced administrative and organisational constraints when dealing with complex funding programs (Hutschenreiter et al., 2019), and empirical evidence suggests that firms with weaker internal R&D and innovation capabilities derive lower returns from subsidy programmes (Hottenrott & Lopes-Bento, 2019). Similarly, policy analyses highlight that smaller firms are disadvantaged in managing external funding requirements, such as detailed reporting, monitoring and partnership coordination (European Parliament, 2021).

All in all, these patterns suggest that public support strengthens R&D persistence among small firms by reducing financial fragility and among large firms by reinforcing strategic continuity but exerts limited influence among medium-sized firms due to policy misalignment and organizational constraints.

C.2 Subsidies and technological regime

Our estimations by technological regime reveal an interesting pattern in the association between R&D subsidies and R&D persistence. Specifically, the results indicate that public R&D support is positively correlated with longer R&D durations among medium-technology firms, whereas no significant relationship emerges for low- or high-technology firms. To explore this heterogeneity further, this appendix provides a detailed examination of how R&D subsidies relate to the duration of R&D spells across technological regimes.

Table C2: Some statistics on R&D subsidies and R&D persistence

	Low-tech	Med-tech	High-tech
Share of firm-year observations with positive R&D subsidy that correspond to each technological class	34.18	38.85	26.97
Share of spells for which the firm was granted an R&D subsidy at least half of the years of the spell that correspond to each technological class	35.13	35.79	29.08
Share of ending R&D spells for which the firms enjoyed R&D subsidies at least half of the years of the spell	18.25	19.21	21.75

Table C2 illustrates clear heterogeneity in the distribution of R&D subsidies across technological regimes, shedding light on how public support interacts with firms' R&D persistence. Across technological regimes, med-tech firms exhibit the largest share of subsidized R&D activities, as 38.8% of subsidized firm-year observations correspond to med-tech firms. Low-tech firms, closely follow med-tech (34.2% of their corresponding firm-year observations are subsidized), while high-tech firms exhibit the lowest share (27%). This pattern suggests that public support mechanisms may be strategically oriented or more accessible for med-tech firms, which usually show both significant potential for technological upgrading and comparatively constrained internal R&D resources.[23]

The second row of Table C2 shows a similar pattern when considering the share of R&D spells classified as "subsidized," i.e., spells for which firms received R&D support in at least half of the years of the spell. Again, med-tech and low-tech firms record higher rates (35.8% and 35.1%, respectively) compared with high-tech firms (29.1%). These figures reinforce the idea that public support may ease more continuous R&D involvement in less technology-intensive sectors, where R&D investment tends to be more sporadic and financially constrained. In contrast, high-tech firms appear less dependent on public funding, reflecting their stronger internal R&D capabilities, greater access to private finance, and typically more established innovation routines.

The lower share of R&D spell terminations among subsidized spells for low-technology firms suggests that public support exerts a stronger persistence-enhancing effect in this group, i.e. subsidies seem to play a more decisive role in sustaining R&D continuity where firms face tighter liquidity constraints and limited access to external finance.[24] This finding suggests that public funding can reshape firms innovation behaviour by allowing them to sustain R&D activities that might otherwise be discontinued (Dimos & Pugh, 2016; Zúñiga-Vicente et al., 2014). In contrast, high-technology firms, which show the highest share of subsidized R&D spell terminations, seem less sensitive on public support for maintaining R&D engagement. Medium-technology firms occupy an intermediate position, displaying some

[23] Appelt et al. (2020) suggest that the effectiveness of R&D incentives is especially pronounced among firms in medium-technology sectors, where external support alleviates liquidity constraints and reinforces cumulative learning. Similarly, Dimos and Pugh (2016) find that the crowding-in effects of R&D subsidies are strongest in these industries, suggesting that the interaction between public support and private investment is most productive where innovation capacity is significant but financial constraints persist.

[24] The mean of our financial score variable (Score E), that includes both external and financial constraints measures, is 5.21, 5.32 and 5.59 for low-tech, med-tech and high-tech firms. Recall that the higher the financial constraints index the lower the financial constraints stringency.

persistence-enhancing response to subsidies but less pronounced than in low-tech industries.[25] Overall, these results point to a declining influence of public R&D support on R&D persistence as technological intensity increases, with the greatest response observed low-tech firms.

In the univariate analysis performed in this appendix, the observed decline in the association between R&D subsidies and persistence with increasing technological intensity likely reflects heterogeneous dependence on public support. Low-tech firms rely more on subsidies to maintain R&D continuity, whereas high-tech firms' persistence is very likely primarily driven by internal capabilities and cumulative learning. However, once firm-level heterogeneity and other covariates are controlled for in the multivariate duration analysis, the significant association of subsidies with R&D duration is significant only for med-tech firms. This likely reflects that medium-tech firms possess sufficient absorptive capacity to transform public funding into sustained innovation effort but still face liquidity constraints that make external support relevant (Appelt et al., 2020; Dimos & Pugh, 2016; Hottenrott & Lopes-Bento, 2019).

Appendix D:

Digitalization intensity and the determinant of R&D investment persistence

It is plausible that firms engaged in more digital-intensive R&D activities may experience a faster depreciation of accumulated knowledge, such that learning processes associated with past R&D experience become less effective over time. Ideally, this hypothesis would be tested using firm-level information distinguishing between digital and non-digital R&D. However, the available data do not allow for such a distinction.

As an indirect approach, we examine whether the direct channel of R&D experience varies with the digital intensity of the industry in which firms operate. This allows us to assess whether the degree of digitalization modifies the relationship between different forms of accumulated R&D experience and R&D persistence. To this end, firms are classified into low,

[25] This pattern is consistent with prior evidence showing that firms in med-tech sectors combine substantial innovative potential with moderate financial constraints, making public support complementary to the continuity of their R&D investments (Hottenrott & Lopes-Bento, 2014,; Appelt et al., 2020)

medium-, and high-digitalization sectors following the OECD taxonomy proposed by Calvino et al. (2018). The corresponding sectoral classification is reported in Table D.1.

Table D1. Sector digitalization intensity classification (NACE- 2009 two-digit industrial classification)

Digitalization intensity	**Sector**
Low	Meat industry; Food and tobacco; Beverages; Textiles and clothing; Leather and shoes; Furniture; Other manufacturing goods
Medium	Wood; Paper industry; Printing and printing products; Chemical products; Rubber and plastic; Non-metallic mineral products; Ferrous and non-ferrous metals; Metallic products; Industrial and agricultural machinery; Vehicles, cars, and motors; Other transport equipment
High	Office machines; Electric and electronic machinery and material

The estimates reported in Table D.2 reveal clear heterogeneity in the direct channel of R&D experience across digital intensity groups.[26] The coefficient *of Log(Surv. time)* is negative and statistically significant across all groups, supporting H1a and indicating the presence of within-spell learning.

The coefficient of previous R&D investment experience is negative and statistically significant in low- and medium-digitalization sectors, providing support for H1b. This indicates that accumulated experience is associated with longer R&D spells in environments where knowledge accumulation is more gradual. However, the coefficient is not statistically significant for high-digitalization firms. This suggests that cumulative R&D experience is less strongly associated with persistence in these sectors, possibly reflecting faster technological change and shorter knowledge cycles, which may reduce the relevance of past experience (Brynjolfsson and McAfee 2014; Calvino et al., 2018).

The coefficient on the previous number of spells is positive and statistically significant in low- and medium-digitalization sectors, consistent with H1c. This finding indicates that a more fragmented history of R&D activity is associated with shorter subsequent R&D spells, in line with weaker routine-based learning and the depreciation of accumulated knowledge

[26] For the sake of space, we show only the estimates corresponding to the variables associated to the direct channel. Results on the rest of variables are available under request.

(Argote and Epple, 1990). By contrast, the coefficient is not statistically significant in high-digitalization sectors, suggesting that punctuated R&D experience is less strongly related to persistence in these industries.

Overall, the results indicate that the importance of learning mechanisms underlying R&D persistence varies with the degree of digitalization. While both within-spell and cumulative learning appear to play a role in low- and medium-digitalization sectors, persistence in highly digitalized industries seems to depend primarily on within-spell learning. One possible interpretation is that the more complex and rapidly evolving nature of R&D activities in these sectors leads to a faster depreciation of accumulated experience when interruptions occur.

Table D2: Determinant of the duration of R&D investments by industry digitalization intensity

	Low-digitalization (1)	**Med-digitalization (2)**	**High-digitalization (3)**
Log(Surv. Time)	-0.236**	-0.337***	-0.163*
	(0.108)	(0.0677)	(0.0866)
Prev. R&D Inv. Experience	-0.053*	-0.0658***	0.105
	(0.030)	(0.0211)	(0.076)
Prev. Number of spells	0.213*	0.221***	0.087
	(0.113)	(0.0766)	(0.221)
TFP	-0.485	-0.208*	0.935**
	(0.173)	(0.119)	(0.407)
Unobserved heterogeneity: LR tess of Gamma Variance			
Chibar2(01)	3.250	5.110	4.440
Prob≥chibar2	0.036	0.012	0.018
Observations	3,701	4,426	6,389

Standard error in parentheses. *** p<0.001, **p<0.05, p<0.1

Appendix E: R&D Subsidies Persistence

Appendix E examines whether the estimation results for the direct and indirect channels of R&D are sensitive to replacing the R&D subsidy dummy with a measure of R&D persistence, defined as the number of consecutive years during which firms receive R&D subsidies.

The results reported in Table E1 for small, medium, and large firms indicate that introducing the R&D persistence variable does not alter the findings associated with Hypotheses H1a, H1b, and H2c across firm size groups. In particular, the estimated coefficients for *Log(Surv. time), Previous R&D Investment Experience,* and *Previous Number of Spells* remain qualitatively unchanged and quantitatively very similar to those reported in Tables 6.[27]

Consistent with the baseline specification using the subsidy dummy, total factor productivity (TFP) remains statistically significant for small and medium-sized firms. Accordingly, the results for the indirect channel are unaffected. This is expected, as the indirect channel relies on the estimation of productivity in equation (3) and on the coefficients of the relevant variables in equation (5) (δ_1, δ_2 and δ_3) which do not depend on the proxy used for R&D subsidies.

Regarding the comparison between the estimates based on the R&D subsidy dummy and those using the R&D persistence variable across firm size groups, the results indicate that while the subsidy dummy is statistically significant for both small and large firms, R&D subsidy persistence is significant only for large firms. This suggests that, for small firms, what matters is whether benefited from R&D subsidies last year, rather than the duration of uninterrupted subsidy receipt.

Table E.1: Determinants of the duration of R&D investments: R&D subsidy persistence

	Small	Medium	Large
	(1)	(2)	(3)
Log(Surv. Time)	-0.0314	-0.371***	-0.275***
	(0.142)	(0.128)	(0.0604)
Prev. R&D Inv. Experience	-0.0906***	0.00794	-0.0472*
	(0.0317)	(0.0279)	(0.0266)
Prev. Number of spells	0.173*	0.193**	0.280***
	(0.094)	(0.0980)	(0.106)
TFP	-0.312*	-0.759***	-0.0653
	(0.176)	(0.168)	(0.165)
R&D Subsidy Persistence	0.0422	-0.064	-0.113***
	(0.045)	(0.045)	(0.0330)
Unoberved heterogeneity: LR Test of Gamma Variance			
Chibar2(01)	8.189	4.255	9.025
	0.002	0.020	0.001
Observations	3,036	4,426	7,054

Standard error in parentheses. *** p<0.001, **p<0.05, p<0.1

[27] For the sake of brevity, we present results for size groups. Results by technological regime are available under request. Analogously, for reasons of space, Table E.1 reports only the variables relevant to testing our hypotheses. Estimates for the remaining variables are also available upon request.