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Does Knowledge Diffusion between University and Industry Increase Innovativeness? [1]

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Does Knowledge Diffusion between University and Industry Increase Innovativeness?

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Abstract

This paper rigorously explores the impact of firm's collaboration with universities on innovation. Specifically, using a representative dataset of manufacturing and service firms we have applied recent matching techniques to examine the hypotheses that whether academic knowledge has a positive impact on innovative sales and the propensity to apply for patents. Econometrically, the paper illustrates the differences that emerge from different matching estimators and samples. On balance, we find robust evidence that university collaboration positively influences innovative performance for large manufacturing firms. In contrast, whatever estimator is chosen, the data show no significant association between university collaboration and the average service firm's innovation sales or propensity to apply for patents.

Keywords: R&D investment, innovation, patents, university industry linkages, matching methods.

JEL Classification: C24; L10; O30; O31; O38; 040

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1. INTRODUCTION

The diffusion of technology and knowledge is a salient feature in the recent literature on technological change, innovation and growth. Much attention has been given to the role of universities. Although there is a considerably variety across industries, many studies provide pieces of evidence for the strategic importance of the link between university and industry in modern economies. The key empirical indicators of the growing relationships between universities and firms are (i) industrial funding of university research and partnering projects, (ii) patenting by universities, (iii) start-up companies from universities and (iv) joint authorship of articles from university and industry research. Counts of patent or innovations, market to book value and stock return are common variables used for measuring the impact of academic knowledge on firm performance.

The formulation of absorptive capacity by Cohen and Levinthal (1989) and the 'non-linear model' by Pavitt (2003) and others[i] have facilitated a broader theoretical understanding of academia's interaction with commercial firms. Most of the empirical research on science, university and industry relation are focused on the U.S. However, it has been shown that the experiences of university-industry linkage in the American economy often correspond to findings from European and other countries.

Hall *et al.* (2001) report that about 60 percent of the research projects funded by the Advanced Technology Program in the U.S. involved firms in collaboration with universities. Caloghirou *et al.* (2001) analyze over 6,000 research joint ventures (RJVs) in 42 nations that received funding from the European Commission during 1983-1996 and find that the share of RJVs that involved one or more universities was 67 percent in 1996. Zucker *et al.* (1998) studied the formation of firms in biotechnology, which is an industry closely linked to fundamental molecular biology. Their analysis shows that top U.S: university researchers contribute to set up biotechnology firms. Harhoff (1999) studies the formation of firms in the regions of West Germany and reports that the nearness to scientific personnel is important mainly for technology intensive entry. Mansfield (1998) finds that industrial innovations that could not have been developed (without a delay of a year or more) in the absence of academic research accounted for over 5 percent of total sales in major firms in the U.S. in 1994. Through a postal questionnaire survey of 2,300 companies, Baise and Stahl (1999) replicate

Mansfield's survey in Germany and find that approximately 5 percent of new product sales could not have been developed without academic research.

Despite extensive evidence for the importance of partnering between university and industry, many scholars emphasize that our knowledge on the interaction between university and industry is still limited and unambiguous when it comes to issues such as systematic data analysis and the economic consequences associated with knowledge diffusion. [See, for example Hall *et al.* (2003), Jacobsson (2002) and Fontana, *et al.* (2003)].

Even though the practical benefits for industry of much, or perhaps most, university research probably emerges from indirect and hard-to-measure processes, and even if universities in general are in the business of the creation and free dissemination of knowledge "for its own sake" (See Henderson, *et al.* 1998), it is naturally unsatisfactory if the largest sector for basic research in the society is not properly evaluated.

The present paper aims to contribute through a unique quantitative evaluation of the practical importance of the industry-university linkages. To assess the impact of collaboration with universities on a firm's innovative performance we use the estimators recently developed by Abadie and Imbens (2002) and Abadie *et al.* (2004). These estimators estimate the average effect of academic knowledge by comparing the outcomes of collaborators with control observations of non-collaborators using nearest matching neighbours across a dataset on 2,071 observations of firms in Sweden taken from the Community Innovation Survey.

Deploying two alternative performance measures, we use 19 alternative estimators with both the total sample and four subsamples of manufacturing and service firms. We show that nearest neighbour matching estimators are sensible for sample weights, exact matching, bias correction and number of matches. We also show that there are differences between manufacturing and service firms and between small firms and larger firms.

The rest of the paper is organised as follows. Section 2 briefly reviews some important theoretical and empirical papers on knowledge diffusion and university-industry linkages. In Section 3, we delineate our database. Section 4 introduces the methodological approach. Section 5 states the empirical results. Finally, in Section 6, we summarise our findings with some concluding remarks.

2. UNIVERSITY-INDUSTRY LINKAGES

A number of empirical studies support the hypothesis that the use of academic knowledge is beneficial to technological change, innovation and growth in the private sector through new theoretical insights, new techniques and new skills of a kind that industrial firms find it difficult to provide themselves [See for instance Jaffe (1989), Adams (2002 and 2006), Pavitt (2003), Adams *et al*. (2003) and Adams *et al*. (2004)]. Patent information is often assumed to be a useful indicator of the linkages between university and industry. As discussed by Narin *et al.* (1997), there was a threefold increase in the number of academic citations in industrial patents in the US through the mid 1990s, which can be seen as strong evidence on the growing integration between academic and private knowledge.

Other studies, however, give conflicting results on this issue. Klevorick *et al.* (1995), while assessing the commercial value of academic output measured as knowledge flows, find that the direct impact of recent university research is small in most industries compared to other sources of information.[ii] Evidence contradicting the importance of university-industry cooperation is also reported by Doutriaux (2003) and Medda *et al*. (2006). Based on results from a recent study on Canadian industrial clusters, Doutriaux (2003) suggests that universities tend to be followers (‘catalysts’) of technological innovation rather than leaders (‘drivers’). Using firm-level data from Italian manufacturing firms, Medda *et al.* (2006) find strong evidence of positive returns to collaborative research with other companies, while collaborative research with universities does not appear to enhance productivity.

Lee (1996), surveying about 400 research ventures in the USA, finds that respondents ranked the access to new research and the development of new products as the two most important reasons for collaborating with universities. However, most firms (even R&D firms) do not participate in any R&D cooperation with universities at all. Some main reasons can be identified. Intellectual property rights have been described as an “insurmountable barrier to partnering” (Hall, 2001). In their survey of 38 industry participants in a project funded by the Advanced Technology Program, Hall *et al.* (2001) show that about 30 percent of the firms had a university as a research partner and approximately the same proportion reported that IP issues are the important obstacle to university collaboration. Pavitt (2003) points out organisational and cultural differences as another major problem. He reports that managers often complain that universities operate on extended time lines and have little regard to the urgent deadline of business. Geographic limits on knowledge spillovers are a third issue which is assumed to hamper R&D cooperation with universities. Another paper by Mansfield and Lee (1996) finds that firms prefer to work with local university researchers, usually within 100 miles from the firm's R&D laboratories, though differences are identified between basic research and applied research.

Relatively few studies are there trying to evaluate the elasticity of firm's research productivity with respect to academic knowledge or the economic impact of university collaboration have generally shown positive results. Jaffe (1989), while estimating the elasticity of corporate patenting with respect to university results, finds a strong association between them.

Mansfield (1998) reports a significant decrease in average time lag between the result of academic research and the first commercial introduction of new products and processes based on these results. A plausible interpretation is that firms which are quick to utilize the findings of recent academic research can obtain considerable economic benefits. It should be noted that Mansfield (1997) in an earlier paper discusses a quite different implication of the decreased time lag between academic research; the risk of a shift from patient and time consuming basic research toward more applied and short-term work.[iii]

One of the major problems with the university-industry linkages studies reviewed in this section is that most of them suffer from a *selectivity bias* problem. Firms participating in university partnership are likely to be those with the largest innovation propensity, implying that they will have more incentives to invest in R&D and greater ability to produce innovative output than those of non-collaborating firms. When the analysis is based on selected groups we cannot use the results for generalization.

To estimate the real effect of academic knowledge on the innovative performance of firms it is necessary to address questions like: How much would the collaborating firms invest in R&D had they not participated in innovative projects with universities? What would be the innovative output of firms without complementary knowledge from universities? To our knowledge so far only a few studies on university and industry attempts to model this counterfactual situation.

3. THE DATA

The data used in this study is obtained from the Community Innovation Survey (CIS) III in Sweden. The survey was collected in 2001 and it spans the period 1998 to 2000. It spans both the manufacturing sector and business services. The *original sample* contains 2,114 firm level observations, of which all firms were dropped that had R&D and other innovation expenditures exceeding sales by 200% or more (42 observations, See table I). One firm defined as non innovative which reported university collaboration on innovation was also removed. After deducting those firms we have a total sample of 2,071 observed firms, of which 1,083 are classified as innovative (positive innovation input and/or positive innovation sales and/or patent application). Then we separate the total sample into four subgroups: (i) 1, 242 manufacturing firms, (ii) 366 manufacturing firms with 100 or more employees, (iii) 829 service firms and (iv) 232 service firms with 100 or more employees. The data provides information on characteristics of the firm that affect its decision to collaborate with universities.

Table II reports the size dimension of the pattern of industry-university linkages. Considering the smallest innovative firms in our sample (10-24 employees), it is shown that only one out of eight firms are utilizing universities as a cooperation partner. The proportion is about the same within the size class of 25-49 employees. In the size class of 50-99, one out of six firms collaborates and the share increases to one out of five in the size class of 100-199 employees. One out of three firms collaborates in the size class of 200-499 employees. For firms with 500 or more employees, the share of cooperation is over 50 percent.

Looking at industry classes, Table III shows the share of collaborating innovative firms ranging from 7 to 36 percent among the 20 industry classes studied. The highest percentages are found in basic and fabricated metal (38%), and medical, precision and optical instruments (36%) and activities auxiliary to financial intermediation (34%). The share of collaborators is lowest within textile, apparel and leather (8%) and wholesale trade (7%).

In Table IV, the exogenous variables and the endogenous variables are defined. We use four quantitative control variables (innovation input, human capital, export ratio and firms size) and eight dummy variables (public R&D funding, possession of patent, lack of finance and skills as obstacles to innovation, demand pull innovations, foreign owned firms, domestic firms that belongs to a group with only national affiliates and global market focus). The performance variables are innovation sales and patent application.

The summary statistics of the endogenous and the exogenous variables are reported in Table V. The first column of the table shows the summary statistics of firms collaborating with universities, the second column informs about non-collaborative innovative firms and the third column shows non-innovative firms. A large difference is observed in firm characteristics between innovative collaborators and innovative non-collaborators as well as between innovative collaborators and non-innovative non-collaborators. This highlights the issue of collaborators being a selective group when discussing causal inferences from the relationship between universities and firms.

4. METHODOLOGY

In a non-experimental framework, this study estimates the average effect of collaboration with universities on innovative sales and patent application. In a non-experimental evaluation, as pointed out by Smith (2000), "statistical techniques are used to adjust the outcomes of persons who choose to participate to look like what the participant would have experienced, had they not participated. In contrast, an experiment directly produces the counterfactual of interest by forcing some potential participants not to participate."

Conventional methods in causality studies are based on parametric estimators such as instrumental variable estimators, the two-step estimator of Heckman (1979) or difference-in-difference. This paper, however, is based on the non-parametric matching estimator developed by Abadie *et al.* (2004) and Abadie and Imbens (2002). The choice of estimators is partly motivated by the cross-sectional nature of the data and partly by the nature of the research problem. Some important conditions are applied to the use of matching estimators. A number of studies provide critical discussion on strengths and discussions on matching estimators. [See Heckman *et al.* (1997), Heckman *et al.* (1998a), Heckman *et al.* (1998b), Smith and Todd (2004), and Smith (2000).]

Matching, whether on a vector X of determinant variables or a scalar of estimated average probability variables p(X), relies on a conditional independence assumption. In our case, the assumption states that once we condition on X, the participation in university collaboration is independent of the outcome in the non-collaboration state. This requires that all variables that affect both collaboration and outcomes in the absence of collaboration must be included in the matching. As emphasised by Smith (2000), making this conditional independence assumption plausible in practise requires access to a very rich data source. We are also required to consider carefully, guided by economic theory, what variables do and do not affect participation and outcomes.

The literature on diffusion of technology suggests a long list of characteristics of the firm that affect its decision to adopt external technology which includes firm size, R&D expenditure, market share, market structure, input prices, labor relations, firm ownership and other institutional factors and characteristics of technology (Karshenas and Stoneman, 1995). In the absence of a robust theoretical guidance, we assume that these and other similar factors are also the relevant determinants for the relationship between firms and universities.

Smith and Todd (2005) suggest that evaluation estimators are only found to work well when they are applied to comparison of group data which are supposed to satisfy the following criterions: (a) the same data sources are used for participants and non participants, (b) the data contain a rich set of variables relevant for modelling the participating decision, and (c) participants and non-participants belongs to the same market.

Although the assessment estimators discussed by Smith and Todd concern labor-market programs, we assume that the criteria can be generalized into other markets. If so, we conclude that the information collected from Community Innovation Survey fulfil criteria (a) and at least partly (c)[2]. In addition, we find support for (b) in Almus and Czarnitzki (2003), who argue that the CIS-data contains comprehensive information on firms for identifying a similar control observation for every treated firm.

4.1 Formal notation

We now proceed to the more formal notation of the estimation approach applied in this study. The presentation draws on Heckman *et al.* (1998b) and Abadie and Imbens (2002).

We are interested in estimating the average effect of university collaboration on a firm's innovation sales and propensity to apply for patents. For firm i, i=1…, N, let (Yi(1), Yi(0)) denote the two potential innovation performances:.

- Yi(1) is the innovation performance of firm i when it is collaborating with universities (UIC=1), and
- Yi(0) is the innovation performance of firm i when it is has no university collaboration (UIC=0).

If both Yi(0) and Yi(1) were observable, the effect of university collaboration on the innovation performance of firm i would be Yi(1) – Yi(0). Note, however, that we can only observe the innovation output for a firm either if it has collaborated or if it has not collaborated, but never both situations. Therefore, without statistical techniques we cannot compute the causal effect of university collaboration on a firm, i.e. to know the innovation output the collaborators would have experienced, had they not collaborated. This is the problem that we will try to solve with the matching approach.

The basic idea behind the matching estimators we will apply in this paper is the following: If the decision to participate in collaboration on innovation with universities or not is "purely random" for firms with similar values of the determinant variables X, then the simple approach would be to use the firms who were not participating in any form of university-industry cooperation on innovation (UIC) as a control group. Thus, our method of matching is aimed at identifying non-collaborators (UIC=0 firms) with the same probability to partner with universities as the actual collaborators (UIC=1 firms). That is, conditional on some X, Y(0) is independent of UIC, or the decision to participate in UIC is purely random:

$$Y(0) \perp UIC \mid X \qquad (1)$$

where "⊥" denotes independence and the variables to the right of "|" are the conditioning variables.

This assumption generates a control group with the following characteristics: conditional on X, the distribution of $Yi(0)$ given UIC=1 is the same as the distribution of $Yi(0)$ given UIC = 0. For each collaborating firm *i*, the matching approach identifies non-collaborators in the CIS data whose X-variables are similar to that of the collaborators. Considering the expected value, the implication of (1) is

$$E(Yi(0) \mid X, UIC=1) = E(Yi(0) \mid X, UIC=0) \qquad (2)$$

Traditional matching methods pair each participant, with a single non- participant (a "twin"). Nearest neighbours may be far apart. For that reason a metric criterion is imposed in this paper to ensure that the match is sufficiently close:

$$C(X_i) = \min_j |X_i - X_j|,\ i \in \{UIC=1\}\ j \in \{UIC=0\} \qquad (3)$$

Smith (2000) points out that nearest neighbour matching can be operationalized with more than one nearest neighbour and with and without replacement, where "with replacement" means that a given non-participant observation can form the counterfactual for more than one participant.

4.2 Estimators

In order to pair UIC observations to the closest match in the non-UIC group to provide an estimate of the counterfactual UIC outcome, this paper applies the matching approach developed by Abadie *et al.* (2004) and Abadie and Imbens (2002).

The framework allows for matching over a flexible set of X-variables and for different kinds of sensitivity analysis. We exploit five different options in determining optimal matches provided by the particular matching approach; (i) Weighting matrix. We use weights provided in the CIS-data. (ii)

Exact matching on a subset of variables. That is, exact matching or as close as possible.[iv] (iii) Bias correction of the UIC-effect.[v] (iv) Different distance measures between two vectors of X-variables[vi] and finally, (v) number of matches. We compare results for 1, 4, 16 and 64 matches. The benefit of many matches is that it increases the information to be used in the estimation, and the drawback is that the quality goes down when the variables no longer match exactly. Abadie and Imbens (2002) suggest that one should typically choose a fairly small number. In their estimation, using four matches is found to perform well in terms of mean-squared error. For more background on, and formal derivation and definition of the estimators used in this paper, see Abadie and Imbens (2002).

5. RESULTS

We may now establish the results concerning the estimators presented in section 4. The results show that the nearest neighbour matching estimators are sensitive to sample weights, exact matching, bias correction and the number of matches. Table VI and VII present the estimates of causal effect of university collaboration on innovation performances using various matching adjustment estimators. Column 1-5 of each table report the results of the overall sample of manufacturing firms, manufacturing firms with 100 or more employees, service and service firms with 100 or more employees, respectively. Panel A-E of both tables show the results using simple matching or weight-adjusted matching, exact matching, bias adjusted matching and different number of matches.

The first line (Panel A) of Table VI and Table VII reports matching estimates for each of the five samples based on non weighted samples, no requirement on exact matching on some variables, population average, four matches and non bias adjustment.

In panel B, line 2 imposes sample weights provided by the Community Innovation Survey. Line 3 adds the restriction that the matching on the innovation input variable is exact, whereas the other variables not are matched exactly. In line 4, in contrast, the matching are exact for all the eight indicator variables: possession of patents, public funding, financial obstacles of innovation, skill obstacles of innovation, demand pull innovation, main focus on the global market, domestic firm belonging to a group and foreign owned company. The other, more continuously distributed variables (for example, innovation input, firm size, export ratio and human capital) are not matched exactly.

Panels C-E present the results for corrected bias estimators with sample weights for the four different numbers of matches and two different distance measures. In Panel C, there is no restriction on exact matching, Panel D matches exactly on innovation input and Panel E matches exactly on the indicator variables.

5.1 Innovation sales

The simple matching with no adjustments and four matches is presented in Table VI, where line 1 reports that collaboration on innovation with universities increases innovation sales with about 7 percent for the average innovative firm. The estimate is highly significant (at 1% level) for the overall sample and for manufacturing firms. The estimate is significant at the 5% level for the sample of service firms. The subsample of service firms with 100 or more employees is the only sample for which we find no significant impact of UIC.

Panel B-E compare the performance of the non-adjusted estimator with the averages of various adjustments. First, line 2 of Panel B shows that sampling weights is an important issue. For the overall sample and for the typical service firm, the average effect of UIC is not significantly different from zero at neither the 5% nor the 1% level when sampling weights are applied in the estimation. In this estimation set-up, UIC has a causal and positive effect on innovation sales significantly different from zero only for the manufacturing firms.

When matching exact (innovation input and the eight discrete variables respectively, see Line 3 and 4) is added to the weight-adjustment the estimates for the total sample shows a positive effect only on innovation input. For manufacturing firms, the estimates are significant only for the firms with 100 or more employees. With this set-up, UIC has no positive influence on innovation sales for service firms.

Panel C adds biased adjustment to the sample weights but remove the requirement of exact matching. Moreover, two other distance measures are compared to the four matches. If we increase the number of matches the results only changes marginally over all samples. Comparing line 6 and 7 informs us that that the choice of distance measure is not important when no matches are exact. The main result reported in Panel C is that UIC is associated with an increase in innovation sales for the average innovative manufacturing firm but not for the typical innovative service firms.

When we match exactly on all the innovation input variables, the estimates for manufacturing firms with 100 or more employees are significant or highly significant (See Panel D, row 10-14). For the total sample of manufacturing firms, the estimate is significantly different from zero when the number of matches is greater than or equal to 16. In the case of the Mahalanobis distance measure between the vectors or matches, we also find a significant association between UIC and innovation sales for all manufacturing firms when only four matches are used. The estimates for the service firms are not significant.

Panel E (row 15-19) presents matching outputs when we use the set of discrete variables (but not R&D and other innovation input) as exact matches. The results show that the average innovative firm in the economy does not benefit from academic knowledge in terms of increased innovation sales. One exception is found for the subgroup of manufacturing firms with 100 or more employees, where the choice of distance measures has no significant impact on the estimated relationships.

5.2 The propensity to apply for patents.

Table VII gives the results obtained from matching the cross-sectional data with respect to a firm's propensity to apply for patents. There are four major points to be made about these estimates. The first is that, using the same framework as for the estimations presented in Table 6, the estimated results, considered together, tells a similar story as the one for innovation sales. Thus, some of the estimates suggest interaction between universities and firms affects innovation performance and some does not. The differences are on the one hand explained by firm size and by sector, on the other hand by the different applications of matching estimators.

The second is that UIC contributes significantly to the explanation of cross-sectional differences in the propensity to apply for patents among manufacturing firms with 100 or more employees. Given a bias adjusted estimator and a weights sample, the results suggest that UIC increases the propensity to apply for patents in a range of 17-32 percent depending on number of matches, distance between the matched pars of covariates (determinants) and the requirement of exact matching.

The third major finding of interest is that we cannot reject the null hypothesis for neither the subsample of service firms, nor the subsample of service firms. All 18 estimators show non-significant results when weighted samples are used.

The fourth finding is that the results for the overall sample including all 2,071 firms and the subsample with 1,242 manufacturing firms are inclusive.

The concluding robust finding for all firms in our sample (Column 1) is that the influence from universities are significant only when the bias adjusted estimator match exactly on R&D and other innovation inputs. In contrast, the most interesting lessons to emerge from the empirical analysis reported in Column two (manufacturing firms) is that whether we choose to match exactly on either the indicator variables or the innovation input or choose to not match exactly on any variables at all, the data show a significant association when the number of matches is 64. Otherwise no systematic pattern can be established.

6. SUMMARY

Does collaboration on innovation with universities boost firms' innovation sales and propensity to patent? While Mansfield (1998) and others find support for the idea that the relationship with universities positively influence the firm's innovation output, in general their results do not imply a causal link between university collaboration and innovation output. The root of the problem is that we can only observe the innovation output for either the collaborating firms or the non-collaborating firms, while our main interest is to determine the innovation output the collaborators would have experienced, had they not collaborated. Since the university collaborators is a selective group with larger R&D intensity, more patents, more demand pull oriented innovations, more innovation sales as a share of total sales, larger propensity to apply for patents, more human capital, larger export intensity and larger firm size, the challenge is to find a proper control group.

In this paper we have applied recent matching techniques in order to evaluate the importance of innovation collaboration between university and industry. Using 19 alternative estimators, one overall sample of 2,071 observations from the Swedish Community Innovation Survey, four subsamples of manufacturing and service firms, and two alternative performance measures we show that nearest neighbour matching estimators are sensible for sample weights, exact matching, bias correction and number of matches. We also show that there are differences between manufacturing and service firms and between small firms and larger firms. On balance, robust evidence is found that university collaboration positively influences innovation sales as well as the propensity to apply for patent for manufacturing firms with 100 or employees. In contrast, whatever estimator is chosen, the data show no significant association between university collaboration and the average service firm's innovation sales or propensity to apply for patents.

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NOTES

[i] Contrary to the 'linear model' where fundamental research by university scientist leads to a discovery, the practical importance of which is recognised by a business firm, which collaborates with the university scientist in order to exploit it (Pavitt 2003), the works by Pavitt and others explore issues such as the importance of increasing specialization and complexity, organizational behaviour, and the difficulties of matching technological opportunities with market needs.

[ii] Cohen, Nelson and Walch (2003) stressed that the Klevorick *et al.* (1995) finding is not necessarily inconsistent with other studies which reported the impact from university research to be substantial.

[iii] Salter *et al.* (2000) are discussing the potential for increased commercial exploitation of university knowledge, but they are questioning the importance of various kinds of “technology transfer” programs since the underlying assumption often is the much discredited linear model of innovation.

[iv] Exact: In the estimation we specify which covariates (or variables) we attempt to match exactly on. In the study we compare two alternatives (i) Exact matching on the continuous variable *innovation input as a proportion of sales*, and (ii) exact matching on a set of discrete covariates: *possession of patents*, *public funding*, *financial obstacles to innovation*, *skill obstacles to innovation*, *demand pull innovations*, *main focus on the global market*, *domestic firm belonging to a group*, and *foreign owned company*.

[v] Bias adjusted: The simple matching estimator will be biased in finite samples when the matching is not exact. The bias-corrected matching estimator adjusts the difference within the matches for the differences in their covariates values. In this paper, the bias-corrected matching estimator uses the variable Human capital as the covariate distinct from the set used in matching.

[vi] Distance measure: The metric for measuring the distance between two vectors of covariances. Letting $||x||_V=(x'Vx)^{1/2}$ be the vector norm with positive definite weight matrix V, we define $||z-x||_V$ to be the distance between the vectors x and z. We use two alternatives for V. *Inverse*: V is the diagonal matrix constructed by putting the inverses of the variance of the covariates on the diagonal. Mahalanobis: V=S-1, where S is the sample covariance matrix of the covariates

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Table I
Original sample, data treatment, overall sample and subsamples

Original sample	OBS
Observed firms in the original sample	2,114
Firms with innovation input >3 times total sales	-42
Non innovative firms collaborating with universities on innovation	- 1
Used sample and subsamples	
Overall sample	2 071
Subsample manufacturing	1 242
Subsample manufacturing with >=100 employees	366
Subsample services	829
Subsample service firms with >=100 employees	232

Table II
Summary Statistics

Employment	Obs	UIC[1]	Innovative[2]	UIC/Innovative
10-24	817	38	331	11,5 %
25-49	386	22	185	11,9 %
50-99	270	23	149	15,4 %
100-199	173	21	115	18,3 %
200-499	246	51	166	30,7 %
500-	179	73	137	53,3 %
Total	2, 071	228	1083	21,1 %

Note: (1) University industry collaboration, (2) Innovation input>0 and/or innovation sales >0 and/or patent application>0.

Table III
Summary Statistics

	Overall sample			Innovative firms[1]		
Industry, Nace codes	Obs	UIC	%	Obs	UIC	%
Manufacturing						
15-16 Food, beverages, tobacco	80	6	7,5	40	6	15,0
17-19 Textile, apparel, leather	77	3	3,9	39	3	7,7
20-21 Wood, pulp, paper	157	19	12,1	76	19	25,0
22-23 Publishing, coke, petroleum	79	4	5,1	38	4	10,5
24-25 Chemicals, rubber, plastics	146	24	16,4	102	24	23,5
26 Other non metallic products	49	6	12,2	27	6	22,2
27 Basic metals	49	12	24,5	31	12	38,7
28 Fabricated metal products	104	7	6,7	47	7	14,9
29 Machinery and equipment	128	24	18,8	87	24	27,6
30-32 Computers, electrical machinery, communication equipment	73	7	9,6	43	7	16,3
33 Medical, precision and optical instruments	119	33	27,7	92	33	35,9
34-35 Motor vehicles and transport equipments	110	9	8,2	60	9	15,0
36-37 Furniture, recycling	71	3	4,2	36	3	8,3
Services						
40-41 Gas, steam, water	71	7	9,9	30	7	23,3
51 Wholesale trade	109	4	3,7	58	4	6,9
60-63 Land, water and air transport	232	4	1,7	56	4	7,1
64-66 Post and telecommunication, finance and insurance	101	5	5,0	53	5	9,4
67-69 Activities auxiliary to financial intermediation	125	27	21,6	79	27	34,2
72-74: Computers and related activities, Research and development, other business activities	191	24	12,6	89	24	27,0
Total	2, 071	228	11,0	1, 083	228	21,1

(1) Innovation input>0 and/or innovation sales >0 and/or patent application>0.

Table IV
Exogenous and endogenous variables

Variable	Definition
Panel A: Exogenous Variables	
Innovation input	Total innovation expenditures (intramural R&D, extramural R&D, external knowledge, acquisition of machinery, training , market introduction and other preparation related to innovation.
Human capital	Employees with a university education/total employees
Export ratio	Export as a share of sales
Firm size	Employment
Public funding	Public funding of innovation
Possession of patents	Possession of valid patents
Innovation obstacle: Finance	Sources of finance as an important factor hamering innovation
Innovation obstacle: Skill	Qualified personnel as an important factor hampering innovation
Demand pull innovation	A Composite variable created by the following CIS indicators describing effects of innovation: (i) Increased market or market share, (ii) Increased range of goods and services, (iii) Improved quality in goods and services.
Foreign owned firms	The headquarter of the firm is outside Sweden
Domestic non-MNE belonging to a group	Domestic non multinational firm which belongs to a group of firms.
Global market focus	The firm's most significant market is the global market
Panel B: Endogenous variables	
Innovation sales	Income from new or improved products introduced during 1998-2000 as a proportion of sales year 2000.
Patent application	The firm applied for at least one patent year 2000 to protect inventions

Table V
Summary statistics

	Innovative firms With UIC[1]		Innovative firms With no UIC[1]		Non innovative firms	
	N=228		N=855		N=988	
	Mean	S.D	Mean	S.D	Mean	S.D
Panel A: Exogenous Variables						
Innovation input/sales	15.1	27.4	5.5	16.1	0.0	0.0
Public R&D-funding	37.2	48.4	11.9	32.4	0.0	0.0
Human capital	24.8	29.6	18.0	24.0	16.2	22.8
Most important market: Global	57.8	49.4	34.3	47.5	17.4	37.9
Export ratio	41.7	36.5	24.4	30.6	12.1	32.6
Employment, log	5.3	1.8	4.1	1.4	3.6	1.2
Domestic firms belonging to a group	28.5	45.2	36.6	48.2	51.5	50.0
Foreign firm	30.7	46.2	22.4	41.7	12.1	32.6
Possession of patents	67.5	49.2	32.3	46.8	5.3	22.5
Innovation obstacles: Finance	17.5	38.1	9.7	29.6	6.3	24.4
Innovation obstacles: Skill	15.3	36.1	12.0	32.5	7.1	25.8
Demand pull innovation	51.3	50.0	40.8	49.1	0.0	0.0
19 Industry dummies[1]	Included		Included		Included	
Panel B: Endogenous Variables						
Innovation sales/Total sales	22.3	27.2	15.1	22.7	0.0	0.0
Propensity to apply for patents	64.0	48.0	26.7	44.3	0.0	0.0

Note: (1) UIC=University innovation collaboration

Table VI

Estimation results, dependent variable is Innovation Sales

	All firms		Manufacturing		Manufacturing Employment>99		Services		Services Employment>99	
	N= 2, 071		N= 1,242		N=366		N=830		N=233	
Estimator	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err
A: 1	0.074***	0.019	0.071***	0.023	0.074***	0.023	0.082**	0.040	0.052	0.051
B: 2	0.089	0.047	0.095**	0.046	0.115***	0.026	0.074	0.074	0.026	0.073
B: 3	0.085**	0.039	0.043	0.046	0.071***	0.026	0.102	0.077	0.011	0.089
B: 4	0.089	0.053	0.038	0.049	0.078***	0.028	0.108	0.070	0.056	0.069
C: 5	0.078	0.045	0.107**	0.045	0.118***	0.025	0.067	0.071	-0.072	0.074
C: 6	0.082	0.048	0.104**	0.047	0.117***	0.027	0.085	0.074	0.005	0.067
C: 7	0.071	0.033	0.098**	0.038	0.123***	0.024	0.094	0.063	-0.003	0.073
C: 8	0.074	0.052	0.098**	0.0443	0.086**	0.026	0.058	0.077	0.031	0.076
C: 9	0.090	0.074	0.084**	0.037	0.099***	0.025	0.072	0.093	- [1]	- [1]
D: 10	0.069	0.043	0.067	0.044	0.076**	0.031	0.050	0.073	-0.087	0.083
D: 11	0.080**	0.039	0.075	0.053	0.069***	0.026	0.074	0.075	0.022	0.086
D: 12	0.064	0.041	0.103**	0.041	0.081***	0.081	0.032	0.065	-0.051	0.078
D: 13	0.061	0.043	0.101**	0.044	0.063**	0.027	0.053	0.081	0.021	0.086
D: 14	0.075	0.048	0.088**	0.040	0.066**	0.027	0.088	0.077	- [1]	- [1]
E: 15	0.079	0.050	0.018	0.046	0.068	0.035	0.109	0.064*	-0.055	0.071
E: 16	0.096	0.054	0.044	0.050	0.092***	0.029	0.112	0.069	0.066	0.064
E: 17	0.051	0.042	0.042	0.048	0.088***	0.029	0.097	0.057	0.056	0.063
E: 18	0.104	0.055	0.039	0.043	0.115***	0.026	0.079	0.078	0.082	0.069
E: 19	0.098	0.063	0.057	0.029	0.101***	0.025	0.073	0.079	- [1]	- [1]

Note: Significant at the 1% (***) and 5% (**) level of significance. (1) Too few observations

Guide to Table 6: Estimators

Estimator	Sample Weights	Exact	Number of matches	Bias adjustment	Distance measures[1]
A: 1	No	No	4	No	Inverse
B: 2	Yes	No	4	No	Inverse
B: 3	Yes	R&D-input	4	No	Inverse
B: 4	Yes	All discrete indicators	4	No	Inverse
C: 5	Yes	No	1	Yes (Human capital)	Inverse
C: 6	Yes	No	4	Yes (Human capital)	Inverse
C: 7	Yes	No	4	Yes (Human capital)	Mahalanobis
C: 8	Yes	No	16	Yes (Human capital)	Inverse
C: 9	Yes	No	64	Yes (Human capital)	Inverse
D: 10	Yes	R&D-input	1	Yes (Human capital)	Inverse
D: 11	Yes	R&D-input	4	Yes (Human capital)	Inverse
D: 12	Yes	R&D-input	4	Yes (Human capital)	Mahalanobis
D: 13	Yes	R&D-input	16	Yes (Human capital)	Inverse
D: 14	Yes	R&D-input	64	Yes (Human capital)	Inverse
E: 15	Yes	All discrete indicators	1	Yes (Human capital)	Inverse
E: 16	Yes	All discrete indicators	4	Yes (Human capital)	Inverse
E: 17	Yes	All discrete indicators	4	Yes (Human capital)	Mahalanobis
E: 18	Yes	All discrete indicators	16	Yes (Human capital)	Inverse
E: 19	Yes	All discrete indicators	64	Yes (Human capital)	Inverse

(1) The metric for measuring the distance between two vectors of covariances. Letting $||x||_V=(x'Vx)^{1/2}$ be the vector norm with positive definite weight matrix V, we define $||z-x||_V$ to be the distance between the vectors x and z. We use two alternatives for V. *Inverse*: V is the diagonal matrix constructed by putting the inverses of the variance of the covariates on the diagonal. *Mahalanobis*: V=S-1, where S is the sample covariance matrix of the covariates.

Table VII

Estimation results: Dependent variable is Patent application

	All firms		Manufacturing		Manufacturing Employment>99		Services		Services Employment>99	
	N= 2, 071		N= 1,242		N=366		N=830		N=233	
Estimator	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err	Coeff	Std err
A: 1	0.252***	0.040	0.257***	0.050	0.280***	0.052	0.059	0.052	0.148*	0.089
B: 2	0.085	0.075	0.144**	0.089	0.227***	0.061	0.021	0.099	0.040	0.122
B: 3	0.178***	0.064	0.128	0.109	0.172***	0.060	0.061	0.085	0.014	0.122
B: 4	0.013	0.067	0.068	0.086	0.244***	0.061	0.039	0.072	0.045	0.082
C: 5	0.105	0.069	0.174	0.086	0.246***	0.055	0.014	0.088	-0.028	0.110
C: 6	0.090	0.076	0.157	0.094	0.229***	0.058	0.020	0.094	0.019	0.097
C: 7	0.128**	0.065	0.210***	0.079	0.296***	0.052	0.015	0.073	-0.033	0.114
C: 8	0.088	0.084	0.152	0.092	0.252***	0.058	0.004	0.099	0.005	0.110
C: 9	0.075	0.119	0.197**	0.080	0.275***	0.051	-0.017	0.120	-[1]	-[1]
D: 10	0.151**	0.071	0.165	0.095	0.119	0.073	0.051	0.083	-0.161	0.108
D: 11	0.175***	0.062	0.165	0.106	0.172***	0.060	0.050	0.082	0.027	0.128
D: 12	0.238***	0.077	0.299***	0.085	0.198***	0.055	0.044	0.077	-0.047	0.143
D: 13	0.173**	0.075	0.193**	0.086	0.223***	0.065	0.054	0.094	-0.026	0.142
D: 14	0.207**	0.088	0.246***	0.089	0.248***	0.0717	0.195	0.122	-[1]	-[1]
E: 15	0.020	0.064	0.053	0.088	0.324***	0.080	-0.019	0.067	-0.124	0.107
E: 16	0.016	0.067	0.068	0.085	0.243***	0.062	0.038	0.071	0.045	0.077
E: 17	0.066	0.084	0.066	0.084	0.246***	0.061	0.041	0.057	0.047	0.075
E: 18	0.065	0.083	0.108	0.084	0.281***	0.056	0.028	0.089	0.107	0.087
E: 19	0.088	0.092	0.174***	0.060	0.248***	0.053	-0.002	0.108	-[1]	-[1]

Note: Significant at the 1% (***) and 5% (**) level of significance. (1) Too few observations

Guide to Table VII: Estimators

Estimator	Sample Weights	Exact	Number of matches	Bias adjustment	Distance measures[1]
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C: 6	Yes	No	4	Yes (Human capital)	Inverse
C: 7	Yes	No	4	Yes (Human capital)	Mahalanobis
C: 8	Yes	No	16	Yes (Human capital)	Inverse
C: 9	Yes	No	64	Yes (Human capital)	Inverse
D: 10	Yes	R&D-input	1	Yes (Human capital)	Inverse
D: 11	Yes	R&D-input	4	Yes (Human capital)	Inverse
D: 12	Yes	R&D-input	4	Yes (Human capital)	Mahalanobis
D: 13	Yes	R&D-input	16	Yes (Human capital)	Inverse
D: 14	Yes	R&D-input	64	Yes (Human capital)	Inverse
E: 15	Yes	All discrete indicators	1	Yes (Human capital)	Inverse
E: 16	Yes	All discrete indicators	4	Yes (Human capital)	Inverse
E: 17	Yes	All discrete indicators	4	Yes (Human capital)	Mahalanobis
E: 18	Yes	All discrete indicators	16	Yes (Human capital)	Inverse
E: 19	Yes	All discrete indicators	64	Yes (Human capital)	Inverse

(1) The metric for measuring the distance between two vectors of covariances. Letting ||x||V=(x'Vx)1/2 be the vector norm with positive definite weight matrix V, we define ||z-x||V to be the distance between the vectors x and z. We use two alternatives for V. Inverse: V is the diagonal matrix constructed by putting the inverses of the variance of the covariates on the diagonal. Mahalanobis: V=S-1, where S is the sample covariance matrix of the covariates.