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Do Innovation and Offshoring Make a Difference? An Empirical Exploration of the Effects on the Performance of European Firms

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Abstract

This study attempts to answer the question of whether European manufacturing firms that undertake offshoring, innovation or both benefit from higher productivity and profitability. From a methodological point of view, the driving forces that push firms to innovate and/or to offshore can be seen as self-selection mechanisms that make the estimation of their economic impact more difficult if the confounding factors affecting these mechanisms also affect the economic performance of the firms. To disentangle the effect of both offshoring and innovation on firms' performances from the effect of firm characteristics, the propensity score matching methodology in a multi-overlapping treatment setting is used. The study targets European countries using the EU-EFIGE/Bruegel-Unicredit dataset. Decisions to offshore and innovate do not seem to have a significant effect on productivity, whereas the decision to innovate only has a significant effect on firm profitability.

Keywords: matching, multi-treatment propensity score, productivity, profitability

1. Introduction & Motivation

In past decades innovation has been widely regarded as an important means of improving the performance of firms in terms of efficiency and profitability (Hall, 2011; Huergo & Jaumandreu, 2004; Janz, Loof & Peters, 2003). With the advent of globalization also the practice of offshoring, which can be thought as an inter-organizational innovation (Brandau & Hoffjan, 2010), has experienced a phenomenal growth and its effects on firm performance have begun to constitute an empirical question (see for example Grossman & Helpman, 2005; Girma & Görg, 2004; Hijzen, Inui & Todo, 2010).

Recently, Altomonte, Aquilante, Békés and Ottaviano (2013) document the pattern of interaction between firm reallocation, innovation and productivity across seven European countries, using a representative cross-country comparable sample of manufacturing firms (EFIGE), a rich firm-level dataset containing detailed information on both phenomena (internationalization and innovation). Using the same dataset, our goal is to assess the conjoint effect of both innovation and offshoring on firm performance, as measured by its productivity and profitability.

Our work relates to three strands of the literature: the literature on innovation and firm performance, the literature on offshoring and firm performance and the literature on complementarities between innovation and internationalization. In particular, our research questions stem from the following considerations: i) innovation is generally positively linked to productivity and profitability (although, at least in the case of profitability, the precise nature of the relationship is unclear), ii) offshoring firms generally perform better than non-offshoring firms, iii) the interaction between innovation and internationalization has been pointed out by many studies and there is a growing consensus that both are the result of the endogenous choices of firms. Therefore, the present study focuses on the following questions: how do these influences interact? Do firms undertaking one or both actions perform better than those doing nothing or undertaking only one of the two actions?

From a methodological point of view, the driving forces that push firms to innovate and/or to offshore can be seen as self-selection mechanisms, which make the estimation of their economic impact more difficult if the confounding factors affecting these mechanisms also affect the economic performance of the firms. Hence, we use Propensity Score Matching (PSM) to "correct" the estimation of the treatment effect of innovation and/or offshoring, controlling for the existence of a set of confounding factors, motivated by the literature. The use of PSM is not new in empirical economics (see, for example, Wagner, 2011; Dachs & Ebersberger, 2013). But, because we consider two overlapping treatments jointly, we perform a relatively new method that is, the PSM in a multi-treatment framework, rather than the PSM for binary treatment.

We focus on European countries using the EFIGE dataset. It is known that in Europe firms invest less in innovation than in United States (Hall, Lotti & Mairesse, 2012) and that European firms have started to find offshoring attractive but lag behind American ones. Hence, it is important to try to understand whether this is eventually due to a scarcity effect of such strategies on European firms' performance, by evaluating the productivity and profitability of the innovation/offshoring efforts undertaken by firms.

The contribution of this work is threefold. First, to the best of our knowledge, it is the first work that investigates the conjoint effect of internationalization and innovation on both firms' productivity and profitability adopting the specific definitions that we explain in the rest of the paper. Second, the EFIGE dataset can be uniquely used to analyse the mode of internalization and innovation adopted by different European countries and evaluate how those choices affect firms' performance. Third, to the best of our knowledge, a multi-treatment PSM method has rarely been used to analyse overlapping treatments applied to economic data (see, for example, Becker & Egger, 2013; Lo Turco & Maggioni, 2015).

The remainder of this paper is structured as follows. Section 2 provides a review of the literature concerning offshoring, innovation and their effects on firms' productivity and profitability separately, and a short review of the literature on the relationship between the two phenomena. In Section 3, the EFIGE dataset is described, and the variables considered in the analysis are defined. Section 4 provides some descriptive statistics. In Section 5, the methodology used is described. Section 6 shows the results obtained considering i) the individual treatments separately (Section 6.1) and ii) the two treatments jointly (Sections 6.2 and 6.3). In Section 7, some concluding remarks are reported.

2. Background

2.1 Offshoring

The phenomenon of geographically fragmented production processes has increased without precedent over the last two decades because information and communication technologies (ICTs) have made it possible to divide the value chain and perform activities in any location (Grossman & Helpman, 2005) and the continuous decline of transportation costs has facilitated the worldwide flow of goods.

Because of its increase, offshoring has been in the focus of economic debates in the US and Europe at least in the last decade. Various theories have been posited regarding offshoring. The transaction costs analytical framework, however, represents the main theoretical reference. According to that theory, offshoring is attractive only when transaction costs incurred from asset specificity, incomplete contracting and search efforts are lower than advantage in production costs (Williamson, 1975). Hence, the effect on a firm's performance depends on the trade-off between the two types of costs, which is influenced also by the location of the offshore production, namely in developing or developed countries (Jabbour, 2010).

The relationship between offshoring and firms' productivity has been studied by international production theorists. The theory predicts that multinational firms tend to have higher productivity than their domestic counterparts at any given level of corporate innovativeness because gains typically arise from the exploitation of the comparative advantages and economies of scale offered by external suppliers (Antras & Helpman, 2004; Grossman & Helpman, 2005). Goods and services may be more efficiently produced in another country and, consequently, imported at a lower price. This access to better, cheaper and more varied (final and intermediate) inputs helps improve firms' productivity (see also Schwörer (2013) for other channels through which offshoring affects firms' performance).

Nevertheless, the effect of offshoring on companies' accounting figures have only recently been studied in a more systematic and in-depth manner. One reason is that these variables can be revealed only by empirical studies conducted at the firm level. It is generally rather difficult to measure offshoring because firms are sometimes reluctant to offer details on their offshoring policies and the public surveys necessary to measure offshoring are only available in a few OECD countries (Daveri & Jona-Lasinio, 2008). Regarding micro data analysis, empirical studies have focused on the effects of offshoring on productivity (Girma & Görg, 2004; Görg, Hanley & Strobl, 2008; Hijzen et al., 2010, Jabbour, 2010; Wagner, 2011); its effect on profits has been analysed in a few studies, such as those of Görg and Hanley (2004) and D'Attoma and Pacei (2014). Those studies provide some evidence that offshoring can increase productivity, but the identified effects are quite heterogeneous depending on the country, the firm's specific characteristics (exporters versus non-exporters, foreign-owned versus domestic) and the kind of activities offshored (materials or services) (Schwörer, 2013).

The information that we have from the survey regarding the firm's decision to offshore is a dummy variable. Our definition of offshoring includes the allocation of production processes to any foreign country without distinguishing whether the provider is external or affiliated with the firm (Wagner, 2011). Further details on the definition of offshoring and characteristics of the survey used are presented in Section 3.

2.2 Innovation

The analysis and the quantification of the productivity effects of innovative activities were already challenging tasks in past decades in many empirical economic studies (see, for example, Griliches, 1958; Mansfield, 1965).

Most of the studies on the effect of innovation on productivity carried out at the firm level apply some variants of the CDM model (Crépon, Duguet & Mairesse, 1998) on data from the Community Innovation Survey (CIS) (see, for example, Lööf, Heshmati, Asplund & Nåås, 2001; Janz et al., 2003; Mairesse & Robin, 2009). The CDM model formalizes the relationship between R&D, innovation and productivity through a structural model consisting of three sets of equations.

Hall (2011), in her extensive review of the recent empirical evidence on the productivity effects of product and process innovation, concludes that product innovation has positive impacts on revenue productivity. Less evident is the impact of process innovation. She argues the latter result is primarily due to the difficulty in measuring the real quantity effect of process innovation already mentioned.

The literature has largely studied innovation’s effect on productivity, but few researchers have focused on the link between innovation and profitability. The results obtained at the firm level suggest that innovators are persistently more profitable than non-innovators (Geroski, Machin &Van Reenen, 1993; Leiponen, 2000; Cefis & Ciccarelli, 2005). The reasons could be the market position of innovators, which enables them to protect their new products from competition, which normally erodes such profits, or the possibility that innovators have to introduce multiple innovations over time to maintain high profits, as the profit effect of any individual innovation may be transitory. In addition, the process of innovation helps build the internal capabilities of firms and makes them less sensitive to adverse macroeconomic shocks.

The innovation activity and its effect on firm performance have been studied in the literature using different definitions of innovation. To this purpose, the Olso Manual provides guidelines for the definition of various types of innovation, which are used by surveys on innovative activities in firms conducted in many countries around the world (Hall, 2011).

As in many other studies (see, for example, Griffith, Huergo, Mairesse & Peters, 2006; Parisi, Schiantarelli & Sembenelli, 2006; Hall, Lotti & Mairesse, 2008), in this paper we define an innovative firm as a firm that has carried out process and/or product innovation during the last three years. Product and process innovation can both be seen as the result of an invention but are distinct; further, one of the two activities does not necessarily imply the other. The introduction of a new product is strongly directly associated with R&D spending, whereas this is not true for the introduction of a new process. The latter is strongly associated with spending on new fixed capital, which may allow for the embodiment of technological progress (Parisi et al., 2006).

The use of information on innovation through dummy variables has some drawbacks (Hall, 2011), and some researchers prefer to consider a continuous measure, such as the share of sales of innovative products, which provides an indication of how important product innovation is overall for a firm. However, this measure cannot be used to capture process innovation. Moreover, considering our aim of studying the effect of both phenomena, innovation and offshoring, and given that the information on offshoring decisions is available in the form of a dummy variable, we opt for the use of a dummy indicator for innovation, as we have done for offshoring.

2.3 Offshoring and Innovation

Several studies find a correlation between productivity, outsourcing, R&D expenditures and, hence, innovation processes. Nevertheless, the direction of causality between innovation and being globally engaged is unclear.

A strand of the literature argues that internationalization affects innovation. Many studies show that globally engaged firms tend to innovate more (Altomonte et al., 2013; Fritsch & Görg, 2013; Criscuolo, Haskel & Slaughter, 2010; Cusmano, Mancuso & Morrison, 2008). The idea is that, by offshoring, firms may focus on their core skills and, thus, increase their level of innovation. Other studies offer another theory in which offshoring hurts domestic innovation, as opposed to stimulating it. Pisano and Shih (2012) argue that offshoring of manufacturing has seriously eroded the domestic capability needed to turn inventions into high-quality, cost-competitive products in USA. The reason is that the realization of the product is the main source for product innovation. Feedback loops between production activities, product development and R&D are the main source of new ideas, and these links are most beneficial when advanced production is concentrated in a domestic location (Dachs & Ebersberger, 2013).

Another strand of the literature argues that the causation goes from innovation to internationalization (Altomonte et al., 2013; Becker & Egger, 2013). Innovation capabilities might improve gaining advantages from offshoring strategies.

Innovation may imply rigorous structures and systems in place to improve business practices, implying accumulated experience of which offshoring strategies may profit. Therefore, innovators are more fully equipped to seize the benefits from offshoring strategies (Roza, 2011).

A recent strand of the literature concerns the complementarities between innovation and some forms of internationalization and focus on the simultaneity of the two decisions (Costantini & Meliz, 2008; Aw, Roberts & Xu, 2011; Lecerf, 2012; Louart & Martin, 2012; Bøler, Moxnes & Ulltveit-Moe, 2015). Innovations are in general mainly introduced in the operating core of an organization; hence, activities involved in innovation match those involved in offshoring. Bøler et al. (2015), for example, find that complementarity arises as R&D on average increases future profits and revenue, thus, making it more profitable to cut costs by sourcing inputs internationally, while enhanced international sourcing in turn makes R&D investment more profitable.

3. Data and Variables

This paper exploits the EU-EFIGE/Bruegel-Unicredit dataset (Note 1) (hereafter the EFIGE dataset). Data are collected within the EFIGE project (European Firms in a Global Economy: internal policies for external competitiveness) supported by the Directorate General research of the European Commission through its 7th Framework Programme and coordinated by Bruegel. The data consist of a representative sample of manufacturing firms with a lower threshold of 10 employees in seven European countries (Germany, France, Italy, Spain, United Kingdom, Austria and Hungary). The sample is stratified according to industry, region and firm size structure. Large firms (more than 250 employees) are oversampled to allow for adequate statistical inference for this size class of firms (Altomonte et al., 2013).

The data were collected through a survey carried out in 2010 and cover the three years immediately prior (from 2007 to 2009). Most questions relate to the year 2008, with some questions requesting information for 2009 and previous years. Some items of the balance sheet data, drawn from the Amadeus database managed by Bureau van Dijk, available continuously since 2001, are used to complement the survey questions. These data contribute to the characterization of firms included in the survey, in particular by enabling the calculation of a firm-specific measure of labour productivity. The EFIGE survey covers different broad areas: the structure of the firms, workforces, investment, technological innovation, R&D, export and internationalisation processes, the market structure and competition, the financial structure and bank-firm relationships (Altomonte & Aquilante, 2012).

The original sample consists of 14,759 firms. From the overlaid EFIGE and balance sheet data, it is possible to calculate the labour productivity and an indicator of profitability for 59.5% and 60.1% of the firms present in the dataset, respectively. The remaining firms are excluded from the analysis because of missing data in Amadeus. Altomonte, Aquilante and Ottaviano (2012) compare the final and restricted samples and find similar aggregate statistics. The only difference concerns the country representativeness, as Italy, France and Spain are the countries with the highest frequency of firm-level productivity data.

In our analysis, the decision to offshore in conjunction with the decision to innovate is considered a treatment in a broad sense. We define offshoring firms as firms that currently relocate at least part of their production activity in another country (via contracts and arm’s-length agreements with local firms or via direct investment). A related term is international outsourcing.

We define innovating firms as those firms that carried out some product or process innovation (or both) in the years 2007-2009. Product innovation refers to the introduction in the market of new or significantly improved products; whereas, process innovation refers to the implementation of a new or significantly improved production process, distribution methods or support activity for goods or services produced.

To perform our multiple treatment analysis, we create a categorical variable such that each firm falls into one of the following exhaustive and mutually exclusive ‘treatment statuses’: domestic firms that do not carry out any process/product innovation (henceforth “nothing”, 4,926 firms in the original sample); offshoring firms only (henceforth “only offshoring”, 252 firms); innovating firms only (henceforth “only innovation”, 8,578 firms); offshoring firms that carry out innovation (henceforth “both”, 1,002 firms).

We consider as outcome variables “value added per employee” and “per capita gross earnings before taxation” in 2009, which represent, respectively, labour productivity and the profitability of operations before depreciation charges and provisions are deducted. Value added per employee is calculated as the ratio between the operational value added and the average number of employees. The operational value added is calculated as the difference between the sales revenue net of changes in the finished product inventory and the cost of raw materials, semi-finished goods and services. Gross earnings before taxation is the difference between the value added and the labour costs (Note 2).

As already discussed, the four groups of firms do not constitute a random sample and may differ along many observed or unobserved characteristics that may influence offshoring and/or innovation decisions (self-selection into treatment) and the outcome. The EFIGE survey allows for an essentially cross-sectional estimation and we have not longitudinal data to identify the causal effect of innovation and offshoring. Therefore, for the purpose of treatment effect identification, we have to rely on a strategy, the Propensity Score Matching, which assumes that, after controlling for a suitable set of observable variables, participation in innovation and offshoring does not depend on the firm performance. This is a strong assumption and there is no way to test whether it is justified in an application (Note 3). However, Hall (2011) notices that the few studies using lagged measures of innovation found not notably different results from those using contemporary measures, thus reinforcing the reliability of cross-sectional and long-run nature of these results.

To control for self-selection and reduce bias in the effect estimation, important determinants of offshoring and innovation must be controlled. Motivated by well-established works on the determinants of offshoring and innovation and the effect of both decisions on productivity (Girma & Görg, 2004; Wagner, 2011; Capasso, Cusmano & Morrison, 2011; Hall et al. 2012; Hall, 2011; Fritsch & Görg, 2013), we control for the following dimensions: firm size, sector (Note 4), country, labour composition and labour costs indexes, capital and export intensity, competitors' location and market information. The exact definition of the variables is reported in the Appendix A.

4. Descriptive Statistics

The statistics reported herein refer to the full sample. The statistics are weighted with absolute weights provided in the EFIGE data. The percentage of innovating firms is 64%, the percentage of offshoring firms is 7% and the percentage of firms that both offshore and innovate is 5.6%. Hence, the percentage of firms that offshore without innovating is very low and represents very particular firms.

Among the innovating firms, 75% carry out product innovation, 66% carry out process innovation and 42% carry out both. Hence, very often the two types of innovation are carried out at the same time. Among the firms that run at least part of their production activity in another country, 55% use direct investments, 53% use contracts and arm's-length agreements with local firms and 8% use both modalities. In this case, the overlap between strategies is low because firms tend to choose one of the two. Table 1 shows the percentage of innovating and offshoring firms in each country.

Table 1. Percentage of innovating firms and offshoring firms in the EU Countries

Country	Innovating firms (%)	Offshoring firms (%)	Number of firms
Austria	74	9.3	443
France	58	8.7	2,973
Germany	63	8.2	2,935
Hungary	54	4.0	488
Italy	66	6.2	3,021
Spain	69	3.8	2,832
UK	65	8.9	2,067
Total	64	7.4	14,759

The country where firms innovate the most is Austria (74%), followed by Spain, Italy, the UK and Germany, with values close to the overall mean. Hungary (54%) has the lowest percentage of innovating firms. Austria is also the country where offshoring is the most prevalent (9.3%), followed by the UK (8.9%) and France (8.7%). In Spain and Hungary, the percentage of offshoring firms is much lower, 3.8% and 4%, respectively.

The means and the coefficients of variation obtained by treatment status for some firm characteristics are reported in Table 2. Offshoring firms are more productive on average (treatment status 1 and 3), whereas innovation (treatment status 2 and 3) seems to affect, above all, the profitability. Innovation can have a (long-term) effect on profitability, whereas offshoring can have an immediate effect on productivity. The very high coefficients of variation highlight the high heterogeneity among firms, especially in the case of firms that do not carry out innovation or offshoring (treatment status 0).

Some other expected results regard the other characteristics considered. Offshoring and innovating firms are the largest on average, followed by only offshoring firms. Firms doing nothing are much smaller. The same ranking among treatment status is observed for the percentage of firms more than 20 years old and the percentage of firms belonging to a national or foreign group. Hence, offshoring and innovating firms tend to be larger, older and to belong to a group, creating the image of more established and stable companies. Offshoring firms (treatment status 1 and 3) show the highest percentage of white collar workers on average, as expected, because blue collar skills are usually offshored and, as a consequence, the wage rates tend to be higher for that category of firms. The export intensity is found to be more relevant for offshoring firms, which is not surprising given that offshoring tends to be connected to exports. The capital intensity is instead much higher, on average, for the category of only offshoring firms: high capital-intensive firms are usually, according to the Pavitt classification, scale-intensive firms that benefit from economies of scale and undertake offshoring more often than others.

These results show that offshoring/innovating firms are different from non-offshoring/non-innovating firms with respect to many characteristics. However, the difference between the average values could hide confounding effects due to other not considered factors. For example, we have to consider that offshoring involves substantial sunk costs related to searching for a foreign partner, conducting market research, fixing contractual arrangements and so on. Only larger, more productive firms could overcome these sunk cost barriers (Wagner, 2011). Therefore, the probable self-selection of offshoring firms must be taken into account in the comparison between the means obtained for offshoring and non-offshoring firms. A possible selection bias has to be taken into account also in the case of innovation, as innovators may have different capabilities from non-innovators, before the decision to innovate, which may explain their superior profitability.

Regarding the distribution of the outcome variables, we notice the presence of some outliers in both the right and left tails, which can influence the results of the analysis. Therefore, we discard values that are lower than the 0.5 percentile or greater than the 99.5 percentile (Note 5).

Table 2. Descriptive statistics by treatment status

	Nothing		Only Offshoring		Only Innovation		Both	
	Mean	CV	Mean	CV	Mean	CV	Mean	CV
Productivity	49.5	538	53.0	326	51.0	334	54.5	247
Profitability	10.6	1764	10.7	1212	11.9	998	13.9	905
Employees	39.2	1356	150.5	1193	137.3	17927	228.8	1780
Capital intensity	184.1	2917	331.8	1770	181.3	534	215.0	537
Wage rate	35.8	406	40.8	339	35.5	216	40.1	161
Export intensity	26.8	446	35.5	337	31.9	393	39.6	298
White collars incidence	22.1	450	31.2	337	26.0	389	34.2	278
	%		%		%		%	
Over 20 years old firms	55.8		59.9		57.6		65.2	
Belonging to a group	13.8		33.7		17.6		39.6	

5. Research Methodology

5.1 Identification and Estimation of the Effects of Multiple Treatments

Our analysis focuses on the PSM methodology in a multi-treatment setting. The literature on multiple treatments is not as extensive as that on the binary case (two treatment status) and is relatively recent.

The seminal papers of Imbens (2000) and Lechner (2001, 2002) extend the binary treatment matching methodology to the multiple treatment case where treatments are mutually exclusive. We consider the case of overlapping treatments following Bradley and Migali (2012), who study the overlapping case simply by defining a treatment status where two policies are active in some place at the same time.

We explicitly recognize that firms can undertake one or both treatments – offshoring and innovation. If the treatment status for the two treatments are denoted by V and Z, where V, Z= {0,1}, there are four distinct combinations of the overall treatment status. These four combinations can be described by a single treatment status variable T taking four different values T=0, 1, 2, 3, corresponding to the mutually exclusive cases:

T=0 if (0, 0) = no offshoring or innovation (no treatment case)

T=1 if (1, 0) = only offshoring

T=2 if (0, 1) = only innovation

T=3 if (1, 1) = offshoring and innovation.

In this way, by recasting the two binary treatments into the mutually exclusive categories (0, 0), (v,0), (0,z) and (v,z), the Lechner framework applies.

The definition of the causal evaluation problem is as follows. T+1 mutually exclusive treatments are considered (the treatment denoted by t takes on values in a set T = {0,1,…,T}). In our analysis a firm is considered treated if it innovates, decides to offshore or does both. The control group may be represented by firms that do not innovate and do not offshore or by firms that undertake only one of the two. Associated with each value of the treatment, t, is a potential outcome, $Y_i(t)$. For each unit, i, we can observe only one of the potential outcomes, which means that for $T = t$ we observe $Y_i(t)$ and the other T outcomes are counterfactuals. We are interested in the expected average treatment effect of treatment t relative to the treatment S for the participant in treatment t:

$$\vartheta^{t,s} = E(Y_i(t) - Y_i(s)|T = t) = E(Y_i(t)|T = t) - E(Y_i(s)|T = t) \quad (1)$$

The above equation denotes the expected effect for an individual randomly drawn from the population of participants in treatment *t*. If participants in treatments t and s differ in a way that is related to the distribution of attributes (or exogenous confounding variables), *X*, and if the treatment effects vary with *X*, then $\vartheta^{t,s} \neq -\vartheta^{s,t}$; that is, the treatment effects on the treated are not symmetric.

From equation (1), we derive that the evaluation problem is a missing data problem in the multi-treatment setting as well: the expected outcome $E(Y_i(s)|T = t)$ cannot be observed for the same unit *i*. Imbens (2000) and Lechner (2001, 2002) considered identification under the Conditional Independence Assumption (CIA) in a model with multiple treatments. The CIA defined to be valid in a subspace of the attribute space is formalized by the following:

$$Y(1), Y(2), \dots, Y(T) \amalg T|X = x \qquad \forall x \in \chi \tag{2}$$

This assumption requires the researcher to observe all characteristics that jointly influence the outcomes as well as the selection into the treatments. In addition to independence, it is required that all individuals in that subspace actually can participate in all states, i.e.,

$$P(T = t|X = x) \quad \forall t = 0,1, \dots, \mathrm{T}, \quad \forall x \in \chi \tag{3}$$

This condition is called the common support condition: for any pairwise comparison, it is sufficient that, for all values of X for which those treated have positive marginal probability, there could be comparison observations as well. Lechner (2001) shows that: i) the CIA identifies the effects defined in equation (1), ii) some modified versions of the balancing score properties hold in this more general setting of multiple treatments as well and iii) the following result holds for the effect of treatment *t* compared with treatment *s* on participants in treatment *t*:

$$\vartheta^{t,s} = E(Y^t|T = t) - E_{P^{s|ts}(X)}\left[E\{Y^s|P^{s|ts}(X), T = s\}|T = t\right] \tag{4}$$

and

$$P^{s|ts}(x) = P^{s|ts}(T = s|T \in \{t, s\}, X = x) = P^s(x)/[P^s(x) + P^t(x)] \tag{5}$$

where $P^j(x) = P(T = j|X = x)$ denotes the marginal probability of treatment *j* conditional on *X*. If a consistent estimator of $P^{s|ts}(x)$ is available, the dimension of the estimation problem is reduced to 1. The term appearing in equation (4) can be estimated by matching on the balancing score $P^{s|ts}(x)$, as in the binary framework.

Lechner (2001, 2002) illustrates a step-by-step procedure very similar to the implementation of the binary treatment Propensity Score methodology. In the first step, the balancing score can be estimated using different estimators: if $P^{s|ts}(x)$ is modelled directly, no information from subsamples other than those containing participants in *t* and *s* is needed for the identification and estimation of $\vartheta^{t,s}$. Otherwise, one can specify jointly the choice of a particular treatment from all (or a subset of) the available options (using a discrete response models, e.g., Multinomial Logit/Probit or other models whenever appropriate). $P^{s|ts}(x)$ could then be computed from that model. In the second step, the comparison group is selected, which means that if we are interested in the treatment effect of treatment t relative to the treatment S, we need to find an observation in the sub-sample of treated in S that is as close as possible to the one chosen in *t* in terms of $P^{s|ts}(x)$. The procedure is repeated until no participant in t is left. In the third step, using the matched-comparison group, the respective conditional expectations are computed by the sample mean. Matching on the propensity score (Lechner, 2001) provides a consistent estimator of the counterfactual mean, $E(Y_i(s)|T = t)$.

5.2 Estimation of the Balancing Scores

Following Lechner (2001) and Bradley and Migali (2012), the balancing scores $P^{s|ts}(x)$ may be obtained by a Multinomial Logit/Probit model (MNL/MNP). The multiple treatment variable *T* becomes the dependent variable in the MNL/MNP specification.

In this work, the estimation procedure deviates from Lechner and Bradley and Migali on a very important point. The probability model P(·) must take into account that the observed treatments are a combination of two different decision processes that can be potentially correlated. Additionally, we do not want to restrict the correlation between unobserved characteristics affecting offshoring and innovation. Hence, an appropriate (parametric) model could be a Bivariate Probit for the two dependent binary variables of offshoring and innovation.

From the Bivariate Probit, the following joint probabilities can be estimated: $P_{00}, P_{10}, P_{01}, P_{11}$, where $P_{vz} = P(V = v, Z = z|X) = P(T = j|X)$ and the conditional probabilities to be used as balancing score $P^{(s|ts)}(x) = P^s(x)/[P^s(x) + P^t(x)]$.

In this special case, some conditional probabilities can take a particularly simple form; for example, to estimate the effect of only offshoring over doing nothing on a randomly chosen firm that only offshores (*t*=(1,0) over *s*=(0,0)), the balancing score has the following expression:

$$P^{s|ts}(x) = P^{s|ts}(T = s|T \in \{t, s\}, X = x) =$$

$$P_{00}(x)/[P_{00}(x) + P_{10}(x)] = P(V = 0, Z = 0|X = x)/P(Z = 0|X = x) = P(V = 0|Z = 0, X = x)$$

which corresponds to the conditional probability of not offshoring among firms that do not innovate.

6. Empirical Results

6.1 The Effect of a Single Treatment

To evaluate the effect of offshoring/innovation on productivity and profitability, we estimate a PSM using a Logit model for the probability of offshoring/innovation given the set of firm traits described in Section 3. This analysis does not take into account the existence of overlapping effects between the two treatments. The results of the Logit estimates used in the matching are neither reported nor discussed because the more comprehensive findings obtained from the Bivariate Probit will be discussed in Section 6.2.

Generally, the use of the Propensity Score assumes that the conditional independence assumption holds. This means that differences between the treated and untreated units with the same observed covariates are due to the treatment and that no confounding variables exist. In our analysis, we assume that this assumption holds once all available variables potentially related to the offshoring/innovation decision and firms' performances are included (as indicated in the recent literature).

Following Lechner (2002), we implement the "one nearest neighbour with replacement" matching algorithm. When comparing multiple treatments, it could happen, as in our case, that the number of participants in a treatment is larger than the number of participants in another treatment; hence, a "with replacement" algorithm has to be used.

To implement matching, we use STATA 11 and the PSMATCH2 command (Leuven & Sianesi, 2003). To evaluate matching quality, we use the standardized median bias and the pseudo-R^2 (see Sianesi for definitions, 2004). As observed in Table 3, the standardized median bias and pseudo-R^2 are almost always smaller after matching than before for all of the comparisons carried out. The pseudo-R^2 after matching is always close to zero, correctly suggesting that the covariates have no explanatory power for predicting the offshoring decision in the matched data. Therefore, we may conclude that matching is effective in removing the differences in observable characteristics between offshoring and non-offshoring firms. Then, the average treatment effect on the treated (ATT) is estimated using matching pairs of firms. A common support condition is imposed by excluding offshoring firms whose estimated propensity score (PS) is higher than the maximum or lower than the minimum estimated PS of the matched non-offshoring firms.

Allowing the use of the same observations more than ones, it could happen that a few observations are used many times, leading to an unnecessary inflation of variance. Following Lechner (2002), we check the occurrence of this problem by calculating two indicators: i) the mean of weights for matched comparison observations and ii) the share between the sum of the largest 10% of weights and the total sum of weights, in percentage, in the comparison sample (concentration ratio). As expected, such measures are higher for the comparison between innovating and non-innovating firms than for the comparison between offshoring and non-offshoring firms because in the first comparison, the group of control units is almost one half of the group of treated units.

The ATT obtained for the comparison between the profitability of innovating firms versus non-innovating firms is positive, whereas all of the other ATTs are negative; however, none of them are significant (Table 4). The decisions to offshore and to innovate do not seem to have a significant effect on the two indicators of firm performance considered (Note 6).

Table 3. Single treatment - Measures of the quality of matching (Nearest neighbour with replication)

Comparison	Treated Firms	Control Firms	Treated firms off support	Median bias		Pseudo R2		Excess use of single observation	
				Before	After	Before	After	Mean	Top10
Profitability									
innovation vs nothing	4519	2269	3	15.9	4	0.175	0.011	3.510	42.936
offshoring vs nothing	551	6243	2	18.1	3.6	0.177	0.009	1.206	30.054
Productivity									
innovation vs nothing	4847	2369	3	10.9	3.2	0.173	0.008	3.548	43.971
offshoring vs nothing	629	6587	3	18.9	3.3	0.173	0.007	1.196	28.434

Table 4. The causal effect of a single treatment on productivity and profitability (Nearest neighbour with replication)

Outcome	Comparison	Treated firms on support	ATT	Standard Error	t-value
Profitability	innovation vs nothing	4516	0.0043	0.0065	0.65
	offshoring vs nothing	549	-0.0038	0.0077	-0.50
Productivity	innovation vs nothing	4844	-1.1380	1.1911	-0.96
	offshoring vs nothing	626	-1.2106	1.7594	-0.69

6.2 The Joint Effect of Offshoring and Innovation

Considering the four treatment statuses obtained cross-classifying firms according to the decision to offshore and the decision to innovate (see Section 3), the focus is on the comparison between all of the other treatment status with the treatment status "nothing", that is: i) "only offshoring" vs "nothing"; ii) "only innovation" vs "nothing"; iii) "both" vs "nothing". In addition, we compare "both offshoring and innovation" vs "only innovation". This last comparison is performed due to the following consideration. The phenomenon of offshoring is much less widespread than that of innovation. Hence, it is interesting to understand whether adding offshoring to innovation may lead to an improvement in firms' performance.

6.2.1 The Determinants of Offshoring and Innovation

The Bivariate Probit, which simultaneously models the two phenomena, enables us to obtain a clearer and more complete picture of firms' choices and their determinants than the Logit models estimated in the previous section. Because missing values in the target outcomes regard different observations, we estimate one Bivariate Probit on the observations with no missing data on productivity and one on the observations with no missing data on profitability. We do not eliminate observations to estimate a single model for both outcomes, in order to retain most of the available information. However, the coefficients estimated by the two Bivariate Probit are very similar; hence, we show only the results obtained in the case of productivity (Table 5).

Table 5 shows that the correlation between the error terms of the two equations is not significant at the 5% level. Because correlations between the residuals of the equations embody unobserved characteristics for the same firms, the non-significance of the correlation between the two equations' residuals may be interpreted as there being no unobserved firm characteristics that favour/disfavour innovation and favour/disfavour offshoring.

Table 5. Bivariate Probit regression used to estimate the propensity score

	OFFSHORING		INNOVATION	
Baseline characteristics	Estimated parameter	p-value	Estimated parameter	p-value
Germany & Austria	0.0136	0.869	0.0150	0.838
France	-0.8507	0.000*	0.2054	0.195
Hungary	-0.4164	0.000*	0.2292	0.002*
Italy	-0.5095	0.000*	0.4865	0.000*
Spain	-0.0730	0.494	0.4646	0.000*
<6 years	0.0858	0.453	-0.0431	0.569
6-20 years	0.0672	0.541	-0.0360	0.626
Belonging to a national group	-0.1235	0.117	0.0927	0.201
Belonging to a foreign group	-0.1840	0.003*	0.0986	0.050*
Public financial incentives	0.0192	0.744	-0.3182	0.000*
Sector1	-0.2558	0.028*	0.3122	0.000*
Sector2	0.1142	0.272	0.1641	0.025*
Sector3	0.4960	0.000*	0.1667	0.004*
Sector4	0.2451	0.021*	0.3009	0.000*
Sector5	-0.0678	0.579	0.0392	0.679
Sector6	0.2621	0.033*	0.0549	0.584
Sector7	0.1489	0.283	0.2783	0.001*
Sector8	0.1837	0.019*	0.0907	0.097
Sector9	0.0907	0.289	0.0444	0.471
Competitors in the home country	-0.4128	0.150	-0.3612	0.038
Competitors also in other countries	0.0314	0.610	0.1285	0.018*
Ln(White collar percentage)	0.0764	0.000*	0.0391	0.003*
Ln(wage rate 08)	-0.1975	0.003*	-0.0286	0.614
Ln(Export intensity 08)	0.1274	0.000*	0.0543	0.000*
Ln(capital intensity 08)	0.1286	0.000*	0.0591	0.018
Ln(employees 08)	0.2480	0.000*	0.0665	0.001*
Ln(R&D investment intensity)	0.0649	0.000*	0.2846	0.000*
Constant	-2.6002	0.000*	-0.1459	0.556
Rho	0.0265			
Likelihood-ratio test of rho=0: chi2 = 0.6027, Prob > chi2 = 0.438				

Note. * Denotes significance at 5%

Some covariates are significant for both phenomena, whereas others are determinant specific for only one decision, offshoring or innovation. The probability to offshore or innovate depends on the country, the sector, the size and the capital intensity, the export intensity, the R&D investment intensity, the white collar ratio and membership to a foreign group. The probability to innovate depends in addition on the use of public financial incentives and the presence of competitors in the home country or also in other countries, whereas the probability to offshore depends in addition on the wage rate.

In particular, France, Hungary and Italy tend to offshore less than the United Kingdom, whereas Hungary, Italy and Spain tend to innovate more than the United Kingdom. This result is quite in line with the descriptive statistics for the countries (Table 1). Firms belonging to a foreign group tend to innovate more than firms that do not belong to a group but tend to offshore less than firms that do not belong to a group. Evidently, firms belonging to a foreign group, being themselves foreign companies with respect to the property, recourse less to the work of other enterprises outside of their country. Larger firms and firms with a higher level of capital intensity innovate and offshore more than smaller firms and firms with a lower level of capital intensity, as expected. The same positive sign is observed for the export intensity and the white collar ratio, as expected, especially for the probability to offshore because firms involved in other international strategies are more likely to be involved in offshoring, and the reduction of blue collar workers is often associated with a higher involvement in offshoring. R&D investment intensity has, obviously, a positive effect not only on innovation but also on offshoring. This is consistent with the strand of literature on the effect of the R&D investment on internationalization (Aw et al., 2011). Firms with higher average wage rates have a lower probability to offshore. A positive sign is expected when the motivation to offshore is to reduce labour costs by offshoring labour-intensive activities. The evidence of a negative relationship between the wage rate and offshoring points out a different reason for offshoring. Firms having competitors also in other countries tend to innovate more than firms not having competitors at all, which is clearly the effect of greater competition, which drives companies to innovate to remain competitive in the market. Finally, firms that benefit from financial incentives provided by the public sector tend to innovate less than firms that do not benefit from them, highlighting the fact that public financial incentives may have a negative effect on the probability to innovate, if they are not explicitly aimed at innovation.

6.2.2 The Effects

From the Bivariate Probit, we estimate the balancing scores and proceed with matching. Quality of matching measures are reported in Table 6, together with the information on the number of treated and control firms. Values of the standardized median bias let us conclude that matching is effective in removing the differences in observable characteristics between treated and control firms. The mean of weights and the concentration ratio are higher for the comparisons “Only innovation” versus “Nothing” and “Both” versus “Nothing”. While in the first case, it is expected because the group of control units is almost one half of the group of treated units, in the second comparison, this is less understandable and suggests further analysis about overlapping support, which will be discussed in Section 6.3.

All of the ATTs evaluated for productivity are negative but not significant (Table 7). Both decisions to offshore and to innovate, considered individually or together, do not seem to have a significant effect on productivity.

Table 8 reports the quality of matching measures obtained for the profitability indicator. The results obtained are similar to those already discussed for productivity. The standardized median bias reduction between before and after matching is always relevant and the multiple use of a single observation is still more important for the comparisons “Only innovation” versus “Nothing” and “Both” versus “Nothing”.

Table 6. Measures of matching quality for productivity

COMPARISON	Treated firms	Control firms	Treated firms off support	Median bias before matching	Median bias after matching	Excess use of single observations	
						Mean	Top 10
“Only offshoring” vs “Nothing”	138	2,231	1	16.7	4.9	1.15	24.82
“Only innovation” vs “Nothing”	4,356	2,231	4	7.0	2.2	3.36	41.04
“Both” vs “Nothing”	491	2,231	1	23.9	8.0	2.00	40.41
“Both” vs “Only Innovation”	491	4,356	3	20.4	6.8	1.24	33.81

Table 7. The causal effect of offshoring and innovation on productivity

COMPARISON	Treated firms on support	ATT	Standard Error	t-value
"Only offshoring" vs "Nothing"	137	-3.7131	3.6377	-1.02
"Only innovation" vs "Nothing"	4,352	-0.4971	1.5725	-0.32
"Both" vs "Nothing"	490	-6.7776	3.6810	-1.84
"Both" vs "Only Innovation"	488	-1.2545	1.9665	-0.64

Note. * Denotes significance at 5%

Table 8. Measures of matching quality for profitability

COMPARISON	Treated firms	Control firms	Treated firms off support	Median bias before matching	Median bias after matching	Excess use of single observations	
						Mean	Top 10
"Only offshoring" vs "Nothing"	122	2,189	1	18.3	6.7	1.12	20.66
"Only innovation" vs "Nothing"	4,201	2,189	6	8.3	3.1	3.41	43.17
"Both" vs "Nothing"	453	2,189	1	26.7	6.5	1.94	40.71
"Both" vs "Only Innovation"	453	4,201	2	22.9	3.7	1.23	32.15

Table 9. The causal effect of offshoring and innovation on profitability

COMPARISON	Treated firms on support	ATT	Standard Error	t-value
"Only offshoring" vs "Nothing"	121	2.4174	3.2574	0.74
"Only innovation" vs "Nothing"	4,195	2.1209*	0.9123	2.32
"Both" vs "Nothing"	452	1.0530	1.9664	0.54
"Both" vs "Only Innovation"	451	-1.3146	1.6423	-0.80

Note. * Denotes significance at 5%

In this case, all of the ATTs estimated are positive apart from the one obtained for the comparison "Both" vs "Only Innovation", which is negative; however, only the ATT for the comparison "Only innovation" vs "Nothing" is found out to be significant. Hence, the practice of innovation (without offshoring) has a positive important effect on profitability with respect to doing nothing (not innovating or offshoring).

In general, the decision to offshore does not seem to have a significant effect on the two indicators of firm performance considered. In addition, a significant effect on productivity/profitability deriving from the combination of decisions to offshore and to innovate is not confirmed by our results (Note 7).

6.3 Heterogeneity of the Effects

Almost all of the estimated ATTs show a non-significant effect of offshoring, innovation or both on productivity and profitability, apart from innovation having a positive effect on profitability; however, the positive effect on profitability vanishes when offshoring is considered together with innovation. A not significant effect may be due to the heterogeneity of the effect for different subgroups of treated units. To shed some light, more detailed analysis is warranted. One way to proceed is to study how the treatment effect changes in different regions of the participation probability to the treatment for the units that participate in the treatment. The latter probability is exactly the complement to one of the balancing score used in matching treated-control units.

The overall ATT is, conceptually, a weighted average of the differences in outcomes between treated-controls with weights determined by the distribution of the respective participants.

It is acknowledged that average treatment effects might obscure the changing effects within heterogeneous populations. Hence, we carry out a graphical analysis by plotting, on the same graph, the kernel-smoothed regressions of the outcome variable on the conditional participation probability to the treatment ($P^{t|ts}(x) = P^t(x)/[P^s(x) + P^t(x)]$), obtained for the two groups of units compared. The smoothed densities of the participation probability in the two groups are plotted to check for the presence of regions of sparse data (Figure B1 and Figure B2 in Appendix B). Moreover, the density plots enable us to find eventual non-overlapping regions between the treatment and control groups.

Starting from the results about productivity, we observe that productivity increases with the probability of being treated, which is true for all of the comparisons carried out. Moreover, we can notice that the effect of the treatment varies with the probability of being treated for all of the comparisons considered. Productivity lines for the treated and control units intersect at least once in all graphs. For example, offshoring firms have a higher productivity than firms that do not offshore and do not innovate for high values of the probability of participating in the treatment, whereas they have a lower productivity for low values of the participation probability. Instead, in the case of the comparison “both” vs “only innovation”, the productivity is higher for participants in the treatment “both” for the lowest and the highest values of the probability of being treated, whereas it is lower for the central interval of those values. Therefore, the obvious consequence is the null (not significant) average effect on productivity that appeared before. A substantial similarity in the productivity patterns is observed in the comparison between the treatments “only innovation” and “nothing”. Finally, comparing “both” vs “nothing”, the kernel densities appear different; one density is concentrated on low values of the participation probability (“nothing”), whereas the other is almost uniform (“both”).This may suggest an unsubstantial overlap.

Moving to profitability, the difference in outcomes for the treatments “only offshoring” versus “nothing” and the treatments “both” versus “only innovation” is quite small and becomes large only for high values of the probability of being treated. However, those values correspond to the right tail of the distribution where data are sparse in both groups, and enter in the overall effect with a small weight. Then, the significant effect of the treatment “only innovation” versus “nothing” is due to the difference in profitability in correspondence with the highest values of the probability of being treated, in this case supported by the existence of overlap. Finally, the comparison between the treatments “both” and “nothing might reflect the uncertainty due to the small number of observations, in correspondence to high positive differences.

7. Discussion and Concluding Remarks

In this work, following the strand of the literature on complementarities between innovation and internationalization, we investigate the effects of innovation and offshoring on firm’s performance. We use data taken from the sample survey EFIGE, which uniquely provides information on both innovation and offshoring strategies adopted by European firms. In consideration of the fact that firms may decide to offshore, innovate or simultaneously undertake both strategies, we depart from previous empirical literature and focus on the joint effect of both innovation and offshoring. For this purpose, we consider a framework that allows us to take into account multiple treatments.

The result highlights the positive effect of innovation alone on firms’ profitability, whereas offshoring does not further improve profitability for innovating firms. This insight on the effect of innovation and offshoring on firms’ performance was obscured when the phenomena were studied one at a time. Still, the effect of the adoption of both strategies versus no strategy at all remains unclear in our analysis because of the difficulty in matching observations between the two groups.

Therefore, our results support the assumption that firms’ innovative efforts positively affect the firms’ ability to generate profit, and are in line with the positive impact found for Finland and UK by, respectively, Leiponen (2000) and Cefis and Ciccarelli (2005). Nevertheless, our data do not deliver a support to a positive effect of offshoring on European firm performance, either with or without innovation. Hence, the better performances of offshoring firms, emerging from the descriptive analysis, appear mainly driven by a self-selection mechanism. This finding is indeed consistent with the findings of other studies on European manufacturing firms as, for example, Schwörer (2013) who finds no productivity effect due to offshoring of core activities for European countries.

We are aware that the information available in the dataset limits in some ways the analysis. First, the cross-sectional nature of the dataset does not allow us to discover improvements in performance after starting to offshore or to innovate or, for example, whether innovation produces a “one-off effect” when begins, or offers an increasing profitability during subsequent periods thereafter. Second, we have no information on the magnitude of offshoring and we do not use the information about innovation’s intensity. At least for what concerns innovation, future researches might involve the analysis of innovation intensities on firms’ performance in a continuous treatment framework.

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Notes

Note 1. The authors have benefited from the access to the EU_EFIGE/Bruegel – UniCredit database, managed by Bruegel and funded by the European Union's Seventh Framework Programme ([FP7/2007-2013] under grant agreement n °225551), as well as by UniCredit.

Note 2. The availability of only certain items of the balance does not allow us to consider a profitability measure that captures capital costs.

Note 3. Conditional mean independence is also assumed in regression methods for inference of average treatment effects. The alternative method of Instrumental Variables rests on weaker assumptions than Propensity Score Matching in many regards but makes stronger assumptions about the stochastic terms in the model and requires to find suitable valid instruments (Becker and Egger; 2013).

Note 4. The names of sectors in the EFIGE dataset are not available to avoid disclosure problems, impeding the interpretation of the results with regards to the sector of activity.

Note 5. Comparing the descriptive statistics obtained with different trimming thresholds, we find results substantially robust to the choice of different percentiles.

Note 6. The results obtained for the significance of ATTs are robust with respect to other matching algorithms, such as "one nearest neighbour caliper (0.001) with replacement" and kernel (kerneltype=normal; bandwidth = 0.05).

Note 7. The results obtained for the significance of ATTs are robust with respect to other matching algorithms, such as "one nearest neighbour caliper (0.001) with replacement" and kernel (kerneltype=normal; bandwidth = 0.05)

Appendix A

Definition of Variables Constructed from the EFIGE data

Variable	Definition	Type
Geographic location	Countries considered in the EFIGE data (Germany and Austria are considered together because of the large number of missing data in Amadeus for those two countries)	Categorical
Sector	The sector to which the firm belongs whose modalities are aggregates from NACE-Clio classes	Categorical
White collars incidence	The number of white collar workers over the total number of employees in the firm in 2008	Continuous
Wage rate	The cost of labour over the total number of employees in the firm in 2008	Continuous
Capital-intensity	The ratio of total assets on employees in 2008	Continuous
Firm size	The number of employees in 2008	Continuous
Export intensity in 2008	The percentage of annual turnover represented by export activity	Continuous
R&D investments	The percentage of the total turnover invested in R&D	Continuous
Group	A dummy variable representing whether the firm belongs to a national or international group of firms	Binary
Financial Incentives	A dummy variable representing whether the firm uses public financial incentives	Binary
Location of firm competitors	Three modalities: 1. having competitors in the home country, 2. having competitors in other countries as well and 3. Having no competitors at all (excluded modality)	Categorical
Age	Three modalities: 1. less than 6 years, 2. between 6 and 20 years and 3. more than 20 years (excluded modality)	Categorical

Appendix B

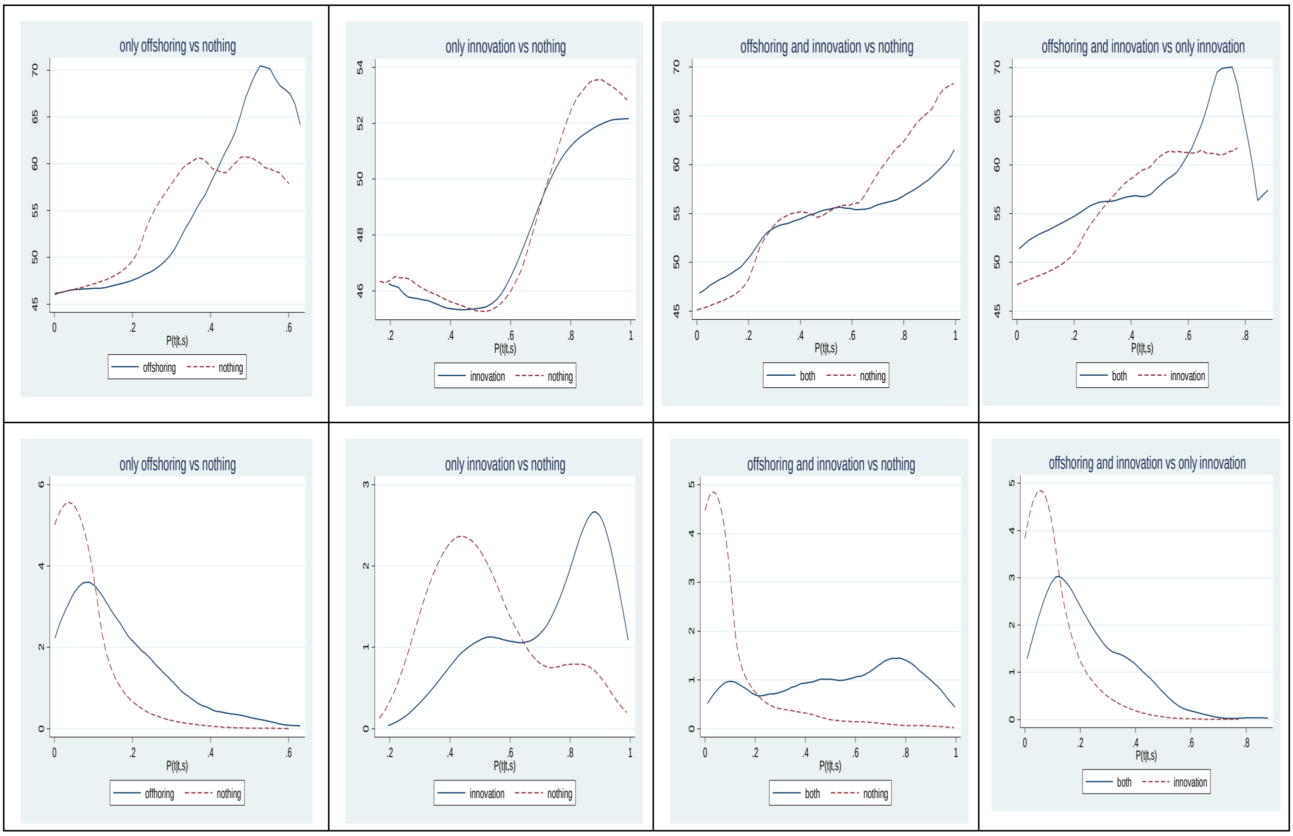

Figure B1. Nonparametric Regression of the Conditional Participation Probabilities on the PRODUCTIVITY in Respective Subsamples.

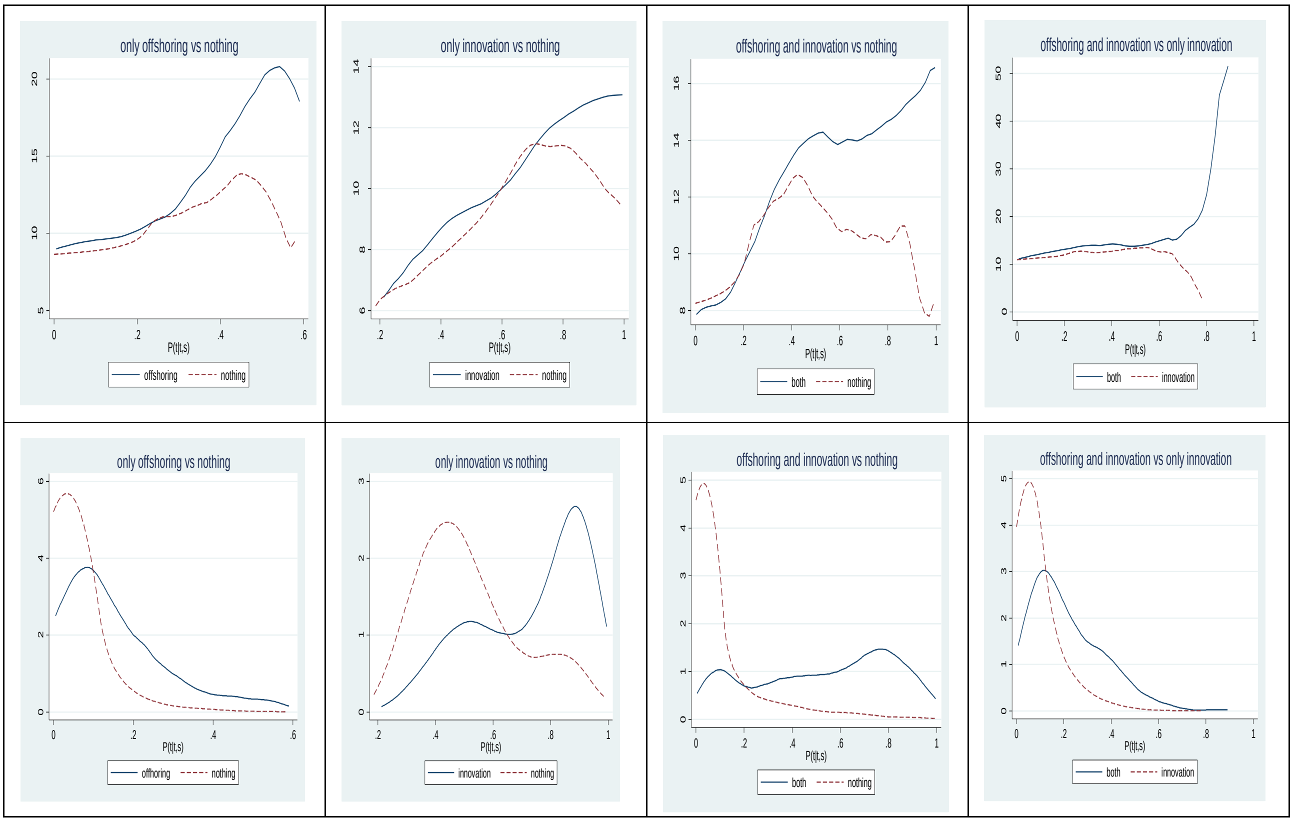

Figure B2. Nonparametric Regression of the Conditional Participation Probabilities on the PROFITABILITY in Respective Subsamples.