ON THE ROLE OF PROCESS INNOVATIONS ON SMEs PRODUCTIVITY*

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Abstract

In this paper we explore in depth the direct effect of process innovations on total factor productivity growth for small and medium enterprises (SME). First, we analyse whether the ex-ante more productive SMEs are those that start introducing process innovations; then, we test whether process innovations boost SME productivity growth using matching techniques to control for the possibility that selection into introducing process innovations may not be a random process. We use a sample of Spanish manufacturing SMEs for the period 1990-2002, drawn from the *Encuesta sobre Estrategias Empresariales*. Our results show that the introduction of process innovations by a first-time process innovator yields an extra productivity growth as compared to a non-process innovator, and that the life span of this extra productivity growth has an inverted U-shaped form.

Keywords: Process innovations, TFP, stochastic dominance, non-parametric tests, matching techniques.

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1. Introduction.

It has been broadly recognised that small and medium enterprises (SMEs henceforth) are a driving force for economic growth in the world economy. SMEs hold the key to the revitalization of the economy, and to the preservation and generation of employment, what is especially important when the economy undergoes severe circumstances. Fostering SMEs productivity, as a way to ensure their survival and growth in the economy, is therefore a major issue, both to managers and policy makers. In this process, the key role of innovation, has been generally acknowledged, starting with the seminal works of Schumpeter (1934, 1942), and his concept of creative destruction, as the mechanism driving and shaping the evolution of markets and economic growth.

A large number of empirical studies have analysed the links between firms' innovation and productivity, following the pioneering works of Griliches (1958, 1980) and Mansfield (1968). The general finding has been that productivity is positively associated with firms' innovation output (see, e.g., Griliches and Mairesse, 1984, Griliches, 2000). However, most of the studies suffer from an endogeneity problem. It may be the case that innovation boosts productivity, but also that only the most productive firms are capable of generating enough resources to invest in innovative activities. In order to properly assess the impact of the introduction of innovations on firms' productivity, dealing with this endogeneity problem constitutes an econometric challenge, and in this paper we address this issue using appropriate econometric techniques.

The aim of this paper is to explore in depth the direct effect of process innovations on total factor productivity for small and medium enterprises. In particular, we aim to analyze both the extent and the life span of the productivity gains brought about by the introduction of process innovations. In order to do this, we first analyse whether the ex-ante more productive SMEs are those that start introducing process innovations; then, we test whether process innovations boost SMEs productivity growth using matching techniques to control for the possibility that selection into introducing process innovations may not be a random process.

Our focus is therefore to analyse the impact of process innovations on SMEs' productivity. Among the different types of innovation output, we consider productivity to be more directly related to process innovations than to product-related innovations. Product innovations entail the development of new products and their goals are usually aimed at exploiting new markets or expanding the existing markets where the SME operates. By contrast, process innovations involve changes in the production process aimed at reducing costs, wastes and lead time, or at improving production efficiency. Thus, one may expect process innovations to have a direct and immediate impact on the productivity performance of the SME, whereas product innovation are supposed to affect productivity in the medium or long run, given that it takes time for new products to settle in the market, and to yield the benefits of economies of scale and learning effect that result in productivity improvements.[1] There is also empirical evidence supporting a stronger effect of process innovations, as compared to product innovations, on firms' performance (see, e.g., Yamin *et al.*, 1997, Parisi *et al.*, 2006, and Lee and Kang, 2007, among others).

We also focus on SMEs, not only because they have grown into an important force in the world economy, but also because the introduction of

[1] Within the theoretical industrial organization literature, it is usual to assume that product innovation change SMEs' demand curve whereas process innovations reduce production cost and increase SMEs' productivity (see, e.g., Levin and Reiss, 1988, and Smolny, 1998). However, this distinction is made for conceptual convenience, since the design and development of improved products often requires accompanying process improvements.

process innovations may constitute an important source of competitive advantage for these companies, as compared to their large counterparts. Given their organizational simplicity, SMEs may implement process innovations faster and at lower switching costs than large firms (Buckley and Mirza, 1997). In addition, due to the limited resources and small scale production, SMEs may find easier to follow an innovation strategy aimed at obtaining incremental innovations, such as process innovations, rather than investing huge amounts in the development of sophisticated R&D projects, and indeed, there is empirical evidence supporting the view that SMEs are process innovation oriented (see Acs and Audretsch, 1990, Baldwin, 1997, Smolny, 1998, among others). Thus, for a number of reasons, the introduction of process innovations may be considered as an important innovation strategy for SMEs.[2]

Our paper contributes to the empirical literature dealing with the measurement of the impact of process innovation on productivity growth using firm level data. A number of papers have analysed the impact of innovation output on productivity growth using a production function approach. A noticeable example of this approach is Crépon *et al.* (1998), where the production function includes innovation output (patents per employee or the share of innovative sales) as a determinant of productivity growth. In this line, Verspagen (1999), Gu and Tang (2003), Huergo and Jaumandreu (2004), Parisi *et al.* (2006) and Lee and Kang (2007), considering direct measures of innovation output (such as patents, products or process innovations), find that process innovations have a positive impact on productivity. We depart from these studies by explicitly exploring the causal links between the two,

[2] There is also empirical evidence showing that large firms are more process R&D-oriented, as compared to product R&D-oriented, than small firms (see, e.g. Davies, 1979, Sherer, 1991, Pavitt *et al.*, 1987, Cohen and Klepper, 1996). However, this is not inconsistent with the fact that SMEs are more prone to implement process innovations.

that is, taking into account an endogeneity problem characterizing this relationship: the introduction of process innovations may increase firms' productivity, but it may also be true that only the most productive SMEs are able to generate the resources needed to implement process innovations. In order to solve this problem, we use matching techniques that allow dealing with non-random selection into the introduction of process innovations.[3]

To perform the analysis, we use data on SMEs drawn from the Encuesta sobre Estrategias Empresariales (ESEE, hereafter) for the period 1990-2002. This survey data is representative of Spanish manufacturing SMEs classified by industrial sectors and size categories.[4] The panel data nature of the data set allows classifying SMEs according to their process innovation patterns over time and to analyse the extent and the life span of the impact of process innovations on SMEs productivity growth. The empirical work is carried out using both stochastic dominance and matching techniques.

To anticipate our results, we find that the introduction of process innovations yields a delayed (not contemporaneous) extra productivity growth to a SME implementing a process innovation for the first time, as compared to a SME that does not introduces process innovations, and this extra productivity growth has an inverted U-shaped form.

Our findings contribute to improve the understanding of the links between innovation and SMEs productivity growth and thus may serve to assist the design of both more effective policies to promote SMEs and managerial strategies aimed at fostering productivity growth. Our results

[3] Mañez *et al.* (2005) focus on analysing the possible double way causality between R&D activities and productivity. Rochina-Barrachina *et al.* (2008) also analyse the relationship between process innovations on firm productivity taking into account the possibility of a double way causality.

[4] The ESEE does not include SMEs with less than 10 employees. Given the sampling procedure of this survey, we consider as SMEs those having between 10 and 200 employees. See section 2 for details.

suggest that SME policy should be on support of innovative SMEs, and in particular, on undertaking and developing initiatives aimed at facilitating SMEs the introduction of process innovations, such as tax incentives, access to finance and grant schemes, and also incentives heading for the maintenance and improvement of SMEs skills to innovate and to adapt and develop new technologies. This issue is especially important in Europe since increasing the share of innovative SMEs in the overall industrial sector is one of Europe's major challenges.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 is devoted to the analysis of the relationship between process innovations and SMEs productivity. Section 4 analyses whether ex-ante more productive SMEs are those that start introducing process innovations. Section 5 examines whether process innovations boost SMEs productivity growth. Finally, section 6 concludes.

2. Data and innovation-related activities for small SMEs.

2.1. The data.

The data used in this paper are drawn from the *Encuesta sobre Estrategias Empresariales* (ESEE, hereafter) for the period 1991-2002. This is an annual survey that is representative of Spanish manufacturing firms classified by industrial sectors and size categories. It provides exhaustive information at the firm level, including information on innovation activities performed by firms. As for SMEs, the sampling procedure of the ESEE excludes all firms with less than 10 employees, and firms with 10 to 200 employees were randomly sampled, holding around 5% of the population in 1990. Important efforts have been made to minimise attrition and to annually incorporate new firms with the same sampling criteria as in the base year, so that the sample of firms remains representative of the Spanish manufacturing SMEs over time.[5] The total sample of SMEs corresponding to the period 1991-2002, is made up of 12929 observations. This means an annual average of 1077 SMEs throughout the entire period.

The panel nature of the dataset allows classifying SMEs according to their process innovative activities over time. Regarding process innovations, the particular question in the ESEE is as follows: "Indicate if during 199X the SME introduced some important modification of the productive process (process innovation)". If the answer is yes, indicate the way: a) introduction of new machines; b) introduction of new organization methods for production; c) both". We select those SMEs that report information both on the process innovation question and on all the variables involved in the construction of the productivity measure. Applying this criterion we end up with a sample of 11626 observations (see Table 1).

[Table 1 about here]

Regarding the introduction of process innovations, Table 2 shows that 50.30% of SMEs introducing a process innovation do so through new machines, 15.66% through new organization methods for production, and 34.04% introduce simultaneously both new machines and new organization methods for production (which might be associated to process innovations of a greater scope).

[Table 2 about here]

[5] See http://www.funep.es/esee/ing/i_esee.asp for further details.

3. Process innovations and productivity for SMEs.

On theoretical grounds, there are, at least, three strands in the literature supporting a positive relationship between the introduction of process innovations and firms' productivity growth. The first strand is based on the well-known *R&D capital stock model* of Griliches (1979) that analyses the relationship among R&D investments, achievement of innovations and productivity growth. Since this seminal work, other authors have incorporated more explicitly the role of process innovations on productivity growth. For instance, Klette and Johansen (1998) incorporated the output elasticity of knowledge capital to point out the opportunity for process innovations, and Smolny (1998) assumed that process innovations reduce production costs by increasing the productivity of labour and/or capital. The second strand in the literature rendering theoretical support to the relationship between process innovations-and productivity growth is the *active learning model* (Ericson and Pakes, 1992, 1995, and Pakes and Ericson, 1998). According to this model, R&D investments, if successful, contribute to improve firm' productivity over time. If the successful output of firms R&D activities is the production of a process innovation and this is actually implemented, we expect an increase in productivity growth in such a firm. Therefore, in the *active learning model* the relationship between R&D activities and productivity growth runs through the achievement and implementation of process innovations. Finally, endogenous growth theory is the third strand of the literature stressing the importance of innovations for productivity growth (see, e.g., Romer, 1990, Aghion and Howitt, 1992).

In order to get a first picture of the effects of process innovations on the productivity levels of SMEs, we check whether SMEs introducing process innovations present higher productivity levels than SMEs that do not introduce them. To measure productivity we use a total factor productivity index (TFP, hereafter), calculated at the firm level using a multilateral productivity index that is an extension of Caves *et al.* (1982) index, and adapted to the ESEE by Delgado *et al.* (2002).[6]

Figure 1 displays the relative distribution functions of TFP for SMEs process innovators in *t* and non process innovators in *t*, respectively, for each year of the period 1991-2002.[7] These figures represent the equivalence between each of the quantiles of the TFP distribution for SMEs that have achieved process innovations in the quantile scale of the TFP distribution for non-process innovators SMEs. The diagonal represents the uniform distribution [0,1], i.e. the relative distribution if both distributions were identical. The position of the relative distribution below the diagonal suggests that the distribution represented in the vertical axis stochastically dominates the distribution in the horizontal axis. In particular, the relative TFP distribution for process innovating SMEs lie below the diagonal for ten out of twelve years (except for 1991 and 1992), suggesting that the TFP distribution for SMEs process innovating in *t* stochastically dominates that for the non-process innovators in each period *t*.

[Figure 1 about here]

On the basis of the observed differences in Figure 1, we formally test whether the TFP distribution of SMEs process innovators in *t* stochastically

[6] See Rochina *et al.* (2009) for a detailed description of the TFP index construction.
[7] See Handcock and Morris (1999) for the technical details about relative distributions.

dominates the TFP distribution of non process innovators in *t*. Thus, for each time period, we compare

$$F_t(y_t) \quad vs. \quad G_t(y_t), \quad t = 1991,\ldots,2002 \qquad (1)$$

using the Kolmogorov-Smirnov (KS, hereafter) one and two-sided tests, where F_t and G_t are the yearly TFP distribution functions for SMEs process innovators and non process innovators in *t*, respectively.[8]

Table 3 shows the results for the KS tests for TFP differentials. We reject the null hypothesis of equality of the two distributions (at a 5% significance level) for all years, except for 1991 and 1992. Further, we can never reject the null that the TFP of SMEs implementing process innovations in *t* is higher than that of non-process innovators. Thus, in general terms, for the SMEs in our sample, product innovators are more productive in terms of TFP than non-process innovators.

[Table 3 about here]

4. Self selection of most productive SMEs into implementing process innovations.

We now proceed to check whether among non-process innovators today, those that will introduce process innovations in the future are *ex-ante* more productive than those that will not. If (future) process innovators are *ex-ante* more productive, one would find that these firms would experience higher productivity in the future even without introducing process innovation. We want to test whether the most productive SMEs self select into obtaining process innovations. On theoretical and empirical grounds, we expect the productivity level of process innovators to be not lower than that of non-process innovators as: (i) the expenditures associated to innovation activities

[8] See Delgado *et al.*(2002) for a description of the application of the Kolmogorov-Smirnov tests for testing for stochastic dominance.

(both formal and informal) limit the access to innovation activities to the most productive firms;[9] and, (ii) performing innovation activities might be a previous condition to obtain process innovations.[10]

Thus, as a fist step, we test for non-random selection into implementing process innovation, that is, we first test whether among non-process innovators in *t*-1 those introducing process innovations in *t* are more productive in *t-1*. In order to do so, we compare TFP (previous to obtain a process innovation) of SME implementing a process innovation for the first time, with TFP of non-process innovators. We define first-time process innovating SMEs in *t* as those SMEs that implement a process innovation for the first time (in our sample) in period *t*; and, as non-process innovators those SMEs that have not implemented a process innovation until *t*-1, and do not implement it at time *t* either. However, the small size of first-time process innovators cohorts between 1992 and 2002 (reported in table 4) suggests not carrying out year-by-year KS tests as their results would be scarcely reliable.

[Table 4 about here]

To overcome this limitation we apply this test jointly for the whole sample period. Therefore, we compare,

$$F_{1991,\ldots,2002}\left(z_{1991,\ldots,2002} \mid \text{n} = \text{n}_0\right) \quad vs. \quad G_{1991,\ldots,2002}\left(z_{1991,\ldots,2002} \mid \text{n} = \text{n}_0\right), \quad \text{n}_0 = l, s \qquad (2)$$

[9] This is especially relevant for the case of R&D investments due to its sunk costs nature (Sutton, 1991, Máñez *et al.*, 2009).

[10] Some support for the self-selection hypothesis into R&D activities (formal part of innovation activities) of the most productive firms can be found, among others, in Hall, 1990 (who uses a financial constraint argument), González and Jaumandreu, 1998, González *et al.*, 1999, and Máñez *et al.*, 2005.

where $F_{1991,\ldots,2002}$ is the previous TFP distributions of the twelve cohorts of first-time process innovators and $G_{1991,\ldots,2002}$ is the yearly average productivity distribution over the period 1991-2002 for the non-process innovators.

To get the previous TFP distribution function for the first-time process innovators we follow two alternative approaches. In the first one, this distribution is calculated using TFP in t-1 for first-time process innovators in t, for t = 1992,..., 2002. In the second approach, this distribution is built up with the previous average TFP, starting from the first year a SME is observed in the sample until t-1.

Figures 2(a) and 2(b) map the kernel estimates of the cumulative previous TFP distribution functions for first-time process innovators and non-process innovators using the two alternative approaches defined above. We can see from the figures that, independently of the approach used to calculate previous TFP distribution for the first-time process innovators, the distribution for first-time process innovators is to the right of that of non-process innovators, suggesting that SMEs that eventually introduce process innovations had higher TFP levels than non-process innovators previously to implementing a process innovation.

[Figure 2 about here]

Further, the results of formal KS tests of stochastic dominance using the two approaches described above confirm the patterns of stochastic dominance suggested by our graphical regularities (see Table 5). Thus, regardless the approach considered, we always reject the null hypothesis of equality of TFP distributions and we cannot reject the null hypothesis (at any reasonable significance level) of favourable differences to first-time process innovators.

Therefore, the KS tests indicate that SMEs that eventually introduce process innovations had higher previous TFP levels than their non-process innovators counterparts. Thus, we find evidence on the existence of non-random selection into the introduction of process innovations that should be taken into account when analyzing the effects of process innovation in SMEs productivity growth.[11]

[Table 5 about here]

5. Do process innovations boost SMEs productivity growth?

If selection into introducing process innovation is not random, it is not correct to assess the impact of introducing process innovations on SMEs productivity growth by simply comparing the TFP growth of first-time process innovators and non-process innovators, since the ex-ante more productive first time process innovator would experience higher productivity in the future even without introducing any process innovation.

To properly control for the direction of causality from implementing process innovations to productivity growth, one need to use a methodology that explicitly takes into account this non-random selection process. One needs to compare the actual TFP growth of first time process innovators (after introducing the process innovation) with the TFP growth of the same firm *if it would not* have introduced any process innovation. The problem we face is that we do not have information about this counterfactual situation, that is, about the TFP growth of first time process innovators if it would not have introduced any process innovation. In order to overcome this problem one

[11] Rochina-Barrachina *et al.* (2009) also found evidence of self selection into the introduction of process innovations by the most productive Spanish manufacturing firms for the period 1990-1998.

may use matching techniques, which provide a way to construct the counterfactual situation. Matching techniques identify a control group from the pool of non-process innovators, to be compared with the group of first-time process innovators. This control group includes those SMEs for which the distribution of observed characteristics affecting TFP growth in the period previous to implementing a process innovation is as similar as possible to the distribution of the first-time process innovators group. The control group provides for each first time process innovator a matched non-process innovator unit that is as close as possible, in terms of observable characteristics influencing TFP growth, to that particular first time process innovator. If the matching procedure is appropriate, differences in TFP growth between first time process innovators and matched non-process innovators may be attributed to the introduction of process innovations by the former.

More formally, let Δy denote the growth rate of TFP and $D_{it} \in \{0, 1\}$ be an indicator of whether SME i is a first-time process innovator in period t (as opposed to a non-process innovator). Thus, we can use $\Delta y^{1}_{i(t-1)+s}$ to define the TFP growth between t-1 and $(t$-1$)+s$, s>0, for SME i classified as first-time process innovator in t, and $\Delta y^{0}_{i(t-1)+s}$ as the growth outcome for SME i if it had not implemented any process innovation. Thus, the causal effect of implementing a first process innovation for SME i at time period $(t$-1$)+s$ can be defined as

$$\Delta y^{1}_{i(t-1)+s} - \Delta y^{0}_{i(t-1)+s} \tag{3}$$

Following the policy/treatment evaluation literature (see Heckman *et al.*, 1997), we can define the average effect of implementing a process innovation on SMEs that obtain a process innovation for the first time as

$$E\left(\Delta y^{1}_{i(t-1)+s} - \Delta y^{0}_{i(t-1)+s} \mid D_{it} = 1\right) = E\left(\Delta y^{1}_{i(t-1)+s} \mid D_{it} = 1\right) - E\left(\Delta y^{0}_{i(t-1)+s} \mid D_{it} = 1\right) \quad (4)$$

The main problem of causal inference is that in observational studies the counterfactual $\Delta y^{0}_{i(t-1)+s}$ is not observed, and therefore it has to be generated. Thus, causal inference relies on the construction of the counterfactual for this term, which is the average productivity growth that first time-process innovators would have experienced had they not implemented any process innovation. We overcome this problem using matching techniques to identify among the pool of non-process innovators in *t* those with a distribution of observable variables, *X*, affecting productivity growth and the probability of implementing a process innovation, as similar as possible to that of first-time process innovators in *t*-1. It is then assumed that, conditional on *X*, SMEs with the same characteristics have a random probability to implement a process innovation. Thus, $E\left(\Delta y^{1}_{i(t-1)+s} - \Delta y^{0}_{i(t-1)+s} \mid X_{it-1}, D_{it} = 1\right)$ in expression (4) can be rewritten as

$$E\left(\Delta y^{1}_{i(t-1)+s} \mid X_{it-1}, D_{it} = 1\right) - E\left(\Delta y^{0}_{i(t-1)+s} \mid X_{it-1}, D_{it} = 0\right) \quad (5)$$

Since the set of observable variables that can potentially affect the SMEs probability of implementing a process innovation and their productivity growth is quite large, we need to deal with the choice of the appropriate variables to match SMEs, and their appropriate weights. We solve this problem using the propensity score techniques proposed by Rosenbaum and Rubin (1983). Adapted to process innovations, it can be shown that if implementing a first process innovation is random conditioning upon *X*, it is also random conditioning on the probability of implementing a process innovation (what they call propensity score).

Therefore, before performing the matching procedure, we obtain the probability of implementing a process innovation for the first time (propensity score) as the predicted probability of the following probit model

$$P(D_{it} = 1) = F(X_{it-1}) \tag{6}$$

where the set of observable characteristics included in X_{it-1} is detailed in Table A.1 in the Appendix.

In order to construct the counterfactual we have chosen the method one-to-one nearest neighbour matching.[12] This method matches all the first-time process innovators with the nearest neighbour among some (all) non-process innovators. Matching is performed using the *psmatch2* command (Leuven and Sianesi, 2003).

In the matching analysis, we compare the productivity growth of first-time process innovators and matched non-process innovators for the periods $t-1$ to t, t to $t+1$, $t+1$ to $t+2$, $t+2$ to $t+3$ and $t+3$ to $t+4$. Table 6 reports the results of these comparisons.[13] For first-time process innovators, the extra productivity growth becomes significant only one year after implementing the process innovation: the extra productivity growth for $t-1/t$ is not statistically significant but it is significant for $t/t+1$, $t+1/t+2$, and for $t+2/t+3$; the extra productivity growth stops being statistically significant for $t+3/t+4$. Further, this extra productivity growth reaches its maximum at 5.1% from $t+1/t+2$ (the second time it is significant) and then smoothly decreases (a 3.3% from $t+3$ to $t+4$, although at a 10% significant level of significance). To check the matching quality we present in Table A.2 in the Appendix, the indicators of the resulting

[12] To check the robustness of our results to the matching method used we have also performed kernel matching using the Epanechnikov kernel which is usual when applying matching techniques. This method matches all fist-time process innovators with a weighted average of some (all) non-process innovators, with weights inversely proportional to the distance between the propensity score of fist-time process innovators and non-process innovators (Becker and Ichino, 2002). As the results obtained are the same, we only report the results for the one-to-one matching.

[13] Since we have previously estimated the propensity scores, *p*-values are calculated using bootstrapping techniques with 2000 replications.

balancing of the observable variables within the matched samples, for the periods for which we obtain significant effects, in summary form.

[Table 6 about here]

Hence, from the above results we can summarize the patterns of extra productivity growth for first-time process innovating SMEs as follows: (i) implementing a process innovation for the first time does not guarantee contemporaneous productivity rewards; (ii) the productivity gains require more than one year after implementing the process innovation to take place; and, (iii) the extra-productivity growth of first-time process innovators reaches its maximum two years after the introduction of the process innovation, then decreases for one extra period and ceases after four years.

We may interpret this inversed U-shaped form following Rosenberg (1982). When an innovation process is introduced, it continues to improve and develop as operating experience is gained, that is, with “learning by using” the new process. This ongoing development after implementation would explain the increase in the extra TFP achieved one and two years after the process innovation has been introduced by the SME. Then the process innovation is fully developed and exploited within the firm and its potential for productivity improvement gradually fades away, so that the extra TFP vanishes and the path of TFP growth of both process and non-process innovators converge.

Our results are consistent with existing empirical literature reporting a positive impact of process innovation on productivity growth. Huergo and Jaumandreu (2004) analyzed the productivity growth impact of process innovations introduced by firms taking into account their different ages, and using a sample of Spanish manufacturing firms, found that process innovation induces (a contemporaneous) extra productivity growth that tends to persist although attenuated, for a number of years.[14] Parisi *et al.* (2006), using a large sample of Italian firms, provide evidence on the positive impact of the introduction of process innovation on productivity growth, although they cannot fully address self-selection problems due to data restrictions. Lee and Kang (2007) also provide evidence on a positive impact of process innovation on productivity growth using a sample of Korean manufacturing firms. Rochina-Barrachina *et al.* (2009), using a sample of large and small Spanish manufacturing firms but without controlling for non-random selection into process innovating, also provide evidence on a contemporaneous impact of process innovations on firm productivity growth, and found that this impact is larger and longer in the case of large firms. Thus, compared to related literature analysing the impact of process innovation on productivity growth, we obtain a positive effect that it is not contemporaneous, but instead induces a delayed increase in productivity growth, which lasts three periods, when controlling for non-random selection into process innovating using matching techniques.[15]

6. Concluding remarks.

In this paper we have provided panel data evidence on the causal links between the introduction of process innovations and productivity growth for a sample of Spanish manufacturing SMEs. First, using stochastic dominance

[14] Huergo and Jaumandreu (2004) use the same dataset than ours but for the period 1990-1998 and including large firms. They measure productivity growth by means of the Solow residual and estimate a semiparametric model, with special focus on firm's age.

[15] Parisi *et al.* (2006) found that the effect of the introduction of process innovation on productivity growth is positive over a period of three years. However, in their data, information on innovations is not available on a yearly basis but on a (three years) period basis. Thus, they cannot evaluate the time span of this effect. Gu and Tang (2003) provide empirical evidence, using a paned data sample of manufacturing industries, that (different measures of) innovations have a positive impact on productivity and that it takes from one to three years, depending on the industry, for innovations to raise productivity.

techniques, we have found evidence on the existence of non-random selection into the introduction of process innovations. Therefore, in order to assess the impact of introducing process innovations on SMEs productivity growth, that is, to properly control for the direction of causality from implementing process innovations to productivity growth, we have used matching techniques, a methodology that explicitly takes into account this non-random selection process. We have found that the introduction of process innovations yields a delayed (not contemporaneous) extra productivity growth to a SME implementing a process innovation for the first time, as compared to a SME that does not introduces process innovations, and that the life span of this extra productivity growth has an inverted U-shaped form.

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Figure 1. Yearly relative TFP distribution functions of process innovators in *t* to non-process innovators in *t*.

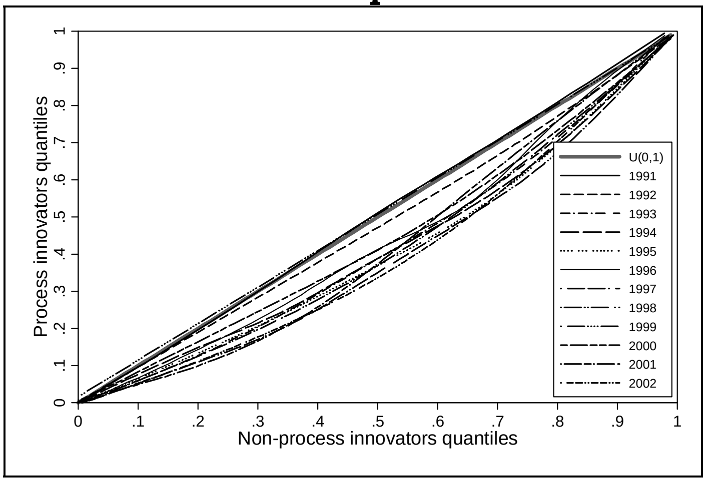

Figure 2. Comparing the TFP growth of first-time process innovators and non-process innovators.

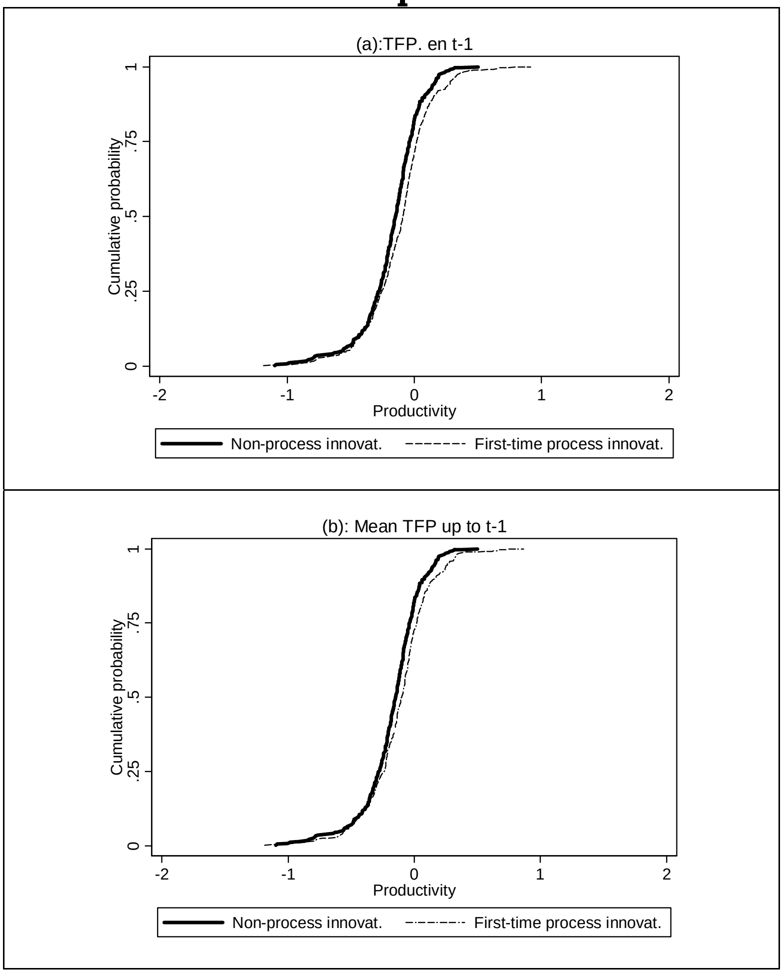

Table 1. Yearly number of SMEs and process innovators

Years	Total	Process innovators
1991	683	205
1992	848	260
1993	985	301
1994	967	302
1995	910	269
1996	969	272
1997	1129	374
1998	1036	353
1999	1068	338
2000	1049	333
2001	991	269
2002	991	237
Total 1991-2002	11626	3513

Table 2. Distribution of process innovations.

Type of process innovation	%
New machines	50.30
New organization methods for production	15.66
Both	34.04

Table 3. Yearly TFP differences between SMEs first-time process innovators in *t* and non-process innovators in *t*.

Year	Number of observations			Equality of distributions		Differences favourable to first time process innovators	
	First-time process innovators	Non-process innovators	TFP differences[a]	Statistic	*p*-value	Statistic	*p*-value
1991	205	478	0.002	0.387	0.998	0.309	0.826
1992	260	588	0.026	0.970	0.272	0.206	0.918
1993	301	684	0.068	1.866	0.001	0.098	0.981
1994	302	665	0.054	2.164	0.000	0.022	0.999
1995	269	641	0.066	2.095	0.000	0.086	0.985
1996	272	697	0.045	2.001	0.000	0.257	0.876
1997	374	755	0.067	2.644	0.000	0.021	0.999
1998	353	683	0.054	2.094	0.000	0.003	1.000
1999	338	730	0.053	2.719	0.000	0,092	0.983
2000	333	716	0.036	1.809	0.002	0,069	0.990
2001	269	722	0.037	2.206	0.000	0,306	0.829
2002	237	754	0.060	2.419	0.000	0,175	0.941

[a] TFP differences (between both groups of SMEs) are calculated at the median of the distributions.

Table 4. Yearly number of SMEs first-time process innovators.

Year	
1992	47
1993	51
1994	36
1995	30
1996	21
1997	28
1998	43
1999	26
2000	24
2001	33
2002	12
Total 1992-2002[a]	351

[a] We do not report data for 1991 as we need to start the test from 1992 onwards to calculate t-1 TFP.

Table 5. Comparison of previous TFP of SMEs first-time process innovators and non-process innovators.

				Equality of distributions		Favourable diff. to first-time process innovators	
	First-time process innovators	Non-process innovators	TFP diffs.[a]	Statistic	*p*-value	Statistic	*p*-value
TFP in *t-1* for first-time process innovators	351	334	0.061	1.969	0.004	0.050	0.995
Mean previous TFP for first-time process innovators	351	334	0.052	1.843	0.016	0.215	0.912

[a] TFP differences (between both groups of SMEs) are calculated at the median of the distributions.

Table 6. Estimates of the extra productivity growth for first-time process innovators.

			Number of SMEs	
Period	**EPG**	**Confidence Interval**	**First-time process innovators**	**Matched controls**
t-1/t	-0.0189	[-0.043,0.004]	346	269
t/t+1	0.0384**	[0.002,0.087]	195	169
t+1/t+2	0.0510***	[0.030,0.104]	132	121
t+2/t+3	0.0330*	[0.045,0.066]	93	87
t+3/t+4	-0.0199	[-0.064,0.009]	68	65

Notes:

(1) EPG stands for extra productivity growth of first-time process innovators over matched non-process innovators.

(2) We report confidence intervals using boostrapped standard errors (2000 replications), *, ** and *** denote significance at the 10%, 5% and 1%, respectively.

(3) We also report the number of first-time process innovators and the number of matched non-process innovators.

(4) The sample of non-treated from which we draw the matched controls is 1319.

Appendix

Table A.1. The determinants of becoming a first-time process innovator.

	Probit regression of the probability of becoming a first-time process innovator	
Export Intensity$_{t-1}$	0.1562	(0.056)***
Significant market share$_{t-1}$	0.0131	(0.022)
log(employment)$_{t-1}$	0.0343	(0.014)**
log(TFP)$_{t-1}$	0.1070	(0.041)***
Advertising intensity$_{t-1}$	1.0021	(0.680)
Foreign capital participation$_{t-1}$	0.0002	(0.036)
Legal form$_{t-1}$	0.0454	(0.022)**
R&D Intensity$_{t-1}$	3.2809	(1.245)***
Complementary R&D activities$_{t-1}$	0.0888	(0.024)***
Number observations	1667	

Notes:

(1) * significant at 10%, ** significant at 5% and *** significant at 1%.
(2) Robust standard errors in parentheses.
(3) The regression includes year dummies and 2-digit year dummies.

Table A.2. Covariate balancing indicators before and after matching.

Period	N	Probit pseudo R^2		$P > \chi^2$		Median bias		% lost to common support
		Before	After	Before	After	Before	After	
t/t+1	195	0.041	0.007	0.000	0.931	17.963	5.328	0.005
t+1/t+2	132	0.052	0.020	0.000	0.594	25.111	4.843	0.008
t+2/t+3	93	0.050	0.032	0.000	0.499	26.118	6.842	0.010

Notes:

(1) The number of controls which are used to match treated is 1319.

(2) Pseudo R^2 from probit of treatment (implementing a process innovation in our case) on covariates before matching and in matched samples (after matching).

(3) $P > \chi^2$ is the *p*-value of the likelihood-ratio test after matching, testing the hypothesis that the regressors are jointly insignificant, i.e. that are well balanced in the two samples.

(4) Median bias refers to median absolute standardised bias before and after matching, the median is calculated taking over al regressors. Following Rosenbaum and Rubin (1985), for a given covariate, the standardised difference before matching is the difference of the sample means in the full treated and non-treated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups. The standardised difference after matching is the difference of the ample means in the matched treated (i.e., inside the common support) and matched non-treated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups.

(5) The % lost to common support is the share of the treated group falling outside of the common support, imposed at boundaries.