Knowledge flows, the influence of national R&D structure and the moderating role of public-private cooperation

Joaquín M. Azagra-Caro[1,2,*] · Davide Consoli[1]

Abstract This paper analyses country-specific determinants of knowledge flows with a view to uncover the role of cross-organizational interactions. Using a sample of some 600,000 patents from the EU27 member states in the period 1990-2007, we take backward citations as dependent variable and find that technological sophistication and research size have a positive effect on knowledge flows. While a national bias towards applied research and development has a negative impact, individual public-private cooperation has a moderating effect due to the generation of scientific knowledge by public institutions. The present study contributes to the debate concerning the direction of R&D investments and provides empirical support to policies aimed at the enhancement of public-private cooperation.

Keywords Knowledge flows • National innovative capacity • Patents • Citations

JEL codes O31 • O33 • O34

1. Introduction

A knowledge flow consists in the transmission of information between two parties via specific communication channels whose viability is crucial for successful knowledge creation, both within organizations and countries (Nonaka 1994). In spite of well-known limitations, patent citations are widely held as reliable indicators of knowledge flows (see e.g. Jaffe et al. 1993; Roach and Cohen 2013). Patents are codified sources of

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[*] J. M. Azagra-Caro (✉)
INGENIO (CSIC-UPV), Universitat Politècnica de València, Camino de Vera s/n, E-46022 Valencia, Spain
European Commission, Joint Research Centre (JRC)-Institute for Prospective Technological Studies (IPTS), Edificio Expo, C/Inca Garcilaso 3, E-41092 Sevilla, Spain
e-mail: jazagra@ingenio.upv.es

D. Consoli
INGENIO (CSIC-UPV), Universitat Politècnica de València, Camino de Vera s/n, E-46022 Valencia, Spain

scientific and technological information about new knowledge (invention) and knowledge flows (the state-of-the-art). Examiners and applicant(s) include citations to previous patents and other documents that question or vindicate the novelty of the invention, thus conveying a description of part of the knowledge flows related to the patent (Narin et al. 1997). Depending on the direction, patent citations can be either backward or forward. The former include citations to a document that was published prior to the document citing one while posterior documents citing prior literature generate ‘forward citations’. Backward citations are commonly used as an indicator of the pool of knowledge underpinning the patented invention or, put otherwise, to capture its degree of localization (Almeida and Kogut 1997). Forward citations instead are used to gauge the technological impact of an invention (Bacchiocchi and Montobbio 2009).

While by and large previous research has focused on forward citations (e.g. Fier and Pyka 2014) less attention has been paid to backward citations and to their links with the broader institutional environment. Backward citations are good predictors of forward citations and, thus, of the value of a patent (Harhoff et al. 2003; Hall et al. 2005; Kamiyama et al. 2006; Yang e al. 2010). In our view, understanding the determinants of backward citations holds the promise of revealing important features of knowledge flows. The amount of citations contained in a patent varies across technologies, years, filing through the United States or the European Patent Office, but these characteristics tend to be discussed in a rather descriptive fashion (Tijssen 2001; Callaert et al. 2006). In this paper we focus on the effect of *country-specific characteristics* on backward citations as a peculiar yet understudied feature of patents, in light of the widely accepted notion that resource endowment and technological specialization shape patterns of knowledge generation and diffusion (Antonelli 2008). In so doing we also uncover the connection between country-specific characteristics and knowledge flows.

The focus proposed here has conceptual and practical relevance. Country-specific characteristics are at the heart of an ongoing debate concerning the reliability of national comparisons of innovation system performance. Policy-oriented studies seeking to establish rules of thumb for enhancing innovation opportunities have spurred benchmarking studies that analyse innovation indicators to identify best practices and to derive policy recommendations (see e.g. OECD 1998). However, as Balzat and Hanusch (2004) point out, although this stream of research enriches the set of empirical indicators and methods, it obscures systemic dissimilarities across different national contexts. In relation to the theoretical debate the present paper addresses this shortcoming by proposing a connection between different approaches to national competitiveness. More specifically, we explore the influence of the background conditions for knowledge flows such as technological sophistication, research size, composition of R&D funding and expenditure, and public-private cooperation along the tracks of previous work (Griliches 1992; Branstetter 1998).

The remainder of the paper is structured as follows. Section 2 introduces the main conceptual issues; Section 3 presents the data and the methodology, and Section 4 provides a discussion of the results and their implications. Section 5 concludes and summarizes the main findings.

2. Background literature and research hypotheses

This section reviews three strands of literature and elaborates the three main hypotheses of the paper.

2.1. Technological sophistication and research size

For the purposes of this paper we focus on the concept of 'National Innovative Capacity' (NIC) proposed by Furman et al. (2002: 900). NIC is defined as 'the ability of a country to produce and commercialize a flow of innovative technology over the long term' as a framework to analyse the interplay among quality of common innovation infrastructure, cluster conditions and linkages to measure. This concept draws on endogenous growth theory (see e.g. Romer 1990), international competitiveness (Porter 1990) and the traditional national innovation systems approach (Freeman 1987).

Quality of the common innovation infrastructure (not to be confused with quality of innovation) is a term also coined by Furman et al. (2002) in reference to several types of inputs for innovative capacity, e.g. technological sophistication and research size. Empirical measures expressing economic, scientific or technological strength are positively related to NIC (Furman et al. 2002; Furman and Hayes 2004; Hu and Matthews 2005; Hu and Matthews 2008; Doyle and Connor 2013).

This positive association suggests that large technological sophistication and research size mitigate the complex coordination challenges that usually arise in the presence of distributed knowledge-creating entities. This leads us to put forth the following:

Hypothesis 1. Technological sophistication and research size positively influence knowledge flows.

2.2. The structure of funding and performance of research and development

In this section, we examine two measures of the R&D structure: share of business R&D funding, and share of university R&D expenditure. According to Sapir (2003) a large share of business funding of R&D is a good indicator of differences between more or less innovative country blocks (such as US versus EU), or between countries within Europe –for example Finland, Sweden and Germany compared to Mediterranean countries. The widespread decrease in business R&D funding observed across OECD countries in 1981–2003 (Dinges et al. 2007) has occasionally become the target for policy. For example, the Lisbon Strategy in 2000 set a target of two-thirds of total R&D funding should be business funding compared to the (then) 55% share (target set at Barcelona in 2002, EC 2002: 24).[1]

Furman et al. (2002) put business R&D funding at the core of their NIC concept, and use the fraction of total R&D spending funded by the private sector as the main indicator of the vitality of the national environment for innovation. The main result of this study is that business R&D funding has a positive effect on NIC (measured as number of patents) in various developed OECD economies (Furman et al. 2002). This holds true also for catching-up countries (Furman and Hayes 2004), most prominently latecomer East Asian economies (Hu and Matthews 2005) and China (Hu and Matthews 2008). The positive effect holds only for small open economies while in others the effect is negative (Doyle and Connor 2013).

Despite this established view that a large share of business R&D funding at country level has a positive impact on knowledge production, we expect the impact on knowledge flows to be negative. This is because business firms tend to fund corporate R&D that is expected to be profitable while governments pursue social benefits that other actors are unlikely to support (Nelson 1959; Arrow 1962; Wallsten 2000). Put otherwise, business funding is usually aimed at less risky inventive efforts and shorter-term research with tangible results, that is, applied R&D rather than basic research. Applied R&D is more likely to generate incremental rather than radical innovations and, as Azagra-Caro et al. (2009) show, knowledge flows are scarce in geographic contexts where incremental invention prevails. Moreover, sectors specialized in incremental innovation benefit especially from changes in demand and interactions with customers and suppliers, compared to sectors oriented more towards radical innovation and, consequently in search of scientific and technological knowledge flows, for example, science-based sectors (Schartinger et al. 2002). The preference among business R&D funders for

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[1] Interestingly, if we include also non-university public research organizations, the share of business funding of R&D in the higher education and government sectors is found to increase in Europe, and is higher than in US (De Backer et al. 2008).

activities that involve less intensive knowledge flows raises concern when firms outsource these activities to universities or public research organizations (Goldfarb 2008).

However, business R&D funding is only one facet of the institutional structure of national R&D. The share of university expenditure on R&D is another important determinant of innovation according to the NIC approach. Furman et al. (2002) advocate that university research is more accessible to industry than government laboratory research, and that universities are a locus of exchange of ideas and produce skilled graduates for industry. While they find a positive effect of share of university R&D in innovation results are less robust in relation to the funding structure, in particular the effect is insignificant for follower countries (Furman and Hayes 2004), and latecomer East Asian countries (Hu and Matthews 2005) except China (Hu and Matthews 2008). The effect is positive, but smaller for Spain (Buesa et al. 2002) and for small open economies, while it is negative for the remaining countries (Doyle and Connor 2013). A caveat in the article by Furman et al. may explain the scant evidence available. Their argument about the importance of universities suggests a positive effect of the intensity of university R&D expenditure on innovation, for example, university R&D over GDP. However, their construct – share of university expenditure over total government expenditure on R&D (GERD) – has little to do with the intensity of academic R&D because countries with a high share of university R&D expenditure may simply have very few firms able to conduct R&D, which is not necessarily to imply that their universities are scientifically strong. In fact, it is difficult to predict the effect of the institutional structure of R&D expenditure on patenting. By contrast, empirical evidence that a large proportion of R&D performed by universities in a country produces a direct positive effect on patenting suggests that the former is an indicator of the industrial orientation of universities' R&D, e.g. because they work for industry and/or because they own many patents, which varies across countries (Azagra-Caro 2014; Fisch et al. 2014).

As in the case of a large share of business funding, we posit that industrial orientation of national R&D carried out in universities leads to fewer knowledge flows because of narrower involvement of universities with the remit of industry compared to academic activities. On the basis of these premises we propose:

Hypothesis 2. Patents originating from countries with higher shares of business funding of R&D relative to other sources, and higher shares of university expenditure of R&D relative to other performers, will capture fewer knowledge flows.

2.3. The moderating role of public-private cooperation

Empirical studies show that the interplay between firms and their operating environment is essential for knowledge creation. A chief cause of growing reliance on external knowledge is the necessity to coordinate different forms of knowledge embedded in increasingly complex production processes (Howells 2000). Cross-country studies on innovative activities in the manufacturing industries show that information networks are crucial for innovative outcomes (see e.g. De Bresson and Amesse 1991). In a nutshell, isolated firms achieving innovation through their own resources are 'rare events'. At the same time, collaboration with public research institutions is not always a recipe for success. As Hall (2002) shows, universities tend, perhaps naturally, to be involved in radically new applications of previously known technology. The broader point is that public-private cooperation occurs more frequently in endeavours where the expertise of research institutions is needed to reduce the margins of uncertainty. This echoes the old adage that public R&D is a framework condition for innovative performance (Mansfield 1998). From the point of view of academics, engagement in contract research coincides with increased publication output without affecting the nature of the publications involved (Van Looy et al. 2004)[2]. Building on the above, we put forth the following:

Hypothesis 3. Public-private cooperation has a positive moderating effect on the relationship between the share of business R&D funding and knowledge flows, and on the relationship between the share of university R&D expenditure and knowledge flows.

3. Methodology and data

The remainder of the paper proposes an empirical verification of the hypotheses based on a large sample of patents in the period 1990-2007. We focus on applications filed at the European Patent Office (EPO) because it is a quality patent system (Saint-George and van Pottelsberghe 2013) and references may reflect knowledge flows better than national patent systems. Moreover, the case of EPO is adequate to the goal of this paper

[2] Other forms of cooperation encompass private-private and public-public. We focus on public-private cooperation because of its inter-sectoral nature, as opposed to the intra-sectoral style of private-private and of public-public cooperation. In a study on knowledge flows measured by patent citations, inter-sectoral cooperation appears as the most appealing option because it entails accounting for the diversity of attitudes and cultural differences towards openness and intellectual property (Stevens et al. 2013). Actually, in studies about patents the most analysed inter-sectorial co-patenting activity is university-firm patents, which makes sense because it is associated with higher market value (Belderbos et al. 2013). Conversely, public-public co-ownership is very marginal and often subsumed within one category of single-authorship (Callaert et al. 2013).

because it is an international patent office with the same requirements for every country, so national differences cannot be attributed to different patent systems.

Our measure of knowledge flows is number of backward citations in patent data collected by the Institute for Prospective Technological Studies (IPTS) in 2009.[3] Backward citations are citations to previous patents or other published documents, mainly scientific articles. Figure 1 synthesizes the sample construction.

{Figure 1 around here}

Using EPO Worldwide Patent Statistical Database (PATSTAT) we constructed a dataset of nearly 650,000 patents applied for by applicants located in any of the EU27 Member States in the period 1997-2007. The data set, similar to the one prepared by Lecocq et al. (2008), contains individual patent applications and grants and excludes utility models. The original dataset containing the number of backward citations of direct EPO patents was integrated with additional information on the number of backward citations of EPO-PCT filings using OECD patent databases.

In the final sample of over 700,000 patents the average number of applicants from different countries per patent is 1.1.[4] Patents with missing information (mainly related to technology class) and outliers (patents with at least 20 backward citations, according to the Hadi method) are excluded. Finally, we matched country of the citing applicant (in a given year) to Eurostat national economic and R&D statistics (with a lag of two years). The final sample includes more than 560,000 observations.[5]

The average number of backward citations per patent is about 5. Figure 2 suggests that there is country variation in the number of citations per patent. Most differences in this figure are significant according to t-tests. Patents with US co-applicants include more citations (6.01), perhaps due to the cultural differences created by the USPTO duty of candour, which requires applicants not to report the state-of-the art so selectively as the EPO system. Among EU27 countries, the highest numbers of citations (5.44) are in patents from Belgium while the lowest numbers (4.66) are in patents from Sweden.

{Figure 2 around here}

We explain the determinants of backward citations using the following model:

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[3] 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.
[4] Patents featuring a non-EU27 co-applicant were counted twice. For the econometric analysis, we use as a weight variable the share of number of applicants to avoid double counting.
[5] Since we dropped many observations due to missing national data, there may be a bias. We deal with this issue at the end of the results section.

$$nbackcit_{ijk} = f(epopct_i, appy_i, IPC_i, institutional\ \text{sector}_j, public\text{-}private\ cooperation_j, \\ non-EU27\ co\text{-}applicants_j, per\ capita\ GDP_k, sHTE_k, GERD_k, sBFRD_k, sHERD_k, \\ sBFRD_k \times public\text{-}private\ cooperation_j, sHERD_k \times public\text{-}private\ cooperation_j, u_i, \varepsilon_k) \tag{1}$$

i=patent, j=applicant, k=country of applicant

Table 1 presents the list of variables and their description.

Country variables are lagged two years before application year. Per capita GDP, sHTE and GERD measure technological sophistication and research size and allow us to test Hypothesis 1. The variables sBFRD and sHERD directly refer to Hypothesis 2. The interaction terms sBFRD x public-private cooperation and sHERD x public-private cooperation allow us to test Hypothesis 3, u is the idiosyncratic error and ε is an unobserved cluster-effect capturing the influence of the group (country). The remainder are control variables for patent and applicant characteristics.[6]

{Table 1 around here}

The number of backward citations is a count outcome and negative binomial is preferred to Poisson on the basis of overdispersion tests. Preference for standard or zero inflated negative binomial changes across tables according to Vuong statistic (see table foots). Models include standard errors clustered by country.

4. Results

Table 2 presents some descriptive statistics for the whole sample. 55% of the patents are EPO direct applications, 45% are EPO-PCT applications. The most represented technology is in the class ‘Performing Operations; Transporting’. Business firms comprise 88% of patent applicants in collaboration with university or government bodies in only 0.4% of cases. The sample includes 1% of non-EU27 co-applicants. The countries considered have real per capita GDP over 25,000 euros, a share of 19% of high-tech exports over total exports, a GERD of almost 30,000 million Purchasing Power Standards (PPS), 57% of BFRD over GERD and 19% of HERD over GERD.

{Table 2 around here}

[6] To test Hypothesis 1, we tried to include additional national characteristics such as full-time R&D personnel, human resources in science and technology, value of high-tech exports, gross domestic product, etc. We were particularly interested in full-time R&D personnel to closely replicate other works on national innovative capacity (see references in section 2), however, they were excluded because of high multi-collinearity. To test Hypothesis 2, we used share of the sum of higher education plus government expenditure rather than higher education only, which is sensible because in some countries, both are heavily intertwined and the results are similar. However, because we found less theoretical support for this procedure, we prefer to present the results for higher education only. Finally, we tried country fixed effects but they were highly collinear.

In Table 3, we can see correlations between variables and the Variance Inflation Factor, which indicates no multicollinearity.

{Table 3 around here}

Table 4 shows that EPO-PCT patents have more citations than direct EPO patents. The positive, significant time trend (application year) shows that more recent patents receive more citations. There is variation according to the technology class of the patent: belonging to classes A, B, C, F and G increases the number of citations, being in E has no effect, and being in D and H decreases the number. For institutional sectors, companies are the benchmark. Patents applied for by applicants from other institutional sectors have more citations, as shown by the positive and significant coefficients. Our variable for public-private cooperation is also positive and significant, so if companies co-apply for patents with universities and/or government bodies, the number of citations increases. Having non-EU27 co-applicants does not have a significant effect.

{Table 4 around here}

Regarding applicant country characteristics, more citations correspond with higher levels of per capita GDP, larger shares of high-tech exports, the proxies for technological sophistication. This partially supports Hypothesis 1 and resonates with previous literature. Both GDP per capita and high-tech export capacity signal the existence of sound knowledge pathways which is in turn a key precondition for the proliferation of innovation activities. This is especially true in a systemic perspective whereby accumulated knowledge is essential not just in the exploratory stages, but throughout the entire innovation process, via incremental feedback generated through collaboration across specialized actors (sees e.g. Kline and Rosenberg 1986). In turn citations reflect, if partially, the overall commitment of actors within these systems to develop and improve incrementally technology either by developing internally new knowledge or through acquisition from external sources. However in this first specification, research size measured through GERD, is not significant, which means that Hypothesis 1 is not confirmed.

Looking at the marginal effects, the number of backward citations increases by 10 with a 1% increase in per capita GDP and by 0.7 with a 1% increase in share of high-tech exports.

The average patent has fewer citations if the applicant is from a country with higher shares of business funding and university expenditure over total R&D, although the latter effect is not significant. This partially supports Hypothesis 2. Marginal effects indicate that a 1% increase in share of BFRD causes a 1.0 decline in the number of backward citations.

The interaction terms between sBFRD, sHERD and the variable 'public-private cooperation' are positive and significant. This confirms Hypothesis 3 and suggests that individual interactions moderate the negative effect of R&D oriented towards applied purposes.

The negative sign of HERD, even if not significant, may sound counterintuitive. Our interpretation after section 2.2 is that high shares of HERD do not indicate strength of universities but industrial and applied orientation. To illustrate, 0 shows no correlation between the share of university R&D expenditure in total GERD with university R&D intensity, while a correlation exists between share of business funding of university R&D (positive sign) and share of university R&D corresponding to basic research (negative sign). Hence, in Eurostat countries (mostly European) where universities account for the largest share of basic research, business firms fund relatively more R&D, mostly applied in nature.

{Table 5 around here}

A field in the database reproduces PATSTAT classification of citations according to citations to patent and non-patent literature (PL and NPL). We split the sample to carry out a robustness test given that PL is more closely associated with a more applied knowledge base compared to NPL. Since we justified that the negative effect of share of business funding and university expenditure on the knowledge base on the basis that they indicate an applied orientation of the economy, we expect that Hypothesis 2 and Hypothesis 3 will hold especially for NPL –NPL in view of the fundamental nature of the knowledge base.

The results in Table 6, Column 1, show that for PL, Hypothesis 1 holds for research size and not for technological sophistication. Hypothesis 2 does not hold. Notice also that the coefficient of public-private cooperation is no longer positive but negative and significant (0.11 in Table 4 versus -0.06 in Table 6, Column 1). This lessens the expectation that Hypothesis 3 will hold, because the sign of public-private cooperation for PL goes in the same direction as that of share of business funding. Actually, the interaction terms are not significant so we find no support for Hypothesis 3: i.e. public-private cooperation does not moderate the impact of the composition of R&D funding and expenditure on PL.

In Column 2, we see that for NPL, in general, all the hypotheses hold. The only surprising exception with regards to Hypothesis 1 for NPL is the negative sign of GERD, but the marginal effect is not significant. On the other hand, the evidence supports Hypothesis 2. The support is stronger compared to the aggregate model, since both the share of BERD and of HERD are negative and significant. The sign of public-private cooperation is positive (as in the pooled regression of Table 4) to indicate a moderating effect on the composition of R&D funding and expenditure. Thus, we conclude, Hypothesis 3 is valid for PL.

The opposite effect of public-private cooperation on PL and NPL deserves some more attention. Universities and government bodies have a higher propensity to include backward citations (Table 4), which is due to larger numbers of citations to NPL, since the number of citations to PL is smaller (Table 6). An interpretation of the opposite effect of public-private cooperation on PL and NPL may be that cooperation with business firms does not alter the nature of the knowledge base of universities and of government bodies. Rather business firms adapt to the higher scientific and fewer technological content of their public partners' knowledge base. Such an impact is strong enough at national scale to moderate the negative effect of the applied orientation of R&D on scientific knowledge flows, not on technological knowledge flows.

{Table 6 around here}

The issue of sample selection because of missing data deserves further research. We conducted a Kruskal-Wallis rank test between the sample used so far (563,360 observations with data on country characteristics) and the lost data (back to Figure 1: 131,610 observations). The test rejects the equality of both populations (χ^2=447.9 with 1 d.f. significant at 1%). In an attempt to correct this, we define the variable "sample" equal to 1 if the observation has information about country characteristics, and estimate a Heckman selection model where the selection equation is:

$$\begin{aligned} sample_{ijkt} = f\,(&epopct_{it}, appy_{it}, IPC_{it}, institutional\ \ sector_{jt}, public\text{-}private\ cooperation_{jt}, \\ &non\text{-}EU27\ co-applicants_{jt}) \end{aligned} \qquad (2)$$

Estimation of equation 2 is available upon request. Table 7 contains the estimation of equation 1 after selection into the sample[7]. While previous results hold in general, Hypothesis 1 is found to be reinforced: GERD is significant for the aggregate (Column 1) and per capita GDP is significant for PL (Column 2).

{Table 7 around here}

5. Concluding remarks and further research

Our empirical analysis of the determinants of knowledge flows suggests that the overall economic, scientific and technological resources of a country are positive predictors of knowledge flows. This resonates with the literature on the use of backward citations in patents as a measure of knowledge flows (see e.g. Jaffe et al. 1993; Narin et al. 1997) as well as with empirical studies calling for a deeper understanding of the role of technological

[7] This specification requires the transformation of the dependent variable *nbackcit* into log(*nbackcit*+1).

sophistication and research size on knowledge flows (Griliches 1992; Balzat and Hanusch 2004). The policy implication stemming from our work is that promoting both knowledge creation in the terms of other studies as well as knowledge flows in the terms of the present study is compatible through improvements in the resources of a national innovation system.

At the same time we find that the composition of R&D by institutional sector (funding and expenditure) matters for knowledge flows. This calls for policies that set targets for share of business R&D funding and share of university R&D expenditure. Indeed we find that a stronger bias towards private enterprise in the composition of total R&D has a negative impact on the extent to which inventors and examiners acknowledge the state-of-the-art. This result casts under a new light on the role of business R&D especially compared to the literature about NIC (Furman et al. 2002). We ascribe this difference to the predominance of an incentive system that particularly privileges applied inventions and, therefore, relies on a narrower (as opposed to basic scientific) knowledge base. Since the effect of the composition of R&D by institutional sector on national patenting found in other works (see section 2.2) goes in the opposite direction, our findings suggest the existence of a trade-off between knowledge creation and knowledge flows. The intuition is that the applied orientation of research in a country will lead to higher levels of patenting but, also, to fewer knowledge flows. Policymakers seeking to maximize both will need to take this into account when setting targets for the composition of R&D.

Conversely, public-private cooperation is observed to mitigate the aforementioned bias. The policy implication is that institutional characteristics (public-private cooperation) moderate the bias of the national context. This applies more to basic than applied knowledge, that is, individual public-private cooperation changes the negative influence of an adverse applied context such that it increases the basicness of the knowledge base.

These results complement the literature on knowledge flows that so far has tended towards the analysis of forward citations (Roach and Cohen 2013) or the importance of proximity and border contiguity (Quatraro and Usai 2014). Considering the broader economic, scientific and technological environment as the explanatory dimension seems a reasonable starting point to unpack the effect of country characteristics on knowledge flows. Our study adds to the ongoing debate on the impact of resource endowments and direction of inventive efforts across national innovation systems, and confirms that the interplay between firms and their public institutional counterparts is an important propeller of knowledge flows. This latter finding resonates with the broader tendency to rely on a broader knowledge base as way to coordinate different capacities in the context of increasingly complex production systems.

No doubt, this preliminary study has several limitations. First, the aggregate level of analysis does not capture inter-industry differences in patenting, and the associated spillovers in the form of inputs to future R&D. Furthermore, the ambiguous sign of the R&D coefficient in the determination of NPL may be due to some endogenous effect of allocation decisions on the part of either public research organizations or business firms as a response to opportunities allowed by specific technological advances. At present these questions remain open and can only be unpacked by means of micro-level studies that control for the effects of cross-industry and temporal changes in the distribution of technological opportunities. In a similar fashion, our focus on inter-sectoral cooperation, although justified (see footnote 2), could be extended to extra-sectoral cooperation, thus including private-private and public-public co-ownership of patents. Finally, the extent to which private R&D is affected by particular appropriability conditions or by publicly generated benefits in areas of new technological opportunities may depend on the particular circumstances of individual countries. Greater availability of international data would allow deeper investigation of these issues in the future.

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Figures

Figure 1
EPO patents in 1990-2007 from Patstat

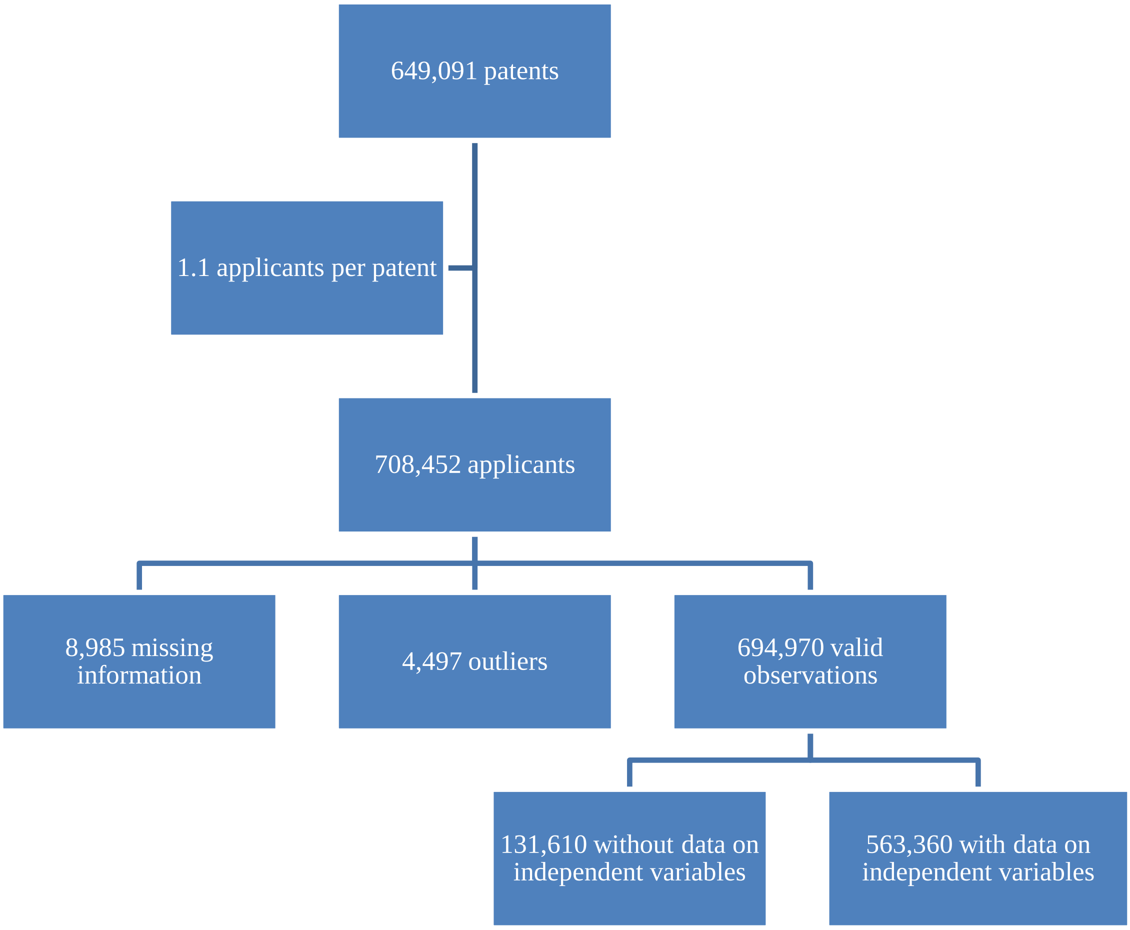
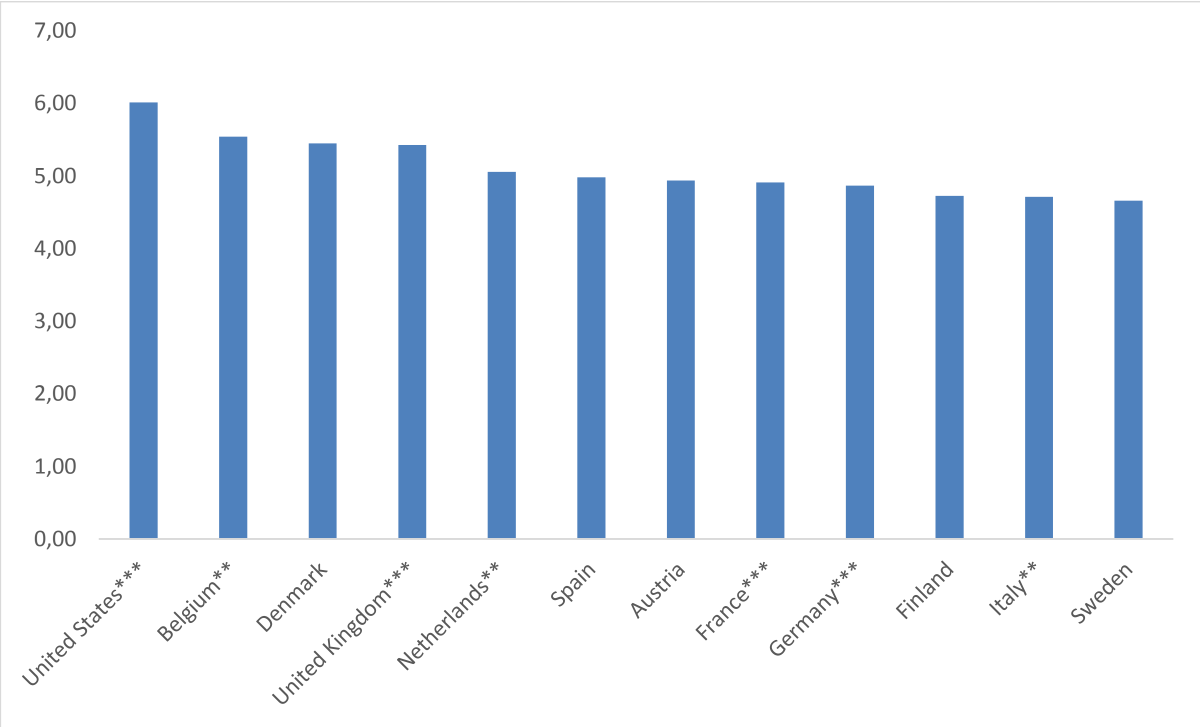


Figure 2
Mean number of citations per patent in the top applicant countries (n= 563,360)



Countries with at least 1% of total number of patent applications (over 4,500 each). Jointly they apply for 98% of all patents (45%. Germany, 53% the rest). Asterisks indicate significance of the mean difference between one country and the next one, according to t-tests. E.g. the mean number of citations per patent in US is significantly higher than in Belgium, but that number in Denmark is not significantly higher than in United Kingdom: *** Significant at 1%. ** Significant at 5%.

Tables

Table 1 List of variables

Variable	Description	Function
Patent characteristics		
nbackcit	Number of backward citations	Operationalization of knowledge flows (dependent variable)
appshare	1/Number of applicants (used as weight)	Weight variable
epopct	Dummy=1 if EPO-PCT patent, 0 if direct EPO patent	Control variables
appy	Application year	
IPC: A, B, C, D, E, F, G, H	Dummy=1 if patent classified in a given IPC	
Applicant characteristics		
Institutional sector: company, individual, non-profit, university, government, hospital	Dummy=1 if applicant classified in a given institutional sector	
Public-private cooperation (PPC)	Dummy=1 if at least one applicant is a company and at least one applicant is either a university or a government body	
Non-EU27 co-applicants	Dummy=1 if the applicant's country does not belong to the EU27	
Applicant country characteristics		
Per capita GDP	Real Gross Domestic Product (GDP): Euro per million inhabitants	Operationalization of technological sophistication and research size (to test H1)
sHTE	High-technology exports: Share of manufactured exports	
GERD	Total intramural Gross R&D expenditure (GERD): Purchasing Power Standards (PPS) at 2000 prices	
sBFRD	Business R&D funding: Share of GERD	Operationalization of shares of business funding of R&D relative to other sources and of university expenditure of R&D relative to other performers (to test H2)
sHERD	Higher education R&D expenditure: Share of GERD	
Interaction terms		
sBFRD x PPC		Operationalization of moderating effect of PPC (to test H3)
sHERD x PPC		

Sources: IPTS extraction of Patstat (patent and applicant characteristics), Eurostat (per capita GDP, GERD, sBFRD, sHERD), United Nations (sHTE).

Table 2 Descriptive statistics (n= 563,360)

Variable	Mean	Std. Dev.	Min	Max
nbackcit	4.936	2.717	0.000	19.000
epopct	0.447	0.497	0.000	1.000
appy	1,999.434	4.326	1990.000	2007.000
A Human Necessities	0.198	0.399	0.000	1.000
B Performing Operations; Transporting	0.279	0.449	0.000	1.000
C Chemistry; Metallurgy	0.197	0.398	0.000	1.000
D Textiles; Paper	0.030	0.171	0.000	1.000
E Fixed Constructions	0.058	0.234	0.000	1.000
F Mechanical Engineering; Lighting; Heating; Weapons; Blasting	0.141	0.348	0.000	1.000
G Physics	0.195	0.396	0.000	1.000
H Electricity	0.206	0.404	0.000	1.000
Company	0.877	0.328	0.000	1.000
Individual	0.083	0.276	0.000	1.000
Nonprofit	0.016	0.124	0.000	1.000
University	0.011	0.104	0.000	1.000
Government	0.013	0.113	0.000	1.000
Hospital	0.000	0.016	0.000	1.000
Public-private cooperation	0.004	0.063	0.000	1.000
Non-EU27 co-applicants	0.007	0.086	0.000	1.000
Per capita GDP †	0.025	0.003	0.002	0.065
sHTE †	0.187	0.061	0.012	0.590
GERD †	0.030	0.019	0.000	0.249
sBFRD †	0.567	0.085	0.137	0.907
sHERD †	0.192	0.044	0.002	0.671
sBFRD x Public-private cooperation	0.000	0.005	-0.396	0.198
sHERD x Public-private cooperation	0.000	0.003	-0.091	0.416

Weight variable: share of number of applicants. † Centered for the estimations.

Table 3 Correlation matrix and VIF (n= 563,360)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	VIF
1	epopct	1.00																								1.11
2	appy	0.14	1.00																							2.00
3	A	0.09	-0.02	1.00																						1.45
4	B	-0.07	-0.04	-0.20	1.00																					1.43
5	C	0.13	-0.07	0.10	-0.09	1.00																				1.28
6	D	-0.01	-0.02	-0.04	-0.02	0.01	1.00																			1.05
7	E	-0.07	-0.01	-0.10	-0.07	-0.10	-0.03	1.00																		1.16
8	F	-0.05	0.00	-0.16	-0.05	-0.15	-0.05	-0.03	1.00																	1.29
9	G	0.04	0.01	-0.15	-0.17	-0.14	-0.07	-0.09	-0.14	1.00																1.31
10	H	0.01	0.02	-0.23	-0.24	-0.19	-0.08	-0.11	-0.14	-0.01	1.00															1.54
11	Individual	0.02	-0.04	0.09	0.02	-0.09	-0.02	0.11	0.00	-0.03	-0.09	1.00														1.05
12	Nonprofit	0.04	0.00	0.01	-0.01	0.09	-0.01	-0.02	-0.03	0.03	-0.02	-0.04	1.00													1.01
13	University	0.06	0.04	0.05	-0.04	0.06	-0.01	-0.02	-0.03	0.03	-0.01	-0.03	-0.01	1.00												1.04
14	Government	0.04	-0.01	0.00	-0.03	0.05	-0.02	-0.02	-0.03	0.06	0.01	-0.03	-0.01	-0.01	1.00											1.04
15	Hospital	0.01	0.00	0.02	-0.01	0.01	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	1.00										1.00
16	Public-private cooperation (PPC)	0.03	0.01	0.02	-0.02	0.05	-0.01	-0.01	-0.02	0.01	0.00	-0.02	0.00	0.15	0.13	0.00	1.00									1.34
17	Non-EU27 co-applicants	0.02	0.00	0.02	-0.02	0.04	-0.01	-0.01	-0.02	0.02	0.00	0.00	0.00	0.02	-0.01	0.03	0.07	1.00								1.98
18	Per capita GDP	0.15	0.59	-0.01	-0.05	-0.02	-0.02	-0.02	-0.02	0.04	0.03	-0.08	-0.01	0.02	-0.03	0.01	0.01	0.14	1.00							2.13
19	sHTE	0.20	0.24	0.04	-0.10	0.00	-0.04	-0.03	-0.06	0.09	0.07	-0.06	-0.01	0.06	0.02	0.01	0.03	0.15	0.42	1.00						1.68
20	GERD	-0.06	0.21	-0.04	0.04	0.01	-0.01	-0.01	0.06	-0.01	-0.04	-0.02	0.01	-0.02	-0.01	0.02	0.04	0.56	0.11	-0.07	1.00					3.18
21	sBFRD	0.03	0.36	-0.08	0.04	-0.02	0.02	-0.01	0.05	-0.03	0.00	-0.04	0.00	-0.04	-0.07	-0.01	-0.02	0.09	0.33	-0.24	0.48	1.00				2.30
22	sHERD	0.11	0.08	0.04	-0.05	-0.02	-0.01	0.01	-0.07	0.03	0.02	0.03	-0.02	0.04	-0.03	0.00	-0.01	-0.10	0.08	0.15	-0.58	-0.47	1.00			2.21
23	sBFRD x PPC	-0.01	0.02	-0.01	0.01	-0.02	0.00	0.00	0.01	-0.01	0.00	0.01	0.00	-0.01	-0.08	0.00	-0.28	0.08	0.03	0.00	0.07	0.06	-0.02	1.00		1.32
24	sHERD x PPC	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	0.01	0.00	-0.03	-0.06	0.00	-0.28	-0.11	-0.01	-0.02	-0.10	-0.02	0.07	-0.30	1.00	1.32

Weight variable: share of number of applicants. Mean VIF: 1.51.

Table 4 Negative binomial estimation of the determinants of number of backward citations

	1 Baseline	2 Selected marginal effects	3 + Moderation terms	4 Selected marginal effects
epopct	0.15***		0.15***	
	(0.01)		(0.01)	
appy	0.23*		0.22*	
	(0.13)		(0.13)	
A Human Necessities	0.14***		0.14***	
	(0.01)		(0.01)	
B Performing Operations; Transporting	0.02***		0.02***	
	(0.00)		(0.00)	
C Chemistry; Metallurgy	0.15***		0.15***	
	(0.01)		(0.01)	
D Textiles; Paper	-0.02*		-0.02*	
	(0.01)		(0.01)	
E Fixed Constructions	0.00		0.00	
	(0.01)		(0.01)	
F Mechanical Engineering; Lighting;	0.06***		0.06***	
Heating; Weapons; Blasting	(0.01)		(0.01)	
G Physics	0.05***		0.05***	
	(0.00)		(0.00)	
H Electricity	-0.01*		-0.01*	
	(0.01)		(0.01)	
Individual	0.03*		0.03*	
	(0.02)		(0.02)	
Nonprofit	0.15***		0.15***	
	(0.02)		(0.02)	
University	0.24***		0.24***	
	(0.01)		(0.01)	
Government	0.14***		0.14***	
	(0.01)		(0.01)	
Hospital	0.27***		0.27***	
	(0.04)		(0.04)	
Public-private cooperation	0.11***		0.13***	
	(0.02)		(0.01)	
Non-EU27 co-applicants	-0.01		-0.01	
	(0.05)		(0.05)	
Per capita GDP	2.03*	10.00*	2.03*	10.03*
	(1.14)	(5.61)	(1.13)	(5.58)
sHTE	0.14*	0.70*	0.14*	0.71*
	(0.08)	(0.41)	(0.08)	(0.41)
GERD	0.51	2.52	0.51	2.54
	(0.36)	(1.77)	(0.36)	(1.77)
sBFRD	-0.20*	-0.97*	-0.20*	-0.98*
	(0.10)	(0.51)	(0.10)	(0.51)
sHERD	-0.06	-0.30	-0.06	-0.32
	(0.15)	(0.76)	(0.15)	(0.76)
Constant	-3.08		-3.05	10.03*
	(2.63)		(2.62)	(5.58)
sBFRD x Public-private cooperation			0.52***	0.71*
			(0.15)	(0.41)
sHERD x Public-private cooperation			0.67***	2.54
			(0.26)	(1.77)
Ln α	-2.75***		-2.75***	
	(0.09)		(0.09)	
Observations	563,360		563,360	
Log likelihood	-1,183,346		-1,183,339	
Clusters in country	33		33	

*** Significant at 1%. ** Significant at 5%. *Significant at 10%. Standard errors, clustered by country, below coefficients. *Company* is the benchmark for institutional types. Weight variable: share of number of applicants. Vuong statistic shows indifference of standard against zero inflated negative binomial. We have tried time dummies instead of time trend, with identical results but higher collinearity.

Table 5 Higher education expenditure on R&D in Eurostat countries, 1988-2005

	Observations	Mean	Correlation with share of gross expenditure on R&D
Share of gross expenditure on R&D	414	0.25	1.00
Percentage of gross domestic product	453	0.32	0.11
Share of business funding	389	0.07	0.21*
Share of basic research	197	0.54	-0.43*

* Significant at 1%. Source: own elaboration from Eurostat data.

Table 6 Zero inflated negative binomial estimation of the determinants of number of backward citations: PL vs. NPL

	1 Patent literature	2 Selected marginal effects	3 Non-patent literature	4 Selected marginal effects
epopct	0.03***		0.97***	
	(0.01)		(0.02)	
appy	0.19		0.15	
	(0.13)		(0.21)	
A Human Necessities	0.07***		0.28***	
	(0.01)		(0.03)	
B Performing Operations;	0.11***		-0.98***	
Transporting	(0.01)		(0.03)	
C Chemistry; Metallurgy	-0.06***		0.88***	
	(0.01)		(0.06)	
D Textiles; Paper	0.06***		-0.82***	
	(0.01)		(0.07)	
E Fixed Constructions	0.07***		-1.60***	
	(0.01)		(0.06)	
F Mechanical Engineering; Lighting;	0.13***		-1.29***	
Heating; Weapons; Blasting	(0.00)		(0.04)	
G Physics	-0.04***		0.50***	
	(0.01)		(0.04)	
H Electricity	-0.07***		0.39***	
	(0.01)		(0.04)	
Individual	0.06***		-0.19	
	(0.01)		(0.13)	
Nonprofit	-0.09***		0.49***	
	(0.01)		(0.03)	
University	-0.20***		0.58***	
	(0.01)		(0.06)	
Government	-0.14***		0.46***	
	(0.01)		(0.04)	
Hospital	-0.25***		0.57***	
	(0.10)		(0.12)	
Public-private cooperation	-0.06***		0.30***	
	(0.02)		(0.03)	
Non-EU27 co-applicants	-0.09		0.17**	
	(0.06)		(0.07)	
Per capita GDP	1.65	6.92	5.90*	4.00
	(1.02)	(4.30)	(3.09)	(2.08)
sHTE	0.05	0.20	0.41**	0.28*
	(0.06)	(0.27)	(0.20)	(0.14)
GERD	0.71*	2.97*	-0.79*	-0.54
	(0.41)	(1.70)	(0.48)	(0.33)
sBFRD	-0.12	-0.51	-0.45***	-0.31**
	(0.11)	(0.45)	(0.13)	(0.09)
sHERD	0.02	0.08	-0.51***	-0.35**
	(0.14)	(0.60)	(0.18)	(0.12)
sBFRD x Public-private cooperation	-0.01	-0.04	1.78***	1.21**
	(0.25)	(1.06)	(0.33)	(0.22)
sHERD x Public-private cooperation	-0.38	-1.60	2.26***	1.53**
	(0.51)	(2.15)	(0.47)	(0.31)
Constant	-2.41		-3.51	
	(2.55)		(4.07)	
Inflation constant	-4.98***		0.24***	
	(0.30)		(0.07)	
Ln α	-3.20***		-0.25**	
	(0.14)		(0.11)	
Observations	563,360		563,360	
Zeros	17,391		440,620	
Log likelihood	-1,127,824		-451,567	
Clusters in country	33		33	

*** Significant at 1%. ** Significant at 5%. *Significant at 10%. Standard errors, clustered by country, below coefficients. *Company* is the benchmark for institutional types. Weight variable: share of number of applicants. Vuong statistic shows preference of zero inflated against stardard negative binomial. We have tried time dummies instead of time trend, with identical results but higher collinearity.

Table 7 Heckman selection model of the determinants of number of backward citations

	1 All citations	2 Patent literature	3 Non-patent literature
epopct	0.12***	0.01	0.15***
	(0.02)	(0.03)	(0.01)
appy	-0.98	-0.01	-0.03
	(0.93)	(0.11)	(0.07)
A Human Necessities	0.11***	0.06***	0.11***
	(0.01)	(0.02)	(0.01)
B Performing Operations; Transporting	0.02***	0.11***	-0.15***
	(0.01)	(0.00)	(0.01)
C Chemistry; Metallurgy	0.08***	-0.07**	0.34***
	(0.01)	(0.03)	(0.02)
D Textiles; Paper	-0.00	0.09***	-0.13***
	(0.01)	(0.01)	(0.01)
E Fixed Constructions	0.00	0.07***	-0.12***
	(0.01)	(0.01)	(0.01)
F Mechanical Engineering; Lighting; Heating; Weapons; Blasting	0.04***	0.11***	-0.13***
	(0.01)	(0.01)	(0.01)
G Physics	0.03**	-0.06***	0.16***
	(0.01)	(0.02)	(0.01)
H Electricity	-0.03	-0.07**	0.10***
	(0.02)	(0.03)	(0.01)
Individual	0.04***	0.08***	-0.06**
	(0.02)	(0.01)	(0.03)
Nonprofit	0.08**	-0.15***	0.35***
	(0.04)	(0.03)	(0.05)
University	0.20***	-0.22***	0.63***
	(0.04)	(0.05)	(0.02)
Government	0.05*	-0.22***	0.41***
	(0.03)	(0.03)	(0.02)
Hospital	0.21**	-0.31**	0.70***
	(0.08)	(0.12)	(0.11)
Public-private cooperation	0.10***	-0.09***	0.28***
	(0.02)	(0.03)	(0.03)
Non-EU27 co-applicants	0.10	0.07	0.14***
	(0.16)	(0.19)	(0.04)
Per capita GDP	1.90**	1.57*	1.02
	(0.96)	(0.88)	(1.37)
sHTE	0.12**	0.03	0.18**
	(0.06)	(0.05)	(0.09)
GERD	0.56*	0.59*	-0.30
	(0.32)	(0.35)	(0.23)
sBFRD	-0.19**	-0.10	-0.15***
	(0.08)	(0.09)	(0.03)
sHERD	-0.05	0.02	-0.16*
	(0.12)	(0.12)	(0.08)
sBFRD x Public-private cooperation	0.46***	-0.06	0.80**
	(0.12)	(0.22)	(0.40)
sHERD x Public-private cooperation	0.65**	-0.29	1.40**
	(0.29)	(0.41)	(0.68)
Constant	21.35	1.92	0.80
	(18.59)	(2.23)	(1.31)
Atanh ρ	-1.16***	-1.42***	-0.08
	(0.07)	(0.03)	(0.05)
Ln σ	-0.66***	-0.56***	-0.62***
	(0.05)	(0.04)	(0.05)
Observations	694,970	694,970	694,970
Censored	131,610	131,610	131,610
Uncensored	563,360	563,360	563,360
Log likelihood	-606,705	-642,929	-719,371
Clusters in country	105	105	105

*** Significant at 1%. ** Significant at 5%. *Significant at 10%. Standard errors, clustered by country, below coefficients. *Company* is the benchmark for institutional types. Weight variable: share of number of applicants. Likelihood ratio tests justify the Heckman selection equation.