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ON THE ROLE OF PROCESS INNOVATIONS ON SMES PRODUCTIVITY GROWTH?

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Abstract

In this paper we explore in depth the effect of process innovations on total factor productivity growth for small and medium enterprises (SMEs), taking into account the potential endogeneity problem that may be caused by self selection into these activities. First, we analyse whether the ex-ante most 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. We use a sample of Spanish manufacturing SMEs for the period 1991-2002, drawn from the *Encuesta sobre Estrategias Empresariales*. Our results show that the introduction of process innovations yields an extra productivity growth, and that the life span of this extra productivity growth lasts for only one period.

Keywords: Process innovations, TFP, stochastic dominance, matching techniques.

JEL Classification: C14, C21, D24, L1, L25, O3.

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1. Introduction.

It has been broadly recognised the role of small and medium enterprises (SMEs henceforth) as a driving force for economic growth. SMEs are crucial 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. Amongst the determinants of firms productivity growth, the key role of innovation has also 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 number of empirical papers have analysed the links between firms' innovation output and productivity using a production function approach. A remarkable 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. In this line, Huergo and Jaumandreu (2004), Parisi *et al.* (2006), Griffith *et al.* (2006), Lee and Kang (2007), and Rochina-Barrachina *et al.* (2010), considering direct measures of innovation output (such as patents or process innovations), find that process innovations have a positive impact on firms' productivity. However, despite the acknowledgement of this positive relationship, little is known about the direction of causality between firms' process innovations and productivity. In particular, do process innovations enhance firms' productivity growth, or are the most productive firms becoming process innovators, or both? Discerning the direction of this causality is important in order to draw conclusions that may guide firms' strategies.

In this paper we depart from previous studies by explicitly exploring the causal links between process innovations and productivity, that is, by taking into account the potential endogeneity problem characterizing this relationship: the introduction of process innovations may increase SMEs' productivity, but it may also be the case that only the most productive SMEs are able to generate the resources needed to implement process innovations. To properly assess the impact of the introduction of process innovations on firms' productivity, dealing with this problem of endogeneity, 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 (TFP, hereafter) for SMEs. In particular, we aim to analyse both the extent and the life span of the productivity gains brought about by the introduction of process innovations, taking into account the potential endogeneity problem between process innovation and productivity growth. In order to do this, we proceed in two steps. Firstly, we analyse whether the ex-ante most productive SMEs are those that start introducing process innovations. Second, 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.

To perform the analysis, we use data on SMEs drawn from the Encuesta sobre Estrategias Empresariales (ESEE, hereafter) for the period 1991-2002. This survey data is representative of Spanish manufacturing SMEs classified by industrial sectors and size categories.[1] 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.

Our paper contributes to the empirical literature dealing with the measurement of the impact of innovation output on productivity growth using firm level data. To our knowledge, this paper is the first to look at the productivity gains from introducing process innovations for the first time at the firm level, using matching techniques to deal with the potential endogeneity problem that may arise from self-selection into these activities.

To anticipate our results, we find that the introduction of process innovations yields an extra productivity growth to a SME implementing a process innovation for the first time, as compared to a SME that does not introduce innovations, and that this extra productivity growth lasts for one period after the introduction of the process innovation. These findings shed light on the understanding of the links between process innovation and SMEs productivity growth and thus may serve to assist not only the design of management strategies but also more effective policies to promote SMEs**.** From a strategic management point of view, our results may be used to outline managerial recommendations relating the rate and timing of introducing process innovations as a strategic tool to boost productivity growth, and in turn, to improve the competitive position of the firm in the market. Regarding policy implications, our findings also suggest that understanding the different

[1] The ESEE does not include SMEs with less than 10 employees. Therefore, given the sampling procedure of this survey, we consider as SMEs those firms having between 10 and 200 employees. See section 3 for details.

factors inducing firms to introduce process innovations may provide useful insights about the sources of productivity growth and, in turn, economic development. Our results indicate that in order to boost SMEs' productivity growth, public policy should be on support of innovative SMEs, and in particular, on developing initiatives aimed at facilitating SMEs the introduction of process innovations, focusing on those factors that are found to enhance SMEs probability to become a first-time process innovator.

The rest of the paper is organized as follows. Section 2 briefly describes the relationship between process innovations and SMEs productivity. Section 3 presents the data and the methodology for testing stochastic dominance. Section 4 analyses whether the ex-ante most productive SMEs are those that start introducing process innovations. Section 5 examines whether process innovations boost SMEs productivity growth. Finally, section 6 concludes.

2. Process innovations and productivity for SMEs.

Our focus in this paper is to analyse the impact of process innovations on SMEs' productivity. 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 the productivity growth of 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).

Our interest in SMEs is not only because they have grown into an important force in the world economy, but also because the introduction of process innovations may constitute an important source of competitive advantage for these companies, as compared to their larger counterparts. In the case of Spain, SMEs represent 96.78% of total firms, 64.08% of total employment, 53.08% of total sales and 33.78% of total R&D expenditures. 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 direct rewards in terms of productivity, 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 tool of strategic management for SMEs.[2]

3. Data, productivity and process innovation status for SMEs.

The data used in this paper are drawn from the ESEE 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. As for SMEs, the sampling procedure of the ESEE excluded those 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.[3] 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 innovation activities over time. A process innovation is assumed to occur when the firm answers positively to the question in the ESEE on

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[2] There is also empirical evidence showing that large firms are more process R&D-oriented, as compared to other innovation strategies, 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.

[3] This annual survey classifies as SMEs those firms with less than 200 workers and as large firms those with more than 200 workers. Since the sampling criteria for both groups are different it would result quite complicated to include those firms with workforce between 200 and 250 workers to follow the EU definition of SMEs. See http://www.funep.es/esee/en/einfo_que_es.asp for further details.

whether it has introduced some significant modification of the productive process (process innovation affecting machines, organizational methods or both) during the year.

To measure productivity we use a TFP index. This is calculated at the firm level using a multilateral productivity index that is an extension of the Caves *et al.* (1982) index.[4] We deflate both output and inputs using, correspondingly, firm individual price indexes provided by the ESEE. This allows controlling for the possibility of output and input prices not only being different or evolving differently over time for process innovators than non innovators, but also among firms, irrespective to their process innovation status. Therefore, our TFP measure is robust to firm differences in market power.[5,6] 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 10302 observations (see Table 1).[7]

[Table 1 about here]

Table 2 reports average values of the TFP index and the variables involved in its calculation, both for non-innovators and for process innovator SMEs. By inspection, we observe that non-innovator SMEs present lower TFP than

[4] This extension was developed in Good *et al.* (1996) and Delgado *et al.* (2002). It may also be found in Máñez *et al.* (2005) and Rochina-Barrachina *et al.* (2010). Notice that since this TFP index considers different reference firms across industries the possible differences in TFP across industries are eliminated, which allows considering jointly firms belonging to different industries (see Appendix A).

[5] Deflating by more aggregated price indexes would generate bias in the calculus of the TFP as far as there is not perfect competition in the product and/or input markets.

[6] For further details on the TFP index calculation see Appendix A.

[7] We do not use any observation for 1990 as we cannot compute TFP for this year in the survey.

process innovators, on average. In addition, non-innovators present lower average values for the following variables: real output, the quantity of labour input, the quantity of other intermediate inputs, and capital input (in real terms). Finally, regarding input cost shares, we observe that the cost share of labour is larger for non-innovators, and the cost shares of capital and other intermediate inputs are smaller for non-innovators.[8]

[Table 2 about here]

In order to get a further picture of the relationship between process innovations and SMEs productivity, Figure 1 displays the relative distribution functions of TFP levels for process innovators in *t* (SMEs that introduce a process innovation in year *t* without introducing simultaneously a product innovation) and non-innovators in *t* (SMEs that do not implement either a process or a product innovation in year *t)*, respectively, for each year of the period 1991-2002.[9] In the figure we can see that the relative TFP distribution for process innovators lies below the diagonal for nine out of twelve years (except for 1991, 1992 and 1999), suggesting that the TFP distribution for process innovators in *t* stochastically dominates that for the non-innovators at each period *t*.

[Figure 1 about here]

[8] All differences are significant at a 1% significant level.

[9] These distributions represent the equivalence between each of the quantiles of the TFP distribution for SMEs that have introduced process innovations, in the quantile scale of the TFP distribution for non-innovators. 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. See Handcock and Morris (1999) for technical details about relative distributions.

On the basis of the observed differences in Figure 1, we formally test, using the method proposed by Davidson and Duclos (2000), whether the TFP distribution of process innovators in t stochastically dominates the TFP distribution of non-innovators in t. Thus, for each year, we compare

(1)

where and $F_{B,t}$ are the TFP distribution functions for process innovators and non-innovators in year t, respectively. Let and , distribution A is said to stochastically dominate distribution B if , with strict inequality for some x (for the sake of simplicity, we have omitted the t sub-index).

Davidson and Duclos (2000) show that if we have a random sample of N independent observations on the productivity variable, y_i, a natural estimator for $F(x)$ is

$$\hat{F}(x) = \frac{1}{N}\sum_{i=1}^{N} I(y_i \leq x) \qquad (2)$$

where $I(\cdot)$ is an indicator function, which is equal to one when its argument is true and equal to zero otherwise.

As we apply this estimator to two independent samples (one of process innovators and another one of non-innovators) for each year t, the variance of the difference of the two estimators is

(3)

with the estimator of given by:

(4)

Therefore, it is possible to calculate *t*-statistics to test the null hypothesis:

(5)

for a series of test points.

The TFP distribution of process innovators (distribution A) is said to stochastically dominate the TFP distribution of non-innovators (distribution B) in those cases in which being the *t*-statistics significant, the differences are negative. Recall that the stochastic dominance condition requires , with strict inequality for some *x*.

We have chosen as test points each of the percentiles of the combined TFP distribution of process innovators and non-innovators. In summary, in the upper panel of Table 3 we show the results corresponding to percentiles 1%, 5%, 10%, 25%, 75%, 90%, 95% and 99%. In the lower panel, we show the largest percentile interval for which the difference is strictly negative.

As it may be observed in the upper panel of Table 3, neither for 1991 nor for 1992 we reject the null of equality of the TFP distributions of process innovators and non-innovators for any of the test points (no *t*-statistic is significant at the conventional 5% level). However, for the rest of the years all the significant *t*-statistics are negative suggesting that the TFP distribution of process innovators dominates that of non-innovators. Further, the lower panel of Table 3 shows that for all the years from 1993 to 2002, the difference is strictly negative for a substantial portion of the central part of the TFP distribution (i.e., the TFP distribution of process innovators is strictly at the right of that of non-innovators). Thus, in general terms, process innovators are more productive in terms of TFP than non-innovators.

[Table 3 about here]

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

We now proceed to assess whether among non-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 innovations. 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-innovators as: (i) the expenditures associated to innovation activities (both formal and informal) limit the access to innovation activities to the most productive firms;[10] and, (ii) performing innovation activities is a previous condition to obtain process innovations.[11]

Thus, as a first step, we test for non-random selection into implementing process innovations, that is, we test whether among non-innovators in t-1 those introducing process innovations in t are previously more productive. In order to do so, we compare the level of TFP (previous to obtaining a process

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

[11] 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.

innovation) of SMEs introducing a process innovation for the first time, with the level of TFP of non-innovators. To classify a SME as a first-time process innovator in year *t* we require three conditions: i) the SME implements a process innovation in year *t* without simultaneously introducing any product innovation; ii) during the sample period previous to year *t*, the SME has not introduced a process or product innovation; and, iii) for at least two years previous to *t*, we observe the SME in the sample.[12,13] To classify a SME as a non innovator in year *t* we require: i) that the SME has not introduced any process or product innovation in year *t* or in previous years of the sample; and, ii) that for a minimum of two years previous to *t,* we observe the SME in the sample.[14] However, the small size of first-time process innovators cohorts between 1993 and 2002 (reported in table 4) suggests not carrying out year-by-year stochastic dominance 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,

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[12] A previously higher productivity level of process innovating SMEs could also arise from innovations that these firms could have introduced previously to the first time they are observed in the sample. However, as we cannot control for this, since this information is not available in the ESEE, we intend to minimise its possible impact by also requiring to each firm to be observed in the sample for a minimum of two previous years without introducing any kind of innovation to consider that firm as a first time process innovator.

[13] Accomplishment of these three criteria imply that we cannot include the cohort of first-time process innovators in 1992 in our sample, as we do not know whether or not those firms that introduced a process innovation in 1992 also introduced any kind of innovation in 1990.

[14] Notice that the definitions of the two groups of firms under comparison have changed with respect to section 3, where for descriptive purposes we were comparing contemporaneous productivity levels for firms introducing process innovations in a given period *t* with those of firms not introducing them in that particular period.

(6)

where F_{FTPI} is the previous TFP distribution of the ten cohorts of first-time process innovators, and F_{NI} is the yearly average TFP distribution over the period 1991-2001 for non-innovators (that are now re-defined as firms that do not introduce any innovation during the whole sample period and for which we have information in the sample for at least two years).[15]

Before performing the stochastic dominance analysis, we describe the two alternative approaches we use to obtain the previous TFP distribution function of first-time process innovators. In the first approach, we calculate the previous TFP distribution of a first time process innovator in t using its TFP in t-1, for t = 1993,..., 2002. In the second one, this distribution is constructed with the previous average TFP, starting from the first year a SME is observed in the sample until t-1. Thus, for instance, following the first approach the previous TFP for a first time process innovator in 1995 is its TFP in 1994; and, following the second approach, the previous TFP is the average of TFP since its first year in the sample up to 1994.

Figures 2(a) and 2(b) map the kernel estimates of the cumulative previous TFP distribution functions of first-time process innovators and non-innovators using the two alternative approaches defined above. We may observe from the figures that, independently of the approach used, the previous TFP distribution of first time process innovators is to the right of that of non-innovators, indicating that SMEs that eventually introduce process

[15] This definition for non-innovators is made in order to satisfy the independence assumption required by the stochastic dominance test. In particular, the application of the test requires independence of observations both between the two sub samples under comparison, and among the observations of a given sub sample. For this reason, the stochastic dominance tests carried out along the paper take into account this methodological issue.

innovations had higher TFP levels than non-innovators previously to implementing those process innovations.

[Figure 2 about here]

In order to test for stochastic dominance of the previous TFP distribution of first time process innovators over the corresponding for non-innovators, let and ; and, and their respective estimators, as proposed by Davidson and Duclos (2000). If we define and it is possible to calculate *t*-statistics to test the null hypothesis:

(7)

for a series of test points.[16]

If the distribution of first time process innovators dominates that of non-innovators, all the *t*-statistics should be negative and significant or non significant (a negative and significant *t*-statistic is required at least in one test point, since the stochastic dominance condition requires that , with strict inequality for some *x*).

Analogously to section 3, we test the null at each of the percentiles of the combined TFP distribution of first time process innovators and non-innovators. In the upper panel of Table 5, we show the results of these tests at percentiles 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% and 99%; the low panel shows the longest interval for which (i.e., the previous TFP distribution function for first time process innovators is strictly at the right of that for non-innovators).

[16] In section 3 we describe the formulae to calculate and .

The results of the stochastic dominance tests using the two approaches described above to calculate the previous TFP for first time process innovators confirm the patterns of stochastic dominance suggested by our graphical regularities (see Table 5). Thus, we observe in the upper panel of Table 5 that for both approaches all the significant *t*-statistics are negative, suggesting that the previous TFP distribution of first time process innovators dominates that of non-innovators. Further, it is possible to infer, from the test results in the lower panel of Table 5, that regardless the approach used, the previous TFP distribution of first time process innovators is strictly at the right of that of non-innovators for an important part of the upper half of the distribution (we obtain that is strictly negative from percentile 59% to percentile 87% using the first approach, and from percentile 51% to percentile 98% using the second approach).

Therefore, our results indicate that SMEs that eventually introduce process innovations exhibit higher previous TFP levels than their non-innovator 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 analysing the effects of process innovations on SMEs productivity growth.

[Table 5 about here]

5. Do process innovations boost SMEs productivity growth?

5.1. Econometric model.

If selection into introducing process innovations is endogenous, it is not appropriate 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-innovators, since the ex-ante more productive first-time process innovators 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 needs to use a methodology that explicitly takes into account this endogenous selection process.

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-innovator). Therefore, we can use $\Delta y^{1}_{i(t+s)-(t+s+1)}$ to define the TFP growth between (t+s) and (t+s+1), $s \geq -1$, for SME i classified as first-time process innovator in t, and $\Delta y^{0}_{i(t+s)-(t+s+1)}$ as the TFP growth for SME i should it had not implemented any innovation. Thus, the causal effect of implementing a first process innovation for SME i at time period t may be defined as

$$\Delta y^{1}_{i(t+s)-(t+s+1)} - \Delta y^{0}_{i(t+s)-(t+s+1)} \tag{8}$$

Following the policy/treatment evaluation literature (see Heckman *et al.*, 1997),[17] we may define the average effect of implementing a process innovation for the first time on SMEs productivity as

(9)

The main problem of causal inference is that in observational studies the counterfactual $\Delta y^{0}_{i(t+s)-(t+s+1)}$ for a SME that has introduced a process innovation 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

[17] Becker and Egger (2009) use a treatment approach to empirically analyse the effect of innovations on export propensity at the firm level and to allow for non-random self-selection of firms into innovation.

experienced had they not implemented any innovation. We overcome this problem using matching techniques to identify, among the pool of non-innovators in *t*, those with a distribution of observable variables (*X* in *t-1*) 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, in expression (9) may be rewritten as

$$E\left(\Delta y^{1}_{i(t+s)-(t+s+1)} \mid X_{it-1}, D_{it}=1\right) - E\left(\Delta y^{0}_{i(t+s)-(t+s+1)} \mid X_{it-1}, D_{it}=0\right) \tag{10}$$

Since the set of observable variables that may 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 may be shown that if introducing a process innovation for the first time is random conditioning upon *X*, it is also random conditioning on the probability of introducing a process innovation. 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

$$P\left(D_{it}=1\right) = F\left(X_{it-1}\right) \tag{11}$$

where *F(.)* is the normal cumulative distribution function.

In order to guarantee that the second term in (10) is a good counterfactual for the final term in (9), we need to assume that all relevant differences between first-time process innovators and the control group of non-innovators may be properly captured by the vector of observables *X*. This is the so-called Conditional Independence Assumption, CIA henceforth, which also means that the potential productivity growth in case of no introducing a first-time process innovation is independent of the treatment assignment between being a first-time process innovator or a non-innovator, conditional on *X*. Therefore, in our probit model we control for previous productivity, initial productivity (productivity of the first year the SME is observed in the sample), and other relevant lagged firm characteristics. The inclusion of previous productivity in our specification of the propensity score matching model allows controlling for self selection of most productive firms into process innovations, and it clearly reduces the problem of observational equivalence.[18] The productivity of the firm the first year it is observed in the sample is used as initial condition. Further, by including other firm characteristics that could be linked to higher productivity we argue that productivity growth differentials between firms introducing process innovations and their non-innovator counterparts are driven by the introduction of process innovations.

The group of other relevant firm and market characteristics included in the reduced form probit model are variables that have been suggested by the theoretical literature and that have found empirical support as being relevant for the decision to implement process innovations.[19] Variables included in X_{it-1}

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[18] Including the lagged value of TFP in the underlying matching also strengthens our causal effect identification strategy, as our TFP measure captures all (firm specific) unobservable factors that could be generating additional productivity gains, conditional on inputs and inputs shares.

[19] There are a number of studies analysing the determinants of firms' innovative activities using the same dataset than us but for different periods and with different focus (Martínez-Ros, 2000; Máñez *et al.*, 2009a; and, Martínez-Ros and Labeaga, 2009). As for other countries, there are also a number of studies (see, e.g. Kraft, 1990, Cabagnols and Le Bas, 2002, and Baldwin *et al.*,

may be classified into the following groups:[20] absorptive capacity and inputs of the innovative process (R&D performance, complementary R&D activities, skilled labour, and cash flow); economic opportunities and demand conditions (export participation and expansive demand); variables capturing the market structure in which firms operate, the intensity of competition and the price elasticity of demand (number of competitors, significant market share, price-cost margin and advertising intensity); measures of firm success (firm age and size); technological opportunities (industry dummies); and, other firm characteristics (foreign capital participation and legal form). In addition, we include time dummies to control for macroeconomic-business cycle factors.

Firms' absorptive capacity may facilitate the implementation and development of innovation activities (Cohen and Levinthal, 1989). The performance of R&D activities within the firm and the labour force qualification are factors positively related to firms' absorptive capacity (Bartel and Lichtenberg, 1987). Moreover, these factors may also be considered as inputs into the production function of innovations. In particular, performing innovation activities, such as R&D and complementary R&D activities, might be a pre-condition to obtain process innovations. In addition, we consider liquidity constraints (the level of cash-flow), which may act as an obstacle for the introduction of process innovation (Hall, 2002).

The incentives to innovate also depend on the economic opportunities and demand conditions faced by firms, that is, the market possibilities to exploit

2002, among others). In these studies the dependent variable is not whether the firm becomes a first-time process innovator but whether the firm, in a particular year, introduces or not a process innovation, a more general decision that may include starting, continuing or exiting from the performance of this activity.

[20] Note that some of the firm/market characteristics could be classified in more than one group. See notes to Table 6 for a definition of these variables.

innovation results (Schmoockler, 1966). To capture this we consider firms' export participation, since exporting firms may need to innovate to face a higher competitive pressure in international markets (Kleinschmidt and Cooper, 1990, and Kotable, 1990). In addition, according to Cohen and Levinnthal (1989), foreign markets may facilitate the transfer of technology and so stimulate firm innovation activities. Secondly, we also consider a dummy variable capturing whether the firm faces an expansive demand. We expect the incentives to undertake innovation activities and, in particular, process innovation, to be higher for firms facing an expanding demand as they have more possibilities to exploit innovation results (Dasgupta and Stiglitz, 1980).

Following Dasgupta and Stiglitz (1980), variables capturing market structure, product market competition and price elasticity of demand may also be important drivers for process innovations. In order to control for these factors, we introduce dummies accounting for the firm number of competitors, a dummy for significant market share, the price-cost margin, and advertising intensity.[21] Regarding the effect of these variables on innovation, the empirical results reported in the literature are mixed.

The Schumpeterian usual claim regarding firms' success is that the best performing firms are more prone to undertake innovative activities. To proxy for firm success we include two variables that are standard in the literature as indicators of firm success: age and size. Firm age captures firm experience and knowledge accumulation, as well as information on the product life cycle (see,

[21] According to Dasgupta and Stiglitz (1980), the number of competitors is also related to the price elasticity of demand (the lower the number of competitors the lower the demand elasticity). Furthermore, firm advertising intensity (a proxy for horizontal product differentiation) could be capturing a higher firm monopoly power and also a decrease in the firm elasticity of demand.

e.g., Huergo and Jaumandreu, 2004, and references therein).[22] Regarding the association between firm size and innovation, there is a considerable amount of literature on this issue (see, e.g., Cohen and Klepper, 1996, Lee and Sung, 2005, and references therein). The exploitation of economies of scale and scope, larger market size, lower risk, higher appropriability conditions, etc., are the usual arguments to support a positive association between firm size and innovative activities. Empirical results are mixed, but, in general, they suggest a positive association.

Technological opportunities refer to the possibility of converting research resources into new products or better production techniques (Cohen and Levinthal, 1989). It is generally accepted that industries differ in their opportunities for technical progress, and we proxy for them by including industry dummies.

Finally, regarding other firm characteristics, we control for two variables. First, we consider foreign capital participation, as foreign ownership may have a discipline effect on the innovation activities of the firm, although the evidence from existing studies is inconclusive (see e.g., Baldwin *et al.*, 2002, Martínez-Ros and Labeaga, 2009, and, references therein). Secondly, we also control for the legal structure of the firm, and in particular, whether the firm is a limited liability corporation. The argument here is that these firms are relatively less risk averse (as compared to owned-managed firms) and thus more willing to undertake risky activities such as innovative activities (Love *et al.*, 1996).

[Table 6 about here]

[22] In order to capture possible non-linearities in the relationship between firms' age and the probability to become a first-time process innovator, we include a quadratic term in age.

Table 6 reports the results from the estimation of the probit model. These estimates are used to calculate the propensity score (probability of becoming a first-time process innovation, FTPI). These results are in general consistent with existing literature on the drivers of process innovations.[23] The performance of R&D increases the probability to become a FTPI.[24] In addition, a number of indicators of the demand conditions and market structure are also key drivers of FTPI; in particular, the variables expansive demand, number of competitors, price-cost margin and advertising intensity have a positive and significant impact on the probability to become a FTPI. Age is also found to have a positive (and non linear) effect on the probability to introduce a process innovation for the first time, in line with the evidence reported in Huergo and Jaumandreu (2004), and finally, foreign capital participation and legal form have also a significant and positive impact on the probability to become a FTPI.

However, there could still be a problem in identifying the causal effect from introducing a process innovation on productivity growth if the firm propensity to introduce a process innovation for the first time is correlated with an unobservable factor inducing an increase in the firm productivity. In section 5.3 we perform a sensitivity analysis of our propensity score matching estimators to assess the robustness of the estimated causal effect to deviations from the CIA. The plausibility of the CIA relays on the quality and amount of

[23] See, among others, e.g., Parisi *et al.* (2006), Lee and Kang (2007), Griffith *et al.* (2006), Martínez-Ros and Labeaga (2009), and references therein.

[24] This result is in line with existing studies such as Mairesse and Mohnen (2005), Baldwin *et al.* (2002), and Griffith *et al.* (2006), who also find R&D to be positively correlated with process innovations.

information contained in the set of explanatory variables of the probit model used to estimate the propensity score.

With the aim of ensuring the robustness of our results to the propensity score matching method, we use three different matching methods to construct the counterfactual, namely, nearest neighbours, radius matching and kernel matching. Nearest neighbours matches first-time process innovators with an average of the k non-innovators with the closest propensity score. Radius matching matches first-time process innovators with an average of the non-innovators within a given radius. Kernel matching matches first-time process innovators with a weighted average of some (all) non-innovators, with weights inversely proportional to the distance between the propensity score of first-time process innovators and non-innovators.[25]

5.2. Results.

We compare, using matching techniques, the productivity growth of first-time process innovators and matched non-innovators for the periods $t-1$ to t, t to $t+1$, $t+1$ to $t+2$, and $t+2$ to $t+3$.[26] Table 7 reports the results of these

[25] Matching is performed using the Stata *psmatch2* command (Leuven and Sianesi, 2003). Since we have previously estimated the propensity scores, p-values corresponding to the extra-productivity growth (EPG) are calculated using bootstrapping techniques with 2000 replications for kernel and radius matching. However, Abadie and Imbens (2008) show that due to the extreme non-smoothness of nearest neighbours matching, the standard conditions for bootstrap are not satisfied, leading the bootstrap variance to diverge from the actual variance. This may be corrected either by subsampling (Politis *et al.*, 1999) or using the Stata *nnmatch* command (Abadie *et al.*, 2004).

[26] When a first-time process innovator introduces a second innovation, its TFP growth from $t+k$ to $t+k+1$ (with $k \geq 0$) is only computed up to the previous period in which the second process innovation is introduced. First-time process innovators are considered in the analysis only up to

comparisons. To evaluate the quality of the matching analysis we provide, in summary form, the indicators for the resulting balancing of the observable variables within the matched samples (see Appendix B for details).[27]

[Table 7 about here]

We may describe our results using Figure 3. In the vertical axis of this figure we represent TFP, and in the horizontal axis the sequence of time from t-1 onwards. The analysis of self-selection into the introduction of process innovations suggested that the previous TFP level of SMEs that eventually introduce a process innovation is higher than that of non-innovators. As a result, the intercept of the first-time process innovators (FTPI) line is higher than that of the non-innovators (NI) line (A>A').

[Figure 3 about here]

Regardless of the matching procedure, our results suggest that implementing a process innovation for the first time does not guarantee immediate productivity rewards, that is, between t-1 and t the slope (α) is the same for the FTPI and NI lines. However, after its implementation (period t), as operating experience is gained (i.e. with "learning-by-using" the new process), the process innovation is improved and developed, and this in turn results in an extra productivity growth for process innovators in the subsequent period $t/t+1$. Thus, in Figure 3, the slope of the FTPI line for the sub-period t to $t+1$, (β) is greater than the slope of the NI line (α). Further, this extra productivity growth is significant at a 5% level and its value is around 4,5% (these

the year previous to the introduction of the second process innovation, and as far as in between also did not introduce product innovations.

[27] Imposing the balancing constraint ensures that the mean propensity score is not different between first-time process innovators and the matched non-innovators. We will therefore match firms on the probability to implement a process innovation for the first time captured by regressors.

estimates are reported in Table 7). Therefore, from Figure 3 it may be observed that introducing a process innovation increases the productivity gap with respect to non-innovators.

Our results also imply that the extra TFP growth of FTPI ceases after one period, and therefore, in Figure 3, the slope of FTPI and NI lines is the same from t+1 onwards (regardless of the matching procedure, there is no difference between the productivity growth of FTPI and NI, see the estimation results in Table 7). This result suggests that, as the potential for productivity improvement fades away one period after the process innovation is introduced by the firm, the path of TFP growth both for process innovators and non-innovators converges.

Our findings are consistent with existing empirical literature reporting a positive impact of process innovations on productivity growth. Parisi *et al.* (2006), using a large sample of Italian firms, provide evidence on the positive impact of the introduction of process innovations on productivity growth, although they cannot fully address the self-selection problems due to data restrictions. They found that the effect of the introduction of process innovations 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 reported over a 3-years period. Thus, they cannot evaluate the time span of this effect. Parisi *et al.* (2006) have only two observations *per* firm since they use two CIS surveys and, therefore, they cannot fully address the endogeneity issues and the causal links between innovation and productivity. We have instead annual data on the introduction of process innovation.

Lee and Kang (2007), using a cross-sectional sample of Korean manufacturing firms for 2002 (with information over the previous 3 years) also provide evidence on an instantly positive impact of process innovations on productivity growth (and that this impact is around 8.8%). The main limitation of this study is that it is confined within short term effects while the effects of innovations may continue into the long run.

Griffith *et al.* (2006) estimate the structural model of Crépon *et al.* (1998) using cross-sectional data (from CIS3 survey) for manufacturing firms in four countries. They find that in the case of France the introduction of process innovations is on average associated to a 6% increase in labour productivity (measured as sales per worker). However, for manufacturing firms in Germany, Spain and the UK they do not find this positive relationship between process innovations and productivity. Notwithstanding, Griffith *et al.* (2006) note two shortcomings in their study: on the one hand, they acknowledge that the lack of association between process innovations and productivity for Germany, Spain and the UK could be due to the fact that they are measuring revenue productivity (sales per employee, in logs) deflated using industry deflators, instead of firm specific deflators; on the other hand, as they only have cross-sectional data, they are only able to recover correlations, and these are not necessarily casual relationships.

In the case of Spain, Huergo and Jaumandreu (2004) analysed the productivity growth impact of process innovations introduced by firms taking into account firms' age, using a sample of Spanish manufacturing firms. They found that a process innovation induces (a contemporaneous) 1.5% extra productivity growth that tends to persist although attenuated, for 3 additional years.[28] Rochina-Barrachina *et al.* (2010), using a sample of large and small Spanish manufacturing firms for the period 1991-1998, but without

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

controlling for non-random selection into process innovation, 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 the existing related literature analysing the impact of process innovations on productivity growth, when controlling for non-random selection into process innovation using matching techniques, we obtain a positive effect that it is not contemporaneous, but instead induces a one year delayed increase in productivity growth. The short duration of the extra productivity growth achieved by first-time process innovators SMEs is likely to be related to the characteristics of the innovation activities performed by SMEs and the nature of the innovations they obtain as a result. Rochina-Barrachina *et al.* (2010) suggest, in a descriptive analysis, that informal innovation activities play a major role in the innovation strategies of Spanish SMEs. Those Spanish SMEs engaging in formal innovation activities usually restrict themselves to simple innovation strategies mainly based on in-house R&D. Furthermore, innovation activities of Spanish SMEs are characterised by a high degree of discontinuity. The result of these innovation strategies is mainly incremental process innovations (utility models) whose effect, in terms of extra-productivity growth, exhaust quite rapidly.

5.3. The relevance of unobservable variables in determining our results.

In this section we implement the sensitivity analysis for propensity score matching estimators proposed by Ichino *et al.* (2008). They suggest simulating potential unobservable variables in order to assess the robustness of the estimated causal effects with respect to deviations from the CIA.[29] Their simulation-based procedure relies on a simple idea. Suppose that the CIA is not satisfied given observable variables but would be satisfied if one could observe and include in the set of matching variables an additional binary variable (proxying for the omitted unobservable variable affecting both the potential productivity growth in case of not introducing a first-time process innovation, and the probability of being a first-time process innovator, after controlling for the observables in *X*).[30] They explain how to simulate convenient unobservables in order to challenge the CIA. Then, the comparison of the estimates obtained with and without matching also on the simulated unobservable is used to assess the robustness of our estimates.

In Nannicini (2007) two useful simulation approaches are proposed. According to the first one, the distribution of the unobservable is simulated by mimicking the empirical distribution of important observed variables included in the propensity score matching (that should be originally binary or a binary transformation). This simulation reveals the extent to which our estimates are robust to deviations from the CIA induced by the impossibility of observing factors similar to the ones used to generate the distribution of the unobservable. According to the second approach, by selecting those parameters characterising the distribution of the unobservable we can generate a huge decrease in the estimated causal effect of introducing a first-time process innovation on productivity growth, in comparison to our baseline potential causal effect. If this happens only under a very unlikely scenario for

[29] Nannicini (2007) presents the Stata program *sensatt* that allows performing this simulation-based sensitivity analysis.

[30] In order to make feasible the simulation, the potential unobservable should be a binary variable.

an unobservable, generating a very implausible effect on the probability of introducing a first-time process innovation, and on the potential productivity growth in case of not having introduced such an innovation, this simulation would support the robustness of the estimates derived under the CIA. That is, if only "implausible" unobservables decrease importantly our baseline potential causal effect, our sensitivity analysis would support the robustness of our matching results to departure from the CIA.

The potential unobservable to be considered under these two approaches is what is called a "dangerous" one, that is, one which may induce a positive and significant effect on productivity growth due to the introduction of a first time process innovation, even in the absence of a true causal effect. A prerequisite of such an unobservable is that it has to increase both the potential productivity growth in case of not introducing a first-time process innovation, and the probability of being a first-time process innovator, conditioning on *X*.

The results of this validation procedure are reported in Table 8. The two last columns measure how much the inclusion of the simulated unobservable affects both the probability of being a first-time process innovator, and the productivity growth of first time process innovators in case of becoming non-innovators. In these two columns, the reported figures should be greater than 1 for the simulated unobservable to be considered as a "dangerous" one.[31] In the first approach we have generated sequentially unobservables mimicking the empirical distribution function of the relevant (that is, the statistically significant) variables in the probit (see Table 6). For each simulated unobservable we have re-run the propensity score matching analysis for the period t to $t+1$ (sub-period for which we have obtained a statistically

[31] The last two columns in Table 8 report the results as odd ratios.

significant and positive effect of the introduction of a first-time process innovation on productivity growth), including in *X* also the corresponding simulated unobservable.[32] From this analysis we obtain as potential "dangerous" unobservables those mimicking the distribution of the variables *R&D performance, Age*, *Age squared*, *Expansive demand*, *More than 25 competitors* or *Advertising intensity*. However, these unobservables may not finally be considered as "dangerous" because their associated estimated effects (extra productivity growth, EPG in Table 8) are extremely similar to the ones obtained in our baseline without unobservables (see Table 7).

[Table 8 about here]

Although the results of this analysis illustrate the robustness of our baseline results to unobservables, they could also arise from the particular characteristics of the regressors used to simulate the unobservables, rather than from the fact that the baseline is robust to possible deviations from the CIA. However, similar conclusions arise from the second proposed approach as showed at the bottom of Table 8. In this second approach, the distribution of the unobservable has been created in order to have a large positive effect on the probability of being a first-time process innovator, and also a large positive effect on the productivity growth outcome in case of not being a first-time process innovator. More precisely, the simulated unobservable increases the relative probability of being a first-time process innovator by a factor greater than 200, and the relative probability of an increase in productivity growth in case of not introducing a process innovation by a factor greater than 9. However, even under this highly unrealistic scenario for the potentially

[32] For the sake of brevity, and given the extremely similar results obtained under the propensity score with nearest neighbours, kernel and radius matching, respectively, the results presented in Table 8 correspond to the propensity score using kernel matching.

"dangerous" simulated unobservable, the estimated effect is still extremely similar to the baseline estimate. Therefore, the sensitivity analysis carried out in this section, jointly with the balancing properties assessment, reinforces both that our set of observable variables in X is fairly comprehensive, and that our baseline results are robust.

6. Concluding remarks.

In this paper we have explored the causal effect of process innovations on productivity growth for a panel data sample of Spanish manufacturing SMEs. In particular, we have investigated both the extent and the life span of the productivity gains arising from the (first-time) introduction of process innovations, accounting for the endogeneity problem between the introduction of process innovations and productivity. Using stochastic dominance 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 introduce any innovation, and that the life span of this extra productivity growth lasts for one period.

From a strategic management point of view, our findings suggest that the introduction of process innovations, by boosting productivity growth, may be considered as a strategic tool through which SMEs may enhance their competitive position in the market. This is of especial relevance as competition intensifies as a result of increased globalization of markets.

Finally, from a policy point of view, understanding the links between process innovations and productivity growth is important for at least two reasons. First, deeper understanding on the key factors inducing SMEs to become first-time process innovators may help to acknowledge one of the mechanisms by which firms may achieve increased productivity growth, and this contributes to a greater knowledge about the sources of economic development. Second, our findings also suggest the convenience of implementing policy measures inducing SMEs to introduce process innovations, such as tax incentives and access to finance for the performance of R&D activities, and also measures enhancing product market competition and product differentiation. We have obtained that the probability to introduce (first-time) process innovation increases with R&D spending. Thus, we have found evidence on the role of R&D activities in enhancing SMEs "absorptive capacity" in terms of favouring the adoption of new technologies through the introduction of process innovations. Our results also suggest that older firms, with foreign capital participation and having a limited liability legal structure are more prone to become a (first-time) process innovator, so that policy makers should take these factors into account when establishing mechanisms aiming at stimulating SMEs process innovations. This issue is of especial relevance in Europe since increasing the share of innovative SMEs in the overall industrial sector is one of Europe's major challenges.

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Figure 1. Relative TFP distribution of process innovators and non-innovators in *t* (for *t* = 1991,...,2002).

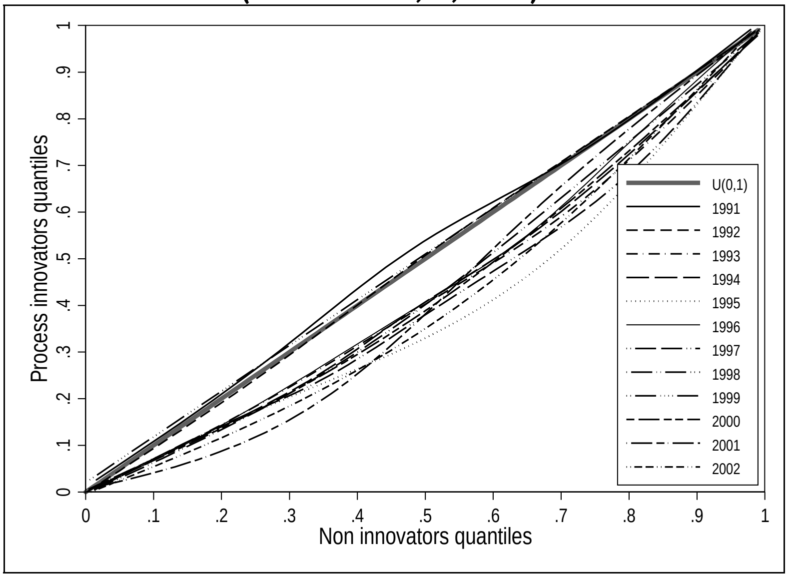
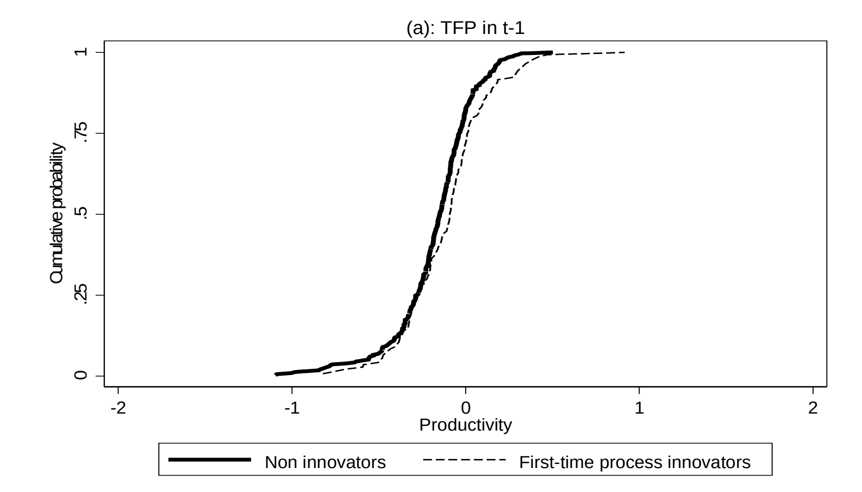


Figure 2. Comparison of the pre-entry TFP of first-time process innovators and non-innovators.

(a) Previous TFP of first time process innovators proxied by their TFP in t-1



(b) Previous TFP of first time process innovators proxied by their mean TFP up to t-1

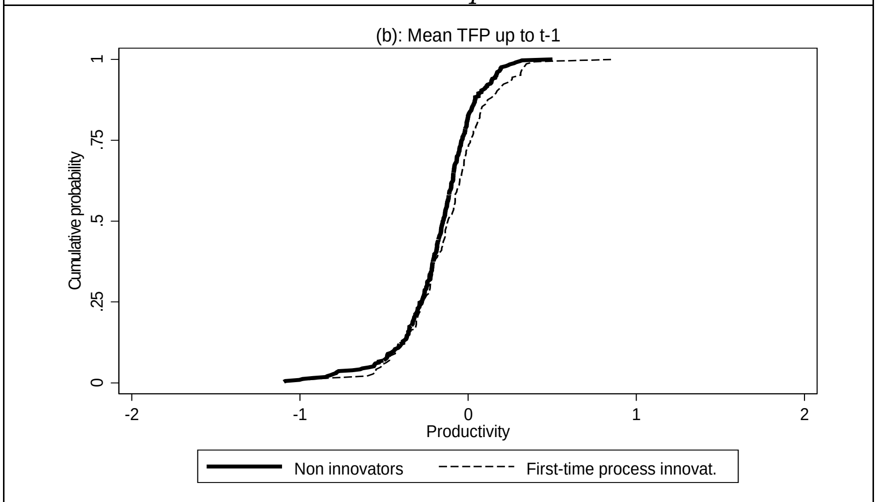
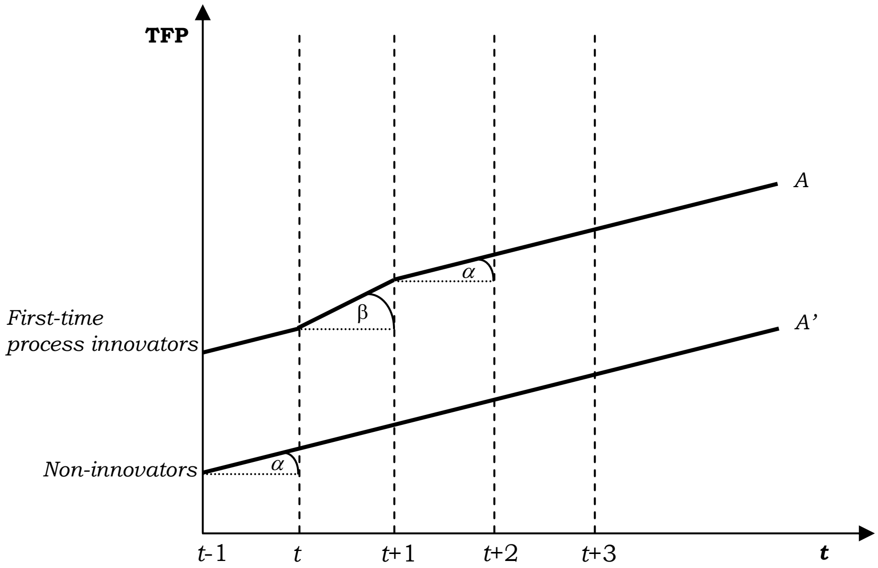


Figure 3. Summary of the matching analysis results.



Notes:

(1) A first time process-innovator in *t* is a firm that fulfils three conditions: i) it implements a process innovation in year *t* without simultaneously introducing any product innovation; ii) during the sample period previous to year *t*, it has not introduced a process or product innovation; and, iii) for at least two years previous to *t*, we observe the firm in the sample. Note also that when a first-time process innovator introduces a second innovation, its TFP growth from $t+k$ to $t+k+1$ (with $k \geq 0$) is only computed up to the previous period in which the second process innovation is introduced.

(2) We define as non-innovators those firms that do not introduce any innovation during the whole sample period and for which we have information in the sample for at least two years.

(3) Period *t* is when the firm has introduced the first-time process innovation.

Table 1. Yearly number of process innovators and non-innovators.

Years	Non-innovators	Process innovators
1991	478	116
1992	588	148
1993	684	189
1994	665	183
1995	641	169
1996	697	160
1997	755	231
1998	683	237
1999	730	212
2000	716	210
2001	722	185
2002	754	149
Total 1991-2002	8113	2189

Notes:

(1) Non-innovators are firms that do not implement any process or product innovation in year *t*.

(2) Process innovators are firms that implement a process innovation in year *t* and do not implement a product innovation in year *t*.

Table 2. TFP index and components.

Variables	**Non-innovators: Mean (Std. Dev.)**	**Process innovators: Mean (Std. Dev.)**	**Difference in means (*t*-value)**
TFP index	-0.11	-0.07	-0.04
	(0.25)	(0.25)	(-6.68)
Log of real output	12.65	13.08	-0.43
	(1.34)	(1.25)	(-13.56)
Cost share of labour input in %	33.30	30.08	3.22
	(0.19)	(0.16)	(-7.39)
Cost share of other intermediate inputs in %	63.24	65.80	-2.56
	(0.19)	(0.17)	(-5.58)
Cost share of capital input in %	3.46	4.12	-0.66
	(0.05)	(0.05)	(-5.74)
Log quantity of labour input in real terms	10.77	11.02	-0.25
	(0.90)	(0.87)	(-11.61)
Log quantity other inter. inputs in real terms	12.15	12.63	-0.48
	(1.60)	(1.42)	(-12.67)
Log quantity of capital input in real terms	10.55	11.26	-0.71
	(1.86)	(1.67)	(-16.26)

Notes:

(1) Non-innovators are firms that do not implement any process or product innovation in year *t*.

(2) Process innovators are firms that implement a process innovation in year *t* and do not implement a product innovation in year *t*.

(3) In the last column we report the test of the difference in means between non-innovators and process innovators, i.e. Diff. = Mean (non-innovators) – Mean (process innovators).

Table 3. TFP differences between process innovators in *t* and non-innovators in *t* (*t*=1991,..., 2002).

Percentile		1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
1%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.009	-0.005	-0.006	0.007	0.007	-0.013	-0.008	-0.009	0.005	-0.002	-0.007	-0.013
	t-statistic	0.69	-0.64	-0.64	0.73	0.77	-3.02	-1.3	-1.48	0.51	-0.21	-1.04	-3.18
5%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.012	-0.037	-0.010	-0.016	-0.016	-0.016	-0.246	-0.003	0.003	-0.009	-0.016	-0.037
	t-statistic	0.51	-0.19	-0.61	-0.95	-1.14	-0.9	-1.89	-1.95	0.15	-0.54	-0.99	-2.58
10%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.016	-0.033	-0.007	-0.016	-0.016	-0.060	-0.041	-0.019	-0.019	-0.044	-0.045	-0.056
	t-statistic	0.49	-1.31	-0.29	-0.68	-1.22	-2.89	-2.01	-1.85	-0.86	2.10	-2.07	-2.60
25%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.00	-0.01	-0.08	-0.07	-0.10	-0.06	-0.07	-0.10	-0.10	-0.05	-0.12	-0.14
	t-statistic	-0.02	-0.21	-2.28	-2.00	-2.94	-1.75	-2.37	-2.25	-3.14	-1.59	-3.99	-4.30
50%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.021	0.009	-0.076	-0.068	-0.153	-0.092	-0.127	-0.134	-0.134	-0.086	-0.086	-0.156
	t-statistic	0.41	0.18	-2.42	-1.98	-3.63	-2.11	-3.44	-2.35	-3.49	-2.21	-2.09	-3.59
75%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.001	0.000	-0.099	-0.059	-0.139	-0.044	-0.132	-0.133	-0.133	-0.639	-0.033	-0.087
	t-statistic	0.02	0	-2.48	-2.59	-3.45	-1.37	-3.79	-1.74	-3.68	-1.98	-0.91	-2.12
90%	$\hat{F}_A(x)-\hat{F}_B(x)$	-0.003	-0.001	-0.093	-0.099	-0.053	0.007	-0.023	-0.034	-0.034	-0.013	-0.003	0.016
	t-statistic	0.1	-0.04	-1.07	-0.96	-1.82	0.26	-0.97	-0.56	-1.35	-0.54	-0.12	-0.12
95%	$\hat{F}_A(x)-\hat{F}_B(x)$	0.007	-0.007	-0.028	-0.026	-0.027	0.023	0.004	-0.015	-0.015	-0.016	-0.004	0.028
	t-statistic	0.33	-0.43	-0.53	-0.70	-1.28	1.43	0.25	-0.39	-1.30	-0.86	-0.23	0.63
99%	$\hat{F}_A(x)-\hat{F}_B(x)$	-0.000	0.003	-0.002	-0.002	0.005	-0.004	0.001	-0.012	-0.012	-0.006	0.000	0.005
	t-statistic	-0.03	0.44	-0.22	-0.22	0.70	-0.41	0.09	-0.48	-1.22	-0.67	0.03	0.32
Longest percentile interval for which $\hat{F}_A(x)-\hat{F}_B(x)<0$ and significant at 5% level													
From	**percentile**			17%	21%	13%	34%	17%	12%	17%	31%	15%	1%
	$\hat{F}_A(x)-\hat{F}_B(x)$			-0.060	-0.067	-0.053	-0.081	-0.057	-0.049	-0.055	-0.074	-0.053	-0.013
	t-statistic			-2.23	-2.13	-2.06	-2.04	-2.21	-2.2	-2.03	-2.14	-1.98	-3.18
To	**percentile**			78%	76%	89%	66%	84%	73%	85%	75%	50%	80%
	$\hat{F}_A(x)-\hat{F}_B(x)$			-0.076	-0.083	-0.071	-0.092	-0.062	-0.080	-0.063	-0.070	-0.086	-0.082
	t-statistic			-2.1	-2.21	-2.29	-2.14	-2.1	-2.31	-2.07	-1.98	-2.09	-2.09

Notes:
(1) Non-innovators are firms that do not implement any process or product innovation in year *t*.
(2) Process innovators are firms that implement a process innovation in year *t* and do not implement a product innovation in year *t*.

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

Year	
1993	32
1994	18
1995	17
1996	11
1997	9
1998	12
1999	15
2000	10
2001	13
2002	7
Total 1993-2002	144

Notes:

(1) A first time process-innovator in *t* is a firm that fulfils three conditions: i) it implements a process innovation in year *t* without simultaneously introducing any product innovation; ii) during the sample period previous to year *t*, it has not introduced a process or product innovation; and, iii) for at least two years previous to *t*, we observe the firm in the sample.

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

		TFP in *t*-1 for first-time process innovators	Mean previous TFP for first-time process innovators
	First-time process innovators	144	144
Percentile	Non-innovators	344	344
1%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.005	-0.015
	t-statistic	-0.55	-2.25
5%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.032	-0.022
	t-statistic	-1.7	-1.10
10%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.045	-0.021
	t-statistic	-0.5	-0.73
25%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.011	0.000
	t-statistic	-0.27	0.01
50%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.080	-0.093
	t-statistic	-1.6	-1.88
75%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.081	-0.100
	t-statistic	-1.96	-2.22
90%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.055	-0.066
	t-statistic	-1.69	-1.99
95%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.060	-0.051
	t-statistic	-2.35	-2.03
99%	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.018	-0.018
	t-statistic	-1.45	-1.46
Longest percentile interval for which $\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x) < 0$ ***and significant at 5% level***			
From	**Percentile**	59%	51%
	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.102	-0.101
	t-statistic	2.06	2.04
To	**Percentile**	87%	98%
	$\hat{F}_{FTPI}(x) - \hat{F}_{NI}(x)$	-0.090	-0.043
	t-statistic	-2.52	-2.32

Notes:

(1) A first time process-innovator in *t* is a firm that fulfils three conditions: i) it implements a process innovation in year *t* without simultaneously introducing any product innovation; ii) during the sample period previous to year *t*, it has not introduced a process or product innovation; and, iii) for at least two years previous to *t*, we observe the firm in the sample.

(2) We define as non-innovators those firms that do not introduce any innovation during the whole sample period and for which we have information in the sample for at least two years.

Table 6. Probit estimates to calculate the propensity score (probability of becoming a first-time process innovator).

Variables	Marginal effects	Standard Error
Initial TFP	0.003	(0.015)
TFP_{t-1}	0.004	(0.023)
Absorptive capacity and inputs of the innovative process		
R&D performance$_{t-1}$	0.067***	(0.035)
Complementary R&D activities$_{t-1}$	-0.005	(0.009)
Share of engineers over total workforce$_{t-1}$	-0.000	(0.001)
Cash-flow$_{t-1}$	0.003	(0.003)
Economic opportunities and demand conditions		
Export participation$_{t-1}$	0.010	(0.010)
Expansive demand$_{t-1}$	0.040***	(0.016)
Market structure, competition and elasticity of demand		
From 10 to 25 competitors$_{t-1}$	0.028**	(0.015)
More than 25 competitors$_{t-1}$	0.028*	(0.018)
Price-cost margin$_{t-1}$	0.001**	(0.000)
Significant market share$_{t-1}$	-0.004	(0.009)
Advertising intensity$_{t-1}$	0.648***	(0.257)
Firms' success		
Age$_{t-1}$	0.002**	(0.001)
Age squared$_{t-1}$	-0.00003**	(0.000)
log(employment)$_{t-1}$	0.005	(0.006)
Other firm characteristics		
Foreign capital participation$_{t-1}$	0.029*	(0.021)
Legal form$_{t-1}$	0.020**	(0.010)
Number of observations	1262	

Notes:
(1) See the definitions for first-time process innovators and non-innovators in table 5.
(2) Variable definitions:
TFP: total factor productivity index.
Initial TFP: TFP in the first period the firm is observed in the sample.
R&D perform.: dummy variable taking value 1 if the firm declares positive R&D expenditures, and 0 otherwise.
Complementary R&D activities: dummy variable taking value 1 if the firm does any of the following activities: technical and scientific information services, quality normalization and control, imported technology assimilation efforts or design activities, and 0 otherwise.
Share of engineers over total workforce: ratio of engineers to total workforce.
Cash-flow: cash flow ratio on sales (in %). Cash flow is calculated as sales + stocks variation in sales – intermediate inputs – labour costs + R&D expenditures. Intermediate inputs are calculated as purchases + external services – stocks variation in purchases.
Export participation: dummy variable taking value 1 if the firm declares positive exports, and 0 otherwise.
Expansive demand: dummy variable taking value 1if the firm faces an expansive demand, and 0 otherwise.
From 10 to 25 competitors: dummy variable taking value 1 if the firm has more than 10 and less than (or equal to) 25 competitors with significant market share in its main market, and 0 otherwise.
More than 25 competitors: dummy variable taking value 1 if the firm has more than 25 competitors with significant market share in its main market.
Price cost margin: it has been calculated as the firm's ratio of (output - labour costs - intermediate inputs costs) over output. See Appendix A for the used measures to construct this index per firm.
Significant market share: dummy variable taking value 1 if the firm declares to have a significant market share, and 0 otherwise.
Advertising intensity: advertising expenditures normalized by sales.
Age: Number of years since the firm was born.
Age squared: Number of years since the firm was born to the square.
Log(employment): Log of the number of employees of the firm.
Foreign capital participation: dummy variable taking value 1 if the foreign participation in the firm capital is greater than 25%, and 0 otherwise.
Legal form: dummy variable taking value 1 if the firm is a limited liability corporation, and 0 otherwise.
(3) The regression also includes year dummies and 2-digit industry dummies.
(4) * significant at 10%, ** significant at 5% and *** significant at 1%.

Table 7. Estimates of extra productivity growth for first-time process innovators.

Period	Matching method	EPG	s.e.	Obs.
t-1/t				
	Nearest neighbours (A&I)	-0.0016	0.0154	128(1130)
	Nearest neighbours (ss)	-0.0016	0.0167	128(1130)
	Radius matching	-0.0022	0.0151	128(1130)
	Kernel matching	-0.0011	0.0157	128(1130)
t/t+1				
	Nearest neighbours (A&I)	0.0451**	0.0191	80(1130)
	Nearest neighbours (ss)	0.0451**	0.0216	80(1130)
	Radius matching	0.0448**	0.0198	80(1130)
	Kernel matching	0.0459**	0.0196	80(1130)
t+1/t+2				
	Nearest neighbours (A&I)	0.0079	0.0245	50(1130)
	Nearest neighbours (ss)	0.0079	0.0286	50(1130)
	Radius matching	0.0039	0.0257	50(1130)
	Kernel matching	0.0054	0.0271	50(1130)
t+2/t+3				
	Nearest neighbours (A&I)	0.0276	0.0235	34(1130)
	Nearest neighbours (ss)	0.0276	0.0278	34(1130)
	Radius matching	0.0248	0.0257	34(1130)
	Kernel matching	0.0259	0.0259	34(1130)

Notes:

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

(2) See the definitions for first time process-innovators and non-innovators in table 5. Note also that when a first-time process innovator introduces a second innovation, its TFP growth from $t+k$ to $t+k+1$ (with $k \geq 0$) is only computed up to the previous period in which the second process innovation is introduced.

(3) A&I means that standard errors have been calculated using Abadie and Imbens (2008) correction.

(4) ss means that in the estimation with nearest neighbours we calculate sub-sampling based standard errors (2000 draws). For radius and kernel matching we use bootstrapped standard errors (2000 replications).

(5) Kernel estimation uses the Epanechnikov Kernel.

(6) Obs. stands for observations: number of first-time process innovators and number of control observations in parentheses imposing common support.

(7)*, **, *** indicates significance at 10%, 5% and 1% level, respectively.

Table 8: Sensitivity analysis for the baseline (Table 7) matching estimation of extra productivity growth for first-time process innovators

Period	First approach: Unobservables mimicking the relevant variables in the probit	EPG	Effect on the prob. to be a FTPI	Effect on the ΔPG of FTPI in case of being NI
t/t+1				
	R&D performance $_{t-1}$	**0.045**	**5.427**	**1.965**
	Expansive demand$_{t-1}$	**0.045**	**1.647**	**1.214**
	From 10 to 25 competitors$_{t-1}$	0.045	2.136	0.961
	More than 25 competitors$_{t-1}$	**0.045**	**1.138**	**1.452**
	Price-cost margin$_{t-1}$	0.045	1.500	0.560
	Advertising intensity$_{t-1}$	**0.045**	**1.604**	**1.110**
	Age $_{t-1}$	**0.045**	**3.392**	**1.012**
	Age squared $_{t-1}$	**0.045**	**3.379**	**1.023**
	Foreign capital $_{t-1}$ participation$_{t-1}$	0.045	3.006	0.876
	Legal form$_{t-1}$	0.045	2.053	0.561

Period	Second approach: "Implausible" unobservables	EPG	Effect on the prob. to be a FTPI	Effect on the ΔPG of FTPI in case of being NI
t/t+1	**p11=p10=0.99; p01=0.5; p00=0.1**	**0.045**	**242.207**	**9.354**

Notes:

(1) EPG stands for extra productivity growth of first-time process innovators over matched non-innovators.
(2) FTPI stands for a first-time process innovator.
(3) ΔPG stands for the productivity growth increase of FTPI in case of becoming non-innovator.
(4) NI stands for non-innovators.
(5) See the definitions for FTPI and NI in table 5.
(6) The parameters p11=p10=0.99; p01=0.5; p00=0.1, have been found to characterize the FTPI distribution function on an "implausible" unobservable. See Nannicini (2007) for the mathematical definition of these parameters.

Appendix A.

A.1. Measurement of productivity.

In order to calculate TFP we define the following dummy variables,

$$p_{f\tau} = \begin{cases} 1 \text{ if firm } f \text{ belongs to size group } \tau \ (\tau = \text{SMEs, large}) \\ 0 \text{ otherwise,} \end{cases}$$

$$j_{fs} = \begin{cases} 1 \text{ if firm } f \text{ belongs to industrial sector } s \ (s\text{=1,...,20, NACE-93}) \\ 0 \text{ otherwise.} \end{cases}$$

Having a sample of N firms (f=*1,...,N*) for T years (t=*1,...,T*), and assuming that observations from different firms are independent, one can calculate the TFP index ($z_{f\tau st}$) for firm f belonging to size group τ and to industry s in year t, with the following expression:

$$\begin{aligned} z_{f\tau st} = \ln Y_{f\tau st} - \overline{\ln Y_{\tau s}} - \frac{1}{2}\sum_{i=1}^{I}\left(\varpi^i_{f\tau st} + \overline{\varpi^i_{\tau s}}\right)\left(\ln X^i_{f\tau st} - \overline{\ln X^i_{\tau s}}\right) + \\ \overline{\ln Y_{\tau s}} - \overline{\ln Y_s} - \frac{1}{2}\sum_{i=1}^{I}\left(\overline{\varpi^i_{\tau s}} + \overline{\varpi^i_s}\right)\left(\overline{\ln X^i_{\tau s}} - \overline{\ln X^i_s}\right), \end{aligned} \tag{A.1}$$

where $Y_{f\tau st}$ is the output of firm f belonging to industry s with size τ in year t, $\varpi^i_{f\tau st}$ is the cost share of input i (i=1,...,I) and $X^i_{f\tau st}$ is the quantity of input i used. Finally, for a generic variable $m_{f\tau st}$, which is alternatively $\ln Y_{f\tau st}$, $\varpi^i_{f\tau st}$ or $\ln X^i_{f\tau st}$, we define the following averages: $\overline{m_{\tau s}} = \frac{1}{NT}\sum_{f=1}^{N}\sum_{t=1}^{T} m_{f\tau st}\, p_{f\tau}\, j_{fs}$ and $\overline{m_s} = \frac{1}{NT}\sum_{f=1}^{N}\sum_{t=1}^{T} m_{f\tau st}\, j_{fs}$, where $\overline{m_{\tau s}}$ is alternatively $\overline{\ln Y_{\tau s}}$, $\overline{\varpi^i_{\tau s}}$ or $\overline{\ln X^i_{\tau s}}$, and $\overline{m_s}$ is alternatively $\overline{\ln Y_s}$, $\overline{\varpi^i_s}$ or $\overline{\ln X^i_s}$. The definition of the three inputs considered (labour, other intermediate inputs and capital), their input cost shares, and the measure of output can be found in A.2 in this Appendix.

The above index measures the TFP proportional difference of a firm f from industry s and size τ in year t in relation with a reference firm. The reference firm varies according to industry. For industry s, in particular, it is defined as the firm whose outputs and inputs are equal to the geometric mean, across the sample period, of the outputs and inputs of those firms that belong to industry *s* and, also, as the firm whose input cost shares are equal to the arithmetic mean, during the sample period, of the input cost shares of the firms belonging to industry *s*.

The first component of this index (the three first terms in expression A.1, first row after the equal), compares the output and the use of inputs for each firm in period *t* with those of the mean, across time, of firms belonging to the same industry and size group. This allows for transitivity in the comparisons across firms belonging to the same size group. The second component (three last terms in expression A.1, second row after the equal), preserves transitivity in the comparison between firms belonging to the same industry but to different size groups. This second term measures the difference between TFP of a mean firm from a given industry and size group, and TFP of a reference firm (the mean firm of those belonging to the same industry, regardless its size). Finally, as we consider a different reference firm across industries, we eliminate possible differences in TFP across industries, which will also allow considering jointly firms belonging to different industries.

A.2. Construction of the variables involved in the TFP index calculation.

To calculate the TFP index we need to construct the following variables:

Output. Real output is obtained by deflating sales plus inventory changes. The price indices used are Paasche-type firm individual indices, constructed starting from the price changes on output reported by firms.

Labour. Measured as the number of hours worked (normal hours plus overtime minus lost hours).

Other intermediate inputs. Real intermediate consumption is obtained by deflating raw materials and services purchases plus energy and fuel costs. The price indices used are Paasche-type firm individual indices, constructed starting from the price changes on inputs reported by firms.

Capital. It is computed from a measure of the stock of capital obtained starting from the firms' investments in equipment goods. It takes into account the equipment price indices published by the Spanish National Institute of Statistics.

Input cost shares. For each input, the cost share is the proportion that represents that input on the total cost of inputs, where total cost is the sum of labour costs, intermediate inputs costs and the cost for capital. Labour costs are measured as the sum of wages, insurance and other labour costs paid by the firm. The cost of capital is calculated through the estimation of the user cost of capital, which is calculated as the firm's interest rate paid by long-run debt plus an industrial estimate of equipment depreciation minus the rate of change in the price index for capital goods.

Appendix B.

There are several approaches to evaluate whether the matching procedure is able to balance the distribution of the relevant variables both for first-time process innovators and matched non-innovators, when one conditions on the propensity score. Following Sianesi (2004), we report in Table B.1 a pseudo R^2 test and a joint significance test as matching quality indicators. In particular, Sianesi (2004) suggests re-estimating the propensity score on the matched sample, that is, only on first-time process innovators and matched non-innovators, and comparing the probit pseudo R^2 before and after the matching. The probit pseudo R^2 indicates how well the regressors X explain the probability of introducing a first time process innovation. After matching, there should be no systematic differences in the distribution of the regressors between both groups, and therefore the pseudo R^2 should be fairly low when performed in the matched sample. As reported in Table B.1, we obtain very small values for the pseudo R^2 after matching for all the three matching procedures we use. In addition, Sianesi (2004) proposes an F-test on the joint significance of all the probit regressors before and after matching. The interpretation of this test is that the joint significance of the regressors should be rejected after matching but not before. We obtain this result in the three matching procedures we estimate.

Another indicator used to assess the distance in marginal distributions of the X variables is the median bias, suggested by Rosenbaum and Rubin (1985). Median bias refers to median absolute standardised bias before and after matching. The median is calculated over all regressors. Following Rosenbaum and Rubin (1985), for a given regressor, the standardised difference before matching is the difference of the sample means between first-time process innovators and non-innovators as a percentage of the square root of the average of the sample variances from the two sub samples (first-time process innovators and non-innovators, respectively). The standardised difference after matching is analogously calculated using the corresponding values for the matched samples. One potential problem in interpreting the standardised bias approach is that there is no clear indicator of the success of the matching procedure. In our results we obtain a substantial reduction in the standardised bias that seems to be consistent with the results obtained in other empirical studies.

Finally, it is also important to evaluate the proportion of observations lost to common support. The common support condition ensures that for each first-time process innovator there are non-innovators with the same observables to be matched with. In our empirical application, the number of lost observations from the group of first-time process innovators is very small, as showed in Table B.1, indicating that we do not have the problem of lack of common support.

Table B.1. Covariate balancing indicators before and after matching.

Probit pseudo R^2				
		After		
	Before	*NN*	*Radius*	*Kernel*
t-1/t	0.099	0.007	0.095	0.005
t/t+1	0.115	0.041	0.112	0.037
t+1/t+2	0.111	0.077	0.108	0.056
t+2/t+3	0.126	0.085	0.114	0.119
$P > \chi^2$				
		After		
	Before	*NN*	*Radius*	*Kernel*
t-1/t	0.000	1.000	0.744	1.000
t/t+1	0.000	1.000	0.928	0.976
t+1/t+2	0.000	0.909	0.993	0.982
t+2/t+3	0.002	0.770	0.995	0.884
Median bias				
		After		
	Before	NN	Radius	Kernel
t-1/t	23.353	2.970	16.832	2.040
t/t+1	25.765	5.085	17.374	5.237
t+1/t+2	17.404	9.933	14.269	5.141
t+2/t+3	17.113	14.169	14.832	9.145
N and % lost to common support				
	N		**% lost to common support**	
t-1/t	128		4/132	
t/t+1	80		2/82	
t+1/t+2	50		1/51	
t+2/t+3	34		1/35	

Notes:

(1) NN stands for nearest neighbours matching.
(2) The number of non-innovators used to match first-time process innovators is 1130.
(3) Probit pseudo R^2 for first-time process innovators on covariates before matching and in matched samples (after matching).
(4) $P > \chi^2$ 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.
(5) Median bias refers to median absolute standardised bias before and after matching.
(6) The % lost to common support is the share of the treated group falling outside of the common support, imposed at boundaries.