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Corporate patents and knowledge sourcing from universities

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Abstract This paper provides empirical evidence on the link between different external knowledge sourcing strategies from universities and firms' innovation output measured by the number of patent applications. Three strategies for acquiring external knowledge are distinguished: buying, cooperating and contracting out. The empirical model is based on the instrumental variable version of the ordered probit model. Geographical distance to local universities is employed as an instrument for the different knowledge sourcing strategies. The empirical results show that buying knowledge from universities is significantly positively related to the number of patent applications, while cooperating with universities and contracting out does not have an impact. This also holds for buying knowledge from domestic universities.

Keywords R&D cooperation · R&D subcontracting · Acquisition of know-how · Patent applications · Simultaneous probit models

JEL Classification O 32 · O 34

1 Introduction

External knowledge sourcing is seen as an important factor for successful industrial innovations, in particular, knowledge sourcing from universities. Knowledge sourcing from universities has many forms, such as university-industry collaborations (e.g. R&D joint ventures and partnerships, licensing and cross-licensing agreements, sharing of equipment and research tools), R&D contracting, industry financing of university research, university spin-offs and licensing as well as a hiring of university researchers (Cassiman et al. 2008; Fontana et al. 2006; Teece

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1986). Increasing literature on the importance of science for industrial research has suggested that external knowledge sourcing activities from universities increase the innovative performance of firms. In particular, knowledge sourcing from universities is seen as an important factor for radical innovations, while firm–firm interactions often lead to incremental innovations (Rosenberg and Nelson 1994; Mansfield 1995, 1998; Monjon and Waelbroeck 2003; Etzkowitz et al. 2000). Many countries have implemented policies to promote university-industry partnerships (see Fontana et al. 2006). Recent studies suggest that the links between universities and firms and firm-to-firm links have increased in the last decade (Cassiman and Veugelers 2006).

The aim of this paper is to investigate the association between public knowledge sourcing and firms' innovative output defined as the number of patent applications. Besides the relation between R&D cooperation and the number of patent applications, we will also investigate the role of two other external knowledge and technology sourcing channels, namely contract research and buying of knowledge on the market. A simultaneous two equation ordered probit model and binary probit model, which accounts for possible endogeneity of the different knowledge sourcing strategies, is used to study the link between various forms of knowledge sourcing activities and firms' patent applications. The data is based on 970 Austrian firms for the period 2005–2007. Unlike empirical studies based on Community innovation surveys, information on knowledge sourcing strategies is also available for non-innovative firms. Furthermore, we focus on two forms of knowledge sourcing that are rarely examined in the previous literature, namely buying and contracting out. Another novelty of the paper is that we distinguish between foreign and domestic sources. We address two major questions: (1) Given the level of R&D and other innovation input factors, what is the relationship between the different public knowledge sourcing activities and the number of patent applications and (2) what are the differences between domestic and foreign sources of knowledge?

The following summary of the literature reveals that while there are a number of studies on the relation between R&D collaboration and innovation output, relatively little research has focused on the role of contract research and the acquisition of external knowledge on innovation output. A notable exception is the paper by Vega-Jurado et al. (2009), who investigated the effects of external knowledge sourcing strategies (i.e. buying and cooperating) on the introduction of technological innovations. By distinguishing between industrial agents and scientific agents, the authors found that cooperation with scientific agents is not a significant determinant of technological innovations.

Few studies investigate the link between knowledge sourcing activities and patenting. Arvanitis and Woerter (2009) investigate the impact of knowledge and technology transfer on the propensity to patent as well as the share of new products in total sales. Using Swiss firm level data from 2005, the authors found that knowledge and technology transfer activities related to "core" transfer activities, such as R&D subcontracting, are more strongly correlated with innovation performance compared to strategies related to "softer" transfer forms. Using data on 147 US publicly traded biotechnology companies, George et al. (2002) found that industry-university cooperation has a significant impact on patents. Using CIS data for Belgium, Peeters and van Pottelsberghe (2006) found that R&D collaborations with scientific institutions raised the propensity to patent as well as the number of patents. Using Swedish firm-level data, Lööf and Broström (2008) found that university industry collaboration increases the propensity to apply for patents in a range of 17–32 %. However, other forms of collaborations are not examined. Using the German innovation panel, Licht and Zoz (1998, 2000) found that firms that regard universities and PROs as a primary source of information for their innovation activities, given their R&D expenditures, apply more often for patents. This indicates that science based knowledge sourcing increases the productivity of R&D.

A number of studies have investigated the impact of different types of R&D cooperation on innovation output measured as the probability of introducing new market products (new products, alternatively) or the sales share of new market products (Arvanitis et al. 2008a, b; Arvanitis and Woerter 2009; Aschoff and Schmidt 2008; Belderbos et al. 2004). These studies show that the impact of different types of R&D cooperation impact innovation performance differently. Using the German innovation survey for the year 2004, Aschoff and Schmidt (2008) found that firms that cooperate with universities or research institutions in their R&D and innovation activities have a higher share of sales from market novelties than firms that do not cooperate. In addition, innovation cooperation with other partners, such as competitors, suppliers and customers, does not lead to a higher share of sales with market novelties. This result is consistent with the findings of Belderbos et al. (2004), who found that R&D collaboration with universities (as well as with competitors) increases the growth of sales with market novelties per employee using the Dutch innovation survey for the period 1996–1998. However, cooperation with competitors, suppliers, and customers does not have a significant effect. In addition, the authors investigate the impact of university incoming spillovers measured as the importance of universities, innovation centres and research institutions as a source of knowledge for the firm’s innovation process. Based on the Swedish community innovation survey, Lööf and Broström (2008) found evidence that firms collaborating with universities have a larger share of sales of new products per employee Using propensity score matching estimates, the authors found that collaboration on innovation with universities increases innovation sales at about 7 % for the average innovative firm. Using a survey of manufacturing in Spain for the period 1998–2002, Un et al. (2010) found that collaborating with suppliers and universities boosts both the likelihood of introducing production innovations and the number of product innovations, whereas collaborating with customers and competitors has no effect. In addition, the authors found that the effect of supplier cooperation is much larger than that of university collaborations. Monjon and Waelbroeck (2003) investigated the impact of different types of R&D cooperation and found that cooperation with universities significantly increases the probability of introducing new market products. Arvanitis et al. (2008a, b) found that knowledge technology transfer activities with research institutions and/or institutions of higher education seem to considerably improve the innovation performance of firms both in terms of R&D intensity and sales of new products. Using firm level data drawn from the Irish innovation panel, Roper et al. (2008) found that unlike the other knowledge sources, links to public knowledge sources (i.e. universities, public and industry owned laboratories) have no direct impact on either the probability of process or product innovation, or its success. However, enterprises' public knowledge sourcing does have an indirect positive effect on innovation through their strong complementarity with other knowledge sourcing activities.

To sum up, while there are a number of studies investigating the relation between R&D cooperation or alliances and joint ventures, little is known on the relation between contract R&D (outsourcing of R&D) and acquisition of R&D services and innovation performance. Furthermore, studies distinguishing between the effects of knowledge sourcing from domestic and foreign sources are not available to the best of our knowledge.

The structure of the paper is as follows: in Sect. 2, the empirical model and the hypotheses are given; in Sect. 3, some summary statistics are presented; in Sect. 4, the empirical results for the impact of knowledge sourcing is provided; and in Sect. 5, concluding remarks are made.

2 Empirical model and hypothesis

A large number of studies have investigated the impact of the firm's own R&D activities on patenting (Pakes and Griliches 1980; Hausman et al. 1984; Hall et al. 1986; Hall and Ziedonis 2001; Czarnitzki et al. 2009; Crépon and Duguet 1997).[1] Hall et al. (1986) suggest that "annual R&D expenditures of a firm are considered to be investments that add to the firm's stock of knowledge". In addition to conducting in-house research and development, firms typically tap knowledge sources external to the firm through licensing, contracting out R&D, formal R&D cooperation, R&D joint ventures, acquisition of knowledge, or attracting qualified researchers embodying relevant knowledge (Teece 1986). Acquisition of knowledge can take many forms, such as patents, licences, know-how, software, trademarks, etc. Schartinger et al. (2002) identified sixteen types of 'knowledge interactions' grouped into four categories: joint research (including joint publishing), contract research (including consulting, financing of university research assistants by firms), mobility (staff movement between universities and firms, joint supervision of students) and training (co-operation in education, training of firm staff at universities, lecturing by industry staff). Knowledge interaction is generally regarded as valuable for in-house R&D and innovation output. Typical sources of knowledge are other firms, either competitors or specialized technology suppliers, universities and public research institutions. The use of these complementary resources from universities or other firms is a way to increase the stock of knowledge and thereby increase the likelihood and number of inventions.

[1] It is well known that there are a number of shortcomings of patents as a measure of innovation output (see Griliches 1990).

We explicitly focus on three forms of knowledge acquisition, namely R&D and innovation cooperation, outsourcing of R&D and related activities and acquisition of external knowledge related to R&D and innovation activities. The patent production function introduced by Pakes and Griliches (1980) and Hausman et al. (1984) is specified as follows:

$$PAT_i^* = f(RD_i),$$

where i denotes the firm, PAT_i^* represents a latent measure of the number of patent applications and RD_i is R&D intensity measured as the ratio of employment in R&D and innovation activities to total employment. The patent production function is augmented by different indicators of knowledge sourcing activities and control variables. It is obvious that the different types of knowledge sourcing are choice variables. Firms decide to engage in R&D alliances with universities, contract out research, or acquire external technology. Large firms have a higher probability of R&D and/or innovation collaboration. Another factor is the geographical distance to universities with decreasing probability to engage in knowledge sourcing activities the larger the distance. Therefore, each of the types of knowledge sourcing strategies is treated as endogenous. The resulting two equation models consist of the patent production function and the decision to engage in different knowledge sourcing activities:

$$\begin{aligned} PAT_i^* &= \beta_1 RD_i + X_i'\gamma + KS_i'\theta + \varepsilon_{1i}, \\ KS_i^* &= \beta_2 RD_i + X_i'\gamma + \pi Z_i + \varepsilon_{2i}, \end{aligned}$$

where ε_{1i} and ε_{2i} are error terms that are allowed to be correlated:

$$\begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} = N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}\begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix}\right].$$

KS_i^* represents a set of dummy variables indicating (1) whether or not firms are engaged in contract R&D activities, (2) whether or not firms acquired knowledge and technology and (3) whether or not firms have outsourced R&D activities. X_i' is a vector of control variables, such as previous experiences with R&D activities in years, whether or not the firm has an R&D department and whether or not the firms conduct R&D on a continuous basis as compared to occasionally. In addition, two dummy variables are included: whether the firm is part of an industrial group with a domestic and foreign headquarter, respectively, and a dummy variable indicating young firms. We also included 14 industry dummy variables with machinery as the reference category. Finally, firm size measured as a set of dummy variables is included.

The two equation model is a recursive model that does not allow for feedback effects. To identify the system, some exclusion restrictions are necessary. We employ geographical distance as the instrument since it has a significant impact on the decision to engage in knowledge acquisition with universities, but does not have an impact in the patent production function. The system is estimated simultaneously using the conditional mixed process command estimated by ML and developed by Roodman (2009). The number of patents is measured as an ordinal variable. Therefore, the ordered probit specification is employed.

$$PAT_i^* = \beta_1 RD_i + X_i'\gamma + KS_i'\theta + \varepsilon_{1i},$$

where PAT is expressed as follows:

$$PAT_i = \begin{cases} 0 & \text{if} -\infty \le Y_i^* < \gamma_1 \\ 1 & \text{if } \gamma_1 \le Y_i^* < \gamma_2 \\ 2 & \text{if } \gamma_2 \le Y_i^* < \gamma_3 \\ 3 & \text{if } \gamma_3 \le Y_i^* < \gamma_4 \\ 4 & \text{if } \gamma_4 \le Y_i^* < \gamma_5 \\ 5 & \text{if } \gamma_5 \le Y_i^* < \gamma_6 \\ 6 & \text{if } \gamma_6 < Y_i^* \le +\infty \end{cases}$$

$\gamma_1, \ldots, \gamma_6$ are the unknown threshold parameters to be estimated. The underlying Y takes seven possible values: 0 for no patents, 1 for one patent, 2 for two patents, 3 for two patents and 4 for four to five patents, 5 for six to 10 patents, and 6 for 11 or more patents.

The main hypothesis is that the firm's number of patent applications will be positively correlated with different types of external knowledge sourcing. However, the relationship between innovation performance and external knowledge sourcing is likely to differ across the different types. Meyer-Kramer and Schmoch (1998) suggest that collaborative research and informal contacts are ranked higher than contract research and consultancy. Therefore, one can expect a stronger link between R&D cooperation and innovation performance than that of between R&D contracting and innovation performance. It should be noted that contract research is also different from simply buying technology in the sense that the research outcomes of contract research are transferred to the client with all exploitation rights (Teece 1988). Furthermore, we investigated whether firms that use foreign knowledge sources as compared to domestic sources have higher R&D productivity.

3 Data and descriptive results

The data used were collected from a questionnaire survey of firms conducting R&D and/or innovation activities on an occasional or permanent basis in 2008 and refer to the period 2005–2007. The survey is based on a stratified random sample of firms with R&D and/or innovation activities with at least one employee. The survey covers all relevant industries and is targeted to firms with R&D and innovation input activities with at least one employee. Hence, the sample is not representative of the total economy, but for those firms with R&D and/or innovation activities. The R&D funding survey 2008 was administered via mail. We conducted a non-response analysis. The questionnaire contains detailed definitions to increase response accuracy. Answers were received for 1200 firms, resulting in an overall response rate of 28 %. A Non-response analysis does not indicate a selection bias. Most of the firms are in the business and technical services (14 %), machinery industry (13 %), information technology and software (13 %), and metal industry (13 %). Table 1 contains the means of the variables. Information on the share of R&D personnel refers to the year 2007. Unfortunately, our data do not contain

Table 1 Descriptive statistics for different types of innovation cooperation

	Means (median)		%
Number of patent applications between 2005 and 2007 (count)	3.2 (0.0)	*Industry affiliation: (0/1)*	
Ratio of R&D employment 2005–2007 (share)	33.2 (16.7)	Food and leather and textile	3.8
Indicators of knowledge sourcing (all 0/1)		Wood, paper and printing	2.2
Acquisition of R&D from other firms	24.6	Coke, chemicals, plastics and rubber	6.9
Acquisition of R&D from higher education and public research inst.	15.3	Pharmaceuticals	1.4
Acquisition of R&D from universities	10.8	Non-mineral products, metals	7.5
Acquisition of R&D from domestic universities	8.9	Electronics and electrical products	12.0
Acquisition of R&D from universities from abroad	4.7	Machinery	13.0
Acquisition of R&D from technical colleges	3.9	Transport equipment	2.3
Acquisition of R&D from public research institutions	7.9	Water, electricity and construction	7.1
R&D cooperation with other firms	65.0	Trade	6.2
R&D cooperation with higher education and public research inst.	65.3	Transport and telecommunication	2.4
R&D cooperation with universities	51.6	Information technology	13.3
R&D cooperation with domestic universities	48.0	Business services	13.6
R&D cooperation with universities from abroad	22.6	R&D sector	5.8
R&D cooperation with higher technical colleges	31.3	Other services	2.5
R&D cooperation with public research institutions	37.4	*Firm size (0/1)*	
R&D contracts to other firms	25.3	Size $1 \leq L < 5$	24.3
R&D contracts to higher education and public research inst.	30.8	Size $5 \leq L < 10$	12.0
R&D contracts to universities	23.5	Size $10 \leq L < 25$	16.5
R&D contracts to domestic universities	22.4	Size $25 \leq L < 50$	8.8
R&D contracts to universities from abroad	7.2	Size $50 \leq L < 100$	10.0
R&D contracts to higher technical colleges	11.0	Size $100 \leq L < 250$	11.8
R&D contracts to public research institutions	18.1	Size $L \geq 250$	16.7
Experience with R&D activities all (0/1)		*Other variables*	
11 years or more of R&D experience	41.6	R&D department (0/1)	41.2
Between 7 and 10 years of experience	13.4	Continuous R&D activities (0/1)	76.4
Between 3 and 6 years of experience	28.2	Domestic multinationals (0/1)	26.0
Between 0 and 2 years of experience	14.3	Foreign multinationals (0/1)	11.9
Years of R&D experience unknown	2.5		
Firm age	2.5		
Founded between 1994 or earlier	53.0		
Founded between 1995 and 2004	31.9		

Table 1 continued

	Means (median)	%
Founded in 2005 or later	12.1	
Firm age not known	3.0	

Source WIFO R&D funding survey 2008

information on previous R&D personnel. However, previous studies show that current R&D expenditures contain most of the information about the level of knowledge. For instance, Hall et al. (1986) found that past R&D does not have an impact on patenting. The median value of the share of employment in R&D and related innovation activities is 16.7 %.

The average number of patent applications is 3.2, while the median is 0 (see Table 1). Concerning external knowledge sourcing, the most common form is R&D cooperation between other firms and R&D cooperation between firms and higher education & public research institutions being undertaken by 65 % of establishments for both types. The share of firms with R&D contracts to higher education & public research institutions is 30.8 %. Acquisition of knowledge from higher education institutions and PROs is less common. The frequencies are similar for external knowledge sourcing from firms.

Table 2 shows the distribution of patent applications for the total sample as well as for firms with external knowledge sourcing.

4 Empirical results

Table 3 contains the separately estimated results of the standard ordered probit model for three types of knowledge sourcing strategies. The table contains the βs, the corresponding *z* values and the marginal effects. The marginal impact of each independent variable is calculated while holding all other independent variables constant at their means. Unreported results show that the threshold parameters are statistically significant in all cases and show the expected ordering. A positive and significant coefficient means that firms are significantly more likely to fall in the highest category of 11 or more patent applications (and significantly less likely to fall in the lowest category, corresponding to no patent applications) when the explanatory variables change.

The ordered probit estimates show that the probability and frequency of patent applications depend significantly on R&D effort measured as the share of R&D employees, whether or not firms conduct continuous R&D and whether or not firms exhibit an own R&D department. The probability and frequency of patent applications also increases with R&D experience and firm size. Domestic multinationals firms have a significantly higher probability and frequency of patent applications than both domestic firms and foreign subsidiaries. The negative marginal effects in the first category on R&D intensity, R&D department and

Table 2 Descriptive statistics for the patent distribution

# of patents	Total sample		Firms that acquire knowledge from higher education and public research institutions		R&D cooperation between firms and higher education and public research institutions		Firms that contract out R&D activities to higher education and public research institutions	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
0	552	57	66	43	306	48	113	38
1	126	13	18	12	85	13	42	14
2	99	10	17	11	77	12	43	14
3	51	5	14	9	39	6	23	8
4	27	3	7	5	25	4	14	5
5	24	2	3	2	20	3	10	3
6–10	39	4	13	9	35	6	19	6
11–20	30	3	3	2	24	4	17	6
21–50	16	2	6	4	14	2	9	3
>50	11	1	5	3	10	2	10	3
Total	975	100	152	100	635	100	300	100
Total patents	3,075		920		2,599		1,883	

Source WIFO R&D funding survey 2008

continuous R&D activities means that firms with different R&D activities are less likely to record zero patent applications. Similarly, firms with longer years of experience with R&D activities (11 years or more and between 3 and 6 years) are less likely to report zero patent applications.

The key variables of interest are the three different external knowledge sourcing activities. We found that all three types of external knowledge sourcing are positive and significantly different from zero. The marginal effects show that firms that cooperate with universities have a 15 % point lower probability of having no patent applications and have a significantly higher probability of patent applications in the six patent categories ranging between 2 and 4 % points. Similar findings can be observed for acquisitions of R&D services and for firms that outsource parts of their R&D activities. The size of the marginal effects does not vary much between the different knowledge sourcing strategies. However, results should be interpreted with caution since the different knowledge sourcing strategies are assumed to be exogenous, which is unlikely to be the case.

In the next step, we accounted for the endogeneity of the different knowledge sourcing strategies with the logarithm of geographical distance used as an instrument. Unreported results show that the logarithm of distance has no significant effect on the number of patent applications and is therefore suitable as an instrument.

Table 4 shows that acquisition of knowledge from universities remains positive and significant, while cooperation with universities is no longer significant. This indicates that given the geographical distance to universities, innovation

Table 3 Ordered probit models of the patent production function (marginal effects)

	Coef	z	Marginal effects						
			cat = 0	cat = 1	cat = 2	cat = 3	cat = 4	cat = 5	cat = 6
Specification with R&D and innovation coorporation									
R&D employment ratio in %	0.77***	4.79	−0.30	0.06	0.08	0.05	0.05	0.03	0.03
Continuous R&D (0/1)	0.48***	4.02	−0.18	0.04	0.05	0.03	0.03	0.02	0.02
R&D department (0/1)	0.68***	7.85	−0.26	0.04	0.07	0.04	0.05	0.03	0.03
11 years or more of R&D experience (ref. cat. 0–2 years)	0.35**	2.23	−0.14	0.02	0.04	0.02	0.02	0.02	0.02
Between 7 and 10 years of experience (0/1)	0.15	0.85	−0.06	0.01	0.02	0.01	0.01	0.01	0.01
Between 3 and 6 years of experience (0/1)	0.29**	2.18	−0.12	0.02	0.03	0.02	0.02	0.01	0.01
R&D and innovation cooperation with universities (0/1)	0.39***	4.49	−0.15	0.03	0.04	0.02	0.03	0.02	0.02
Domestic multinational (0/1)	0.21**	2.04	−0.08	0.01	0.02	0.01	0.01	0.01	0.01
Foreign subsidiary (0/1)	0.13	0.92	−0.05	0.01	0.01	0.01	0.01	0.01	0.01
Young firm ≤5 years (0/1)	0.20	1.58	−0.08	0.01	0.02	0.01	0.01	0.01	0.01
6–9 (reference category 1–5) (0/1)	0.04	0.28	−0.02	0.00	0.00	0.00	0.00	0.00	0.00
10–24	0.35**	2.37	−0.14	0.02	0.03	0.02	0.03	0.02	0.02
25–49	0.60***	3.37	−0.24	0.02	0.05	0.04	0.05	0.04	0.04
50–99	0.59***	3.07	−0.23	0.02	0.05	0.04	0.05	0.04	0.04
100–249	0.66***	3.52	−0.26	0.02	0.06	0.04	0.05	0.04	0.05
≥250	1.13***	5.51	−0.42	0.01	0.08	0.07	0.09	0.08	0.10
Industry dummies	Yes								
Specification with acquisition of knowledge									
R&D employment ratio in %	0.74***	4.60	−0.29	0.05	0.08	0.05	0.05	0.03	0.03
Continuous R&D (0/1)	0.50***	4.21	−0.19	0.04	0.05	0.03	0.03	0.02	0.02
R&D department (0/1)	0.72***	8.33	−0.28	0.04	0.07	0.05	0.05	0.04	0.04
Acquisition of knowledge related to R&D & innovation (0/1)	0.35***	3.03	−0.14	0.02	0.03	0.02	0.03	0.02	0.02

Table 3 continued

	Coef	z	Marginal effects						
			cat = 0	cat = 1	cat = 2	cat = 3	cat = 4	cat = 5	cat = 6
11 years or more of R&D experience (ref. cat. 0–2 years) (0/1)	0.39**	2.51	−0.15	0.03	0.04	0.03	0.03	0.02	0.02
Between 7 and 10 years of experience (0/1)	0.23	1.33	−0.09	0.01	0.02	0.02	0.02	0.01	0.01
Between 3 and 6 years of experience (0/1)	0.34**	2.49	−0.13	0.02	0.03	0.02	0.02	0.02	0.02
Domestic multinational (0/1)	0.26**	2.55	−0.10	0.02	0.03	0.02	0.02	0.01	0.01
Foreign subsidiary (0/1)	0.16	1.13	−0.06	0.01	0.02	0.01	0.01	0.01	0.01
Young firm ≤5 years (0/1)	0.24*	1.90	−0.10	0.02	0.02	0.02	0.02	0.01	0.01
6–9 (reference category 1–5) (0/1)	0.02	0.12	−0.01	0.00	0.00	0.00	0.00	0.00	0.00
10–24	0.35**	2.32	−0.14	0.02	0.03	0.02	0.03	0.02	0.02
25–49	0.57***	3.17	−0.22	0.02	0.05	0.04	0.04	0.03	0.04
50–99	0.60***	3.13	−0.24	0.02	0.05	0.04	0.05	0.04	0.04
100–249	0.63***	3.30	−0.25	0.02	0.05	0.04	0.05	0.04	0.04
≥250	1.17***	5.66	−0.43	0.01	0.07	0.07	0.09	0.08	0.11
Industry dummies	Yes								
Specification with acquisition of knowledge									
R&D employment ratio in %	0.77***	4.74	−0.30	0.06	0.08	0.05	0.05	0.03	0.03
Continuous R&D (0/1)	0.47***	3.88	−0.18	0.04	0.05	0.03	0.03	0.02	0.01
R&D department (0/1)	0.69***	7.93	−0.27	0.04	0.07	0.04	0.05	0.03	0.03
11 years or more of R&D experience (ref. cat. 0–2 years) (0/1)	0.40**	2.55	−0.16	0.03	0.04	0.03	0.03	0.02	0.02
Between 7 and 10 years of experience (0/1)	0.25	1.47	−0.10	0.01	0.03	0.02	0.02	0.01	0.01
Between 3 and 6 years of experience (0/1)	0.34**	2.51	−0.13	0.02	0.03	0.02	0.02	0.02	0.02
Contracting out of R&D activities (0/1)	0.37***	4.16	−0.15	0.02	0.04	0.02	0.03	0.02	0.02
Domestic multinational (0/1)	0.23**	2.22	−0.09	0.01	0.02	0.02	0.02	0.01	0.01
Foreign subsidiary (0/1)	0.15	1.05	−0.06	0.01	0.01	0.01	0.01	0.01	0.01

Table 3 continued

	Coef	z	Marginal effects						
			cat = 0	cat = 1	cat = 2	cat = 3	cat = 4	cat = 5	cat = 6
Young firm ≤5 years (0/1)	0.23*	1.78	−0.09	0.01	0.02	0.01	0.02	0.01	0.01
6–9 (0/1) (reference category 1–5)	0.03	0.23	−0.01	0.00	0.00	0.00	0.00	0.00	0.00
10–24 (0/1)	0.37**	2.51	−0.15	0.02	0.04	0.02	0.03	0.02	0.02
25–49 (0/1)	0.62***	3.51	−0.24	0.02	0.05	0.04	0.05	0.04	0.04
50–99 (0/1)	0.61***	3.16	−0.24	0.02	0.05	0.04	0.05	0.04	0.04
100–249 (0/1)	0.65***	3.46	−0.26	0.02	0.06	0.04	0.05	0.04	0.05
≥250 (0/1)	1.13***	5.50	−0.42	0.01	0.08	0.07	0.09	0.08	0.11

z values are based on robust standard errors. *** $p < 0.01$, ** $p < 0.01$, * $p < 0.1$. Dummy variables for sector affiliation are included but not reported. Constant and threshold values are not reported. The number of observations is 975. The reference categories are “2 years or less of R&D experience” for R&D experience, “founded 2002 or earlier” for firm age and “machinery (NACE rev. 1)” for sector affiliation

Table 4 Ordered probit models of the patent production function accounting for endogeneity of the knowledge sourcing strategies (marginal effects)

	Patent production function		Decision to engage in knowledge sourcing	
	Coef	z	Coef	z
Specification with cooperation				
R&D intensity in %	0.78***	4.79	0.15	0.78
Continuous R&D (0/1)	0.54***	4.50	0.40***	3.66
11 years or more of R&D experience (ref. cat. 0–2 years) (0/1)	0.72***	8.36	0.34***	3.45
Between 7 and 10 years of experience (0/1)	0.38**	2.49	0.25	1.58
Between 3 and 6 years of experience (0/1)	0.24	1.37	0.59***	3.31
R&D department (0/1)	0.34**	2.53	0.28**	2.01
Cooperation with universities (0/1)	−0.12	−0.40		
Log distance to universities			−0.11***	−3.24
Domestic multinationals (0/1)	0.26**	2.47	0.29**	2.41
Foreign multinationals (0/1)	0.15	1.07	0.13	0.78
Young firms ≤5 years (0/1)	0.22*	1.74	0.10	0.73
6–9 (ref. cat. 1–5)	0.06	0.38	0.06	0.38
10–24	0.37**	2.47	0.16	0.94
25–49	0.64***	3.61	0.27	1.32
50–99	0.61***	3.19	0.25	1.14
100–249	0.68***	3.58	0.22	1.00
≥250	1.23***	5.97	0.75***	3.12
Correlation coefficient	0.31*	1.84		
Specification with acquisition of knowledge				
R&D intensity in %	0.52***	2.88	1.07***	4.01
Continuous R&D (0/1)	0.44***	3.69	0.34***	2.01
11 years or more of R&D experience (ref. cat. 0–2 years) (0/1)	0.38**	2.53		
Between 7 and 10 years of experience (0/1)	0.22	1.35		
Between 3 and 6 years of experience (0/1)	0.32**	2.52		
R&D department (0/1)	0.67***	7.48		
Acquisation of knowledge from universities (0/1)	1.40***	3.49		
Log distance to universities			−0.06	−1.55
Domestic multinationals (0/1)	0.25***	2.66		
Foreign multinationals (0/1)	0.14	1.11		
Young firms ≤5 years (0/1)	0.28**	2.27	−0.29*	−1.81
6–9 (ref. cat. 1–5)	−0.11	−0.70	0.69***	3.25
10–24	0.23	1.52	0.57**	2.55
25–49	0.32	1.58	1.27***	4.79
50–99	0.49***	2.60	0.42	1.41
100–249	0.39*	1.83	1.16***	4.29

Table 4 continued

	Patent production function		Decision to engage in knowledge sourcing	
	Coef	z	Coef	z
≥250	0.92***	4.18	1.12***	4.17
Correlation coefficient	−0.57	−2.93		
Specification with contracting out of R&D services				
R&D intensity in %	0.74***	4.27	0.29	1.39
Continuous R&D (0/1)	0.62***	5.93	0.62***	4.62
R&D department (0/1)	0.69***	7.91	0.35***	3.37
11 years or more of R&D experience (ref. cat. 0–2 years) (0/1)	0.29**	2.38		
Between 7 and 10 years of experience (0/1)	0.18	1.33		
Between 3 and 6 years of experience (0/1)	0.25**	2.44		
Contracting out (0/1)	−1.08***	−6.23		
Log distance to universities			−0.04	−1.62
Domestic multinationals (0/1)	0.23**	2.34	0.07	0.57
Foreign multinationals (0/1)	0.08	0.60	−0.07	−0.42
Young firms ≤5 years (0/1)	0.18*	1.81		
6–9 (ref. cat. 1–5)	0.17	1.16	0.26	1.51
10–24	0.34**	2.19	0.03	0.16
25–49	0.60***	3.28	0.22	1.04
50–99	0.59***	3.05	0.23	0.98
100–249	0.77***	4.07	0.54**	2.46
≥250	1.32***	6.40	0.87***	3.80
Correlation coefficient	0.85***	8.73		

z values are based on robust standard errors. *** $p < 0.01$, ** $p < 0.01$, * $p < 0.1$. The reference categories are “2 years or less of R&D experience” for R&D experience, “founded 2002 or earlier” for firm age and “machinery (NACE rev. 1)” for sector affiliation. Dummy variables for sector affiliation are included, but not reported. The number of observations is 975

cooperations with universities do not increase the number of patent applications. However, geographical distance to universities is only marginally significant for both the contracting out decision and the decision to purchase knowledge from universities. In the case when instruments are only weakly correlated with the endogenous regressors, IV estimates are biased and may not be consistent. In fact, the F statistic of the significance of geographical distance in the first stage probit model is larger than 10 for the innovation cooperation probit equation and therefore larger than the critical values calculated by Stock and Yogo (2005). For the two remaining knowledge sourcing strategies, the significance of the instrument is low and therefore the results should be interpreted based on the standard ordered probit estimates.

Table 5 Ordered probit models of the patent production function with knowledge acquisition of domestic universities

	Ordered probit model		IV ordered probit model			
			Patent production function		Decision to engage in knowledge sourcing	
	Coef	z	Coef	z	Coef	z
R&D intensity in %	0.75***	4.67	0.59***	3.09	1.04***	3.34
Continuous R&D (0/1)	0.50***	4.17	0.44***	3.62	0.57***	3.12
Acquisition of knowledge (0/1)	0.34**	2.59	1.27**	2.17		
Log distance to universities (0/1)					−0.09*	−1.79
11 years or more of R&D experience (ref. cat. 0–2 years) (0/1)	0.39**	2.48	0.38**	2.51		
Between 7 and 10 years of experience (0/1)	0.22	1.30	0.21	1.28		
Between 3 and 6 years of experience (0/1)	0.34**	2.51	0.33*	2.50		
R&D department (0/1)	0.72***	8.32	0.69***	7.60		
Domestic multinationals (0/1)	0.26**	2.55	0.25**	2.56		
Foreign multinationals (0/1)	0.15	1.06	0.14	1.02		
Young firms ≤5 years (0/1)	0.23*	1.83	0.26**	2.11	−0.28	−1.51
6–9	0.02	0.15	−0.07	−0.48	0.81***	3.44
10–24	0.36**	2.36	0.27*	1.70	0.69***	2.72
25–49	0.58***	3.22	0.38*	1.71	1.39***	4.68
50–99	0.62***	3.20	0.54***	2.81	0.30	0.83
100–249	0.66***	3.45	0.49**	2.26	1.14***	3.59
≥250	1.18***	5.73	1.00***	4.22	1.19***	3.87
Correlation coefficient	−0.50*	−1.75				

z values are based on robust standard errors. *** $p < 0.01$, ** $p < 0.01$, * $p < 0.1$. The reference categories are “2 years or less of R&D experience” for R&D experience, “founded 2002 or earlier” for firm age and “machinery (NACE rev. 1)” for sector affiliation. Dummy variables for sector affiliation are included, but not reported. The number of observations is 975

The next step is to investigate the impact of knowledge sourcing from domestic universities. Table 5 shows the estimation results of the ordered probit model and the IV version of the ordered probit model. The results show that acquisition of knowledge from domestic universities has a significant impact on the number of patent applications. This finding also remains true when accounting for the endogeneity of the knowledge sourcing activity.

We have conducted several robustness checks. Cohen and Levinthal (1989) pointed out that firms must have a certain level of absorptive capacity in order to benefit from the new external knowledge by successfully incorporating the new knowledge into the innovation process. This suggests that the higher the R&D

intensity, the higher the level of absorptive capacity and the ability to exploit new knowledge. In order to test this hypothesis, one can include an interaction term between the different types of knowledge sourcing R&D intensity. However, unreported results show that interaction terms between the different types of knowledge sourcing and the level of R&D intensity are not significantly different from zero.[2] This indicates that the link between knowledge sourcing and patents is independent of the level of R&D intensity. Furthermore, as another robustness check, we included R&D intensity squared in order to test a non-linear relationship between R&D intensity and the number of patents. However, unreported results show that the squared terms are close to zero and insignificant in all cases, indicating no improvement over our linear specification.

Another approach to estimate the relationship between knowledge sourcing activities and patenting is to use the matching estimator. In particular, we employed the matching algorithm from Abadie et al. (2004) to estimate the counterfactual outcome, that is the number of patents (normalized by firms' employment) that would prevail in the absence of knowledge sourcing from universities. Unreported results show that the positive effect of the knowledge sourcing activities on patenting is robust to the use of a matching estimator.

5 Conclusions

External knowledge sourcing from universities is regarded as an important stimulus of innovation performance. In this paper, we have focused on the link between external knowledge sourcing and the number of patents by distinguishing between three different types: (1) collaborative research and innovation activities with universities (2) involvement in academic research through contract R&D or related innovation input activities and (3) acquisition of academic knowledge. In addition, we distinguished between foreign and domestic sources. Using an IV version of the ordered probit model based on a large and comprehensive data set for Austria, we found that the effects of the knowledge sourcing strategies differ significantly across strategies. In particular, we found that acquisition of knowledge from universities is significantly positively associated with patent applications given the internal investment in R&D measured as the ratio of R&D employment to total employment and other innovation input factors. However, innovation cooperation with universities is not significantly related to patenting. The insignificance of innovation cooperation with universities is also important for innovation policy makers since collaborative research projects with universities often receive public subsidies.

It is worth noting a number of limitations of the empirical analysis. Firstly, drawing causal inferences from cross-sectional firm level data is not possible. Secondly, information on the presence of firm-university innovation linkages is measured as a dummy variable only.

[2] These results are available from the authors upon request.

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References

Abadie A, Drukker D, Herr JL, Imbens GW (2004) Implementing matching estimators for average treatment effects in stata. Stata J 4(3):290–311

Arvanitis S, Woerter M (2009) Firms' transfer strategies with universities and the relationship with firms' innovation performance. Ind Corp Change. doi:10.1093/icc/dtp029

Arvanitis S, Sydow N, Woerter M (2008a) Is there any impact of university-industry knowledge transfer on the performance of private enterprises? An empirical analysis based on swiss firm data. Rev Ind Organ 32:77–94

Arvanitis S, Sydow N, Woerter M (2008b) Do specific forms of university-industry knowledge transfer have different impacts on the performance of private enterprises? An empirical analysis based on swiss firm data. J Technol Transfer 33:504–533

Aschoff B, Schmidt T (2008) Empirical evidence on the success of R&D cooperation—happy together? Rev Ind Organ 33:41–62

Belderbos R, Carree M, Lokshin B (2004) Cooperative R&D and firm performance. Res Policy 33(10):1477–1492

Cassiman B, Veugelers R (2006) In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. Manage Sci 52(1):68–82

Cassiman B, Veugelers R, Zuniga P (2008) In search of performance effects of (in) direct industry science links. Ind Corp Change 17(4):611–646

Cohen WM, Levinthal DA (1989) Innovation and learning: the two faces of R&D. Econ J 99:569–596

Crépon B, Duguet E (1997) Estimating the innovation function from patent numbers: GMM on count data panel. J Appl Econom 12:243–263

Czarnitzki D, Kraft K, Thorwarth S (2009) The knowledge production of 'R' and 'D'. Econ Lett 105:141–143

Etzkowitz H, Webster A, Gebhardt C, Terra BRC (2000) The future of the university and the university of the future: evolution of ivory tower to entrepreneurial paradigm. Res Policy 29(2):313–330

Fontana R, Geuna A, Matt M (2006) Factors affecting university-industry R&D projects: the importance of searching, screening and signalling. Res Policy 35(2):309–323

George G, Zahra SA, Wood DR (2002) The effects of business-university alliances on innovative output and financial performance: a study of publicly traded biotechnology companies. J Bus Ventur 17:577–609

Griliches Z (1990) Patent statistics as economic indicators: a survey. J Econ Lit 28:1661–1707

Hall BH, Ziedonis RH (2001) The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979–1995. RAND J Econ 32(1):101–128

Hall BH, Griliches Z, Hausman JA (1986) Patents and R and D: is there a lag. Int Econ Rev 27:265–283

Hausman JA, Hall BH, Griliches Z (1984) Econometric models for count data with an application to the patents-R&D relationship. Econometrica 52:909–938

Licht G, Zoz K (1998) Patents and R&D. An econometric investigation using applications for German, European and US Patents by German Companies. Annales d'Économie et Statistique 49/50:329–360

Licht G, Zoz K (2000) Patents and R&D: an econometric investigation using applications for German, European and US patents by German companies. In: Encaoua D et al (eds) The economics and econometrics of innovation. Kluwer, Dordrecht, pp 307–338

Lööf H, Broström A (2008) Does knowledge diffusion between university and industry increase innovativeness? J Technol Transf 33(1):73–90

Mansfield E (1995) Academic research underlying industrial innovations: sources, characteristics, and financing. Rev Econ Stat 77:55–65

Mansfield E (1998) Academic research and industrial innovation: an update of empirical findings. Res Policy 26(7–8):773–776

Meyer-Kramer F, Schmoch U (1998) Science-based technologies university-industry interactions in four fields. Res Policy 27:835–852

Monjon S, Waelbroeck P (2003) Assessing Spillovers from universities to firms: evidence from French firm-level data. Int J Ind Organ 21:1255–1270

Pakes A, Griliches Z (1980) Patents and R&D at the firm level: a first report. Econ Lett 5:377–381

Peeters C, van Pottelsberghe de la Potterie B (2006) Innovation strategy and the patenting behaviour of firms. J Evol Econ 16:109–135

Roodman D (2009) Estimating fully observed recursive mixed-process models with CMP. CDG working paper no 168, Center for Global Development, Washington, DC

Roper S, Du J, Love JH (2008) Modelling the innovation value chain. Res Policy 37(6):961–977

Rosenberg N, Nelson RR (1994) American Universities and technical advance in industry. Res Policy 23:323–348

Schartinger D, Rammer C, Fischer MM, Fröhlich J (2002) Knowledge interactions between universities and industry in Austria: sectoral patterns and determinants. Res Policy 31(3):303–328

Stock J, Yogo M (2005) Testing for weak instruments in linear IV regression. In: Andrews DWK (ed) Identification and inference for econometric models. Cambridge University Press, New York, pp 80–108

Teece DJ (1986) Profiting from technological innovation. Res Policy 15(6):285–305

Teece DJ (1988) Technological change and the nature of the firm. In: Dosi G, Freeman C, Nelson R, Silverberg G, Soete L (eds) Technical change and economic theory. Pinter Publishers, New York, pp 256–281

Un CA, Cuervo-Cazurra A, Asakawa K (2010) R&D collaborations and product innovation. J Prod Innov Manage 27(5):673–689

Vega-Jurado J, Gutierrez-Gracia A, Fernandez-de-Lucio I (2009) Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry. Ind Corp Change 18(4):637–670