The dynamics of trade and innovation: a joint approach

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Abstract: This paper analyzes the joint dynamics of internationalization and innovation decisions at the firm level. A main concern is to disentangle the observed persistence that arises from true state dependence from that emerging from firm heterogeneity, which could lead to spurious state-dependence. To this end, we use alternative econometric approaches, ranging from static pooled probit to dynamic random effects probit models that deal with the initial conditions problem. Later, we explicitly account for interdependence between these two decisions and cross-persistence by estimating a bivariate extension. Export and R&D participation are initially used as indicators of internationalization and innovation decisions, respectively. Then we extend the analysis to imports and alternative measures of innovation, particularly product and process innovations. The empirical analysis is carried out using a firm-level longitudinal dataset drawn from the ESEE, a representative sample of Spanish manufacturing, over the period 1990-2006.

Keywords: innovation, exports, persistence, binary choice panel data models

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1. Introduction

The literature on either innovation or export decisions at the firm level has been very prolific during the last decade. Rather frequently, these studies have considered one of these activities to be a determinant of the other. Previous research had already pointed out a close relationship between the two decisions. For instance, the global-economy models of endogenous innovation and growth (Grossman and Helpman, 1991) showed a strong interdependence between export and innovation. Recently, both the theoretical developments of dynamic models of heterogeneous firms facing sunk costs of entering markets and the availability of longitudinal datasets have boosted micro-level studies on the decision to export. These studies have showed that export activity is closely related to observed heterogeneity across firms in their efficiency levels, so that only the most efficient firms participate in export markets. They have also examined heterogeneity between exporters and non-exporters in several other performance dimensions by testing the self-selection and learning-by-exporting hypotheses (among others, Bernard and Jensen, 1999 and 2004). They find that exporters are usually larger and enjoy advantages in other features closely related to productivity, such as average wages and capital intensity (see Greenaway and Kneller, 2007, for a survey of empirical studies).

A shortcoming of these models is that the origin of the heterogeneity in efficiency levels across firms remains unexplained, that is, heterogeneity is assumed rather than derived. In other words, these models focus on the link between efficiency distribution across firms and export (and import) involvement, but do not step back to ask what the drivers of the observed differences in efficiency levels across firms are. In that sense, it seems reasonable to think that productivity is closely related to decisions previously pursued by firms, particularly those linked to innovation strategies. Indeed, endogenous growth theory has long emphasized the role played by innovation activity to explain productivity growth. The robust relationship that empirical evidence has found between export and efficiency can be driven by different causal mechanisms between innovation and export. For instance, it could be argued that exporters are ex-ante more productive because they carried out innovation activities before entering export markets, that is, a firm's decision to start exporting may be driven by its prior decision to innovate and consequently enhance its productivity. Alternatively, participation in export markets may enhance process innovation boosting exporters' productivity.

The primary goal of this paper is to shed more light on the empirical determinants of export and innovation decisions taking into account persistence and the interdependence between them. Specifically, this paper provides insights to address some interesting questions: (i) which firms engage in export and R&D activities?; (ii) are participation rates in both activities similar or is one activity more common than the other?, and why?; (iii) is there persistence in export/innovation activities?; if so, is it "true" or spurious persistence?; (iv) is there interdependence between exports and innovation?; (v) are export and innovation decisions driven by the same observed/unobserved firm characteristics? If so, correlation between exports and innovation may be spurious; (vi) is the observed (simultaneous) correlation between exports and innovation spurious or is it real state dependence across these two participation decisions over time, due to sunk costs or learning effects?; (vii) which is the direction of the causal mechanism? Are exporters compelled to innovate before entering export markets and/or do exporting enhances innovation participation?

It is important to bear in mind that the dynamics of the relationship between innovation and internationalization may be complex. On the one hand, if exporters enjoy *ex-ante* efficiency advantages over non-exporters (a finding broadly supported by the empirical literature, which is consistent with the self-selection hypothesis), past innovation behaviour may be relevant to explain current export strategies. The measurement of innovation, particularly the distinction between product and process innovation, can also play a relevant role here. Product innovation rather than process innovation may enhance productivity facilitating access to export markets. Thus, firms would enjoy the monopolistic position that emerges from supplying a differentiated product from competitors making it easier access export markets. Alternatively, participation in export markets may enhance efficiency gains through a process of learning-by-exporting that accrues from access to technology, best international practices, and tougher competition. In this setting, exporting firms may have a stronger incentive than home-based firms to introduce process innovation as the costs of the investment can be spread over a larger amount of output. Hence, an effect may run from export towards process innovation, although the empirical support to learning-by-exporting effect is modest (see Wagner, 2007, for a survey).

On the other hand, both innovation and export status have been found to be highly persistent (Roberts and Tybout, 1997, Geroski *et al.*, 1997, for exports and innovation, respectively). That is, being and exporter/innovator in one period raises the probability of carrying out that activity in the next period. Persistence may arise due to true state dependence (caused by sunk entry costs, *success breads success* or learning-by-doing effects) or due to observed/unobserved firm heterogeneity. A main challenge in the empirical analysis is to differentiate between the persistent behaviour that emerges from true state dependence and the persistence that arises from unobserved firm heterogeneity that could lead to spurious state-dependence. In the first case, there is a casual effect because the decision to export (or to innovate) in one period enhances the probability of exporting (or innovating) in the subsequent period. Alternatively, in the second case, firms may possess certain characteristics which make them more likely to export (to innovate). If these characteristics persist over time, they will induce persistence in the decision. Some of those characteristics will be observable (e.g., firm size, foreign ownership,..) and controlled for in the empirical analysis. The difficulties arise with unobservable characteristics (technological opportunities; managerial abilities, risk attitudes …) that affect the firms' decision to export (innovate) and that are correlated over time. Past behaviour could then affect present behaviour only due (or largely due) to these persistent unobservable firm characteristics.

In this paper, we use firm-level data from the Encuesta Sobre Estrategias Empresariales (ESEE, hereafter), a survey conducted annually since 1990 for Spanish manufacturing firms with more than 10 employees. In particular, we use a representative longitudinal dataset of Spanish manufacturing firms for a long period of time: 1990-2006. The study of the Spanish manufacturing sector over this period merits further comments. First, exporting activities of Spanish firms grew very fast over the 1990s. The initial years of the sample period are coincident with the last phase of transitory period the Spanish economy went through after joining the EU in 1986 and the process of attaining the Single European Market. Besides, exchange rate turmoil in the EMS in early nineties and subsequent domestic currency devaluations improved price competitiveness. The combination of EU membership and currency devaluation boosted access to foreign markets by domestic firms during the 1990s. This internationalization trend has attenuated in recent years, although Spanish export share in world markets has grown over the complete period despite the increasing competition from Asian countries since the late nineties. Secondly, innovation activities have been rather modest over the whole period. In spite of policy makers concerns, aggregated innovation activities of the economy make the Spanish economy to be ranked in the last positions among European countries.

The analysis is carried out using univariate and bivariate dynamic binary choice panel data models for the decisions to export and innovate in order to take account of the interactions between these two decisions. These models allow explaining the source of persistence and cross-persistence in the two activities. One of the main features of the univariate dynamic binary choice model with random effects is that it permits distinguishing between unobserved heterogeneity and genuine state dependence. In addition, the bivariate model accounts for correlation between innovation and export activities taking into account persistence. The remarkable length of the time span of the data, seventeen years, is rather unusual in the context of firm panel datasets and may enhance the robustness of the dynamic analysis.

This paper contributes to the literature in a number of ways. First, the empirical approach takes into account the dynamic characteristics of both innovation and internationalization activities as well as the interdependence between the two decisions. The econometric methods deal with the issue of initial conditions and correlated unobserved heterogeneity in dynamic binary choice models using both Wooldridge (2005) and Heckman (1981) methods. The paper assumes explicitly that both export and innovation are endogenous variables. We use then a dynamic random effect probit to address crossed-links between both strategies. The empirical work builds upon recent papers that have applied this framework to analyze the relationship between unemployment and low-wage employment (Stewart, 2007) and the joint ownership of stocks and mutual funds (Alessie *et al.*, 2005). Other authors have also addressed the interdependence between innovation and exports using bivariate probit models [Aw *et al*., 2007, 2008; Damijan, Kostevc and Polanec, 2008; Girma *et al.*, 2008]. Secondly, the nature of both innovation and internationalization activities are carefully analyzed. We initially measure innovation with R&D expenses, a very common measurement of technological activities by firms. Later, we shift from an input to an output perspective on innovative activities, and use both process and product innovation to proxy innovation activities. Thirdly, the robustness analysis is extended to include import activities as an alternative measurement of internationalization.

The paper is organized as follows. Section 2 provides a description of the related literature on the relationship between trade and innovation. Section 3 describes the data and provides some preliminary evidence. The econometric model is sketched out in section 4, and estimation results as well as some extensions are discussed in section 5. Finally, Section 6 summarizes main conclusions.

2. Trade and innovation: a revision of related literature

The relationship between international trade and innovation has been widely addressed by the economic literature. International trade theory has long pointed to technological differences in order to explain trade patterns across countries (Bloomfield, 1994). This relationship was made more explicit when market imperfections were incorporated to trade models, as in neo-technological models that emphasized the role played by persistent technological gaps among countries (Posner, 1961) or in those models based on the effects of the product cycle life on the decision to export (Vernon, 1966). Later, several models dug deeper into the role played by technological activities in international trade flows, under the premise that these activities are a main source of product differentiation (Grossman and Helpman, 1995).

The empirical work devoted to examine the effects of innovation activities on aggregated export flows (at cross-country and/or cross-industry level) is widespread. Wakelin (1998a) estimated this relationship for a panel of OECD countries finding high inter-industry heterogeneity. The availability of micro-level data boosted firm-level empirical studies that obtained rather mixed results. For example, Hirsch and Bijauoui (1985) and Willmore (1992) did not obtain evidence in favor of a positive relationship for Israeli and Brazilian firms, respectively, while Kumar and Siddhartan (1994), Braunerhjelm (1996), and Wakelin (1998b) did find a positive association. These studies differ both in the proxies used for innovation and in the features of the subsamples of firms investigated (innovators, exporters,..). Furthermore, most of them examined the relationship between innovation and export intensities rather than participation decisions.

Recently, a number of firm-level (and plant-level) studies have resumed the investigation of the link between innovation and internationalization. In contrast to the aforementioned studies, recent work emphasizes the importance of heterogeneity in efficiency levels across firms. Wagner (2007) summarizes the main findings of this literature. First, exporters are different from non-exporters in several dimensions (productivity, size…). Secondly, evidence is broadly consistent with self-selection hypothesis that predicts that only more efficient firms enter export markets. Thirdly, evidence supporting the existence of a productivity-enhancing effect of exporting (learning-by-exporting hypothesis) is mixed. This empirical work builds upon Clerides *et al.* (1998) and Melitz (2003) dynamic models of heterogeneous firms that face sunk costs of entering export markets, inspired by Jovanovic (1982) model of firm dynamics. A main characteristic of these models is that firms draw their productivity level from a known statistical distribution. Only more productive firms enter a market (home, foreign), or stay in if they had entered previously. Less productive firms either do not enter or decide to exit a market. Hence, firms differ in their productivity levels, but these levels are given and not derived endogenously in the model. Thus, these theoretical models predict *ex-ante* (before entering foreign markets) productivity advantages of exporters over non-exporters, although they do not preclude additional efficiency gains that may later (after entry) accrue to exporters (learning by exporting).

Interestingly, Melitz (2003) suggests that higher productivity may also be thought of as producing a higher quality variety at equal cost. Though it might be reasonable to relate quality varieties with product innovations, there is not an explicit role for the latter in his model. More recently, Costantini and Melitz (2008) develop a model where both innovation and export are endogenous decisions. Their model predicts that the anticipation of trade liberalization brings forward the firm's decision to innovate relative to that of entering export market, which may influence the causation link between export status and productivity. Their model excludes a learning-by-exporting channel, so innovation- or productivity-enhancing effects derived from export experience are precluded. This model is similar to that by Atkeson and Burstein (2007), who also examine the two decisions though considering that each firm chooses a different level from a continuum of innovation intensities. By contrast, Costantini and Melitz (2008) consider it as a more radical decision: either adoption of a new technology or major product quality upgrades/redesign.

When assessing the direction of causality between innovations and export decision the distinction between product and process innovation may be important. On the one hand, it might be argued that product innovations aim at attaining new consumers are more relevant to explain the decision to export. The supply of a differentiated product confers firms some market power facilitating their access to foreign markets. This is coherent with the classical product life-cycle theory (Klepper, 1996), which suggests that product innovation dominates in early stages, while process innovations are more relevant in mature phases of the life cycle, when production scale is larger so productive efficiency becomes increasingly important. Thus, Damijan *et al.* (2008) find that product innovation is crucial to explain the export decision for Slovenian firms.[1] On the other hand, process innovation, associated to cost-savings and improvements in technical conditions, enhances firm efficiency, which could stimulate export activity. This positive effect of process innovation on export is probably more relevant in homogeneous-product industries where price competition is more intense. Recent research on the link between innovation and productivity emphasizes the role played by process innovations (Griffith *et al.*, 2006). In sum, probably both types of innovation may help explain the self-selection of more efficient firms into export markets.

The causal link between innovation and exports may be easily reversed in presence of learning effects related to the participation in foreign markets. In this case, it seems that process innovation could play a more relevant role than product innovation. Export activities allow firms to enlarge their relevant market raising the potential benefits from process innovations. In addition, tougher competition in international markets and access

[1] Becker and Egger (2007) and Cassiman and Golovko (2007) find similar results.

to best-practices (knowledge spillovers) also strengthen the incentive to innovate. Besides, exporting may also enhance product innovation when the dynamics of the market forces firms to introduce new varieties in order to maintain their competitive position. The empirical evidence on the effect of exporting on innovation activities is more scarce (e.g., Salomon, 2006), which is consistent with the little empirical support for the learning-by-exporting hypothesis.

The aforementioned literature suggests that the relationship between exports and innovation may run in both directions. On the one hand, the link running from product innovation to productivity and then to the decision to export may explain how a firm's decision to carry out R&D and make product innovations improves its productivity and fosters the decision to enter export markets. On the other hand, the relationship running from exporting to innovation may help explain the link between exporting activity and productivity growth.

Therefore, the analysis of this relationship ought to take this interdependence into consideration. Some recent papers have examined this issue in the context of bivariate decision analysis. Aw *et al.* (2007) estimate how participation in export and innovation influences a firm's future productivity trajectory using a selection model that accounts for the endogenous decision of a firm to exit production. Aw *et al.* (2008) develop a structural model in which a domestic firm makes three dynamic decisions in each period: a discrete decision to export and two continuous decisions regarding the level of R&D and the investment in physical capital. Girma *et al.* (2008) use R&D expenditures as an indicator of innovation for Irish and British firms. Their results are mixed: while previous exporting experience enhances the innovative capability of Irish firms through increasing R&D activity, there is no effect for British firms. Damijan *et al.* (2008) estimate a bivariate probit model to assess the two-way relationship between exports and innovation. Besides, they also use propensity-score matching techniques, applied to both the export participation equation (they compare the likelihood to start exporting of innovators and non-innovators) and to the innovation participation equation (comparing innovation efforts of exporters and non-exporters). They do not find support for the hypothesis that either product or process innovations increases the probability of becoming a first-time exporter. However, they find evidence that, in a sample of medium and large first-time exporters, process (but not product) innovations lead to productivity improvements.

Lileeva and Trefler (2007) have introduced an interesting aspect in this debate between exporting, innovation and productivity. They suggest that the effect of market openness on the incentives to start exporting and making productivity-enhancing investments differs according the initial productivity level of the firm. Lower-productivity firms will incur such investments because new access to foreign markets provides them with enough sales volumes. As a result, we should observe a complementary relationship between innovation and exports for those firms. By contrast, higher-productivity firms will export without incurring in such investment. They find support for this dichotomy analyzing the effect of the FTA on Canadian firms.

A final consideration is related to the fact that export activity is not the only channel of internationalization that may be related to innovation. Access to best international practices and technology can take place through exports, but also through the acquisition of goods and services. However, the shift from export to imports is not straightforward and requires some caution. To some extent, the link between both activities emerges because a share of intermediate-good imports is reprocessed and later exported (Hummels *et al.*, 2001), which quite often is closely related to the role of multinational enterprises in international trade. A connection between productivity and import activities is expected insofar as these imported inputs provide access to foreign technology (Grossman and Helpman, 1991). Besides, firms can also attain a higher variety and/or quality of inputs through imports. In this line, some recent papers have started to incorporate imports to explain efficiency heterogeneity across firms (e.g., Kasahara and Rodrigue, 2005; Altomonte and Békés, 2008; Castellani *et al.*, 2008; and Fariñas and Martin, 2008, for Chilean, Hungarian, Italian and Spanish plants/firms, respectively). The results suggest that importers are more productive than non-importers. Kasahara and Lapham (2008) have developed a theoretical model in which more productive firms self-select into importing. Similarly to exports, the argument hinges on the existence of sunk costs related to start importing. Apparently, the argument of sunk costs related to import activity is less compelling than in the export case. These costs may arise, however, when either client-supplier relationships are the result of a matching process after which both parts establish stable sourcing relationships (see, for example, Grossman and Helpman, 2002) or importers incur in complementary costs to adapt intermediate import (and incorporated technologies) to their production processes.

3. Data and preliminary evidence.

3.1 Data

The data used in this paper are drawn from the *Encuesta Sobre Estrategias Empresariales* survey (Survey on Business Strategies), for the period 1990-2006. This survey is conducted yearly since 1990 by Fundacion SEPI, on behalf of the Spanish Ministry of Industry. The sampling scheme is as follows. Manufacturing firms with less than 10 employees are excluded from the survey. Firms with 10 to 200 employees (SMEs, henceforth) are randomly sampled by industry (at two-digit NACE level) and size strata, holding around a 4% of the population. All firms with more than 200 employees (large firms, henceforth) are requested to participate, obtaining a participation rate around 60%. The ESEE is representative of Spanish manufacturing firms classified by industrial sectors and size categories and includes exhaustive information at the firm level, especially regarding exporting and innovation activities. The relatively long sample period, which comprises 17 waves, ensures that we can observe firms' innovation and exporting behaviour over different phases of the business cycle and study their dynamics.

[INSERT TABLE 1 HERE]

The ESEE survey is an unbalanced panel,, given that some firms exit the market, shift to nonmanufacturing activities or leave the survey. These firms are replaced by others with similar characteristics in order to maintain the representativeness of the survey. Some of the econometric methods used in order to analyse the dynamics of firms' innovation and exporting behaviour require using a sample without missing data (blanks) within the temporal period for each firm. Therefore, we restrict attention to those firms that stayed in the survey at least 7 consecutive years.[2] Table 1 summarizes the main characteristics of the dataset. The sample is made up of a total of 21700 observations: 14430 observations for SMEs (those with 10 to 200 employees) and 7270 for large firms (those with more than 200 employees). These observations correspond to 1813 firms (1202 SMEs and 611 large firms) that are observed, on average, over a period of 12 consecutive years. In contrast to other studies that analyze dynamics using very short time-dimension panels, twelve years is an ample inter-temporal variation to carry out an analysis of persistence. The right column of table 1 corresponds to a full-balanced sample, comprising those firms staying in the survey over the entire period 1990-2006. This implies a huge decrease in available sample and it increases attrition problems. Unless otherwise stated, the analysis lies on the unbalanced panel.

3.2 Preliminary evidence

The focus of this paper lies in examining in depth the determinants of firm-level innovation and export participation, taking into account the dynamics and the relationship between these two decisions. Innovation is defined initially as a binary variable taking value one when the firm carries out investment in R&D in a given year t. Alternative measures of innovation will be discussed later. The export participation variable is also a binary variable that is equal to one if the firm exports in year t and zero otherwise. As figure 1 indicates, the percentage of innovating firms remains relatively stable over time, while there appears to be a smooth increase in the percentage of exporting firms, especially among SMEs, which is more intense during the nineties. The latter mimics the trend of the Spanish economy, which increased its openness over this period in the context of the fulfillment of the Single Market and consecutive phases of the EMU.

[INSERT FIGURE 1 HERE]

Table 2 provides a snapshot of the pattern of firm participation in export and innovative activities of large and SMEs in four different years. Each firm is classified into four categories according to whether it participated in both activities, exported only, carried out R&D only, or did carry neither of them. Among SMEs, the percentage of firms that participated in export markets rose from 32.3% in 1991 to 53.1% in 2006, whereas the percentage of firms with expenditures on R&D remained fairly stable around 20-22% over the sample period. As expected, both activities are far more common among large firms. In each year, a substantial share of exporting firms chose to invest in R&D. Over the sample period, about two thirds (15%) of large firms (SMEs)

[2] We select seven years because it both coincides with the average period in which a firm is in the survey over 1990-2006, and provides a temporal window long enough to carry an analysis of persistence. In some (few) occasions, two potential spells are available for the same firm; in such cases the larger spell has been selected**.**

participated in both activities, while less than 10% (42-61%) of large firms (SMEs) did not participate in either activity.

Overall, participation in the export market is more common among all firms than R&D activities. While 21.3% to 29.7% (18.9%-35.4%) of large firms (SMEs) in each year chose to export but not carry out R&D, the share of firms that only invested in R&D is relatively small. Furthermore, table 2 reveals that large firms that export are far more likely to innovate than not to innovate by almost 40 percentage points. As for SMEs, the percentage of firms exporting and carrying out R&D is smaller than that of exporting but non-innovating. In addition, exporters are far more likely to innovate than non-exporters for the two size groups.

[INSERT TABLE 2 HERE]

The evidence so far (figure 1 and table 2) points to a positive (cross-section) relationship between exporting and innovation. However, the aggregate picture hinders the dynamics of firms' individual innovation and exporting behavior over time. In particular, is it the same group of firms which continuously carry out R&D investments and/or compete in export markets (persistence)? Or, is there a high turnover in both activities while simultaneously the aggregated picture remains rather stable over time? Table 3 provides information on the dynamics of each participation decision taking the whole observed period.. Both SMEs and large firms depict a remarkably high persistence in innovation and exporting activities. Thus, 80% (for exports) and 53% (for R&D) of large firms do not change their status. For SMEs, such percentage is similar in both activities (about 64%), but the distribution between the two persistent states (never and always) is the opposite of that observed for large firms. The bottom row shows that the highest share of switchers takes place for R&D activities, and then in export participation for SMEs.

[INSERT TABLE 3 HERE]

Table 4 provides a clearer snapshot of time-persistence by depicting two-period (i.e. between period *t-1*and *t*) transition probabilities over the period 1990-2006. At first glance, the previous status of a firm is strongly positively related with its current status. Between 94% and 99% of exporters persisted to export, while 83%-93% of non-exporters continued as non-exporters. In round numbers, the probability of being an exporter (innovator) at *t* was around 80 percentage points higher for exporters (innovators) at *t-1* than for non-exporters (non-innovators). Additionally, a remarkable result is that, while for SME the transition rates in both ways (from export to non-export and viceversa) are very similar, exit from export activity is very strange for large firms. A similar pattern emerges for innovation activity, except for the higher probability of exiting than entering innovation activities for SMEs.

[INSERT TABLE 4 HERE]

Finally, table 5 examines the co-movement between participation in one activity at *t-1* and participation in the other at *t*. The results suggest that there is cross-persistence between both activities: the probability of exporting in year *t* is larger for those firms carrying out R&D investments in year *t-1* than for those not carrying out R&D in year *t-1*. The same pattern emerges for innovation with respecto to the export status at *t-1*. For example, among SMEs, 12.2% of innovators in period *t-1* make the transition to export (switched from non-exporters at *t-1* to export at period *t*). That percentage is twice the corresponding to non-innovators (6.6%). This relative difference is similar (22.6% vs. 14.5%) for large firms. Regarding the innovation transitions, 7.4% of SMEs exporters at *t-1* make the transition to innovate at *t* (vs. 3.3% of non-exporters), and for large firms the figure is 15.7% (vs. 9.0% of non-exporters).

[INSERT TABLE 5 HERE]

3.3 Determinants of export market and innovation participation

The preliminary evidence suggests the existence of persistence in each activity and a positive link between innovation and export participation. As has been indicated, the primary goal of this paper is to uncover whether this positive correlation is due to genuine state dependence effect or to (observed or unobserved) heterogeneity. This section further introduces the factors that may be driving these results.

[INSERT TABLE 6 HERE]

The probabilities of exporting and innovating over the sample period are presented in table 6. The raw *unconditional* probability of exporting (innovating) at period *t* is 60.8% (36.1%). Columns 2 and 3 of the table provide conditional probabilities by status at *t-1*. The first row of the two panels again suggests the existence of considerable state dependence in both activities: a firm exporting (innovating) at *t-1* is about 12.2 (13.7) times as likely to be exporting at *t* as a firm not exporting (not innovating) at *t-1*. However, a share of the persistence exhibited in the first row of the two panels of Table 6 could be due to heterogeneity. To account for it, we include a set of explanatory variables: firms' age, size, productivity, foreign ownership and advertising (see table A1 for variable definitions).[3] They are control variables that may positively affect both export and innovation decisions and are widely supported by the literature. Table 7 describes their average or median values (in first year in the sample) in relationship to both innovation and exporting status. Interestingly, for the sub-sample of SMEs, exporters/innovators are clearly more productive, larger, and older than both exporters/ non-innovators, and non-exporters/innovators. Non-exporters/non-innovators are the least productive, smallest and youngest firms. Furthermore, differences between innovators and non-innovators (when export status is controlled for) in productivity, size and age are remarkable. In addition, innovation and advertising seem to be quite correlated in the sample. Finally, foreign capital participation is higher among exporters than across non-exporters. Some of these results are less clear for large firms. In particular, non-exporters/innovators seem to outperform the rest of

[3] Average sales and capital stock could be alternative candidates. We have decided not to include them because they are highly correlated with productivity.

categories. However, we must bear in mind that this is a very small group of firms, which in 2006 represented 1.5% of large firms (see table 2).

[INSERT TABLE 7 HERE]

Turning to table 6, it also depicts the probabilities of exporting and innovating, (both unconditional and conditional on status at *t-1*, for sub-samples of firms according to explanatory variables. As expected from previous evidence, the probability of exporting and innovating is higher for large, foreign-owned, more productive, and older firms, as well as for those advertising. The differences between the probabilities conditional on status at *t-1* are evident within all subgroups. In addition, an exporter is more likely to carry out R&D by about 40% (0.876 vs. 0.456), a similar difference for innovating in relationship with exports (0.523 vs. 0.115). Even if there were no structural persistence for individuals, this heterogeneity would cause those firms exporting (carrying out innovative effort) at *t-1* to have a higher probability of exporting (innovating) at *t* than those who were not exporting (not investing in R&D).

In sum, there seems to be a positive link between innovative activity and exporting status, even though the direction of the relationship between both activities is not evident from the above results. In addition, innovation and exporting may be driven by the same determinants. Variables such as firm size, age and foreign ownership may be positively correlated with both innovation and export and, consequently, the observed correlation between both of them may be spurious. The regression analysis is aimed to investigate whether and to which extent the observed persistence is due to underlying differences in individual characteristics or due to a genuine causal effect of past on future status of both decisions.

4. Model specification and estimation

This section sets up the econometric modeling strategy and discusses some specification and estimation issues. We model two binary indicators of export participation and innovation participation, for firm i ($i=1,\ldots,n$) in year t ($t=1,\ldots,T$). The binary dependent variable y_{it} can be modeled in terms of a continuous latent variable y^*_{it} as given by equation (1). Each indicator variable is a function of (i) a vector of lagged observable explanatory variables, $\boldsymbol{x}_{it-1}$ (some of them may be time-invariant), including firms' age, size, productivity, foreign ownership, advertising and innovation (export) status in the export (innovation) equation;[4] (ii) state dependence through lagged export/innovation status indicator y_{it-1}; (iii) unobservable time-invariant firm-specific random effect as modeled by the component μ_i; and (iv) a time-varying idiosyncratic random error term, u_{it}:

$$y_{it} = \begin{cases} 1 & y^*_{it} > 0 \\ 0 & else \end{cases} \qquad \text{i = 1,…,N; t=2,..,T} \qquad (1)$$

$$y^*_{it} = \gamma y_{it-1} + x'_{it-1}\beta + \mu_i + u_{it}$$

[4] Explanatory variables are lagged one period to mitigate potential endogeneity problems.

We start with the estimation of pooled and random-effects univariate static models, that is, assuming implicitly no state dependence (γ=0), to later estimate pooled and random effects univariate dynamic probit models. Finally, the case of bivariate models is considered. This strategy allows us to observe changes in estimated parameters when alternative econometric approaches are used.

In dynamic probit models, it is assumed that $u_{it} \mid y_{i1}, y_{i2}, ... y_{i,t-1}, x_{it}$ is iid as N(0,1) and u_{it} is uncorrelated with $\left(y_{i1}, x_i, \mu_i\right)$. However, a shortcoming of the standard random effects model is that it relies on the assumption that individual effects (μ_i) are uncorrelated with regressors. Alternatively, Mundlak (1978) and Chamberlain (1984) allow correlation between the individual effects (μ_i) and the observed characteristics (x_{it}) by assuming that $\mu_i = \overline{x}_i a + \zeta_i$, ζ_i~*iid* normal and independent of x_{it} and u_{it} for all *i,t*. Additionally, for estimation of dynamic models such (1) we have to solve two important problems: (i) the treatment of initial conditions (y_{i1}); and (ii) persistence (time-series correlation)[5] and unobserved individual heterogeneity (μ_i). Furthermore, bivariate models bring about the problem of cross-persistence.

The initial conditions problem arises in a longitudinal binary process when the process has a first-order Markov property and contains unobserved heterogeneity. The data generation process is such that the first observation (initial condition) –y_{i1}- for each firm is affected by the same process and so is endogenous. In random effects modelling, because of the correlation between the individual-specific error term and the initial conditions, treating these endogenous initial conditions as exogenous leads to inconsistent estimates. There are, at least, three possible solutions. The first and simplest solution (Lee, 1997) is to assume that the initial value (y_{i1}) is exogenous, i.e. it is a non-random constant. That is, it is assumed that y_{i1} and μ_i are independent, which is a very strong and unrealistic assumption. If initial conditions are correlated with μ_i, the degree of state dependence (γ) will be overestimated. A second solution is the two-step estimation method proposed by Heckman (1981). In the first step we have to add a reduced form equation for the initial value of the latent variable y^*_{i1}, excluding the lagged dependent variable but including a set of exogenous instruments. The set of instruments must include some variables not included in the main equation. Then, in the second step the maximum likelihood estimates of the complete model are worked out. A third alternative was proposed by Wooldridge (2005) and it is based on conditional maximum likelihood (for serially independent errors). The author assumes that y_{i1} is random and specifies the distribution of μ_i conditional on y_{i1} and x_i.

[5] In model (1), even when u_{it} are assumed serially independent, the composite error term $\left(\mu_i + u_{it}\right)$ is correlated over time due to the individual-specific time invariant μ_i term.

$$\begin{aligned} &\mu_i = \alpha_0 + \alpha_1 y_{i1} + \alpha_2 \overline{x}_i + \zeta_i \qquad \zeta_i \sim iid\ N\left(0,\sigma_\zeta^2\right) \text{ and uncorrelated to } y_{i1} \text{ and } \overline{x}_i \\ &y_{it}^* = x_{it-1}^{'}\beta + \gamma y_{it-1} + \alpha_0 + \alpha_1 y_{i1} + \alpha_2 \overline{x}_i + \zeta_i + u_{it} \end{aligned} \quad (2)$$

The second problem in dynamic models such as (1) is related to time-series correlation, which can arise from either true state dependence or unobserved individual heterogeneity (μ_i). These two possible origins lead to quite different interpretations of correlation over time and therefore have different policy implications (Cameron and Trivedi, 2005, p. 763). On the one hand, true state dependence occurs when correlation over time is due to the causal mechanism that the decision last period determines the decision this period [$y_{it-1} \rightarrow y_{it}$]. This dependence is relatively large if the individual effect $\mu_i \approx 0$ as then $Corr\left(y_{it}, y_{it-1}\right) \approx \gamma$. This occurs when σ_μ is very small relative to σ_u . On the other hand, correlation can be caused by unobserved individual heterogeneity. In that case, even if there is not a causal mechanism (γ=0), the correlation between y_{it} and y_{it-1} is different from zero, leading to spurious state dependence.[6] Precisely, a desirable feature of random effects dynamic binary-choice models is that it allows distinguishing between unobserved heterogeneity and genuine state dependence.

Given that both export status and innovation activity are highly serially correlated and their interdependence of the two decisions (as they are both dependent and explanatory variables in equation (1)), the error terms of the two participation equations are likely to be correlated. To deal with it, in next step we estimate the two decisions simultaneously by estimating a dynamic bivariate binary choice model. This model allows examining the sources of cross-persistence (see Alessie *et al.*, 2005). Next equations, in which firm indexes are supressed, extend the previous univariate model to a bivariate context:

$$y_{jt} = \begin{cases} 1 & y_{jt}^* > 0 \\ 0 & else \end{cases} \qquad \begin{matrix} j = 1,2 \\ t = 2,\ldots,T \end{matrix} \quad (3)$$

$$y_{1t}^* = \gamma_{11} y_{1,t-1} + \gamma_{12} y_{2,t-1} + x_{t-1}^{'}\beta_1 + \mu_1 + u_{1t} \quad (4)$$

$$y_{2t}^* = \gamma_{21} y_{1,t-1} + \gamma_{22} y_{2,t-1} + x_{t-1}^{'}\beta_2 + \mu_2 + u_{2t} \quad (5)$$

where the dependent variables are indicator variables that refer to exporting (y_{1t}) and innovation (y_{2t}). As in the univariate case, the same independent variables are used in the two participation equations, while (μ_1, μ_2) is assumed to be bivariate normal with variances $\sigma_{\mu_1}^2$ and $\sigma_{\mu_2}^2$ and covariance $\sigma_{\mu_1}\sigma_{\mu_2}\rho_\mu$. Finally, error terms (u_{1t},u_{2t}) are assumed to be bivariate standard normal with covariance ρ and to be independent over time. It is also assumed that (μ_1, μ_2), u_{jt} and x_{t-1} are independent.

The empirical model given by equations (3)-(5) relates probabilities of exporting and innovating in period t to lagged firm characteristics. Lagged dummy for innovation is the key variable of interest in the exporting equation. The corresponding coefficient captures whether innovating firms are more or less likely to be exporters. The explanatory variable of particular interest in the innovation equation is the lagged export status. If $\gamma_{12} = 0$, the equation for exports does not contain the lagged innovation participation dummy. In this case, the parameters β_1, γ_{11} and $\sigma^2_{\mu_1}$ can be estimated consistently by considering only equation (4). This is the standard univariate panel data probit model for binary choice, with state dependence as well as unobserved heterogeneity. Secondly, if $y_{2,t-1}$ enters equation (4) but error terms and random effects in the fourth equation are independent of error terms and random effects in the fifth equation, then $y_{2,t-1}$ is weakly exogenous in the equation for y_{1t}. In this case (4) could be treated as a univariate model with (weakly) exogenous regressors only. Similar arguments are applied to equation (5). In this paper we estimate a dynamic bivariate probit model in which the two components of the error terms are pooled.

5. Results

The descriptive analysis in section 3 pointed out that export and innovation activities exhibit a high degree of persistence and are highly correlated. This result can be due to a genuine effect of past behavior on future activities or to underlying differences in firm characteristics (observed and unobserved) that are permanent. The former mechanism is identified as "true" state dependence, versus the "spurious" state dependence that defines the latter (Heckman, 1981). The preliminary evidence in section 3.3 also showed remarkable differences in some firm-level characteristics according to firms' degree of involvement in both activities. The goal of this section is to investigate the factors driving the observed persistence when controlling for a number of firm-level characteristics. We proceed in three steps. First, each decision is separately examined by means of a univariate approach. Secondly, both decisions are jointly considered using a bivariate framework. Finally, some sensitivity analyses are carried out introducing import and product/process innovations as alternative measures of internationalization and innovation decisions.

5.1 Univariate results

In this section we start with the simplest approach to model the decisions to export and to innovate. Table 8 depicts the results obtained from the estimation of univariate probit models for export (panel A) and innovation (panel B) participation decisions. The explanatory variables are innovation, export, foreign ownership, age, productivity, size and advertising. All of them are included with one lag to reduce potential endogeneity problems, so we assume that these variables constitute the set of x_{it-1} exogeneous explanatory variables. We also include a set of industry and time dummies.

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[6] Specifically, $Corr\left(y_{it}, y_{it-1}\right) = \rho = \sigma^2_{\mu} / (\sigma^2_{\mu} + \sigma^2_{u})$

Columns 1-3 of Table 8 present the results from static probit models. In all cases partial effects, evaluated at the sample means of the regressors, are presented to make easier the interpretation of results. In pooled regression (columns 1 and 2) coefficients are consistent and standard errors are robust to intra-group (firm) correlation. All variables have a significant effect on the decision to export and to innovate. The results of column 1 indicate that firms that innovated at *t-1* have a 23.8 % higher probability of exporting at *t* than non-innovators in the previous period, conditional on average values of the rest of variables. The effect of past exports on current innovation is similar, as shown in panel B. The main difference between the two decisions relates to the effect of foreign ownership, which is non-significant in the innovation decision. Industrial and time effects are always jointly significant, while average predicted probability overestimates (underestimates) the observed proportion of exporters (innovators).

In column 1, explanatory variables and the idiosyncratic error term (μ_i) are assumed independent. Column 2 reports the results using Mundlak (1978) approach to deal with the possible correlation between them. We include the within-individual mean of productivity as an additional explanatory variable. The results are fairly similar to those in the previous column, except for the marginal effect of lagged productivity which loses its significance in the export decision. The differences in productivity between firms are larger than within firms, which is likely driving the observed reduction in the productivity coefficient.

The estimates in columns 1 and 2 have not made use of the panel dimension of the dataset. As is well known, the common approach with a probit is a random-effects model, because there is not a sufficient statistic for a conditional fixed-effect model. The RE probit model provides more efficient estimates and allows assessing how much of the random volatility in both decisions is attributable to the unobservable individual effect. The results of column (3) show that, though significance remains, partial effects are generally reduced when individual random effects are considered. [7] Only the partial effects for size and age are larger.[8]. The intra-class correlation coefficient ρ is large (close to one) and highly significant. This implies that a high percentage of the unexplained variation both in exporting and innovation is attributed to the individual effect, suggesting that it could explain a relevant fraction of the persistence in the two decisions.

The natural next step is to estimate a dynamic random effect probit model. However, in a dynamic context two main econometric issues emerge: unobserved heterogeneity and initial conditions. As was described in Section 4, the problem with unobserved firm heterogeneity is that it can also exhibit persistence over time that, if it is not properly controlled for, leads to an overstatement of the true state dependence in each strategy (innovate or export). Then, we sketched out two approaches proposed to deal with both issues, based on

[7] We tested the stability of results using different quadrature points in reported regressions. Some initial instability led us to increase the number to 24. It improves the accuracy of results at the cost of slowing down convergence.

[8] A basic assumption of this model is that errors are not correlated with the regressors. Again, the solution in this context is to parameterize the effect by augmenting the RE model with the Mundlak specification to allow for individual effects that are correlated with the within-individual means of the regressors.

Heckman (1981) and Wooldridge (2005).

Columns 4-5 of Table 8 report the results when the lagged dependent variable is included in the set of explanatory variables in order to capture state dependence. As a benchmark, column (4) provides the results from a dynamic pooled probit model robust to clustering within individuals. Column 5 presents the results using the method proposed by Wooldridge (2005). Even after accounting for individual unobserved heterogeneity, the lagged dependent variable remains highly significant, supporting the hypotheses of true state dependence. There is some reduction in the partial effect of lagged dependent variable when the adjustment for initial conditions is included. The rest of explanatory variables reduce their marginal effect, although they are still significant. Besides, innovation (exports) at *t-1* has a positive effect on current exports (innovation). Interestingly, the intra-class correlation coefficient ρ sharply falls (when compared to the results in the random effects static model of column 3), pointing out that introducing the lagged dependent variable reduces the importance of unobserved heteregoneity in exports and innovation models. The results further show that the initial condition is also highly significant in both decisions. This implies a substantial correlation between firms' initial export status and the unobserved heterogeneity.

A potential shortcoming of Wooldridge (2005) approach is that it specifies a complete model for the individual unobserved effects (μ_i), so that the estimates could be sensitive to mis-specification of this effect. We have compared the estimated coefficients to those obtained with the approach proposed by Heckman (1981), which relies on weaker assumption.[9] Coefficients do not show large differences with those using Wooldridge (2005) approach.

In sum, previous results indicate that the partial effect of the lagged dependent variable is large; reflecting that even after accounting for individual unobserved heterogeneity, past behaviour has a relevant effect on current decisions both for exports and R&D. This true state dependence can be caused by the presence of sunk costs or learning-by-doing effects. Particularly, sunk entry costs in both export and R&D represent a barrier for entry and exit and, as consequence, can induce state dependence. Peters (2007) also emphasizes a kind of "success breads success" effect as an important factor to explain why state dependence is expected for innovation, suggesting that successful innovations stimulate subsequent innovations due to increasing market power or broader technological opportunities. Another potential reason could be the risky nature of innovation projects and asymmetric information, which may lead to financial constraints that are probably less severe for those firms that had previously succeeded.

Table 9 presents predicted probabilities of exporting and innovating for different lagged status of export and innovation (columns) and different points along the distribution of unobserved firm effects (rows), after controlling for the rest of observable exogenous determinants (at their sample means). The predictions are

[9] The Heckman estimator of dynamic random effects probit model has been obtained using the *redpace* Stata command by Stewart (2006). In the reduced form for the initial period we included a binary variable that takes value one when the firm belongs to a group.

derived using the dynamic random effect estimations in column 5 of Table 8. The comparison of panels A and B point out that innovation is a less likely outcome than exporting, but they also suggest a considerable state dependence in both decisions. For example, for those firms with an unobserved permanent effect equal to zero, the predicted probability of exporting in period *t* for firms that neither exported nor innovated in *t-1* is 30.3%. If the firm exported in *t-1* (but did not simultaneously innovate) the probability increases to 93.2%. To carry out innovative activities has also a positive effect on the predicted probability of exporting irrespectively of previous exporting status, though its effect is relatively larger for non-exporters in *t-1* (the predicted value raises from 30.3% to 42.7%) than for exporters (it increases from 93.2% to 96.6%). As we move downwards through Table 9 the predictions correspond to firms that are above-the-mean permanent firm component μ_i. For these firms expected profits for exporting (and innovating) are higher and, accordingly, predicted probabilities are also higher. It is noteworthy that the increase in the predicted probability over the distribution of the permanent firm component is greater than that corresponding to state dependence for firms with similar characteristics and μ_i=0. For example, in panel B the predicted probability of innovating at *t* for an exporter (at *t-1*) varies from 12.4% for non-innovators at *t-1* to 67.8% for innovators at *t-1*. This increase of 55.4 percentage points is smaller than 67.0 (=67.34 - 0.29), which is the variation in the probability of innovation at *t* for a firm that moves rightwards from the lower tail of the distribution of unobservables (-2σ) to the upper tail (+2σ). These results are in line to those obtained by Roberts and Tybout (1997) and Kaiser and Kongsted (2008) for Colombian and German export firms, respectively.[10]

5.2 Bivariate results

The univariate dynamic random effects model estimated in previous section allows assessing the relative importance of unobserved heterogeneity and genuine state dependence in explaining persistence in the decision to export and to innovate. In addition, the univariate regression results also pointed out to the existence of strong correlation between export and innovation, which is consistent with the preliminary evidence in section 3. The bivariate model permits the joint estimation of the two decisions allowing for correlation between the error terms in the export and innovation equations.

Table 10 reports the results of the dynamic pooled bivariate model that consists of the export and innovation decision equations. Equation (3)-(5) specify that a firm's export (R&D) participation decision in year *t* depends on the firm's participation choice of both exports and R&D in previous year, as well as on other profit-shifting characteristics. Notice that this specification does not include intertemporal correlation but it does permit the contemporaneous correlation between the two choices, *Corr* (ε_{1it}, ε_{2it}), to be non-zero. The top panel of table

[10] These authors split the columns according to 25th, 50th and 75th percentiles of the observables index. In contrast to them, most of the explanatory variables in our paper are binary, so these percentiles are less representative than average values. We have calculated Table 9 introducing these three percentiles for productivity, which is a continuous variable, and results remain qualitatively similar.

10 presents estimated coefficients. Again, previous experience in one activity has a significant effect on current participation in that activity. In addition, the results point out a positive and significant effect of past participation in exports (R&D) on current participation in R&D (exports). As for the control variables, larger, older, more productive firms that engaged in advertising in *t-1*, are more likely to participate in export and R&D activities in *t*. Foreign capital participation has a positive effect on export participation, but not in innovation. The estimated value of the correlation between the error terms of the two equations of the bivariate model is positive (0.179) and statistically significant. This implies that unobservable factors that make a firm participate in one activity tend to lead it to participate in both simultaneously.

Notwithstanding, the interpretation of bivariate binary choice model is not straightforward (Greene, 2008). Table 10 presents some relevant results in Panel A to C. Panel A shows the predicted probabilities for combinations of status at period t, while Panel B reports the predicted probability of either exporting or innovating at *t*, conditional on exporting and innovation status at *t-1*. The results point out that, after controlling for explanatory variables, both decisions remains remarkably persistent. Yet, the effect of past experience is larger for exports than for innovation. The results also suggest the existence of cross-persistence in these activities. That is, the probability of exporting (innovating) at *t* is higher when the firm innovated (exported) at *t-1* than when it did not innovate (export), independently of the export (innovation) status at *t-1*. For example, the probability of exporting at t when the firm innovated at *t-1* is 16.8%, whereas this probability falls to 9.6% when the firm did not innovate at *t-1*. Finally, Panel C shows the average treatment effect of past export and innovation status on current probabilities of exporting and innovating. For example, the effect of exporting at *t-1* for a non-exporter is an increase in the probability of exporting at *t* of 83.8%. Similarly, the reduction in the probability of exporting at t for an exporter in *t-1*, if it had not exported, would have been of 77.1%. These panels reinforce the finding of strong effects of past behaviour on current status and interdependence between both decisions.

5.3 Alternative measures of internationalization and innovation

In previous sections we have analyzed extensively the export “side” of firms’ internationalization activities. This is the approach followed by the vast majority of theoretical and empirical work devoted to examine self-selection and learning-by-exporting hypotheses in relation to efficiency heterogeneity across firms/plants. However, as discussed in Section 2, the import “side” could provide useful insights about the relationship between innovation and internationalization. On the one hand, import links could have a positive effect on innovative activities of firms channelled through knowledge externalities that accrue from contact with foreign providers. For example, rather commonly a firm innovation arises from collaboration with either foreign or domestic suppliers. Indeed, the ESEE database indicates that technological collaboration with providers is the most frequent way of collaboration. Specifically, 54.7% of firms that invested in R&D in 2006 claimed to have technological collaboration with their suppliers.[11] However, the opposite direction of this causality (from innovation to imports) is less evident.

It is important to bear in mind that imports are not the mirror image of exports. Thus, when assessing imports at the firm level two broad considerations are in order. First, industrial firms tend to export their internally-produced goods, so there is an obvious connection between production and sales in foreign and domestic markets. However, imports are more heterogeneous that exports, Firms can import three main types of goods:[12] intermediate inputs, machinery and final goods. The first category refers to the type of international outsourcing that the literature has emphasized in last years. Firms acquire technology that is incorporated in these intermediate good, which are later transformed, or in equipment goods. In addition, even though we are dealing with manufacturing firms, some of them also engage in wholesaling activities. In fact, the line distinguishing a "manufacturer" from a "trader" is some times very thin. For example, many footwear manufacturers use their domestic sales network to distribute their own brands as well as other foreign brands. Pharmaceutical companies also import some final products from their parent companies or affiliated in foreign countries, while they elaborate some products for domestic markets. Secondly, the acquisition of foreign inputs is not necessarily carried out by the final user, but it can be channelled through a domestic intermediary. In such a case, intermediate consumption is not longer qualified as imports. A similar problem emerges for exports, in whose case some firms use other domestic firms, usually within the same group, to channel their sales in foreign markets.[13] The evidence suggests that the extent of vertical relationships in imports is smaller.

Bernard *et al* (2007) point out that importing is relatively less common than exporting across firms. In contrast to their findings, Table A2 suggests the existence of a high coincidence between participation in export and import activities at the firm level. This correlation is particularly high for large firms: only about 10% of them exported but did not import, or *vice versa*, for selected years. The increase in the percentage of firms involved in both exports and imports is parallel to the decrease in the percentage corresponding of firms involved neither in exports nor in imports. Table A3 points out a remarkable difference between both "sides" of internalization: imports are more volatile than exports. The percentage of switchers in imports ranges between 13.7 and 28.9 for large firms and SMEs, respectively, which exceeds the corresponding figures for exports in 4 and 8. The percentage of "ones" for switching SMEs is very similar in both trade activities: 44.5% and 45.7% for export and imports, respectively. The difference is larger for large firms: 67.4% and 74.3% for exports and imports, suggesting that a switching pattern correspond to a more intensive import activity (with respect to export) for large firms (and in both cases more intensive than for SMEs).

[11] Collaboration with clients (44.4%) and with universities and technological centres (37.2%) are other relevant ways of technological collaboration. Much less important are collaboration with competitors (3.8%) and joint-ventures (5.6%).

[12] We do not consider import of services, due to the lack of data. Complementary evidence suggests that, though the outsourcing of services is relevant, it is basically domestic. See Merino and Rodriguez (2007) for a discussion.

[13] For that reason the ESEE survey includes exports channelled through other companies belonging to the same group. This seems to be an increasing strategy in the context of multinational groups.

With regard to the proxy for innovation, we have used so far a dummy variable that takes value one if R&D expenses (internal or external) are positive. This variable has been quite often used in the literature.In fact, if the driving force of the two-way relationship between innovation and exports is productivity, R&D investment may be more appropriate than output measures of innovation to proxy this productivity-enhancing mechanism (see, for instance, Aw et al., 2007). However, R&D expenses could be more adequate to measure innovative activity in large firms. In that sense, Roper (1998) pointed out that large firms undertake frequent research activities that require a larger degree of formality (i.e., laboratories), in which cost accounting may be simpler. By the opposite, costs related to more informal innovative activities could be accounted as general costs by firms, and they would not be reflected as R&D investments. An open question remains whether alternative indicators could lead to different results of the dynamic relationship between internationalization and innovation. This concern may rest upon theoretical grounds, which relates with the plausible relationship between product/process innovation and the product life cycle theories as discussed in Section 2.

Table A4 shows the degree of coincidence of participation in R&D, product and process innovation for some years in the period 1991-2006.[14] For smaller firms, in about 75-85% of cases the indicator is the same irrespectively of the indicator used. In any year, about 10% of SMEs do not innovate but claim to incur R&D expenses. That percentage is much higher for large firms. The explanation for these results may be twofold. On the one hand, some R&D outlays may not result in innovations. On the other hand, even if R&D leads to innovation, this outcome may arise in future periods. Both reasons seem play even a bigger role for large firms. A doubt remains on whether smaller firms introduce an upwards bias in the innovations results. The results in Table A4 suggest that R&D expenses may underestimate innovation activities of SMEs because the percentage of firms that never involved in R&D is clearly higher than the corresponding figures for both product and process innovations.

The non-simultaneity of R&D investment and innovation outcomes could also explain partially that some firms indicate that they do not incur R&D expenses but, at the same time, they claim to have attained innovations, particularly process innovations. In this case, some actions other than R&D outlays taken by firms may explain the innovation result. The ESEE provides information (every four years) about complementary actions to obtain innovation resources (such as the use of scientific and technical information services, standardization and quality control work, efforts for assimilating imported technologies, market research and others). We obtain that almost all firms that declare not to invest in R&D but to obtain innovations are involved in some of these complementary activities. This group of innovators not simultaneously involved in R&D is reduced over the analyzed period.

[14] Other potential distinction is that between in-house R&D expenditures and outsourced R&D. The first one is probably more relevant to build up a firm's knowledge stock. If that is the case, we would expect a larger impact on export activity. This distinction has not been dealt with in this paper.

The results obtained from the estimation of the dynamic random effects probit models using Wooldridge (2005) for alternative measures of internationalization and innovation are showed in table 11. These results are qualitatively similar to those obtained with R&D and export variables. The positive correlation between innovation and internalization appears to be a robust result, irrespective of the proxies used to measure these activities. In addition, the effect of the explanatory variables are quantitatively fairly similar in the export equation (panel A), whereas some differences arise in the innovation equation (panel B) when alternative proxies of internalization and innovation are considered. In particular, the positive effect of age and productivity on export (and also on imports) when we use the R&D proxy (columns 1 and 2 of panel B) vanishes when we proxy innovation activities with either product or process innovations. This result provides support to the argument that R&D outlays boosts productivity, which is a major driver of the relationship between innovation and internationalization activities.

6. Conclusions

The findings of this paper indicate the existence of true state dependence in both export and innovation status. Firms with prior export and innovation experience are more likely to participate in export and innovation, respectively. After controlling for unobservable heterogeneity, this suggests that adjustment costs, sunk entry costs, self-enhancing success and/or learning may important factors in explaining the observed persistence. The empirical findings are consistent with the hypothesis of self-selection of more efficient firms into export. Besides, the results give also support to the hypothesis of learning-by-exporting through the innovation channel: export participation boosts innovation (R&D outlays, process as well as product innovation) given that the larger export market provides higher returns to R&D (as modeled by Lileeva and Trefler, 2007, and Constantini and Melitz, 2007), which stimulates productivity growth. Besides, the firm decisions to export and innovate are positively affected by firm productivity, size, advertising and age. These findings are broadly consistent with most previous empirical literature.

Furthermore, we find strong correlation between export and innovation and cross-persistence between the two activities. Prior innovation (exporting) is positively correlated with current export (innovation) participation. The estimation results point out a positive and significant correlation between the error terms in the innovation and export equation. Next step is to estimate a dynamic bivariate random effects model in order to disentangle the sources of cross-persistence: firm observed/unobserved heterogeneity and/or true state dependence.

Finally, it is important to point out what's behind (cross) persistence for both its policy implications and the implications on the literature on the export and productivity link (learning versus ex ante “ability” or self-selection). From a policy standpoint, it is important to disentangle the different sources of true persistence (sunk costs, learning, self-enhancing success). For instance, the distinction between permanent innovation activities due to firm-inherent factors and true state dependence has some important implications. If innovation is state dependent, innovation–stimulating policy measures such as government support programmes are supposed to have a more profound effect because they do not only affect the current innovation activities but are also likely to induce a permanent change in favour of innovation. If, on the other hand, individual heterogeneity induces persistent behaviour, support programmes are unlikely to have long–lasting effects and economic policy should concentrate more on measures which have the potential to improve innovation–relevant firm–specific factors.

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Table 1
Characteristics of the panel

	Unbalanced with at least seven consecutive years		Balanced (t=17)	
	SMEs	Large	SMEs	Large
Number of observations	14430	7270	4505	2023
Number of firms	1202	611	265	119
Average number of consecutive obs. per firm	12.00	11.87	17	17

Table 2
Export and R&D in Spanish manufacturing firms
(per cent of firms of each column total)

	Year			
	1991	1996	2001	2006
SMEs firms (Nº of observations)	*656*	*913*	*971*	*691*
Export & R&D	13.4	13.8	15.1	18.1
Export & No R&D	18.9	30.7	35.4	35.0
No Export & R&D	6.7	5.4	5.2	4.5
No Export & No R&D	61.0	50.1	44.2	42.4
Large firms (Nº of observations)	*371*	*499*	*480*	*332*
Export & R&D	62.0	60.1	65.6	66.0
Export & No R&D	21.3	29.7	28.1	26.2
No Export & R&D	6.7	4.0	2.5	1.5
No Export & No R&D	10.0	6.2	3.6	6.3

Table 3
Persistent and non-persistent behaviour
(1990-2006; per cent of column total)

	Export		R&D	
	SMEs	Large	SMEs	Large
Persistent				
- Never	37.10	2.45	56.99	10.80
- Always	27.04	78.72	6.41	42.06
No persistent				
- Entrants	11.56	6.55	5.99	9.66
- Exiters	3.99	3.11	4.99	7.86
- Switchers	20.30	9.17	25.62	29.62

Table 4
Transition Probabilities, Whole Period 1990-2006 (univariate)

Export

	Year t					
	SMEs			Large		
Year t-1	No	Yes		No	Yes	
No	92.90	7.10	100	82.56	17.44	100
Yes	6.25	93.75	100	1.33	98.67	100
TOTAL	53.33	46.67	100	8.79	91.21	100

Innovations

	Year t					
	SMEs			Large		
Year t-1	No	Yes		No	Yes	
No	95.12	4.88	100	85.57	14.43	100
Yes	18.39	81.61	100	6.97	93.03	100
TOTAL	79.57	20.43	100	32.09	67.91	100

Table 5
Transition Probabilities, Whole Period 1990-2006 (bivariate)

SMEs firms

t-1		t	
Export	Innovate	Yes export	Yes Innovate
No	No	6.57	3.31
No	Yes	12.24	73.01
Yes	No	92.33	7.43
Yes	Yes	96.66	84.56

Large firms

t-1		t	
Export	Innovate	Yes export	Yes Innovate
No	No	14.54	9.02
No	Yes	22.57	82.30
Yes	No	97.47	15.67
Yes	Yes	99.16	93.60

Table 6
Unconditional and conditional probabilities of export and innovate

	Unconditional	Export at t-1	No export at t-1
EXPORT (t)			
All	0.608	0.962	0.079
Size: SMEs	0.457	0.937	0.071
Large firms	0.908	0.987	0.174
Foreign owned: Yes	0.737	1.000	0.167
No	0.527	0.952	0.072
Productivity > median	0.770	0.976	0.114
<= median	0.446	0.939	0.066
Age > median	0.751	0.977	0.090
<= median	0.469	0.937	0.074
Advertising: Yes	0.661	0.966	0.095
No	0.468	0.949	0.054
R&D: Yes	0.876	0.984	0.169
No	0.456	0.938	0.067
INNOVATE (t)	Unconditional	R&D at t-1	No R&D at t-1
All	0.361	0.888	0.065
Size: SMEs	0.201	0.816	0.049
Large firms	0.678	0.930	0.144
Foreign owned: Yes	0.631	1	0
No	0.286	0.862	0.057
Productivity > median	0.519	0.917	0.098
<= median	0.203	0.808	0.045
Age > median	0.503	0.910	0.090
<= median	0.222	0.837	0.049
Advertising: Yes	0.409	0.892	0.075
No	0.249	0.873	0.045
Export: Yes	0.523	0.908	0.102
No	0.115	0.746	0.033

Table 7
Firm characteristics

	SME				Large			
Export:	No		Yes		No		Yes	
Innovate:	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Foreign ownership	2.9	8.1	12.1	19.3	33.3	39.4	46.1	50.0
Age	9	11	11.5	17	26	32	27	33.5
Productivity	17.9	22.0	23.0	29.5	26.7	35.9	31.6	34.5
Size (employees)	19	23.5	30.5	65	347.5	442	321	413
Advertising	49.7	72.6	63.9	78.1	64.3	87.9	68.1	78.9

Notes: Firm characteristics are measured in the first year of the spell. Foreign ownership and advertising reflect the percentage of foreign owned firms and firms investing in advertising, respectively. Median values are reported for age, productivity and size. Productivity (real added value per employee, in euros) is measured at 1990 constant prices. Individually adjusted price-indexes have been used to deflate value added. The number of firms is 1202 and 611 for SME and large firms, respectively.

Table 8
Results: univariate probit

Panel A: Exports

	Static			Dynamic	
	Pooled (1)	Pooled Mundlak (2)	RE (3)	Pooled (4)	RE Wooldridge (5)
Export $_{t-1}$				0.836	0.600
				(63.65)	(32.28)
Innovate $_{t-1}$	0.238	0.227	0.082	0.108	0.091
	(12.19)	(11.55)	(5.43)	(8.35)	(5.79)
Foreign $_{t-1}$	0.195	0.176	0.083	0.089	0.070
	(6.9)	(6.02)	(4.71)	(5.08)	(3.11)
Size $_{t-1}$	0.284	0.269	0.510	0.130	0.137
	(11.03)	(10.41)	(9.16)	(8.45)	(6.04)
Age $_{t-1}$	0.214	0.200	0.314	0.067	0.113
	(3.75)	(3.48)	(3.76)	(2.32)	(2.55)
Productivity $_{t-1}$	0.021	0.001	0.002	0.008	0.001
	(4.4)	(0.25)	(1.24)	(3.25)	(0.36)
Advertising $_{t-1}$	0.151	0.147	0.053	0.054	0.056
	(8.12)	(7.92)	(3.96)	(4.38)	(3.61)
Mproducti		0.034			0.025
		(4.12)			(4.22)
Export $_{1}$					0.461
					(17.15)
$W_{industries}$ (*p-value*)	0.000	0.000	0.000	0.000	0.011
W_{time} (*p-value*)	0.000	0.000	0.000	0.003	0.003
Wald chi^2	842.4	854.7	990.7	6536.6	4498.8
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R^2	0.2853	0.2897		0.7106	
Obs. Prob	61.42	61.42	61.42	61.42	61.42
Pred. Prob	68.68	69.56	58.95	72.50	62.07
σ_u			3.163		0.887
ρ			0.909		0.441
(*p-value*)			(0.000)		(0.000)
Posit. pred.(%)	81.99	82.29	80.06	96.21	94.00
Negat. pred.(%)	68.57	69.24	65.35	92.07	91.91
N. observations			19884		

Panel B: Innovation

	Static			Dynamic	
	Pooled (1)	Pooled Mundlak (2)	RE (3)	Pooled (4)	RE Wooldridge (5)
Innovate $_{t-1}$				0.753	0.530
				(59.98)	(35.6)
Export $_{t-1}$	0.232	0.232	0.129	0.110	0.102
	(11.94)	(11.92)	(8.17)	(9.04)	(6.77)
Foreign $_{t-1}$	0.017	0.016	0.026	0.002	0.004
	(0.66)	(0.64)	(1.25)	(0.17)	(0.21)
Size $_{t-1}$	0.308	0.308	0.682	0.146	0.207
	(12.56)	(12.54)	(18.73)	(10.65)	(8.55)
Age $_{t-1}$	0.139	0.139	0.231	0.059	0.065
	(3.16)	(3.18)	(3.66)	(2.54)	(1.78)
Productivity $_{t-1}$	0.022	0.022	0.012	0.012	0.010
	(6.22)	(6.17)	(4.99)	(5.56)	(4.41)
Advertising $_{t-1}$	0.112	0.112	0.066	0.052	0.047
	(6.22)	(6.23)	(5.4)	(4.29)	(3.41)
Mproducti		0.000			0.000
		(1.63)			(1.2)
Innovate $_1$					0.385
					(15.24)
$W_{industries}$ (*p-value*)	0.000	0.000	0.000	0.000	0.011
W_{time} (*p-value*)	0.000	0.000	0.000	0.003	0.000
Wald chi^2	1030.70	1033.8	870.2	6128.9	4456.9
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R^2	0.2897	0.2898		0.6080	
Obs. Prob	36.19	36.19	36.19	36.19	36.19
Pred. Prob	31.13	31.12	31.65	28.28	34.11
σ_u			1.970		0.801
ρ			0.795		0.391
(*p-value*)			(0.000)		(0.000)
Posit. Pred.(%)	72.58	72.56	71.92	88.84	87.41
Negat. pred.(%)	82.00	82.00	80.35	93.50	90.32
N. observations			19884		

Estimators:
1. Static Pooled Probit
2. Static pooled probit with Mundlak (1978) correction for correlated individual effects
3. Static standard Random Effects Probit (initial condition taken to be exogenous)
4. Dynamic Pooled probit
5. Dynamic Random Effects Probit: Wooldridge (2005) estimator

Notes:
1. Marginal effects are reported, with t-ratios in brackets
2. Robust standard errors in pooled probit model, adjusted for clustering on firms.
3. A constant (significant at the 1% level in all cases) as well as time and industry dummies are included in each regression, but not reported

Table 9
Predicted probabilities of exporting (panel A) and innovation (panel B)

a) Export

Export:	Y_{t-1}=0		Y_{t-1}=1	
Innovation:	Y_{t-1}=0	Y_{t-1}=1	Y_{t-1}=0	Y_{t-1}=1
Firm effect				
$-2\sigma_\mu$	0.0110	0.0250	0.3883	0.5187
$-\sigma_\mu$	0.0803	0.1418	0.7271	0.8251
0	0.3033	0.4269	0.9322	0.9658
$+\sigma_\mu$	0.6454	0.7591	0.9913	0.9966
$+2\sigma_\mu$	0.8963	0.9442	0.9995	0.9998

b) Innovation

Innovation:	Y_{t-1}=0		Y_{t-1}=1	
Export:	Y_{t-1}=0	Y_{t-1}=1	Y_{t-1}=0	Y_{t-1}=1
Firm effect				
$-2\sigma_\mu$	0.0001	0.0029	0.0702	0.1274
$-\sigma_\mu$	0.0110	0.0253	0.2504	0.3679
0	0.0683	0.1245	0.5509	0.6785
$+\sigma_\mu$	0.2459	0.3625	0.8236	0.8970
$+2\sigma_\mu$	0.5452	0.6734	0.9582	0.9806

Note: Predicted probabilities are calculated using the results in column 5 of Table 8.

Table 10
Export and innovation: bivariate probit

	Export		Innovation	
	Coeff.	t-ratio	Coeff.	t-ratio
Export $_{t-1}$	2.899	63.62	0.338	9.16
Innovate $_{t-1}$	0.341	8.57	2.383	59.99
Foreign $_{t-1}$	0.277	5.01	0.007	0.16
Size $_{t-1}$	0.407	8.42	0.415	10.61
Age $_{t-1}$	0.200	2.32	0.172	2.51
Productivity $_{t-1}$	0.024	3.26	0.036	5.60
Advertising $_{t-1}$	0.160	4.41	0.157	4.28
Corr (ε_{1it}, ε_{2it})		0.179		
LR Chi^2 (p-value)		41.2 (0.000)		
$W_{industries}$	0.000	0.000	0.000	
W_{time}	0.000	0.000	0.000	
Wald chi^2		12,273.5		
(prob > chi^2)		(0.000)		
Panel A: Predicted probabilities (%) of export (t), innovation (t):				
(1,1)		31.84		
(1,0)		29.60		
(0,1)		4.38		
(0,0)		34.18		
Panel B: Predicted probabilities (%):				
(export t-1,innovation t-1)	Export t		Innovation t	
(1,1)	97.50		87.29	
(1,0)	94.72		9.61	
(0,1)	16.78		78.52	
(0,0)	9.60		4.90	
Panel C: Marginal effects:				
Export t-1	Export t		Innovation t	
No	0.8377		0.0396	
Yes	0.7715		0.0561	
Innovate t-1				
No	0.0440		0.6890	
Yes	0.0254		0.7301	
N. observations		19,884		

Notes: Marginal effects in Panel C are calculated, using coefficients of Table 10, as the average change in the probability over all firms related to the variable v (i.e, Export $_{t-1}$ and Innovate $_{t-1}$):
ATE= $\Phi\,[X\gamma^d + \beta^d] - \Phi[X\gamma^d]$ if v = 0
ATE= $\Phi\,[X\gamma^d] - \Phi[X\gamma^d - \beta^d]$ if v = 1
where the superscript d indicates the decision equation (1 for the exporting decision; 2 for the innovating decision), X are firm-specific values, γ^d is the vector of estimated parameters for each equation, and β^d is the (scalar) estimated parameter related to the v variable.

Table 11

Robustness analysis: Import, product and process innovations
Dynamic Random Effects Probit using Wooldridge (2005) estimator

Panel A: Internationalization

	Export			Import		
	R&D	Product innovation	Process innovation	R&D	Product innovation	Process innovation
Internationalization $_{t-1}$	0.600	0.603	0.602	0.555	0.556	0.551
	(32.28)	(32.58)	(32.36)	(30.49)	(30.4)	(29.97)
Innovation $_{t-1}$	0.091	0.058	0.041	0.079	0.046	0.036
	(5.79)	(4.05)	(3.32)	(5.46)	(3.5)	(3.12)
Foreign $_{t-1}$	0.070	0.072	0.074	0.111	0.111	0.112
	(3.11)	(3.25)	(3.31)	(5.75)	(5.69)	(5.73)
Size $_{t-1}$	0.137	0.152	0.152	0.204	0.219	0.220
	(6.04)	(6.91)	(6.86)	(10.61)	(11.68)	(11.59)
Age $_{t-1}$	0.113	0.122	0.126	0.133	0.140	0.144
	(2.55)	(2.76)	(2.81)	(3.5)	(3.67)	(3.73)
Productivity $_{t-1}$	0.001	0.002	0.001	0.008	0.009	0.008
	(0.36)	(0.49)	(0.42)	(2.42)	(2.65)	(2.59)
Advertising $_{t-1}$	0.056	0.059	0.059	0.062	0.065	0.065
	(3.61)	(3.76)	(3.78)	(4.38)	(4.51)	(4.5)
Mproducti	0.025	0.027	0.027	0.027	0.029	0.029
	(4.22)	(4.5)	(4.45)	(5.05)	(5.34)	(5.32)
Export $_{1}$	0.461	0.468	0.476	0.243	0.253	0.259
	(17.15)	(17.44)	(17.73)	(11.67)	(12.06)	(12.25)
$W_{industries}$ (*p-value*)	0.011	0.011	0.011	0.000	0.000	0.000
Wald chi^2	4498.8	4520.8	4470.8	4478.4	4424.6	4356.7
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs. Prob	61.42	61.42	61.42	61.97	61.97	61.97
Pred. Prob	62.07	62.22	62.22	62.14	62.17	62.19
σ_u	0.888	0.887	0.901	0.798	0.813	0.829
P	0.441	0.440	0.448	0.389	0.398	0.407
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Posit. pred.(%)	94.00	93.89	93.76	93.08	93.10	93.01
Negat. pred.(%)	91.91	92.04	91.84	89.08	89.19	89.02
N. observations	19884					

Panel B: Innovation

	R&D		Product innovation		Process innovation	
	Export	Import	Export	Import	Export	Import
Innovation $_{t-1}$	0.530	0.533	0.353	0.354	0.368	0.368
	(35.6)	(35.74)	(28.02)	(27.98)	(37.53)	(37.48)
Internationalization $_{t-1}$	0.102	0.063	0.052	0.038	0.030	0.030
	(6.77)	(4.16)	(5.52)	(4.04)	(2.76)	(2.73)
Foreign $_{t-1}$	0.004	0.008	-0.009	-0.008	0.006	0.006
	(0.21)	(0.4)	(-0.84)	(-0.75)	(0.45)	(0.42)
Size $_{t-1}$	0.207	0.217	0.052	0.054	0.106	0.105
	(8.55)	(8.86)	(3.85)	(3.99)	(6.99)	(6.94)
Age $_{t-1}$	0.065	0.074	-0.029	-0.026	-0.077	-0.077
	(1.78)	(2)	(-1.38)	(-1.24)	(-3.21)	(-3.21)
Productivity $_{t-1}$	0.010	0.011	-0.001	-0.001	0.000	0.000
	(4.41)	(4.5)	(-0.68)	(-0.65)	(-0.14)	(-0.19)
Advertising $_{t-1}$	0.047	0.051	0.037	0.039	0.019	0.020
	(3.41)	(3.76)	(4.5)	(4.77)	(1.93)	(1.99)
Mproducti	0.000	0.000	0.000	0.000	0.000	0.000
	(1.2)	(1.29)	(1.04)	(1.11)	(-0.98)	(-0.96)
Export $_1$	0.385	0.393	0.150	0.155	0.138	0.138
	(15.24)	(15.45)	(10.75)	(11.01)	(9.73)	(9.79)
$W_{industries}$ (*p-value*)	0.011	0.000	0.011	0.011	0.012	0.010
Wald chi^2	4457.0	4460.7	2259.0	2530.4	2570.9	2568.9
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs. Prob	36.19	36.19	24.78	24.78	32.65	32.65
Pred. Prob	34.11	34.14	15.91	15.91	22.75	22.67
σ_u	0.801	0.801	0.603	0.610	0.468	0.469
ρ	0.391	0.391	0.267	0.271	0.180	0.180
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Posit. pred.(%)	87.41	87.52	74.71	74.65	73.63	73.56
Negat. pred.(%)	90.32	90.41	84.67	84.36	79.42	79.35
N. observations			19884			

Notes:

1. Marginal effects are reported, with t-ratios in brackets
2. A constant (significant at the 1% level in all cases) as well as time and industry dummies are included in each regression, but not reported

Appendix:

Table A1
Variable definitions

Variable	Type	Definition
Alternative dependent variables		
Export	0/1	1 if the firm exported at t, directly or channelling those exports through an affiliated of the group
Import	0/1	1 if the firm imported at t, directly or channelling those imports through an affiliated of the group
R&D	0/1	1 if the firm invested in R&D at t (internal or external expenses)
Product innovation	0/1	1 if the firm obtained a product innovation at t. Encompasses completely new products, or with modifications such that they are different from those produced earlier
Process innovation	0/1	1 if the firm introduced a process innovation at t
Explanatory variables		
Size	0/1	1 if a firm i has more than 200 employees at t
Productivity	Continuous	Added value (defined as the sum of the sales, the variation in stocks and other management income, minus the purchases and external services) per employee at 1990 constant price
Foreign	0/1	1 if the firm's social capital was directly or indirectly participated by foreign capital at t
Age	Continuous	Number of years since the firm was created
Adv	0/1	1 if the firm spent on advertising and/or public relations at t
Group	0/1	1 if the firm i is part of a companies' group

Table A2

Export and Import in Spanish manufacturing firms

(per cent of firms of each column total)

	Year			
	1991	1996	2001	2006
SMEs firms (Nº of observations)	*656*	*913*	*971*	*691*
Export & Import	20.7	30.6	38.1	39.4
Export & No Import	11.6	13.9	12.5	13.7
No Export & Import	13.7	10.8	11.5	12.6
No Export & No Import	54.0	44.7	37.9	34.3
Large firms (Nº of observations)	*371*	*499*	*480*	*332*
Export & Import	77.9	86.4	90.0	88.6
Export & No Import	5.4	3.4	3.7	3.6
No Export & Import	10.2	7.2	4.78	6.0
No Export & No Import	6.5	3.0	1.5	1.8

Table A3

Persistent and non-persistent behaviour

(1990-2006; per cent of column total)

	Export		Import		R&D		Product		Process	
	SMEs	Large	SMEs	Large	SMEs	Large	SMEs	Large	SMEs	Large
Persistent										
- Never	37.1	2.5	32.9	0.3	57.0	10.8	44.8	20.1	24.9	7.7
- Always	27.0	78.7	23.5	76.6	6.4	42.1	1.7	5.2	1.1	6.1
No persistent										
- Entrants	11.6	6.5	10.4	6.5	6.0	9.7	4.0	8.8	2.8	7.7
- Exiters	4.0	3.1	4.2	2.8	5.0	7.9	6.9	9.0	7.6	11.8
- Switchers	20.3	9.2	28.9	13.7	25.6	29.6	42.5	56.8	63.6	66.8

Table A4

R&D and Innovation processes in Spanish manufacturing firms

(per cent of firms of each column total)

	Product Innovation				Process Innovations			
	1991	1996	2001	2006	1991	1996	2001	2006
SMEs firms (Nº of observations)	*656*	*913*	*971*	*691*	*656*	*913*	*971*	*691*
R&D & Innovation	9.6	9.2	9.7	11.6	10.4	8.1	9.2	9.8
R&D & No Innovation	10.5	10.0	10.7	11.0	9.8	11.1	11.2	12.7
No R&D & Innovation	10.1	11.1	6.1	4.6	18.1	16.6	15.8	9.7
No R&D & No Innovation	69.8	69.7	73.5	72.8	61.7	64.2	63.8	67.7
Large firms (Nº of observations)	*371*	*499*	*480*	*332*	*371*	*499*	*480*	*332*
R&D & Innovation	34.2	31.7	33.9	27.7	42.3	38.7	40.6	32.2
R&D & No Innovation	34.5	32.5	34.2	39.8	26.4	25.4	27.5	35.2
No R&D & Innovation	5.1	5.0	4.0	4.2	13.2	10.0	7.9	6.9
No R&D & No Innovation	26.2	30.9	27.9	28.3	18.1	25.8	24.0	25.6