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Innovation persistence and employment dynamics

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Abstract

This paper examines the effect of persistence in product and process innovations on the employment dynamics of a representative sample of Spanish manufacturing firms observed over more than 20 years. We build a conceptual framework that links innovation, its persistence, and different trajectories of employment growth. This framework suggests that firms might show different responses in terms of their employment growth and its persistence depending on the degree of persistence in their product and process innovations. We construct a synthetic indicator of innovation persistence at the firm-level and link this indicator to different employment trajectories. We find that persistence in product innovation affects both employment growth and the sustainability of job creation over time significantly, whilst persistence in process innovation does not play any relevant role. Also, the positive effect of persistence in product innovation is particularly strong for SMEs. The evidence we provide supports the notion that product innovation is more effective in spurring sustained employment growth when carried out systematically.

JEL codes: D22, O31, O32, O33

Keywords: Firm growth, Job creation, Persistence in innovation, Innovation spell, Path-dependence

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1 Introduction

The adverse effects of scientific advances and technological changes on employment are a long-standing issue in economic thought. Historically, the direct labour-saving impact of process innovation is supposed to be counterbalanced by other mechanisms. For instance, the initial displacement of jobs resulting from technological change may be offset by the labour-friendly nature of product innovation, as new goods or new variants of existing goods allow new economic branches to develop and additional jobs to emerge. Alas, the antagonistic forces at stake together with a wide set of historical and institutional circumstances make the relationship between innovation and employment much more complex.¹

Notwithstanding its vastness, the literature on the relationship between innovation and employment is still underdeveloped in some respects. A major limitation is the paucity of studies concerning one of the key properties of the innovation process: its path-dependent and persistent nature (see, among others, Breschi et al., 2000; Malerba, 2007; Dosi and Nelson, 2010). Do firms that systematically achieve innovation outcomes experience different dynamics of employment compared to firms that only innovate irregularly? The lack of evidence on this question is somewhat unpleasant given the conspicuous body of economic and management literature focused on persistence in innovation activities at the firm-level.

It is widely accepted that persistence in innovation finds several theoretical explanations. Successful innovation broadens both a firm's technological opportunities and its market power which in turn positively affect the conditions for subsequent innovations. According to the so-called "success-breeds-success" hypothesis, the cumulative and additional nature of technological knowledge is such that firms are likely to experience dynamic increasing returns in their innovation activities. Firms may also experience a process of "learning-by-innovating" which enhances knowledge stocks and technological capabilities, ultimately inducing state dependence in firms' innovative behaviour (Dosi et al., 2008). Knowledge accumulation and technological learning are indeed two cornerstones in the literature on technological changes, which assumes that innovation persistence occurs predominantly within a technological landscape characterized by Schumpeterian patterns of creative accumulation (Malerba et al., 1997; Malerba and Orsenigo, 1997; Breschi et al., 2000). Furthermore, innovation activities are frequently characterized by high sunk start-up costs that have to be incurred to build research infrastructure and to hire qualified R&D personnel. This means that once the decision to initiate the innovation process has been taken, the opportunity costs to stop may often be too high (Mañez et al., 2009).

These theoretical contributions are complemented by a vast empirical literature.² Most studies target the output side of innovation, relying on such measures as patents (see, e.g.

¹Vivarelli (2014), for instance, undertakes an exhaustive survey of theoretical and empirical literature on the quantitative and qualitative employment impact of technological change, and concludes that "[o]n the whole, previous microeconomic evidence is not fully conclusive about the possible employment impact of innovation" (p.138). A detailed review of the extant literature linking innovation and employment at the firm and industry-level is beyond the scope of this article. Interested readers may consult up-to-date surveys in Vivarelli, 2014; Calvino and Virgillito, 2017.

²Table 1 provides a concise overview of some relevant studies on innovation persistence.

Geroski et al., 1997; Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001; Cefis, 2003), share of sales stemming from innovative products (Raymond et al., 2010), the development of process and/or product innovations (Antonelli et al., 2012) as well as marketing and organizational innovation (Tavassoli and Karlsson, 2015). A certain degree of persistence in product and process innovation is conventionally supported in the data, whilst patent-based studies find little evidence of persistence. Other contributions consider the input side of innovation activity and identify a high degree of persistence in intra and extra-mural R&D investments (Peters, 2009; Triguero and Córcoles, 2013; García-Quevedo et al., 2014).³

Despite the substantial theoretical and empirical research effort, little is known about the effects of innovation persistence on firms' performance. However, there are a few recent exceptions in this regard. Cefis and Ciccarelli (2005), for instance, show that the corporate profitability of a sample of UK manufacturing firms observed over the period 1988–1992 depends upon the degree of persistence in their innovative activities (patents). They also find a long-run effect of persistence in patenting, with persistent innovators being able to sustain their higher profit margins over longer periods of time. Huergo and Moreno (2011), exploiting the same data as we use in this study (although for a different time window), estimate a multi-equational model that relates the R&D investment decision and the achievement of product and process innovations to productivity gains. Their results underline the positive role of persistence of innovation inputs and innovation outputs on productivity growth. Demirel and Mazzucato (2012) focus on a sample of small and large publicly quoted US pharmaceutical companies observed over the period 1950–2008 and highlight the key role that persistence in patenting plays in allowing firms to benefit from their R&D efforts. They show that sales growth is positively affected by R&D investments only for those (small) firms that have patented persistently over time, whereas no growth premium is found for firms that patent sporadically. Deschryvere (2014) uses a panel of Finnish firms to reach similar conclusions. On the contrary, Guarascio and Tamagni (2016) show that persistent innovators, defined according to various innovation proxies, do not outperform their competitors both in terms of sales growth and persistence of this growth in the long-run.

This somehow diffuse evidence suggests that more research into the effects of innovation persistence on industrial dynamics is needed. Apart from the aforementioned contributions, studies that seek to link persistence in innovation to employment are undeniably scarce. One exception in this regard is Triguero et al. (2014a) who test the employment impact of persistence in product and process innovations. The authors propose a dynamic model where persistence degree is captured by different lags (first and second lag, respectively) of innovation variables, and find that persistence in process (but not in product) innovation positively affects employment growth.

³Previous literature has most often put emphasis on large firms, although sustained innovative activities extends also to a relatively large number of highly innovative small companies. Some differences, however, might exist on how innovation persistence occurs in SMEs and large innovators. For instance, Corradini et al. (2016) show that innovation persistence in large companies originates predominantly from economies of scale in innovation, whilst small firms tend to generate further innovation recombining their previous knowledge and screening technological landscape that are not so far from their original technological competences.

Our paper builds upon this emergent stream of literature and aims to contribute at least on two fronts. First, unlike most of the previous studies, we propose and implement a synthetic *indicator of innovation persistence* at the firm-level, contemplating the idea that long-term innovation history matters. The indicator is based on the concept of “innovation spell”, defined as the number of successive years in which a firm innovates without interruption. As such, it is designed to account for two characteristics of technological knowledge, namely cumulativeness and non-exhaustibility (David, 1992; Antonelli, 1997). Both these features have implications in our framework, as the generation of knowledge embedded in new products and/or new processes is typically conditioned by the existing stock that can be used, given its non-exhaustibility, as an input. Second, we investigate the relationship between innovation persistence and patterns of *sustained employment growth*. The existence of stable competitive advantages would run counter the notion of randomness in firm performance, according to which outperforming firms are simply “luckier” than their competitors (Barney, 1986, 1997). Being fooled by randomness is a particular concern in economics and management sciences, and the idea of dismissing random variation as an explanatory mechanism for industrial dynamics has recently attracted increasing attention within the scientific community (Coad et al., 2013; Denrell et al., 2014).⁴

The rest of the article proceeds as follows. In Section 2, we identify some of the theoretical roots of our study. We describe the data and the construction of the indicator of innovation persistence in Section 3. Section 4 illustrates the methodology we employ in our analysis. Empirical results are presented in Section 5. Finally, Section 7 discusses the implications of our results in light of the existing literature and concludes.

2 Theoretical roots

2.1 The innovation-employment nexus

The existing economic theory linking innovation to employment is our starting point. It is well established that the net effects of product and process innovation on employment are theoretically unclear (see, among others, Pianta, 2005; Lachenmaier and Rottmann, 2011; Harrison et al., 2014; Vivarelli, 2014; Calvino and Virgillito, 2017). Firms introducing new products on the market stimulate consumption and create new demand, thus allowing additional jobs to emerge. Less intuitively, however, negative indirect effects could be at stake. For instance, if new products substitute existing ones and the production of the new generation of products requires fewer workers than the production of the old products this might hinder employment (“cannibalization”, to use the jargon). Similar arguments apply in the case of process innovation. Firms may change their production process to improve the productivity of inputs, including labour (Vivero, 2002). Thus, the negative effect of process

⁴To note that such a concern is also shared among policy-makers. In fact, the implicit message of most recent policy actions is that not only are firms expected to generate new jobs, but they are expected to do so over a number of consecutive years. Randomness as a convincing explanation for firm-industry dynamics would unfortunately leave little room for political intervention.

Table 1: Empirical studies on the persistence of innovation

Study	Sample	Innovation activities	Methodology	Measure of persistence	Finding
Geroski et al. (1997)	British manufacturing firms, 1969-1988	Patents granted by USPTO	Duration dependence Weibull model	Length of innovation spell	Low persistence
Malerba and Orsenigo (1999)	Firms and institutions from USA, Japan, Germany, UK, France and Italy, 1978-1991	Patent applications by EPO	Transition probability matrix	Probability of remaining in the same state	Persistent innovators few in number but large in terms of patents
Cefis and Orsenigo (2001)	French, German, Italian, Japanese, British, and American manufacturing firms, 1978-1993	Patent applications at EPO	Transition probability matrix	Probability of remaining in the same state	Both great innovators and non-innovators have a high probability to remain in their state
Cefis (2003)	British manufacturing firms, 1978-1991	Patent applications at EPO	Transition probability matrix	Probability of remaining in the same state	State dependency (particularly strong for product innovators)
Peters (2009)	German manufacturing and service firms, 1994-2002	Binary variable obtained considering six different innovation input measures	Dynamic random effects discrete choice model	Lagged (t-1) dependent variable	High persistence
Raymond et al. (2010)	Dutch manufacturing firms, 1994-2002	Achieve product and/or process innovations; Share of innovative sales over total sales	Dynamic type 2 Tobit model	Lagged (t-1) dependent variables	High level of persistence
Antonelli et al. (2012)	Italian manufacturing firms, 1998-2006	Achieve product and/or process innovations; Engage in R&D	Dynamic random effects discrete choice model	Lagged (t-1) dependent variables	High persistence
Triguero and Corcoles (2013)	Spanish manufacturing firms, 1990-2008	Achieve product and/or process innovations; Engage in R&D	Dynamic random effects discrete choice model	Lagged (t-1) dependent variables	High persistence
Garcia Quevedo et al. (2014)	Spanish manufacturing firms, 1990-2009	Engage in R&D; Investment in R&D	Dynamic type 2 Tobit model	Lagged (t-1) dependent variables	High persistence (in particular for old firms)
Tavassoli and Karlsson (2015)	Spanish manufacturing firms, 2002-2012	Achieve product, process, marketing and organizational innovations	Transition probability matrix, dynamic probit model	Lagged (t-1) dependent variables	True state dependence among all types of indicators but for organizational innovation

innovation occurs when a firm can produce the same level of output with fewer workers. Yet, in this case also, there is a possible indirect effect related to the increase in productivity: higher productivity in competitive markets implies a reduction in prices, and lower prices should increase demand.

The first argument we propose here is that the degree of persistence in product and process innovation may in some way overcome these theoretical indeterminacies and quantify the magnitude of the relationship between innovation and employment. Let us start with product innovation. There are at least three complementary reasons why persistent product innovators should be in a better position of benefiting from their recent innovation. First, we would expect firms to introduce new products at different points in their history so that their performance at any point in time is related to each of the innovations that have been introduced. Recent innovations may still be made in a monopolistic situation while the older products might be exposed to imitation and, more generally, to a greater level of competition (Roberts, 1999; Dosi and Nelson, 2010; Cohen, 2010). Second, the new demand generated is likely to be amplified by the “brand awareness” effect, as customers typically perceive continuous innovators to be “good” companies that possess the ability to move ahead technologically on a regular basis (Kapferer, 2012). Third, a continuous stream of new

products on to the market typically entails a continuous stream of higher profits that can, in turn, be employed by the firm to fuel additional growth (for example, by opening a new establishment or a new R&D department). These patterns are unlikely to apply to occasional innovators, however. If markets efficiently select firms based on their technological traits, the forces of competition should gradually erode the comparative advantage that occasional innovators have built upon their past (and perhaps obsolete) product innovation outcomes. Furthermore, occasional innovators frequently act as imitators, and start producing already existing products to overcome increasing market pressure (Malerba et al., 1997; Bottazzi et al., 2001; Cohen, 2010). The ultimate effect of innovation on their performance should, therefore, be weaker. In line with the preceding, persistence in product innovation can be expected to amplify the positive effects of innovation on employment growth. In other words, persistent product innovators should gain greater rewards from their innovation outcomes in terms of employment than other companies, all other things being equal.

The case of process innovation is equally interesting, although theoretical expectations are less clear-cut. One reason is that process innovations are subject to considerable variation and embrace a number of heterogeneous activities. Reichstein and Salter (2006), by way of example, argue that process innovation typically involves the introduction of new machinery and changes to the production process, the use of ICT and the adoption of new management practices. Regardless of the type of activity, firms introduce new processes with the aim of achieving lower costs and/or higher product quality. According to the classical literature, a sustained cost reduction due to higher productivity should lead to a consequent reduction in the level of employment, at least in the short-term. However, the traditional labour saving effect of process innovation may be less evident or even non-existent in the case of a continuous stream of new or significantly improved production practices. In the medium-long term, indeed, different kind of mechanisms may compensate or reverse the initial expected job displacement. The reiterated introduction of new production processes may considerably drive cost down, in turn allowing firms to obtain important competitive advantages over their rivals (Cabral and Leiblein, 2001). In particular, firms may have the possibility to implement aggressive price strategies, which translate into considerable extra profits. Firms can use these additional profits to extend their production possibilities with the aim of increasing their market shares, eventually creating new growth opportunities. Furthermore, systematic improvements in the process of production may be perceived as the ability of the firm to respond to changes of the external environment. Seen from this perspective, persistence in process innovation implies the existence of “dynamic capabilities” of the firm that are beneficial for its performance, including growth (Teece and Pisano, 1994; Eisenhardt and Martin, 2000). In conclusions, there are theoretical arguments suggesting that the expected negative short-term effect on firms’ employment growth could be easily compensated or even reversed in a context of prolonged introduction of new or improved production practices.⁵

⁵It is important to emphasize the existence of associations and complementarities between product and process developments. For example, the introduction of product innovations often involves a rethinking of the production process as a result of the properties of the new products. It is complicated to make strong

2.2 Patterns of sustained employment growth

The framework linking persistence in innovation to employment growth allows us also to make some conjectures about the determinants of another largely unexplored, but increasingly important, dynamic: namely, the persistence of employment growth – i.e., gaining a better understanding of not only whether a firm generates new jobs but whether it can do so over a period of subsequent years.

It is widely accepted that the dynamics underlying an increase in firm size vary substantially from company to company: some firms sporadically respond to market shocks, other companies present a more erratic and unpredictable behaviour, and other firms sustain their growth over long periods of time (Geroski, 2002; Delmar et al., 2003). Persistent employment growth has become a concern for many different agents, including policy-makers, economists and management scholars. On the one hand, the longstanding debate about Gibrat’s law – according to which firm growth is merely the result of a multiplicative random shock model – has given rise to a strand of literature that seeks to identify persistence in the growth process. The existence of persistence would run counter to Gibrat’s law and, in general, to the notion of randomness in firm performance, according to which “luck” is a good explanation for sustained interfirm differences.⁶ On the other hand, persistence in job creation is also attractive for policy-makers since such growth can be expected to help economies to sustain employment and value creation in the long-run, and to allow the early identification of “good” companies with high growth potential (see the discussion in Coad et al., 2014).

Many studies have focused on the structure of the growth process, conventionally by examining the autocorrelation of growth rates over time (under different autoregressive lags).⁷ Overall, we lack robust evidence of persistence in firm growth. Recent contributions suggest no or negative autocorrelation of growth rates over time (Hölzl, 2014; Daunfeldt and Halvarsson, 2015), in particular for small units (Coad, 2007), whilst others find that young (but not necessarily small) companies typically experience more structured growth processes compared to their older counterparts (Coad et al., 2017). On the pessimistic side, Geroski (2002) succinctly concludes that “[t]he most elementary ‘fact’ about corporate growth thrown up by econometric work on both large and small firms is that firm size follows a random walk” (p.169).⁸

inferences about how a company’s product and process development strategies co-evolve and what effects they can have on firm performance (Reichstein and Salter, 2006). Thus, the clear-cut distinction between the effects of the persistence in product and process innovations on employment growth illustrated in this paper does not directly address the issue of complementarities of different innovation forms.

⁶For details on theories of the “random school of thought” in economics and management sciences, interested readers may consult the seminal works by Barney (1986, 1997) and more recent discussions in Denrell et al. (2014) and Barney (2014).

⁷Even though ideally the time series should be long enough to estimate unbiased parameters, positive values of autoregressive terms imply that the growth process extends beyond that of the random case and displays memory. More recently, scholars have started to exploit quantile autoregression techniques to take into consideration the entire distribution of the growth rates.

⁸Similarly, Coad et al. (2013) theorize a Gambler’s Ruin framework to model growth and survival, and show that while survival is non-random and depends on the stock of resources accumulated by the firm, growth is (close to) a random walk, when seeking either the determinants of annual growth in any given year,

We also know little about the determinants of persistent growth performance. Whilst original “steady state” models suggest a high degree of persistence as firms are assumed to choose long-run stable growth paths depending on their utility functions and on their resource and other constraints, models of firm-industry evolution with differentiated producers suggest that firms with sounder operating capabilities (i.e., higher profits and productivity) should exhibit some degree of persistence in their growth process (see, e.g., Silverberg et al., 1988; Ericson and Pakes, 1995; Cooley and Quadrini, 2001; Luttmer, 2007). On the other hand, recent empirical contributions highlight the existence of persistent growing and high-growing companies, but most fail to identify the structural factors that spur this growth behaviour (Delmar et al., 2003; Capasso et al., 2014; Brenner and Schimke, 2015; Bianchini et al., 2017).⁹

The task, therefore, becomes one of explaining the other factors that might account for interfirm variance in employment growth persistence, if any. In this paper we investigate whether the systematic development of new products and/or processes may induce a less erratic structure in the process of firm growth. To put it succinctly, we ask whether persistence in innovation is one of these factors that helps firms to sustain their growth over time.

Consistent with a framework in which each product innovation yields a series of temporary, monopolistic positions (together with all the other benefits described above), persistent innovators can be expected to exploit their greater competitive advantages over time, translating these advantages into constant opportunities for growth. And for the case of process innovation, we have already seen that the negative short-run effect on firms’ employment growth may be compensated or reversed when firms introduce a continuous stream of new production practices. In short, we could expect persistent innovators to be well placed to generate new jobs over a number of consecutive time-steps.

The above arguments are consistent with the extensive management literature on dynamic capabilities and resources as source of sustained superior performances. Underpinning these theories is the idea that competitive advantages are the basis of firm performance, and the presence of such advantages relies upon the possession of the finest resources, technological and production capabilities (Eisenhardt and Martin, 2000; Teece, 2007). The inherent firm-specific nature of these capabilities induce non-transitory competitive advantages which get reflected into sustained superior performance. Whilst these concepts have been mostly applied to explain profitability dynamics, they can also be relevant to explain patterns of persistent growth (Dosi et al., 2008).

3 Data and measurement

In this study, we draw upon firm-level data from the Survey on Business Strategies (Encuesta Sobre Estrategias Empresariales, henceforth ESEE) which has been conducted yearly

or the regularities in long-term growth over a number of subsequent years.

⁹The contribution by Ciriaci et al. (2016) is the only exception in that they exploit a longitudinal sample of Spanish companies to show that innovation can be a significant driver of sustained high growth.

since 1990 by the SEPI foundation, on behalf of the Spanish Ministry of Industry. This annual survey gathers extensive information on around 2,000 manufacturing companies operating in Spain and employing at least ten workers. The sampling procedure ensures representativeness for each two-digit NACE-CLIO manufacturing sector, following both exhaustive and random sampling criteria.¹⁰ More specifically, in the first year of the survey all Spanish manufacturing firms employing more than 200 workers were required to participate (715 in 1990) and a sample of firms employing between 10 and 200 workers were selected by stratified sampling (stratification across 20 manufacturing sectors and four size intervals) with a random start (1,473 firms in 1990). With the aim to guarantee a high level of representativeness, all newly created companies with more than 200 employees (rate of response around 60%) together with a random sample of firms with fewer than 200 workers and more than 10 (rate of response around 40%) have been incorporated in the survey every year.

In this paper, we refer to data obtained between 1991 and 2012. From the initial sample at our disposal we discard all firms involved in M&A transactions since ESEE only reports a dummy indicating whether a firm has undergone an M&A, without reporting if “M” or “A” actually occurred (and if a firm was the acquirer or the acquired in the case of an “A”).¹¹ The resulting sample is an unbalanced panel of 24,086 firm-year observations (3,444 firms) for which the variables used in our empirical exercises are non-missing.

3.1 Growth, innovation, and measures of persistence

Our main variable of focus is represented by the firm’s growth rate measured in terms of employment and defined as follows:

$$\text{Growth Empl}_{i,t} = \log(\text{Empl}_{i,t}) - \log(\text{Empl}_{i,t-1}) \quad (1)$$

where $\text{Empl}_{i,t}$ is the number of employees in firm i in year t . Next, we construct a variable capturing the degree of persistence in growth performance. As the data are recorded annually, this variable is represented by what we refer to as a “growth spell”, indicating the number of consecutive years in which a firm shows a positive growth rates (as defined in equation 1). As such, a growth spell is considered as having started in year t if the firm did not grow in $t - 1$, and analogously the spell is considered to end in year T when the firm stops growing after one or more consecutive years of positive employment growth. By construction, the spell is both a left and right-truncated discrete variable ranging from 0 – when firms never grow – to the maximum time horizon spanned by our data – in the case of firms observed for the whole period that always exhibit positive growth records. Note that our “growth spell” captures a notion of persistence that goes beyond the short-term notion typically adopted in other studies, based on one-year autocorrelation or short-term transition probability matrices.

¹⁰NACE is the standard industrial classification of economic activities within the European Union while CLIO is the nomenclature used by the Spanish input-output tables. The Spanish Accounting Economic System (National Institute of Statistics: <http://www.ine.es>) officially recognizes both classifications.

¹¹These firms were eliminated from the sample in the years following the merger or acquisition.

To measure the innovative performance of firms, we construct two binary indicators singling out those that have introduced new products and/or new processes. Whilst the dichotomous variable of process innovation has the standard interpretation of capturing the reorganization of production or the implementation of new processes, the dummy variable for product innovation captures whether innovation in the product is due to the inclusion of new parts or intermediate products, the inclusion of new materials, or the adoption of new functions performed by the product. We consider a product innovator as being a firm that satisfies at least one of these criteria.¹²

We use these binary variables to construct the respective indicators of the degree of persistence in firms’ innovation performance. Although there are no commonly accepted criteria in the literature, in part due to the lack of studies trying to quantify persistence of innovation (as opposed to verify its very existence), the basic intuition is that a persistent innovator must perform innovation activities and/or introduce new products or processes consecutively over a number of time-steps. We operationalize this notion by building our own indicator. In principle, the easiest way to construct such an indicator would be to simply look at the frequency with which a firm innovates in a given time window. However, due to the unbalanced nature of our panel, this measure would be highly sensitive to the number of years for which each firm is observed. Most importantly, given a certain time window (say 5 years), this indicator would take the same value for a firm registering innovation in a discontinuous way for some years (say 1 0 1 0 1, where 1 stands for innovation) to another company achieving innovation for the same number of years but without interruption (say 0 0 1 1 1). While the first company is evidently a discontinuous innovator, the second persistently introduces new products/processes during the last three years; and these different patterns of innovations are likely to lead to different trajectories of employment. To overcome these drawbacks, we must resort to the concept of “spell”. Analogously to the “growth spell”, the “innovation spell” is defined as the number of years in which a firm innovates without interruption (Figure 1).

We take the spell of time in which a firm innovates as our unit of analysis, and model the probability that the spell will end at any given time. Since some internal characteristics of the firm and the context in which it operates may influence its innovative behaviour (Antonelli et al., 2013; Triguero et al., 2014b), we model the degree of duration dependence in the innovation path by controlling for internal (i.e., size and age) and external (i.e., industry and time trends) factors. This implies that, at least partially, our measure of innovation persistence is independent of these variables.

A discrete time proportional hazard model is implemented since, even if transitions oc-

¹²We experimented with a more restrictive criterion, i.e. considering product innovators as being only those firms that introduce products that are new in all layers (parts, materials and functions). However, the number of product innovators complying with this definition is extremely small, which prevented us from drawing any meaningful statistical inferences. Notice also that our variable is uninformative about the degree of novelty of the product, which may be either new to the market or new to the firm. It may be that this distinction matters in some instances but, unfortunately, we are constrained here by our data. We return to this issue in Section 5.1 when we check the robustness of our results to alternative proxies of innovation (i.e., patents).

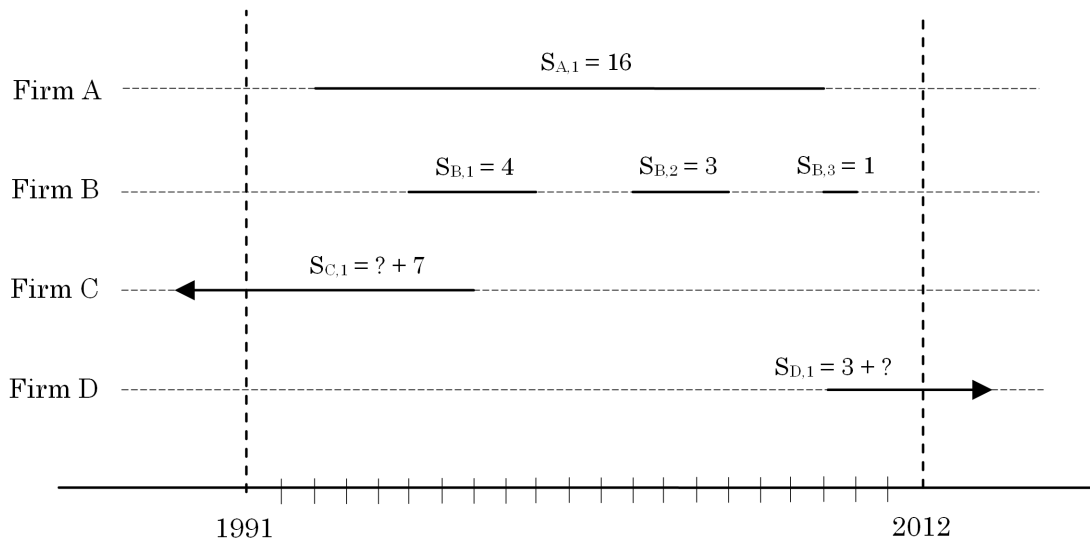


Figure 1: An illustrative example of “innovation spells” for different firms. Firm A experiences only one long innovation spell (16 years). Firm B exhibits multiple spells, frequent but shorter in time. Firms C and D are two cases of left and right-censored spells, respectively.

curred during the year, we only record data annually. Formally, the methodology involves estimating a discrete time representation of the underlying continuous time proportional hazard function, parametrized as follows:

$$\lambda_{i,t} = \theta_i \lambda_{0,t} \exp\{\mathbf{Z}'_{i,t} \beta\} \quad (2)$$

where $\lambda_{i,t}$ is the hazard function, $\lambda_{0,t}$ is the baseline hazard at time t (an arbitrary non-negative function of t), $\mathbf{Z}_{i,t}$ is the vector of covariates defined for firm i (age, size, and industry affiliation) and β is a vector of parameters. Finally, θ_i is a random variable that is assumed to be independent of $\mathbf{Z}_{i,t}$ and represents the “frailty” of the model, an unobserved random factor that modifies multiplicatively the hazard function of each firm. We choose the natural logarithm of time ($\ln(t)$) as the baseline hazard function to account for the risk of the spell ending exclusively because of the passage of survival time. Any continuous distribution with positive support and finite variance may be employed to represent the frailty distribution. We assume a normal distribution, $N(0, \sigma^2)$, for the random effects θ_i .

It can be assumed that the discrete hazard is given by a complementary log logistic (Prentice and Gloeckler, 1978). Hence, we can obtain the discrete time counterpart of the underlying continuous time proportional hazard of equation 2, that is:

$$\lambda_{i,t} = 1 - \exp\{-\exp(\mathbf{Z}'_{i,t} \beta + \lambda_{0,t}) + \theta_i\} \quad (3)$$

The innovation spells can be characterized by censored survival times. Indeed, it might be the case that some spells come into operation before the first year used in our analysis and/or in the last year of observation (see Figure 1). Right-censoring does not represent any problems to model estimation, but left-censoring can be problematic as it implies restrictive assumptions on the baseline hazard. Thus, all left-censored observations were prudently

excluded from the analysis.¹³ We estimate the model of equation 3 separately for product and process innovations and predict the hazard rate for each firm i at time t , measuring the exit probability from the innovation spell.¹⁴ Finally, the indicator of innovation persistence is calculated as $1 - \text{Hazard Rate}$. This transformation has the sole purpose of simplifying the interpretation as a higher value of the indicator implies a higher degree of persistence of innovation. We label the indicator as *Pers Inno*, where *Inno* can be either product or process innovation.

The indicator proposed here, of course, is not exempt from criticism. A plausible objection might be that innovations introduced far back in time do not necessarily affect a firm's performance after a certain point, or more generally that the return on innovation decreases with time. This problem might have been overcome by placing a constraint (or threshold) on the time window over which the indicator of persistence is calculated (say, 5 years or so). Alternatively, we could have introduced a discount rate aimed at reducing the weight of innovation over time. We believe that our indicator is superior in several respects to these alternatives. First and foremost, it takes into account two characteristics of technological knowledge, namely cumulativeness and non-exhaustibility (David, 1992; Antonelli, 1997). Both these features are relevant in our framework, as the generation of knowledge (embedded in new products or new processes) is typically conditioned by the existing stock that can be used, given its non-exhaustibility, as an input. Second, the idea of imposing an arbitrary threshold after which innovation has exactly zero effect on performance seems imprudent and not theoretically grounded. In sum, despite its obvious limitations, we are confident that our indicator is well designed to capture the innovative behaviour of firms throughout their full history.¹⁵

3.2 Other variables

We consider an additional set of explanatory variables to account for other factors that might influence the propensity of firms to increase their employment capacity. We draw these from theoretical models of firm-industry evolution with heterogeneous firms, originally developed within the evolutionary disequilibrium approach with no anticipating or strategic agents (see, e.g., Nelson and Winter, 1982; Silverberg et al., 1988; Dosi et al., 1995), and revisited within a more standard partial equilibrium frameworks with (possibly bounded) rational agents and strategic interaction (such as in Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Cooley and Quadrini, 2001; Melitz, 2003; Asplund and Nocke, 2006; Luttmer, 2007). Despite differences in the core assumptions from alternative schools of thought, these models share a common mechanism of firm selection and growth, which is made explicit in

¹³To test the sensitivity of our findings to this methodological choice, we re-estimated the indicators of innovation persistence by considering left-censored observations and adding a dummy variable to control for left-censored spells. The results obtained are virtually the same as those presented in this article.

¹⁴Estimates are available upon request.

¹⁵We are very grateful to two anonymous referees for providing insightful suggestions on the construction of this indicator.

disequilibrium models, while it is implicitly described as the convergence to the equilibrium path in equilibrium models. Briefly, the predicted pattern begins typically with an idiosyncratic shock to incumbent firms, or with an idiosyncratic initial endowment of entrants, as the first driver. The shock is related to firm-specific unobserved factors, such as technological and organizational traits, capabilities, strategic and managerial practices, and is reflected as heterogeneous efficiency across the firms. The more efficient firms grow and gain market shares at the expense of less efficient units, either directly via lower prices, or indirectly via increasing profits which, in combination with sounder financial conditions, provide the more productive firms with the access to the resources needed to invest and pursue further growth.

In the light of these dynamics, we need to include three structural dimensions of the firm in our analyses: productivity, profitability, and financial conditions. We proxy the efficiency of firms with a standard labour productivity index computed as the ratio between value added and the number of employees. In the case of profitability, we consider the index of Return on Sales (ROS), defined as operating profits over total sales. Financial leverage is computed as the ratio between stockholders' equity and total liabilities. Finally, we include an additional set of control variables. We consider the age of the firms (computed by exploiting the available data on their year of foundation); sales as a proxy of size; export intensity (computed as the ratio between the value of exports and total sales); and, a proxy of market concentration (calculated as the weighted sum of the company's market-shares in the markets in which it sells its products).¹⁶ Definitions, labels, and basic descriptive statistics of the variables used in this paper are included in the Appendix.

3.3 Descriptive analysis

Conforming with previous studies, the statistical distributions of growth rates of our sample display the usual fat-tailed shape. Maximum likelihood estimates of the shape parameter b of a power exponential distribution indicate that growth rates distributions are always very close to a Laplace (Bottazzi and Secchi, 2006). The estimates of the shape parameter b of the power exponential distribution ranges from 0.92 to 1.12 depending on the year-sector considered (in the case of a Laplace distribution the b parameter equals 1). When we bring together all the observations the estimate of b is equal to 0.98. The fat-tails property holds for year and sector disaggregation, pointing to a relatively high frequency of (positive and negative) extreme growth events affecting the firms in our sample, regardless of the periods and the technological intensity of the sectors of their activity.

Table 2 shows the distribution of growth spell lengths and the maximum spell length experienced by each firm. First, we see that a fairly high proportion of firms in our sample (about 50%) are “one-shot” growers: they grow in one period and then stop. Second, the total number of spells (5,974) is much larger than the total number of firms (2,601), indicating that

¹⁶Value added, sales and export were deflated using industry-specific deflators. Specifically, information provided in current prices in the ESEE database were converted into constant prices by using (2-digit) sectoral GDP deflators (source: INE-Spanish National Statistics Institute) centred on the year 2010.

Table 2: Distribution of employment growth spell lengths and maximum spell lengths

Length	All spells		Max spells	
	Freq	%	Freq	%
1	3,824	64.01	1,244	45.50
2	1,272	21.29	738	26.99
3	482	8.07	377	13.79
4	192	3.21	177	6.47
5	99	1.66	95	3.47
6	49	0.82	47	1.72
7	26	0.44	26	0.95
8	14	0.23	14	0.51
9	7	0.12	7	0.26
10	2	0.03	2	0.07
11	2	0.03	2	0.07
12	3	0.05	3	0.11
13	0	0.00	0	0.00
14	2	0.03	2	0.07
Total	5,974	100.00	2,734	100.00

Notes: 843 firms in our sample shrink for all the years in which they are observed.

most firms experience more than one (typically short) spell during their history. Third, it is worth noting that, although we track firms over a period of 21 years, the maximum length of the spells is 14 years, and only about 7% of the firms in our sample sustain their growth over more than five consecutive years. These findings are consistent with most empirical studies that highlight the erratic nature of firms’ growth profiles, and reinforce the idea that persistent employment growth seldom occurs (Hölzl, 2014; Coad et al., 2014; Daunfeldt and Halvarsson, 2015; Bianchini et al., 2017).

For the purposes of this descriptive section, we identify three categories of firms according to the degree of persistence of their innovative activities, based on arbitrary thresholds imposed on the indicator *Pers Inno*: (i) non-innovators ($Pers\ Inno = 0$), i.e., those firms that never introduce new products or new processes; (ii) innovators with low degree of innovation persistence ($0 < Pers\ Inno \leq 0.5$); and (iii) innovators with high degree of innovation persistence ($Pers\ Inno > 0.5$). This categorization of the firm’s “innovation status” is carried out separately for the indicators of persistence in product and process innovation. This means that some firms appear as non-innovators with respect to one variable but as persistent innovators with respect to the other.

The frequencies of the “innovation status” are shown at the bottom of Table 3. Unsurprisingly, we find that non-innovators represent the largest subsample – especially when innovation is proxied by product innovation, followed by the subsample of firms characterized by a low degree of innovation persistence. More than half of the firms in our sample never introduce new products and roughly a third never introduce new processes. The share of persistent innovators is rather low in general, and particularly for firms that develop product

innovations (about 13%).

In Table 3, we also report some basic descriptive statistics for the variables used in this study, broken down by “innovation status” (as defined above). We find substantial differences across groups of firms, with highly persistent innovators being markedly dissimilar from the firms in other categories. The former are found to be older, larger, more productive, more export-oriented, and operating in more concentrated markets. Greater efficiency and greater orientation to foreign markets might point to the overall superior performance. However, we do not observe any differences in terms of profitability and financial leverage. Our finding of equal profitability across categories contrasts with studies that support a positive link between persistence in innovation and profits (Cefis and Ciccarelli, 2005), whilst our evidence that persistent innovators tend to operate in more concentrated markets is in line with the seminal Schumpeterian hypothesis, according to which companies in these markets have more to lose by not innovating than potential new entrants do (Cohen, 2010). Furthermore, we find that non-innovators are younger and smaller, followed in these respects by innovators with low and high degree of innovation persistence, respectively. A plausible explanation might be that large incumbents not only benefit from greater economies of scale and scope but also face higher barriers to exit and sunk costs (Mañez et al., 2009). This, in all likelihood, produces some path-dependence in their innovation process.

When we focus on our main variables, we initially observe a similarity in terms of growth performance (mean values) across all categories and for all types of innovation outcomes. This is somewhat at odds with the framework proposed in Section 2, according to which we should expect persistent product innovators to be characterised by higher employment growth. Nevertheless a closer look at the standard deviations and the min/max values of persistent innovators’ employment growth rates (not reported here) suggests that these firms display the lowest volatility and experience the largest jumps.

Finally, to provide an initial assessment of the relationship between persistence of innovation and persistence of growth, we estimate Kaplan-Meier survival functions for the sample of persistent innovators and for the other two categories. Survival curves are defined as the probability of surviving over a given length of time, with time being considered in many small intervals. Thus, for each time interval, the probability of survival is calculated as the number of firms that survive (i.e., the growth spell continues in the following year) divided by the number of firms at risk of failure (i.e., the growth spell ends). Firms that do not survive are not counted as being at risk in the subsequent interval. Total probability of survival until a given time interval is given by multiplying all the probabilities of survival in all the time intervals preceding that time. Figure 2 shows that the survival curves of persistent innovators clearly dominate those of occasional innovators and non-innovators, without any marked differences between product and process innovators. The statistical significance of these differences are confirmed by the results of a Gehan-Breslow-Wilcoxon test for equality of survival functions.

Table 3: Descriptive statistics, by “innovation status”

	Product			Process		
	Non-Inn.	Low Pers.	High Pers.	Non-Inn.	Low Pers.	High Pers.
Growth Empl	-0.03 (0.23)	-0.02 (0.20)	-0.01 (0.18)	-0.04 (0.26)	-0.02 (0.20)	-0.01 (0.16)
Ln(Age)	2.95 (0.71)	3.18 (0.67)	3.26 (0.74)	2.90 (0.71)	3.11 (0.67)	3.19 (0.75)
Ln(Sales)	7.79 (1.75)	8.64 (1.84)	9.61 (1.89)	7.40 (1.64)	8.22 (1.74)	9.46 (1.88)
ln(Labor Productivity)	3.29 (0.95)	3.55 (0.94)	3.70 (0.89)	3.13 (0.97)	3.49 (0.93)	3.66 (0.89)
ROS	0.08 (0.15)	0.09 (0.14)	0.09 (0.12)	0.07 (0.16)	0.08 (0.14)	0.10 (0.12)
Export intensity	0.11 (0.21)	0.20 (0.27)	0.27 (0.27)	0.10 (0.20)	0.15 (0.25)	0.25 (0.28)
Market share	0.08 (0.17)	0.12 (0.19)	0.15 (0.19)	0.08 (0.17)	0.09 (0.17)	0.14 (0.19)
Leverage	0.44 (0.24)	0.44 (0.23)	0.44 (0.22)	0.43 (0.25)	0.45 (0.24)	0.44 (0.22)
Frequency	12,915	7,914	3,295	6,898	10,777	6,449
%	53.42	32.89	13.69	28.51	44.73	26.76

Notes: Mean and SD (in brackets). Figures computed pooling over the working sample - 24,086 observations.

4 Econometric modelling

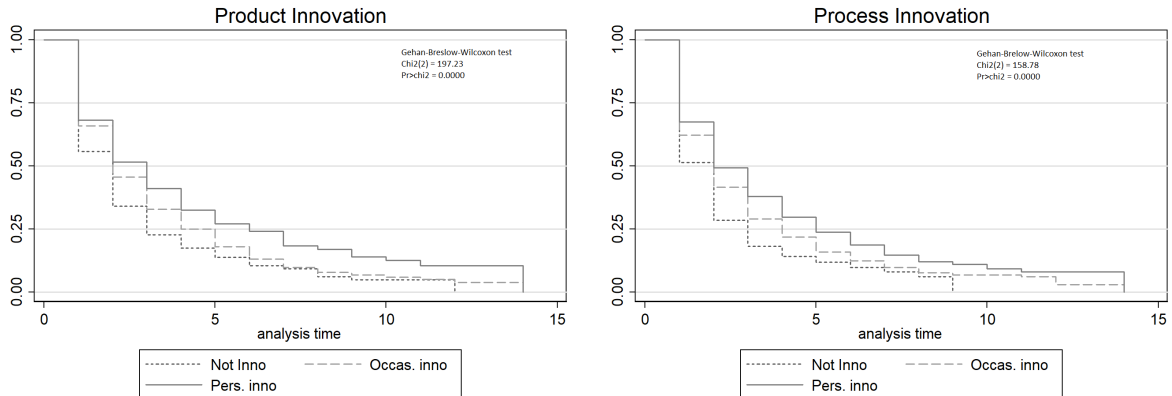
Our empirical strategy consists of two steps. First, we investigate the effect of persistence in product and process innovations on a firm’s employment growth (*Growth Empl*, as defined in equation 1), conditional on a set of controls. The basic model is the standard econometric approach adopted by most existing studies linking innovation to employment growth, but considers indicators of persistence of innovation instead of common innovation variables (either dichotomous or defined as a share of innovative sales). Hence, the first set of estimates tells us whether and (if so) the extent to which persistent innovators experience, on average, higher growth rates than other firms. Second, we link the indicators of persistence in innovation to the growth spell (measuring the degree of persistence in employment growth as defined in Section 3.1), evaluating whether persistent innovators exhibit, on average, longer periods of positive growth.

More formally, we start with the following panel equation:

$$Growth\ Empl_{i,t} = \alpha_0 + \alpha_1 Pers\ Prod_{i,t-1} + \alpha_2 Pers\ Proc_{i,t-1} + \mathbf{Z}'_{i,t-1}\beta + \delta_t + \gamma_s + u_i + \epsilon_{i,t} \quad (4)$$

where *Pers Prod* and *Pers Proc* stands for the two indicators of persistent innovation (product *vis-à-vis* process), \mathbf{Z} is a set of firm-level control variables as discussed in Section 3.2, δ_t is a vector of time fixed effects, γ_s a vector of two-digit sector fixed effects, u_i is a firm fixed-effect, and $\epsilon_{i,t}$ a standard error term. We are primarily interested in verifying the sign

Figure 2: Kaplan-Meier survival function of firm growth by type of innovation and “innovation status”



and the significance of the coefficients α_1 and α_2 . Positive and significant estimates would point to positive effects of innovation persistence on employment growth.

All variables enter with a one-year lag to account for the time that innovation plausibly needs to affect employment and also to control partially for the potential simultaneity between our response variable and the whole set of covariates.¹⁷ Equation 4 suffers from endogeneity due to the presence of the lagged dependent variable in the model, which is necessary to introduce dynamics into the growth equation. Endogeneity may also stem from the other covariates included in our specification due to the possible reverse causality between innovation and growth, as well as between the operating capability of the firm and its growth performance. As a consequence, the natural option for rectifying this bias is to implement the Generalized Method of Moments estimator proposed in Blundell and Bond (1998) (henceforth, GMM), which mitigates endogeneity via a system of equations in first differences and in levels, exploiting lags of the regressors as internal instruments. While GMM techniques are well-suited to cope with endogeneity, they involve some degree of arbitrariness in the specification choices. First, all the explanatory variables (innovation performance and operating capabilities) have been prudently considered as being endogenous to firm growth and have, thus, been instrumented. Second, we always consider age, year and sectoral dummies to be exogenous variables, whilst different lags of the other covariates are used as instruments, based on the standard Arellano-Bond tests for serial correlation and on the Sargan and Hansen tests for overidentifying restrictions. Third, the sets of instruments are always collapsed to avoid instrument proliferation that can overfit endogenous variables and in turn fail to expunge their endogenous components. Last but not least, we apply the finite-sample correction for the asymptotic variance of the two-step GMM estimator to obtain robust standard errors (Windmeijer, 2005).

¹⁷By way of a robustness check, we estimated the same models when including a longer lag structure (up to a third-order lag), thus increasing the distance between innovation and growth. The baseline models presented throughout this article were chosen by sequential rejection of the statistical significance of more distant lags.

We depart from this econometric setting and adopt duration model techniques in order to investigate further the relationship between the persistence of innovation and the persistence of growth. Our prime concern is verifying whether the systematic achievement of innovation outcomes is connected to longer periods of sustained growth. The empirical setting we choose to model the degree of duration dependence in the growth path is based on the setting employed in survival methods: we take the spell of time in which a firm grows as our unit of analysis, and model the probability that the spell will end at any given time. Also in this context we only record data annually, even if growth transitions occurred during the year. Thus, we resort to the discrete time proportional hazard model (discrete hazard represented by a complementary log logistic), already presented and discussed in Section 3.1. Formally, we estimate the following equation:

$$\lambda_{i,t} = 1 - \exp\{-\exp(\alpha_1 Pers Prod_{i,t-1} + \alpha_2 Pers Proc_{i,t-1} + \mathbf{Z}'_{i,t-1}\beta + \delta_t + \gamma_s + \lambda_{0,t}) + \theta_i\} \quad (5)$$

where $\lambda_{i,t}$ is the hazard function of the growth spell, $\lambda_{0,t}$ is the baseline hazard at time t (an arbitrary non-negative function of t), $\mathbf{Z}_{i,t-1}$ is the vector of covariates defined for firm i , β is a vector of parameters, δ_t is a vector of time fixed effects, γ_s a vector of two-digit sector fixed effects, and θ_i represents the “frailty” of the model.¹⁸ The coefficients α_1 and α_2 capture the relationship between the degree of persistence in product and process innovations and the risk of spell ending.

To estimate the model of equation 5 the unit of analysis must be the “growth spell”, therefore the dataset must be re-organised so that, for each firm, there are as many data rows as there are time intervals at risk of the event occurring. In practical terms our dependent variable is a binary indicator taking value zero for the survival period (positive growth rate), and one when the growth spell ends (the failure). Some “growth spells” could come into operation before the first year used in our analysis and/or in the last year of observation. This gives rise to left and right-censored observations, respectively. As discussed in Section 3.1, we excluded all the left-censored observations from the analysis. Robust standard errors in this context are obtained via bootstrap.¹⁹

¹⁸In all the specifications presented in this article we use the natural logarithm of time ($\ln(t)$) as the baseline hazard function to account for the risk of the spell ending exclusively because of the passage of survival time. To check whether our findings were influenced by the choice of the baseline hazard, we re-estimated the model using a flexible high-order polynomial in survival time. We tested both quadratic and cubic polynomial specifications and the results were in line with those presented throughout this paper. As for the “frailty” of the model we assume a normal distribution, $N(0, \sigma^2)$.

¹⁹Note that in this case also a problem of endogeneity might arise since the “innovation status” co-evolves with the growth spell, and the former may be pre-determined by the latter. To overcome this potential bias we experimented the approach proposed in Geroski et al. (1997), thus, we defined the firm’s “innovation status” at the beginning of each growth spell on the basis of the indicators of innovation persistence and kept this status constant throughout the spell. Results are virtually identical to those presented along this article, implying that endogeneity bias is very marginal (if any). However, at least a priori, this approach is especially unjustified for long spells of firm growth since it is hard to assume that a firm’s “innovation status” remains constant in these cases.

Table 4: GMM estimation results

	(1)	(2)	(3)	(4)	(5)	(6)
Pers. Product t_{-1}	0.0643** (0.0263)	0.0570** (0.0262)			0.0584** (0.0269)	0.0519** (0.0262)
Pers. Process t_{-1}			0.0313 (0.0217)	0.0227 (0.0340)	0.0340 (0.0209)	0.0224 (0.0225)
Growth Empl t_{-1}	-0.0657*** (0.0182)	-0.1554 (0.1105)	-0.0807*** (0.0178)	-0.1873* (0.1137)	-0.0688*** (0.0181)	-0.1788* (0.1086)
ln(Age) t	-0.0132** (0.0058)	-0.0262* (0.0147)	-0.0451** (0.0181)	-0.0264* (0.0141)	-0.0144** (0.0059)	-0.0232** (0.0110)
ln(Sales) t_{-1}	-0.0012 (0.0054)	0.0176 (0.0146)	0.0308 (0.0193)	0.0134 (0.0132)	-0.0015 (0.0054)	0.0082 (0.0111)
ln(Labor Productivity) t_{-1}		-0.0313 (0.0355)		0.0044 (0.0296)		-0.0002 (0.0244)
ROS t_{-1}		0.4928*** (0.1654)		0.3619** (0.1540)		0.3862*** (0.1180)
Export Intensity t_{-1}		-0.0315 (0.0477)		-0.0279 (0.0450)		-0.0345 (0.0439)
Market Share t_{-1}		0.0609 (0.0756)		0.0168 (0.0752)		0.0448 (0.0743)
Leverage t_{-1}		0.0013 (0.0484)		-0.0116 (0.0466)		-0.0136 (0.0475)
Constant	0.0009 (0.0282)	0.0310 (0.1309)	-0.1816* (0.0998)	-0.0989 (0.1116)	0.0123 (0.0270)	-0.0438 (0.0601)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	26,687	24,086	26,687	24,086	26,687	24,086
AR(1)	0.0000	0.0001	0.0000	0.0007	0.0000	0.0002
AR(2)	0.1080	0.2422	0.0924	0.1397	0.0736	0.1462
# Instruments	54	132	54	132	72	146
Sargan	0.0883	0.4807	0.1011	0.2195	0.0999	0.1194
Hansen	0.1110	0.2142	0.1390	0.3731	0.1030	0.1787

Notes: This table reports coefficients of the two-step GMM-SYS estimations of Equation 4. The dependent variable is the growth rate of employment as defined in Equation 1. All other explanatory variables are defined in Section 3. AR(1) and AR(2) are the p -values for the Arellano-Bond tests for the first and second order autocorrelation. Sargan and Hansen are the p -values for the tests of overidentifying restrictions. Windmeijer standard errors in parentheses: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

5 Results

The first set of results regarding the impact of innovation persistence on employment growth is reported in Table 4. The first four columns show the effect of product (Model 1 and 2) and process (Model 3 and 4) innovation when taken alone, whilst in the last two columns (Model 5 and 6) we include these two variables jointly in order to isolate their net effect. The regressions presented here include the list of control variables defined in 3.2, industry (2-digits) and time dummies. Tests on serial correlation AR(1) and AR(2), together with Sargan and Hansen tests for overidentifying restrictions, indicate that the set of internal instruments chosen to cope with endogeneity is appropriate in all specifications.

The most evident result refers to the positive and significant effect of persistence in product innovation on employment growth. The magnitude of the coefficient is stable to the different specifications, although it decreases slightly in the most complete one (Model 6).

This evidence corroborates the theoretical argument forwarded in Section 2, to the effect that a high degree of persistence in product innovation is expected to amplify the positive effect that innovation has on the growth of employment. Besides the positive forces identified in the classical innovation-employment framework, there appear to be other dynamics related to the presence of persistence in product innovation. Recent innovations, for instance, are often made in a monopolistic situation and furnish higher rents than their earlier innovations, thus generating more growth opportunities that firms can eventually exploit. The consumption of new products is likely to be boosted when firms signal their ability to consistently move ahead in technological terms. Furthermore, firms that innovate on a regular basis constitute the core of ‘real’ innovators, whereas an erratic pattern is a peculiarity of imitators, who typically do not achieve significant rewards from their innovations (at least not as high as those achieved by ‘real’ innovators). Moreover, the continuous stream of higher profits that characterize persistent innovators is a further element that could in principle fuel higher growth. Yet, due to the nature of our data, we are not in a position to test which of these channels actually plays the strongest role.

On the other hand, we find no significant effect of persistence in process innovation. This null effect is particularly interesting and lends, at least partially, support to our conjectures. Indeed, we see that the expected short-term negative effect of process innovation on firms’ employment growth disappears once a certain degree of persistence characterizes this activity. We argued that the reiterated introduction of new production processes may generate substantial cost reductions and extra profits, stimulating in turn new investments and new hirings. If anything, we see here that persistence in process innovation is not disruptive for employment.

The estimates on the control variables are by and large in line with theoretical expectations (see the discussion in Section 3.2). The autoregressive term is negative and significant (especially when we control only for the demographic characteristic of the firm), supporting the notion that growth, on average, follows a quite erratic pattern (Geroski, 2002). Our results for firm age and size are in line with recent evidence showing that young age, rather than small size, is the main contributor to employment and job creation (Haltiwanger et al., 2013). The positive and significant effect of profitability on growth could capture part of the “virtuous cycle” of the innovation process advocated in previous studies (Bogliacino and Pianta, 2012), so that a sustained interlink between high profits and innovation success should allow firms to gain market shares and create new growth opportunities. We do not see any significant association between productivity and growth. This result is somewhat at odds with theoretical models of firm-industry dynamics that consider efficiency as a central channel to achieve higher growth, but is consistent with some empirical studies questioning the mechanisms underpinning market selection (i.e., Bottazzi et al., 2010; Dosi et al., 2015).²⁰

²⁰It is fair to note that labor productivity becomes significant (p -value < 0.05) when we exclude the profitability index (ROS) from the regressors. Since the correlation coefficient between these two measures of operating capabilities is equal to 0.33, we are confident of the low risk of multicollinearity in our model and the lack of bias that this could entail. From our estimates, therefore, it seems that the productivity effect is absorbed by the “profits-feed-growth” effect.

Table 5: Survival model estimation results

	(1)	(2)	(3)	(4)	(5)	(6)
Pers. Product t_{-1}	-0.1732*** (0.0654)	-0.1692** (0.0683)			-0.1452** (0.0676)	-0.1628** (0.0712)
Pers. Process t_{-1}			-0.1144** (0.0529)	-0.0552 (0.0562)	-0.0823 (0.0548)	-0.0186 (0.0586)
ln(Age) t	0.1660*** (0.0204)	0.1532*** (0.0226)	0.1635*** (0.0205)	0.1517*** (0.0226)	0.1642*** (0.0204)	0.1528*** (0.0226)
ln(Sales) t_{-1}	-0.0817*** (0.0089)	-0.0680*** (0.0140)	-0.0816*** (0.0092)	-0.0713*** (0.0143)	-0.0783*** (0.0092)	-0.0671*** (0.0144)
ln(Labor Productivity) t_{-1}		-0.0023 (0.0274)		-0.0008 (0.0275)		-0.0027 (0.0275)
ROS t_{-1}		-1.0195*** (0.1438)		-1.0116*** (0.1439)		-1.0173*** (0.1440)
Export Intensity t_{-1}		-0.0145 (0.0658)		-0.0160 (0.0657)		-0.0137 (0.0659)
Market Share t_{-1}		-0.1789** (0.0872)		-0.1822** (0.0872)		-0.1781** (0.0872)
Leverage t_{-1}		0.2009*** (0.0682)		0.2020*** (0.0683)		0.2003*** (0.0682)
ln(t)	-0.1315 (0.1384)	-0.1121 (0.1385)	-0.1310 (0.1386)	-0.1133 (0.1387)	-0.1303 (0.1384)	-0.1118 (0.1385)
Constant	0.2299** (0.1066)	0.1532 (0.1305)	0.2466** (0.1065)	0.1789 (0.1302)	0.2179** (0.1067)	0.1517 (0.1305)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	10,335	9,354	10,335	9,354	10,335	9,354
Log Likelihood	-6,821.76	-6,129.52	-6,822.97	-6,132.15	-6,820.56	-6,129.46
σ	0.1060***	0.1270***	0.1053***	0.1264***	0.1029***	0.1263***
ρ	0.0068***	0.0097***	0.0067***	0.0096***	0.0064***	0.0096***
LR test ($\rho = 0$)	0.5429***	1.0905***	0.5283***	1.0723***	0.4842***	1.0695***

Notes: This table reports coefficients of the proportional hazard model with random effects subsumed in the frailty term, see Equation 5. The dependent variable is the hazard rate of the growth spell ending and all other explanatory variables are defined in Section 3. Negative (positive) coefficients are interpreted as a decrease (increase) in the hazard rate. Bootstrapped standard errors in parentheses (100 replications): ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Finally, we find that market concentration and financial conditions do not affect the growth patterns of the companies in our sample.

Persistence in innovation also generates some interesting patterns of sustained job creation. For the sake of comprehension, the estimated coefficients reported in Table 5 represent the effect of the covariates on the hazard of ending a growth spell, our measure of persistence in job creation. Thus, negative (positive) coefficients are interpreted as a decrease (increase) in the hazard rate, or an increase (decrease) in the expected duration of the growth spell.

The first notable result is the negative and significant coefficient of persistence in product innovation. This evidence, which holds across all the specifications, corroborates the univariate analysis proposed in Section 3.3 and points to a positive association between innovation persistence and the length of the employment growth spell that follows. Product innovation yields higher competitive advantages and these advantages seem to be more durable if innovation is achieved systematically across a number of time-steps. We suggested that persistent product innovation increases the competitiveness of the firm (for example, via the

“brand awareness” effect or via other previously described mechanisms) and opens up new growth opportunities (for instance via the systematic creation of new economic branches). Our findings suggest that persistent innovators do actually benefit from these advantages and continuously exploit their new growth opportunities, thus sustaining the growth process across a number of years. This implies that persistent product innovators not only grow more, but that they are also the economic actors that contribute most significantly to sustained job creation.

The lack of significance in the case of persistence in process innovation (except in the case of Model 3) points again to the existence of potential compensation mechanisms put in motion by the continuous introduction of new production practices and that counterbalance the potential job displacement.

The results in Table 4 and 5 can be read from a different perspective. They show that a certain degree of persistence in product innovation is a necessary condition to achieve higher growth and to sustain this growth over time. It seems, therefore, that the forces of competition erode rather quickly the competitive advantages that firms build from their innovation successes. Markets seem to make an efficient selection of firms based on their technological traits (and to lesser extent on their productivity levels) and to re-allocate resources and market shares to these firms. In this respect, the concern of many economists and policy-makers that markets do not efficiently select “good” firms is not entirely supported by our data.

5.1 Robustness checks

In what follows, we test the robustness of our findings to the use of alternative measures of innovation persistence and firms’ innovative output – i.e., the number of patent applications filed both nationally and internationally. We also propose an investigation into the potential effects of firm size.

The first set of exercises consists of discrete versions of the main analyses discussed above, with the aim at disentangling more clearly what we might call a “persistence effect” *vis-à-vis* an “innovation effect”. To this end, we resort to the definition of innovation status introduced in Section 3.3 and consider three categories of firms, namely: (i) non-innovators; (ii) innovators with low persistence of innovation; and (iii) innovators with a high degree of persistence of innovation. We then model the link between this innovation status, employment growth, and persistence of employment growth. Since our criterion for defining the innovation status of firms leads to three mutually exclusive categories, we select non-innovative units as the benchmark group. Notice that the estimated coefficients for the other two categories (low and high persistence, respectively) capture in first instance the effect of being innovative. At the same time, the comparison between the magnitude and statistical significance of these coefficients allows us to examine the employment impact of different degrees of innovation persistence.

Table 6 shows the results. A joint reading of the estimates in columns 1–3 suggests that firms with a high degree of persistence in product innovation experience higher employment

growth than other firms. Also of interest is the fact that a low level of persistence in product innovation does not translate into any benefit for growth. With regard to process innovation, if anything, we observe a barely significant effect of a low degree of innovation persistence. Columns 4–6, on the link between innovation status and persistence of employment growth, points to similar findings. In summary, this first exercise consolidates the results already discussed and suggests that the effect of product innovation only materializes after a certain degree of persistence. Put another way, it seems that what counts for achieving superior growth performance is not the fact of being innovative or not, but the ability to innovate persistently over time.

The second set of exercises involves the use of patents to capture the innovation activity of firms in our sample. Although widely used in the economics of innovation literature, patents are a flawed and imprecise measure of innovative output. Many inventions are not patented, the value and cost of patents vary significantly across sectors and firms, and they are mostly related to the product rather than to process innovations. Despite these caveats, patent applications can still be informative as they capture, at least in part, the subset of innovative products and/or processes that a company deems valuable. This would be particularly true for patents filed abroad, on the ground that patenting abroad is significantly more costly than domestic patenting and that often implies delays of extending protection. The additional costs arise not only from the fees that have to be paid in the different jurisdictions, but also from informational and bureaucratic expenses that tend to grow proportionally with geographical distance. Firms might be willing to accept additional costs and delays of extending protection to other countries only if they consider it worthwhile.

We do not have the precise number of jurisdictions in which patent protection has been sought, but we know the number of patent applications filed at the national patent office and the number of applications filed abroad. Thus, following the procedure described in 3.1, we construct three new indicators of persistence in innovation by using the available information on the total number of patent applications filed by firm i in year t , and distinguishing between national and international patents. The use of these alternative measures of innovative output allows us to ascertain, at least to a certain extent, whether our main results hold also when controlling for a proxy of innovation quality.²¹ As in the main analysis, we study the effect of these three indicators on both the firm’s employment growth and on its persistence by re-estimating equations 2 and 4 through GMM and survival models.

The set of results regarding the impact of persistence in patenting activity on employment growth and its persistence is reported in Table 7. Columns 1 and 4 show the effect of innovation persistence when innovation is proxied by the total number of patents (*Pers. Patents Total*), while columns 2–5 and columns 3–6 report the estimations of the indicators related to national (*Pers. Patents National*) and international patents (*Pers. Patents Abroad*), respectively. The estimated coefficient of our focal variable points to an overall positive relationship between persistence in firms’ patenting activity and employment growth, albeit at

²¹We are grateful to an anonymous referee for pointing out this issue.

Table 6: Alternative measures of innovation persistence

	GMM			Survival Model		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Persistent Product Indicator</i> [†] :						
Low Pers. Product t_{-1}	0.0392 (0.0563)		0.0345 (0.0570)	-0.0894 (0.0623)		-0.0849 (0.0625)
High Pers. Product t_{-1}	0.0674*** (0.0231)		0.0614** (0.0252)	-0.1285*** (0.0461)		-0.1270*** (0.0466)
<i>Persistent Process Indicator</i> [‡] :						
Low Pers. Process t_{-1}		0.0976* (0.0534)	0.0886* (0.0534)		-0.0808 (0.0536)	-0.0727 (0.0538)
High Pers. Process t_{-1}		0.0250 (0.0206)	0.0126 (0.0249)		-0.0215 (0.0376)	-0.0016 (0.0380)
<i>Control variables</i> :						
Growth Empl t_{-1}	-0.1663* (0.0997)	-0.1751* (0.1049)	-0.1972* (0.1047)			
ln(Age) t	-0.0336*** (0.0128)	-0.0287** (0.0127)	-0.0267** (0.0132)	0.1530*** (0.0225)	0.1514*** (0.0226)	0.1522*** (0.0225)
ln(Sales) t_{-1}	0.0174 (0.0120)	0.0171 (0.0117)	0.0132 (0.0123)	-0.0671*** (0.0141)	-0.0749*** (0.0144)	-0.0694*** (0.0146)
ln(Labor Productivity) t_{-1}	-0.0072 (0.0281)	-0.0094 (0.0257)	-0.0051 (0.0284)	-0.0038 (0.0274)	0.0004 (0.0274)	-0.0032 (0.0275)
ROS t_{-1}	0.3161** (0.1457)	0.3109** (0.1440)	0.3363** (0.1540)	-1.0138*** (0.1437)	-1.0083*** (0.1440)	-1.0079*** (0.1439)
Export Intensity t_{-1}	-0.0234 (0.0449)	-0.0110 (0.0452)	-0.0265 (0.0453)	-0.0125 (0.0659)	-0.0151 (0.0656)	-0.0103 (0.0659)
Market Share t_{-1}	0.0688 (0.0738)	0.0710 (0.0729)	0.0577 (0.0758)	-0.1759** (0.0872)	-0.1830** (0.0872)	-0.1756** (0.0871)
Leverage t_{-1}	-0.0040 (0.0474)	-0.0101 (0.0477)	-0.0180 (0.0480)	0.1998*** (0.0681)	0.1994*** (0.0682)	0.1964*** (0.0681)
Constant	-0.0583 (0.1090)	-0.0621 (0.1005)	-0.0517 (0.1090)	0.1562 (0.1312)	0.2079 (0.1314)	0.1821 (0.1323)
ln(t)				-0.1131 (0.1385)	-0.1151 (0.1387)	-0.1145 (0.1385)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24,086	24,086	24,086	9,354	9,354	9,354
AR(1)	0.0001	0.0002	0.0002			
AR(2)	0.1437	0.1320	0.0831			
# Instruments	156	156	178			
Sargan	0.5572	0.4839	0.6184			
Hansen	0.4663	0.3912	0.6046			
Log Likelihood				-6,127.91	-6,131.32	-6,126.90
σ				0.1257***	0.1232***	0.1218***
ρ				0.0095***	0.0091***	0.0089***
LR test ($\rho = 0$)				1.0488***	0.9678***	0.9231***

Notes: This table reports coefficients of the two-step GMM-SYS estimations of Equation 4 (columns 1-3) and the proportional hazard model with random effects subsumed in the frailty term, as in Equation 5 (columns 4-6). The dependent variable in columns 1-3 is the growth rate of employment as defined in Equation 1. The dependent variable in columns 4-6 is the hazard rate of the growth spell ending. Negative (positive) coefficients are interpreted as a decrease (increase) in the hazard rate. All other explanatory variables are defined in Section 3. Windmeijer and bootstrapped standard errors in parentheses (100 replications): ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

[†]Excluded category: “No Product Innovation”.

[‡]Excluded category: “No Process Innovation”.

a low significance level. Interestingly, we see that this overall effect is driven exclusively by the subset of patent applications filed abroad, whilst no role is played by domestic patents. We also observe a positive association between innovation persistence and the length of the employment growth spell that follows. Here, however, all indicators are statistically significant and similar in magnitude. Taken together, the results of Table 7 confirm the robustness of our main findings and allow us to add a further insight: high and sustained employment growth rates are achieved in particular by those firms that persistently produce inventions that are supposedly more valuable (at least as perceived by firms).

Finally, we propose a third set of results aimed at analysing in more detail the potential interplay between firm size and persistence of innovation. Large companies are generally better placed to innovate and to do so persistently compared to their smaller counterparts. In our context, firm size may represent a potentially relevant confounding factor, as the results discussed so far could be driven by a mere size effect rather than by a persistent innovation effect. To exclude this possibility, we re-estimate equations 4 and 5 separately for SMEs (fewer than 250 employees) and large companies.

Estimates are presented in Table 8 and provide interesting insights. We see that large companies do not seem to be taking any particular advantage of the protracted introduction of new or improved products. Persistently innovating SMEs, on the contrary, are more likely to grow faster and experience sustained patterns of job creation. This new evidence, therefore, excludes the possibility of potential confounding effects of firm size, and it offers new guidance on the relevance of innovation activity in promoting the growth pattern of (potentially) more “fragile” firms, such as is the case of SMEs.

6 Concluding remarks

In recent decades, a large body of empirical research has sought to link innovation and employment. According to economic theory, the indeterminate nature of the net effect of innovation on employment is due to the opposing forces that originate when heterogeneous companies launch new products onto the market and/or achieve new production processes. Whilst the benefits associated with innovations of these types are numerous and indisputable, theoretical studies propose also a set of indirect mechanisms that, in principle, might neutralize these benefits. The existence of negative forces might in fact explain the inconclusiveness of empirical findings in supporting the claim that innovation actually affects employment.

Another strand of the economic and management literature has in parallel examined whether innovation displays persistence. The majority of such studies have shown that most innovation activities present a path-dependence property, so that a firm that innovates successfully in a given period is likely to be successful in the next. This finding can be accounted for by various arguments, ranging from the increasing returns hypothesis to the existence of sunk costs in R&D activities. And yet some firms are unable to sustain their superior innovative performance over time. As a consequence modern economies are populated by very

Table 7: Alternative measures of innovation

	GMM			Survival Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Pers. Patents Total t_{-1}	0.0855* (0.0498)			-0.2683** (0.1203)		
Pers. Patents National t_{-1}		0.0397 (0.0503)			-0.3327** (0.1367)	
Pers. Patents Abroad t_{-1}			0.0481** (0.0234)			-0.3085** (0.1511)
Growth Empl t_{-1}	-0.1401 (0.1125)	-0.2085* (0.1232)	-0.1922* (0.1158)			
ln(Age) t	-0.0236** (0.0100)	-0.0261** (0.0109)	-0.0239** (0.0105)	0.1531*** (0.0226)	0.1534*** (0.0226)	0.1539*** (0.0226)
ln(Sales) t_{-1}	0.0142 (0.0109)	0.0122 (0.0129)	0.0107 (0.0120)	-0.0703*** (0.0139)	-0.0701*** (0.0139)	-0.0714*** (0.0138)
ln(Labor Productivity) t_{-1}	-0.0137 (0.0259)	-0.0040 (0.0306)	-0.0008 (0.0287)	-0.0037 (0.0275)	-0.0037 (0.0275)	-0.0027 (0.0275)
ROS t_{-1}	0.4303*** (0.1149)	0.5220*** (0.1338)	0.4784*** (0.1263)	-1.0103*** (0.1437)	-1.0122*** (0.1437)	-1.0105*** (0.1437)
Export Intensity t_{-1}	-0.0278 (0.0435)	-0.0013 (0.0449)	-0.0091 (0.0450)	-0.0125 (0.0659)	-0.0154 (0.0658)	-0.0133 (0.0658)
Market Share t_{-1}	0.0302 (0.0733)	0.0415 (0.0725)	0.0442 (0.0735)	-0.1815** (0.0872)	-0.1799** (0.0872)	-0.1863** (0.0872)
Leverage t_{-1}	-0.0054 (0.0460)	-0.0106 (0.0481)	-0.0169 (0.0467)	0.2006*** (0.0683)	0.1983*** (0.0683)	0.2029*** (0.0683)
Constant	-0.0260 (0.0622)	-0.0539 (0.0707)	-0.0574 (0.0681)	0.1687 (0.1306)	0.1684 (0.1306)	0.1713 (0.1307)
ln(t)				-0.1120 (0.1384)	-0.1121 (0.1383)	-0.1121 (0.1386)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24,086	24,086	24,086	9,354	9,354	9,354
AR(1)	0.0002	0.0010	0.0005			
AR(2)	0.2915	0.1249	0.1369			
# Instruments	136	136	137			
Sargan	0.5126	0.3942	0.3914			
Hansen	0.6581	0.4113	0.3490			
Log Likelihood				-6,130.02	-6,129.46	-6,130.66
σ				0.1286***	0.1280***	0.1301***
ρ				0.0100***	0.0099***	0.0102***
LR test ($\rho = 0$)				1.1679***	1.1453***	1.2131***

Notes: This table reports coefficients of the two-step GMM-SYS estimations of Equation 4 (columns 1-3) and the proportional hazard model with random effects subsumed in the frailty term, as in Equation 5 (columns 4-6). The dependent variable in columns 1-3 is the growth rate of employment as defined in Equation 1. The dependent variable in columns 4-6 is the hazard rate of the growth spell ending. Negative (positive) coefficients are interpreted as a decrease (increase) in the hazard rate. All other explanatory variables are defined in Section 3. Windmeijer and bootstrapped standard errors in parentheses (100 replications): ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

different types of innovators: some firms innovate occasionally; others do so systematically. Does this distinction matter for studies of employment dynamics? Our findings suggest that it does.

In this paper we have built a conceptual framework that links innovation, its persistence, and different trajectories of employment growth. This framework informs us that firms might show different responses in terms of their employment growth and its persistence depending on

Table 8: Size classes: SMEs vs Large firms

	GMM		Survival Model	
	(1) (SMEs)	(2) (Large)	(3) (SMEs)	(4) (Large)
Pers. Product t_{-1}	0.1018*** (0.0378)	0.0032 (0.0114)	-0.1806** (0.0915)	-0.1162 (0.1138)
Pers. Process t_{-1}	0.0397 (0.0295)	0.0078 (0.0119)	0.0350 (0.0726)	-0.1466 (0.0978)
Growth Empl t_{-1}	-0.2314** (0.1078)	-0.2657*** (0.0144)		
ln(Age) t	-0.0274** (0.0116)	-0.0197*** (0.0042)	0.1942*** (0.0257)	0.0083 (0.0473)
ln(Sales) t_{-1}	0.0152 (0.0163)	0.0119 (0.0101)	-0.1114*** (0.0206)	0.0641 (0.0494)
ln(Labor Productivity) t_{-1}	-0.0108 (0.0350)	0.0246** (0.0109)	0.0313 (0.0338)	-0.1139 (0.0717)
ROS t_{-1}	0.3906*** (0.1286)	0.0884** (0.0407)	-1.0165*** (0.1598)	-0.9593*** (0.3382)
Export Intensity t_{-1}	-0.0407 (0.0645)	0.0132 (0.0207)	-0.0465 (0.0814)	0.0110 (0.1139)
Market Share t_{-1}	0.0632 (0.0910)	0.0998*** (0.0336)	-0.2636** (0.1056)	0.0846 (0.1654)
Leverage t_{-1}	-0.0018 (0.0537)	0.0075 (0.0309)	0.3057*** (0.0728)	-0.3039* (0.1735)
Constant	-0.0435 (0.0761)	-0.2391*** (0.0906)	0.2636* (0.1553)	-0.2655 (0.4088)
ln(t)			-0.0630 (0.1446)	-0.1733 (0.1804)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Obs	19,713	4,373	7,333	2,021
AR(1)	0.0006	0.0000		
AR(2)	0.0594	0.0000		
Sargan	0.1720	0.0039		
Hansen	0.3723	0.5562		
Log Likelihood			-4,734.18	-1,358.39
σ			0.1404***	0.0015***
ρ			0.0118***	0.0000***
LR test ($\rho = 0$)			1.1828***	0.0002***

Notes: This table reports coefficients of the two-step GMM-SYS estimations of Equation 4 (columns 1 and 2) and of the proportional hazard model with random effects subsumed in the frailty term, as in Equation 5 (columns 3 and 4). The dependent variable in columns 1 and 2 is the growth rate of employment as defined in Equation 1. The dependent variable in columns 3 and 4 is the hazard rate of the growth spell ending. Negative (positive) coefficients are interpreted as a decrease (increase) in the hazard rate. All other explanatory variables are defined in Section 3. Windmeijer and bootstrapped standard errors in parentheses (100 replications): ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

the degree of persistence in their product and process innovations. The degree of persistence in innovation can, therefore, determine the net effect of innovation on different employment dynamics. We have derived a set of conjectures and have attempted to validate them using a dataset of Spanish companies observed for more than 20 years. Overall, our results point to the fact that persistence in product innovation matters for employment, whilst persistence

in process innovation does not play any relevant role. *Ceteris paribus*, persistent product innovation stands out as a significant driver both of employment growth and of persistence in employment growth.

Our study points the way towards a number of useful and interesting extensions of the research reported here. First, it is clearly important to validate these results in contexts other than Spain and, possibly, to test our framework on other sectors of the economy. Do the mechanisms at work differ greatly from one country to another? Do we observe any radical differences between the dynamics induced by persistence of innovation in manufacturing and in the service sectors? Second, our analysis focuses on just two types of innovation outcome, although the definition of firm-level innovation often encompasses a much broader set of activities. Firms, for instance, can be simultaneously active in other areas, such as organizational or marketing innovation. Does the presence of these activities influence our outcomes? If so, in what direction? Third, much work could be undertaken in defining (and testing) different definitions of persistence in innovation, possibly exploiting more fine-grained data on new products and processes. Finally, on the policy side, overall employment might be far more important than employment at the single firm. As such, particularly useful would be to extend our finding to different levels of aggregation. Answering all these questions would not only complement the findings reported in this paper but, more importantly, it would increase our overall understanding of the dynamics governing the evolution of firms and industries.

Appendix

Table A1: The variables for this study: labels and definitions

Label	Definition
Empl	Total number of employees
Growth Empl	Employment growth rates, log-difference
Growth Spell	Number of consecutive years with positive employment growth
Pers. Product	Indicator of persistence in product innovation, as defined in Section 3
Pers. Process	Indicator of persistence in process innovation, as defined in Section 3
ln(Age)	Natural logarithm of firm age, calculated as years elapsed since founding
ln(Sales)	Natural logarithm of the total sales
ln(Labor Productivity)	Natural logarithm of the ratio between value added and numbers of employees
ROS	Return on Sales, as the ratio between operating profits and total sales
Export Intensity	Value of exports normalized by total sales
Market Share	Weighted sum of the company's market-shares in the markets in which it sells its products
Leverage	Financial leverage, as the ratio between stockholders' equity and total liabilities

Table A2: Descriptive statistics of the variables

	Mean	SD	Median	Min	Max
Growth Empl	-0.02	0.21	0.00	-3.37	3.14
Growth Spell	1.73	1.28	1.00	1.00	14.00
Pers. Product	0.10	0.23	0.00	0.00	0.94
Pers. Process	0.19	0.29	0.00	0.00	0.95
ln(Age)	3.07	0.71	3.09	0.00	5.42
ln(Sales)	8.31	1.90	8.03	2.04	15.83
ln(Labor Productivity)	3.45	0.96	3.37	-5.54	6.21
ROS	0.08	0.14	0.08	-3.50	0.74
Export Intensity	0.16	0.25	0.02	0.00	1.00
Market Share	0.10	0.18	0.00	0.00	1.00
Leverage	0.44	0.24	0.43	0.00	1.00

Notes: Figures computed by pooling the working sample - 24,086 observations.

Table A3: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11
1. Growth Empl	1.00										
2. Growth Spell	-0.07*	1.00									
3. Pers. Product	0.02*	0.12*	1.00								
4. Pers. Process	0.05*	0.13*	0.36*	1.00							
5. ln(Age)	-0.05*	0.08*	0.13*	0.11*	1.00						
6. ln(Sales)	0.02*	0.22*	0.31*	0.38*	0.43*	1.00					
7. ln(Labor Productivity)	0.04*	0.06*	0.12*	0.15*	0.31*	0.49*	1.00				
8. ROS	0.09*	0.06*	0.02*	0.08*	-0.01	0.10*	0.33*	1.00			
9. Export Intensity	0.01	0.07*	0.18*	0.19*	0.21*	0.43*	0.20*	0.01	1.00		
10. Market Share	0.01	0.06*	0.13*	0.16*	0.11*	0.29*	0.11*	0.09*	0.09*	1.00	
11. Leverage	-0.01	0.01	0.02*	0.00	0.25*	0.05*	0.15*	0.11*	0.04*	0.09*	1.00

Notes: * indicates significance at the 1% level. Figures computed by pooling the working sample - 24,086 observations.

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