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Access to universities' public knowledge: Who's more regionalist?

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Abstract: This paper tracks university-to-firm patent citations rather than the more usual patent-to-patent or paper-to-patent citations. It explains regional and non-regional citations as a function of firms' absorptive capacity and universities' production capacity in the region rather than explaining citations as a function of distance between citing and cited regions. Using a dataset of European Union regions for the years 1997-2007, we find that fostering university R&D capacity increases the attractiveness of the local university's knowledge base to firms in the region, but also reduces wider searches for university knowledge. Increasing the absorptive capacity of local business encourages firms to access university knowledge from outside the region.

Resumen: En este artículo se investigan las citas en patentes de empresas a universidades, en lugar de realizar un análisis más convencional sobre citas de patentes a patentes o de patentes a artículos. Las citas regionales y no regionales se explican en función de la capacidad de absorción de las empresas y de la capacidad productiva de las universidades de la región, en vez de explicar las citas en función de la distancia entre las regiones citantes y citadas. Mediante el uso de una base de datos de las regiones de la Unión Europea con información desde 1997 a 2007, los resultados muestran que estimular la capacidad universitaria en I+D aumenta la predilección de las empresas de la región por la base de conocimiento de universidades locales, pero también reduce su interés por realizar búsquedas más amplias de conocimiento universitario. Incrementar la capacidad de absorción de las empresas locales fomenta su acceso al conocimiento universitario de otras regiones.

Keywords: Knowledge flows, patent citations, spillovers, regions
JEL Codes: O31, O33, R12

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1 Introduction

The significance of geographical proximity has been a key argument for encouraging firms' scientific strengths and the supply of university outputs. Some regions have invested heavily in stimulating their firms' R&D for its effects on innovation, including steps to increase the use of local university knowledge that could modernize the production model. Many regional authorities have also fostered the generation of scientific and technological knowledge by their universities for parts of this knowledge to spill over to firms and generate economic growth. This is the case of a number of countries, which have regionalised political, administrative and budgetary competences relevant to regional innovation policy to a substantial degree (for example, several Spanish regions, Belgium, Germany and Italy)[2]. Nevertheless, knowledge sourcing occurs on a variety of different spatial scales, including supra-regional and global, both of which might be equally important to firms as external knowledge sources. Hence, there may be a mismatch between regional production and use of codified university knowledge. In this paper, we discuss some characteristics of the region that explain the extent to which university knowledge flows are regional or non-regional.

Previous research has not addressed this question directly. A large body of empirical work on university spillovers concludes that they are localized (e.g. Jaffe, 1989, 1993; Anselin et al., 1997, 2000; Feldman and Florida, 1994; Fischer and Varga, 2003; Del Barrio-Castro and Garcia-Quevedo, 2005), but it does not focus on the distinction between regional and non-regional borders. Other analyses emphasize different reasons for regional and non-regional university knowledge flows (Arndt and Sternberg, 2000;

[2] Obviously many different situations coexist in Europe as the level of spending depends on the capacity of the region to put in practice their own innovation policy. Baier et al. (2013) propose a set of indicators to account for aspects of regional autonomy that allow assessing to which degree European regions are actually able to develop and shape innovation policies.

Bathelt et al., 2004; Gallié 2009), but these flows are not expressed as a function of regional characteristics. Two streams of literature suggest which characteristics are relevant. On the one hand, absorptive capacity of firms in the region is positively related to collaboration with domestic partners, notably universities (Drejer and Vinding, 2007; De Jong and Freel, 2010; Laursen et al., 2011; Mukherji and Silberman, 2013). On the other hand, the capacity of universities to produce scientific and technological knowledge is positively related to different types of benefits for local firms (Audretsch and Feldman, 1996; Zucker et al., 2002; Branstetter, 2001; Laursen et al.; 2011); and with local firm formation or location (Audretsch et al., 2004; Harhoff, 1999; Woodward et al., 2006; Abramovsky et al., 2007). However, these two streams have never been combined to express differences in university knowledge flows inside/outside the region. Hence, there is lack of a conceptual framework and empirical evidence that distinguishes university knowledge flows inside and outside the region, and explains it as function of characteristics of the region like firms' absorptive capacity and universities' production capacity.

The current paper addresses this gap. First, by building hypotheses about possible relationships between regional/non-regional knowledge flows and relevant characteristics of regional firms and universities. Second, by testing the hypotheses with a regional sample for the European Union 27 of around 6,000 academic backward citations (to patents and papers) contained in 4,000 firm patents from the EU27 regions in 1997-2007. Moreover, this methodology adds value for providing European evidence at large scale using university-to-firm patent citations rather than the more usual patent-to-patent or paper-to-patent citations.

The paper is organized as follows. Section 2 reviews the literature and establishes the hypotheses. Section 3 discusses the empirical framework. Section 4 explains the data and provides summary statistics. Section 5 presents the econometric results. Section 6 provides a summary of our conclusions, some policy implications, and suggestions for future research.

2 Literature review and hypotheses

Knowledge embedded in university patents and academic research contributes substantially to technological innovation (Narin et al., 1997; McMillan et al., 2000; Mansfield, 1991, 1998; Tijssen, 2001; Branstetter and Ogura, 2005); it also affects other variables such as firms' location (Audretsch et al., 2005; Woodward et al., 2006). Codification has positive consequences for the technologies of learning and directly influences the speeding-up of knowledge creation, innovation and economic change (Cohendet and Meyer-Krahmer, 2001). These consequences can take place inside or outside the region of the university that produced the codified information. Despite the significant role of proximity found by the spillover literature (see introduction), several papers have shown that knowledge sourcing occurs on a variety of different spatial scales, including supra-regional and global, both of which might be equally important to firms as external knowledge sources (Arndt and Sternberg, 2000; Bathelt et al., 2004; Gallié 2009). There are recent cases in the empirical literature explaining why many firms do not acquire their knowledge from geographically proximate areas. For example, Davenport (2005) concludes that some factors may work against geographically proximate knowledge-acquisition activities such as the role of foreign firms and multi-nationals, or firms working on a specific technology. Cooke (2005) provides several examples that recognize that research knowledge is central for regional development, but that universities cannot promote innovation alone –other regional agents in the system must also work well. Furthermore, the relevance of different geographical spheres reinforces the viewpoint by Cooke et al. (2000) suggesting that it is impossible to discuss the innovation process and policies without reference to the interactions of local–regional, national and global actors and institutions.

A certain degree of "absorptive capacity" is necessary for using university knowledge, because not all the knowledge that spills over in the region can be absorbed and exploited (Caragliu and Nijkamp, 2012). That is, firms must have the "ability to recognise the value of new, external information, assimilate it, and apply it" (Cohen and Levinthal, 1990). Cohen and Levinthal consider the investment in internal R&D as fundamental factor in the acquisition and utilisation of external knowledge and technology[3]. Firms with well-developed absorptive capacity can collaborate for innovation with more distant sources of knowledge. This can be explained for the difficulties to deal with the role of different types of factors, apart from geography, to facilitate the flow of knowledge. For example, Torre and Rallet (2005) distinguish between geographical and organized proximity: organized proximity (the ability of an organization) to make its members interact offers powerful mechanisms of long-distance coordination. Boschma (2005) argues that although geographical proximity facilitates interaction and cooperation for the acquisition of knowledge, other forms of proximity may act as substitute of geographical proximity. He suggests that distance it is neither a necessary nor a sufficient condition for interactive learning to take place and the capacity of firms to absorb new knowledge requires cognitive proximity. Some empirical papers point to this direction; for example, Maggioni et al. (2007) determined the importance of 'geographic' versus 'functional' distance as forces shaping the interregional (international) structure of knowledge flows networks in Europe. Mora and Moreno (2010) show evidence

[3] The discussion about this way of capturing absorptive capacity continues in the empirical framework section.

indicating that physical distance still plays a significant, and even more influential role than similarity in explaining specialisation of European regions. Basile et al. (2012) provide a theoretical framework and empirical evidence on the role played by other kinds of proximities, namely relational, social and technological proximity, in explaining productivity growth. Marrocu et al. (2013) show that technological proximity outperforms the geographic one, whilst social and organizational networks play a limited role in explaining knowledge flows.

This background points to that innovation depends on appropriate combinations of knowledge inputs from local and regional, as well as national and global sources, and to that opportunities for using knowledge can be found beyond the home regions (Gittleman, 2007, Kratke, 2010). Firms will search knowledge outside the region if they have the need –and the resources– to overcome the greater cost of distance. Increases in absorptive capacity can reduce cognitive and other non-geographic types of distance (more resources in R&D increases the firm’s skill to cope with new or more complex knowledge). However, if firm absorptive capacity is low, geographically proximate collaborations may be their only option (De Jong and Freel, 2010).

This review leads to the following hypotheses related to the influence of absorptive capacity on the use of university knowledge produced inside and outside the region.

Hypothesis 1: The use of codified knowledge in the form of patents and papers produced by universities inside the region is negatively related to regional firms’ absorptive capacity.

Hypothesis 2: The use of codified knowledge in the form of patents and papers produced by universities outside the region is positively related to the firms’ absorptive capacity.

The analysis of academic knowledge flows should take account of the other party, the university knowledge. The production and availability of knowledge that can lead to innovation may condition the firm's search strategy (see the literature on organizational learning, e.g. Garriga et al., 2013). This implies that firms located in regions with scarce opportunities for acquiring university knowledge might need to obtain it outside the region despite the high costs, whereas regions with a local presence of knowledge sources may not need to search outside the region. Similarly, university ideas will be commercialized in distant locations if there are no nearby receptive companies (Azagra, 2007; Breznitz and Feldman, 2012).

Some empirical research stresses the role of the university knowledge production to encourage the flow towards firms at the regional level. The results by Audretsch and Feldman (1996) at U.S. state level indicate the relative economic importance of new knowledge to the location and concentration of industrial production. Zucker et al. (2002) relate the input "number of local research stars" to the output "number of new local biotech firms", and examine the variance in this relationship across geographic space at the economic region level. They found that the number of local stars and their collaborators is a strong predictor of the geographic distribution of U.S. biotech firms in 1990. Branstetter (2001) identifies a positive relationship between ‘‘scientific publications from the University of California’’ and patents from the state of California that cite those papers. Laursen et al. (2011) show that university quality matters; they conclude that being located close to a top-tier universities promotes collaboration. Furthermore, firms appear to give preference to the research quality of the university partner over geographical closeness. Related literature on firm formation/location also suggests the importance of the characteristics of the academic knowledge for the occurrence of spillovers in the region. For example, Audretsch et al. (2004) focus on whether knowledge spillovers are the same across scientific fields. They found that firms' locational-decisions are shaped both the output of universities (for instance, students and research) and the nature of that output (i.e. specialized nature of scientific knowledge). Several empirical studies of different spatial contexts point to the potential positive relationship between local university R&D expenditure and number of high technology firms established locally (e.g. Harhoff, 1999 for Germany; Woodward et al., 2006 for the U.S.). Abramovsky et al. (2007) provide evidence of business sector R&D activity near high quality university research departments in the U.K.

Thus, we expect that a territorial environment with universities capable of producing useful outputs (patents and papers) will increase the opportunities for companies to access and absorb that relevant knowledge compared to companies located in regions with poor supply of academic knowledge. We expect also that firms in regions with fewer technological and scientific opportunities will acquire academic knowledge from outside the region. This leads to the following hypotheses:

Hypothesis 3: The use of codified knowledge in the form of patents and papers produced by universities in the region is positively related to the universities' capacity to produce scientific and technological knowledge in the region.

Hypothesis 4: The use of codified knowledge in the form of patents and papers produced by universities outside the region is negatively related to the capacity of home region universities to produce scientific and technological knowledge.

3 Empirical framework

The basic model for testing our hypotheses relates use of university knowledge (UKA) by firms in a region to two main factors: absorptive capacity (AC) and universities' capacity to produce new scientific and technological knowledge in the region (U).

The general form of the regional function is written as:

$$UKA_{rt} = \phi(AC_{rt}, U_{rt}) \text{ for r} = 1, 2, ..., N; \text{ t=1,2,...,T}$$

The subscripts r and t refer respectively to region r and time t. This is a University Knowledge Acquisition Function (UKAF) and relates to the activities of firms in a region to capture the use of inward and outward regional university knowledge (university knowledge produced in universities located in or outside the firms' region). This model differs from the models used in the empirical literature to capture regional flows of knowledge. The regional knowledge production function (KPF) (Griliches, 1979; Jaffe, 1989) captures the effects of local knowledge sources for industrial innovation, and is represented in an aggregate production function of outputs –e.g. innovation counts, patents, etc.– and depends on factors such as industry R&D expenditure, local academic research (to capture university spillovers), and other control variables (such as population and economic activity). This allows analysis of the effects of spillovers on innovation, and identifies the effect, in particular, of university spillovers on regional innovation. The spatial interaction modeling perspective accounts for the causes of these spillovers (Roy and Thill, 2004) and relates flows of knowledge –generally captured by citations counts– to their origin and destination characteristics and some measure of separation of the regions (e.g. geographical distance between them, technological compatibility, etc.)[4].

To explain the use of knowledge more thoroughly we extend the UKAF in two directions such that:

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[4] Spatial interactions models have been widely used to account for spillovers and collaboration between spatial units. They can be grouped under the generic heading gravity models. Spatial interaction models represent a variable capturing the flow of knowledge between region i to region j in function of factor characterising the region i and the region j plus a factor that measures the separation from i to j.

- The model controls for the technological specialization and regional technological size. Although to our knowledge there is no empirical research on the effects of technological diversification (or specialization) on the use of university knowledge, high tech regions might rely more on external rather than regional internal knowledge. For example, some authors (e.g. Acosta and Coronado, 2003; Laursen and Salter, 2004) suggest that in some industry sectors, the relationship between universities and industrial innovation appears very tight, while in sectors such as textiles it appears weaker. On the other hand, European regions differ in size. To avoid spurious correlation the model needs to control for the extent of technological inward and outward knowledge;

- Regions are grouped in countries, and consequently some correlation is expected among regions in the same country. For example, how national innovation measures, incentives, and firm policies influence its regions. The presence of spatial hierarchical structures with different characteristics would suggest the present of multilevel factors influencing the use of university knowledge.

We can reformulate our initial model to include these additional factors in an extended UKAF:

$$UKA_{grt} = \phi(AC_{grt}, U_{grt}, Spe_{grt}, Z_{grt}, \varepsilon_{gt}, u_{grt}) \text{ for } r = 1, 2, \ldots, N \quad \text{t=1,2,...,T} \quad g = 1, 2, \ldots, G$$

where g is the group or cluster; Spe controls for regional technological specialization; Z is region size; ε is an unobserved cluster-effect capturing the influence of the group (country) on regional acquisition of inward and outward knowledge; and u is the idiosyncratic error. The empirical estimations also include dummies for temporal fixed effects. All the explanatory variables consider a two-year lag.[5]

We next describe the measurement of our variables.

Dependent variables. We consider two dependent variables in two separate models:

- Acquisition or use of inward regional university knowledge is captured by number of citations in firms' patents to universities located in the firm's region;
- The acquisition or use of outward regional university knowledge is captured by the number of citations in firms' patents to universities located outside the firm's region.

Independent variables:

- Absorptive capacity (AC). The empirical literature on absorptive capacity is limited mostly to R&D expenditure amounts, or presence of an R&D unit to measure absorptive capacity at firm and regional levels. Other indicators of absorptive capacity include human resources and networks. In this paper we use R&D effort as a proxy for absorptive capacity (firms' R&D as a percentage of GDP -gross domestic product). Cohen and Levinthal (1990) used data on firms' internal R&D activity to proxy for absorptive capacity in their empirical section and several later studies us firm R&D to analyze firms' capabilities to access knowledge from external sources (e.g. seminal papers such as Kim, 1997, and Kodama, 1995, stress the crucial role of internal R&D in determining the firm's ability to acquire and assimilate external knowledge). However, use of this indicator requires the assumption that information search and information access are perfectly correlated

[5] 2, 3 or even 5 year lags between the dependent and independent variables are considered in the patenting literature. In our case the specification of lag structures should not be of major concern because the explanatory variables are supposed to be stable over the years.

with internal knowledge development, which requires university knowledge to be freely available and means that to exploit this knowledge the firm has no need to invest resources additional to those devoted to developing innovation;

- Presence in the region of university technological opportunities (U). We capture the capacity of universities to produce high-quality patents in each region by regional expenditure on university (higher education) R&D as a percentage of regional GDP. This variable proxies for the ability of the university system to produce outputs. We expect that greater university R&D efforts should lead to more university outputs which should increase the opportunities for firms to acquire and exploit university knowledge;
- To control for regional specialization (Spe) we calculate a measure similar to the revealed technological advantage index: TAI= $\frac{P_{ij} / \sum_{s=1}^{S} P_{is}}{\sum_{i=1}^{N} P_{is} / \sum_{i=1}^{N} \sum_{s=1}^{S} P_{is}}$, where $P_{is} / \sum_{s=1}^{S} P_{is}$ is the number of patents of region i in sector j over the number of patents of region i in all sectors; $\sum_{s=1}^{N} P_{is} / \sum_{i=1}^{N} \sum_{s=1}^{S} P_{is}$ is the number of patents for all regions in sector s over total number of patents. To construct the index we use eight sections of the International Patent Classification (IPC);
- To control for region size (Z) we use number of firms' patents in each region. This variable avoids spurious relationships (regions with more patents are expected to have more citations).

To estimate the models, we apply a conditional fixed and random effects negative binomial estimator, which assumes that units (regions) are positively correlated within clusters (countries). The econometric estimations are framed in cluster count data models. The decision to use a two-level hierarchical analysis (regions grouped in countries) has two main objectives: (a) to evaluate unobserved heterogeneity along with the fixed effects of regional acquisition of knowledge; the inclusion in the model of random effects assumes geographical heterogeneity across regions of the same country; (b) to estimate confidence intervals accurately, taking account of the intra regional correlations among regions in the same country. Failure to account for clustering of data produces serious biases (see, e.g. Moulton, 1990; Antweiler, 2001; Wooldridge, 2003, 2006).

Below we summarize, the empirical base models:

- A negative binomial model with a hierarchical data structure (regions grouped into countries) to analyze the use of inward regional knowledge;

- A negative binomial model with a hierarchical data structure (regions grouped into countries) to analyze the use of outward regional knowledge.

The above are the base specifications. Because of the structure of our sample, the nature of the data, and considerations such as the number of zeros in the sample, we consider some additional models:

- A negative binomial model and a zero inflated negative binomial model with a pooled data structure and clustered robust standard errors (clusters are countries) to analyze use of inward regional knowledge;

- A negative binomial model and a zero inflated negative binomial model with a pooled data structure and clustered robust standard errors (clusters are countries) to analyze the use of outward regional knowledge.

4 Data

We measure the firms' use of university knowledge via citations in patent documents, which reflect codified knowledge and, to some extent, learning on the part of industrial inventors through multiple channels (Branstetter and Ogura, 2005). The reading of a patent or academic paper by a private inventor might also give rise to other kind of tacit knowledge. Any scientist wishing to build on new knowledge must gain access to a research team or laboratory setting with know-how, otherwise working in that area may be very difficult if not impossible (Zucker, 1998).

The data collection process was designed by the Institute for Prospective Technological Studies (IPTS) in 2009. An international consortium of researchers from the University of Newcastle, Incentim (KU Leuven Research and Development), and the Centre for Science and Technology Studies (CWTS) (Leiden University) implemented the data collection. Figure 1 describes the data construction. The European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT) was used to construct a dataset of 228,594 direct EPO patents applied for in the period 1997-2007. The team identified 10,307 patents with university references, i.e. citations to patents applied for by universities or to scientific articles listed on the Web of Science by authors with a single university affiliation. This single-university affiliation criterion is the main limitation of the database and is due to resource constraints; it implies that both the number of patents with references and the share of papers with university references are underestimated.

Figure 1 about here

Each patent has an average of 1.2 applicants, resulting in a total of around 12,000 applicants; and each applicant cites 2 university references on average, so the starting number of citations to university references is slightly over 24,000. In order to match the

NUTs II region of the citing applicant and the cited university, we exclude citations from non-EU27 applicants and a few EU27 applicants for whom we have no regional information (Figure 2). In order to test our hypotheses, we exclude applicants other than firms, which yields a total of around 13,000 citations for which we were able to check whether there was a match between applicant region and region of a citation from a university. In 2 percent of cases we found a positive match.

Figure 2 about here

We aggregated patent and citation counts, per region and per year, to obtain a panel linkable to Eurostat regional R&D statistics, resulting in 2,365 observations (Figure 3). Of these, 1,181 observations had no firm patents, resulting on many fewer observations for our analysis. The models estimated in the section below include firm and university R&D intensity as explanatory variables. Since there are many missing data for these variables at regional level, our number of observations is further reduced to 503 for 22 countries in the UE27 from 1997 to 2007. The number of patents drops to around 4,000 and number of citations to universities falls to around 6,000, 2 percent of which are regional citations.

Figure 3 about here.

In Section 3 we referred to the nature of the data suggesting grouped and pooled model specifications. Tables 1 and 2 present the descriptive statistics for each type of model. Note that use of the fixed effects estimator requires that countries with only one observation are omitted, which is why the number of observations differs depending on the model type (Figure 3).

Tables 1 and 2 about here.

The two dependent variables show remarkably different behavior. In the model with 464 observations, inward acquisition of university knowledge from the firm's region includes 388 observations with zero citations and 76 observations with one or more citations (Table 1). In models with 499 observations, outward acquisition of knowledge includes 5 observations with zero citations and 494 with one or more citations (Table 2).

Figure 4 shows that the number of citations has remained fairly stable over time. Over the period of observation, it oscillated around a near horizontal line for both inward and outward citations, with the share of regional in total citations reaching an average of 2 percent with no clear upward or downward pattern.

Figure 4 about here.

Figure 5 shows cross-sectional variation. If we compare the top ten regions for number of inward versus outward citations (upper and lower parts of Figure 5, respectively), only three –Île de France, London, and Berlin– appear in both rankings. This suggests that the processes of university knowledge acquisition depends on different factors according to the inward or outward nature of the flow. It is also an empirical validation of the interest of the topic raised in the introduction.

Figure 5 about here.

5 Econometric results

5.1 Baseline results

This section presents the results for both analyses (inward and outward use of knowledge) and takes account of the different data types (hierarchical and pooled):

Table 3, Columns 1 and 2, and 4 and 5, show the estimated models for the use of inward and outward knowledge according to the hierarchical data (with fixed and random effects estimators). In order to enable comparison of the results for these estimators, we used the same number of observations (464 for the inward knowledge acquisition and 499 for the outward).

Table 3 about here.

Table 3, Columns 3 and 6 show the pooled models for the same numbers of observations. Given the nature of the dependent variable, we provide the zero-inflated negative binomial (ZINB) estimations if the dependent variable is use of inward knowledge (which has many zeros), and the negative binomial (NB) if the dependent variable is use of outward knowledge (the preferred models according to the Vuong statistic).

The results for the variables for inward university knowledge are based on Table 3, Column 3 because the likelihood ratio test suggests that pooled data models (Column 3) are preferred to hierarchical models (Columns 1 and 2). Column 3 shows that the absorptive capacity of the firms in the region does not play a role in determining use of university scientific and technological knowledge generated in the firm's home region. There is no support for Hypothesis 1. This is coherent with previous empirical evidence reporting a regional mismatch in Europe between industrial potential and production of new university technological knowledge, which are not related (Acosta et al 2009). It may be also due to the weight of regions with low absorptive capacity, where innovation relies on acquisition of machinery (Zabala et al 2007) and knowledge flows codified in patent citations are scarce, making it had to find significant relationships with determining factors.

Columns 4 and 5 show that the absorptive capacity of firms in the region determines the use of outward university knowledge (grouped data preferred to pooled data according to likelihood ratio (LR) test). That is, regions with greater firm R&D activity have better capacity to absorb scientific and technological knowledge from universities outside the region (i.e. in other countries or other regions in the same country). This supports Hypothesis 2.

In relation to the influence of regional university knowledge, Column 3 shows that firms' use of university scientific and technological knowledge from universities in their region is positively related to the intensity of university R&D expenditure. This means that the higher the research capacities of universities in the region, the more that firms will benefit from scientific and technological knowledge from these universities, supporting Hypothesis 3.

Columns 4 and 5 test for a significant effect of university knowledge in the region on the use of outward university knowledge. The quality of the universities in the region is negatively related to the acquisition by private firms of university knowledge from outside the region, which provides support for Hypothesis 4.

5.2 Robustness check

The fixed effects panel models estimated so far are computable only for the 464 and 499 observations used in the previous section. In the former models, we used the same number of observations in order to facilitate comparison. As a robustness check, we estimate the same specifications as in previous section but without restrictions on the number of observations for each model, which allows us to count on more data for the estimations. However, comparisons to select the models are more difficult. The number of observations increases to 503 in the random effects, ZINB, and NB models. Table 4 provides the descriptive statistics.

Table 4 about here.

For these 503 observations the preferred model to analyze inward UKA is ZINB with pooled data (Table 5, Column 3). The preferred model for outward UKA is a hierarchical NB (Table 5, Column 6).

Table 5 about here.

These new estimations, using a different number of observations, confirm the previous results and support or not the same hypotheses.

6 Conclusions

In this paper, we argued that the knowledge that firms in a region can acquire from university spillovers is a function of both the absorptive capacity of the firms developed by investing in knowledge, and the opportunities for university knowledge spillovers. To test our hypotheses we proposed an external knowledge acquisition function to explain the factors affecting regional inward and outward use by firms of university knowledge.

Our models reject Hypothesis 1, but support Hypotheses 2, 3 and 4. We find that absorptive capacity does not explain the use of inward scientific and technological knowledge from universities but that absorptive capacity has a relevant and positive effect on the acquisition of outward university knowledge. We found also that opportunities for university spillovers have a positive effect on the use of local knowledge by firms in the same region, and a negative influence in the acquisition of external university knowledge (from another region or country).

Our findings have some policy implications. Firm competitiveness is an important issue for regional governments, which should focus on encouraging economic growth and enhancing knowledge acquisition to promote innovation. Whether to bring attention on use of knowledge within or outside the region matters to implement one or another strategy: university R&D investments in the region to produce more university knowledge for facilitating spillovers or enhancement of absorptive capacity of private business sector to acquire knowledge from a wider environment. Thus:

- If the objective of regional governments is encouraging the use of university knowledge produced in the region by firms in the region, our results suggest that the focus should be on the supply side, i.e. on investment in the production of university scientific and technological knowledge. We found a negative relationship between use of external to the region knowledge and production of knowledge by universities in the home region, which points to a trade-off (the production of more technological knowledge promotes the use of inward knowledge but decreases the use of knowledge from universities outside the region). This might be due to knowledge availability. Firms look outside the region for what they cannot find inside. Thus, if the volume of university knowledge available to local firms increases, then the probability of using knowledge from the home region will also increase (and the probability of acquiring knowledge from outside the region will decrease). If the same level of knowledge exists in both locations (the firm's region and another region/country), firms will prefer to use technological information from a proximate location because it will be easier to understand and apply (e.g. the language of the patent is the native language of the user). Proximity will also facilitate direct interaction with the university inventor/author. Note, however, that it is not just a matter of allocating greater amount of R&D funds to universities in the region. This strategy involves programs promoting scientific and technological fields of research in the university with more connections to the industrial areas in which the region specializes.

- If the objective is the use of knowledge by the firm more generally (globally, rather than regionally), then absorptive capacity of the business sector is relevant; that is, the stimulation of the demand side in line with suggestions by Huggins and Kitagawa (2012).

These implications are the result of an aggregate study and consequently they just provide some clues about how to stimulate the use of university knowledge. However, as pointed by Hewitt-Dundas (2012), promoting the flow of knowledge requires taking into account organizational specificities (e.g. there are different types of universities in Europe and different degrees of autonomy in regional governments for implementing innovation policies); therefore, uniform policies may be inappropriate and specific analysis for particular regions are necessary.

This study has several limitations, some of which point to avenues for future research. We focus on one mechanism of acquisition of university knowledge –patents – via citations to universities. Patent citations capture a very specific type of knowledge acquisition via patented inventions. It would be interesting to explore channels of tacit knowledge acquisition (although, as we argued at the beginning of the paper, citations in patents might also involve tacit knowledge). Future research could investigate a larger data sample with citations differentiated by university, literature type (patents or other documentation), and origin of the citation (inserted by patent application or patent examiner). In our study, the number of regional citations is too small to produce meaningful results. It would be interesting also to compare the traditional approach to patent citations involving the role of distance with the region perspective adopted in this study to investigate which is more informative - distance or borders (Mukherji and Silberman, 2013b). Adding more measures of firms' absorptive capacity and university supply of knowledge would have enriched this study but requires their definition at regional level; this was beyond the scope of the present study. It would be worth investigating whether cooperation with a university shapes citation patterns. Replicating the analysis at the NUTs III level might be useful although, at that level, regions have smaller margins for implementing their own policies, and the number of regional citations would be lower and R&D statistics less readily available.

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Figures

Figure 1 - University references in direct EPO patents, 1997-2007

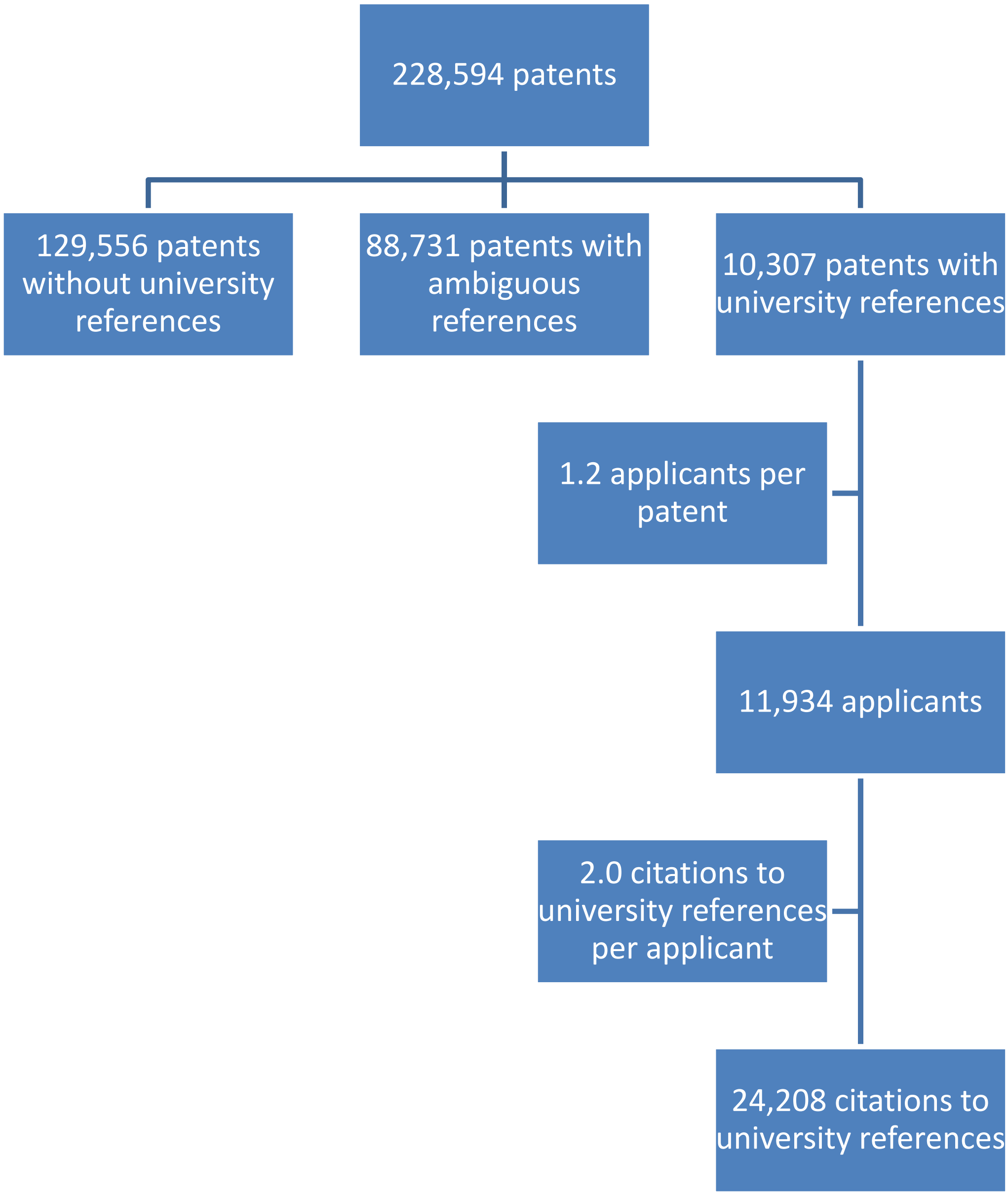


Figure 2 - Citations to university references in direct EPO patents, 1997-2007

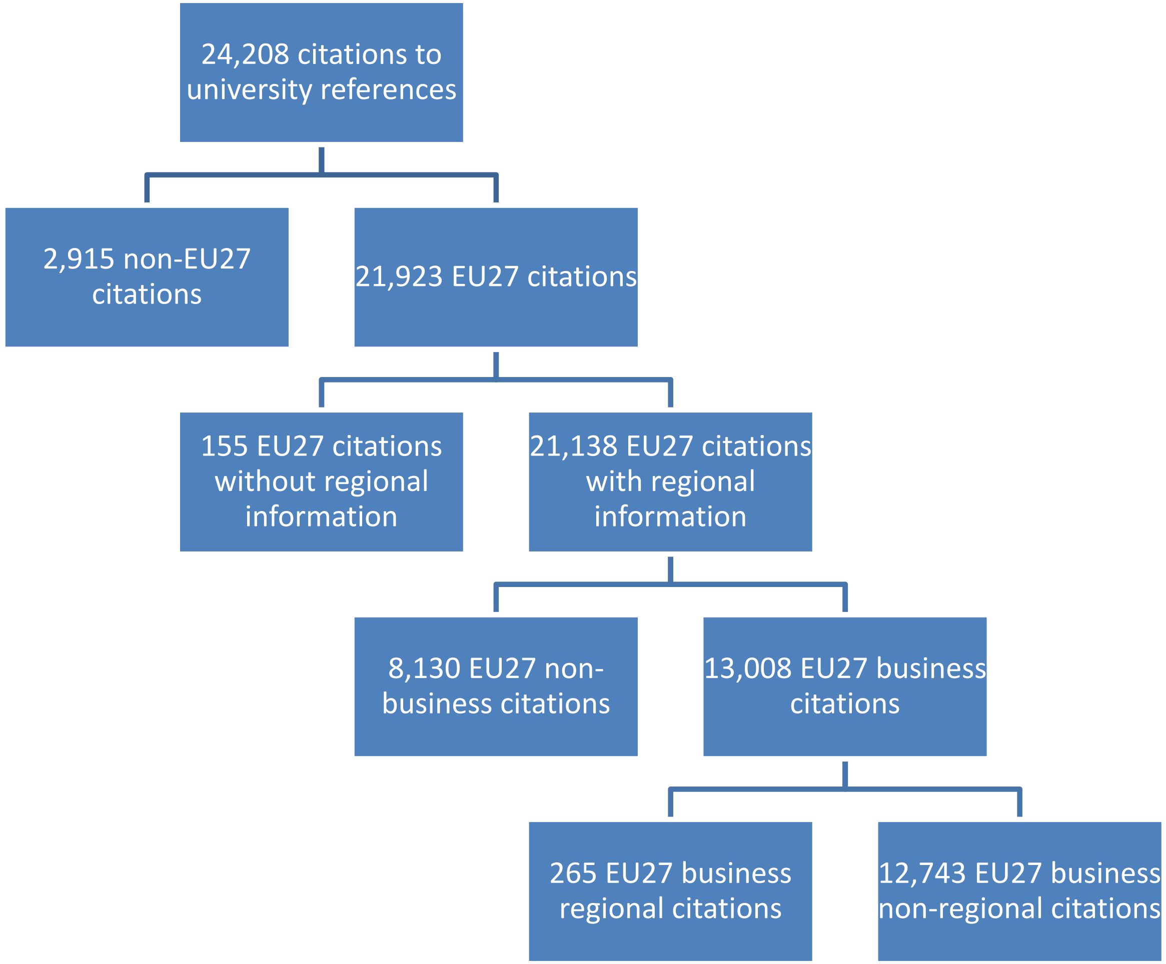


Figure 3 – The panel

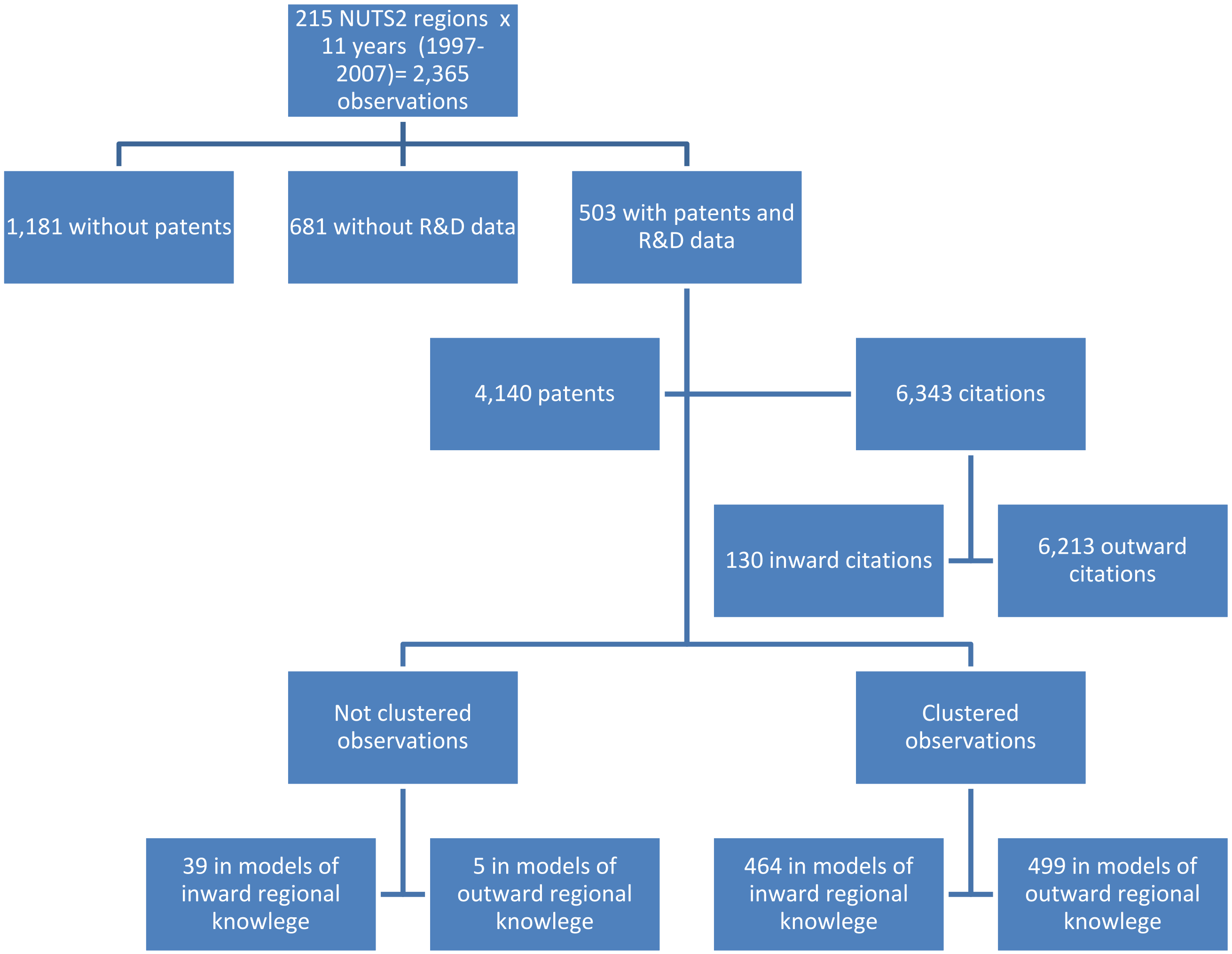


Figure 4 - Stability on the evolution of firm citations to university references

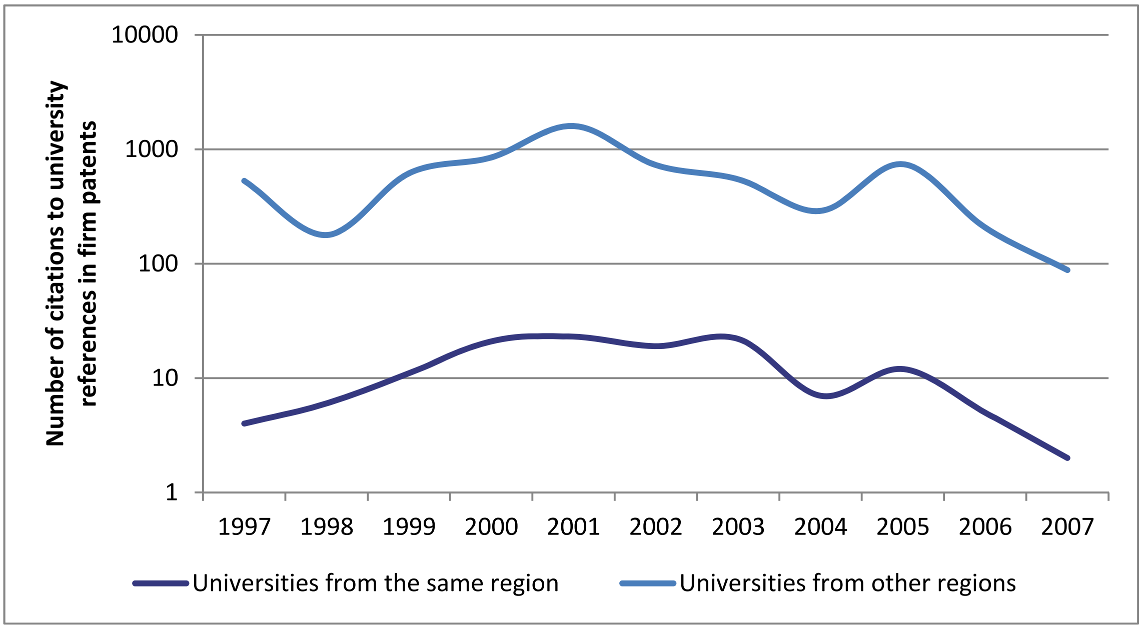
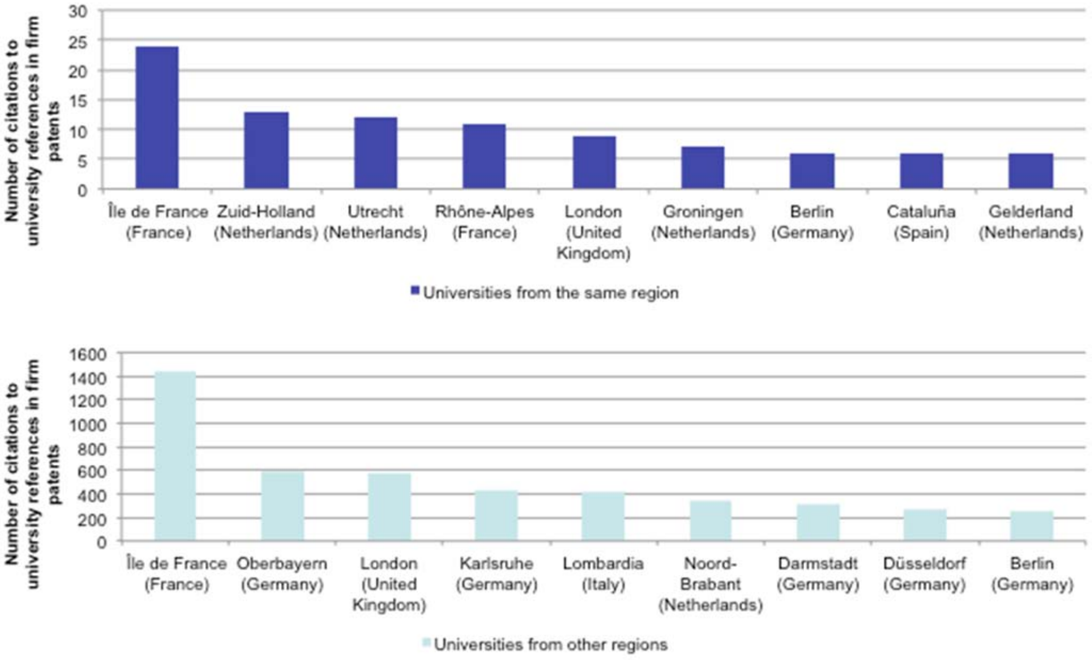


Figure 5 - Cross-regional variation in firm citations to university references: top regions in number of citations



Tables

Table 1

Descriptive Statistics 464 observations				
	Mean	Std. Dev.	Min	Max
Acq. inward reg. know	0.280	0.763	0	6
A=Firms' R&D/GDP	1.135	0.890	0.04	6.83
U=Universities' R&D/GDP	0.395	0.205	0.01	1.30
Z=Number of patents	8.933	17.515	1	151
SpeA	0.931	0.690	0	3.83
SpeB	0.684	0.960	0	7.42
SpeC	0.693	0.595	0	2.17
SpeD	0.313	1.504	0	22.19
SpeE	0.294	1.320	0	17.20
SpeF	0.505	1.211	0	8.57
SpeG	0.598	0.618	0	3.94
SpeH	0.447	0.738	0	5.15

Table 2

Descriptive Statistics 499 observations				
	Mean	Std. Dev.	Min	Max
Acq. outward reg. know	12.790	26.366	0	243
A=Firms' R&D/GDP	1.136	0.902	0.04	6.83
U=Universities' R&D/GDP	0.398	0.225	0	1.32
Z=Number of patents	8.531	16.988	1	151
SpeA	0.917	0.698	0	3.83
SpeB	0.698	1.002	0	7.42
SpeC	0.693	0.597	0	2.17
SpeD	0.291	1.452	0	22.19
SpeE	0.308	1.385	0	17.20
SpeF	0.513	1.231	0	8.57
SpeG	0.581	0.610	0	3.94
SpeH	0.444	0.733	0	5.15

Table 3

Dependent Variable: UKA (University knowledge Acquisition)												
	I. Acquisition of inward regional knowledge						II. Acquisition of outward regional knowledge					
	Negative binomial models for grouped data				ZINB model for pooled data		Negative binomial models for grouped data				NB model for pooled data	
	1 FE		2 RE		3 Robust Std Err Adjusted (country)		4 FE		5 RE		6 Robust Std Err Adjusted (country)	
Constant	-18.715		-21.740		-16.595	**	-1.156	**	-1.216	**	-0.523	**
AC=Firms' R&D/GDP	-0.347	*	-0.340	*	-0.291		0.078	**	0.088	**	0.049	
U=Universities' R&D/GDP	2.460	**	2.265	**	2.137	**	-0.330	**	-0.258	*	0.138	
Z=Number of patents	0.017	**	0.018	**	0.016	**	0.022	**	0.021	**	0.040	**
SpeA	0.742	**	0.866	**	1.595	**	0.459	**	0.474	**	0.484	**
SpeB	0.290		0.292		0.282	**	0.161	**	0.163	**	0.131	**
SpeC	1.255	**	1.190	**	-0.042		0.872	**	0.874	**	0.888	**
SpeD	-0.042		-0.044		0.190		0.014		0.017		0.041	**
SpeE	0.142		0.147		-0.072		0.021		0.023		0.019	
SpeF	0.267		0.195		0.265		0.080	**	0.079	**	0.089	*
SpeG	0.433		0.363		0.315		0.506	**	0.524	**	0.527	**
SpeH	0.578	**	0.503	**	-0.011		0.311	**	0.312	**	0.283	**
Ln_r			3.122						2.464			
Ln_s			2.160						3.306			
Inflation model (logit)												
Constant					1.583							
SpeA					1.134							
SpeB					-0.270							
SpeC					-2.849	**						
SpeD					0.289							
SpeE					-0.703							
SpeF					0.295							
SpeG					0.515	*						
SpeH					-1.657							
Number of obs.	464		464		464		499		499		499	
Number of groups	9		9		9		18		18		18	
Wald chi2	115.20	**	122.66	**			2746.73	**	2823.93	**		
Loglikelihood	-201.35		-230.51		-220.41		-1334.04		-1417.03		-1314.75	
LR Test Panel vs Pooled			1.63						57.44	**		

Notes:
IPC Sections to construct specialization indexes (spe): A Human Necessities; B Performing Operations; Transporting; C Chemistry; Metallurgy; D Textiles; Paper; E Fixed Constructions; F — Mechanical Engineering; Lighting; Heating; Weapons; Blasting: G Physics; H Electricity.
- **, * denote that coefficients are statistically different from zero at the 5% and 10% levels, respectively.
- All models include year dummies for 1997-2007.
- VIF suggests no signs of multicollinearity.
- Likelihood ratio test favors Poisson rather than NB in Models 3 and 6
- Vuong statistic favors ZINB rather than NB in Model 3 and NB rather than ZINB in Model 6.

Table 4

Descriptive Statistics 503 observations				
	Mean	Std. Dev.	Min	Max
Acq. inward reg. know	0.258	0.737	0	6
Acq. outward reg. know	12.704	26.278	0	243
A=Firms' R&D/GDP	1.128	0.903	0.02	6.83
U=Universities' R&D/GDP	0.396	0.225	0	1.32
Z=Number of patents	8.473	16.933	1	151
SpeA	0.917	0.711	0	3.83
SpeB	0.698	1.003	0	7.42
SpeC	0.693	0.600	0	2.17
SpeD	0.412	3.113	0	62.12
SpeE	0.305	1.379	0	17.20
SpeF	0.509	1.227	0	8.57
SpeG	0.577	0.610	0	3.94
SpeH	0.442	0.732	0	5.15

Table 5

Dependent Variable: UKA (University knowledge Acquisition)						
	I. Acquisition of inward regional knowledge			II. Acquisition of outward regional knowledge		
	Negative binomial models for grouped data		ZINB model for pooled data	Negative binomial models for grouped data		NB model for pooled data
	1 FE	2 RE	3 Robust Std Err Adjusted (country)	4 FE	5 RE	6 Robust Std Err Adjusted (country)
Constant	-18.715	-21.893	-16.987**	-1.156**	-1.217**	-0.527 **
A=Firms' R&D/GDP	-0.347 *	-0.421**	-0.311	0.078**	0.091**	0.057
U=Universities' R&D/GDP	2.460**	1.973**	1.943**	-0.330**	-0.259 *	0.132
Z=Number of patents	0.017**	0.018**	0.015**	0.022**	0.021**	0.039 **
SpeA	0.742**	0.850**	1.774**	0.459**	0.469**	0.478 **
SpeB	0.290	0.304 *	0.334**	0.161**	0.163**	0.128 **
SpeC	1.255**	1.195**	0.204	0.872**	0.873**	0.885 **
SpeD	-0.042	-0.031	0.188	0.014	0.005	0.007
SpeE	0.142	0.132	-0.089	0.021	0.022	0.018
SpeF	0.267	0.170	0.331	0.080**	0.083**	0.095 **
SpeG	0.433	0.425 *	0.428	0.506**	0.522**	0.522 **
SpeH	0.578**	0.545**	0.052	0.311**	0.314**	0.285 **
Ln_r		2.556			2.411	
Ln_s		1.488			3.210	
Inflation model (logit)						
Constant			0.964			
SpeA			1.254			
SpeB			-0.160			
SpeC			-2.249**			
SpeD			0.198			
SpeE			-0.545			
SpeF			0.462			
SpeG			0.451			
SpeH			-1.472			
Number of obs.	464	503	503	499	503	503
Number of groups	9	22	22	18	22	22
Wald chi2	115.20**	122.40**		2746.73**	2832.37**	
Loglikelihood	-201.35	-237.10	-227.67	-1334.04	-1425.57	-1323.28
LR Test Panel vs Pooled		3.28**			58.84**	

Notes:
IPC Sections to construct the specialization indexes (spe): A Human Necessities; B Performing Operations; Transporting; C Chemistry; Metallurgy; D Textiles; Paper; E Fixed Constructions; F — Mechanical Engineering; Lighting; Heating; Weapons; Blasting: G Physics; H Electricity.
- **, * denote that coefficients are statistically different from zero at the 5% and 10% levels, respectively.
- All models include year dummies for 1997- 2007.
- VIF suggests no signs of multicollinearity.
- Likelihood ratio test favors Poisson over NB in Models 3 and 6.
- Vuong statistics favors ZINB over NB in Model 3 and NB over ZINB in Model 6.