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University-industry R&D collaboration and firm innovativeness

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Abstract

PRELIMINARY VERSION: PLEASE DO NOT CITE OR QUOTE WITHOUT AUTHOR'S PERMISSION. This paper investigates the impact of university-industry (U-I) research & development (R&D) collaboration on firms' innovativeness. We aim at providing new evidence on the effect that collaborative partnerships have on firms' R&D inputs, hence we test the hypothesis that project participation has a positive effect on firms' R&D intensity and share of R&D employment. We further make a distinction between occasional participants and recurrent participants on the basis of the number of projects entered. The paper exploits a novel source of data, made up of a set of U-I projects funded by the UK Engineering and Physical Sciences Research Council (EPSRC) in the UK between 1999 and 2007, matched with firm-level data. Propensity score matching is applied to select an appropriate control group of untreated firms and estimate the impact of participation to U-I projects on firms' R&D variables. The results show a positive and significant impact on the share of R\&D employment, whereas a systematic and consistent effect cannot be traced as far as R&D intensity is concerned. Recurrent participants experience a larger impact than occasional participants on the share of R&D employment.

Jelcodes:O38,O33

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This paper investigates the impact of university-industry (U-I) research & development (R&D) collaboration on firms' innovativeness. We aim at providing new evidence on the effect that collaborative partnerships have on firms' R&D inputs, hence we test the hypothesis that project participation has a positive effect on firms' R&D intensity and share of R&D employment. We further make a distinction between occasional participants and recurrent participants on the basis of the number of projects entered. The paper exploits a novel source of data, made up of a set of U-I projects funded by the UK Engineering and Physical Sciences Research Council (EPSRC) in the UK between 1999 and 2007, matched with firm-level data. Propensity score matching is applied to select an appropriate control group of untreated firms and estimate the impact of participation to U-I projects on firms' R&D variables. The results show a positive and significant impact on the share of R&D employment, whereas a systematic and consistent effect cannot be traced as far as R&D intensity is concerned. Recurrent participants experience a larger impact than occasional participants on the share of R&D employment.

Keywords: university-industry collaboration, R&D intensity, R&D employment, propensity score matching

Jel codes: O33, O38

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1 Introduction

Economic development is primarily driven by the generation and use of new scientific knowledge, the main sources of which are firms and universities. Firms need to find and use new sources of knowledge in order to innovate and grow and universities are often the main repository of such knowledge. The exchange of knowledge between academia and industry is therefore an essential mechanism to bring science to the market and foster innovation and economic growth (OECD, 1998, 2002a). University-industry knowledge transfer is a broad concept identifying a wide set of interactions between firms and universities. In particular, university-industry research collaboration is a specific channel of inter-organisational knowledge flows and potential spillovers from (and to) academic research aimed at carrying out specific R&D projects, particularly involving pre-competitive and basic research (D'Este and Fontana, 2007; D'Este and Iammarino, 2010; D'Este et al., 2013; OECD, 1998, 2002a). Cooperative research partnerships are among the most typical forms of U-I research collaborations, followed by contract research, research consortia, consulting and founding of co-operative research centres (Fontana et al., 2006; OECD, 1998). The relevance of this type of interaction channel is showed by the fact that it represents one of the most frequent policy instruments put in place by local and national policy-makers to foster pre-competitive research and firms' innovation activities (D'Este and Iammarino, 2010; Fisher et al., 2009; OECD, 1998, 2002a).

U-I cooperative R&D projects can be seen as a voluntary (or intended) and reciprocal information mechanism that enhances learning processes and performance of the partnering organisations (Feldman and Kelley, 2006). For this reason U-I R&D cooperation is considered a valid proxy for explaining knowledge generation associated with knowledge spillovers (see e.g. Cincera et al., 2003). However, the innovation literature has been, so far, only partly conclusive with regards to the impact that these activities have on firms' performance. Following the perspective that R&D cooperation can be seen as a vehicle for voluntary knowledge transfer, the present study intends to fill this gap by assessing the effect of publicly funded U-I R&D projects on firms' innovativeness. By relying on a novel dataset of U-I partnerships and firm-level data and by employing a propensity score matching method, we investigate the impact of U-I R&D projects on firms' R&D intensity and share of R&D employment.

This paper contributes to the literature by bringing new evidence on the impact that the voluntary exchange of knowledge between university and firms - in the form of R&D collaborative partnerships - has on firms' internal effort on R&D, and by overcoming some of the existing limitations. The data on U-I partnerships used for the analysis provides information on a full range on projects funded during a 9 years time span; it also allows to distinguish an important feature, that is, the number of projects that each firms entered. Furthermore, by matching this data with firm-level data we create a new and original dataset that allows us to carry out an evaluation study on a specific U-I R&D policy. For this reason, we also consider in our analysis the specific objectives of the program under study and its intended contribution to firms. Finally, the employment of propensity score matching helps us to tackle the issue of selection bias typically arising in quasi-experimental settings and provides a useful tool to work out a sensible control group of non-participating firms. Our results indicate a positive impact of U-I cooperative R&D projects on the share of R&D employment, which increases after participation, whereas a clear impact cannot be traced on R&D intensity.

The remainder of the paper is organised as follows: in section 2 we provide a review of the literature (2.1 and 2.2), which, together with an overview of the program under study (2.2), leads to the hypotheses of the paper, presented in 2.3; in section 3 we describe our data and illustrate the construction of the dataset; section 4 is dedicated to the illustration of the methodology (4.1) and to the implementation of its first phase (4.1 and 4.2); in section 5 we describe the outcome variables (5.1), present the empirical results (5.2) and evaluate the quality of the propensity score matching (5.3); finally, we conclude the paper by summing up and discussing our findings in section 6.

2 Literature and hypotheses

2.1 U-I knowledge interaction

External knowledge acquisition is necessary for innovation activities carried out by firms, especially in the current context of market globalisation and rapid technological change. Both the early literature on technological change (see e.g. Allen and Cohen, 1969; Allen, 1977) and the more recent studies on the knowledge sourcing strategies of firms (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009) assert that firms cannot rely only on their internal resources and have to tap into knowledge outside their boundaries in order to successfully produce innovation. In particular, the seminal works of e.g. Griliches (1987), Jaffe (1989) and Adams (1990), have uncovered the role of knowledge from universities for innovation activities of firms and for economic development more in general. Since then, the literature on university-industry knowledge interaction has developed (see e.g. Mansfield, 1995; Mansfield and Lee, 1996; Cohen et al., 2002) and grown substantially, showing that firms exploit university knowledge in order to produce innovations and stay competitive on the market.

U-I knowledge transfer is a broad concept identifying a wide set of interactions between firms and universities that are aimed at the exchange of knowledge related to research, science and technology. Research collaborations betweeen universities and businesses are among the most frequent policy instruments put in place by local and national policy-makers to foster pre-competitive research and firms' innovation activities (D'Este and Iammarino, 2010; Fisher et al., 2009; OECD, 1998, 2002a). Collaborations include research partnerships, contract research, research consortia, consulting and founding of co-operative research centres. In this paper we study U-I cooperative R&D partnerships, which are aimed at carrying out specific R&D projects, particularly involving pre-competitive and basic research. These typically involve formal agreements that entail cash and in-kind contributions by both sides, so that university and firms share not only their knowledge and competencies but also their R&D facilities and personnel (D'Este et al., 2013).

2.2 U-I reseach collaboration and firms' performance

The relationship between U-I research collaboration and firm-level performance has been addressed by different strands of the empirical literature. It is mostly within the literature on R&D cooperation, knowledge spillovers and productivity - in which U-I collaboration is considered a typology of R&D cooperation - that this issue is addressed. In addition, within the innovation literature focusing on technology and knowledge transfer, the attention has recently extended to the effects of U-I activities. Furthermore, a relatively recent and growing number of contributions has focused on the methodological approach and, in particular, has been trying to assess the impact of R&D subsidies by employing propensity score matching techniques to address the issue of selection bias and the possible endogeneity of the subsidies.

The literature on R&D cooperation, knowledge spillovers and productivity analyses firms' R&D interactions with external organisations (including universties) and predicts that firms engage into cooperative R&D because this enables them to internalise knowledge spillovers and eliminate the disincentive effect of spillovers on R&D (Steurs, 1995; De Bondt, 1997; Cassiman and Veugelers, 2002; Belderbos et al., 2004; Schmidt, 2005; Lopéz, 2008). Firms engage in joint R&D also because it allows the acquisition and utilization of external resources for their own purposes directly and systematically (Hagedoorn, 1993; Hite and Hesterly, 2001; Caloghirou et al., 2003; Scott, 1996) and sharing costs and risks among partners (Sakakibara, 1997; Beath et al., 1998). Hence, the benefits associated to R&D cooperation can be attributed to: reducing uncertainty; joint financing of R&D; realizing cost-savings; realizing economies of scale and scope (Becker and Dietz, 2004; Camagni, 1993; Robertson and Langlois, 1995). Accordingly, the empirical literature has been searching for the impact of R&D cooperation at the level of both firms' innovativeness (input and output) and firm productivity.

A positive impact of engaging in R&D cooperation has been tracked down on the innovation performance (innovation output) of firms, such as sales of innovative products (see e.g. Klomp and Van Leeuwen, 2001; Lööf and Heshmati, 2002; Criscuolo and Haskel, 2003; Faems et al., 2005), patenting (Vanhaverbeke et al., 2002), and sales growth (Cincera et al., 2003). Some of these sutdies also examine the effect of different cooperation types, but have produced ambiguous results. Faems et al. (2005) used cross-section data from the Belgian CIS survey in 1992 and found a positive association between university cooperation and the share in firm sales of innovative products new to the market, while an aggregate measure of other cooperation types was positively associated with the share in firm sales of innovative products new to the firm (but not new to the market). Monjon and Waelbroeck (2003) regressed innovative sales levels of firms in a French CIS survey on a range of collaboration and incoming knowledge spillover variables and found a mixture of negative and positive impacts of R&D cooperation and spillovers. Belderbos et al. (2004), using the Dutch CIS, distinguish between four types of cooperation and find that R&D collaboration with competitors and universities has a significant and positive impact on the growth of innovative sales, but has no significant impact on labour productivity. Furthermore, a number of studies look at R&D cooperation supported by public funding, particularly EU funding: for instance, Benfratello and Sembenelli (2002) showed that firms participation to the

EUREKA research joint ventures program experienced an improvement in their economic performance, while firms participating to the third and fourth FP showed no clear impact; Barajas et al. (2011), using data on Spanish participants to the EU FP research joint ventures, confirm that R&D cooperation has a positive effect on the technological capacity of firms, which is found to be positively related to productivity. Some of these studies use one or more waves of innovation surveys, hence relying on self-reported measures and, often, cross-sectional data, which could explain the reason for such a high variation in the results. In addition, there may be unobservable firm characteristics that affect both the innovation or productivity outcome and, at the same time, the decision to engage into cooperative research, that are only rarely accounted for.

The innovation literature on technology and knowledge transfer has extensively looked at the determinants, characteristics and barriers of U-I knowledge transfer activities. More recently the focus has moved on the effects of these actitivies. Similarly to the literature on firms' R&D cooperation, the empirical studies in this strand of literature distinguish between the impact of knowledge transfer on firms' innovativeness and the impact on overall firms' economic performance. Most of the studies that exploit direct measures of knowledge interactions, such as U-I R&D cooperation, or the use of university as an external knowledge source, find positive effects on firms' innovativeness, including R&D intensity (innovation input), the propensity to register new patents as well as the introduction and sales of new products (innovation output) (see e.g. Arvanitis et al., 2008; Becker, 2003; Fritsch and Franke, 2004; Lööf and Broström, 2008). On the contrary, studies that investigate the impact of university knowledge on the overall economic performance of firms (i.e. labour productivity, total factor productivity) show contradicting evidence: Medda et al. (2006) found no significant effect of collaborative research undertaken by Italian manufacturing firms and universities on the growth of total factor productivity, while other studies found a positive effect on different measures of labour productivity, sales productivity or sales growth (see e.g. Belderbos et al., 2004; Branstetter and Ogura, 2005). The observed differences among the findings of these studies can be partly traced back to the nature of the investigation (cross-section versus longitudinal), but also to differences with respect to the industrial sectors covered by these studies.

Recently, the innovation literature focusing on the impact of R&D subsidies has been trying to address the issue of selection bias of the subsidies by employing matching estimators, extensively applied in the evaluation of labour market policies (see e.g. Almus and Czarnitzki, 2003; Czarnitzki and Licht, 2006; Aerts and Schmidt, 2008; Corsino et al., 2012; Guerzoni and Raiteri, 2012). The potential selection bias arises from the fact that public institutions decide who the recipients will be, hence making the public funding receipt an endogenous variable. The difficulty is that it is impossible to carry out a counter-factual analysis by comparing the performance of participants (or treated) firms with the case of the same firms not receiving the treatment. Similarly, it is highly unlikely that researchers are able to carry out an experiment in which treated and non-treated firms are perfectly randomized and hence their mean performance can be compared after the treatment. As suggested by Almus and Czarnitzki (2003), the best solution at hand when working with non-experimental data is to work as if we are in a quasi-experimental setting, in which a potential control group of non-treated firms is made statistically identical to that of treated firms. Almus and Czarnitzki (2003) apply a propensity score matching to find a suitable control group for a sample of German firms that received R&D subsidies and end up with a complementarity effect of the subsidy with respect to private R&D. On the same vein, Czarnitzki and Licht (2006) indicate the additionality of R&D subsidies for Western and Eastern Germany, González and Pazó (2008) show the absence of a crowding-out effect of R&D subsidies in a sample of Spanish firms, and, more recently, Guerzoni and Raiteri (2012) show that the interaction of different policies (R&D subsidies and public procurement) has the highest impact on firms' R&D expenses and innovative turnover.

To sum up, this overview of the literature on the impact of U-I collaboration on firms shows that, even though this subject has attracted attention from different strands of the literature, evidence is still quite mixed. To some extent, there seems to be convergence towards a positive impact on firms, but this is far from being unquestionable. In addition, it is sometimes unclear the rationale for choosing to evaluate the impact on firms' performance or innovativeness and, in the second case, whether it is more appropriate to look at innovation input or output measures.

2.3 U-I research collaborations in engineering and physical sciences in the UK

This paper considers U-I collaborative partnerships that have been funded between 1999 and 2007 by the Engineering and Physical Sciences Research Council (EPSRC) in the UK. The EPSRC is one of the UK research councils responsible for administering public funding for research in the UK. It distributes more than 20% of the total UK science budget, being the largest council in terms of the volume of research funded (D'Este et al., 2013). These partnerships are aimed at contributing to joint upstream research for the creation of new knowledge and, thus, they are far from industrial applications. They exclude contract research paid by the company to have a specific, well-defined outcome. Intended benefits for partnering companies include the provision of financial support for the project, helping companies to develop closer relationships with the science base and creating the opportunity for recruiting appropriately trained staff at the end of the project. In each project, UK Higher Education Institutions take the role of project co-ordinator (i.e. Principal Investigator) whereas collaborators from industry, commerce and other organisations work as partners. As far as the selection process is concerned, the EPSRC receives applications proposals from the principal investigators and expects that the participants in a collaborative projects develop an agreement that clarifies the contribution of each partners; however, it does not get involved in the negotiation of the agreement, nor in the selection of partners from industry.

U-I collaborative partnerships in engineering and physical sciences funded by the EPSRC have been the focus of a number of empirical studies and reports (see e.g. D'Este and Patel, 2007; D'Este and Fontana, 2007; Ambos et al., 2008; Bruneel et al., 2009, 2010; D'Este and Iammarino, 2010; Bishop et al., 2011; Crespi et al., 2011; D'Este et al., 2012, 2013), which uncovered the determinants and types of collaboration, as well as the ways to reduce the barriers in these collaborations. However, these studies offer little evidence on the effect of U-I interaction, especially on firms. One exception is represented by Bruneel et al. (2009), whose report summarizes the results of two extensive surveys carried out in 2004 and 2008, designed to shed new lights on industry and university researchers' attitudes to collaborate. The surveys involved university and industry partners that participated to EPSRC collaborative projects after 2000. The report shows that the most important benefit of working with universities for firms is to create a long-term connection with the latter, followed by the opportunity to identify and recruit employees. The main benefits are hence focused on developing knowledge and methods and getting access to "highly skilled problem solvers" (Bruneel et al., 2009). On the contrary, short-term benefits, such as cost reduction, turned out to be only marginally relevant for the respondents. Therefore, although not yet tested empirically, it emerges that UK firms collaborating with universities under the umbrella of the EPSRC look at universities as a source of ideas and talented people rather than a low cost pool of research services.

2.4 Hypotheses

The review of the literature in section 2.1 shows that scholars have searched for the impact of U-I collaboration both on firms' innovativeness and firms' productivity measures. In the first case, both R&D input (e.g. R&D expenditure) and output (i.e. sales of new products) have been used as outcome measures, although the former is less commonly employed than the latter. Results are quite mixed, although there seems to be agreement on a positive relation between U-I collaboration and firms' innovativeness. Turning to the specificities of the EPSRC projects, we highlighted that their aim is to contribute to pre-competitive and upstream research and, in practice, they support the companies financially, help them to establish a close relationship with universities and to create the conditions and opportunities for recruiting highly trained personnel. These aspects, which are all linked to R&D and innovation inputs, are confirmed by the findings in Bruneel et al. (2009), who shows that firms declared to find more beneficial the contribution of university to knowledge and recruitment of personnel rather than to the production of short-term outputs, such as new products. As a consequence, we argue that the impact of the EPSRC U-I research projects, because of their pre-competitive nature, should be searched on firms' R&D inputs. First, we expect that firms' R&D intensity, measured as the ratio of intramural R&D expenditure to sales, benefit from the exchange of knowledge and resources with university that arises from participation to U-I R&D projects. R&D intensity is one of the firm-specific determinants that influence the innovative behaviour of firms and is commonly used as a measure of R&D input (Becker and Dietz, 2004). We argue that collaborating with university has the effect of increasing the amount of resources, as well as their intensity, devoted to R&D because it entails a higher firms' engagement in research. Hence, we put forward the following hypothesis:

Hp 1: U-I partnerships have a positive impact on the R&D intensity of participating firms.

Secondly, we argue that, through the network of relationships arising from the partnerships, U-I projects provide both the opportunity of hiring new R&D personnel at the end of the project and the chance of learning for existing staff. As stated in the OECD Frascati Manual (OECD, 2002b), data on the utilisation of scientific and technical personnel provide concrete measurement of resources devoted to R&D. We expect that the share of employees working on R&D related tasks inside the firms increases after participation, hence we put forward our second hypothesis:

Hp 2: U-I partnerships have a positive impact on the share of R&D employment in participating firms.

In addition, we make a distinction between occasional and recurrent participants, on the basis of the number of projects that each firm enters. The reason for making this distinction is that occasional and recurrent participants may have different characteristics and motivations for getting involved into to U-I projects and, as a consequence, they may experience a different impact. In fact, due to repeated participation recurrent participants have longer time to establish a profitable relationships with university. In addition, they develop internal capabilities and experience to participate; hence, they may only need support in reducing costs and risks associated with R&D, whereas occasional participants need support throughout the whole lenght of the project (Barajas et al., 2011). We argue that firms participating more than once in the time frame under analysis (i.e. recurrent participants), experience a larger impact than firms participating only once (i.e. occasional participants) on both outcome variables. We expect this because recurrent participants, who have gained experience, bear a cost of participation that is lower than the cost for occasional participants. Hence, they may benefit from U-I partnerships more than how much occasional participants do. As a consequence, we hypothesise that:

Hp 3: U-I partnerships have a positive and larger impact on recurrent participants than on occasional participants.

3 Data

The test for our hypotheses relies on a unique dataset, resulting from the merge of a dataset of EPSRC U-I partnerships funded between 1999 and 2007 with firm-level data gathered from two databases provided by the UK Office for National Statistics (ONS). The advantage of our dataset of U-I partnerships over other similar sources of data is that it provides information on actual interactions between firms and university departments. Moreover, data are collected by the funding agency, thus ruling out any bias due to self-reported data, as it is the case for survey-based data. Hence, we believe that these data may represent a reliable proxy for knowledge transfer activities between businesses and academia.

The EPSRC dataset includes 4,990 projects involving 3,331 UK firms. In order to match it with firm-level data we exploited the information on firms' names and addresses provided in the dataset. The ONS matched firms' names and addresses to the Inter Departmental Business Register (IDBR) and returned to us the anonymised list of successful matches, consisting of a list of unique firm identifiers. Notwithstanding a number of potential matching issues, such as incorrect spelling of names and addresses, changes of names, companies stopping reporting any economic activities, a unique identifier has been retrieved for almost half of the sample (1,488 firms; 45%[1]). Through the unique identifier provided by the ONS, we could match our data with two main sources of data: the Business Structure Database (BSD), which provides basic information about firms (e.g. employment, turnover, industry classification codes and location) that we will use to implement a propensity score matching, and the Business Expenditure on R&D database (BERD), that provides R&D data and represents our main data source for the construction of the outcome variables. The BERD is an annual survey carried out by the ONS with the main aim to supply data on R&D. It uniquely provides information on total R&D expenditure in the UK by business enterprises and total R&D employment.

The merge of the data on U-I partnerships with the firm-level data allows to work in a situation that is typical of evaluation studies (with observational data), in which it is possible to separate firms on the basis of the receipt of the treatment. After completing the matching and cleaning of the data we end up with a sample of 12,469 firms with complete information on pre-participation characteristics (year 1998) and post-participation R&D variables (year 2008). Out of 12,469 firms, 348 received the treatment, that is, they participated at least once to a U-I project between 1999 and 2007[2]. These participated, on average, to 1.5 projects with universities[3] and each project lasted, on average, 2 years and 9 months. We are left with 12,121 ($= 12,469 - 348$) non-treated firms, that form a pool of potential controls. Being this much larger than the treated group, it increases the chance to find the most suitable control group.

4 Method

4.1 Propensity Score Matching

In order to assess the impact of U-I research projects on participating firms we implement a propensity score matching (PSM), extensively applied in the literature on the evaluation of labour market policies and recently extended to innovation policy studies for the evaluation of R&D programs (see e.g. Almus and Czarnitzki, 2003; Czarnitzki and Licht, 2006; Aerts and Schmidt, 2008; Corsino et al., 2012; Guerzoni and Raiteri, 2012). This is a matching technique that attempts to estimate the impact of a treatment by accounting for the factors that predict the receipt of the treatment. The underlying idea is to find a plausible control group of non-treated firms that are similar to the treated ones in pre-treatment characteristics and to use this group as a substitute for non-observable counterfactuals (Caliendo and Kopeinig, 2008).

The reason for applying propensity score matching is to reduce the potential selection bias arising

[1]We carried out a sample representativeness analysis by comparing project related variables between the group of matched firms (1,488 firms) and the initial sample (3,331 firms) as well as between the former and the group of unmatched firms (1,843 firms). It emerges that matched firms display very similar or slightly lower figures than the full sample, hence we are confident that matched firms represent a random selection of the whole sample. See Appendix A, Table 6 columns (a)-(e).

[2]We carried out a sample representativeness analysis by comparing project related variables between the group of 348 treated firms and the whole sample of treated (3,331) (see Appendix A, Table 6 columns (f)-(g)) and by comparing firm-level characteristics between the group of 348 treated firms and the sample of treated for which basic information on year 1998 is available (see Appendix A, Table 7). In both cases, treated firms are not different from the whole samples and, where significant differences exist, these are fairly small.

[3]18% of firms participate to 2 projects, 15% to 3-4 projects, 8% to 5+ projects.

from the fact that firms are selected into treatment by the funding agency (hence not randomly), most likely on the basis of a number of peculiar characteristics and probably with a "picking the winner" or "aiding the poor" strategy. In addition, a bias might as well come from the firm side: some firms can in fact have advantages over other firms to search and find funding opportunities, either because of their past experience or because of their intrinsic characteristics, or both. As a consequence, treated and non-treated firms would behave differently notwithstanding the treatment, thus the simple difference in means in their performance after the treatment cannot be interpreted as causal impact.

The PSM tries to get an estimate of the Average Treatment Effect on the Treated (ATT) of the policy, defined as:

$$ATT = E(Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1) \tag{1}$$

where Y_1 and Y_0 indicate the value of a given outcome variable Y in the presence and absence of the treatment respectively, and D denotes the status of the treatment, where $D = 1$ for treated and $D = 0$ for non-treated. $E(Y_0 \mid D = 1)$, the outcome of non-treated units under treatment, is by definition non observable and hence needs to be replaced with a suitable control group of firms that did not participate to any U-I R&D project funded by the EPSRC in the years 1999-2007. In order to do so, treated firms are matched with non-treated ones on the basis of the so-called propensity score $P(X) = P(D = 1 \mid X)$, defined as the probability of being treated given a set of pre-treatment characteristics X. In order to consistently estimate the ATT through the PSM, two assumptions must be satisfied. The first is the Conditional Independence Assumption (CIA), or unconfoundedness, expressed as $E(Y_1, Y_0) \perp D \mid X$, stating that assignment to treatment is independent of the outcomes, given a set of observable covariates X. In other words, the observables must account for all the differences related to the outcome between treated and control units. The second assumption, referred to as the Common Support Condition, and expressed as $0 < Pr(D = 1 \mid X) < 1$, ensures that the vector of covariates X does not perfectly predict whether a firm receives or not the treatment. As long as both assumptions hold, the PSM provides an unbiased estimate of the ATT, by taking the difference in mean outcomes over the region of common support, weighted by the propensity score of firms (Caliendo and Kopeinig, 2008). The PSM estimate of ATT is thus given by:

$$ATT_{PSM} = E_{P(X)|D=1}\{E[Y_1 \mid D = 1, P(X)] - E[Y_0 \mid D = 0, P(X)]\} \tag{2}$$

The reason for implementing a PSM in our case is twofold. First, after the merge of the data on U-I partnerships to firm-level data, we are in a situation that is typical for evaluation because we are able to separate treated and non-treated firms. Furthermore, the group of non-treated is large enough to draw the control group on the basis of a propensity score. Second, given that a rich dataset on pre-treatment characteristics is available, we can implement the PSM and assume the CIA to hold. In the next section, the propensity score specification is illustrated.

4.2 Propensity score specification

We will carry out a propensity score matching on three typologies of treatment. First, we estimate the impact of participating versus not participating ($Ntreated = 348$), in which case we will derive the propensity score that expresses the probability of being treated or not. Second, we will distinguish firms that get treated only once in the period under analysis ($Ntreated = 204$) versus firms that get treated more than once ($Ntreated = 144$). We call them occasional and recurrent participants respectively: we thus estimate two different propensity scores, the first being the probability of participating to only one U-I project versus none (hence excluding from the sample the recurrent participants) and the second being the probability of participating to two or more projects versus none (hence excluding occasional participants from the sample). The reason for estimating the last two propensity scores is, as stated in the previous sections, that occasional and recurrent participants may have on the one hand, different characteristics and motivations for participating to U-I projects, and on the other hand, they may experience different impact.

As explained in the previous section, the propensity score measures the probability that a firm enters a U-I project, given a set of observable characteristics. The propensity score is recovered through the estimation of a probabilistic choice model where the dependent variable is the treatment variable. Two decisions have to be made at this stage: the first one concerns the model to be estimated and the second one concerns the variables to be included in this model. As for the model, since for binary treatments a probit or a logit usually yield similar results (Caliendo and Kopeinig, 2008), we decided to implement a probit model, following existing empirical evidence (Almus and Czarnitzki, 2003)[4]. The choice of the variables to include in the model is very important and more advice is available in the literature. We refer here to the guidance provide by Caliendo and Kopeinig (2008) as well as to what has been done in the empirical literature on the evaluation of R&D policy.

The first important caveat is that all variables must be measured before the treatment takes place, or must be fixed in time, so that we can rule out the possibility that those are affected by the treatment, hence endogenous. We first discuss the choice of the variables measured before the treatment and then we illustrate the choice of the variables that are fixed in time. We start by including in the vector of covariates an important set of factors that may influence both the participation to U-I projects and the outcome measures, which relate to the firms' economic performance. Hence we include in the probit estimation a measure of labour productivity in 1998, calculated as the logarithm of sales over employment, as well as a market share variable that measures competition in the market, calculated as the firm's sales over the industry's sales, measured on the SIC 5 digits level. Unfortunately, due to missing values, we are not able to recover any other firm-level characteristics, such as export and import ratio or capital intensity as it is done in other works. However, we think that labour productivity and market competition, together with the comprehensive list of dummies illustrated below, may reduce the unexplained variance due to potentially omitted variables. In other empirical works a variable to control for

[4]We carried out both a probit and a logit model and results are indeed very similar.

whether firms carry out R&D is usually included. However, in our case this is not necessary because we are dealing with a sample of innovative firms only. In fact, the BERD survey, which represents our main source of data to build the outcome variables and select the control group, only involves UK R&D doers.

As for the variables that are fixed in time, we include a set of 35 dummies to control for industry determinants, by using the Standard Industrial Classification codes (SIC 1992) at two digits level. These should pose no problems in terms of potential changes in time, being at two-digits. We also include dummies for the location of the firms, which are all UK based. After several trials and considerations, we decided to include 12 regions, these being the nine English regions[5] along with Wales, Scotland and Northern Ireland. By including these dummies, we aim at matching treated firms with non-treated firms that are located in the same area and thus are subject to similar external factors, such as local economic shocks. Size dummies are introduced for the following size groups: micro (1-9 employees), small (10-49 employees), medium (50-249 employees) and large firms (250 employees and more). These variables capture the different behaviour that firms of different size has with respect to R&D activities. Alternatively, the number of employees could also be used. In this respect, we are aware of potential problems due to firms growing in size (or the opposite), thus we prefer to use size bands, because the chance that changes in employment move one firm from one size group to the other is relatively low. In addition, we control for the firms' age, through three dummies indicating whether the firms were established during the 70s, 80s, or 90s, which should further capture different firms' attitudes towards collaboration with university.

4.3 Propensity score estimation

Table 1 and Figure 1 describe the variables that we will use to estimate the propensity score. We test for the difference in means between treated and the raw sample of untreated firms[6]. Treated and untreated firms display statistically significant differences (both positive and negative) in their market shares, labour productivity and distribution across size bands. In particular, imbalances can be found in the share of large firms, which is higher among treated than untreated firms. The distribution across UK regions show some differences too, especially with respect to the South East, where treated firms are over represented with respect to untreated, and North East, where it is the opposite. As for the distribution across sectors, we notice a large presence of firms in service sectors: the majority of firms (both treated and untreated) operate in business activities, such as legal, accounting, IPRs and other management activities, followed by firms operating in computer and related activities, such as hardware and software consultancy. We can also notice a larger presence of treated than untreated firms in manufacturing of medical products and manufacturing of chemicals, and the opposite in wholesale and trade and in manufacturing of furniture. These descriptives show that treated firms and the raw group of untreated firms are quite different as far as their pre-treatment characteristics are concerned, thus supporting

[5]London (LON), South East (SE), South West (SW) East of England (EE), Yorkshire and The Humber (YH), West Midlands (WM), East Midlands (EM), North West (NW) and North East (NE).

[6]We do not report figures for the industry dummies but differences between treated and untreated in sectoral composition can be visually analysed in Figure 1.

the need to select an ad hoc control group that is as similar as possible to the treated group. We hence proceed by carrying out the first phase of the propensity score matching, by estimating via probit model the propensity score with the above described variables.

TABLE 1 ABOUT HERE

FIGURE 1 ABOUT HERE

The probit estimations presented in table 2 shows that the market share of firms is positively and significantly affecting the probability of participating to U-I R&D projects and this is stronger for recurrent participants than for occasional participants, while labour productivity, although positive, does not seem to matter significantly. With respect to the size of firms, medium and large firms have higher probability of receiving the treatment than micro firms (the baseline category); as expected, the dummy for large firms is the only significant size dummy when it comes to recurrent participants, since it is more likely that large firms engage more often into U-I partnerships than smaller firms. Older firms have lower probability to be selected, but this is not true for recurrent participants. Region dummies mostly have a negative sign with respect to the baseline category South East, which is quite in line with the distribution of economic activities and top tier universities in the UK. Finally, our results show that firms in manufacturing sectors generally have a higher probability of participating to U-I projects (although this is not the case for firms in the construction sector and manufacturing of furniture) than firms in service sectors, such as trade and media.

With the estimated propensity scores at hand we can now proceed to the estimation of the ATT via matching. It is possible to implement the pairing of treated to non-treated firms by using several matching algorithms. All of them are summarised and discussed by Caliendo and Kopeinig (2008). The choice of a given algorithm with respect to another is a matter of trade-off between bias and variance of the estimates. We follow Caliendo and Kopeinig (2008), who suggest that, if there are many comparable untreated units, it is advisable to use more than one nearest-neighbour to gain precision in the estimates. Hence, we implement a nearest neighbour matching with 5 untreated firms (N:5), in which each firm is matched to the 5 most similar ones in terms of propensity score, and a kernel matching that uses weighted averages of all (or nearly all) firms in the control group. In the first case, the outcome of each participant firm is compared with the average outcome of the 5 most similar non-participant firms. In the second case, the outcome of each participant is compared to the weighted average of all (or nearly all) untreated firms, where higher weights are assigned to firms that are closer in terms of propensity score and lower weights are assigned to more distant ones. With both N:5 and Kernel matching a lower variance (than with other algorithms) is achieved, because more information is used (i.e. more than one control firm per treated firm), hence the estimates are more precise. On the other hand, it may be that observations that are bad matches are used, hence leading to a relatively higher bias. We expect this not to be a major concern because the group of untreated is much larger than the sample of treated, which increase the chance to find good matches. To sum up, we estimate the ATT of three treatments and we implement two types of matching algorithms. Since we are interested in two outcome variables, we implement in total twelve estimations, six for each outcome variables. In the following section we describe our outcome variables and provide descriptive statistics, and then show our main results.

TABLE 2 ABOUT HERE

5 Results

5.1 Outcome variables

As said in sections 2.3, we expect that EPSRC funded U-I projects may have a direct impact on innovation input of firms. Therefore, we employ a measure of R&D intensity in 2008 (henceforth *R&D_intensity*) in logarithm, calculated as R&D expenditure on sales, and a measure of the share of R&D employment in 2008 (henceforth *share_R&D_empl*), calculated as the ratio of R&D personnel[7] over total employment in 2008. To build both measures, we use data from the BERD survey carried out in 2009, which provides information on firms' R&D activities at the end of the previous financial year.

Table 3 shows the descriptive statistics for *R&D_intensity* (in log) and *share_R&D_empl* for the whole sample and for the subsamples of treated and untreated firms. Similarly to what we did for pre-treatment characteristics, we also test for the difference in means, which provides a some information about the possible effect of U-I partnerships. *R&D_intensity* is on average -4.14, it is larger for treated than for untreated firms and the difference (0.29) is significant at 1% level. As for *share_R&D_empl*, the mean value for the whole sample is 0.06, which means that, on average, 6% of the workforce works in R&D business units or, more generally, on R&D tasks. The mean value for treated firms is 0.09 and it is significantly (at 1% level) higher than that of untreated firms by 0.0364.

TABLE 3 ABOUT HERE

5.2 Results

Our results are presented in Table 4 and show the estimated ATT of EPSRC funded U-I partnerships on firms' R&D intensity and share of R&D employment. We implement a nearest neighbour matching with 5 untreated firms (N:5) and a kernel matching[8]. In the first case, each participant is matched to the 5 most similar non-participants in terms of propensity score and its outcome is compared to the average outcome of those five. Kernel matching uses weighted averages of all (or nearly all) firms in the control group so that the outcome of each treated firm is compared to the outcome of all the the untreated firms, calculated as a weighted average with higher weights on closer firms in terms of pscore and lower weights on more distant ones. We replicate the same exercise for three different treatments: receipt of the treatment (YES/NO), participating to one project only (occasional participants) and participating to more than one project (recurrent participants). The main result is that there is no significant effect of U-I partnerships on *R&D_intensity*, whereas there is a positive and significant ATT on *share_R&D_empl*, in the

[7] This is the number of engineers, technicians and others working on R&D within the company

[8] We use the Stata command *psmatch2*, developed by Leuven and Sianesi (2012)

region of 0.018-0.034, depending on the matching method employed and on the treatment under consideration.

TABLE 4 ABOUT HERE

The top panel of Table 4 displays the results for the receipt of the treatment (YES/NO), where the whole sample of treated firms ($Ntreated = 348$) is considered. In both matching methods two observations are discarded, because it is not possible to find suitable controls for those firms. The number of potential controls is 11,198 but, while with the kernel matching all the observations are used, with the N:5 matching five observations for each treated firms are used. The N:5 matching allows to re-use the same observation more than once (matching with *replacement*) unless otherwise specified[9]. For each outcome variable, the mean for treated firms is reported, along with the mean for the selected untreated firms. The ATT is the difference between treated and untreated with the usual significance levels. The ATT on *R&D_intensity* is 0.04 when estimated with N:5 matching and 0.14 when estimated with kernel matching. The quite large difference between the two estimates might be worrying because, for an estimate to be reliable, we would expect very similar results when employing different matching methods. In addition, the standard errors of both figures are quite high, indicating that these estimates are not significant. Hence, we can not reach any conclusion about the impact of U-I partnerships on firms' R&D intensity. On the contrary, the ATT on *share_R&D_empl* is positive and significant at 1%-5% level when estimated with both N:5 and kernel matching and, moreover, the magnitude of the coefficients is very similar (0.018 and 0.025 respectively). Therefore, we can confirm that U-I partnerships have a positive impact on the share of R&D employment of participating firms, who have a share of R&D workforce that is, on average, 2% higher than the one of control firms after participation to the projects. As we previously argued, through the network of relationships that develop out of the collaboration with universities, firms gain the opportunity to recruit staff or to provide adequate training to existing staff, which leads to an increase in the amount of employees working on R&D related tasks inside the company.

The results are quite similar for occasional and recurrent participants as far as R&D intensity is concerned, with the only exception of the ATT for recurrent participants estimated with N:5 matching, which is negative. However, as it was the case for the previous estimates, none of these is significant and hence no conclusion can be reached. As for the share of R&D personnel employed, the ATT on occasional participants is 2% and significant at 5% level, whereas it is slightly higher on recurrent participants, who experience an increase in their share of R&D employment of around 3%. This finding is expected, because, as we argeud, firms that participate more than once have longer time to establish long-term relationships with the science base and this is particularly relevant to fully benefit from the highly skilled human capital offered by universities.

To sum up, our results indicate a positive impact of EPSRC funded U-I partnerships on firms' share of employment in R&D and this is consistent across different treatments and different matching estimations, thus confirming our second hypothesis; instead, no clear indication emerges

[9] A check of the matching procedure shows that there is no over use of the same controls in any of the estimates; if it was the case, we should have worried about the presence of very few good matches and many bad matches.

as for the impact of U-I partnerships on firms' R&D intensity, hence not confirming our first hypothesis; finally, our third hypothesis is partially confirmed because we found that recurrent participants experience larger benefits than occasional ones, but this is only true for the share of R&D employment. Before discussing our findings, we dedicate the next section to assess the quality of the matching procedure just implemented.

5.3 Evaluating the quality of PSM

The main instrument to evaluate the propensity score matching is the so-called *pstest*, which measures the balancing of the covariates used in the estimation of the propensity score. First, the *pstest* carries out a *t-test* on the hypothesis that the mean value of each variable used in the estimation of the propensity score is the same in the treatment group and in the control group. The test is performed before and after the matching. For the matching procedure to be satisfactory, we expect that the mean values of the two groups for every single variable do not differ after matching. Similarly, the standardized bias, defined as the difference of the mean values of each variable for the treatment group and the control group, divided by the square root of the average sample variance in both groups (Rosenbaum and Rubin, 1985), is calculated before and after the matching. As a rule of thumb, we consider a matching procedure to be successful if the bias of each variable after the matching is below 3% or 5% (Sianesi, 2004). The *pstest* also calculates the *Pseudo-Rsq*, which measures how much variation is explained by the probit model used to estimate the propensity score, before and after the matching, and the *p-value* of the likelyhood ratio test on the hypothesis of joint insignificance of the regressors. For these to be satisfactory, we expect that the explanatory power of the model after the estimation, that is, carried out on the matched sample, is very low and that the *p-value* leads to reject the hypothesis of joint insignificance of the regressors before the matching and never reject it after the matching.

Table 5 shows that the three estimations of propensity scores that we carried out (treatment or not, getting only one project, getting more than one project) all yield satisfactory results of the *pstest*. We report the summary table of the *pstest*, which provides information on the *Mean bias*, the *Pseudo-Rsq* and the *p-value*. The *pstest* also shows that the *t-test* (not reported here) on the mean value before and after matching is satisfactory for each variable used in the probit model. The *Mean bias* is always below the 5% threshold after the matching and the *Pseudo-Rsq* is very low after the matching, which means that the models estimated after the matching only explain a small (if any) variation. The likelihood ratio test leads us to always reject the joint insignificance of the regressors before the matching (*p-value* equals 0 in all cases) and to never reject it after the matching (*p-value* equals 1 in all cases).

TABLE 5 ABOUT HERE

An additional way of evaluating the matching procedure is graphically. In Figure 2 we show the density distribution of the propensity score (*pscore*) for treated and controls before and after the matching, for each treatment . This allows us to check the that the Common Support Condition holds, by visualising the overlapping between treatment and control group. Before the matching, the two distributions should at least partially overlap, whereas after after the matching, they should be similar and, hence, have a larger common support. From Figure 2 it can be seen that after the matching, the distribution of the *pscore* of treated and control firms is much more similar than before the matching. Hence, the matching procedure that we implement can be considered successful in creating a control group of firms that is very similar to the group of treated in terms of probability of receiving the treatment.

FIGURE 2 ABOUT HERE

Finally, the *psgraph* further allows to check whether we have enough overlap between the treatment and control group to make reasonable comparisons. The *psgraph*, represented in the left panels in Figure 3 (graphs (a), (d), (g)), is a bar chart that shows the distribution of treated and untreated observations across different values of the *pscore*: it shows how many untreated observations (bottom bars) are there for any treated observation (top bars). From a first look at the three *psgraphs* in Figure 3, one for each treatment, it seems that there is a lack of untreated observations for *pscore* values above 0.1. However, if we zoom in to treated and untreated firms with a *pscore* above 0.1, by plotting an histogram for treated firms and another histogram for untreated firms with *pscore* values higher than 0.1 (histograms (b) and (c), (e) and (f), (h) and (i)), we actually see that there are quite many untreated observations after that *pscore* value[10]. All in all, after evaluating the propensity score matching both statistically and graphically, we are confident that the propensity score matching carried out in this paper can be considered satisfactory.

FIGURE 3 ABOUT HERE

6 Discussion and conclusion

This paper has investigated the impact of university-industry R&D collaboration on firms' innovativeness. We estimate the effect that U-I partnerships in the field of Engineering and Physical Sciences, funded the the EPSRC, have on firm's R&D intensity and share of R&D employment. We use a novel and unique dataset, made up of data on U-I partnerships matched with firm-level characteristics. We apply a propensity score matching to select a control group of firms that is as similar as possible to the group of treated firms in terms of pre-treatment characteristics and to get the average treatment effect on the treated (ATT) of participation to U-I projects. We find that EPSRC U-I collaborations funded between 1999 and 2007 have a positive impact on the share of R&D personnel employed in 2008 by participating firms: these have, on average, 2% of R&D employees more than firms that did not participate and this is significant and consistent across different matching estimations. We could not trace any significant impact on R&D intensity: although the latter seems to be positively related to project participation, the estimates are neither significant nor consistent across different estimations[11]. In addition, we

[10]It should also be noted that the histograms shows densities, hence, recalling that the whole sample of potential controls is much larger than the sample of treated, relatively low densities of untreated does not necessarily means few untreated cases.

[11]This may be due to the fact that intra-mural R&D expenditure, the numerator in R&D intensity, only mirrors short term benefits, thus we may not be capturing any significant change due to our relatively long time span. Another reason could be a potential problem of reverse causality between R&D intensity and participation to cooperative research projects, as documented by Colombo and Garrone (1996), that we may not fully resolve with our empirical analysis.

break down participants into occasional and recurrent participants, on the basis of the number of projects entered. Our findings show that the effect on the share of R&D employment is higher for recurrent participants ($ATT = 3\%$) than for occasional participants ($ATT = 2\%$), whereas no significant impact can be traced as far as R&D intensity is concerned. Finally, we assess the quality of the matching procedure implemented and show that this is satisfactory in selecting a group of untreated firms that is very similar to the group of treated.

This work has a number of limitations that it is worth underlining before turning to its' implications. The first limit concerns the restriction of the analysis to one source of funding for U-I partnerships. It is well known that firms receive a multitude of public funds from different funding agencies for R&D activities and these may have different impact on firms' R&D efforts. In our analysis we only consider U-I partnerships funded by the EPSRC, hence we may only be capturing part of the story. However, the EPSRC funds the bulk of R&D activities in the UK (D'Este et al., 2013) and thus, we are confident that our story is quite representative. In addition, the focus on engineering and physical sciences allows us to better distinguish the aims of funded partnerships, which we do by taking into account the specificities of the program under study. Hence, we formulate our empirical hypotheses not only on the basis of what the academic literature suggests, but also on the basis of the stated aims and objectives of the EPSRC, supported by findings from a number of existing studies on the same set of partnerships. The second limitation of this study is that we focus our attention on one channel of knowledge transfer between university and industry, research collaboration, whereas there are many other types of interaction modes. Although this may cause our story to provide limited evidence, we are aware that cooperative research partnerships are among the most typical forms of U-I research collaborations (Fontana et al., 2006; OECD, 1998) and, indeed, they are one of the most frequent policy instruments put in place by policy-makers to support pre-competitive research and firms' innovation activities (D'Este and Iammarino, 2010; Fisher et al., 2009; OECD, 1998, 2002a). In addition, the focus on U-I collaboration allows to identify more easily the desired impact on firms' innovativeness, whereas this would not be the case if we were considering other typologies of interaction, that are driven by different factors and may affect firms quite differently. Finally, we are aware that the propensity score matching allows us to control for observable factors affecting the probability of receiving the treatment but nothing can be done with respect to unobservable factors[12].

Notwithstanding the limitations, this study has a number of implications for both the academic literature and policy. Existing evidence in the academic literature is somehow confusing on whether the impact of research collaboration, and more generally, U-I interaction, is to be traced on innovativeness or on the overall productivity. We argue that it is on innovativeness, and in particular on the R&D input side, that an impact should be searched. This is due to the pre-competitive nature of the funded projects under study, which are aimed at contributing to upstream and basic research that is far from industrial application, hence far from produc-

[12] Another limitation of our methodoloy is that we do not account for the fact that firms participate to U-I projects in different years. To do so, we should estimate the propensity score in different pre-treatment years, depending on the year of participation. This is the first thing we currently plan to do in order to improve our analysis.

ing R&D outputs. In addition, we carry out our empirical exercise by employing a propensity score matching in order to reduce the selection bias that is typical of evaluation studies in quasi-experimental settings, and this proves to be a robust methodology. We thus provide new evidence on the effect that the voluntary exchange of knowledge between university and industry has on firms' internal effort on R&D by showing that U-I partnerships have a positive impact on the share of employees working on R&D related tasks. The latter increases after participation: we argue that this is channeled by the network created around the cooperative projects, through which firms gain opportunities to hire skilled staff and/or to provide adequate training to existing staff. Investing in people is by definition a long-term goal and this is in line with the findings of Bruneel et al. (2009), who report that firms declared collaborating with university to gain long-run rather than short-run benefits.

This leads to an important implication for science, technology and innovation policy. The main benefits of universities are certainly related to the expertise they provide to the economic system and this is often embodied in knowledge as well as people. Therefore, it is fundamental to create or strengthen (where they exist) mechanisms that support the use of university research as a mean for recruiting appropriately skilled staff, which are likely to be more useful than mechanisms focusing on research or recruitment alone. Finally, the fact that occasional participants experience smaller benefits compared to recurrent participants is suggestive of the need for policy-makers to clearly distinguish between experienced and non-experienced firms, because the latter may need additional support to deal with the learning process, such as public diffusion, information and training, in order to fully benefit from U-I collaboration.

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Tables

Variable	Obs	Mean	St. Dv.	Min	Max	Mean treat.	Mean untr.	Difference
Market share '98	12469	0.0048	0.0271	0	0.8036	0.0178	0.0044	0.0134***
Lab prod '98	12469	197.2155	2027.028	0	143998.3	193.844	189.3079	4.5361*
Micro	12469	0.4240	0.4942	0	1	0.2844	0.4281	-0.1436***
Small	12469	0.3111	0.4629	0	1	0.2385	0.3132	-0.747***
Medium	12469	0.1944	0.3957	0	1	0.2155	0.1937	0.0218
Large	12469	0.0704	0.2558	0	1	0.2614	0.0649	0.1965***
Birth decade 70s	12469	0.2644	0.4410	0	1	0.2471	0.2637	-0.0166
Birth decade 80s	12469	0.3109	0.4629	0	1	0.3448	0.3096	0.0351
Birth decade 90s	12469	0.4245	0.4943	0	1	0.408	0.4266	-0.0185
East Midlands	12469	0.0817	0.2739	0	1	0.089	0.0814	0.0076
East of England	12469	0.1034	0.3045	0	1	0.112	0.1033	0.0087
London	12469	0.1093	0.3120	0	1	0.0862	0.1102	-0.024
North East	12469	0.0361	0.1867	0	1	0.0172	0.0367	-0.0194*
North West	12469	0.0983	0.2977	0	1	0.0948	0.0982	-0.0033
Northern Ireland	12469	0.0180	0.1331	0	1	0.0201	0.0179	0.0021
Scotland	12469	0.0853	0.2794	0	1	0.0833	0.0853	-0.0019
South East	12469	0.1608	0.3674	0	1	0.2212	0.1591	0.0621***
South West	12469	0.0854	0.2795	0	1	0.0804	0.0855	-0.0051
Wales	12469	0.0492	0.2163	0	1	0.0431	0.0494	-0.0492
West Midlands	12469	0.0914	0.2882	0	1	0.0718	0.0921	-0.0203
Yorksh & Humb	12469	0.0805	0.2722	0	1	0.0804	0.0804	0

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 1: Descriptive statistics and mean comparison of pre-treatment characteristics between treated and untreated firms

	(1) Prob(treatment)	(2) Prob(1 prj)	(3) Prob(multiple prj)
Mkt share 98	1.987***	1.475*	1.850***
Lab prod 98	2.96e-06	1.70e-06	4.19e-06
Size small	0.114	0.111	0.0865
Size medium	0.261***	0.319***	0.107
Size large	0.847***	0.792***	0.769***
Birth decade 70s	-0.152**	-0.160*	-0.119
Birth decade 80s	-0.00937	0.0361	-0.0868
East Midlands	-0.0731	-0.0221	-0.133
East of England	-0.0773	-0.108	-0.0398
London	-0.160	-0.134	-0.172
North East	-0.420**	-0.575**	-0.217
North West	-0.0796	-0.184	0.0612
Northern Ireland	-0.0408	0.0490	-0.242
Scotland	-0.0720	0.00486	-0.191
South West	-0.108	-0.0366	-0.228
Wales	-0.112	0.0220	-0.373
West Midlands	-0.243**	-0.312**	-0.121
Yorkshire & Humber.	-0.126	-0.0588	-0.208
Mining of coal	0.712	1.109	
Oil & gas extr.	0.169	0.518	
Oth. mining & quarr.	-0.00987	0.124	-0.0266
Mfg food & bever.	-0.915***	-0.870**	-0.795**
Mfg textiles	-0.816**	-0.432	
Mfg wear. appar.	-0.478		-0.168
Tanning leather	-0.0111		0.265
Mfg wood	-0.559	-0.200	
Mfg paper	-0.227		0.0544
Publ., print. & media	-0.761*	-0.401	
Mfg coke & petrol.	0.634		0.952
Mfg chemicals	0.106	0.250	-0.0701
Mfg rubber & plastic	-0.178	-0.130	-0.175
Mfg oth. mineral	0.0454	0.214	-0.0908
Mfg metals	0.551**	0.437	0.545*
Mfg metal prod.	-0.0153	0.184	-0.204
Mfg machinery	-0.151	0.133	-0.565*
Mfg computers	0.404	0.361	0.419
Mfg electr. machin.	0.0221	0.115	-0.0483
Mfg radio, tv & oth.	0.456**	0.505	0.378
Mfg medical instr.	0.532**	0.650**	0.312
Mfg vehicles	-0.133	-0.0395	-0.172
Mfg oth. transport	0.134	-0.00174	0.261
Mfg furniture	-0.344	-0.0639	-0.752*
Construction	-0.541*	-0.169	
Sell vehicles	-0.368	-0.00779	
Wholesale trade	-0.449**	-0.241	-0.600**
Retail trade	-0.954**	-0.560	
Land transport	-0.557	-0.202	
Post & tlc.	0.0821		0.317
Computer activit.	0.145	0.275	-0.00488
Research & develop.	0.0642	0.206	-0.0743
Oth. business activit.	-0.0231	0.0885	-0.114
Health & social	-0.347	-0.00333	
Culture & sport	-0.0325	0.261	-0.513
Constant	-2.035***	-2.361***	-2.290***
Observations	11,544	11,169	9,676
Pseudo R2	0.109	0.0930	0.109

Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Probit models estimating the probability of getting treated or not (col. 1), of getting 1 treatment or 0 (col. 2) and of getting multiple treatments or 0 (col. 3)

Variable	Obs.	Mean	Std. Dev.	Min	Max	Mean treated	Mean untreated	Difference
R&D intensity (log)	12469	-4.1484	1.8489	-13.7564	6.7594	-3.8598	-4.1568	0.2969***
Share R&D empl.	12469	0.0634	0.1035	0	1	0.0988	0.0623	0.0364***

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 3: Descriptive statistics of the outcome variables and mean comparison between treated and untreated firms

Treatment Y/N			**N:5**				**Kernel**	
	Treated	Untreated	**ATT**	S.e.	Treated	Untreated	**ATT**	S.e.
R&D intensity (log)	-3.849	-3.89	0.0409	0.1192	-3.849	-3.9921	0.1430	0.1096
Share R&D empl.	0.0993	0.0813	0.0180**	0.0085	0.0993	0.0739	0.0254***	0.0079
Treated on support			346				346	
Treated total			348				348	
Untreated			11198				11198	
Occasional p.			**N:5**				**Kernel**	
	Treated	Untreated	**ATT**	S.e.	Treated	Untreated	**ATT**	S.e.
R&D intensity (log)	-3.8163	-3.8933	0.0769	0.1432	-3.8395	-4.01	0.1703	0.1319
Share R&D empl.	0.0943	0.0730	0.0209**	0.01	0.0943	0.0727	0.0211**	0.0093
Treated on support			202				203	
Treated total			204				204	
Untreated			10966				10966	
Recurrent p.			**N:5**				**Kernel**	
	Treated	Untreated	**ATT**	S.e.	Treated	Untreated	**ATT**	S.e.
R&D intensity (log)	-3.8625	-3.844	-0.0184	0.1938	-3.8625	-3.9935	0.131	0.1817
Share R&D empl.	0.1071	0.0793	0.0278*	0.0146	0.1071	0.0728	0.0342**	0.0137
Treated on support			143				143	
Treated total			144				144	
Untreated			9533				9533	

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Results of propensity score estimation

			Mean bias	Pseudo-R2	P>chi2
Treatment Y/N	N:5	before matching	9.1096	0.109	0
		after matching	2.5420	0.011	1
	Kernel	before matching	9.1097	0.109	0
		after matching	2.3115	0.011	1
Occasional participants	N:5	before matching	10.2613	0.093	0
		after matching	2.9597	0.018	1
	Kernel	before matching	10.2613	0.093	0
		after matching	3.3791	0.018	1
Recurrent participants	N:5	before matching	11.2088	0.109	0
		after matching	3.9082	0.02	1
	Kernel	before matching	11.2088	0.109	0
		after matching	3.9854	0.024	1

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 5: Result of the pstest

Figures

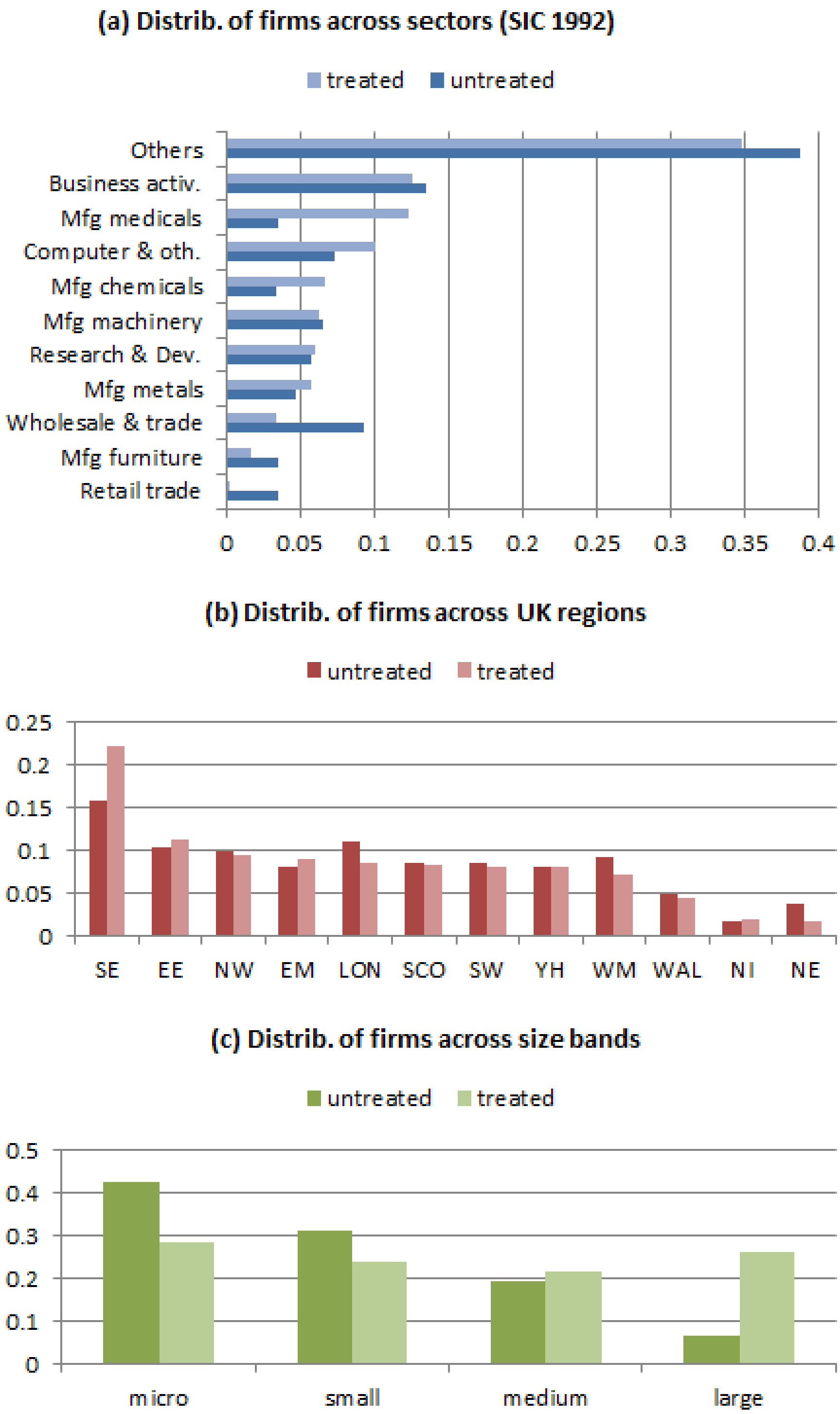

Figure 1: Distribution of firms across sectors (SIC 1992), regions, size bands (year 1998)

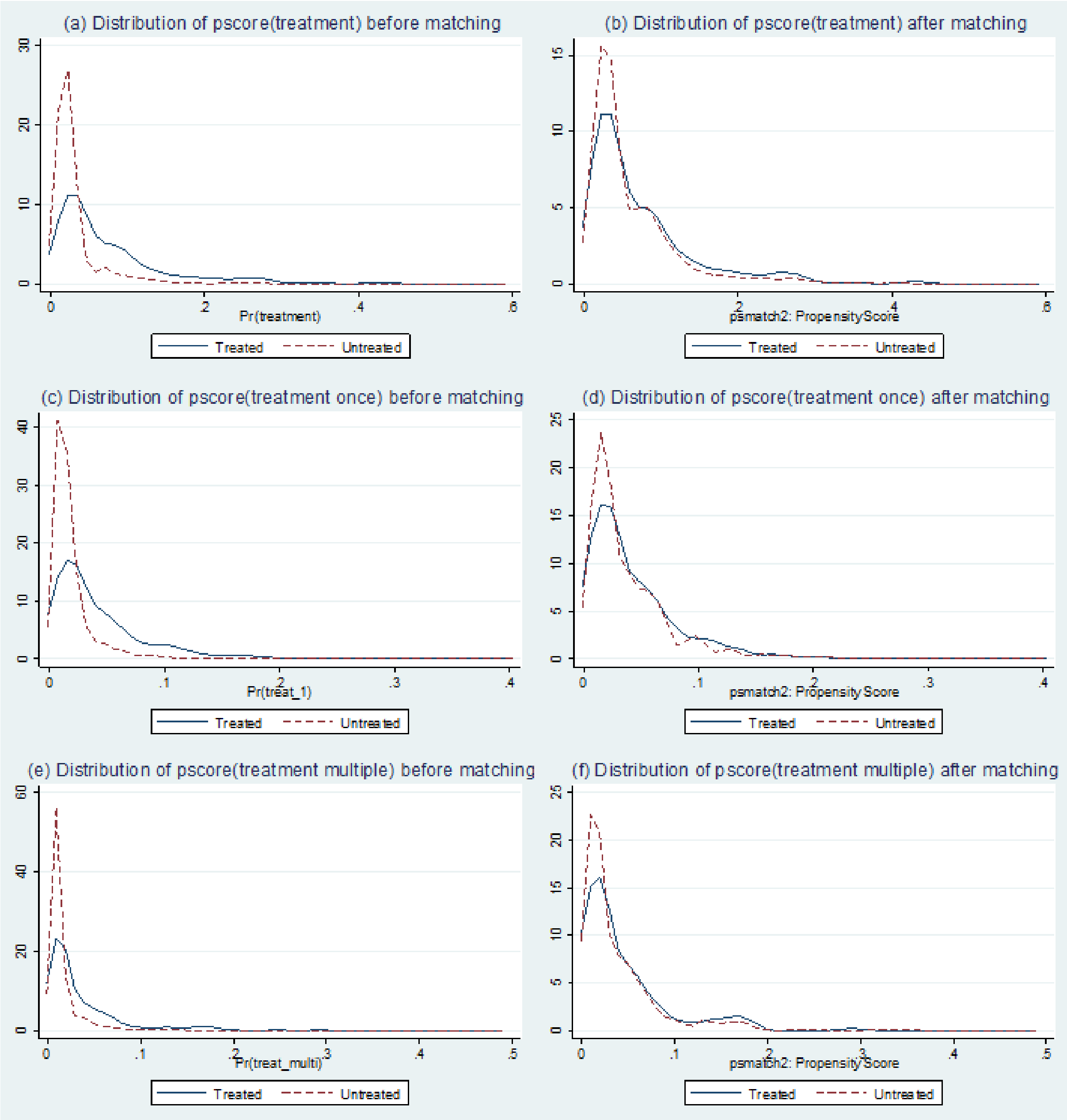

Figure 2: Density function of the probability of receiving the treatment before and after the matching

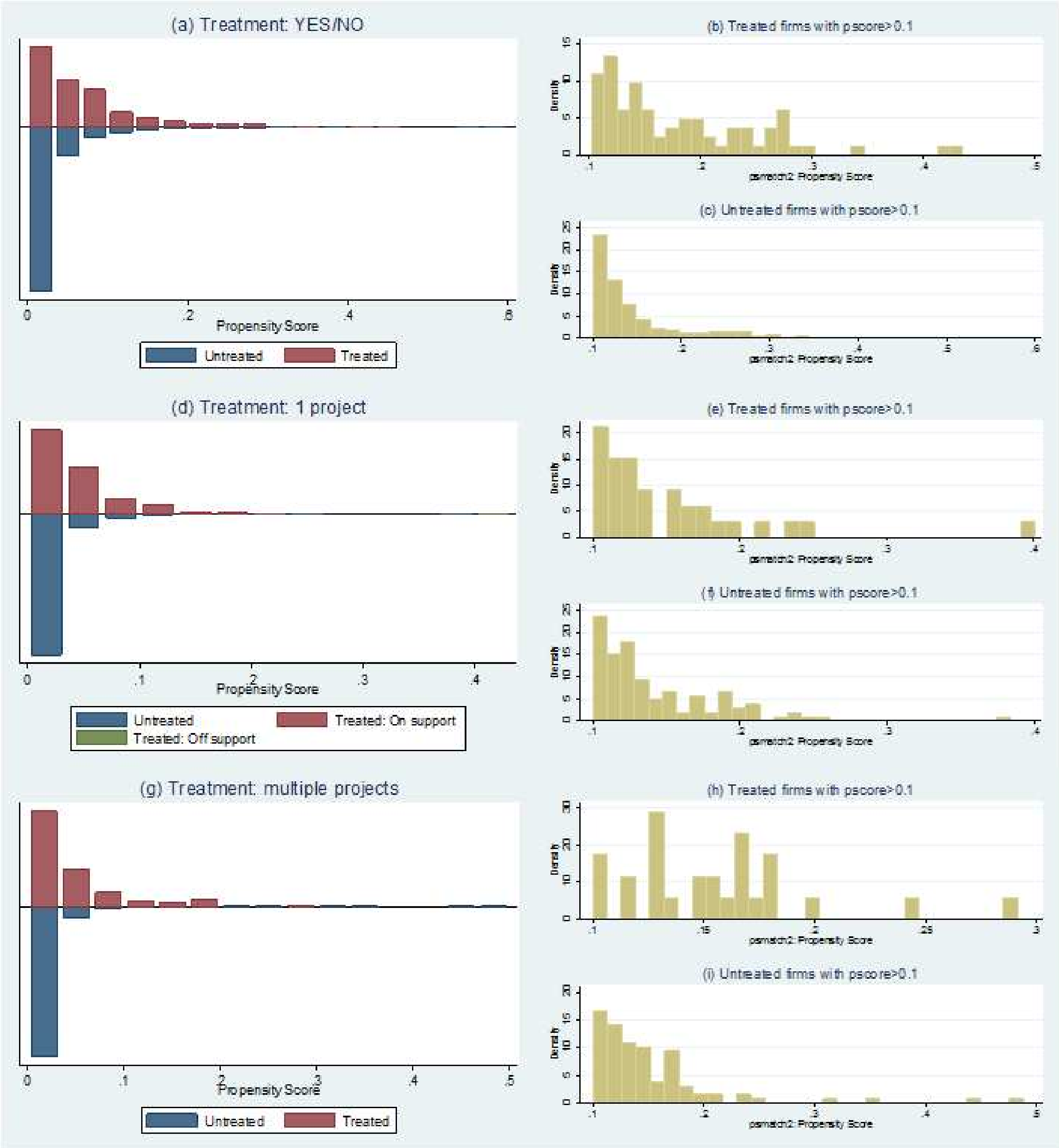

Figure 3: Psgraph

Appendix A: Sample representativeness

	(a) Mean full sample	(b) Mean unmatched	(c) Mean matched	(d) Difference (b)-(c)	(e) Difference (a)-(c)	(f) Mean matched	(g) Difference (a)-(f)
	N=3331	N=1843	N=1488			N=348	
Num of prj	1.498	1.544	1.4401	0.1045**	0.0579**	1.5229	-0.0249
Lenght of prj, yy	2.7553	2.7972	2.7035	0.0937**	0.0518**	2.6932	0.0621
Lenght of prj, dd (log)	6.8128	6.8336	6.7872	0.0464**	0.0256*	6.7829	0.0299
Funding per firm (log)	9.6831	9.6957	9.6674	0.0282	0.0157	9.8133	-0.1302*
Share intra reg. U	0.2908	0.2791	0.3049	-0.0255*	-0.0141	0.3032	-0.0124
Size of U dept	42.8339	43.3462	42.2029	1.1433	0.631	42.8451	-0.0112
Quality of U dept	2.5496	2.5649	2.5307	0.0342	0.0189	2.5926	-0.043

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Sample representativeness for projects characteristics

	(a) Mean	(b) Mean matched	(c) Diff (a)-(b)
	N=1038	N=348	
Turnover 1998	39989.51	42742.35	-2752.84
Empl. 1998	366.6464	355.0029	11.6435
Lab. Prod. 1998	267.1123	193.844	73.2683*
Year of birth	1986.241	1986.003	0.238
Mkt share 1998	0.0108	0.0178	-0.007**
Share of SMEs	0.7986	0.7327	0.0659*

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Sample representativeness for firms characteristics

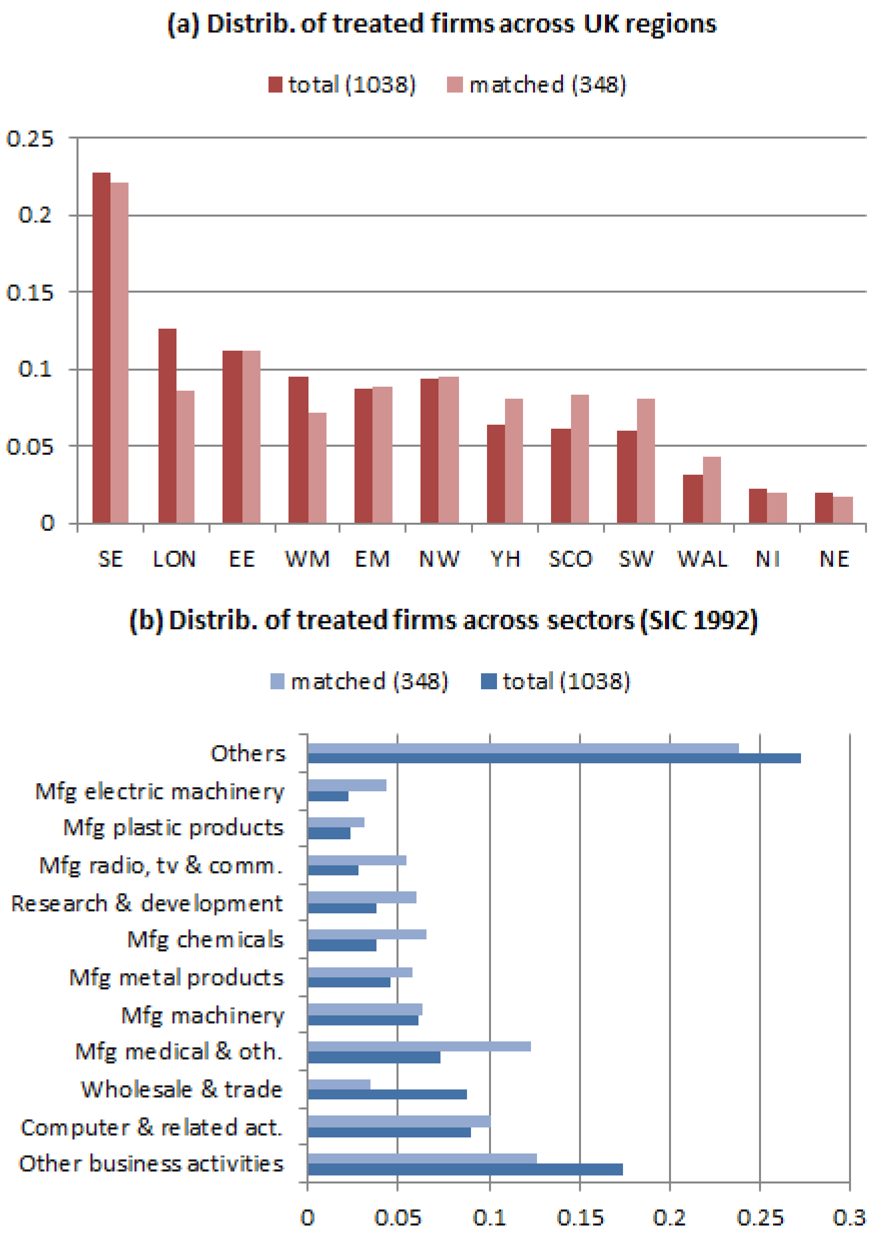

Figure 4: Distribution of treated firms across UK regions and sectors (SIC 1992)