# Innovation, complementarity and exporting.

# Evidence from German manufacturing firms

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## Abstract

This paper assesses whether different kinds of innovation (product, process and organizational) have complementarity effects on a firm's probability of exporting. The issue of complementarity is addressed through the properties of supermodular functions, and firm heterogeneity by export destination is explored. A new econometric strategy to test for pairwise complementarity in function with three independent variables and a binary dependent variable is proposed. The econometric strategy considers either exogenous or endogenous innovation variables using bootstrapping for hypothesis testing in the former case and propensity score matching and instrumental variable treatment effects models in the latter. Using data from the CIS4 (2002-2004) for German manufacturing firms, the analysis shows that combining innovations has a larger impact on the probability of exporting to multiple markets when fixed costs and demand variations are higher. Complementarity among innovation practices is indeed detected for firms that export to both EU and non-EU markets but not for firms that export only to EU markets.

Keywords: Export propensity, complementarity among innovations, multiple hypothesis testing, binary choice model

JEL Classification: C12, C25, F14, O31

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## 1. INTRODUCTION.

The economic literature has recently emphasized the role of innovation in the export-productivity relationship. The linkage between firm investment in innovation and the exporting decision is explored, and using micro-level data, positive correlations between export propensity and innovation variables are documented. In many of these works, the variable used to measure firm innovation activity is investment in R&D[4]. Other works[5] have explicitly considered the heterogeneity of firms' innovation strategies, emphasizing the different roles played by product and process innovation in firms' propensity to export. Specifically, through product innovation, firms increase their competitiveness in foreign markets, improving the quality of their products to meet foreign demand as well as foreign standards and regulations. Instead, through process innovation, firms gain cost advantages and can charge lower and more competitive prices in foreign markets. In most of these works, product innovation plays a more relevant role in firm participation in export markets than other forms of innovation. Van Beveren and Vandenbussche (2010) and Becker and Egger (2013) constitute remarkable exceptions, as they are the only two that explicitly consider the correlation between these two kinds of innovation in their empirical analysis, opening a window into possible complementarity relationships between product and process innovations. In particular, Becker and Egger (2013) show that firms' export probability increase when both kinds of innovation are jointly implemented by applying matching techniques to a sample of German manufacturing firms.

Our aim is to deepen the analysis of firm export propensity and innovation through the lens of complementarity theory. Following Topkis (1995, 1998), Milgrom and Roberts (1990, 1995), Milgrom and Shannon (1994), we investigate complementarity among firm innovation practices when exporting is at stake, through the properties of supermodular functions.

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[4] Aw et al (2007, 2008), Bustos (2011), Lileeva and Trefler (2010), Van Long et al. (2011).

[5] Caldera (2010), Cassiman et al. (2010), Damijan et al. (2010), Van Beveren and Vandenbussche (2010), Cassiman and Golovko (2011), Becker and Egger (2013).

Our empirical analysis is performed using a sample of 2347 German manufacturing firms from the Community Innovation Survey (CIS4), which includes information about three kinds of innovation: product, process and organizational/marketing[6]. Looking at our data, we find that a relevant share of exporting firms (42.5%) introduced all three types of innovation simultaneously, which supports the intuition that it is the combination of product, process and organizational/marketing innovations rather than any of them in isolation that is correlated with firm export propensity.

Our analysis is in line with Becker and Egger (2013) also for the data sample we select (German manufacturing firms) but contributes to the existing literature in two ways.

First, we take explicitly into account firm heterogeneity by export destination in the investigation of potential complementarities among innovation practices. When the number of foreign markets served by a firm is high, both demand variations and fixed costs of exporting increase[7]. Then, we argue that the joint implementation of all kinds of innovation is particularly relevant to enhancing firms' export probabilities. For this purpose, we conduct our empirical analysis of complementarity by admitting differences between two subsamples of firms: those that export only to EU markets and those that export to both EU and non-EU markets. Based on the above considerations, we expect to find complementarity relationships among innovation practices, especially in firms that export to both EU and non-EU markets. If our intuition is confirmed, some policy implications may be derived. Indeed, in expanding the number of foreign markets, policy instruments should contemplate not only direct trade policies but also incentive programs directed toward all types of innovation. When a complementarity relationship is found among some firm variables, a change in just one of them may have little effect if the others remain unchanged.

Furthermore, and even more importantly, the econometric strategy we adopt to test complementarity is different from and innovative with respect to the existing literature. A unified

[6] As organizational/marketing innovations concern new organizational or marketing methods, they may play a role both in the supply of products on foreign markets and in the productive process.

[7] On this point, see Melitz (2003).

framework for evaluating complementarity among innovation practices affecting export propensity is proposed by admitting that such practices can be either exogenous or endogenous. In addressing the issue of complementarity, a preliminary testing procedure is adopted to distinguish exogenous from endogenous innovation cases. We employ the most commonly used methods to evaluate the properties of export propensity functions. The CIS4 dataset includes a rich set of instruments to be used in explaining innovation variables when the endogeneity hypothesis cannot be rejected.

When innovation variables are assumed to be exogenous, we propose a strategy that exploits the properties of supermodular functions by testing inequality constraints that are implied by complementarity and supermodular functions. Constrained and unconstrained logit and multinomial models are estimated, and bootstrapping is proposed to perform joint inequality testing. We contribute to the existing literature because we directly evaluate combined hypothesis testing for more than two innovation practices by overcoming the computational problems associated with the generalization of Wald tests used by Mohnen and Roller (2005) for two practices. Indeed, regressions under inequality constraints are computed, and the critical values of such tests are cumbersome even for dichotomous practices. To the best of our knowledge, the only study performing complementarity testing for more than two innovation practices in linear models is that of Carrée et al (2011). The authors propose an induced test procedure and argue that a combined hypothesis is accepted if the separate hypotheses are all accepted. Our proposal differs from theirs in two respects. First, the methodology is based on a bootstrapping procedure to simultaneously test all separate hypotheses. Second, nonlinear models are considered and additional conditions on coefficients are established to ensure that complementarity tests in the context of linear models can be applied in a non-linear setting.

In the second case (i.e., when the innovation variables are assumed to be endogenous), several econometric approaches estimate logit models with endogenous binary regressors, which can be used for our purposes. In this study, propensity score matching (PSM) and instrumental variable maximum simulated likelihood (MSL) methods are employed. In this framework, we construct binary variables to identify complex innovation strategies. We interpret complex innovators as a treatment group that adopts two or more innovation practices simultaneously. The set of simple innovators, which decide to introduce only one type of innovation, and the set of non-innovators are included in the control group. The estimation methods for treatment effects models can be used to test for complementarity among innovation variables when endogeneity is not statistically rejected. Matching estimators are also used by Becker and Egger (2013). Beside these, we consider MSL models.

This paper is structured as follows: section 2 analyzes the relationship between exporting and complementarity among innovation practices; the theoretical background and the research hypothesis are presented in section 2.1. Section 2.2 explains the methodological issues of supermodular functions, and section 2.3 presents the econometric analyses and the complementarity tests. The endogeneity issue is addressed in section 2.4. Sections 3.1 and 3.2 describe the CIS4 dataset and focus on the relationship between export propensity and innovation activities for a sample of German manufacturing firms. Section 3.3 presents and comments on the econometric results for complementarity. Section 4 provides the robustness analysis and Monte Carlo experiments. Section 5 concludes.

## 2. EXPORTING, INNOVATION STRATEGIES AND COMPLEMENTARITY.

### 2.1 Theoretical background

Since the seminal works of Bernard and Jensen (1999) and Melitz (2003) on heterogeneity in firm productivity and their self-selection into exporting[8], a considerable and growing stream of economic literature has explicitly endogenized firm-level productivity and investigated whether the selection

[8] Firms self-select into export markets if their productivity is high enough to afford the entry costs and competition of the export market. For an exhaustive literature review on this subject, see Bernard et al. (2007) and Wagner (2007).

of more productive firms into exporting is related to firms' prior investments in innovation, which is widely recognized as the main source of firm heterogeneity in productivity (Griliches, 1998).

Concerning the more theoretical studies in this line of analysis, Yeaple (2005) shows that firm heterogeneity arises because firms endogenously choose different technologies, and only firms that use the lowest unit cost technology enter the export market, as they are able to afford the fixed cost of international trade. Bustos (2011) introduces technology choice to Melitz's (2003) model to analyze the impact of trade liberalization on technology upgrading among Argentinean firms. Constantini-Melitz (2007) and Lileeva-Trefler (2010) also explore the linkages between firm investments in innovation and their propensity to export in the context of the liberalization of trade regimes.

On the one hand, in most works, the empirical analysis is conducted considering the link between firm investment in R&D and the export propensity (Aw et al, 2007, 2008; Bustos, 2011; Lileeva and Trefler, 2010;Van Long et al., 2011).

On the other hand, other studies of firm innovation and exporting have explicitly considered the heterogeneity of firms' innovation activities in their empirical analyses. In fact, through product innovation, firms adapt their products to meet both foreign consumers' preferences and foreign market standards and regulations (Cassiman et al., 2010). Through process innovation, the technical efficiency of firms is affected. They improve their production process, which leads to cost advantages; hence, they can charge lower and more competitive prices in foreign markets and expect higher profits from exports, which in turn increases their probability of exporting (Caldera, 2010). In these works, a positive correlation between firm innovation strategies and their attitudes toward exporting is shown, and the empirical results reveal the heterogeneous effects of different types of innovation on firms' export propensities. Specifically, product innovation seems to play a more relevant role in firms' export decisions than does other forms of innovation. For Spanish manufacturing firms, Cassiman et al. (2010) find a very strong effect of product innovation but no effect of process innovation on the decision to export. Caldera's (2010) empirical results for

Spanish manufacturing firms show that the introduction of product innovation influences firms' export probabilities more than the introduction of process innovation. Cassiman and Golovko (2011) find that product innovation influences exporting among Spanish firms through two channels, one direct and one indirect, by enhancing firm-level productivity. Instead, Damijan et al. (2010) do not find any evidence that either product or process innovation increases firm export propensity among Slovenian firms, but exporting increases the probability of becoming process rather than product innovators.

With respect to the above-cited works, which do not explicitly take into account the correlations between product and process innovations in their empirical analyses, Van Beveren and Vandenbussche (2010) and Becker and Egger (2013) constitute remarkable exceptions, allowing for prospective complementarities between these two kinds of innovation.

Van Beveren and Vandenbussche (2010) find that the combination of these two kinds of innovation increases firm propensity to export more than the adoption of either process or product innovation in isolation in a sample of Belgian firms[9]. Becker and Egger (2013) explicitly consider the distinct impact of endogenous firm strategies of product and process innovation on exports. They apply matching techniques to German manufacturing firms, taking the correlation between firms' product and process innovations into account. In their matching analysis, they differentiate among four types of firms: (i) firms that did not innovate (introducing neither product nor process innovations); (ii) firms that introduced product but not process innovations; (iii) firms that introduced process but not product innovation; and (iv) firms that introduced both kinds of innovations (product and process). Their investigation produces three relevant results: (i) firm probability of exporting increases by approximately 10 percentage points when process and product innovation are simultaneously introduced; (ii) when introduced alone, product innovation is more relevant to firm

[9] Specifically, the *anticipation effect* plays a relevant role in their analysis, so firms self-select into both innovation activities simultaneously, as they anticipate their entry in the export market in the future.

export propensity than process innovation; and (iii) process innovation increases firm export probability only when combined with product innovation.

Our aim is to deepen this analysis of the relationship between innovation strategies and exporting through the lens of complementarity theory. In fact, as already shown by Van Beveren and Vandenbussche (2010) and Becker and Egger (2013), the quality improvement and cost reduction induced by product and process innovations, respectively, might better work in combination than in isolation when firms' export propensities are at stake.

In addition to the above-cited works, we want to investigate whether the presence of complementarity relationships among firm innovation practices is confirmed for specific circumstances or firm characteristics. Specifically, we aim to explore whether the dimension of foreign markets served by the firm plays a role in the combined adoption of different kinds of innovation strategies. As already noted, the roles of product and process innovation differ. The first kind of innovation pertains to the firm's strategy of upgrading[10] the quality of its products to meet demand preferences and market conditions. Process innovation can be intended to decrease the marginal costs of production or delivery (Mairesse and Mohnen, 2010). When the number of foreign markets served by the firm increases, both types of innovation become more important. In fact, it is more likely that demand preferences vary and that costs of exporting increase. Concerning costs, as highlighted by Melitz (2003), a firm has to bear the fixed costs of exporting, which involve distribution and servicing costs in every foreign market to which the firm exports. Hence, the greater the number of foreign markets served by the firm, the larger the fixed export costs it has to bear[11].

[10] Through both the production of new and the significant improvement of existing goods or services (Mairesse and Mohnen; 2010).

[11] "A firm must find and inform foreign buyers about its product and learn about the foreign market. It must then research the foreign regulatory environment and adapt its product to ensure that it conforms the foreign standards

Based on the above considerations, we conjecture that when the number of foreign markets served by a firm increases, the joint adoption of both innovation practices enhances the probability of exporting more than the adoption of either in isolation. We hence expect to find complementarity relationships between product and process innovations, especially among firms that export to multiple foreign markets.

In the analysis, we add other innovations to the two usually considered, that is, “organizational and marketing innovation”. Specifically, organizational innovations[12] reinforce process innovations through the reduction of administrative or transaction costs and increased labor productivity due to improved workplace satisfaction. Marketing innovations consolidate product innovations, being aimed at better addressing costumer needs or newly positioning a firm’s product in the market, with the objective of increasing firm sales (Mairesse and Mohnen, 2010).

In pursuit of our goal, the next section presents a theoretical framework for analyzing complementarity as well as our proposed econometric testing of complementarity among the three types of innovation practices (product, process and organizational/marketing) when the firm’s export propensity is considered.

### 2.2 Complementarity: concepts and methods.

(which include testing, packaging, and labelling requirements). Firms can export their products to any country although entry into each of these export markets requires a fixed investment cost” (Melitz, 2003, p. 1706).

[12] They involve variations in workplace organization, in business practices or in firm external relations (Mairesse and Mohnen, 2010).

As innovation practices are typically investigated in discrete settings (e.g., adopting or not, adopting at an intensity higher than the average), we study complementarity among these actions through the properties of supermodular functions[13].

Following Topkis (1995, 1998), Milgrom and Roberts (1990, 1995), Milgrom and Shannon (1994), we state that two variables $x'$ and $x''$ in a *lattice*[14] $X$ are complements if a real-valued function $F(x', x'')$ on the *lattice* $X$ is supermodular in its arguments. That is, if and only if:

(1) $$F(x' \vee x'') + F(x' \wedge x'') \geq F(x') + F(x'') \qquad \forall x', x'' \in X.$$

or expressed differently:

(2) $$F(x' \vee x'') - F(x') \geq F(x'') - F(x' \wedge x'') \qquad \forall x', x'' \in X,$$

that is, the change in *F* from $x'$ (or $x''$) to the maximum $(x' \vee x'')$ is greater than the change in *F* from the minimum $x' \wedge x''$ to $x''$ (or $x'$): increasing one of the variables raises the value of the increase in the second variable as well[15]. It is worth noting that the mathematical approach to complementarity typically considers two independent variables only. However, the

[13] Within this approach to testing complementarity, we cite the contributions of Galia and Legros (2004a), Mohnen and Roller (2005), and Carrée et al. (2011) as the most representative. For surveys of the different methods considered in the economic literature on measuring complementarity, see Galia and Legros (2004a, b) and Mohnen and Roller (2005).

[14] More specifically, "a *lattice* ( $X, \geq$ ) is a set $X$, with a partial order ≥, such that for any $x', x'' \in X$ the set *X* also contains a smallest element under the order that is larger than both $x'$ and $x''$ ( $x' \vee x''$ ) and a largest element under the order that is smaller than both ( $x' \wedge x''$ )" (Milgrom and Roberts, 1995, p. 181). For the Euclidean space $R^N$, $x' \vee x'' = \left(\max\{x_1, y_1\}, \ldots, \max\{x_N, y_N\}\right)$ and $x' \wedge x'' = \left(\min\{x_1, y_1\}, \ldots, \min\{x_N, y_N\}\right)$.

[15] From equations (1) and (2), it is evident that complementarity is symmetric: increasing *x'* raises the value of the increases in *x''*. Likewise, increasing *x''* raises the value of the increases in *x'*.

complementarity relationship may simultaneously involve more than two variables through a chain reaction that starts from a complementarity relationship between two variables and involves a complementarity relationship between one of these variables and a third variable, and so on (Topkis, 1978). It is sufficient to check pairwise complementarities in cases in which the dimensions of the lattice are more than two.

In our case, we consider the exporting function of firm $j$ $(E_j, \text{for } j = 1,2,...J)$ as the dependent variable, and we focus on the innovation practices set of firm $j$, $I_j = (I_{1j}, I_{2j},...,I_{kj},...,I_{Kj})$ [16], which can affect the firm's exporting function:

$$E_j = f(I_{1j} I_{2j},...I_{Kj},\theta_j) = E_j(I_j,\theta_j) \qquad \forall j. \tag{3}$$

The problem for firm $j$ is to choose a set of innovation practices that determines its $E$ function. $\theta_j$ are the firm's predetermined parameters, such as the firm's foreign markets and the firm's sector specificity and/or dimension.

Let the innovation practices set $I_j(I_{kj} \in I_j)$ be a set of elements that form a lattice. Then, complementarity between different innovation practices may be analyzed by testing whether $E_j = E_j(I_j,\theta_j)$ is supermodular in $I_j$.

If we consider, for example, two binary decision variables ($I_{1j}, I_{2j}$), there are four elements in the set $I_j$. If in its $E_j$ maximizing problem, a firm chooses to adopt neither of the two practices, namely, if $I_{1j} = 0, I_{2j} = 0$, the element of the set $I_j$ is $I_{1j} \wedge I_{2j} = \{00\}$. If a firm chooses to adopt both practices, we have $I_{1j} = 1, I_{2j} = 1$, and the element of the set is $I_j$ is $I_{1j} \vee I_{2j} = \{11\}$. Including the mixed cases, we have four elements in the set $I_j$ that form a lattice: $I_j = \{\{00\},\{01\},\{10\},\{11\}\}$.

[16] Where $k=1, 2,..., K$ denotes the kind of practice.

From the above, we can assert that the two innovation practices are complements and, hence, that the function $E_j$ is supermodular if and only if:

$$(4) \qquad E_j(11,\theta_j) + E_j(00,\theta_j) \geq E_j(10,\theta_j) + E_j(01,\theta_j),$$

or:

$$(5) \qquad E_j(11,\theta_j) - E_j(00,\theta_j) \geq [E_j(10,\theta_j) - E_j(00,\theta_j)] + \\ + [E_j(01,\theta_j) - E_j(00,\theta_j)],$$

that is, changes in firm exporting when both forms of innovation practices increase together are stronger than the changes resulting from the sum of separate increases in these two practices.

To sum up, complementarity between the two decision variables exists if the $E_j$ function is shown to be supermodular in these two variables, and this happens when inequality (4), inequality (5) or other derived inequalities are satisfied[17]. As each firm is characterized by specific exogenous parameters $(\theta_j)$, even if the maximization problem is the same for all firms, the $E_j$ function may be supermodular in $I_j$ for some firms but not for others.

Our aim is to derive a set of inequalities, such as those in equations (4) and (5), to be tested in the empirical analysis.

Specifically, through the supermodularity approach, we analyze whether the probability that a firm exports is significantly influenced by the presence of complementarities among innovation practices.

[17] As the substitutability relationship is the opposite of that of complementarity, we can test whether a substitutability relationship exists if and only if: $E_j(11,\theta_j) + E_j(00,\theta_j) \leq E_j(10,\theta_j) + E_j(01,\theta_j)$.

As emphasized above, we are interested in investigating whether complementarity relationships among firm innovation practices are especially present in firms that export to multiple foreign markets[18].

We then empirically analyze complementarities by admitting differences between two subsamples of firms[19]: those that export to EU markets only ($E_{EU}$) and those that export to both EU and non-EU markets ($E_B$).

**2.3 Econometric modeling of and testing strategy for the complementarity hypothesis**

In this section, we concentrate on the evaluation of the complementarity hypothesis by proposing a testing procedure developed for three different innovative activities: product innovation, process innovation, and organizational and marketing innovation. Based on the multiple inequality restrictions, we exploit the concept of strict supermodularity introduced in the previous section to test whether a firm's exporting propensity is significantly influenced by the presence of complementary innovation practices.

In the presence of three firm innovation practices, we have three binary decision variables and eight elements of the lattice $I$ (that is, $2^3$). Specifically:

(6) $$I = \{\{000\},\{001\},\{010\},\{100\},\{101\},\{110\},\{011\},\{111\}\}$$

[18] In line with Milgrom and Roberts (1995), the adoption of both complementary practices by a firm may be attractive in some circumstances but not in others. In our analysis, $\theta_j$ embodies the different circumstances that firms may face.

[19] Actually, in our sample, besides exporting to only EU markets or to both EU and non-EU markets, firms can choose to export to only non-EU markets.

For each firm, $K = 3$ and, as shown in Mohnen and Roller (2005, p. 1463), the number of nontrivial inequalities is $2^{(K-2)} \sum_{i=1}^{K-1} i$, that is, six nontrivial inequalities.

We can assert that for firm *j*, two innovation practices are complements in the presence of three practices if and only if the probability of exporting satisfies the following conditions:

– Complementarity between product and process innovation practices:

$$P(E_j|d110 = 1, \theta_j) + P(E_j|d000 = 1, \theta_j) \geq P(E_j|d100 = 1, \theta_j) + P(E_j|d010 = 1, \theta_j),$$

(6.1)

$$P(E_j|d111 = 1, \theta_j) + P(E_j|d001 = 1, \theta_j) \geq P(E_j|d101 = 1, \theta_j) + P(E_j|d011 = 1, \theta_j),$$

with at least one of the two inequalities holding strictly[20]. We note that $d_i$, with $i \in I$, is a dummy equal to one when the combination of innovation activities is *i* and zero otherwise, where *i* is an element of the lattice *I*, as defined in (6).

– Between product and organizational/marketing innovation practices:

$$P(E_j|d101 = 1, \theta_j) + P(E_j|d000 = 1, \theta_j) \geq P(E_j|d100 = 1, \theta_j) + P(E_j|d001 = 1, \theta_j),$$

(6.2)

$$P(E_j|d111 = 1, \theta_j) + P(E_j|d010 = 1, \theta_j) \geq P(E_j|d110 = 1, \theta_j) + P(E_j|d011 = 1, \theta_j),$$

with at least one of the two inequalities holding strictly[21].

- Between process and organizational/marketing innovation practices:

$$P(E_j|d011 = 1, \theta_j) + P(E_j|d000 = 1, \theta_j) \geq P(E_j|d010 = 1, \theta_j) + P(E_j|d001 = 1, \theta_j),$$

[20] The first condition is met if the third innovation practice is 0; the second, if the third practice is 1.

[21] The first condition is met if the second innovation practice is 0; the second, if the second practice is 1.

(6.3)

$$P(E_j \mid d111=1,\theta_j) + P(E_j \mid d100=1,\theta_j) \geq P(E_j \mid d110=1,\theta_j) + P(E_j \mid d101=1,\theta_j),$$

with at least one of the two inequalities holding strictly[22].

When the null hypothesis of exogeneity cannot be rejected, a bootstrapping procedure is proposed; otherwise, the most used treatment effects models are considered to evaluate the presence of complementarity. The two strategies are detailed in sections 2.3.1 and 2.3.2.

### 2.3.1 Case I: Exogenous innovation variables

Testing of the inequality constraint hypotheses has been widely studied in the literature; the likelihood ratio test (LRT) is generally used to test the inequality constraint hypothesis in nonlinear econometric models. The null distribution of this test is a chi-square distribution with degrees of freedom equal to the difference between the numbers of parameters of the models under comparison. An important result from the work of Barlow et al. (1972), Robertson et al. (1988), and Silvapulle and Sen (2004) is that one of the regularity conditions of the LRT does not hold when testing inequality constraint hypotheses. Consequently, the asymptotic distribution of the LRT is not a chi-square distribution, and its p value cannot be straightforwardly computed. Moreover, model selection criteria, such as the Akaike Information Criterion or Bayesian Information Criterion, cannot be used to distinguish among statistical models with inequality constraints between the parameters of interest. These criteria use the likelihood evaluated at its maximum as a measure of model fit and the number of model parameters as a measure of complexity. The problem is model selection criteria cannot distinguish among hypotheses when these hypotheses do not differ in model fit but only in the number of constraints imposed on the parameters of interest.

[22] The first condition is met if the first innovation practice is 0; the second, if the first practice is 1.

With reference to the literature on complementarity testing, Mohnen and Roller (2005) apply statistical Wald tests along the lines of Kodde and Palm (1986) for dichotomous practices. Linear regressions under inequality constraints are computed, and the critical values of such tests are cumbersome. Carrée et al. (2011) propose a procedure arguing that a combined hypothesis is accepted if the separate hypotheses are all accepted along the lines of Savin (1980).

Our idea is to evaluate informative hypotheses (where the parameter space is restricted) using a parametric bootstrapping procedure to directly test the combined hypotheses, (6.1), (6.2) or (6.3). Bootstrapping is an approach to statistical inference within a broader class of resampling methods (Efron and Tibshirani, 1993).

The procedure adopted here consists of three steps. In the first step, a parametric bootstrap from a population in which the null hypothesis $H_0$ is not rejected is computed. The parameters are estimated under $H_0$ using the observed data. T bootstrap samples of size N are generated, and the parameters are estimated for each replicated dataset under $H_0$. Further, the parameters are estimated under the alternative hypothesis $H_1$. In the second step, these computations are repeated, conditional on the observed dataset. In the final step, a test statistic to investigate the compatibility of the null hypothesis with the observed data is chosen. As in many previous studies (e.g., Barlow et al., 1972; Robertson et al., 1988, Silvapulle and Sen, 2004), we use the LRT to evaluate the hypotheses. This procedure is conducted for each couple of complementarity constraints by estimating the constrained and unconstrained models and testing the null hypothesis using bootstrapping.

Specifically, our testing procedure requires the estimation of the logit model (Model 1):

(7) $$\Pr\left(E_j = 1 \middle| \theta_j\right) = \frac{\exp\left(\theta_j \beta\right)}{1 + \exp\left(\theta_j \beta\right)}$$

with $$\theta_j \beta = a_1 C_j + a_2 \pi_j + \sum_{s \in S} a_s D_{sj} + \sum_{i \in I} b_{i1} D_{ij} + \sum_{i \in I} b_{i2} D_{ij} + \sum_{i \in I} b_{i3} D_{ij} + \varepsilon_j .$$

$D_{ij}$ with $i \in I$ is a dummy equal to one when the combination of innovation activities is i and zero otherwise, where *i* is an element of the lattice *I*, as defined in (6). For example, if *i* = 111, the firm decides to adopt all three innovation practices simultaneously. $C_j$ is a dummy indicating if a firm $j$ is part of a group, $D_{sj}$ is a sector-specific dummy, and $\pi_j$ is a measure of firm's relative profitability, which captures heterogeneity in firm productivity levels. We admit heterogeneous coefficients across three groups of firms related to their size. Coefficients of small, medium and large firms are denoted $b_{i1}$, $b_{i2}$ and $b_{i3}$, respectively.

With reference to complementarity testing for each couple of innovation practices, Model 1 is also estimated by imposing the following constraints:

– Complementarity between product and process innovation practices:

(7.1)
$$b_{000} + b_{110} \geq b_{100} + b_{010} \geq 0$$
$$b_{111} + b_{001} \geq b_{101} + b_{011} \geq 0,$$

with at least one of the two inequalities holding strictly.

– Complementarity between product and organizational/marketing innovation practices:

(7.2)
$$b_{000} + b_{101} \geq b_{100} + b_{001} \geq 0$$
$$b_{111} + b_{010} \geq b_{011} + b_{110} \geq 0,$$

with at least one of the two inequalities holding strictly.

– Complementarity between process and organizational/marketing innovation practices:

(7.3)
$$b_{000} + b_{011} \geq b_{010} + b_{001} \geq 0$$
$$b_{111} + b_{100} \geq b_{101} + b_{110} \geq 0,$$

with at least one of the two inequalities holding strictly.

These inequalities guarantee that the exporting probability given by [7], which is a composition of an increasing function and an increasing supermodular function $\theta_j\beta$, is supermodular in an ordinal sense. Therefore, the single crossing property is satisfied with reference to the theory of supermodular functions[23]. The single crossing property is also checked for the presence of substitutable innovation practices by replacing the ≥ sign with the ≤ sign in all inequalities.

We estimate constrained and unconstrained logit models to compute the LRT from the original dataset of size N. We then draw a random sample of size N with replacement from the original dataset, fit constrained and unconstrained models, and compute the LRT. We repeat this step 500 times, obtaining the sequence $\{LRT_i\}_{i=1}^{i=500}$. However, we do not use the traditional chi-square distribution. Specifically, each value $LRT_i$ is compared with the likelihood ratio for the observed data ($LRT_{data}$). An indicator function $I_i$ is constructed, which takes the value 1 if the inequality $LRT_i > LRT_{data}$ holds and 0 otherwise, and the corresponding standard error is computed. This allows us to calculate a z-statistic and a Normal-based 95% confidence interval to determine whether the null hypothesis can be rejected.

### 2.3.2 Case II: Endogenous innovation variables

As we expect that exporting firms are more likely to be involved in innovation activities, the unweighted regression gives excessive importance to exporting firms in some cases. Given that the innovation choice is potentially endogenous, we are asked to control for the potential endogeneity of different types of innovation.

The dependent variable – the exporting choice – is binary, and the true underlying regression specification is nonlinear. To address the issue of endogeneity in nonlinear models of export propensity, we can use treatment effects models. Since it is not possible to directly compare treatment and control groups, alternative approaches must be introduced. In the econometric

[23] Following Amir (2005, p. 656), a function $f: S \times A \rightarrow R$ has the single-crossing property in (*a*, *s*) if

$$\forall a' > a, s' > s: \; F(s,a') - F(s,a) \geq 0 \Rightarrow F(s',a') - F(s',a) \geq 0 \quad \text{and}$$
$$F(s,a') - F(s,a) > 0 \Rightarrow F(s',a') - F(s',a) > 0.$$

literature, several approaches estimate treatment effects models that consider the effect of an endogenous binary treatment on another binary outcome. However, in this paper, a complementarity testing strategy refers to a multinomial innovation strategy. Specifically, we have three binary decision variables related to product, process and organizational innovations and eight possible combinations of these innovation practices. Given our multiple treatments, we propose to simplify the procedure by referring to pairwise comparisons of innovation strategies. This is possible by recognizing that all strategies can be classified into two groups: complex and simple innovation strategies. A complex strategy requires the simultaneous adoption of (at least) two types of innovation, while simple strategies include the remaining combinations. To this end, we construct a binary treatment to compare a situation wherein the firm introduces a simple innovation strategy to a situation in which the firm chooses a complex innovation strategy from each couple of the three basic product, process and organizational innovation decisions.

Specifically, to evaluate complementarity between product and process innovation, we consider the following dummy:

$$d_{12} = \begin{cases} = 1 \quad if \quad D_{110} = 1 \, or \, D_{111} = 1 \\ = 0 \quad otherwise \end{cases}$$

To evaluate complementarity between product and organizational innovation, we consider the following dummy:

$$d_{13} = \begin{cases} = 1 \quad if \quad D_{101} = 1 \, or \, D_{111} = 1 \\ = 0 \quad otherwise \end{cases}$$

To evaluate complementarity between process and organizational innovation, we consider the following dummy:

$$d_{23} = \begin{cases} = 1 \quad if \quad D_{011} = 1 \, or \, D_{111} = 1 \\ = 0 \quad otherwise \end{cases}$$

In these cases, we interpret complex innovators as a treatment group and the sub-group of simple innovators and non-innovators as the control group.[24]

To test the existence of endogeneity of $d_{12}$, $d_{13}$ and $d_{23}$ variables in nonlinear models for export propensity, a Rivers-Vuong two-stage test is applied. In the first stage, a logit model of innovation is estimated by using the instruments identified by weak instruments, LM and Hansen-Sargan tests. In the second stage, a logit regression for export propensity includes the predicted error term from the first stage among the regressors. Under the null hypothesis of exogeneity, the coefficient of the error term is zero.

When the regression of the outcome of interest on a potentially endogenous binary variable is not linear, applications of the standard two-stage least square (2SLS) estimator in which nonlinearity is ignored can lead to a consistent but biased estimate of the causal effect of the dichotomous variable on the outcome. In this context, some methods are designed to address endogeneity: PSM methods and IV models, such as bivariate probit and MSL methods.

We first consider PSM, which compares exporters and non-exporters with a very similar probability of receiving the innovation treatment (propensity score) based on observables (Rosenbaum and Rubin, 1983, 1985: Heckman et al., 1998). This method has been used by Becker and Egger (2013) to investigate the effects of product and process innovation on export propensities. Our objective is to estimate the average treatment effect (ATE) as the difference between the probability of exporting, conditional on having received a treatment, and the probability of exporting among the untreated (or control) group, that is, the exporting probability conditional on having received no treatment, which are both calculated over the entire population. The idea is to compare two alternatives: one in which all units are exposed to the treatment and one in which none exposed, where the treatment is defined as the introduction of complex innovation policies.

[24] For an extensive econometric and statistical analysis of causal effects, see Imbens and Wooldridge (2009).

Specifically, define a random treatment $t$, where $t$=1 is the treatment level, and $t$=0 is the control level. The expected average effect of treatment $t$ relative to the "no treatment" outcome for a firm drawn randomly from the population is defined as:

$$E[\Pr(E_j = 1 | t = 1, S = 1,0) - \Pr(E_j = 1 | t = 0, S = 1,0)],$$

where $S$ indicates that the treatment effect is calculated for firms selected from the group of treated and untreated units. For the purposes of this paper, we consider three possible outcomes: $t = d_{12}$, $d_{13}$ and $d_{23}$.

PSM is a balancing method, so covariate imbalance after propensity score matching is a concern. Indeed, PSM is very sensitive to the choice of conditioning variables, and robustness can be compromised in cases of misspecification of these conditioning variables (Nichols, 2007; Heckman and Navarro-Lozano, 2004). Thus, we check for the presence of imbalance by calculating the reduction of the median absolute standardized bias in the observables between the treated firms and all control units versus the treated and matched control units. The literature suggests that the remaining bias should be smaller than 20 percent (Rosenbaum and Rubin, 1985). Similarly, when comparing the pseudo-$R^2$ values of the propensity score estimation before and after matching, a decrease in the explanatory power is required, indicating that there is no remaining systematic difference in observables between treated and control firms in the matched sample.

Alternatively, among all possible IV models, the maximum likelihood bivariate probit approach is the simplest way to address endogeneity in complex nonlinear models, as suggested by Freedman and Sekhon (2010)[25]. However, convergence issues emerge in some cases, and the bootstrap standard errors calculated for ATE estimates are very small[26]. These problems are known in the literature (Nichols, 2011). Another IV model employing a MSL approach is used to estimate treatment effects models (Miranda and Rabe-Hesketh, 2006).

[25] For a survey, see Nichols (2007).

[26] The results are available upon request.

A simultaneous model for export propensity and innovation strategy is considered, and latent factors are introduced into model for the likely correlation structure. In our baseline model, export propensity and complex innovation are binary variables; we indicate the former as the outcome and the latter as the treatment. The outcome and treatment equations are specified as:

(8)
$$Pr\left(E_j = 1 \middle| \theta_j\right) = f\left(a_0 + a_1 C_j + a_2 \pi_j + a_3 d_{12} + \sum_{s \in S} a_s D_{sj} + u_j\right)$$

$$\Pr\left(d_{12} = 1 \middle| \theta_j, z_j\right) = g\left(b_0 + b_1 C_j + b_2 \pi_j + \sum_{s \in S} b_s D_{sj} + \sum_{k \in K} b_k z_{kj} + v_j\right)$$

The export propensity model is a logit model that contains the endogenous complex innovation dummy among observed covariates ($d_{12}$ as defined above) and an unobserved or latent random term ($u_j$). The treatment model refers to the endogenous complex innovation dummy. It is a binary probit model that contains a set of K instrumental variables and an unobserved random term ($v_j$) that is correlated with the unobserved random term in the export model ($u_j$). The model above also holds for the dummies $d_{13}$ and $d_{23}$.

The choice of the instruments used in PSM and MSL approaches is driven by the application of weak instrument tests, underidentification LM tests (to verify that the excluded instruments are relevant) and Hansen-Sargan tests of overidentifying restrictions. The same set of instruments is used for the Rivers-Vuong test.

MSL latent factor coefficients represent an additional test of endogeneity of the innovation variables for export propensity, which can be compared to the Rivers-Vuong two-stage tests carried out in the preliminary investigation of innovation variable endogeneity. The effect of latent factors is captured by the estimated value of a $\rho$ parameter, and the exogeneity hypothesis is not rejected when $\rho$ is not significantly different from zero. A positive (negative) $\rho$ means that unobserved characteristics that increase the probability of a complex innovation strategy relative to the control group also lead to a higher (lower) probability of exporting for the treated agents.

## 2.4 Multiple market destinations

As we are interested in exploring whether firm heterogeneity by export destination plays a role, the analysis of complementarities among innovation practices is generalized.

To this end, the dependent variable – the exporting choice – becomes multinomial when export propensity is evaluated by specifying which destination markets are chosen by the firm, that is, if the EU market alone and the EU and non-EU market strategies are studied separately. The testing procedure requires the estimation of a multinomial model.

When multiple exporting strategies are considered and exogenous innovation variables are assumed, the following exogenous multinomial model is considered (Model 2):

$$Pr\left(E_j = m \middle| \theta_j\right) = \frac{exp\left(\theta_j \beta_m\right)}{1 + \sum_m exp\left(\theta_j \beta_m\right)} \tag{9}$$

with $$\theta_j \beta_m = a_{1m} C_j + a_{2m} \pi_j + \sum_{s \in S} a_{sm} D_{sj} + \sum_{i \in I} b_{i1m} D_{ij} + \sum_{i \in I} b_{i2m} D_{ij} + \sum_{i \in I} b_{i3m} D_{ij} + \varepsilon_j$$

with $m$ = {EU only, non-EU only, both EU and non-EU}. The base outcome is given by the non-exporter group. The control and innovation variables are the same as those used in Model 1 (equation 7). The coefficients for innovation variables are heterogeneous by firm size.

The testing procedure of the combined hypothesis of complementarity – reported for all possible pairs of innovation practices in section 2.3.1 – is then performed using parametric bootstrapping for each exporting strategy. The presence of substitutable innovation practices is examined by replacing the ≥ sign with the ≤ sign in all inequalities.

When innovation variables are assumed to be endogenous, PSM and MSL estimators are used to separately calculate the average treatment effects for the EU only as well for the EU and non-EU strategies. Hence, we calculate average treatment effects of complex innovation strategies when firms export to EU countries only by applying the PSM approach described in section 2.3.2. The same approach is adopted when firms export to both EU and non-EU markets. Hence, equation (8) is estimated by MSL technique for each subgroup of exporters.

## 3. INNOVATION AND EXPORTING AMONG GERMAN MANUFACTURING FIRMS

### 3.1 Data description

Our analysis of the relationship between exporting and innovation activities is performed using manufacturing firm–level data for Germany from the Community Innovation Survey 2005 (CIS4). The CIS4 dataset covers the 2002-2004 period for all sectors of the economy. Data on turnover, exports, and dimensions are also available. Table 1 reports the export and innovation data descriptions by sector.

Concerning innovation, the CIS4 considers the distinction made in the 2005 revision of the Oslo manual, and data are collected for three forms of innovation: product, process, and organizational and marketing innovations.

Product innovations involve the introduction of new goods or services or the significant improvement of existing products. Process innovations include the implementation of new or improved production or delivery methods. Organizational and marketing innovations consist of the implementation of new organizational or marketing methods[27].

As with any cross-sectional dataset, the CIS4 suffers from the problems highlighted by Mairesse-Mohnen (2010). In fact, an analysis of the direction of causality with innovation issues and the treatment of econometric endogenous matters should involve a dynamic setting and the availability

[27] New organizational methods involve changes in workplace organization, external relations and business practices. New marketing methods concern changes in product promotion, pricing, design, packaging and placement.

of panel data. As depicted in the previous section, we overcome this difficulty by adequately addressing the endogeneity issue with appropriate econometric techniques for discrete endogenous variables. The sample we consider fits the purpose of our analysis very well because a great number of firms are involved in exporting and innovation activities. As shown in table 2, more than half of firms (68.13%) export, with the percentage increasing with firm size from 47.23% for small firms to 72.06% for medium and 86.33% for large firms. An even greater share of firms innovates. In fact, 86.32% of firms adopt at least one of the three innovation activities (table 3). Manufacturing firms are quite homogenously distributed among the three innovation activities. In this case, size also plays a relevant role, as large firms are more involved in innovation than medium and small firms.

### 3.2 Exporters, non-exporters and innovation

This section is devoted to the analysis of the differences between exporters and non-exporters with respect to their innovation activities and other characteristics. Moreover, the analysis explores the details of the two subsamples: exporters to EU markets ($E_{EU}$) and exporters to both EU and non-EU markets ($E_B$).

We first analyze the productivity levels of exporters versus non-exporters by considering a measure of relative firm profitability ($\pi_j$) proposed by Aw et al. (2008), which is given by the log of a firm's revenue share. It is calculated as the deviation from the mean log market share at the 5-digit industry level [28]. Specifically, $\pi_j = \ln\left(\frac{r_j}{I}\right) - \frac{1}{n}\sum_j \ln\left(\frac{r_j}{I}\right)$, where $r_j$ is firm $j$'s revenue in a reference period, and $R$ is total market size measured in terms of total industry revenues.

[28] Aw et al. (2008) show that the firm's observable revenue share is strictly linked to a theoretical measure of relative firm profitability in a dynamic model of exporting that shares many features with Melitz (2003) and Costantini and Melitz (2007). Such relative profitability depends on firm's productivity level, capital stock, mark-up and return to scale parameters.

In line with previous works (Bernard and Jensen, 1999; Bernard et al., 2003, 2007; Melitz, 2003), the data in table 4 show that exporting firms are more productive than non-exporting firms. Furthermore, productivity is higher for innovating firms than for non-innovating firms.

From the data for our sample, it seems reasonable to consider a positive correlation between innovation practices and exporting at the firm level, as recognized in the existing literature (Caldera, 2010; Cassiman et al., 2010; Van Beveren and Vandenbussche, 2010; Cassiman and Golovko, 2011; Becker and Egger, 2013). In table 5, exporters and non-exporters are compared in terms of innovation practices. Exporters are more innovative than non-exporters, and the relative weight of all three forms of innovation is greater among exporters than among non-exporters. Specifically, the relative weight of product innovation is 25.65% greater among exporters than among non-exporters. For process innovation, the relative weight is 17.34% larger among exporters than among non-exporters and for organizational and marketing innovation the relative weight is 15.30%.

In the sample, three different destinations for firms' exports are present: EU markets, other foreign markets and both destinations (EU and non-EU markets). As explained in section 2, we are particularly interested in investigating the two subsets of firms: those that export to EU markets ($E_{EU}$) and those that export to both markets ($E_B$). The data in table 5 show that the share of $E_B$ firms that do not innovate is significantly smaller than the share of $E_{EU}$ firms that does not innovate (5.92% versus 9.36%), and the percentage of $E_B$ firms that adopts each of the three kinds of innovation is always larger than the corresponding percentage for $E_{EU}$ firms.

As a first step in the analysis of the relationship among firm innovation activities and exporting, we estimate a logit model to identify the determinants of exporting.

Given the unobservable intensity of exporting $E_j$ for any firm *j*, we can model it as follows:

(10) $$Pr\left(E_j = 1 \middle| \theta_j\right) = \frac{exp\left(\theta_j \beta\right)}{1 + exp\left(\theta_j \beta\right)}$$

with $$\theta_j \beta = a_1 C_j + a_2 \pi_j + \sum_{s \in S} a_s D_{sj} + \sum_k b_{k1} I_{1kj} + \sum_k b_{k2} I_{2kj} + \sum_k b_{k3} I_{3kj} + \varepsilon_j ,$$

where $C_j$ is a dummy indicating if firm *j* is part of a group, $D_{sj}$ is a sector dummy, and $I_{1kj}$, $I_{2kj}$, $I_{3kj}$, $k$ = 1, 2, 3, are innovation dummies reported by small, medium and large firms and related to product, process and organizational/marketing practices, respectively. $\pi_j$ is a measure of relative firm profitability, as in Aw *et al*. (2008). It is calculated as the deviation of the log of the firm's revenue share from the mean log market share in the industry. Table A2 reports the list of variables we use in this study and the descriptive statistics.

To analyze firm heterogeneity by export destination, we consider a multinomial logit model:

$$(11) \qquad Pr\left(E_j = m \middle| \theta_j\right) = \frac{exp\left(\theta_j \beta_m\right)}{1 + \sum_m exp\left(\theta_j \beta_m\right)}$$

with
$$\theta_j \beta_m = a_{1m} C_j + a_{2m} \pi_j + \sum_{s \in S} a_{sm} D_{sj} + + \sum_k b_{k1m} I_{1kj} + \sum_k b_{k2m} I_{2kj} + \sum_k b_{k3m} I_{3kj} + \varepsilon_j ,$$

where $m$ = {EU only, non-EU only, both EU and non-EU}, and each outcome is compared to the non-exporting group. The control variables are the same as those included in logit specification (10).

Before applying our complementarity testing methodology to Model 1 and Model 2, marginal effects for the exogenous logit and multinomial estimates for specifications (10) and (11) are presented in table 6. First, the positive link between productivity and exporting is confirmed and is stronger when exporters sell to both EU and non-EU markets. Concerning innovation, the marginal effects of product innovation are positive and strongly significant for small and medium firms, especially when exporting to both EU and non-EU markets. Second, process innovation positively influences the export propensity of large firms. Finally, organizational innovations have mixed effects across firms, and the signs depend on which markets are served.

The results for innovations are quite in line with those emphasized in the literature (Caldera, 2010; Cassiman et al., 2010; Cassiman and Golovko, 2011; Becker and Egger, 2013): the effects of product innovations appear to affect exporting more than those of other kinds of innovation. The stronger effects of product innovation may be explained as a necessary step, which a firm has to address in order to serve foreign markets. In fact, firms have to adjust their products to foreign markets regulations, to meet foreign demand and to differentiate themselves from foreign competitors.

However, as previously highlighted (table 5), a large percentage of exporters (both $E_B$ and $E_{EU}$) in our sample also adopt process and organizational innovations. Moreover, the data in table 7 show that the largest share of exporters (both $E_B$ and $E_{EU}$) jointly adopt all three forms of innovation. We believe that the relationship between innovation and exporting deserves a deeper analysis. Specifically, we next scrutinize whether a complementarity relationship exists among the three kinds of innovation when firm exporting is at stake.

### 3.3 Results of testing complementarity among innovation practices

In this section, we apply the testing procedure explained in sections 2.3-2.4 with the objective of evaluating the presence of complementarity among innovative activities in German firms.

Some preliminary checks have been performed. The data are heteroskedastic; therefore, robust estimates have been calculated for all methods. Moreover, as large differences emerge across firms by dimension, the complementarity analysis is performed by assuming heterogeneous coefficients of innovation variables across small, medium and large firms.

To test for the existence of endogeneity in nonlinear models of export propensity, a Rivers-Vuong two-stage test has been applied, as detailed in section 2.3. The choice of the instruments used in the PSM and MSL approaches is driven by the application of weak instrument, underidentification LM and Hansen-Sargan tests.

All instruments are drawn from the CIS4 dataset: public funding of innovation, cooperation arrangements for innovation activities, acquisition of machinery, and training. Detailed descriptions of these variables are given in table A2 of the Appendix. Instruments are selected according to previous evidence and by means of standard endogeneity tests. First, public funding increases the profitability of innovative projects by reducing the costs of R&D and inducing firms to increase their innovation propensity (Hall, 2002). Second, Guellec and van Pottelsberghe (2000) find that R&D cooperation is positively associated with the probability of patenting an innovation. Third, firms require training for skilled employees to develop both incremental and radical innovations (Amara et al., 2008), and a strong relationship between training intensity and product/process innovation is found for small firms (Freel, 2005). Finally, innovation is also related to external technological knowledge, measured in terms of expenditures for machinery and equipment (Vega-Jurado et al, 2009).

The proposed instruments do influence innovation decisions, as shown by the logit estimates reported in table 8. For small firms, the excluded instruments satisfying underidentification LM, weak instruments and Sargan/Hansen overidentification tests are *machinery* and *training*. The relevant instruments are *collaboration*, *machinery*, and *training* for medium firms, and *collaboration* and *public funding* for large firms. The detailed test results are reported in table 9 and are based on either 2-SLS or GMM estimates depending on the presence of homoscedasticity and heteroscedasticity, respectively. Rivers-Vuong tests (table 10) indicate that endogeneity cannot be rejected for product and organization innovations in small firms exporting only to EU markets and in medium firms exporting to both EU and non-EU markets. Concerning large firms, endogeneity cannot be rejected for product and organization innovations or for process and organization innovations in the export propensity model; for product and process innovations and process and organization innovations for exporters to EU markets only; or for process and organization innovations for exporters to both EU and non-EU markets. Exogeneity cannot be rejected in all other cases.

When assuming exogenous innovation practices, for each couple of complementarity constraints, we estimate the constrained (exogenous) logit model (Model 1) and test it by bootstrapping. The presence of substitutable innovation practices is considered by replacing the $\geq$ sign with the $\leq$ sign in all inequalities. For Model 2 with multiple market destinations (exogenous multinomial logit model), the same methodology is applied for each exporting strategy. The estimates from the unconstrained model of innovation dummy variables are reported in table 11. Summary results are reported in table 12 for small, medium and large firms.

When assuming endogenous innovation practices, complementarity results are obtained by PSM and MSL methods. They are calculated in terms of average treatment effects (ATE), which are the differences between the probability of exporting, conditional on having received a complex innovation treatment, and the probability of exporting of the untreated group. As for the PSM approach, we apply radius matching wherein each treated firm is compared to all firms within a radius of 0.05 around its propensity score. The robustness of this method is checked by considering a smaller radius and alternative matching estimators (nearest-neighbor and kernel matching) in the sensitivity analysis. Imbalance is also tested. Detailed results for the PSM effects and for MSL are reported in table 13 and table 14, respectively. In addition, table 14 shows the tests for the coefficients of the latent factors calculated in the MSL estimates. In some cases, the results confirm our preliminary investigation of endogeneity based on Rivers-Vuong tests.

Table 15 summarizes all the results of the complementarity and substitutability tests, indicating which cases do not reject the hypothesis of exogenous innovation variables and which ones do not reject the hypothesis of endogenous innovation variables.

The results of the analysis confirm our preliminary intuition that the coexistence of different innovation strategies among the exporting firms in the sample suggests the presence of various complementarities. Supermodularity of innovation variables for export propensity is detected. In line with findings in the literature (Van Beveren and Vandenbussche, 2010; Becker and Egger, 2013), firms tend to adopt two or more innovation practices because their joint adoption leads to a higher probability of exporting than the sum of the probabilities from their individual adoption. Specifically, complementarities are found between product and process innovations for large firms. This outcome confirms the findings of Becker and Egger (2013), whose data mainly concern large German manufacturing firms.

Moreover, the results confirm our conjecture that firm heterogeneity by export destination matters. In fact, although complementarity relationships are frequent among firms exporting to both EU and non-EU markets, they are absent among firms exporting only to EU markets. Firms' joint adoption of different kinds of innovation practices enhances their probability of exporting more than does the adoption of each practice in isolation, especially in circumstances in which the demand variations are deeper and the fixed costs of exporting are higher. The results for complementarity are particularly evident among large firms exporting to both EU and non-EU markets. For this subset of manufacturing firms, complementarity arises between product and process innovations, between product and organizational innovations and between process and organizational innovations (all three pairs of innovations). For firms exporting to both EU and non-EU markets, complementarity also arises for small and medium firms between process and organizational innovations and between product and organizational innovations, respectively.

However, a substitutability relationship arises only between product and process innovations and concerns only small firms, regardless of the export destination (EU markets only or both EU and non-EU markets). For these subsets of firms, these two kinds of innovation may be considered substitute pathways for investment spending, and small manufacturing exporters channel their investment spending into only one innovation strategy.

## 4. Robustness analysis and Monte Carlo experiments

In this section, we compare the results of the complementarity bootstrap testing procedure with respect to two alternatives, which estimate different nonlinear model specifications and apply separate induced tests along the lines of Savin (1980). Their performance is then evaluated by Monte Carlo experiments.

The first specification, the lattice model, is based on probability estimates of Model 1 and Model 2 (equations 7 and 9), where dummies associated with the lattice [6] are introduced, following the framework of supermodular functions. We then applied a separate induced test to four constraints on coefficients obtained by conditions (7.1), (7.2) and (7.3). For example, with reference to product and process innovation, we compute estimates, standard errors, and z statistics for the following linear combinations of coefficients for each firm size:

$$b_1 \equiv b_{000} + b_{110} - b_{100} - b_{010}$$

$$b_2 \equiv b_{111} + b_{001} - b_{101} - b_{011}$$

$$b_3 \equiv b_{100} + b_{010}$$

$$b_4 \equiv b_{101} + b_{011}$$

and define the corresponding z statistics as $z_1$, $z_2$, $z_3$, and $z_4$, respectively. Then, the combined test indicates complementarity when:

$$[(z_1 > z^*) \wedge (z_2 > -z^*) \wedge (z_3 > -z^*) \wedge (z_4 > -z^*)] \vee [(z_1 > -z^*) \wedge (z_2 > z^*) \wedge (z_3 > -z^*) \wedge (z_4 > -z^*)] \vee$$
$$\vee [(z_1 > -z^*) \wedge (z_2 > -z^*) \wedge (z_3 > z^*) \wedge (z_4 > -z^*)] \vee [(z_1 > -z^*) \wedge (z_2 > -z^*) \wedge (z_3 > -z^*) \wedge (z_4 > z^*)]$$

where z* is the critical value[29]. Given a significance level for the combined hypothesis of $\alpha = 0.05$, the critical value is z* = 2.241 given that we test 4 constraints. As for the substitutability test, we evaluate the cases in which the following conditions are satisfied:

$$[(z_1 < -z^*) \wedge (z_2 < z^*) \wedge (z_3 < z^*) \wedge (z_4 < z^*)] \vee [(z_1 < z^*) \wedge (z_2 < -z^*) \wedge (z_3 < z^*) \wedge (z_4 < z^*)] \vee$$
$$\vee [(z_1 < z^*) \wedge (z_2 < z^*) \wedge (z_3 < -z^*) \wedge (z_4 < z^*)] \vee [(z_1 < z^*) \wedge (z_2 < z^*) \wedge (z_3 < z^*) \wedge (z_4 < -z^*)]$$

The same procedure is repeated for the constraints implied by conditions (7.2) and (7.3) for the product-organizational/marketing innovation and process-organizational/marketing innovation couples. These results are reported in table 16.

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[29] Following Savin (1980), let $L$ be the set of linear combinations of $b_{000}$, …, $b_{111}$ and $f_i$ be every linear combination in $L$, $i = 1, \ldots, m$. An induced test can be used to test $H_0$: $f_1 = f_2 = \ldots = f_m = 0$ against the alternative $H_1$: $f_1>0$, $f_2>0$, … $f_m>0$. Given a significance level for the combined hypothesis of $\alpha$ and a total of $m$ constraints, the Bonferroni procedure suggests a significance level for separate hypotheses of $\alpha/m$, with $H_0$: $f_i=0$ against the alternative $H_1$: $f_i>0$, $i=1, \ldots, m$. When $\alpha = 0.05$, the Normal critical value for each hypothesis is $z_{\alpha/2} = 1.96$ with 2 constraints and $z_{\alpha/4} = 2.241$ with 4 separate tests.

The second specification, the Carrée model, is strictly connected to the original contribution of Carrée et al. (2011). For the three innovation practices, nonlinear models corresponding to the linear specification of Carrée et al. (2011) are estimated by considering the following specification:

(12) $$Pr\left(E_j = 1 \middle| \theta_j\right) = \frac{exp\left(\theta_j \beta\right)}{1 + exp\left(\theta_j \beta\right)}$$

with
$$\begin{aligned}\theta_j \beta = b_1 C_j + b_2 \pi_j + \sum_k [b_{k1} I_{1kj} + b_{k2} I_{2kj} + b_{k3} I_{3kj} + b_{k12}\left(I_{1kj} I_{2kj} - I_{1kj} I_{2kj} I_{3kj}\right) + \\ + b_{k13} I_{1kj} I_{3kj} + b_{k23} I_{2kj} I_{3kj} + \left(b_{k12} + b_{k123}\right) I_{1kj} I_{2kj} I_{3kj}]\end{aligned}$$

where $I_{1kj}$, $I_{2kj}$ and $I_{3kj}$ are product, process and organizational/marketing innovation dummies for firms of size *k* (*k* = small, medium, large), respectively. Marginal effects of $\left(I_{1kj} I_{2kj} - I_{1kj} I_{2kj} I_{3kj}\right)$ and $I_{1kj} I_{2kj} I_{3kj}$ have been calculated, with the corresponding standard errors calculated by the Delta method and z-statistics. Define the corresponding (separate) test statistics as $z_1$ and $z_2$. The implied combined test is used to detect complementarity between product and process innovation. The complementarity hypothesis cannot be rejected when $[(z_1 > z^*) \wedge (z_2 > -z^*)] \vee [(z_1 > -z^*) \wedge (z_2 > z^*)]$, where z*=1.96. As for the substitutability test, we evaluate when the following conditions are satisfied: $[(z_1 < -z^*) \wedge (z_2 < z^*)] \vee [(z_1 < z^*) \wedge (z_2 < -z^*)]$. The procedure is then repeated for the other two innovation pairs, and the marginal effects are calculated with reference to the following specifications:

$$\begin{aligned}\theta_j \beta = b_1 C_j + b_2 \pi_j + \sum_k [b_{k1} I_{1kj} + b_{k2} I_{2kj} + b_{k3} I_{3kj} + b_{k13}\left(I_{1kj} I_{3kj} - I_{1kj} I_{2kj} I_{3kj}\right) + \\ + b_{k12} I_{1kj} I_{2kj} + b_{k23} I_{2kj} I_{3kj} + \left(b_{k13} + b_{k123}\right) I_{1kj} I_{2kj} I_{3kj}]\end{aligned}$$

for product and organizational/marketing innovation and

$$\begin{aligned}\theta_j \beta = b_1 C_j + b_2 \pi_j + \sum_k [b_{k1} I_{1kj} + b_{k2} I_{2kj} + b_{k3} I_{3kj} + b_{k23}\left(I_{2kj} I_{3kj} - I_{1kj} I_{2kj} I_{3kj}\right) + \\ + b_{k12} I_{1kj} I_{2kj} + b_{k13} I_{1kj} I_{3kj} + \left(b_{k23} + b_{k123}\right) I_{1kj} I_{2kj} I_{3kj}]\end{aligned}$$

for process and organizational/marketing innovation. The results for all pairwise innovations are reported in table 17.

In table 18, the bootstrapping test results are compared to the induced test results for the Carrée and lattice specifications. Concerning the Carrée model, the induced test completely misses the complementarity identification. However, the bootstrapping test and combined test applied to the same model specification produce consistent results for the three cases of complementarity, substitutability and neither.

As a final step, Monte Carlo experiments are presented to compare the performance of the bootstrapping procedure with the combined test used for both the Carrée and lattice models, when complementarity is tested for product and process innovation practices. The data for our experiments are generated following Carrée et al (2011). First, the coefficients of the dummies associated with the lattice [6] are randomly and independently drawn from the standard normal distribution for samples of 2000 observations. In the second step, the variables $x_1$, $x_2$, $x_3$ are drawn from the multivariate standard normal distribution. Product, process and organizational/marketing innovation dummies $I_{1j}$, $I_{2j}$ and $I_{3j}$ are equal to one when $x_1>0$, $x_2>0$, $x_3>0$, respectively, and zero otherwise. Then, the dummies associated with the lattice [6] are calculated from the innovation dummies $I_{1j}$, $I_{2j}$ and $I_{3j}$. To mimic empirical research settings, the correlation structure between product and process pairwise innovations is allowed to depend on the presence of complementarity (or substitutability), which is detected using conditions (7.1), (7.2), and (7.3). When the coefficients associated with innovation dummies indicate complementarity (substitutability), the pairwise correlation coefficient of product, process and organizational innovation dummies $I_1$, $I_2$, $I_3$ is set to 0.5 (-0.5). The correlation coefficient is set to zero if the draw indicates neither complementarity nor substitutability. The following equation is used to generate the data for the export dummy:

$$E_j^* = \sum_{i \in I} b_i D_{ij} + \varepsilon_j ,$$

given three different values of standard deviation $\sigma_{\varepsilon}$: 0.25, 1 and 3.5. The export dummy is equal to one when $E_j^* > 0$ and zero otherwise.

The above procedure has been repeated approximately 3000 times for all testing procedures. Table 19 presents the results of the Monte Carlo experiments. In each of the experiments, we compare the results with the true states of complementarity and substitutability. Our bootstrapping test outperforms the combined tests calculated for the Carrée and lattice models in all cases where the true states are complementarity and substitutability, while the reverse is found when neither strategy is true. This result is valid in the presence of high explanatory power models ($\sigma_{\varepsilon}$ equal to 0.25 or 1) as well as for those with a poor fit ($\sigma_{\varepsilon}$ equal to 3.5).

**5. Conclusions**

This paper contributes to an economic literature on innovation and exporting that considers the joint contributions rather than the isolated contributions of various firm innovation practices in enhancing firm export propensity (Van Beveren and Vandenbussche, 2010; Becker and Egger, 2013).

The issue of complementarity among product, process and organizational-marketing innovations is addressed through the properties of supermodular functions, and firm heterogeneity by export destination is explored.

We provide a unified testing strategy for the multiple inequality constraints implied by the properties of supermodular functions, evaluating the potential endogeneity of binary variables in nonlinear models. These inequality constraints are tested by bootstrapping under the hypothesis of exogenous binary variables. PSM and instrumental variable methods are introduced as flexible tools for answering research questions about complementarity in cases of endogenous regressors. The proposed methodology contributes to the existing literature on complementarity testing by admitting three binary regressors in nonlinear models. Compared to Carrée et al. (2011) in which a combined test à la Savin (1980) is used, we have shown that the bootstrapping procedure has the advantage of detecting the presence of complementarity and/or substitutability more precisely. Moreover, our methodology can be easily generalized to more than three binary regressors and is particularly suitable for treating endogenous regressors and ensuring consistent estimates. Finally, another advantage of bootstrapping and PSM/MSL treatment effects models is the possibility of examining large datasets. Our methodology could hence be useful for detecting complementarity in all cases in which more than two explanatory variables are discrete and endogeneity issues are relevant. Among others, applications could be considered within the innovation literature and in the analysis of the determinants of firm productivity.

In our case, we illustrate and test the usefulness of the proposed strategy using data from the CIS4 for the 2002-2004 period to analyze the presence of complementarity relationships among innovation practices in German manufacturing firms distinguished by their export destinations. Both exogenous and endogenous innovation variables are admitted in the model of export propensity.

Our results, which are in line with those of previous works, confirm that the joint adoption of two or more innovation practices leads to a higher probability of exporting than the sum of the probabilities from their individual adoption, especially for large firms.

In addition to those in the existing literature, our results show that firm heterogeneity by export destination matters. Our conjecture that complementarity relationships among innovation strategies are more likely to exist when firms export to multiple foreign markets, when fixed costs are higher and when demand variations are wider is confirmed by the empirical analysis. Indeed, complementarities among innovation practices are detected only for firms that export to both EU and non-EU countries. However, complementarity is completely absent for firms exporting only to the EU market.  Finally, our analysis shows the existence of heterogeneous results by firm size.

From a policy point of view, our results have some relevant implications. As in previous works, we suggest that when exporting is at stake, policy instruments should contemplate not only direct trade policies but also incentive programs for innovation. Furthermore, these incentives should involve all kinds of innovation and be tailored to firm size. In fact, firm competitiveness abroad increases not only due to product innovation but also due to process and organizational/marketing innovation. This is particularly relevant for large firms exporting to multiple foreign markets.

Ongoing research will be focused on (i) studying whether complementarity among innovation variables also arises in service sector firms; (ii) exploring other methodological approaches for the treatment of endogenous discrete regressors in nonlinear models, such as Deb and Trivedi (2006) and entropy-based semiparametric methods, with reference to the multiple hypothesis testing cases implied by the properties of supermodular functions.

**References**


Amara,N., Réjean L., Nizar B. and Mathieu, O., (2008), Learning and novelty of innovation in established manufacturing SMEs. Technovation, 28(7), 450–463.

Amir, R., (2005), Supermodularity and complementarity in economics: an elementary survey. *Southern Economic Journal*, 636-660.

Aw, B.Y, Roberts, M.J. and Winston, T., (2007), Export Market Participation, Investments in R&D and Worker Training, and the Evolution of Firm Productivity, *The World Economy*, Vol. 14, No. 1, 83-104.

Aw, B.Y, Roberts, M.J., and Yi D. Xu (2008), R&D Investments, Exporting and the Evolution of Firm Productivity, *American Economic Review*, Papers and Proceedings, Vol. 98, No. 2 (May), 451-456.

Barlow R.E., Bartholomew D.J., Bremner H.M. and Brunk H.D. (1972), *Statistical inference under order restrictions*. New York: Wiley.

Becker S.O. and Egger P.H. (2013), Endogenous product versus process innovation and a firm's propensity to export, *Empirical Economics*, 44(1), 329-354.

Bernard, A. B., and Jensen, J. B. (1999), Exceptional exporter performance: cause, effect, or both?. Journal of international economics, 47(1), 1-25.

Bernard, A. B., Eaton, J., Jensen, B.J. and Kortum S. (2003), Plants and productivity in international trade, *American Economic Review*, 93(4), 1268-1290.

Bernard, A. B., Jensen, B.J., Redding S.J. and Scott, P. K. (2007), Firms in International Trade, *Journal of Economic Perspectives*, 21(3), 105-130.

Bustos P. (2011), Multilateral Trade Liberalization, Exports and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinean Firms, *American Economic Review*, vol. 101(1), 304-40.

Carrée M., Lokshin B. and Belderbos R. (2011), A note on testing for complementarity and substitutability in the case of multiple practices, *Journal of Productivity Analysis* 35, 263-269.

Caldera A. (2010), Innovation and Exporting: Evidence from Spanish Manufacturing Firms, *Review of World Economics (Weltwirtschaftliches Archiv)*, vol. 146(4), 657-689.

Cassiman B., Golovko E. and Martínez E. (2010), Innovation, Exports and Productivity, *International Journal of Industrial Organization*, n. 28, 372–376

Cassiman, B. and Golovko, E. (2011), Innovation and internationalization through exports. Journal of International Business Studies, 42(1), 56-75.

Constantini, J. A. and Melitz, M. (2007), The Dynamics of Firm-Level Adjustment to Trade Liberalization, In *The Organization of Firms in a Global Economy*, edited by E. Helpman, D. Marin and T. Verdier. Cambridge: Harvard University Press.

Damijan, J. P., Kostevc, Č. and Polanec, S. (2010), From innovation to exporting or vice versa?. *The World Economy*, 33(3), 374-398.

Deb P. and Trivedi P.K. (2006), Specification and simulated likelihood estimation of a non-normal treatment-outcome model with selection: Application to health care utilization, *The Econometrics Journal*, Volume 9, Issue 2, 307–331.

Efron B. and Tibshirani, R.J. (1993), *An introduction to the bootstrap*. New York: Chapman & Hall.

Freedman D.A. and Sekhon J.S. (2010), Endogeneity in Probit Response Models, *Political Analysis*, 18(2), 138-150.

Freel, M. (2005), Patterns of innovation and skills in small firms. Technovation, 25 (2), 123–134.

Galia, F. and Legros, D. (2004a), Testing for Complementarities between Team, Incentives, Training and Knowledge Management: Evidence from France. ERMES, Paris, *mimeo*.

Galia, F. and Legros, D. (2004b), Complementarities between Obstacles to Innovation: Evidence from France, *Research Policy* 33(8), 1185-1199.

Griliches, Z. (1998), *R&D and Productivity the Econometric Evidence*, Chicago: University of Chicago Press.

Guellec D. and van Pottelsberghe B. (2000), Applications, grants and the value of patent, *Economic Letters*, 69(1), 109-114.

Kodde, D.A. and Palm, F.C. (1986), Wald criteria for jointly testing equality and inequality restrictions, *Econometrica* 54, 1243–1248

Hall B.H. (2002), The Financing of Research and Development, *Oxford Review of Economic Policy*, 18(1), p. 35-51.

Heckman, J.J., Ichimura, H. and Todd, P.E. (1998), Matching as an Econometric Evaluation Estimator", *Review of Economic Studies* 65, 261-294.

Heckman J. and Navarro-Lozano S. (2004), Using matching, instrumental variables and control functions to estimate economic choice models, *The Review of Economics and Statistics*, 86(1), 30-57.

Imbens G.W. and Wooldridge J.M. (2009), Recent Developments in the Econometrics of Program Evaluation, *Journal of Economic Literature*, 47,1, 5–86.

Lileeva, A. and Trefler, D. (2010), Improved Access to Foreign Markets Raises Plant-Level Productivity...for Some Plants, *The Quarterly Journal of Economics*, 125(3), 1051-1099

Mairesse, J. and Mohnen, P. (2010), Using innovation surveys for econometric analysis, *Handbook of the Economics of Innovation*, 2, 1129-1155.

Melitz, M. (2003), The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity, *Econometrica* 71(6), 1695-1725

Milgrom P. and Roberts J. (1990), The Economics of Modern Manufacturing: Technology, Strategy and Organization, *American Economic Review*, 80(3), 511-528.

Milgrom P. and Roberts J. (1995), Complementarities and Fit Strategy, Structure and Organizational Change in Manufacturing, *Journal of Accounting Economics*, 19 (2-3), 179-208.

Milgrom P. and Shannon C. (1994), Monotone Comparative Statics, *Econometrica*, 62(1), 157-180.

Miranda A. and Rabe-Hesketh S. (2006), Maximum likelihood estimation of endogenous switching and sample selection models for binary, ordinal, and count variables, *The Stata Journal*, 6, (3), 285-308

Mohnen P. and Roller L.H. (2005), Complementarities in Innovation Policy, *European Economic Review*, 49(6), 1431-1450.

Nichols A. (2007), Causal inference with observational data, *Stata Journal*, 7(4), 507-541, December.

Nichols A. (2011), Causal inference for binary regression with observational data, CHI11 Stata Conference 6, Stata Users Group.

Robertson T., Wright F.T. and Dykstra, R.L. (1988), *Order restricted statistical inference*. New York: Wiley.

Rosenbaum, P.R. and Rubin, D.B. (1983), The Central Role of the Propensity Score in Observational Studies for Causal Effects, *Biometrika* 70(1), 41-55.

Rosenbaum, P. R. and Rubin D. B. (1985), Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score, *The American Statistician* 39, 33-38.

Savin N.E. (1980), The Bonferroni and the Scheffé multiple comparison procedures. *Review Economic Studies*, 47, 255–273

Silvapulle M.J. and Sen, P. K. (2004), *Constrained statistical inference: Order, inequality, and shape constraints.* London: Wiley.

Topkis D. M. (1998), *Super Modularity and Complementarity*, Princeton, NJ, Princeton University Press.

Topkis D.M. (1995), Comparative statics of the firm. *Journal of Economic Theory* 67, 370–401

Van Beveren, I., and Vandebussche, H. (2010), Product and Process Innovation and Firms' Decision to Export, *Journal of Economic Policy Reform*, 13(1), 3-24

Van Long N., Raff H. and Stahler M. (2011), Innovation and trade with heterogeneous firms, *Journal of International Economics*, 84, 149-159

Vega-Jurado J., Gutiérrez-Gracia A. and Fernandez-de-Lucio I. (2009), Does External Knowledge Sourcing Matter for Innovation? Evidence from the Spanish Manufacturing Industry, *Industrial and Corporate Change*, 18(4), 637-670

Wagner, J. (2007), Exports and productivity : A survey of the evidence from firm-level data, *The World Economy*, 30(1), 60-82

Yeaple, S. R. (2005), A simple model of firm heterogeneity, international trade, and wages, *Journal of International Economics*, 65(1), 1-20

Table 1: Export and Innovation data description by sector

| | *Exporters* | | *Product innovation* | | *Process innovation* | | *Organiz/marketing innovation* | | *Tota* | |
|---|---|---|---|---|---|---|---|---|---|---|
| NACE rev. 1.1 sectors | Frequency | Percentage (%) | Frequency | Percentage (%) | Frequency | Percentage (%) | Frequency | Percentage (%) | Frequency | Pe |
| DA | 70 | 2,98 | 84 | 3,58 | 69 | 2,94 | 100 | 4,26 | 147 | |
| DB | 76 | 3,24 | 60 | 2,56 | 47 | 2,00 | 68 | 2,90 | 106 | |
| DC | 15 | 0,64 | 11 | 0,47 | 9 | 0,38 | 8 | 0,34 | 22 | |
| DF_DG | 148 | 6,31 | 160 | 6,82 | 123 | 5,24 | 153 | 6,52 | 207 | |
| DH | 107 | 4,56 | 92 | 3,92 | 74 | 3,15 | 108 | 4,60 | 148 | |
| DI | 53 | 2,26 | 59 | 2,51 | 40 | 1,70 | 57 | 2,43 | 92 | |
| DK | 245 | 10,44 | 215 | 9,16 | 149 | 6,35 | 205 | 8,73 | 284 | |
| DL | 332 | 14,15 | 358 | 15,25 | 230 | 9,80 | 310 | 13,21 | 443 | |
| DM | 125 | 5,33 | 108 | 4,60 | 95 | 4,05 | 124 | 5,28 | 149 | |
| DN | 64 | 2,73 | 58 | 2,47 | 46 | 1,96 | 64 | 2,73 | 102 | |
| 20_21 | 77 | 3,28 | 64 | 2,73 | 66 | 2,81 | 76 | 3,24 | 136 | |
| 22 | 39 | 1,66 | 64 | 2,73 | 75 | 3,20 | 99 | 4,22 | 125 | |
| 27 | 75 | 3,20 | 50 | 2,13 | 64 | 2,73 | 64 | 2,73 | 92 | |
| 28 | 173 | 7,37 | 141 | 6,01 | 141 | 6,01 | 161 | 6,86 | 294 | |
| **Total** | **1599** | **68,13** | **1524** | **64,93** | **1228** | **52,32** | **1597** | **68,04** | **2.347** | |

Sector descriptions are reported in table A1 in the Appendix

Table 2: Export data by firm size

| | *Total sample* | | *Small firms* | | *Medium firms* | | *Large fi* |
|---|---|---|---|---|---|---|---|
| | Frequency | Percentage (%) | Frequency | Percentage (%) | Frequency | Percentage (%) | Frequen |
| Exporting firms | 1599 | 68.13% | 384 | 47.23% | 552 | 72.06% | 663 |
| Non-exporting firms | 748 | 31.87% | 429 | 52.77% | 214 | 27.94% | 105 |
| Total | 2347 | 100% | 813 | 100% | 766 | 100% | 768 |

Table 3: Innovation data by firm size

| | *Total sample* | | *Small firms* | | *Medium firms* | |
|---|---|---|---|---|---|---|
| | Frequency | Percentage (%) | Frequency | Percentage (%) | Frequency | Percentage (%) |
| Product | 1524 | 64.93% | 420 | 51.66% | 462 | 60.31% |
| Process | 1228 | 52.32% | 294 | 36.16% | 361 | 47.13% |
| Organizational and marketing | 1597 | 68.04% | 452 | 55.60% | 503 | 65.67% |
| At least one of the 3 | 2026 | 86.32% | 633 | 77.86% | 654 | 85.38% |

Table 4: Productivity levels of exporters and innovators

| | Mean | St. Dev. |
|---|---|---|
| Exporters | 0.48 | 2.07 |
| Non-exporters | -1.03 | 1.79 |
| | | |
| Innovators | 0.31 | 2.12 |
| Non-innovators | -0.99 | 1.72 |
| | | |
| All firms | 0 | 2.11 |

Table 5: Innovation and exporting by market destination (frequency and percentage)

| | | Total | No innovation | Product | Process | Org/marketing |
|---|---|---|---|---|---|---|
| All firms | | 2347 | 321 | 1524 | 1228 | 1597 |
| Exporters | | 1599 | 146 | 1169 | 925 | 1166 |
| | *EU only* | *748* | *70* | *456* | *373* | *505* |
| | *Non-EU only* | *115* | *10* | *75* | *50* | *77* |
| | *Both* | *1115* | *66* | *854* | *675* | *850* |
| Non-exporters | | 748 | 175 | 355 | 303 | 431 |
| All firms | | 100,00% | 13,68% | 64,93% | 52,32% | 68,04% |
| Exporters | | 100,00% | 9,13% | 73,11% | 57,85% | 72,92% |
| | *EU only* | *100,00%* | *9,36%* | *60,96%* | *49,87%* | *67,51%* |
| | *Non-EU only* | *100,00%* | *8,70%* | *65,22%* | *43,48%* | *66,96%* |
| | *Both* | *100,00%* | *5,92%* | *76,59%* | *60,54%* | *76,23%* |
| | | | | | | |
| Non-exporters | | 100,00% | 23,40% | 47,46% | 40,51% | 57,62% |
| *Difference between Exp and Non-exp* | | | *-14,27%* | *25,65%* | *17,34%* | *15,30%* |

Table 6: Marginal effects of product, process and organizational/marketing innovations

| | Export propensity | | EU only | | Both | |
|---|---|---|---|---|---|---|
| Part of a group | -0.011 | *0.011* | 0.035* | *0.020* | -0.031*** | *0.007* |
| $\pi_j$ | 0.078*** | *0.019* | 0.017*** | *0.006* | 0.057*** | *0.014* |
| *Small firms* | | | | | | |
| Product innovation | 0.095*** | *0.005* | 0.016*** | *0.005* | 0.093*** | *0.004* |
| Process innovation | -0.027** | *0.013* | -0.001 | *0.003* | -0.010 | *0.008* |
| Organiz./marketing innovation | -0.012 | *0.018* | 0.042*** | *0.010* | -0.054*** | *0.003* |
| *Medium firms* | | | | | | |
| Product innovation | 0.086*** | *0.018* | -0.020* | *0.011* | 0.096*** | *0.014* |
| Process innovation | -0.002 | *0.012* | -0.009 | *0.007* | 0.041*** | *0.007* |
| Organiz./marketing innovation | 0.031*** | *0.008* | 0.028*** | *0.001* | 0.036*** | *0.009* |
| *Large firms* | | | | | | |
| Product innovation | -0.001 | *0.034* | -0.053*** | *0.017* | 0.043* | *0.023* |
| Process innovation | 0.104*** | *0.018* | 0.079*** | *0.002* | 0.043** | *0.018* |
| Organiz./marketing innovation | -0.043** | *0.020* | -0.105*** | *0.007* | 0.081*** | *0.025* |

Logit and multinomial logit estimates with cluster-robust standard errors (by firm size) for model specifications (10) and (11), respectively; *** 1%, ** 5%, * 10% significant marginal effects; Delta method standard errors in italics.

Table 7: Innovation strategies (frequency in numbers and %)

| | **Total** | **000** | **001** | **010** | **100** | **110** | **101** | **011** | **111** |
|---|---|---|---|---|---|---|---|---|---|
| All firms | 2347 | 321 | 240 | 91 | 194 | 144 | 364 | 171 | 822 |
| Exporters | 1599 | 146 | 134 | 51 | 140 | 96 | 254 | 99 | 679 |
| *EU only* | 556 | 70 | 66 | 21 | 42 | 47 | 90 | 46 | 174 |
| *Non-EU only* | 81 | 10 | 8 | 4 | 7 | 4 | 19 | 2 | 27 |
| *Both* | 962 | 66 | 60 | 26 | 91 | 45 | 145 | 51 | 478 |
| | | | | | | | | | |
| All firms | 100% | 13,68% | 10,23% | 3,88% | 8,27% | 6,14% | 15,51% | 7,29% | 35,02% |
| Exporters | 100% | 9,13% | 8,38% | 3,19% | 8,76% | 6,00% | 15,88% | 6,19% | 42,46% |
| *EU only* | *100%* | *12,59%* | *11,87%* | *3,78%* | *7,55%* | *8,45%* | *16,19%* | *8,27%* | *31,29%* |
| *Non-EU only* | *100%* | *12,35%* | *9,88%* | *4,94%* | *8,64%* | *4,94%* | *23,46%* | *2,47%* | *33,33%* |
| *Both* | *100%* | *6,86%* | *6,24%* | *2,70%* | *9,46%* | *4,68%* | *15,07%* | *5,30%* | *49,69%* |

Table 8: Innovation determinants, logit estimates

| | *Product&Process* | | *Product&Organization* | | *Process&Organization* | |
|---|---|---|---|---|---|---|
| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| *Small firms* | | | | | | |
| Machinery | 1.927*** | 0.234 | 1.470*** | 0.190 | 1.581*** | 0.223 |
| Training | 0.656*** | 0.201 | 0.475** | 0.187 | 0.827*** | 0.200 |
| Part of a group | 0.347* | 0.185 | 0.167 | 0.167 | 0.181 | 0.183 |
| $\pi_j$ | -0.089 | 0.106 | 0.205** | 0.095 | 0.033 | 0.105 |
| Constant | -3.276*** | 0.469 | -1.841*** | 0.387 | -2.213*** | 0.412 |
| *Medium firms* | | | | | | |
| Public funding | 0.836*** | 0.206 | 0.797*** | 0.209 | 0.434** | 0.206 |
| Machinery | 1.695*** | 0.243 | 1.094*** | 0.197 | 1.730*** | 0.228 |
| Training | 0.594*** | 0.191 | 0.742*** | 0.179 | 0.787*** | 0.188 |
| Part of a group | 0.185 | 0.196 | 0.216 | 0.182 | 0.246 | 0.194 |
| $\pi_j$ | 0.076 | 0.110 | 0.046 | 0.101 | -0.080 | 0.109 |
| Constant | -2.540*** | 0.409 | -1.412*** | 0.340 | -2.308*** | 0.390 |
| *Large firms* | | | | | | |
| Collaboration | 1.160*** | 0.203 | 1.454*** | 0.223 | 1.349*** | 0.202 |
| Public funding | 0.688*** | 0.238 | 0.465* | 0.263 | 0.616*** | 0.232 |
| Part of a group | -0.220 | 0.299 | 0.450 | 0.306 | -0.137 | 0.297 |
| $\pi_j$ | 0.528*** | 0.082 | 0.406*** | 0.086 | 0.427*** | 0.078 |
| Constant | -1.523*** | 0.508 | -1.900*** | 0.520 | -0.887* | 0.506 |

Table 9: Validity tests of instruments

| | Export propensity | | | | Multi-market export propensity | | | |
|---|---|---|---|---|---|---|---|---|
| | Heteroskedasticity | Underidentification LM test | Weak instruments (Stock and Yogo, 2005) | Sargan/Hansen test of overidentified instruments | Heteroskedasticity | Underidentification LM test | Weak instruments (Stock and Yogo, 2005) | Sargan/Hansen test of overidentified instruments |
| | | Chi-square (p-value) | F-statistics | Chi-square (p-value) | | Chi-square (p-value) | F-statistics | Chi-square (p-value) |
| Small firms | Instruments: machinery-training | | | | | | | |
| Product&Process | yes | 116.75 (0.00) | 71.63 | 0.004 (0.95) | yes | 116.75 (0.00) | 71.63 | 0.28 (0.60) |
| Product&Organization | yes | 97.27 (0.00) | 57.81 | 0.01 (0.93) | yes | 97.27 (0.00) | 57.81 | 0.35 (0.56) |
| Process&Organization | yes | 104.85 (0.00) | 64.07 | 0.001 (0.97) | yes | 104.85 (0.00) | 64.07 | 0.13 (0.72) |
| Medium Firms | Instruments: public funding-machinery-training | | | | | | | |
| Product&Process | yes | 137.16 (0.00) | 65.67 | 2.54 (0.28) | no | 130.19 (0.00) | 50.99 | 0.36 (0.83) |
| Product&Organization | yes | 109.73 (0.00) | 51.6 | 2.76 (0.25) | no | 113.85 (0.00) | 43.47 | 0.17 (0.92) |
| Process&Organization | yes | 144.48 (0.00) | 70.91 | 4.24 (0.12) | no | 142.25 (0.00) | 56.78 | 0.87 (0.65) |
| Large firms | Instruments: collaboration-public funding | | | | | | | |
| Product&Process | yes | 54.32 (0.00) | 32.62 | 1.74 (0.19) | yes | 54.32 (0.00) | 32.62 | 0.42 (0.52) |
| Product&Organization | yes | 56.08 (0.00) | 31.91 | 2.96 (0.09) | yes | 56.08 (0.00) | 31.91 | 2.21 (0.14) |
| Process&Organization | yes | 69.37 (0.00) | 41.71 | 2.11 (0.15) | yes | 69.37 (0.00) | 41.71 | 0.79 (0.38) |

A 2SLS estimator is used for homoskedastic cases. To obtain consistent statistics for heteroskedasticity, a two-step GMM estimator is used.

Table 10: Rivers-Vuong test results

| | Export propensity | EU markets only | Both |
|---|---|---|---|
| | Chi-square (p-value) | Chi-square (p-value) | Chi-square (p-value) |
| Small firms | | | |
| Product&Process | 0.44 (0.51) | 0.44 (0.51) | 0.00 (0.94) |
| Product&Organization | 0.01 (0.93) | 4.13 (0.04) | 0.64 (0.42) |
| Process&Organization | 1.05 (0.31) | 0.88 (0.35) | 0.28 (0.60) |
| Medium Firms | | | |
| Product&Process | 0.77 (0.38) | 1.43 (0.23) | 0.58 (0.45) |
| Product&Organization | 0.71 (0.40) | 1.89 (0.17) | 4.59 (0.03) |
| Process&Organization | 0.06 (0.80) | 0.36 (0.55) | 0.00 (0.94) |
| Large firms | | | |
| Product&Process | 2.60 (0.11) | 3.39 (0.07) | 0.75 (0.39) |
| Product&Organization | 4.42 (0.04) | 3.41 (0.07) | 1.05 (0.30) |
| Process&Organization | 4.81 (0.03) | 0.39 (0.53) | 7.64 (0.01) |

Table 11: Logit and multinomial logit coefficients

| | Export propensity | | EU markets only | | Both | |
|---|---|---|---|---|---|---|
| Part of a group | 0.091 | *0.106* | 0.185 | *0.148* | 0.008 | *0.071* |
| $\pi_j$ | 0.354** | *0.139* | 0.296** | *0.143* | 0.401*** | *0.154* |
| *Small firms* | | | | | | |
| d000 | -1.072*** | *0.313* | -1.028*** | *0.270* | -1.684*** | *0.236* |
| d100 | 0.664*** | *0.044* | 0.308*** | *0.047* | 0.989*** | *0.048* |
| d010 | -0.037 | *0.090* | -0.280*** | *0.094* | -0.379*** | *0.118* |
| d001 | -0.920*** | *0.306* | -0.763*** | *0.288* | -1.774*** | *0.238* |
| d110 | -0.673** | *0.268* | -0.499** | *0.221* | -1.254*** | *0.219* |
| d101 | -0.132 | *0.248* | -0.039 | *0.178* | -0.765*** | *0.250* |
| d011 | -0.683*** | *0.262* | -0.493* | *0.274* | -1.229*** | *0.187* |
| d111 | -0.183 | *0.224* | -0.271 | *0.171* | -0.592*** | *0.224* |
| *Medium firms* | | | | | | |
| d000 | -0.693*** | *0.095* | -0.821*** | *0.166* | -1.195*** | *0.085* |
| d100 | 0.290** | *0.114* | -0.151 | *0.214* | 0.067 | *0.329* |
| d010 | -0.172 | *0.121* | -0.425** | *0.200* | -0.471*** | *0.040* |
| d001 | -0.024 | *0.031* | 0.063 | *0.177* | -0.505*** | *0.145* |
| d110 | -0.263*** | *0.020* | -0.327** | *0.155* | -0.719*** | *0.174* |
| d101 | 0.032 | *0.031* | -0.214 | *0.166* | -0.246 | *0.219* |
| d011 | -0.496*** | *0.103* | -0.535** | *0.225* | -0.653*** | *0.077* |
| d111 | 0.340*** | *0.028* | 0.070 | *0.169* | 0.206 | *0.169* |
| *Large firms* | | | | | | |
| d000 | 0.125 | *0.185* | 0.185 | *0.258* | -0.336 | *0.376* |
| d100 | -0.508 | *0.333* | -0.923** | *0.467* | -0.734 | *0.551* |
| d010 | -0.592* | *0.306* | -0.749* | *0.404* | -0.751 | *0.538* |
| d001 | -0.631*** | *0.188* | -0.775*** | *0.288* | -0.768** | *0.390* |
| d110 | 0.220 | *0.336* | 0.442 | *0.480* | -0.334 | *0.530* |
| d101 | -0.704*** | *0.264* | -1.267*** | *0.392* | -0.793 | *0.499* |
| d011 | 0.018 | *0.252* | -0.057 | *0.331* | -0.277 | *0.461* |
| d111 | 0.206 | *0.376* | -0.330 | *0.487* | 0.215 | *0.637* |

Model 1 and Model 2 specifications reported in (8) and (9), respectively; *** 1%, ** 5%, * 10% significant coefficients; cluster-robust standard errors (by firm size) in italics.

Table 12: Tests on complementarity/substitutability, bootstrapping for exogenous logit

| | **Export propensity** | | | **EU market only ($E_{EU}$)** | | | **EU and non-EU markets ($E_B$)** | | |
|---|---|---|---|---|---|---|---|---|---|
| | product &process | product &organiz | process &organiz | product &process | product &organiz | process &organiz | product &process | product &organiz | process &organiz |
| Small firms | S | | | S | S | | S | | C |
| Medium firms | | | | | | | | | |
| Large firms | C | | C | C | | | C | C | C |

The letter S states that the hypothesis of substitution between two innovation practices cannot be rejected at 5%, the letter C indicates that the hypothesis of complementary innovation practices cannot be rejected at 5%, and no letter is used when there is no significant relationship.

Table 13: Tests on complementarity/substitutability, PSM method

| | **Small firms** | | | | | | **Medium firms** | | | | | | **Large firms** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Radius 0.05** | | **Pseudo $R^2$** | | **Mean bias (%)** | | **Radius 0.05** | | **Pseudo $R^2$** | | **Mean bias (%)** | | **Radius 0.05** | | **Pseudo $R^2$** | | **Mean bias (%)** | |
| | ATE | Bootstr. Std. Err. | Raw | Matched | Raw | Matched | ATE | Bootstr. Std. Err. | Raw | Matched | Raw | Matched | ATE | Bootstr. Std. Err. | Raw | Matched | Raw | Matched |
| *Product&Process* | | | | | | | | | | | | | | | | | | |
| Export propensity | 0.032 | 0.044 | 0.005 | 0.001 | 18.1 | 3.7 | 0.060* | 0.034 | 0.009 | 0 | 23.3 | 9.4 | 0.110*** | 0.047 | 0.026 | 0.008 | 38 | 32.4 |
| EU only | 0.024 | 0.036 | 0.007 | 0.003 | 10.8 | 2.4 | 0.004 | 0.039 | 0.013 | 0 | 11.7 | 5.7 | 0.007 | 0.049 | 0.029 | 0.017 | 22.8 | 18.3 |
| both | 0.007 | 0.034 | 0.007 | 0.003 | 10.8 | 2.4 | 0.068* | 0.036 | 0.013 | 0 | 11.7 | 5.7 | 0.126*** | 0.059 | 0.029 | 0.017 | 22.8 | 18.3 |
| *Product&Organiz* | | | | | | | | | | | | | | | | | | |
| Export propensity | 0.112* | 0.059 | 0.02 | 0.004 | 34.5 | 24.9 | 0.068* | 0.035 | 0.015 | 0 | 28.7 | 13 | 0.017 | 0.040 | 0.009 | 0.004 | 23.3 | 6.4 |
| EU only | 0.042 | 0.050 | 0.015 | 0.003 | 17.1 | 9.4 | -0.012 | 0.038 | 0.019 | 0.001 | 15.5 | 6.7 | -0.077* | 0.040 | 0.033 | 0 | 38.7 | 20.2 |
| both | 0.047 | 0.055 | 0.015 | 0.003 | 17.1 | 9.4 | 0.087*** | 0.035 | 0.019 | 0.001 | 15.5 | 6.7 | 0.107*** | 0.047 | 0.033 | 0 | 38.7 | 20.2 |
| *Process&Organiz* | | | | | | | | | | | | | | | | | | |
| Export propensity | 0.139*** | 0.071 | 0.002 | 0.014 | 12 | 5.5 | 0.115*** | 0.057 | 0.003 | 0.019 | 13.4 | 1.1 | 0.068*** | 0.033 | 0.019 | 0.001 | 32.1 | 16.8 |
| EU only | 0.131*** | 0.065 | 0.003 | 0.031 | 7.3 | 4.9 | 0.165*** | 0.075 | 0.008 | 0.057 | 9.3 | 7.4 | -0.023 | 0.037 | 0.027 | 0.006 | 27.7 | 16.5 |
| both | 0.025 | 0.058 | 0.003 | 0.031 | 7.3 | 4.9 | -0.010 | 0.060 | 0.008 | 0.057 | 9.3 | 7.4 | 0.117*** | 0.047 | 0.027 | 0.006 | 27.7 | 16.5 |

***, ** and * indicate 1%, 5% and 10% significant average treatment effects, respectively

Table 14: Tests on complementarity/substitutability, MSL method

| | Small firms | | | | Medium firms | | | | Large firms | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ATE | Std. Err. | $\rho$ | Std. Err. | ATE | Std. Err. | $\rho$ | Std. Err. | ATE | Std. Err. | $\rho$ | Std. Err. |
| *Product&Process* | | | | | | | | | | | | |
| Export propensity | 0.072*** | 0.001 | -0.120 | 0.157 | 0.139** | 0.078 | -0.270* | 0.154 | 0.081* | 0.060 | 0.071 | 0.231 |
| EU only | -0.001*** | 0.0004 | 0.059 | 0.178 | 0.110*** | 0.0011 | -0.183 | 0.185 | -0.095*** | 0.008 | 0.508*** | 0.131 |
| Both | 0.296 | 0.876 | -0.707*** | 0.002 | 0.160*** | 0.052 | -0.224 | 0.175 | 0.157*** | 0.066 | -0.097 | 0.193 |
| *Product&Organiz* | | | | | | | | | | | | |
| Export propensity | 0.081*** | 0.001 | -0.045 | 0.115 | 0.162** | 0.079 | -0.299** | 0.145 | 0.096 | 0.091 | -0.251 | 0.165 |
| EU only | 0.046*** | 0.013 | 0.015 | 0.140 | 0.150*** | 0.005 | -0.294 | 0.187 | 0.004*** | 0.0002 | -0.073 | 0.254 |
| Both | 0.084* | 0.064 | -0.144 | 0.155 | 0.180*** | 0.042 | -0.242 | 0.162 | 0.140** | 0.074 | -0.220 | 0.165 |
| *Process&Organiz* | | | | | | | | | | | | |
| Export propensity | 0.041*** | 0.001 | -0.016 | 0.130 | 0.076*** | 0.030 | -0.148 | 0.131 | 0.080 | 0.038 | 0.022 | 0.201 |
| EU only | 0.001*** | 0.0003 | 0.096 | 0.154 | 0.079*** | 0.0027 | -0.128 | 0.155 | -0.128*** | 0.012 | 0.501*** | 0.183 |
| Both | 0.066* | 0.045 | -0.093 | 0.174 | 0.093*** | 0.014 | -0.052 | 0.139 | 0.180*** | 0.005 | -0.268* | 0.158 |

***, ** and * indicate 1%, 5% and 10% significant average treatment effects and latent factor coefficients, respectively

Table 15: Tests of complementarity/substitutability, summary results

| | Export propensity | | | EU market only | | | Both EU and non-EU markets | | |
|---|---|---|---|---|---|---|---|---|---|
| | Product & Process | Product & Org/marketing | Process & Org/marketing | Product & Process | Product & Org/marketing | Process & Org/marketing | Product & Process | Product & Org/marketing | Process & Org/marketing |
| Small firms | B: S | B: / | B: / | B: S | MSL: C PSM: / | B: / | B: S | B: / | B: C |
| Medium firms | B: / | B: / | B: / | B: / | B: / | B: / | B: / | MSL: C PSM: C | B: / |
| Large firms | B: C | MSL: / PSM: / | MSL: / PSM: C | MSL: S PSM: / | MSL: C PSM: / | B: / | B: C | B: C | MSL: C PSM: C |

Endogeneity tests of innovation variables are based on MSL latent factor coefficients and Rivers-Vuong procedure
B: Bootstrapping testing for exogenous logit and multinomial logit; MSL: maximum simulated likelihood method; PSM: propensity score matching.
The letter S states that the hypothesis of substitution between two innovation practices cannot be rejected at 5%, the letter C indicates that the hypothesis of complementary innovation practices cannot be rejected at 5%, and the symbol ' / ' is used when there is no significant relationship.

Table 16: Linear combinations of coefficients and induced test results, lattice model

| | $b_1$ | $s_1$ | $b_2$ | $s_2$ | $b_3$ | $s_3$ | $b_4$ | $s_4$ | $z_1$ | $z_2$ | $z_3$ | $z_4$ | TEST |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Small firms* | | | | | | | | | | | | | |
| *Product&Process* | | | | | | | | | | | | | |
| Export propensity | -2.372 | 0.027 | -0.289 | 0.437 | -1.337 | 0.635 | -0.052 | 0.257 | -88.363 | -0.662 | -2.103 | -0.201 | S |
| EU only | -1.555 | 0.233 | -0.502 | 0.513 | -0.807 | 0.755 | -0.232 | 0.309 | -6.689 | -0.979 | -1.068 | -0.751 | S |
| Both | -3.548 | 0.379 | -0.372 | 0.597 | -2.243 | 0.823 | 0.173 | 0.316 | -9.358 | -0.622 | -2.725 | 0.546 | S |
| *Product&Organiz* | | | | | | | | | | | | | |
| Export propensity | -0.947 | 0.514 | 0.135 | 0.759 | -0.796 | 0.443 | 0.489 | 0.335 | -1.844 | 0.178 | -1.798 | 1.462 | |
| EU only | -0.613 | 0.623 | 0.441 | 0.903 | -0.347 | 0.543 | 0.228 | 0.396 | -0.983 | 0.488 | -0.639 | 0.575 | |
| Both | -1.664 | 0.688 | 0.512 | 0.036 | -1.754 | 0.572 | 0.662 | 0.426 | -2.418 | 14.042 | -3.069 | 1.554 | |
| *Process&Organiz* | | | | | | | | | | | | | |
| Export propensity | -0.798 | 0.611 | 0.285 | 0.683 | -0.646 | 0.552 | 0.489 | 0.335 | -1.306 | 0.417 | -1.171 | 1.462 | |
| EU only | -0.479 | 0.736 | 0.575 | 0.814 | -0.213 | 0.670 | 0.228 | 0.396 | -0.650 | 0.706 | -0.318 | 0.575 | |
| Both | -0.761 | 0.880 | 0.416 | 0.880 | -0.851 | 0.791 | 0.662 | 0.426 | -0.864 | 0.472 | -1.075 | 1.554 | |
| *Medium firms* | | | | | | | | | | | | | |
| *Product&Process* | | | | | | | | | | | | | |
| Export propensity | -1.075 | 0.624 | 0.780 | 0.458 | -0.553 | 0.457 | 0.308 | 0.278 | -1.721 | 1.702 | -1.211 | 1.108 | |
| EU only | -0.572 | 0.749 | 0.883 | 0.534 | -0.176 | 0.545 | 0.284 | 0.327 | -0.763 | 1.652 | -0.323 | 0.868 | |
| Both | -1.509 | 0.710 | 0.601 | 0.520 | -0.786 | 0.511 | 0.452 | 0.302 | -2.125 | 1.155 | -1.537 | 1.495 | |
| *Product&Organiz* | | | | | | | | | | | | | |
| Export propensity | -0.927 | 0.496 | 0.928 | 0.594 | -0.258 | 0.366 | 0.603 | 0.390 | -1.867 | 1.563 | -0.705 | 1.549 | |
| EU only | -0.947 | 0.586 | 0.508 | 0.709 | -0.063 | 0.441 | 0.397 | 0.457 | -1.614 | 0.716 | -0.142 | 0.870 | |
| Both | -1.003 | 0.555 | 0.107 | 0.683 | -0.313 | 0.391 | 0.925 | 0.447 | -1.808 | 0.157 | -0.801 | 2.069 | |
| *Process&Organiz* | | | | | | | | | | | | | |
| Export propensity | -0.993 | 0.559 | 0.862 | 0.534 | -0.324 | 0.448 | 0.603 | 0.390 | -1.775 | 1.613 | -0.723 | 1.549 | |
| EU only | -0.995 | 0.665 | 0.460 | 0.634 | -0.111 | 0.543 | 0.397 | 0.457 | -1.495 | 0.725 | -0.204 | 0.870 | |
| Both | -0.872 | 0.649 | 0.238 | 0.593 | -0.182 | 0.517 | 0.925 | 0.447 | -1.343 | 0.402 | -0.352 | 2.069 | |
| *Large firms* | | | | | | | | | | | | | |
| *Product&Process* | | | | | | | | | | | | | |
| Export propensity | 1.445 | 0.019 | 0.261 | 0.647 | 0.728 | 0.649 | 0.910 | 0.316 | 74.463 | 0.403 | 1.121 | 2.882 | C |
| EU only | 2.299 | 0.176 | 0.219 | 0.769 | 0.365 | 0.741 | 0.937 | 0.407 | 13.072 | 0.284 | 0.492 | 2.305 | C |
| Both | 0.815 | 0.102 | 0.517 | 0.719 | 0.400 | 0.688 | 0.008 | 0.339 | 7.974 | 0.719 | 0.581 | 0.023 | C |
| *Product&Organiz* | | | | | | | | | | | | | |
| Export propensity | 0.561 | 0.806 | -0.623 | 0.898 | -0.195 | 0.512 | -0.014 | 0.511 | 0.696 | -0.694 | -0.382 | -0.028 | |
| EU only | 0.616 | 0.947 | -1.464 | 0.035 | -0.344 | 0.648 | -0.772 | 0.546 | 0.650 | -41.261 | -0.532 | -1.414 | S |
| Both | 0.374 | 0.879 | 0.075 | 0.977 | -0.059 | 0.543 | 0.549 | 0.545 | 0.425 | 0.077 | -0.108 | 1.008 | |
| *Process&Organiz* | | | | | | | | | | | | | |
| Export propensity | 1.365 | 0.966 | 0.181 | 0.722 | 0.609 | 0.739 | -0.014 | 0.511 | 1.414 | 0.251 | 0.825 | -0.028 | |
| EU only | 1.653 | 0.120 | -0.427 | 0.845 | 0.693 | 0.881 | -0.772 | 0.546 | 13.776 | -0.506 | 0.786 | -1.414 | C |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Both | 0.906 | 0.067 | 0.607 | 0.767 | 0.474 | 0.812 | 0.549 | 0.545 | 13.553 | 0.792 | 0.583 | 1.008 | C |

The letter S states that the hypothesis of substitution between two innovation practices cannot be rejected at 5%, the letter C indicates that the hypothesis of complementary innovation practices cannot be rejected at 5%, and no letter is used when there is no significant relationship.

Table 17: Marginal effects and induced test results, Carrée model

| | | Small firms | | | | Medium firms | | | | Large firms | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | dy/dx | Std. Err. | $z_1/z_2$ | Test | dy/dx | Std. Err. | $z_1/z_2$ | Test | dy/dx | Std. Err. | $z_1/z_2$ | Test |
| *Product&Process* | | | | | | | | | | | | | |
| Export propensity | $b_{12}$ | -0.127 | 0.084 | -1.52 | | -0.172* | 0.099 | -1.73 | | 0.116 | 0.146 | 0.8 | |
| | $b_{12}+b_{123}$ | -0.045 | 0.074 | -0.6 | | 0.129* | 0.075 | 1.71 | | 0.041 | 0.106 | 0.39 | |
| EU only | $b_{12}$ | 0.138 | 0.108 | 1.28 | S | 0.048 | 0.106 | 0.45 | | 0.091 | 0.139 | 0.66 | |
| | $b_{12}+b_{123}$ | -0.185** | 0.088 | -2.09 | | -0.042 | 0.075 | -0.56 | | -0.008 | 0.103 | -0.08 | |
| Both | $b_{12}$ | 0.196 | 0.127 | 1.55 | S | -0.210 | 0.108 | -1.94 | S | -0.359*** | 0.139 | -2.58 | S |
| | $b_{12}+b_{123}$ | -0.250** | 0.107 | -2.34 | | -0.204*** | 0.078 | -2.61 | | 0.086 | 0.106 | 0.81 | |
| *Product&Organiz* | | | | | | | | | | | | | |
| Export propensity | $b_{13}$ | -0.016 | 0.064 | -0.25 | | -0.165** | 0.077 | -2.15 | S | -0.033 | 0.106 | -0.31 | |
| | $b_{13}+b_{123}$ | 0.067 | 0.092 | 0.72 | | 0.136 | 0.099 | 1.37 | | -0.108 | 0.146 | -0.75 | |
| EU only | $b_{13}$ | 0.001 | 0.075 | 0.02 | S | -0.057 | 0.077 | -0.75 | | -0.011 | 0.113 | -0.1 | |
| | $b_{13}+b_{123}$ | -0.321*** | 0.117 | -2.75 | | -0.147 | 0.106 | -1.38 | | -0.111 | 0.131 | -0.84 | |
| Both | $b_{13}$ | -0.008 | 0.087 | -0.09 | S | -0.082 | 0.079 | -1.05 | | -0.036 | 0.109 | -0.33 | C |
| | $b_{13}+b_{123}$ | -0.454*** | 0.133 | -3.42 | | -0.077 | 0.107 | -0.72 | | 0.410*** | 0.136 | 3.01 | |
| *Process&Organiz* | | | | | | | | | | | | | |
| Export propensity | $b_{23}$ | 0.029 | 0.085 | 0.34 | | -0.158* | 0.090 | -1.74 | | 0.086 | 0.136 | 0.63 | |
| | $b_{23}+b_{123}$ | 0.112 | 0.074 | 1.52 | | 0.143* | 0.086 | 1.66 | | 0.011 | 0.119 | 0.09 | |
| EU only | $b_{23}$ | 0.090 | 14.242 | 0.01 | | 0.059 | 11.474 | 0.01 | | -0.027 | 26.045 | 0 | |
| | $b_{23}+b_{123}$ | -0.232 | 13.801 | -0.02 | | -0.031 | 0.090 | -0.34 | | -0.126 | 0.109 | -1.16 | |
| Both | $b_{23}$ | 0.419 | 24.748 | 0.02 | | 0.193 | 19.938 | 0.01 | C | -0.290 | 45.258 | -0.01 | |
| | $b_{23}+b_{123}$ | -0.028 | 23.983 | 0 | | 0.199** | 0.091 | 2.2 | | 0.156 | 0.105 | 1.49 | |

The letter S states that the hypothesis of substitution between two innovation practices cannot be rejected at 5%, the letter C indicates that the hypothesis of complementary innovation practices cannot be rejected at 5%, and no letter is used when there is no significant relationship.

Table 18: Complementarity test results, bootstrapping, Carrée, and lattice procedures

| | Small firms | | | Medium firms | | | Large firms | | |
|---|---|---|---|---|---|---|---|---|---|
| | Bootstrap-ping | Carrée model | Lattice model | Bootstrap-ping | Carrée model | Lattice model | Bootstrap-ping | Carrée model | Lattice model |
| *Product&Process* | | | | | | | | | |
| Export propensity | S | | S | | | | C | | C |
| EU only | S | S | S | | | | C | | C |
| Both | S | S | S | | S | | C | S | C |
| *Product&Organiz* | | | | | | | | | |
| Export propensity | | | | | S | | | | |
| EU only | S | S | | | | | | | S |
| Both | | S | | | | | C | C | |
| *Process&Organiz* | | | | | | | | | |
| Export propensity | | | | | | | C | | |
| EU only | | | | | | | | | C |
| Both | C | | | | C | | C | | C |

The letter S states that the hypothesis of substitution between two innovation practices cannot be rejected at 5%, the letter C indicates that the hypothesis of complementary innovation practices cannot be rejected at 5%, and no letter is used when there is no significant relationship.

Table 19: Monte Carlo experiment for 2000 observations (3000 draws)

| *True effect* | Complements | Neither | Substitutes | Total | % | Complements | Neither | Substitutes | Total | % | Complements | Neither | Substitutes | Total | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Bootstrapping** | | | | | | | | | | | | | | | |
| Complements | **276** | 543 | 51 | 870 | 31.72% | **117** | 342 | 76 | 535 | 21.87% | **129** | 472 | 139 | 740 | 17.43% |
| Neither | 149 | **947** | 127 | 1223 | 77.43% | 186 | **721** | 196 | 1103 | 65.37% | 270 | **875** | 251 | 1396 | 62.68% |
| Substitutes | 53 | 582 | **295** | 930 | 31.72% | 76 | 352 | **138** | 566 | 24.38% | 136 | 459 | **169** | 764 | 22.12% |
| Correct (%) | | *50.22%* | | | | | *44.28%* | | | | | *40.45%* | | | |
| **Carrée model** | | | | | | | | | | | | | | | |
| Complements | **63** | 798 | 9 | 870 | 7.24% | **19** | 511 | 5 | 535 | 3.55% | **25** | 696 | 22 | 743 | 3.36% |
| Neither | 74 | **1083** | 66 | 1223 | 88.55% | 33 | **1041** | 29 | 1103 | 94.38% | 40 | **1330** | 39 | 1409 | 94.39% |
| Substitutes | 7 | 854 | **69** | 930 | 7.42% | 11 | 533 | **25** | 569 | 4.39% | 21 | 721 | **25** | 767 | 3.26% |
| Correct (%) | | *40.19%* | | | | | *49.16%* | | | | | *47.28%* | | | |
| **Lattice model** | | | | | | | | | | | | | | | |
| Complements | **470** | 245 | 31 | 746 | 63.00% | **111** | 380 | 44 | 535 | 20.75% | **77** | 612 | 54 | 754 | 10.36% |
| Neither | 438 | **598** | 463 | 1499 | 39.89% | 171 | **770** | 162 | 1103 | 69.81% | 142 | **1113** | 154 | 1485 | 78.99% |
| Substitutes | 34 | 255 | **466** | 755 | 61.72% | 42 | 421 | **106** | 569 | 18.63% | 56 | 642 | **63** | 761 | 8.28% |
| Correct (%) | | *51.13%* | | | | | *44.72%* | | | | | *43.01%* | | | |

**Appendix**

Table A1: Description of NACE rev. 1.1 sectors

| Sectors | Description |
|---|---|
| DA | Food products, beverages and tobacco |
| DB | Textiles and textile products |
| DC | Leather and leather products |
| DF-DG | Coke, refined petroleum products and nuclear fuel; chemicals, chemical products and man-made fibers |
| DH | Rubber and plastic products |
| DI | Other non-metallic mineral products |
| DK | Machinery and equipment n.e.c. |
| DL | Electrical and optical equipment |
| DM | Transport equipment |
| DN | Manufacturing n.e.c. |
| 20-21 | Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials; pulp, paper and paper products |
| 22 | Publishing, printing and reproduction of recorded media |
| 27 | Basic metals |
| 28 | Fabricated metal products, except machinery and equipment |

Table A2: Explanatory variables for exporting and innovation propensities

| Variable | Description | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $\pi_j$ | Relative profitability of firm j | 0.00 | 2.10 | -5.84 | 7.81 |
| Part of a group | Enterprise part of a group | 0.65 | 0.48 | 0 | 1 |
| Public funding | Public funding of innovation | 0.19 | 0.39 | 0 | 1 |
| Cooperation | Cooperation arrangements on innovation activities | 0.23 | 0.42 | 0 | 1 |
| Machinery | Engagement in acquisition of machinery | 0.58 | 0.49 | 0 | 1 |
| Training | Engagement in training | 0.47 | 0.50 | 0 | 1 |