

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 on a conceptual framework that links innovation persistence, employment growth and the persistence of this growth in the long-run. Using dynamic panel GMM and survival analysis techniques, 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. 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, Innovation, Persistence in innovation, Path-dependence

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ACKNOWLEDGEMENT: We are grateful for discussions with and comments from Cristiano Antonelli, Timothy Folta, Fabio Landini, Consuelo Pazo, and Marco Vivarelli. We thank participants at the 2015 Governance of a Complex World Workshop (Nice, France), the 2015 XXX Jornadas de Economía Industrial (Alicante, Spain), the 2016 Annual Meeting of the French Economic Association (Nancy, France), the 2016 Schumpeter Society Conference (Montreal, Canada), the seminar at the Department of Economics and Statistics Cognetti de Martiis in October 2015 (Turin, Italy) and the seminar at the Karlsruhe Institute of Technology in April 2016 (Karlsruhe, Germany).

1. INTRODUCTION

1.1. **The issue.** In this paper, we use a representative sample of Spanish companies observed over the period 1991-2012 to investigate the micro-level effects of persistence in product and process innovations on two types of employment dynamics: growth and its long-run persistence. We show that the systematic realization of new products has two main effects. First, a high degree of persistence in innovation boosts the positive effect that innovation has on employment growth. Second, a high degree of persistence in innovation induces a more structured process of job creation, thus allowing firms to sustain higher growth rates over time. In contrast, we find no effect of persistence in process innovation on employment dynamics.

In recent years, particularly after the global financial crisis, job creation has gained momentum becoming a dominant theme in public discourses and a priority in most policy actions. In Europe, for example, the so-called ‘Employment Package’, part of the Europe 2020 strategy, has been designed to achieve one of the five headline targets, namely, raising the employment rate among 20 to 64 year olds to at least 75% by 2020. Similar policy priorities apply to the US, as recently discussed in Stangler (2010) and Mazzucato (2015). A set of policy measures targeting labour and skills supply as well as the functioning of the labour markets (i.e. targeting hiring subsidies to new hiring, reducing the tax on labour, modernising wage-setting system) are expected to offer private businesses a more fertile ground for their (sustained) growth.

Research and development (R&D) and innovation are key components in most policy recommendations addressing the issue of employment and job creation. A recent policy report, for instance, points out that “[i]nvestment in R&D and innovation, by fostering an increase or substantial improvements in the quality of innovative products and services, contributes to the strategy’s smart growth objective, creating jobs and addressing societal challenges” (Eurostat, 2015). Statements of this kind, of course, recall endogenous growth models in which the accumulation of R&D and human capital is considered the primary source of long-term economic growth. The links between innovation and employment at the firm-level are, however, far from straightforward.

The adverse effects of scientific advances and technological changes on employment are a long-standing issue in economic thought. Historically the adverse direct labour-saving impact of process innovation is supposed to be counterbalanced by other mechanisms, including the creation and commercialization of new products. Seen from this perspective, 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. Vivarelli (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”.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, Antonelli, 1997; Malerba, 2007; Dosi and Nelson, 2010). To the best of our knowledge, no single study has explicitly addressed the question as to whether firms that systematically achieve innovation outcomes can experience different dynamics of employment compared to firms that only innovate irregularly.

The lack of evidence on this question is somewhat surprising 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 additionality nature of technological knowledge is such that firms are likely to experience dynamic increasing returns in their innovation activities. Furthermore, firms may 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). Innovation activities are also 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 innovation 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 aimed at examining the degree of persistence in various innovation activities. Most studies target the output side of innovation, relying on such measures as patents (see, e.g. 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), and the development of process and/or product innovations (Antonelli et al., 2012). Whilst a certain degree of persistence in product and process innovation is conventionally supported in the data, 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).

Despite the substantial theoretical and empirical research effort, very 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 267 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

¹A 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 Pianta, 2005; Vivarelli, 2014; Calvino and Virgillito, 2016.

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. Similarly, Deschryvere (2014) uses a panel of Finnish firms to show that the relationship between sales growth and R&D growth is stronger for continuous innovators than for occasional innovators.

This somehow diffuse evidence suggests that more research into the effects of innovation persistence on industrial dynamics is needed. Apart from the afore mentioned contributions we are unaware of any previous studies that seek to link persistence in innovation to two different dimensions of employment dynamics: namely, growth and its long-run persistence. Our paper aims to fill this gap.²

The reminder of the paper is organized as follows. Below, we propose a conceptual framework that links persistence in innovation to different dynamics of employment. Section 2 describes the data and variables, while in Section 3 we present the empirical setting we employ to validate our conjectures. Estimation results are reported and discussed in Section 4. Section 5, finally, concludes.

1.2. Conceptual framework and contributions. The existing theory linking innovation to employment is the starting point for our discussion. It is well established that the net effects of product and process innovation on employment are theoretically unclear due to the opposing forces that operate (see, among others, Lachenmaier and Rottmann, 2011; Harrison et al., 2014; Vivarelli, 2014; Calvino and Virgillito, 2016).

Intuitively, firms introducing new products on the market stimulate consumption and create new demand, thus allowing additional jobs to emerge. Less intuitively, however, there might also be an indirect negative effect: 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 (so-called “cannibalization”). Similar arguments apply in the case of process innovation. Firms may change their production process to improve the productivity of inputs, including labour. Thus, the negative effect of process innovation occurs when a firm can produce the same level of output with fewer workers. Yet, in this case also, there are at least two possible indirect effects related to the increase in productivity. First, higher productivity in competitive markets implies a reduction

²One exception is Triguero et al. (2014) who aim to test the employment impact of persistence in product and process innovation. Nonetheless, the framework they propose does not address the question of persistence in innovation properly. They model the evolution of employment as a function of different lags of innovation variables, but no direct measure of persistence is conceptualized. In short they test the employment impact of innovation produced back in time; hence, though this is an interesting issue, the concept of persistence of innovation and its ultimate effects on firms’ performance are simply not there.

in prices, and lower prices should increase demand. Second, the rise in productivity reduces production costs and increases profits. And, if these profits are re-invested by the firm to increase its production capacity, the initial job displacement can be counterbalanced.

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. Thus, the first contribution of this paper is to give empirical validation for a framework that specifically relates persistence in innovation to employment growth.

But why should persistence in innovation matter? There are at least three 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). Second, the new demand generated is likely to be amplified by the so-called “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 (Aaker, 1996; Kapferer, 2012).³ 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 here persistence might play the opposite role. Organization studies have long documented that firms need time to internalize their routines, and to improve their production practices, gaining experience through a process of “learning-by-doing”. This implies that firms experiencing continuous changes in their production process might not be in a position to learn effectively “how to do things” (Dosi and Marengo, 2000; Zollo and Winter, 2002). What is important here is that a high degree of persistence in process innovation may, at some point, disrupts a firm’s efficiency

³For instance, Kapferer (2012) points out that historically most brands are born out of persistent product innovations which outperformed those of their competitors and “[l]ater, as the product name evolves into a brand, customers’ reasons for purchase may still be the brand’s superior performance image”.

and, eventually, its employment dynamics. Indeed, we have already seen that lower efficiency in a competitive market implies an increase in prices, and higher prices will hamper demand.

The situation in which a firm is simultaneously a persistent product and process innovator leads to greater complications. The presence of strong direct and indirect effects pulling in opposite directions is such that it is very difficult to predict a priori which force, if any, will dominate.

The framework we develop here – 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. Thus, our second contribution is to answer the following question: do firms that persistently innovate persistently generate more jobs?

Let us begin by placing this question in a broader context. 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 outperforming firms are simply “luckier” than their competitors (Barney, 1997; Coad et al., 2013). On the other hand, persistence in job creation is also attractive for policy-makers since such growth can be expected to help economies sustain employment and value its creation in the long-run, and to allow the early identification of “good” companies with high growth potential. The implicit message of most 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 (EU, 2013).

Many studies have focused their attention on the structure of the growth process, conventionally by examining the autocorrelation of growth rates over time (under different autoregressive lags).⁴ Overall, we lack robust evidence of persistence in firm growth, although recent contributions suggest no or negative autocorrelation of growth rates over time (Hölzl, 2014; Daunfeldt and Halvarsson, 2015), in particular for small and young firms (Coad, 2007). 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.”⁵ We also know very little about the determinants of persistent growth performance. Whilst original “steady state” models suggest a high degree of

⁴Even 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.

⁵Similarly, 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

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., 2013; Bianchini et al., 2016). The 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 employment.

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 move away from the “pessimistic view” of growth as a pure random walk (or at least close to a random walk) and 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 job creation over time.

The motivation for such a focus is readily explained. 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. In short, our framework is such that we can expect persistent innovators to be well placed to generate new jobs over a number of consecutive time-steps. In contrast, we have already seen that a high degree of persistence in process innovation can be detrimental for employment and so this negative effect should also apply to the context of persistence in growth performance. The second contribution of our study, therefore, is to provide empirical validation to this second set of conjectures.

2. 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 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.⁶ 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

(close to) a random walk, when seeking either the determinants of annual growth in any given year, or the regularities in long-term growth over a number of subsequent years.

⁶NACE 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.

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 of guaranteeing 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 (i) we discard all firms involved in M&A transactions⁷, and (ii) keep only those firms that are registered for at least four consecutive years, that is, all firms exhibiting at least three time-periods of change. The first decision is dictated by the nature of our dataset 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”). The second decision is an ad hoc judgement, but is consistent with the idea that we seek to observe the innovation pattern of each firm for at least three years (an arbitrary minimum to make the notion of persistence meaningful) and to map this pattern into at least one growth trajectory. The resulting sample is an unbalanced panel of 22,795 firm-year observations (2,631 firms) for which the variables used in our empirical exercises are non-missing.

2.1. 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:

$$(1) \quad \text{Growth } Empl_{it} = Empl_{it} - Empl_{i,t-1} \quad ,$$

where

$$(2) \quad Empl_{it} = \log(E_{it}) - \frac{1}{N} \sum_i \log(E_{it}) \quad ,$$

and E_{it} is the number of employees in firm i in year t , and the sum is computed over the N firms populating the same 2-digit sector. This implies that growth rates are normalized by their annual sectoral average and that they implicitly take into account macro shocks common to all firms, such as business cycles and sectoral demands. Normalized employment growth rates are used as the response variable in our first econometric exercise (i.e., the effect of persistence in innovation on employment growth).

Next, we construct a variable capturing the degree in persistence in growth performance, for use as the response variable in our second exercise (i.e., the effect of persistence in innovation on persistence in employment growth). As the data are recorded annually, this variable is represented by what we refer 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

⁷These firms were eliminated from the sample in the years following the merger or acquisition.

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.

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.⁸ Moreover, in line with recent evidence pointing to possible complementary effects of different innovation activities on firm growth (Goedhuys and Veugelers, 2012), we construct a binary variable to identify those firms that simultaneously undertake both product and process innovations.

We use these three binary variables to construct the respective indicators of the degree of persistence in the firms’ innovation outcomes. 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 look simply 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. By way of example, a firm that is observed for just 5 years and which innovates in each of those years would, at the end of the period, be considered just as persistent as a firm that is observed for 20 years but which innovates in only 5 out of the 20 years. To deal with this problem, we construct a simple weighted indicator of persistence in innovation that takes the following form:

$$(3) \quad Pers\ Inno_{it} = \left(\sum_{t=1}^T Inno_t \right) / T$$

where *Inno* may refer to product innovation, process innovation or a combination of the two, and $T \in [1, 21]$ records the number of years that firm *i* is observed from its first appearance

⁸We 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 when discussing the main results of this paper.

in the dataset to the period in which the indicator is calculated. Intuitively, our indicator ranges from 0 (firm i never innovates) to 1 (firm i always innovates), with values in between capturing various degrees of persistence in innovation outcomes.

FIGURE 1. Measuring persistence in innovation with a simple indicator: An example

Time	Firm A	Firm B	Firm C	Firm D	Firm E	Firm F
1	Inno = 0	Inno = 1	Inno = 1	Inno = 0	Inno = 1	Inno = 0
2	Inno = 0	Inno = 0	Inno = 1	Inno = 0	Inno = 1	Inno = 1
3	Inno = 0	Inno = 1	Inno = 1	Inno = 0	Inno = 0	Inno = 0
4	Inno = 0	Inno = 0	Inno = 1	Inno = 1	Inno = 1	Inno = 1
5	Inno = 0	Inno = 0	Inno = 1	Inno = 0	Inno = 0	Inno = 1
6	.	.	.	Inno = 0	Inno = 0	Inno = 1
7	.	.	.	Inno = 0	Inno = 1	Inno = 0
8	.	.	.	Inno = 1	Inno = 1	Inno = 1
9	.	.	.	Inno = 0	Inno = 0	Inno = 1
10	.	.	.	Inno = 0	Inno = 0	Inno = 1
Pers_Inno	0	0,4	1	0,2	0,5	0,7

An illustrative example may help to contextualize the indicator within the framework proposed here. Figure 1 represents the innovation patterns of a set of firms observed over different time windows and the value of our indicator of innovation persistence calculated at the end of the periods (5 and 10 years, respectively).⁹ Let us first focus on firms A, B, and C. According to the indicator firm A is clearly a non-innovator ($Pers\ Inno_A = 0$), firm B can be classified as an occasional innovator ($Pers\ Inno_B = 0.4$), and firm C is clearly a persistent innovator ($Pers\ Inno_C = 1$). The same logic applies in the case of a longer time window, as shown in the figure. A less extreme scenario, for instance, emerges by looking at the innovation patterns of firms D, E, and F, when the indicator never takes values equal to 0 or 1 but rather captures various degrees of persistence in innovation.

Our indicator, 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 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. Notwithstanding this, we believe that our original indicator is superior in several respects to these alternatives. First and foremost, it takes into full account two characteristics of technological knowledge, namely cumulability and non-exhaustibility (David, 1992; Antonelli, 1997). Both these features have implications 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.¹⁰

⁹In practice, we compute the indicator of persistence in innovation in each period.

¹⁰We nevertheless experimented with arbitrary thresholds of 3, 5, and 7 years. As such, we calculated the degree of persistence in innovation based only upon the innovation patterns presented in windows of 3, 5, and 7 years before a growth rate is recorded, instead of for the full period. The results are in line with those presented below and are available upon request.

Third, the idea of applying a discount factor on dichotomous innovation variables would generate an indicator of persistence that is no longer confined to the original range $[0,1]$, thus complicating the interpretation of the notion of persistence and, more generally, our findings. In sum, despite its obvious limitations, we are confident that our indicator is well designed to capture the innovative behaviour of firms over their full history.

2.2. Other variables. We consider an additional set of explanatory variables to account for other factors that might influence the propensity of firms to grow. 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 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. Next, the more efficient firms grow and gain market shares at the expenses 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, the database at our disposal allows us to include additional control variables that can be assumed to correlate with growth performance. 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).¹¹

Definitions, labels, and basic descriptive statistics of the variables used in this paper are included in the Appendix.

¹¹Value 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 1. Distribution of employment growth spell lengths and maximum spell lengths by firms

Length [years]	All spells		Max spells	
	Freq.	%	Freq.	%
1	3,535	54.72	694	27.73
2	1,689	26.15	777	31.04
3	682	10.56	520	20.78
4	281	4.35	245	9.79
5	161	2.49	156	6.23
6	62	0.96	61	2.44
7	21	0.33	21	0.84
8	15	0.23	15	0.60
9	9	0.14	9	0.36
10	3	0.05	3	0.12
11	1	0.02	1	0.04
13	1	0.02	1	0.04
Total	6,460	100.00	2,503	100.00

Notes: 128 firms in our sample shrink for all the years in which they are observed.

2.3. Univariate descriptive analysis. Conforming with previous studies, the statistical distributions of growth rates of our sample of Spanish companies 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 0.94 to 1.03 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 1 shows the distribution of growth spell lengths and the maximum spell length experienced by each firm. Some considerations are in order. First, as expected, a fairly high proportion of firms in our sample (about 27%) are “one-shot” growers: they grow in one period and then stop. Second, the total number of spells (6,460) is much larger than the total number of firms (2,503), indicating that 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 13 years, and only about 10% 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 (Geroski, 2002; Delmar et al., 2003).

For the purposes of this descriptive section, we identify three categories of firm 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) occasional innovators ($0 < Pers Inno \leq 5$),

TABLE 2. Distribution of the “innovation status”

	Product		Process		Product&Process	
	Freq.	%	Freq.	%	Freq.	%
Non-Innovators	12,005	52.67	6,208	27.23	14,728	64.61
Occasional Innovators	7,654	33.58	10,451	45.85	6,398	28.07
Persistent Innovators	3,136	13.76	6,136	26.92	1,669	7.32
Total	22,795	100.00	22,795	100.00	22,795	100.00

i.e., those firms that exhibit discontinuous and irregular patterns of innovation; and (iii) persistent innovators ($Pers\ Inno > 0.5$), as those firms that show a relatively high degree of persistence in their innovative behaviour. This categorization of what we call “innovation status” is carried out separately for the indicators of persistence in product, process, and 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 others.

The frequencies of “innovation status” are reported in Table 2. Unsurprisingly, we find that non-innovators represent the largest subsample – especially when innovation is proxied by product innovation, followed by occasional innovators. More than half the firms in our sample never introduce new products and roughly a third never introduce new processes. The share of persistent innovators is always low, but this share is lower for firms that develop product innovations (about 13%) and those that simultaneously develop both new product and process innovation (about 7%). The share of fully persistent innovators ($Pers\ Inno = 1$) is extremely low: 3.65% in the case of product innovation, 7.76% for process innovation, and 1.54% for product and process innovation. Previous studies highlight the existence of a relatively stable core of persistent innovators that typically account for the largest share of total innovations (Malerba et al., 1997; Cefis and Orsenigo, 2001).

In Table 3 we 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 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 of persistent innovators. 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 occasional and persistent innovators, 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 higher sunk costs (Mañez et al., 2009). This, in all likelihood, produces some path-dependence in their innovation process.

TABLE 3. Descriptive statistics, by “innovation status”

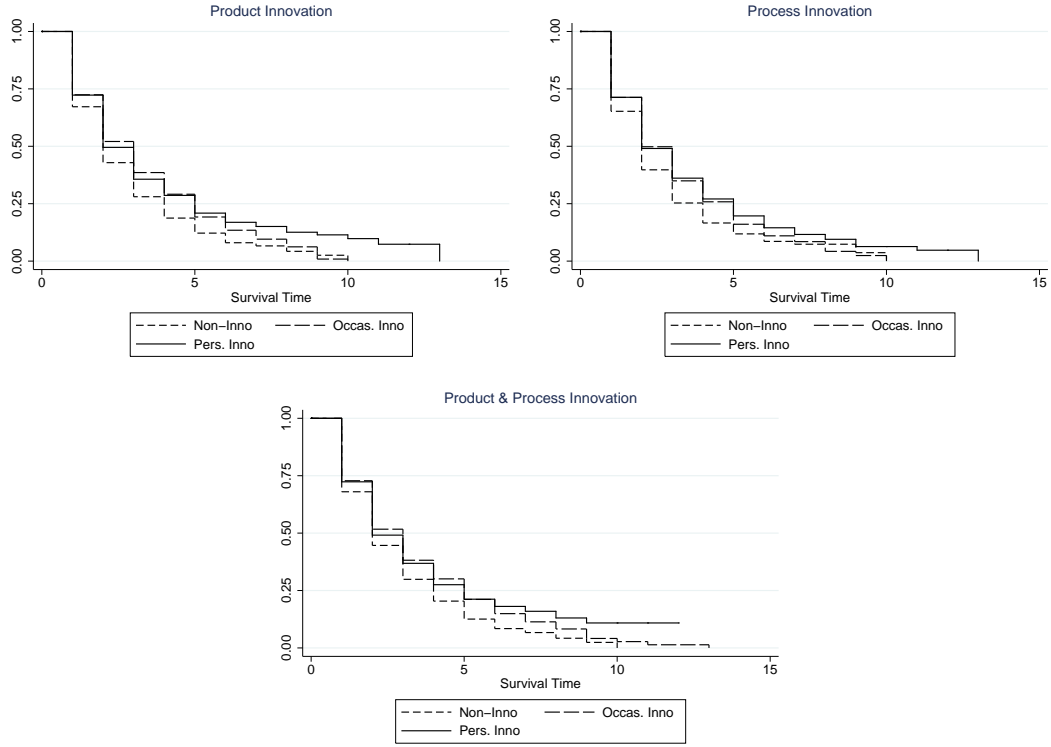
	Product			Process			Product&Process		
	Non-Inn.	Occas.	Pers.	Non-Inn.	Occas.	Pers.	Non-Inn.	Occas.	Pers.
Growth Empl	-0.01 (0.24)	0.00 (0.23)	0.00 (0.21)	-0.01 (0.27)	-0.01 (0.23)	0.01 (0.21)	-0.01 (0.25)	0.00 (0.22)	0.00 (0.19)
ln(Age)	2.97 (0.69)	3.20 (0.66)	3.27 (0.73)	2.93 (0.69)	3.12 (0.66)	3.20 (0.73)	3.01 (0.69)	3.21 (0.66)	3.33 (0.76)
ln(Sales)	7.80 (1.72)	8.64 (1.83)	9.59 (1.88)	7.40 (1.59)	8.22 (1.73)	9.46 (1.87)	7.85 (1.73)	8.96 (1.78)	10.15 (1.87)
ln(Labor prod.)	3.33 (0.95)	3.58 (0.93)	3.72 (0.89)	3.16 (0.98)	3.52 (0.92)	3.69 (0.88)	3.35 (0.95)	3.66 (0.92)	3.78 (0.87)
ROS	0.08 (0.14)	0.09 (0.13)	0.09 (0.12)	0.07 (0.15)	0.08 (0.14)	0.10 (0.12)	0.08 (0.14)	0.09 (0.13)	0.10 (0.12)
Export Intensity	0.11 (0.21)	0.20 (0.27)	0.27 (0.28)	0.10 (0.20)	0.15 (0.25)	0.25 (0.28)	0.12 (0.22)	0.23 (0.29)	0.30 (0.27)
Market share	0.08 (0.16)	0.11 (0.18)	0.15 (0.19)	0.08 (0.16)	0.09 (0.17)	0.14 (0.19)	0.08 (0.17)	0.12 (0.19)	0.17 (0.19)
Leverage	0.45 (0.24)	0.45 (0.23)	0.45 (0.22)	0.44 (0.25)	0.45 (0.24)	0.45 (0.22)	0.45 (0.24)	0.44 (0.23)	0.46 (0.22)
N	12,005	7,654	3,136	6,208	10,451	6,136	14,728	6,398	1,669

Notes: Mean and Sd (in brackets). Figures computed pooling over the working sample - 22,795 observations.

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 our framework proposed in Section 1.2, 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 suggests that these firms display the lowest volatility and experience the largest jumps (see Table A2 in the Appendix).

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 dominate those of occasional innovators and non-innovators, in particular after the fifth/sixth time interval. The difference is particularly marked when innovation is measured in terms of new products, indicating that persistent product innovators experience longer spells of employment growth than other firms. The same applies, albeit to a lesser extent, in the case of process innovation.

FIGURE 2. Kaplan-Meier survival function, by type of innovation and “innovation status”



3. ECONOMETRIC MODELLING

We need to depart from univariate analysis when empirically assessing the role that persistence in innovation plays on employment growth and on its long-run persistence, all other things being equal. Our empirical strategy consists of three steps. First, we separately investigate the effect of product and process innovations on a firm’s employment growth (*Growth Empl*, as defined in equation 1), conditional on a set of controls. This basic model is the same standard econometric setting adopted by most extant studies linking innovation to employment growth. Hence, the first set of estimates tells us whether and (if so) the extent to which different forms of innovation affect firm growth, and they are used as a benchmark. Second, we introduce the concept of path-dependence in innovative behaviour; thus, we relate the indicators of persistence in innovation (*Pers Inno*, as defined in equation 3) to a firm’s employment growth, and test whether persistent innovators experience, on average, higher growth rates than other firms. Third, we link the indicators of persistence in innovation to the growth spell (measuring the degree of persistence in employment growth), evaluating whether persistent innovators exhibit, on average, longer periods of positive growth.

More formally, we start with the following panel equations:

$$(4) \quad Growth\ Empl_{i,t} = \alpha_1 Inno_{i,t-1} + \mathbf{Z}'_{i,t-1}\beta + \theta_t + \gamma_s + u_i + \epsilon_{i,t} \quad ,$$

$$(5) \quad Growth\ Empl_{i,t} = \alpha_2 Pers\ Inno_{i,t-1} + \mathbf{Z}'_{i,t-1}\beta + \theta_t + \gamma_s + u_i + \epsilon_{i,t} \quad ,$$

where *Inno* and *Pers Inno* stand alternatively for one of the three indicators of innovation and persistent innovation, \mathbf{Z} is a set of firm-level control variables as discussed in Section 2.2, θ_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. An additional remark is required here. As discussed above, the two equations are specifically designed to deliver two different messages: coefficient α_1 represents the effect of innovation on employment growth, whereas coefficient α_2 represents the effect of persistence in innovation on employment growth. To validate our conjectures, we are primarily interested in verifying whether α_2 is larger in magnitude and statistically more significant than α_1 . If this was the case (and we show that it is in some instances), the simple interpretation is that persistence in innovation amplifies the positive effect that innovation has 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.¹² Equations 4 and 5 suffer, of course, 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, which we believe merit a few comments. 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).

Later, we depart from this standard 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 job creation. In this case also a problem of endogeneity might arise were we to consider the “innovation status” as coinciding precisely with the growth spell, given that the former may well be pre-determined

¹²By 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. This implies that innovation, when it positively affects growth, does so in the very short-run.

by the latter. A similar problem is highlighted in Geroski et al. (1997) when studying how the persistence in innovation of a sample of UK companies varies according to the intensity of patenting. Intuitively, the problem is that the direction of causality between the intensity of innovation and its path-dependence cannot readily be discerned. They overcome this potential bias simply by looking at the relationship between the number of innovations produced by a firm immediately prior to an innovation spell and the length of the spell that follows. We borrow this strategy and adapt it to our framework: we define the firm’s “innovation status” at the beginning of each growth spell on the basis of the indicators *Inno Pers*, and keep this status constant throughout the spell.

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. A discrete time proportional hazard model is adopted since, even if growth transitions occurred during the year, we only record data annually. The methodology involves estimating a discrete time representation of the underlying continuous time proportional hazard function, parametrized as follows:

$$(6) \quad \lambda_i(t) = \theta_i \lambda_0(t) \exp\{Z_i(t)' \beta\}$$

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), $Z_i(t)$ is the vector of covariates defined for firm i , and β is a vector of parameters. Finally, θ_i is a random variable that is assumed to be independent of $Z_i(t)$ 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.¹³ 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 .

Following the approach introduced by Prentice and Gloeckler (1978), it can be assumed that the discrete hazard is given by a complementary log logistic (cloglog function); hence, we can obtain the discrete time counterpart of the underlying continuous time proportional hazard of equation 6, that is:

$$(7) \quad \lambda_i(t) = 1 - \exp\{-\exp(\alpha Pers Inno_i + Z_i(t)' \beta + \lambda_0(t)) + \theta_i\}$$

To estimate the model of equation 7 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 will be a simple binary indicator taking value zero for the survival period (positive growth rate), and one when the growth spell ends (the failure). It might be the case that some

¹³To 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.

growth spells come into operation before the first year used in our analysis and/or in the last year of observation. This gives rise to the well-known problem of left or right censoring, respectively. To account for this, we include in our specifications two control variables for left and right-censored spells. As in the case of the GMM estimates, the model is estimated separately to study the effect of persistence in product and process innovations. Robust standard errors in this context are obtained via bootstrap.

4. RESULTS

4.1. The innovation-growth relationship. The first set of results regarding the impact of innovation on employment is reported in Table 4. The first column (Model 1) shows the effect of product innovation, the second column (Model 2) the effect of process innovation, and the third column (Model 3) the effect of product and process innovations on employment growth. All regressions presented here include a full list of control variables, 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. In what follows we comment on the effect of each innovation activity, while in the next section we supplement these findings by examining the role of persistence in innovation.

Model(1) shows the positive effect of product innovation on employment growth, although the effect is only statistically significant at 10% level. This low level of significance is in line with theoretical expectations, suggesting that the dynamics of compensation may differ substantially from one firm to another. On the one hand (as discussed in Section 1.2), product innovators may benefit from the fact that new products and new economic branches stimulate consumption, which in turn can promote higher demand and, eventually, greater employment needs. On the other hand, the “cannibalization” of existing products may counterbalance this positive effect. Whether or not new products “cannibalize” the old is not something that can be inferred from our data, but the net positive effect found here suggests, quite plausibly that, on average, the positive forces dominate. An alternative explanation for the weak innovation-growth link might be that our proxy of product innovation does not allow us to distinguish between products that are new to the market and those that are new only to the firm. As such, our sample of product innovators is likely to include some imitators that do not benefit from their innovative behaviour, at least not to the extent that ‘real’ innovators do (see our discussion in Section 1.2). Finally, notice that what we observe in Model(1), as well as in all the other specifications, is the net effect of innovation on the average firm’s growth, thus we cannot see any possible asymmetries in the innovation-growth relationship across growing and shrinking firms. It might be the case that fast-growing firms benefit more from their innovation outcomes, as suggested by the recent strand of literature targeting these firms (Coad, 2009).¹⁴

¹⁴We could estimate quantile regressions to reveal the effect of innovation on the entire growth rate distribution. While this would appear a priori to be quite simple, the quantile regression should ideally be estimated jointly controlling for fixed effects and endogenous covariates to obtain reliable results, and to compare these results with our main estimates. Unfortunately, these techniques, although improving, are somewhat under-developed, due to the difficulties of having an equivalent to GMM that allows for internal instruments. We

TABLE 4. GMM estimation results: The role of innovation

	(1)	(2)	(3)
Prod Inno t_{-1}	0.0447* (0.023)		
Proc Inno t_{-1}		0.0379* (0.020)	
Prod&Proc Inno t_{-1}			0.0396 (0.025)
Growth Empl t_{-1}	-0.1073 (0.093)	-0.1067 (0.089)	-0.1361 (0.093)
ln(Age) t	-0.0553*** (0.016)	-0.0505*** (0.016)	-0.0552*** (0.016)
ln(Sales) t_{-1}	0.0263 (0.016)	0.0190 (0.016)	0.0237 (0.016)
ln(Labor productivity) t_{-1}	0.0600* (0.033)	0.0643* (0.036)	0.0664** (0.034)
ROS t_{-1}	-0.0202 (0.121)	-0.0074 (0.125)	-0.0200 (0.121)
Export intensity t_{-1}	-0.0495 (0.056)	-0.0315 (0.061)	-0.0300 (0.057)
Market share t_{-1}	0.0318 (0.067)	0.0497 (0.066)	0.0558 (0.067)
Leverage t_{-1}	0.0396 (0.043)	0.0454 (0.043)	0.0365 (0.043)
Constant	-0.4195*** (0.131)	-0.4005*** (0.136)	-0.4293*** (0.130)
Year Dummies	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes
AR(1)	0.000	0.000	0.000
AR(2)	0.305	0.269	0.179
Sargan	0.172	0.074	0.161
Hansen	0.273	0.216	0.238
Obs	22,795	22,795	22,795

Notes: This table reports coefficients of the two-step GMM-SYS estimations of Equation 4. The response variable is the normalized growth rate of employment as defined in Equation 1. All other explanatory variables are defined in Section 2. 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% levels, respectively.

Process innovation, in Model(2), positively affects employment growth but here also the statistical significance is very low (10% level). The magnitude of the coefficient is close, though slightly smaller, to that of product innovation indicating that these two variables exert, by and large, the same effect on firm growth, at least in our sample. At first sight, the sign of the coefficient is at odds with the supposedly labour-saving nature of process innovation. Yet, there are possible explanations for this. On the one hand, the introduction of new production processes, or the improvement of existing processes, should allow firms to produce

recognize the importance of this and believe it should be an area of future investigation. We omit any further reference to this issue in what follows.

the same level of output with fewer inputs (including labour). On the other hand, higher productivity generally induces a series of mechanisms that are beneficial for employment (see discussion in Section 1.2). First, higher productivity in competitive markets implies a reduction in prices, which in turn should induce higher demand, thus stimulating employment. Second, the initial job displacement should lead to an excess of labour supply and, consequently, to a reduction in wages. This reduction may eventually spur a second wave of increased labour demand to re-equilibrate the market for labour. Third, the accumulated extra-profits argument forwarded above also holds in this context. Our results suggest that the potential displacement of jobs due to the higher productivity of inputs is, on average, offset. Nevertheless, the low significance of the estimate indicates that while this compensation exists, it is rather weak or, as in the case of product innovation, the weak net effect may simply be the result of very different reactions by firms to this type of innovation activity.

The coefficient of product and process innovation reported in Model(3) is positive, but not statistically significant. This result is, at first sight, surprising, but again there are a number of possible explanations. First, when firms develop new products and new processes simultaneously, it is far from easy to comprehend the net effect of the compensation mechanisms in place. In this sense, the heterogeneity in the way firms adjust their employment dynamics when both types of innovation are introduced is even greater than in the case of product innovation and process innovation when considered alone. The estimate in Model(3) seems to suggest that, overall, positive and negative forces cancel each other out. Second, as shown in Section 2.3, firms that simultaneously generate new products and new processes differ substantially from their counterparts in several respects, most notably being larger and older. It can reasonably be supposed that the potential for growth of such companies might already be largely achieved (or marginally lower than that of younger and smaller units), and it might be that case that innovation does indeed have an effect but on other elements of a firm's operating performance, for instance its profitability.

4.2. The role of persistence in innovation. The argument forwarded by this paper should be familiar by now: persistence in innovation matters. The estimates of the indicators of persistence in product and process innovations, both in terms of their effect on employment growth (Table 5) and on its persistence (Table 6), reveal some interesting patterns.

Starting with the results in Table 5, Model(1) depicts the positive and highly significant effect of persistence in product innovation on employment growth. The magnitude of the coefficient is very large, almost four times that of the estimate on product innovation presented in Table 4. This new empirical evidence corroborates the theoretical argument forwarded in Section 1.2, 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 standard 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. The consumption of new products is likely to be boosted when firms signal their ability to constantly move ahead in technological

TABLE 5. GMM estimation results: The role of persistence in innovation

	(1)	(2)	(3)
Pers Prod t_{-1}	0.1705*** (0.058)		
Pers Proc t_{-1}		0.0005 (0.038)	
Pers Prod&Proc t_{-1}			0.0964* (0.054)
Growth Empl t_{-1}	-0.1244 (0.090)	-0.0701 (0.089)	-0.1088 (0.092)
ln(Age) t	-0.0598*** (0.017)	-0.0478*** (0.016)	-0.0540*** (0.016)
ln(Sales) t_{-1}	0.0211 (0.017)	0.0204 (0.016)	0.0214 (0.016)
ln(Labor productivity) t_{-1}	0.0627* (0.033)	0.0576* (0.034)	0.0685** (0.033)
ROS t_{-1}	-0.0141 (0.121)	0.0137 (0.122)	-0.0276 (0.121)
Export intensity t_{-1}	-0.0207 (0.059)	-0.0161 (0.059)	-0.0328 (0.057)
Market share t_{-1}	0.0492 (0.066)	0.0285 (0.066)	0.0548 (0.067)
Leverage t_{-1}	0.0445 (0.043)	0.0436 (0.043)	0.0352 (0.042)
Constant	-0.3929*** (0.132)	-0.3794*** (0.130)	-0.4281*** (0.129)
Year Dummies	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes
AR(1)	0.000	0.000	0.000
AR(2)	0.212	0.488	0.282
Sargan	0.143	0.149	0.240
Hansen	0.231	0.256	0.252
Obs	22,795	22,795	22,795

Notes: This table reports coefficients of the two-step GMM-SYS estimations of Equation 5. The response variable is the normalized growth rate of employment as defined in Equation 1. All other explanatory variables are defined in Section 2. 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.

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 is likely to fuel higher growth. Yet, due to the nature of our data, we are not in a position to test which of these channels plays the strongest role. However, our results support the hypothesis that persistence in product innovation is an important ingredient for achieving higher growth, and may partially explain the inconclusive evidence provided so far.

As shown in Model(2) we do not find any significant effect of persistence in process innovation. We argued in Section 1.2 that firms need time to internalize their routines and to improve their practices; hence, the continuous changes that persistent process innovation entail may lead to inefficiencies, and, eventually to lower performance. A fall in productivity can indeed be reflected as an increase in prices, which in competitive markets should, in turn, affect demand. According to the estimates reported in Table 5, our theoretical expectations do not entirely match these empirical findings. In fact, what we see is a non significant coefficient for persistence in process innovation. This null effect is particularly interesting, however. The discrepancy between the positive effect of process innovation reported in Table 4 and the null effect found here at least lends some support to our conjectures: the positive impact of process innovation (if any) vanishes as soon as some degree of persistence characterizes this activity. In addition, and somewhat worryingly, note that process innovation is the innovation outcome characterized by the highest degree of persistence, at least in our sample (see Table 2). As such, our results are not particularly encouraging for all those actors interested in promoting job creation in this way.

Finally, Model(3) indicates that persistence in product and process innovations helps firms achieve good growth records, although the statistical significance of the coefficient is very weak (10% level). Overall we see here the net benefits induced by the persistence in product innovation, but the weak significance might be due to the null (or even negative) effect that persistence in process innovation entails.

Our estimates for the main control variables are in line with theoretical expectations (see our discussion in Section 2.2), and are very similar to those presented in Table 4. The autoregressive term is not significant, 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). More productive firms grow at the expense of less efficient units, whereas profits, 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, as hypothesized earlier. In Table 6 we again report the results of three econometric specifications: Model(1) shows the effect of persistence in product innovation, Model (2) the effect of persistence in process innovation, and Model(3) the of persistence in product and process innovation on the persistence in employment growth. For the sake of comprehension, the estimated coefficients 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, shown in Model(1). This evidence corroborates the univariate analysis proposed in Section 2.3 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, according to our framework, these advantages are more durable

TABLE 6. Survival model estimation results: The role of persistence in innovation

	(1)	(2)	(3)
Pers Prod	-0.1073** (0.048)		
Pers Proc		-0.0486 (0.042)	
Pers Prod&Proc			-0.0426 (0.060)
ln(Age)	0.1465*** (0.020)	0.1445*** (0.020)	0.1458*** (0.020)
ln(Sales)	0.0080 (0.012)	0.0072 (0.012)	0.0051 (0.012)
ln(Labor productivity)	-0.1100*** (0.025)	-0.1113*** (0.025)	-0.1100*** (0.025)
ROS	-0.9668*** (0.118)	-0.9598*** (0.119)	-0.9674*** (0.118)
Export intensity	0.0302 (0.061)	0.0295 (0.061)	0.0275 (0.061)
Market share	-0.1155 (0.078)	-0.1218 (0.078)	-0.1212 (0.078)
Leverage	0.0232 (0.059)	0.0264 (0.059)	0.0264 (0.059)
ln(t)	0.0590** (0.025)	0.0580** (0.024)	0.0581** (0.025)
Constant	-0.1247 (0.126)	-0.1040 (0.125)	-0.1059 (0.126)
Year Dummies	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes
Censoring dummies	Yes	Yes	Yes
Obs	12,478	12,478	12,478
Log likelihood	-8,177.66	-8,179.44	-8,179.86

Notes: This table reports coefficients of the proportional hazard model with random effects subsumed in the frailty term, see Equation 7. The response variable is the hazard rate of the growth spell ending and all other explanatory variables are defined in Section 2. Negative (positive) coefficients are interpreted as a decrease (increase) in the hazard rate. Bootstrapped standard errors in parentheses: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

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 time steps. 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 (Model 2) is again partially contrary to our expectations. In general, we can conclude that the employment dynamics of firms that systematically introduce new processes are no different from those of firms that do not innovate systematically, but that the potential benefits associated with persistence in product innovation are attenuated when this innovation outcome is coupled with persistence in process innovation (Model 3).

Finally, the results in Table 5 and 6 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. This implies that the forces of competition seem to erode rather quite quickly the competitive advantages that firms build from their innovation successes. Thus, markets seem to make an efficient selection of firms based on their technological traits (other things being equal) and to re-allocate resources and market shares to these firms; in this sense the concern of many economists and policy-makers that markets do not efficiently select “good” firms is not supported by our data. This claim finds further justification when we consider the other factors influencing the propensity of firms to grow and to sustain this growth. In fact, greater efficiency always stands out as a significant drivers of sustained growth trajectories.

4.3. Summary. The main findings of this paper can be summarized as follow. We detect a positive, but weak, impact of both product and process innovations on employment growth. The data confirm that compensation mechanisms do in fact operate, and that the demand for new products combined with productivity increases, on average, counterbalance job displacements. However, the overall overcompensation is weak and highly heterogeneous across firms. This being the case, there is a need to account for other idiosyncrasies of firms’ innovative behaviour, in particular its degree of persistence. We find that persistence in product innovation has a much stronger impact on the growth performance of firms in our sample. Hence, product innovation is more effective in spurring employment when carried out a regular basis. Moreover, persistence in product innovation boosts structure in the process of employment growth, which allows some firms to persistently outperform their competitors in terms of job creation. Finally, we find no significant effect of persistence in process innovation on either employment or the persistence of growth in employment. We believe that the mixed evidence produced might, in part, be due to the coexistence of persistent and occasional innovators in the analysed samples of innovators. According to our findings, it would seem that these two categories of firms are likely to experience very different employment dynamics.

5. CONCLUDING REMARKS

In recent decades, a large body of empirical research has sought to link innovation and employment. In doing so, most studies have exploited the growing availability of firm-level data which are better able to provide a description of firms’ innovative behaviour. 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 return hypothesis to the existence of sunk cost 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 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 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 an exhaustive 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. We might, for example, construct much more sophisticated measures of persistence than the simple measure proposed here. Fourth, in this study we have remained silent with respect to factors that are derived more directly from management research. Thus, it would be interesting to analyse in greater depth the role played by organizational traits, and differences in a firm's underlying strategies and managerial characteristics. Are some organizational and governance structures more effective than others when it comes to converting persistent innovation success into growth and sustained growth than others? Answering 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
Growth Empl	Normalized employment growth rates between two subsequent periods, as defined in equation 1
Growth Spell	Number of consecutive years with positive normalized employment growth
Prod Inno	Dummy variable indicating whether firms have introduced new or significantly improved products
Proc Inno	Dummy variable indicating whether firms have introduced new or significantly improved processes
Prod&Proc Inno	Dummy variable indicating whether firms have introduced new or significantly improved products and processes
Pers Prod	Weighted indicator of persistence in product innovation, as defined in equation 3
Pers Pros	Weighted indicator of persistence in process innovation, as defined in equation 3
Pers Prod&Proc	Weighted indicator of persistence in product and process innovation, as defined in equation 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	0.00	0.24	0.00	-3.03	3.21
Growth Spell	0.92	1.26	1.00	0.00	13.00
Prod Inno	0.18	0.38	0.00	0.00	1.00
Proc Inno	0.30	0.46	0.00	0.00	1.00
Prod&Proc Inno	0.11	0.31	0.00	0.00	1.00
Pers Prod	0.19	0.28	0.00	0.00	1.00
Pers Proc	0.34	0.32	0.00	0.25	1.00
Pers Prod&Proc	0.12	0.22	0.00	0.00	1.00
ln(Age)	3.05	0.73	3.09	0.00	5.42
ln(Sales)	8.32	1.90	8.05	2.56	15.83
ln(Labor Productivity)	3.41	0.95	3.34	-5.54	6.21
ROS	0.09	0.14	0.09	-3.50	0.91
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 - 22,795 observations.

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