THE DYNAMIC LINKAGES AMONG EXPORTS, R&D AND PRODUCTIVITY

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Abstract

This paper estimates a dynamic model of a firm's decision to export and invest in R&D, in which we allow past export and R&D experience to endogenously affect productivity. In our empirical strategy we proceed in two steps: in the first step, using as starting point the traditional control approach method to estimate total factor productivity, we consider a more general process driving the law of motion of productivity in which we recognise the potential role that export and R&D experience might have in shaping future firms' productivity, and test whether this assumption holds; in the second step, we estimate a bivariate dynamic model of the firm's decision to invest in R&D and export, in which we analyse the linkages among investing in R&D, exporting and productivity. Using a representative sample of Spanish manufacturing firms for the period 1990-2009 we find that both export and R&D positively affect future productivity, which will drive more firms to self-select in those activities.

Key words: export experience, R&D experience, endogenous Markov, Total Factor Productivity, learning-by-exporting, returns to innovation, GMM, dynamic bivariate probit.

1. Introduction.

The relation between exports and productivity has been extensively studied.[1] Using rich micro data sets from a wide range of different countries, this research has consistently found that exporters are generally more productive than non-exporters. This empirical finding could be due to a process of self-selection of the more productive firms into export markets (Melitz, 2003) and/or from potential productivity gains accruing to firms from participation in export markets (learning-by-exporting).[2] However, Aw *et al.* (2011) point out a missing piece in this analysis: firms carrying out some investments in R&D or technology adoption could increase both productivity and the propensity to export, i.e. that the productivity export link could be conditioned by firms' R&D activities. In this line, works such as Bernard and Jensen (1997), Hallward-Dreimeier *et al.* (2002), Baldwin and Gu (2003), Aw *et al.* (2007, 2008), Damijan *et al.* (2008), Mañez *et al.* (2009a), Lileeva and Trefler (2010), Bustos (2011), and Iacovone and Javorcik (2012), find support to this correlation between exporting and firm's R&D activities that could also have an impact on productivity.

Also the relationship between R&D investments and productivity has been object of widespread analysis. There is a large tradition within the Industrial Organization literature that studies the direction of causality between both activities. The common finding of higher average productivity of R&D firms over non-R&D firms could be again the result of either a process of self-selection (only the more productive firms can afford the sunk costs associated to R&D activities, see Sutton, 1991, and Mañez *et al.*, 2009b)[3] and/or the result of the productivity returns to R&D

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[1] See Greenaway and Kneller (2007a) and Wagner (2007, 2012) for thorough reviews of this literature.

[2] Silva *et al.* (2010) provide a detailed survey of the learning-by-exporting literature. Further, Martins and Yang (2009) provide a meta-analysis of 33 empirical studies. Singh (2010) concludes that studies supporting self-selection overwhelm studies supporting learning-by-exporting.

[3] Some support for self-selection into R&D activities can be found, among others, in Hall (2002), who uses a financial constraint argument, González and Jaumandreu (1998), González *et al*. (1999) and Máñez *et al.* (2005).

investments.[4] However, a missing piece in this relationship is whether exporting influences R&D investments. Filling this gap, Bustos (2011), in a context of a trade model with heterogeneous productivity firms, predicts that during trade liberalization periods, both old and new exporters upgrade technology faster than non-exporters. Further, using data for Argentina she detects that new exporters were not more technology intensive than non-exporters before liberalization, but upgraded technology faster as they entered export markets during the liberalization period. In the same line, Atkinson and Burstein (2010) and Constantini and Melitz (2008) develop models that show, also in a context of heterogeneous productivity firms, how trade liberalization can raise the returns of R&D and thus lead to future endogenous productivity gains. Furthermore, productivity gains for firms from participating into export markets could also arise from (among others): growth in sales that allows firms to profit from economies of scale, knowledge flows from international customers that provide information about innovations reducing costs and improving quality, or from increased competition in export markets that force firms to behave more efficiently. These productivity gains could allow firms to reach the minimum R&D threshold and so to start performing R&D.

All in all, a crucial implication of these works is that R&D and export decisions are interrelated, and both activities may endogenously have an effect on firms' future productivity. Thus, the empirical work presented in this paper is related both to the literature analysing whether

[4] There are, at least, three strands in the literature supporting a positive relationship between R&D and firms' productivity growth. The first is based on the well-known *R&D capital stock model* of Griliches (1979, 1980) that analyses the relationship between R&D investments and productivity growth (see Griliches, 2000, for a survey). The second strand in the literature rendering theoretical support to the relationship between R&D and productivity growth is the *active learning model* (Ericson and Pakes, 1992, 1995, Pakes and Ericson, 1998). According to this model, R&D investments contribute to improve firms' productivity over time. Finally, endogenous growth theory is the third strand of the literature stressing the importance of R&D for productivity growth (see, e.g., Romer, 1990, and Aghion and Howitt, 1992).

export market participation has a positive impact on productivity and the effect of firms' R&D activities on productivity. However, instead of analysing the impact of exporting and performing R&D separately, we jointly analyse the linkages among R&D, exports and productivity. Furthermore, we recognise the fact that the R&D and exporting thresholds, identified in previous analyses, are not necessarily exogenous but determined by previous firms' exporting and R&D experience.

For this purpose we estimate a dynamic model of R&D investment and exporting, in which we allow past export and R&D experience to endogenously affect productivity, using data for Spanish manufacturing firms over the period 1990-2009. In the first part of our analysis, using as starting point the traditional control approach TFP (total factor productivity) estimation method (Olley and Pakes, 1997, Levinshon and Petrin, 2003), we consider a more general process driving the law of motion of productivity in which we recognise the potential role that both export and R&D experience might have in shaping future firms' productivity. Moreover, in the specification of the production function we acknowledge that firms with different export and R&D strategies (i.e., only exporters, only R&D firms, firms that both invest in R&D and export and firms that neither perform R&D nor export) may have different demands of intermediate inputs (materials). Further, we incorporate these features into the generalized method of moments (GMM) framework proposed by Wooldridge (2009). Lastly, we test whether the assumption of endogenizing the law of motion for productivity holds, estimating a dynamic model in which we regress firms' productivity on lagged productivity and lagged export/R&D firms' strategies.

In the second part or our empirical analysis we estimate a dynamic discrete choice model of exporting and R&D in which we characterize the firms' joint dynamic decisions as depending on their prior export and R&D experience, productivity, and firms' capital stocks. Therefore, the estimated dynamic bivariate probit model accounts for the existence of sunk costs in both activities and the self-selection/continuation in the performance of them depending on productivity, which, as pointed out by the first part or our empirical analysis, also depends on past exporting and R&D decisions taken by firms and influencing future paths of productivity. The estimation method also takes into account the potential simultaneity in the two firms' decisions, as well as the endogeneity of initial conditions for state variables (Wooldridge, 2005).

Our approach is closely related to that followed by Aw *et al.* (2011). Like this study, we first estimate firms' TFPs to recover the parameters driving the TFP dynamics over time and, then, use these estimated TFPs as regressors in a dynamic bivariate model on R&D and export decisions. However, although closely related, the empirical analysis in our study differs at some points, as it will be explained in detail in Section 2.

To anticipate our results, we find that both exporting and R&D activities have a positive effect on firms' future productivity. Therefore, firm's productivity levels before they start exporting or investing in R&D are not necessarily exogenous when analysing self-selection into exporting or into R&D. These productivity levels should be considered as endogenous as firm's past choices about exporting and performing R&D may result in productivity gains, allowing firms to surpass the exporting or R&D productivity thresholds. Second, we find that sunk costs are relevant both for exporting and performing R&D activities, although larger for exporting than for R&D (differently to Bustos, 2011, and Aw *et al.*, 2011). Third, our results suggest the existence of a phenomenon of self-selection/continuation of the high productivity firms into exporting and R&D activities. This is reinforced by the effect of these activities on future firms' productivity. Fourth, we find that investing in R&D in the past has a positive direct and significant effect on the likelihood of exporting. Similarly, exporting in the past has a positive and significant effect on the probability to engage in R&D. This probably suggests that each decision also affects future returns from the other activity.

The remainder of the paper is organized as follows. Section 2 summarises the related literature. Section 3 describes the data and presents some relevant descriptive statistics. Section

4 is devoted to explain the main features of the production function estimation method and how do we obtain TFP estimates. In Sections 5 and 6 we discuss the main results from our analysis. Finally, Section 7 concludes.

2. Related literature.

The theoretical context of our analysis is related to three streams of the literature: the microeconomic literature that analyses the relationship between exporting and productivity, the stream that studies the relationship between R&D and productivity, and to more recent papers that investigate altogether the linkages among R&D, exports and productivity.

The recent papers that analyse only the relationship between exports and productivity or between R&D and productivity have followed a quite similar methodological approach. This considers a general process driving the law of motion of productivity in which it is recognised the potential role that the export or R&D experience might have in shaping future firms' productivity. Traditionally, the empirical strategy has been to look at whether a productivity estimate, typically obtained as the residual of a production function, increases as a result of firms exporting or performing R&D activities. But for such an estimate to make sense, past export experience or past R&D experience should be allowed to impact future productivity. Yet some previous studies (implicitly) assume that the productivity term in the production function specification is just an idiosyncratic shock while others assume that an exogenous Markov process governs this term. It is this sort of assumptions, often critical to obtain consistent estimates (Ackerberg *et al.*, 2006), what make these analyses of the relationship between exports or R&D and productivity to lack internal consistency.

As for the analysis of the relationship between exports and productivity, Van Biesebroeck (2005) is probably the first study to extend the estimation framework developed by Olley and Pakes (1996) to include lagged export participation status as a state variable in the estimation of productivity. Somehow differently, De Loecker (2010) allows the law of motion for productivity to depend on past export status over time. Following suit, although with some differences, the recent papers by De Loecker and Warzyniski (2011) and Manjón *et al.* (2013) also allow for past export experience to impact future productivity.

As regards the relationship between R&D and productivity, to the best of our knowledge, the first paper endogenizing the law of motion for productivity allowing past R&D experience to affect future productivity is Doraszelsky and Jaumandreu (2010). Añón *et al.* (2011) and Añón and Manjón (2009) also use the same methodology to analyse multinationality and foreignness effects in the returns to R&D on productivity.

Finally, some recent papers recognise the joint role of exporting and performing R&D as productivity enhancing activities. Bustos (2011), Lileeva and Trefler (2010), Mañez *et al.* (2009a), Aw *et al.* (2007, 2008) and Damijan *et al.* (2008) find evidence about exporting being correlated with innovation and also about some linkages among exporting, innovation and productivity. Within this literature, the theoretical works by Constantini and Melitz (2008) and Atkeson and Burstein (2010) show how trade liberalization increases R&D returns and, therefore, creates incentives for firms' R&D investments, with the subsequent effect on productivity growth. Liberalization of trade regimes may lead firms to bring forward the decision to innovate, in order to be ready for future participation in the export market.

Very likely, the paper more related to our work is Aw *et al.* (2011). This paper estimates a dynamic structural model for a firm's decision to invest in R&D and export, allowing the two decisions to endogenously affect future productivity (through an endogenous Markov process for the evolution of productivity over time, in line with De Loecker, 2010, and Doraszelsky and Jaumandreu, 2010). In their model, a firm increases its expected profits from exporting by investing in R&D and exporting also contributes positively to the returns to R&D investments. Further, the returns to each activity also depend on firms' productivity, what contributes to self-selection of the most productive firms into those activities. Finally, undertaking R&D or participating in export markets contributes to future productivity, reinforcing the self-selection mechanism.

Similarly to Aw *et al.* (2011), we first estimate firms' TFPs to recover the parameters driving the TFP dynamics over time, and use these estimated TFPs as regressors in a dynamic bivariate model on R&D and export decisions that explicitly accounts for the correlation between firms' R&D and exporting decisions. However, we differ from them in several respects. First, although they also consider a general process driving the law of motion for productivity that recognises that both export and R&D experience may affect future productivity, in their structural model they do not consider the possibility of different intermediate input demands according to firms' exporting and R&D strategies as we do. In their structural model, intermediate inputs (materials) demand depends only on capital stocks and productivity. Second, when modelling the dynamic decisions to export and invest in R&D, due to the short time span of their data, they treat the firm's capital stock as fixed over time. At difference, we allow the capital to evolve following a deterministic dynamic law of motion. Finally, following their fully structural model they use a sequential approach for TFP estimation. First, they estimate by OLS a domestic revenue function (that uses the inverted demand of materials to proxy for productivity), from where they get an estimated function that captures the combined effect of capital and productivity on domestic revenue. Then, they use the fitted values of this function as dependent variables of a second step regression (estimated by nonlinear least squares) that allows them to incorporate the endogenous law of motion for productivity with respect to past export and R&D experience. In contrast, we estimate simultaneously by a GMM-system (as proposed by Wooldridge, 2009) two convenient transformations of the firm's production function, incorporating on each of them the demand of materials inversion for productivity and the endogenous law of motion for productivity, respectively.

3. Data and descriptive analysis.

The data used in this paper are drawn from the Spanish firms' manufacturing survey (ESEE) for the period 1990-2009. This is an annual survey sponsored by the Spanish Ministry of Industry and carried out since 1990 that is representative of Spanish manufacturing firms classified by industry and size categories.[5] It provides exhaustive information at the firm level, and its panel nature allows following firms over time.

The sampling procedure of the ESEE is the following. Firms with less than 10 employees were excluded from the survey. Firms with 10 to 200 employees were randomly sampled, holding around 5% of the population in 1990. All firms with more than 200 employees were requested to participate, obtaining a participation rate around 70% 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 over time.[6]

We have a sample of 36,436 observations corresponding to 4,603 firms. From this sample, to estimate TFP and to analyse the impact of export and R&D strategies on TFP, we sample out those firms that fail to supply relevant information in any given year. Further, as our TFP estimation method requires that firms supply information for at least three consecutive years, we remove all firms that do not accomplish this criterion. After cleansing the data we end up with a sample of 18,457 observations corresponding to 2,182 firms.

The two variables of interest in this work (exporting and R&D statuses) are obtained from the survey using the following questions. As for the firm's export status the relevant question is: "Indicate whether the firm, either directly, or through other firms from the same group, has exported during this year (including exports to the European Union)". For the R&D status the

[5] We have data at industry 2-digit NACE level.

[6] See http://www.funep.es/esee/sp/presentacion.asp for further details.

question we use is: “Indicate if during this year the firm has undertaken or contracted any R&D activity”.

Figure 1 plots the evolution between 1990-2009 of the proportion of firms only exporting, only undertaking R&D activities, both exporting and doing R&D and neither exporting nor doing R&D. We observe that exporting is a more frequent activity among Spanish firms than engaging in R&D activities. Further, whereas the proportion of firms exporting has increased significantly over the period (from 34.07% in 1990 to 57.59% in 2009), the percentage of firms engaged in R&D activities has only slightly increased (from 21.25% in 1990 to 26.11% in 2009). It is also important to highlight that the proportion of firms that both export and undertake R&D activities has steadily increased (from 14.06% in 1990 to 23.47% in 2009). This supports the idea that exporting and R&D are related activities, although from these figures we cannot disentangle the dynamics behind this relationship.

In Table 1, we report the cross-sectional distribution of exporting, undertaking R&D and performing both activities averaged over all years (panel A), and the conditional probabilities of exporting according to R&D status and *vice versa* (panels B and C). In our sample, we find that 34.20% of the observations correspond to firms that neither export nor engage in R&D. The proportion of observations that correspond to firms that perform R&D but do not export is 4.31%, that corresponding to firms that only export is 29.98% and, finally, the one that corresponds to firms conducting both activities is 31.52%. Both in panels B and C we observe that firms engaged in one of the two activities have a higher probability to start the other one than firms that do not perform any of them.

Table 2 reports transition rates from each combination of export and R&D status in year *t* to the corresponding one in *t+1*. Some features clearly emerge from these rates. First, there is significant persistence in each status over time. Almost 90% of the firms that neither export nor perform R&D continued in that status in *t+1*. Analogously, the empirical probability of being in the same status between t and $t+1$ is 59.63%, 83.19% and 88.13% for performing only R&D, only exporting and performing both activities, respectively. This can be the result of both high sunk costs of entering a new activity and a high degree of persistence in the underlying sources of profit heterogeneity (such as productivity).

Second, firms that already perform R&D (export) are more likely to start exporting (performing R&D) than firms that do neither. In particular, if a firm does not perform either activity in t it has a 7.26% probability of starting to export in t+1, which is lower than the 15.61% that corresponds to firms engaged only in R&D activities in t. Similarly, the probabilities to start performing R&D in $t+1$ that correspond to firms that do neither activity in t and firms that only export in t are 3.65% and 10.75%, respectively.

Third, firms engaged in both activities in year t are less likely to abandon any of the two activities than firms only performing one of them. Firms that undertake both activities have a 10.58% probability of quitting R&D and a 1.92% probability of leaving export markets. In comparison, firms that only perform R&D have a 28.90% probability of stopping this activity, while firms that only export have a 6.48% probability of leaving the export markets.

All in all, this evidence suggests the need to jointly model the firm decision to export and to engage in R&D activities.

Next, we identify some stylized facts about exporters and firms engaged in R&D activities using a simple regression analysis (see Table 3). The objective is to explore the relationship between exporting and R&D strategies (exporting only, performing R&D activities only or both) and some basic firm's characteristics. In particular, we estimate the following reduced form equation:

$$\log(y_{it}) = \beta_0 + \beta_1 Export_{it} + \beta_2 R\&D_{it} + \beta_3 Both_{it} + controls_{it} + e_{it} \tag{1}$$

where the dependent variable y_{it} is alternatively sales, capital and intermediate materials per worker, and size (as measured by the number of employees). The variables $Export_{it}$, $R\&D_{it}$, and

Both$_{it}$ capture firms' export and R&D strategies. Thus, *Export*$_{it}$ is equal to one if the firm *i* only exports in *t* (and zero otherwise), *R&D*$_{it}$ is equal to one if the firm *i* only undertakes R&D activities in *t* (and zero otherwise), and *Both*$_{it}$ is equal to one if the firm *i* both exports and engages in R&D activities in *t* (and zero otherwise). We also control for size and size squared (except for the size regression), industry and year dummies.

The differences (in %) between firms with different exporting/R&D strategies for each of the four considered firm characteristics are computed from the estimated coefficients β as 100(exp(β)-1). It is possible to observe in Table 3 that regardless of their combined export/R&D strategy, firms that only export, only perform R&D or undertake both activities simultaneously, are larger, more capital and materials intensive and have higher labour productivity than firms that neither undertake R&D nor export.

Analogously, the joint consideration of the estimates in Table 3 and the pairwise tests in Table 4 also suggests that firms that both export and undertake R&D activities are significantly bigger, more capital and intermediate materials intensive and have larger labour productivity than firms that only export or only perform R&D. As for the comparison between the firms that only export and only perform R&D, our estimates and pairwise tests suggest that firms that only export are larger, have a higher labour productivity and are more material intensive than firms that only perform R&D. However, we do not find any significant difference between these two types of firms in terms of capital intensity.

Consequently, when estimating productivity it seems important to acknowledge the significant differences between firms that do not perform R&D or export, firms that only export, firms that only perform R&D and firms that undertake both activities. We do this by considering that each of the four groups of firms has a different demand function for intermediate materials. As pointed out by De Loecker (2007, 2010), this might be an important refinement in the analysis of the effects of firms' strategies on productivity.

4. Production function and TFP estimation.

We assume that firms produce using a Cobb-Douglas technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + \omega_{it} + \eta_{it} \tag{2}$$

where y_{it} is the natural log of production of firm *i* at time *t*, l_{it} is the natural log of labour, k_{it} is the natural log of capital, m_{it} is the natural log of intermediate materials, and μ_t are time effects. As for the unobservables, ω_{it} is the productivity (not observed by the econometrician but observable or predictable by firms) and η_{it} is a standard *i.i.d.* error term that is neither observed nor predictable by the firm.

It is also assumed that capital evolves following a certain law of motion that is not directly related to current productivity shocks (i.e. it is a state variable), whereas labour and intermediate materials are inputs that can be adjusted whenever the firm faces a productivity shock (i.e. they are variable factors).[7]

Under these assumptions, Olley and Pakes (1996, hereafter OP) show how to obtain consistent estimates of the production function coefficients using a semiparametric procedure; see also Levinshon and Petrin, (2003, hereafter LP), for a closely related estimation strategy. However, here we follow Wooldridge (2009), who argues that both OP and LP's estimation methods can be reconsidered as consisting of two equations which can be jointly estimated by GMM: the first equation tackles the problem of endogeneity of the non-dynamic inputs (that is, the

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[7] The law of motion for capital follows a deterministic dynamic process according to which $k_{it} = (1-\delta)k_{it-1} + I_{it-1}$. Thus, it is assumed that the capital the firm uses in period *t* was actually decided in period *t-1* (it takes a full production period for the capital to be ordered, received and installed by the firm before it becomes operative). Labour and materials (unlike capital) are chosen in period *t*, the period they actually get used (and, therefore, they can be a function of ω_{it}). These timing assumptions make them non-dynamic inputs, in the sense that (and again unlike capital) current choices for them have no impact on future choices.

variable factors); and, the second equation deals with the issue of the law of motion of productivity. Next we consider each in detail.

Let us start considering first the problem of endogeneity of the non-dynamic inputs. Correlation between labour and intermediate inputs with productivity complicates the estimation of equation (2), because it makes the OLS estimator biased and the fixed-effects and instrumental variables methods generally unreliable (Ackerberg *et al.*, 2006). Both OP and LP's methods use a control function approach to solve this problem, by using investment in capital and materials, respectively, to proxy for "unobserved" firm productivity.

In particular, the OP's method assumes that the demand for investment in capital, $i_{it} = i\left(k_{it}, \omega_{it}\right)$, is a function of firms' capital and productivity. To circumvent the problem of firms with zero investment in capital, the LP's method uses the demand for materials (intermediate inputs), $m_{it} = m\left(k_{it}, \omega_{it}\right)$, instead, as a proxy variable to recover "unobserved" firm's productivity. Since we follow this last approach, we concentrate on the demand of materials hereafter.[8]

Therefore, when estimating productivity using these general versions of OP and LP in a sample where some firms do not participate in foreign markets, others do, and some firms do not perform R&D, while others do, it is assumed that the demand of intermediate materials for the different types of firms according to their exporting and R&D statuses is identical. However, heterogeneity in these firms' strategies may influence the demand of intermediate inputs. Therefore, analogously to De Loecker (2007, 2010), when analysing the effects of exporting on firms' productivity, we consider different demands of intermediate materials for only exporters, only R&D performers, performers of both activities and non-performers. Thus, we write the demand of materials as:

[8] Both the investment of capital demand function and the demand for intermediate materials are assumed to be strictly increasing in ω_{it} (in the case of the investment of capital this is assumed in the region in which i_{it}>0). That is, conditional on k_{it}, a firm with higher ω_{it} optimally invests more (or demands more materials).

$$m_{it} = m_S\left(k_{it}, \omega_{it}\right) \tag{3}$$

where we include the subscript S to denote different demands of intermediate inputs for the different firms' strategies (categories) according to exporting and R&D statuses. Since the demand of intermediate materials is assumed to be monotonic in productivity, it can be inverted to generate the following inverse demand function for materials:

$$\omega_{it} = h_S\left(k_{it}, m_{it}\right) \tag{4}$$

where h_S is an unknown function of k_{it} and m_{it}. Then, substituting expression (4) into the production function (2) we get:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + h_S\left(k_{it}, m_{it}\right) + \eta_{it} \tag{5}$$

Finally, by explicitly considering the four different demand functions for intermediate materials, our first estimation equation for the production function is:

$$\begin{aligned} y_{it} = {} & \beta_l l_{it} + \mu_t + 1(NP)H_{NP}\left(k_{it}, m_{it}\right) \\ & + 1(E)H_E\left(k_{it}, m_{it}\right) + 1(R\&D)H_{R\&D}\left(k_{it}, m_{it}\right) + 1(BOTH)H_{BOTH}\left(k_{it}, m_{it}\right) + \eta_{it} \end{aligned} \tag{6}$$

where 1(*NP*), 1(*E*), 1(*R&D*) and 1(*BOTH*) are indicator functions that take value one for non-performers, only exporters, only R&D performers and performers of both activities, respectively. Further, the unknown functions H in (6) are proxied by second-degree polynomials in their respective arguments.

With the specification in equation 6, the difference in the inverse demand function of firms with different productivity enhancing strategies arises not only from differences in the coefficients of k_{it} and m_{it} but also by the fact that each inverse demand function includes a dummy variable capturing the corresponding firm's strategy or combination of strategies. This is not equivalent to introduce the set of dummies identifying different strategies as additional inputs in the production function, as each one of these dummies is interacted with all the terms k_{it} and m_{it} in its corresponding polynomial. For example, introducing an R&D only dummy as an input in the production function will cause at least two problems. First, an identification problem, as we will need another estimation step to identify the parameter associated to that variable. Second, implies that a firm can substitute any input with R&D performance at constant unit elasticity (see De Loecker, 2007, 2010, for similar arguments applied to export dummies).

Notice, however, that we cannot identify β_k *and* β_m from (6). This is achieved by the inclusion of a second estimation equation in the GMM-system that deals with the law of motion for productivity.

The standard OP/LP's approaches consider that productivity evolves according to an exogenous Markov process:

$$\omega_{it} = E\left[\omega_{it}\right] + \xi_{it} = f\left(\omega_{it-1}\right) + \xi_{it} \tag{7}$$

where f is an unknown function that relates productivity in t with productivity in t-1 and ξ_{it} is an innovation term uncorrelated by definition with k_{it}. However, this assumption neglects the possibility of previous exporting and R&D experience to affect productivity. Consequently, here we consider a more general (endogenous Markov) process in which previous exporting and R&D history can influence the dynamics of productivity:

$$\omega_{it} = E\left[\omega_{it} \middle| \omega_{it-1}, E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right] + \xi_{it} = f\left(\omega_{it-1}, E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right) + \xi_{it} \tag{8}$$

where $E_{\text{it-1}}$, $R\&D_{\text{it-1}}$ and $BOTH_{\text{it-1}}$ indicate whether the firm, in period *t-1*, choses to only export, to only perform R&D, or to do both activities, respectively. Obviously, the reference category is not performing any of these activities.

Let us now rewrite the production function in (2) using (8) as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + f\left(\omega_{it-1}, E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right) + \xi_{it} + \eta_{it} \tag{9}$$

Further, since $\omega_{it} = h_S\left(k_{it}, m_{it}\right)$, we can rewrite $f\left(\omega_{it-1}, E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right)$ as:

$$\begin{aligned} f\left(\omega_{it-1}, E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right) &= f\left[h_S\left(k_{it-1}, m_{it-1}\right), E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right] \\ = F_S\left(k_{it-1}, m_{it-1}\right) &= 1(NP)F_{NP}\left(k_{it-1}, m_{it-1}\right) + 1(E)F_E\left(k_{it-1}, m_{it-1}\right) \\ &+ 1(R\&D)F_{R\&D}\left(k_{it-1}, m_{it-1}\right) + 1(BOTH)F_{BOTH}\left(k_{it-1}, m_{it-1}\right) \end{aligned} \tag{10}$$

with F being unknown functions to be proxied by second degree polynomials in their respective arguments. As before, the firms' strategy dummies are used to define the polynomials and are also included as dummy variables in the corresponding polynomials.

Lastly, substituting (10) into (9), our second estimation equation for the production function is given by:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t \\ &+ 1(NP)F_{NP}\left(k_{it-1}, m_{it-1}\right) + 1(E)F_E\left(k_{it-1}, m_{it-1}\right) + 1(R\&D)F_{R\&D}\left(k_{it-1}, m_{it-1}\right) \\ &+ 1(BOTH)F_{BOTH}\left(k_{it-1}, m_{it-1}\right) + u_{it} \end{aligned} \tag{11}$$

where $u_{it}=\xi_{it}+\eta_{it}$ is a composed error term.

Wooldridge (2009) proposes to estimate jointly the system of equations (6) and (11) by GMM using the appropriate instruments and moment conditions for each equation. Ackerberg *et al.* (2006) showed that there exists an identification problem with a first step estimation of variable inputs coefficients (affecting the labour input) in previous methods relying on a two-step estimation procedure (OP and LP), and derived a mixture of OP and LP's approaches to solve the problem. However, theirs is still a two-step estimation procedure. More recently, Wooldridge (2009) has argued that both OP and LP's estimation methods can be reconsidered as consisting of two equations which can be jointly estimated by GMM in a one-step procedure. This joint estimation strategy has the advantages of increasing efficiency relatively to two-step procedures, making unnecessary bootstrapping for the calculus of standard errors, and also solving the aforementioned identification problem. By this method we obtain, for each one of the 9 considered industries,[9] both the coefficient estimates of the production function (shown in Table A.1. in the Appendix) and firms' productivity estimates as:

$$\hat{tfp}_{it}^{s} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it} - \hat{\mu}_{it} \tag{12}$$

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[9] Following Doraszelski and Jaumandreu (2010) we group the 20 industries in which the ESEE classifies firms into 9 industries. The aim is to get enough observations to carry out industry-by-industry estimations.

where $\hat{tfp}_{it}^{s}$ is the estimated log of the TFP for firm *i* at time *t*, for industry *s*.

5. Estimation of the endogenous dynamic evolution of the TFP process over time.

In this section, we aim to recover the implicit parameters in the endogenous Markov process in (8) to check whether our assumption of considering a more general Markov process, in which we allow past export and R&D to affect future productivity, holds. Therefore, the main point at this stage of our analysis is the specification of the transition process for the state variable TFP, ω_{it}, in expression (8).

Using (8), expression (9) can be rewritten as:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + \omega_{it} + \eta_{it} \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + E\left[\omega_{it} \middle| \omega_{it-1}, E_{it-1}, R\&D_{it-1}, BOTH_{it-1}\right] + \xi_{it} + \eta_{it} \end{aligned} \tag{13}$$

from where, by (11), we can write our estimation equation of interest as:

$$\begin{aligned} \hat{tfp}_{it}^{s} &= y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it} - \hat{\mu}_t \\ &= \beta_0 + E\left[\omega_{it} \middle| \omega_{it-1}, E_{it-1}, \text{R\&D}_{it-1}, BOTH_{it-1}\right] + \xi_{it} + \eta_{it} + \varepsilon_{it} \end{aligned} \tag{14}$$

If we specify the conditional expectation in the above expression as,

$$E\left[\omega_{it} \middle| \omega_{it-1}, E_{it-1}, \text{R\&D}_{it-1}, BOTH_{it-1}\right] = \alpha_1 \omega_{it-1} + \alpha_2 E_{it-1} + \alpha_3 \text{R\&D}_{it-1} + \alpha_4 BOTH_{it-1} \tag{15}$$

we get our final estimation equation of interest:

$$\hat{tfp}_{it} = \beta_0 + \alpha_1 \omega_{it-1} + \alpha_2 E_{it-1} + \alpha_3 \text{R\&D}_{it-1} + \alpha_4 BOTH_{it-1} + s_i + \tau_{it} \tag{16}$$

where $\tau_{it} = \xi_{it} + \eta_{it} + \varepsilon_{it}$ is a composite error. We have explicitly included in estimation a set of industry dummies, s_i, to account for the fact that in the regression analysis we pool all industries' TFP estimates. Positive estimates for α_2, α_3 and α_4 should be interpreted as evidence of learning-by-exporting and/or positive returns of R&D to productivity. Furthermore, a positive estimate for α_1 implies that current productivity will carry forward to the future.

In Table 5 we present and compare the estimates resulting from estimating equation (16) by OLS, panel data random effects and System-GMM. Regardless of the estimation method used we obtain positive and significant estimates for α_2, α_3 and α_4 suggesting that exporting, performing R&D or both activities jointly in the past has a positive direct effect on current productivity. More specifically, the estimate of α_2 suggests that past only exporters have productivity that is between 2.2% to 3.8% higher (in the OLS and System-GMM estimations, respectively). The direct impact of R&D on productivity is slightly smaller (differently to Aw *et al.*, 2011), as the extra productivity for firms that undertake R&D activities only ranges from 1.8% in the OLS estimation to 3.3% in the System-GMM one. Finally, firms that undertake both activities simultaneously have the highest productivity, as they have a productivity that is between 4.4% and 5.4% higher.

Therefore, our *a priori* of considering a more general process for the law of motion of productivity allowing past export and R&D experience to affect productivity seems to be adequate. Further, the positive coefficients of α_2 and α_3 suggest that both the export and productivity thresholds, determining self-section into these activities, are endogenous to firms' R&D and export decisions. For instance, when a firm that neither exported or performed R&D starts exporting, its incorporation to the export markets could lead to an increase in productivity that would make more likely that the firm surpasses the minimum productivity threshold required to perform R&D activities (i.e., the probability that the firms self-select to perform R&D activities increases). Additionally, the estimate for α_1 is also positive and significant, meaning that there is a clear relationship between current and past productivity.

6. Dynamic exporting and R&D decisions.

Finally, we use our TFP estimates, which are robust to the endogenous firms' exporting and performing R&D choices, as regressors explaining the firm joint decisions to export and to invest in R&D in a dynamic bivariate probit model. We also account for sunk costs firms have to incur to undertake either of the two activities.

Our estimation equations are quite similar to the reduced-form model implied by the dynamic structural model in Aw *et al.* (2011). Firms entering export markets will face costs associated with entering foreign markets that may be sunk in nature. For instance, non-exporting firms have to research foreign demand and competition, establish marketing and distribution channels, and adjust their product characteristics to meet foreign tastes and/or fulfil quality and security legislation of other countries. Additionally, the development of R&D activities may involve not only creating an R&D department, purchasing specific physical assets, hiring or training specialized workforce, but also collecting information on new technologies, organizational changes and adjustments to new technologies, among others. These are costs that in turn may be considered, at least partly, as sunk costs. All these arguments imply that the firm's past export and R&D statuses should be considered as state variables in the firm´s export and R&D decisions, respectively.

Within this framework, a firm will decide to export (perform R&D) in year *t* whenever the current increase to gross operating profits associated with the decision to export (engage in R&D) plus the discounted expected future returns from being an exporter (R&D performer) in year *t* exceed sunk costs.

Further, as the value function of a firm that decides to export can be affected by its optimal R&D decision and *vice versa* (as theoretically justified by the structural model in Aw *et al.,* 2011), our joint likelihood will also include the firm's past R&D status when explaining the current probability to export and past export status when explaining the probability to perform R&D. This is the case, when there are non-negligible sunk exporting (R&D) costs and/or exporting (R&D) affects productivity. Notice that if productivity evolves endogenously depending on past exporting and R&D decisions, the firm' payoffs from exporting (R&D) depend positively on how much past exporting (R&D) increases future productivity (this is explicitly recognised in equation 15). Therefore, in our framework, the net benefits from exporting and performing R&D are increasing in productivity. This argument endogenizes the well-known self-selection mechanism[10] in the literature, given that R&D/export firm's choices increase future productivity and, therefore, would positively influence the likelihood of firms' being self-selected or continuing in such activities in the future. This is why we also include the firm's estimated productivity in our specification of the joint likelihood of exporting and investing in R&D.

Therefore, our empirical model of the joint likelihood of exporting and performing R&D will be specified in terms of sunk costs (proxied by the lagged export and R&D status in the respective choice equations) and a reduced-form group of variables proxying for the payoffs to each activity. Among them we find as especially relevant: the opposite lagged choices in each equation, estimates of TFP, and firms' capital stock. Therefore, we are primarily considering that relevant firm's variables affecting profits for each export and R&D strategy are the vector of state variables: $k_{it-1}, \omega_{it-1}, E_{it-1}, R\&D_{it-1}$. In econometric terms, the model is a dynamic discrete choice model of the export and R&D decisions, in which the choice probabilities in year *t* are conditioned on the previous vector of state variables for that year:

$$E_{it} = \begin{cases} 1 & \text{if} \quad \gamma_0^E E_{i,t-1} + \gamma_1^E R\&D_{i,t-1} + \gamma_2^E TFP_{i,t-1} + \gamma_3^E k_{i,t-1} + \beta^E X_{it-1} + \mu_t^E + s_i^E + \varepsilon_{it}^E \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$R\&D_{it} = \begin{cases} 1 & \text{if} \quad \gamma_0^{R\&D} R\&D_{i,t-1} + \gamma_1^{R\&D} E_{i,t-1} + \gamma_2^{R\&D} TFP_{i,t-1} + \gamma_3^{R\&D} k_{i,t-1} + \beta^{R\&D} X_{it-1} + \mu_t^{R\&D} + s_i^{R\&D} + \varepsilon_{it}^{R\&D} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

(17)

where γ_0 identifies sunk costs for each one of the two considered activities, γ_1 accounts for the fact that performing one activity enhances the likelihood of starting the other activity, γ_2 allows for

[10] I.e., that more productive firms are more likely to export and perform R&D.

a self-selection/continuation mechanism to be in work, γ_3 allows for a direct effect of the capital stock state variable in determining firm's exporting and R&D choices, β is the parameter vector for other relevant firm/market characteristics affecting profits in each activity, μ_t is a vector of time dummies accounting for macro conditions and s_i is a vector of industry dummies. Finally, ε_{it}, is an error term for which we assume that has two components, a permanent firm-effect (α_i) and a transitory component (u_{it}).

The estimation of equation (17) poses an "initial conditions" problem as we do not observe prior period choices for *E* and *R&D* for the first year the firms are in the dataset. To solve this problem we follow Wooldridge's (2005) method that proposes to model the distribution of the unobserved effects, α_i, conditional on the initial value of the state variables, i.e. the vector $SV_1 = \left(k_1, \omega_1, E_1, R\&D_1\right)$, and the other controls in the model in all time periods (we call this vector of controls $\bar{X}_i$):[11]

$$\alpha_i = \alpha_0 + \alpha_1 SV_{i1} + \alpha_2 \bar{X}_i + a_i \tag{18}$$

where $a_i \left| \left(SV_{i1}, \bar{X}_i\right) \sim \text{Normal}\left(0, \sigma_a^2\right)\right.$. Thus, SV_{i1} and $\bar{X}_i$ are added as additional explanatory variables in each time period *t* in the two equations in (17).

In Table 6 we report the bivariate probit estimation results. We present two different sets of results that differ in the set of variables included as other controls in the vector *X* (this affects both to equations 17 and 18). The variables included as regressors in both specifications are lagged export and lagged R&D dummies, firm's productivity, log capital stock, and a set of year and industry dummies. In columns 1 and 2 only firm's size and log age are included in vector *X*.[12]

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[11] Following Mundlack (1978) and Chamberlain (1984) we use time-averages for this vector, i.e., $\bar{X}_i = T^{-1}\sum_{t=1}^{T} X_{it}$.

[12] Table A.2. in the Appendix provides detailed information on all the variables involved in estimation of the two firm's choices; any nominal variable has been deflated using specific industry deflators according to 20 sectors of the

In columns 3 and 4 we extend our specification including firm's age and size and other potentially relevant firm/market characteristics in vector *X* (see Máñez *et al*., 2004, 2006, 2008, 2009a, 2009b). The bivariate probit model allows the error terms of the two choices to be correlated (at the bottom of Table 6 it can be seen that these correlations are positive and statistically significant).

Results are very robust to either the more parsimonious or the extended specification. First, sunk costs are high both for exporting and for R&D decisions, but larger for exporting (in Aw *et al.*, 2011, they are larger for R&D). Second, previous exporting (R&D) decisions increase the likelihood of future R&D (exporting) decisions. Third, previous productivity has a positive impact on the performance of both activities, being the magnitude of the effect similar in both decisions. The same holds for the capital stock variable.

Overall, all relevant variables are highly significant, have the expected signs, and are robust to distinct specifications and to the controls for initial conditions of state variables and mean linear projections on variables in the vector *X*. Our reduced-form regressions confirm that our refined estimation measure for TFP is relevant for explaining firms' exporting and performing R&D decisions. Most of our results are in line with the ones in Aw *et al.* (2011).

To assess the fit of the bivariate model we calculate the predicted strategies pursued by firms according to their characteristics and the transition patterns between the choices. In Table 7 we report the percentage of firms for which our model predicts the same strategy than the actual one. In general, we see that our model replicates quite well the actual patterns of export an R&D decisions (the overall fit being 88.34%). We get that our model predicts 92.44% of firms undertaking neither activity, 90.17% of firms engaged in both, 84.62% of firms only exporting, and 68.37% of firms only doing R&D.

NACE-93 classification. In estimation, explanatory variables are lagged one period. The main reason is that variables should be observable to firms when taking their decisions in period *t*.

In Table 8, we report the transition patterns of firms' export and R&D strategies. In general, we see that the predicted transition rates for the four strategies perform quite well, and are similar to the empirical transition rates observed in the data. The predicted transitions also confirm the interdependence of the two strategies. We can observe that firms engaged in one of the activities in year *t* have a higher probability to start the other one than firms that do not perform any of those. Thus, a firm not engaged in any activity in year *t* has a predicted probability of 5.7% of exporting, whereas this probability is 10.27% for firms undertaking R&D. Similarly, a firm not doing any activity in year *t* has a 2.42% probability of doing R&D only, whereas an exporting firm has a 9.25% probability of starting this activity.

7. Conclusions.

In this paper we analyse the dynamic linkages among exports, R&D and productivity. Furthermore, we recognise that the R&D and exporting thresholds are not necessarily exogenous but determined by previous firms' exporting and R&D experience.

We investigate this tenet using a two-step strategy. In the first step, we use a Cobb-Douglas production function to estimate firms' productivity by GMM. In particular, in the specification of the production function we consider that only exporters, only R&D firms, firms that perform both activities and firms that perform neither of them have different demands of intermediate materials. We also assume that firms' expectations about their future productivity depend not only on their current productivity but also on their past export and R&D experience. Further, we test whether the assumption of past export experience and R&D affecting current productivity holds. In a second step, we estimate a bivariate dynamic model of the firms' decision to invest in R&D and export, that: i) explicitly recognises the correlation between firms' R&D and export decisions; ii) accounts for the role for sunk costs (proxied by firms' past R&D and export decisions), and iii) past productivity to account for the self-selection mechanism to be in work.

As expected, we find that productivity evolves endogenously according to firms' export and R&D decisions, as shown by the evidence of a direct positive effect of past exporting and R&D on firms' future productivity. Therefore, firm's productivity levels before they start exporting or investing in R&D should be considered as endogenous as firm's past choices about exporting and performing R&D may result in productivity gains, allowing firms to surpass the exporting or R&D productivity thresholds.

Second, our estimates suggest that sunk costs are important both for investing in R&D and exporting. In the case of Spanish manufacturing, sunk costs for exporting are slightly higher than those for investing in R&D. Notwithstanding, the fact that the proportion of exporting firms is higher than that of firms performing R&D, may point out that the difference between the net returns of exporting and performing R&D, more than compensates the higher sunk costs. Third, we find evidence of a phenomenon of self-selection of the high-productivity firms into exports and R&D activities, which is reinforced by the effect of exporting and R&D on future firms' productivity. Fourth, we find that firms that perform one of the activities have a higher probability to start performing the other. This suggests that firms' decisions on one of the activities very likely affect future returns of the other activity.

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Figure 1. Evolution of the export and R&D strategies, 1990-2009.

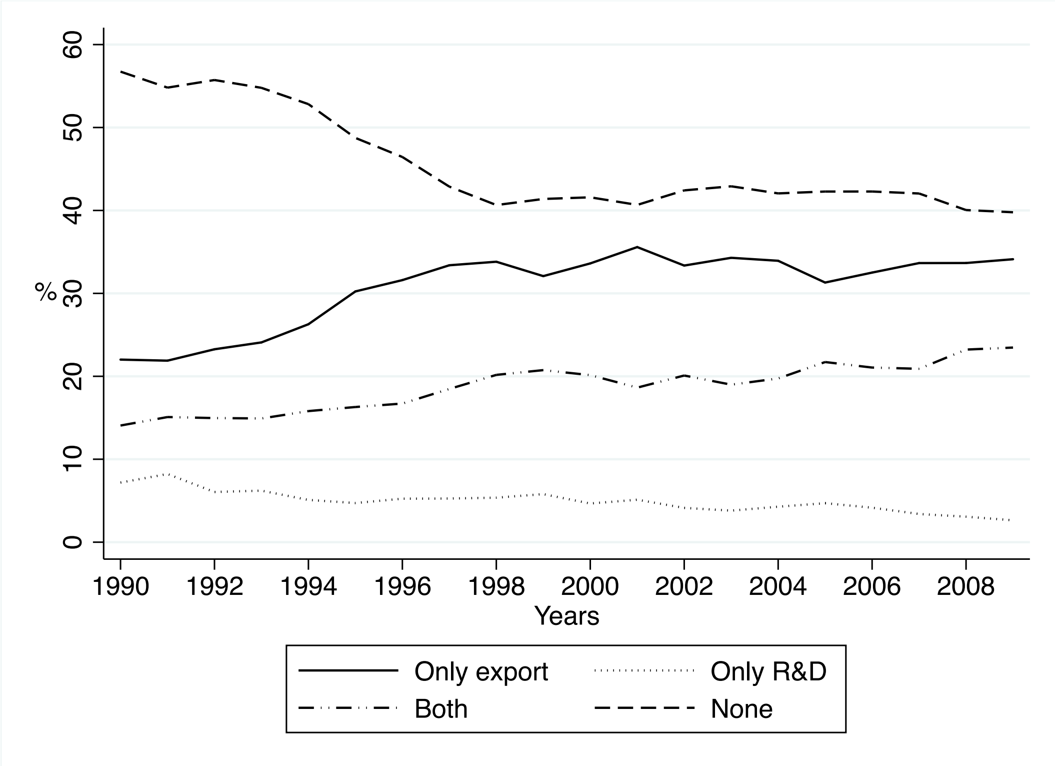

Table 1. Exports/R&D status and conditional probability of exporting.

Panel A: Export/R&D status			
Neither	R&D only	Export only	Both
34.20%	4.31%	29.98%	31.52%
Panel B: Conditional probability of exporting			
Pr(Export=0|R&D=0)	Pr(Export=1|R&D=0)	Pr(Export=0|R&D=1)	Pr(Export=1|R&D=1)
60.71	39.29	22.72	77.28
Panel C: Conditional probability of performing R&D			
Pr(R&D=0|Export=0)	Pr(R&D =1|Export =0)	Pr(R&D=0|Export=1)	Pr(R&D=1| Export =1)
52.88	47.12	11.88	88.12

Table 2. Annual transition rates for continuing firms.

Status year t	Status year t+1			
	Neither	R&D only	Export only	Both
Neither	89.84%	2.90%	6.51%	0.75%
R&D only	24.76%	59.63%	4.14%	11.47%
Export only	6.05%	0.43%	83.19%	10.32%
Both	0.53%	1.29%	10.05%	88.13%

Table 3. Differences across export and R&D strategies undertaken by firms.

	Export	R&D	Both export and R&D
Sales per worker	59.64***	38.24***	84.37***
Capital (net value) per worker	49.17***	40.86***	83.62***
Materials per worker	95.39***	58.18***	129.17***
Size	163.19***	138.79***	775.80***

Note: *** mean significance at the 1% level.

Table 4. Test of the differences across export and R&D strategies undertaken by firms.

	Coefficient	*p*-value
Sales per worker		
Both *vs.* Export	24.72***	0.000
Both *vs.* R&D	46.13***	0.000
Export *vs.* R&D	21.40***	0.000
Capital (net value) per worker		
Both *vs.* Export	34.45***	0.000
Both *vs.* R&D	32.76***	0.000
Export *vs.* R&D	-1.69	0.756
Materials per worker		
Both *vs.* Export	33.78***	0.000
Both *vs.* R&D	70.99***	0.000
Export *vs.* R&D	37.20***	0.000
Size		
Both *vs.* Export	612.61***	0.000
Both *vs.* R&D	63.02***	0.000
Export *vs.* R&D	24.41**	0.029

Note: ***, ** mean significance level at 1% and 5% levels, respectively.

Table 5. Effect of Export and R&D strategies on TFP.

	OLS	RE	System-GMM
tfp_{it-1} (α_1)	0.777***	0.704***	0.260***
	(0.000)	(0.000)	(0.000)
E_{it-1} (α_2)	0.022***	0.028***	0.038**
	(0.000)	(0.000)	(0.021)
$R\&D_{it-1}$ (α_3)	0.018**	0.023***	0.033*
	(0.021)	(0.005)	(0.056)
$BOTH_{it-1}$ (α_4)	0.044***	0.054***	0.051**
	(0.000)	(0.000)	(0.010)
Constant	1.137***	1.512***	3.737***
	(0.000)	(0.000)	(0.000)
N. observations	14,035	14,035	14,035
R-squared	0.972	0.972	
Number of firms	1,966	1,966	1,966

Notes:

1. All estimations include industry dummies.
2. Robust *p*-values in parenthesis.
3. ***, **, * mean significance level at 1%, 5% and 10% levels, respectively.

Table 6. Dynamic bivariate probit model estimations for the export and R&D decisions.

	(1) Export	(2) R&D	(3) Export	(4) R&D
Variables				
Constant	-4.075***	-5.218***	-3.985***	-5.300***
	(0.000)	(0.000)	(0.000)	(0.000)
$Export_{t-1}$	2.858***	0.199***	2.844***	0.187***
	(0.000)	(0.000)	(0.000)	(0.000
$R\&D_{t-1}$	0.175***	2.347***	0.154***	2.333***
	(0.002)	(0.000)	(0.006)	(0.000)
TFP_{t-1}	0.250**	0.278***	0.214**	0.243**
	(0.014)	(0.004)	(0.039)	(0.011)
$Capital_{t-1}$	0.141***	0.123***	0.125***	0.0816**
	(0.000)	(0.000)	(0.000)	(0.025)
Age_t	0.078	0.109*	0.0730	0.0835
	(0.180)	(0.057)	(0.238)	(0.158)
$Size_{t-1}$	0.275*	0.288***	0.328**	0.303***
	(0.087)	(0.004)	(0.044)	(0.003)
$Foreign_{t-1}$	-	-	0.406***	-0.009
			(0.00585)	(0.937)
Market $share_{t-1}$	-	-	-0.0676	-0.047
			(0.309)	(0.453)
Expansive $demand_{t-1}$	-	-	0.107*	0.001
			(0.0666)	(0.986)
Recessive $demand_{t-1}$	-	-	-0.0551	0.041
			(0.341)	(0.431)
Number competitors $0\text{-}10_{t-1}$	-	-	-0.0600	-0.105
			(0.461)	(0.165)
Number competitors $10\text{-}25_{t-1}$	-	-	0.0262	-0.118
			(0.775)	(0.170)
Number competitors $>25_{t-1}$	-	-	-0.0511	-0.111
			(0.534)	(0.172)
Public $sales_{t-1}$	-	-	0.00705	0.064
			(0.926)	(0.398)
$Appropriability_{t-1}$	-	-	0.0599	-0.009
			(0.182)	(0.818)
Initial conditions				
$Export_1$	0.583***	0.0769	0.579***	0.0913*
	(0.000)	(0.124)	(0.000)	(0.0738)
$R\&D_1$	0.060	0.448***	0.043	0.445***
	(0.327)	(0.000)	(0.502)	(0.000)
TFP_1	0.011	0.060	0.019	0.083
	(0.919)	(0.575)	(0.865)	(0.446)
$Capital_1$	-0.047	-0.032	-0.039	-0.000
	(0.163)	(0.337)	(0.275)	(0.992)
Mean values				
Mean age	-0.002	-0.002	-0.002	-0.002
	(0.231)	(0.261)	(0.311)	(0.324)
Mean size	-0.196	-0.161	-0.230	-0.148
	(0.297)	(0.190)	(0.226)	(0.235)
Mean foreign	-	-	-0.242	-0.031
			(0.147)	(0.801)
Mean market share	-	-	0.124	0.297**

			(0.340)	(0.013)
Mean expansive demand	-	-	0.171	0.343***
			(0.163)	(0.002)
Mean recessive demand	-	-	0.050	0.032
			(0.714)	(0.808)
Mean number compet. 0-10	-	-	0.143	0.120
			(0.337)	(0.384)
Mean number compet. 10-25	-	-	0.120	0.302*
			(0.461)	(0.061)
Mean number compet. >25	-	-	0.132	0.055
			(0.428)	(0.747)
Mean public sales	-	-	-0.268**	-0.055
			(0.012)	(0.589)
Mean appropriability	-	-	0.012	0.071**
			(0.779)	(0.042)
Log-likelihood: -5,593.8903			Log-likelihood: -5,492.4247	
N observations: 14,023 (1960 firms)			N observations: 13,914 (1960 firms)	
ρ = 0.147 (s.e. = 0.043)			ρ = 0.147 (s.e. = 0.043)	
LR test ρ = 0, $\chi^2(1)$ = 11.078			LR test ρ = 0, $\chi^2(1)$ = 11.252	

Notes:

1. All estimations include industry and time dummies.
2. Robust *p*-values in parentheses.
3. ***, ** and * mean significant at the 1%, 5% and 10% level of significance, respectively.

Table 7. Actual *vs.* predicted R&D and export patterns (%).

	Predicted			
Actual	Neither	Only R&D	Only export	Both
Neither	92.44	2.49	4.62	0.44
Only R&D	20.07	68.37	1.87	9.69
Only export	6.04	0.34	84.62	8.99
Both	0.53	1.34	7.95	90.17

Table 8. Actual *vs.* predicted transition rates (%).

Status in t		Status in t+1			
		Neither	Only R&D	Only export	Both
Neither	Predicted	91.32	2.42	5.66	0.59
	Actual	85.31	2.82	8.73	3.14
Only R&D	Predicted	19.19	68.22	2.33	10.27
	Actual	21.20	60.67	5.30	12.83
Only export	Predicted	4.82	0.29	85.64	9.25
	Actual	9.13	1.08	77.86	11.93
Both	Predicted	0.47	0.87	7.66	90.99
	Actual	3.49	1.48	10.45	84.58

Appendix.

Table A.1. Production function estimates (by industry).

	Capital		Labour		Materials	
	β_k	s.e.	β_l	s.e.	β_m	s.e.
1. Metals and metal products	0.102***	(0.023)	0.288***	(0.007)	0.503***	(0.082)
2. Non-metallic minerals	0.050**	(0.022)	0.118***	(0.005)	0.783***	(0.066)
3. Chemical products	0.112***	(0.043)	0.221***	(0.009)	0.685***	(0.114)
4. Agric. and ind. machinery	0.000	(0.043)	0.227***	(0.015)	0.584***	(0.170)
5. Transport equipment	0.043**	(0.018)	0.220***	(0.007)	0.696***	(0.070)
6. Food, drink and tobacco	0.047**	(0.020)	0.236***	(0.006)	0.627***	(0.059)
7. Textile, leather and shoes	0.052***	(0.016)	0.273***	(0.007)	0.603***	(0.064)
8. Timber and furniture	0.062	(0.046)	0.337***	(0.018)	0.631***	(0.134)
9. Paper and printing products	0.080***	(0.029)	0.313***	(0.012)	0.659***	(0.070)

Notes:

1. Robust standard errors in parenthesis. Significance level: ****p*<1%, ***p*<5% and * *p*<10%.
2. The production function estimates control for industry dummies.

Table A.2. Variables definition.

Export	Dummy variable taking value 1 if the firm exports, and 0 otherwise.
R&D	Dummy variable taking value 1 if the firm invests in R&D, and 0 otherwise.
TFP	Total Factor Productivity.
Capital	Value of capital stock.
Age	Number of years since the firm was born.
Size	Dummy variable taking value 1 if the number of workers is larger than 200.
Foreign	Dummy variable taking value 1 if the firm's capital is participated by a foreign enterprise.
Market share	Dummy variable taking value 1 if the firm asserts to account for a significant market share in its main market, and 0 otherwise.
Expansive demand	Dummy variable taking value 1 if the firm declares to face an expansive demand.
Recessive demand	Dummy variable taking value 1 if the firm declares to face a recessive demand.
Number of competitors 0-10	Dummy variable taking value 1 if the firm asserts to have less than (or equal to) 10 competitors with significant market share in its main market, and 0 otherwise.
Number of competitors 10-25	Dummy variable taking value 1 if the firm asserts to have more than 10 and less than (or equal to) 25 competitors with significant market share in its main market, and 0 otherwise.
Number of competitors > 25	Dummy variable taking value 1 if the firm asserts to have more than 25 competitors with significant market share in its main market, and 0 otherwise.
Public sales	Dummy variable taking value one if more than 25% of firm sales go to the public sector and zero otherwise.
Appropriability	Ratio of the total number of patents over the total number of firms that assert to have achieved innovations in the firms industrial sector (20 sectors of the two-digit NACE-93 classification) (in %).
Year dummies	Dummy variables taking value 1 for the corresponding year, and 0 otherwise.
Industry dummies	Industry dummies accounting for 20 industrial sectors of the NACE-93 classification.