The influence of international research interaction on national innovation performance
A bibliometric approach

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DOI
10.1016/j.techfore.2015.09.017

Publication date
2016

Document Version
Accepted author manuscript

Published in
Technological Forecasting and Social Change

Elsevier Editorial System(tm) for Technological Forecasting & Social Change
Manuscript Draft

Manuscript Number:

Title: The Influence of International Research Interactions on National Innovation Performance: A Bibliometric Approach

Article Type: SI:DISC2014

Keywords: innovation; research; international; bibliometric; patents

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Abstract: International research interactions (IRIs), specifically co-invention, co-assignment and the international appropriation of inventions, are increasing as a result of globalization and rising technological complexity. Yet the impact of IRIs on national innovation performance is ambiguous. In this study patent-based bibliometric indicators are developed to investigate the influence of IRIs on innovation performance using bibliometric and statistical data covering six knowledge intensive sectors and 32 countries during the 2003-2008 period. This sector-based approach avoids some of the problems of using patents as innovation indicators, notably varying patenting propensities across sectors. The study uses patent grants published by the United States Patent & Trademark Office (USPTO) and statistical data from the OECD to estimate a patent production function. The use of patent-based bibliometric indicators is partially validated using the statistical data and published outcomes from the literature. The results suggest that IRIs have no or a statistically significant negative influence on national innovation performance, especially in the case of the international appropriation of inventions, which can be seen as a proxy for the presence of international organisations such as multinational corporations (MNCs) in a particular sector and country. The potential policy implications and theoretical relevance of these findings are also discussed.

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Submission to TFSC DISC 2014 Special Edition

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15 March 2015

ABSTRACT
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HIGHLIGHTS
* No or negative correlation between international research interaction (IRI) indicators and innovation performance
* Results suggest negative impact of local presence of international organisations on local innovation performance
* Development and validation of patent-based innovation indicators with statistical data and previous studies
* Compares six knowledge intensive sectors instead of aggregate national patent data
* Dataset covers 32 countries during 2003-2008 period

KEYWORDS
innovation; research; international; bibliometric; patents

1 INTRODUCTION

International research interactions, specifically international research collaboration and the global distribution of research activities, are increasing as a result of rising technological complexity and the ongoing process of economic globalization (Audretsch, Lehmann, & Wright, 2014; Locke & Wellhausen, 2014). This leads to increased competition between firms and the global division of labour in Research & Development (R&D), urging firms and other actors in knowledge creation and use (such as universities) to source knowledge internationally and to establish a presence in multiple locations around the world (Altbach, Reisberg, & Rumbley, 2009; Awate, Larsen, & Mudambi, 2014; Castellani, Jimenez, & Zanfei, 2013; OECD, 2007). International research interactions are especially prevalent in knowledge intensive sectors (B Asheim & Gertler, 2005; Malecki, 2014). These sectors have great strategic economic value because of the high barriers to entry created by complex institutional, technological and knowledge networks which cannot easily be replicated (Malerba, 2002; Porter, 1990). Knowledge intensive sectors continue to account for the largest share of economic growth in developed economies (Powell, Snellman, & Walter, 2013).

Despite the rapid growth of international research interactions, its influence on local innovation performance is ambiguous. On the one hand, the positive influence of international knowledge spillovers is supported by theory (Bathelt, Malmberg, & Maskell, 2004; Freeman, Hutchings, Lazaris, & Zyngier, 2010; Gertler, 2003) and several empirical studies (Grossman & Helpman, 1991; Guan & Chen, 2012; Guellec & Van Pottelsberghe de la Potterie, 2001; Hottenrott & Lopes-Bento, 2014; OECD, 2009; Simmie, 2003). On the other hand, international research interactions have been found to weaken local research interactions under particular circumstances (Kwon, Park, So, & Leydesdorff, 2012; Leydesdorff & Sun, 2009; van Geenhuizen & Nijkamp, 2012; Ye, Yu, & Leydesdorff, 2013) and also weaken overall innovation performance in clusters (Chang, Chen, & McAleer, 2013; Propris & Driffield, 2005).

In studying innovation, patents can be regarded as a “paper trail” (Jaffe, Trajtenberg, & Henderson, 1993), containing information about the inventors, assignees, technology and institutional and interpersonal links. While there are limitations and drawbacks to using patent data as an innovation indicator (Kleinknecht, Montfort, & Brouwer, 2002), patents do contain “clues” which can expand our understanding of the innovation process. Patent output has been found to correlate fairly well with other innovation activity indicators (Acs, Anselin, & Varga, 2002). This authors also show that the number of inventors, as revealed by patent data, correlates closely to the number of researchers.

A critical issue in using patent data as an innovation indicator is the variation in patenting propensities between different sectors (Arundel & Kabla, 1998; Malerba & Orsenigo, 1996). This study tackles this problem by studying *sectors* and not aggregate patent statistics for whole *countries*, as was the case in other recent international innovation studies that use patent data (De Prato & Nepelski, 2014; de Rassenfosse & van Pottelsberghe de la Potterie, 2009). In addition to side-stepping an important methodological problem, the comparison of sectors also allows for the exploration of inter-sectoral differences in international research interactions (Iammarino & McCann, 2006; Malerba, 2002).

This study addresses two basic research questions: (1) *Does international research interaction influence national innovation performance according to patent-based indicators?* And (2): *Is there significant variation between sectors?*

By addressing these questions, this paper contributes to two types of literature. First, it contributes to the developing literature on globally distributed innovation and its management, which occurs mainly through collaborative relations within multinational corporations (MNCs). We observe a trend in which the presence of MNCs has a negative influence on innovation performance in the local innovation system. This pattern could be due to ‘reversed’ knowledge integration, in which knowledge that is produced in subsidiaries is utilized by headquarter organizations elsewhere.

The second contribution is to the methodological literature concerning the use of patent-based bibliometric indicators. One of the major drawbacks of using patents as an innovation indicator is the varying patenting propensities between different sectors. The methodology used in this paper largely eliminates variations in patenting propensity by comparing sectors, rather than using aggregate national patent indicators. The paper also offers some validation of the multi-sector comparative approach.

This paper consists of five sections. First the relevant theory is reviewed and hypotheses are formulated (section 2). This is followed by a description of the patent data set and the development of bibliometric indicators (section 3). A summary of the data, the results and analysis (section 4) comes before a brief discussion and the conclusion (section 5).

2 INTERNATIONAL RESEARCH INTERACTIONS: THEORY AND HYPOTHESES

International research interactions (IRIs) can be understood from a variety of theoretical domains, including inter-organisational learning and various concepts of a-spatial proximity, including the competitive and technological pressures that are the drivers of increasing IRIs.

IRIs exist in many forms, however this study considers two of the most significant ones: international research collaboration (both institutional and interpersonal) and the global distribution of research activities by knowledge intensive firms (especially MNCs) and other knowledge using and creating actors such as universities and public research institutions. While international research interactions do occur through other mechanisms, such as the trade in high technology goods and services, technology licensing, contract manufacturing and international labour mobility, international research collaboration appears to be rapidly growing in both developed and developing economies (Awate et al., 2014; Enkel, Gassmann, & Chesbrough, 2009; Locke & Wellhausen, 2014). Furthermore, MNCs are among the largest investors in R&D and they conduct a significant share of their research outside of their home countries, making them the dominant actors in the global distribution of innovation activities (NCSES, 2014).

The need to source knowledge globally can be understood from the perspective of rising technological complexity and global competition. Complexity makes it impossible for firms to create all necessary knowledge within their own region or country, let alone internally. Competition drives compels firms to seek out the best knowledge, wherever it may be (Archibugi & Iammarino, 2002; B Asheim & Gertler, 2005; Bathelt et al., 2004; Chesbrough, 2006; Doz, Santos, & Williamson, 2001).

International research collaboration and the global distribution of research activities are two strategies through which knowledge can be accessed. While innovation is facilitated by proximity, this proximity is not necessarily spatial (Boschma, 2005). Non-spatial proximity also clearly manifests itself as a factor in the innovation process (Bjørn Asheim, Coenen, & Vang, 2007; Birch, 2007; Ponds, Oort, & Frenken, 2007). Non-spatial proximity is related to the concept of cognitive distance, which is the extent to which different actors trust each other and share a common set of values, i.e. the extent to which they “speak the same language”, which although facilitated by geographical proximity, is not automatic and can persist over long geographical distances (Gertler, 2003; Nooteboom, 2013). These insights also build upon inter-organizational learning theory, which attaches importance to the development of interpersonal relationships, institutional support and mutual trust as a prerequisite for successful research collaboration (Dodgson, 1992).

Thus rather than claiming that innovation occurs in and through clusters, a more suitable generalization is that it is facilitated by networks which show varying degrees of spatial concentration (Ponds, Van Oort, & Frenken, 2010). An illustration of this tendency is the fact that innovative collaboration in Europe and North America tends to occur either within regions or within a distinct network of cities and regions, instead of being geographically distributed or highly localized (Acs, Audretsch, & Feldman, 1994; Anselin, Varga, & Acs, 1997; Fischer & Varga, 2003; Jaffe, 1989). Knowledge exchanges also occur in long-distance collaborative networks of social and institutional relationships (Autant-Bernard, Mairesse, & Massard, 2007; Breschi, Lissoni, & Malerba, 2003; Huber, 2012; Knoben, 2009; Ponds et al., 2010; Wilhelmsson, 2009).

Research collaboration is generally assumed to be beneficial for all participants involved (Dosi, Freeman, Nelson, Silverberg, & Soete, 1988; Gertler, 1995), provided that there is a balance of power between the participants; unequal relationships reduce the likelihood that the weaker party will benefit from research collaboration (Lazonick & Mazzucato, 2013). Power inequalities within research networks are therefore tend to reduce research collaboration (Liu, 2014). In many other areas of international relations a balance of power is not always assured, even when it involves seemingly voluntary exchanges between countries (Wallerstein, 1974). This may also be the case for IRIs.

MNCs and other globally distributed organisations have a unique advantage in that they provide an organisational structure and standard culture that reduces the aforementioned cognitive distance and thus facilitates the transfer of tacit knowledge over large distances (Awate et al., 2014; Castellani et al., 2013). MNCs are also among the largest investors in innovation worldwide, for example in the United States 72.2% of all business R&D expenditure came from US MNCs (Archibugi & Iammarino, 2002; NCSES, 2014). At the same time, increased participation by MNCs in a local innovation systems (regional or national), be it through research collaboration or commercially driven, can weaken research interactions among local actors (Kwon et al., 2012; Van Geenhuizen & Nijkamp, 2012; Ye et al., 2013), thus potentially reducing innovation performance.

It should be noted that smaller clusters tend to be more outwardly focussed than larger clusters because they lack internal knowledge resources (Huallacháin & Lee, 2014; Tödtling & Trippl, 2005). However there are also indications that absorptive capacity, i.e. the degree to which local knowledge resources are available, is a necessary factor for firms in a region to benefit from international knowledge interactions (Fu, 2008; Liefner, Brömer, & Zeng, 2012). So while innovation systems can potentially benefit significantly from IRIs (Bathelt et al., 2004), IRIs do not appear to “automatically” improve innovation performance.

The factors that influence innovation performance are summarised in a conceptual model that is shown in figure 1. Here innovation performance is primarily influenced by innovation input, of which the number of researchers is a reasonable proxy. Patent output is used as an indicator for innovation performance. The rate at which innovation inputs are transformed into innovation performance depends on the patenting propensity (which is sector-dependent) and the innovation (or patenting) efficiency, which in this study, depends on IRIs. The derivation of the patent production function that underlies this conceptual model is provided in section 3.1.

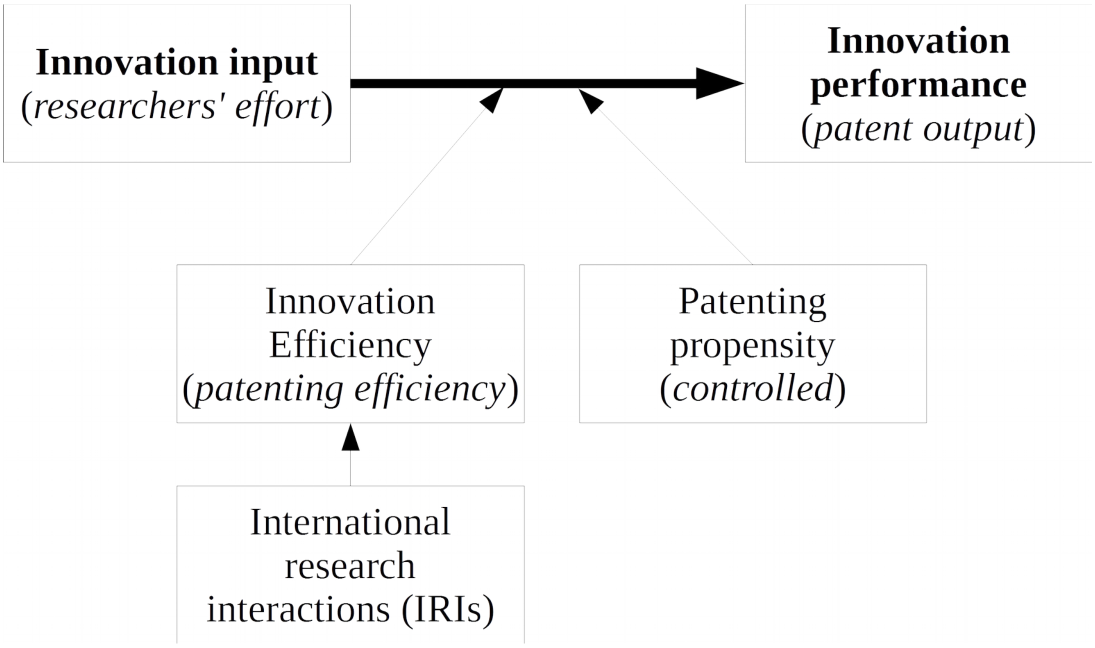


Figure 1: Conceptual model of innovation performance

Given the ambiguity in the literature about the influence of IRIs on innovation performance, we formulate six hypotheses which cover the three types of IRI: international interpersonal research collaboration, international institutional research collaboration and the participation by international entities in the local innovation system, as evidenced by the appropriation of innovation by foreign entities.

H1a: International interpersonal research collaboration correlates positively with innovation performance.
H1b: International interpersonal research collaboration does not correlate or correlates negatively with innovation performance.

H2a: International institutional research collaboration correlates positively with innovation performance.
H2b: International institutional research collaboration does not correlate or correlates negatively with innovation performance.

H3a: The local presence of international entities correlates positively with innovation performance.
H3b: The local presence of international entities does not correlate or correlates negatively with innovation performance.

The above hypotheses will be tested using a patent production function, the estimation results of which are presented in section 4. In the next section (section 3) the patent production function, indicators, dataset and methodology are discussed.

3 MODEL, INDICATORS, DATA AND METHODOLOGY

This section begins with a discussion of the patent production function, which is the model that is estimated in this study (section 3.1) and the bibliometric and statistical indicators that will be used (section 3.2). This is followed by a summary and description of the data (section 3.3) and a brief outline of the methodology, specifically how statistical data are linked to bibliometric data (section

3.4).

3.1 Patent production function

As an indicator of innovation, patent output is a reflection of different factors. In this context, the literature, as summarised by de Rassenfosse & van Pottelsberghe de la Potterie (2009), makes a useful distinction between research effort and the propensity to patent. The two concepts are connected as follows: researchers exert a research effort (L), which depending on how productive (λ) they are, leads to a number of inventions, which depending on the propensity to patent (δ), then leads to a number of patents (P). For a further illustration, also see figure 1. This relationship can also be expressed mathematically in the form of a patent production function, see equation 1. The equation is derived by de Rassenfosse & van Pottelsberghe de la Potterie (2009) from the knowledge production function (Jones, 1995; Romer, 1990).

$$P_i = \delta L_i^{\lambda} \tag{1}$$

Whereby i represents a country, or more abstractly, an innovation system. The propensity to patent (δ) is understood to be determined by IP regulations, or more broadly, by the policy environment (de Rassenfosse & van Pottelsberghe de la Potterie, 2009) and the Science & Technology policy environment of a country that may influence patenting propensity. For example, in South Korea technology venture companies can obtain loan guarantees based on their patent portfolio (O'Donnell, 2012), which is likely to raise the patenting propensity among those firms. Similarly, recent instances of world-wide patent litigation between companies such as Apple Inc. and Samsung Electronics Co. Ltd. have highlighted the strategic commercial value of holding patents.

In addition, Arundel & Kabla (1998) and Kleinknecht et al. (2002) note that patenting propensities vary significantly between industries, and this appears to be driven by technological factors: some technologies and industries may require more incremental patenting, while others have fewer patents relative to the research effort exerted. We confirm this assertion in section 4, when comparing patenting output to researchers.

The main focus of this research lies in research productivity (λ) and so we seek to control the patenting propensity so that differences in patent output can be attributed to research productivity. This is achieved in two ways: by comparing separate industries (and not national economies, whose industry composition differs significantly, see: Malerba & Orsenigo (1996)) and by using the patent data from only one jurisdiction, in this case: the United States. Since the United States is one of the largest and most open markets on earth, in which companies from around the world compete, comparing foreigners' patenting behaviour removes differences in patenting propensity, such as intellectual property rules.

Returning to the original patent production function in equation 1, and following the example of de Rassenfosse and van Pottelsberghe de la Potterie (2009), this function can also be re-written with natural logarithms (ln) as:

$$\ln P_i = \ln \delta + \lambda \ln L_i + \varepsilon_i \tag{2}$$

Here, ε_i is an error term which varies depending on each country. Based on the fact that patent data is obtained from a single industry and comparisons are made at the sectoral level, variation in patenting output relative to input should be caused by various institutional factors, including international research interactions. Thus assuming that the propensity to patent is relatively constant, de Rassenfosse and van Pottelsberghe de la Potterie (2009) propose that the patenting productivity λ consists of a constant "core" productivity, λ_c, and a variable productivity, λ_m, that depends on country-specific factors Y_m. Therefore:

$$\lambda = \lambda_c + \sum_m \lambda_m Y_m \qquad (3)$$

Equation 3 can be combined with equation 2 to yield equation 4, a model where patenting propensity is constant, but patenting efficiency varies between countries. Here Y_{mi} is the value of a particular indicator in a specific country and these indicators are multiplied by the number of researchers to reflect the relative influence of the indicators per researcher.

$$\ln P_i = \ln \delta + \lambda_i \ln L_i + \sum_m \lambda_m \ln L_i Y_{mi} + \epsilon_i \qquad (4)$$

Therefore it becomes possible to estimate various patenting efficiency indicators (λ) using linear regression analysis, and thus link these indicators to innovation performance as represented by patent output, P_i (de Rassenfosse & van Pottelsberghe de la Potterie, 2009).

3.2 Bibliometric and statistical indicators

The estimation of the patent production function as described in the previous section relies on bibliometric and statistical indicators. In total this study considers five bibliometric indicators, which are described in table 1. The first four bibliometric indicators are used in the regression analysis, while the fifth, the number of unique inventors (*INV*) is used for validation purposes, by comparing it to the number of researchers (*RES*) as published in the statistical data. See table 2 for descriptions of the statistical indicators.

Indicator	*Description*	*Formula*
P_i	Total number of patents in a particular country's sector.	n.a.
IN	International interpersonal research collaboration as evidenced by the number of patents with inventors from two or more countries: "internationally co-invented patents" (P_{IN}).	P_{IN}/P_i
AS	International institutional research collaboration as evidenced by the number of patents with assignees from two or more countries: "internationall co-assigned patents" (P_{COAS}).	P_{AS}/P_i
AP	The local presence of international entities as evidenced by the number of patents in which no assignee(s) is/are from the same country as the inventor(s): "internationally appropriated patents" (P_{AP})	P_{AP}/P_i
INV	The number of unique inventors listed on the patent records of a particular country's industry in a particular year based on the patent's application or priority date.	*n.a.*

Table 1: Bibliometric indicators

Indicator	*Description*
RES	The number of full-time equivalent researchers employed in a particular country's sector
EXP	Business research and development expenditure in a particular country's sector expressed in constant 2005 purchasing power parity United States dollars.

Table 2: Statistical indicators

3.3 Data summary and description

The data used in this study is "open" and is freely accessible via the internet. The study uses patent grants data published by the United States Patent & Trademark Office (USPTO)[1] between 2005 and 2014 and statistical data about researchers and research expenditure from the Organization for Economic Cooperation & Development (OECD)[2], see table 2.

Both of these datasets have drawbacks. The USPTO patent data requires considerable processing in order to extract data at the sectoral level, something which is further discussed in section 3.4. The OECD data is only available for a limited number of countries and sectors, and often irregularly so. It is also not a worldwide dataset, covering only countries which voluntarily submit data to the OECD. A summary of the data availability over time is presented in figures 2 and 3.

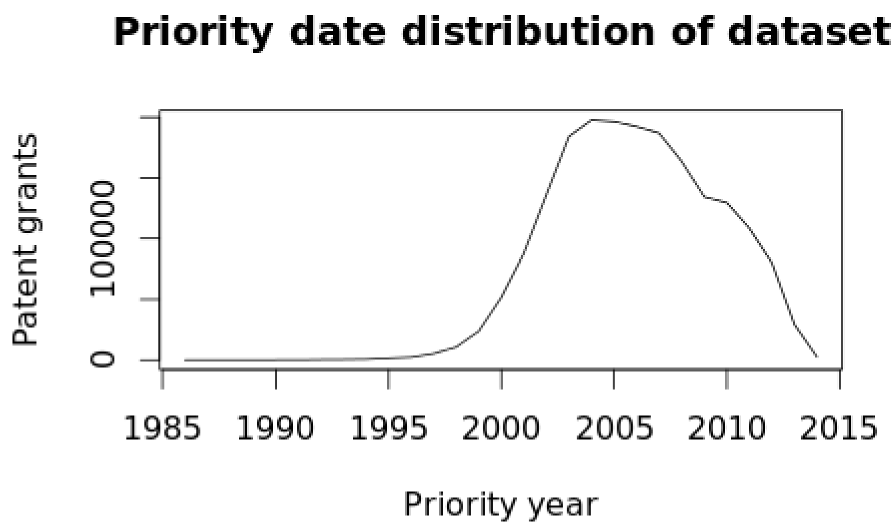


Figure 2: Priority date distribution of USPTO patent dataset

1 USPTO patent bulk data is available at http://www.google.com/googlebooks/uspto-patents.html
2 OECD statistical data is available at http://stats.oecd.org

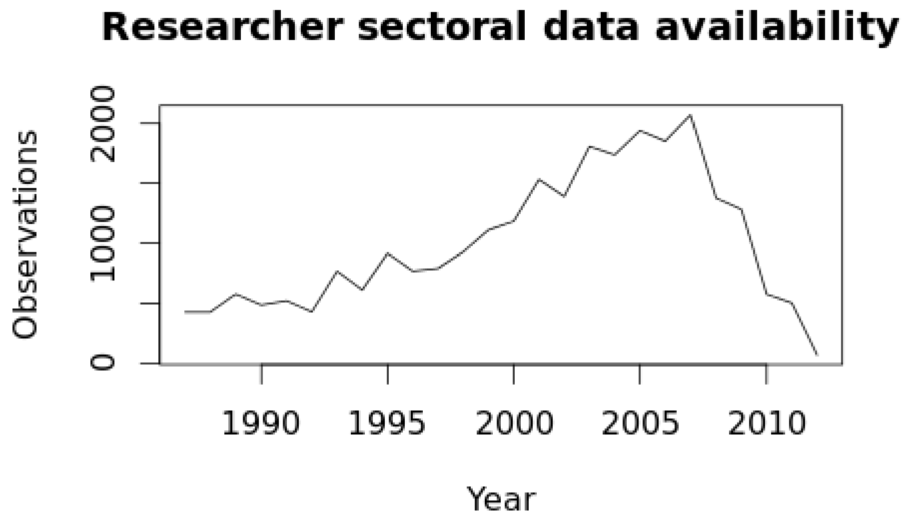


Figure 3: Availability of OECD researcher observations

It therefore appears that the 2003-2008 period (6 years) has the best data coverage, and so this time period is used in the study. Over a six year period around 100 observations are typically available per sector, from a range of different countries and for different years. It is possible to further extend the dataset beyond the 6 year period, but this risks introducing larger temporal changes into the sample, as patenting propensities can also vary with time (Malerba & Orsenigo, 1996).

The statistical data include a number of less technology intensive sectors, such as agriculture, forestry and fisheries. The study therefore limits itself to six more technology intensive sectors for which a large number of observations are available, they are listed, along with their International Standard Industrial Classification (ISIC) code and the top 10 assignees, in table 3. Sector descriptions are the official descriptions from the United Nations statistics division, which produces the ISIC.

ISIC	*Researcher observations (2003-2008)*	*Sector description*	*Top 10 assignees*
11	99	Extraction of crude petroleum and natural gas; service activities incidental to oil and gas extraction, excluding surveying	General Electric, Toyota, Monsanto, United States of America (USA), Honda Motor, Denso, Pioneer Hi-Bred, Robert Bosch, Honeywell, International Business Machines (IBM)
22	92	Publishing, printing and reproduction of recorded media	Canon, Samsung Electronics, Sony, Seiko Epson, Brother, FujiFilm, Panasonic, Hewlett-Packard (HP), Toshiba, Ricoh
23	92	Manufacture of coke, refined petroleum products and nuclear fuel	ExxonMobil Chemical, BASF, 3M, Shell Oil, UOP, BASF, Sumitomo

			Chemical, LG Chem, General Electric, Dupont
31	118	Manufacture of electrical machinery and apparatus	Samsung Electronics, International Business Machines (IBM), Panasonic, Qualcomm, LG Electronics, Fujitsu, Broadcom, Sony, Toyota
32	112	Manufacture of radio, television and communication equipment and apparatus	Samsung Electronics, International Business Machines (IBM), Sony, Toshiba, Panasonic, Canon, Intel, Micron, Fujitsu, Microsoft
33	121	Manufacture of medical, precision and optical instruments, watches and clocks	International Business Machines (IBM), Samsung Electronics, Microsoft, Canon, Sony, Panasonic, Intel, Toshiba, Hewlett-Packard (HP), Fujitsu

Table 3: Overview of sectors

The overlap in top assignees in table 3 is remarkable because it suggests that a small number of actors play a very dominant role in the global innovation process and that many sectors are interrelated, and are thus likely to show similarities in their innovation process. This is especially true in the “electronics” sectors (23, 31, 32 & 33) where there is significant overlap between sectors. Rapid technological change may be a reason why few oil companies are represented among the top assignees in sector 11, and similarly the presence of Toyota in many industries could be related to the car maker's development of electric vehicles. In that sense it shows some of the challenges of designing a classification system such as ISIC.

The OECD dataset for the 2003-2008 period contains data from 32 countries, however the number of observations (i.e. data points) per country varies. The countries with the greatest number of observations are Belgium and the Republic of Korea (36). The country with the least observations is the United States (2). Because countries voluntarily collect and submit data to the OECD, data coverage is not consistent for all countries and years.

Although the United States is part of the dataset it is excluded from this study to avoid the “home bias” associated with using USPTO data: American inventors have a higher propensity to apply for patents in the United States compared to foreigners and are therefore excluded from the sample. An overview of the number of observations per country and industry is provided in table 4. The dataset includes 29 OECD member states, plus Romania, Singapore and Taiwan. The latter three are all upper income or upper middle income economies. The dataset includes both large and small countries in terms of size and population. It is interesting to note that some “small” countries such as Singapore (population 5 million) are not “small” in terms of the number of researchers and patent output in electronics-related sectors (31-33), while “large” countries such as Mexico (population 118 million) have relatively few researchers and low patent output. In this sense “small” and “large” are very relative designations.

Country	*Observations by sector (ISIC)*						
	11	22	23	31	32	33	Sum total
Australia	1	6	6	6	6	6	31
Austria	3	3	3	3	3	3	18
Belgium	6	6	6	6	6	6	36
Canada		6	6	6	6	6	30
Chile	2			2	2	2	8
Czech Republic	6	5	6	2	6	6	31
Denmark	1	1		4	2	5	13
Estonia	4	2		3			9
Finland				5	5	5	15
France		5	5	5	5	5	25
Germany	2	3	3	3	2	2	15
Greece	3	3	2	1	3	3	15
Hungary	4		2	4	6	4	20
Iceland	5	5	5	5	2	5	27
Ireland	3	3	1	3	1	3	14
Italy		5	5	5	5	5	25
Japan				6	6		12
Korea (South)	6	6	6	6	6	6	36
Mexico	1	1	1	1	1	1	6
Netherlands	4	1	1	5	5	5	21
Norway	4	6	3	6	6	6	31
Poland	6		4	6		5	21
Portugal	2	6	6	6	6	6	32
Romania	6		1		1		8
Singapore	5			2	3	5	15
Slovakia	6						6
Slovenia	6	5	6	1	1	6	25
Spain	5	6	6	6	6	6	35
Sweden	1			3	3	1	8
Taiwan	6	6	6	3	6	6	33
Turkey	1	2	2	2	2	2	11
United States				2			2
# of countries	26	22	23	30	28	27	

Table 4: Overview of observations in OECD dataset (researchers)

3.4 Methodology

In addition to the choice of model, indicators and dataset, the study is influenced by three other important methodological steps: the conduct of a sectoral comparison rather than using aggregate national indicators, the “connecting” of patent and statistical data and the method of country assignment.

First, the decision to conduct a theoretical comparison is primarily driven by methodological considerations, i.e. the desire to control patenting propensity. However this raises the prospect of sectoral differentiation or indicators, which is a separate area of research in itself. There are significant differences between sectors in terms of the main actors involved in the innovation process and also the importance of patents (Arundel & Kabla, 1998; Iammarino & McCann, 2006). This suggests that sectors could be differentiated between based on their knowledge base, e.g. knowledge in science-based sectors tends to be more easily codified, which allows collaboration over long distances, and often relies significantly on university-generated basic research. Development-based sectors tend to rely more on tacit knowledge, which is often derived from interactions with customers and suppliers (Bjørn Asheim et al., 2007; Iammarino & McCann, 2006; Ponds et al., 2010). At the same time most sectors incorporate multiple technologies (Pavitt, 1984), which could mean that differences are less pronounced. In this study the sectors being studied are quite broad, and so clear differences are much less likely to reveal themselves. Furthermore, because patents are used as an indicator for all sectors, differentiation is also less likely as only “patentable innovations” are being taken into account, which can be clearly codified.

The second essential part of this study's methodology is the “connecting” of patent data to statistical data, which is necessary for model estimation. This is achieved by using the ISIC of the statistical data and the International Patent Classification (IPC) of the patent data. Using concordance tables created with the 'algorithmic links with probabilities' approach (Lybbert & Zolas, 2014), patents can be assigned an ISIC code, allowing them to be linked to specific sectors. The concordance tables are developed using a probabilistic approach, and therefore a patent can be partially assigned to multiple industry categories. It must also be noted that patents sometimes carry multiple classifications, which leads to double-counting. But since the number of patents that are double-classified is small (less than 0.1%), and some authors have suggested that multiple classification increases their value (Deng, 2007), this “error” is not corrected.

The linking of patent data and statistical information allows for the estimation of a patent production function and the validation of some bibliometric indicators, notably comparing the number of inventors to researchers, all of which are addressed in section 4. All estimations are carried out by using linear least squares regression.

And a third important methodological decision is to assign patents to countries based on their inventors' stated place of residence, as this is likely to correspond most closely to the statistical data which lists the number of local researchers, regardless of whether they are employed by a foreign entity.

4 VALIDATION, RESULTS AND ANALYSIS

In this section the patent production function is estimated based on the statistical and bibliometric indicators described in section 4. The available data also enables the validation of some of the bibliometric indicators (section 4.1), which provides further support for the results (section 4.2).

4.1 Validation

It is possible to validate two aspects of the bibliometric indicators: the number of inventors (*INV*) compared to the number of researchers (*RES*) and the patenting propensity based on the number of researchers (RES) and business R&D expenditure (*EXP*). For a description of these specific variables, refer to section 3.3. The validation primarily involves confirming whether or not bibliometric indicators show a similar result to other non-bibliometric indicators; if this is not the case then confidence in the other bibliometric indicators is not justified.

It is logical to assume that, if patents are a valid innovation indicator, that the number of inventors (as revealed in the patent data) and the number of researchers is highly correlated at the sectoral level. While some industries may have higher patenting propensities per researcher or per unit of research expenditure, if patenting propensities are constant, then the ration between the number of inventors in a particular year and the number of researchers found in the statistical data should be constant, i.e. there is a linear relationship between *RES* and *INV* as expressed in equation 5. While other non-linear relationships may also be found, the existence of a linear relationship inspires more confidence in using *INV* as a proxy for *RES*, as it suggests the existence of a basic and direct link.

$$RES = \alpha + \beta \cdot INV \tag{5}$$

The estimation results for the six different sectors is provided in table 5.

ISIC	11	22	23	31	32	33
β	1.29***	0.44***	0.077	0.47***	0.60***	0.073***
n	99	84	86	116	111	120

*** denotes significance at the 0.1% significance threshold

Table 5: Estimation results of *INV-RES* linear model, equation 5.

The estimation results in table 5 appear to be a good model fit with a 0.1% significance threshold for five of the sectors. The only sector where this is not the case is 23 (manufacture of coke, refined petroleum products and nuclear fuel), here two countries, Germany and Taiwan, have extreme ratios of *INV* to *RES*. If Taiwan is removed from the dataset (Taiwan has very high *RES*, very low *INV*) then β = 0.12 (n = 80) with a significance threshold of 1%. If both Taiwan and Germany are removed then β = 0.30 (n = 77) with a significance threshold of 0.1%. A possible reason for the divergence between Taiwan, Germany and other countries is the broad range of technologies incorporated in sector 23. Nevertheless these results do suggest that *INV* and *RES* are closely correlated, supporting the use of patents as an innovation indicator.

The assumption of constant patenting propensity is an important one as it allows the assumption that variations in patent output relative to input are due to differences in patenting efficiency. To verify this assumption, patenting propensities should vary between sectors and the variation should correlate to the patenting propensity results from earlier studies, such as Arundel & Kabla (1998). Arundel & Kabla (1998) used survey results from 1993 of research managers at firms in France and the European Union (they combined the results of two surveys). These surveys yielded an indication of what share of innovations are patented within specific industries (according to their ISIC classification). Although the study precedes the dataset used in this study by a decade, it is one of the few such studies known to the authors, and, as shown in table 6, it supports the patenting propensity indicators extracted from the dataset. Patenting propensity is calculated by dividing patent output for a particular sector by the innovation input (*RES* or *EXP*).

ISIC	*Patenting propensity*		
	Patents per RES *(2003-2008)*	*Patents per* EXP *(2003-2008)*	*Patented innovations* (Arundel & Kabla 1998)
11	0.27	1.45	n.a.
22	2.30	12.95	n.a.
23	1.10	2.67	25.1%
31	2.64	19.15	43.0%
32	2.25	14.98	36.5%
33	5.29	39.19	52.6%

Table 6: Patenting propensity indicator comparison

The results in table 6 show a large degree of similarity between the different patenting propensity indicators. Sector 23 consistently has the lowest propensity, sector 33 has the highest propensity, with sectors 31 and 32 having a relatively similar propensity that is roughly between 23 and 33. A scatter plot of patents per *RES* and patented innovations (Arundel & Kabla, 1998) is given in figure 4.

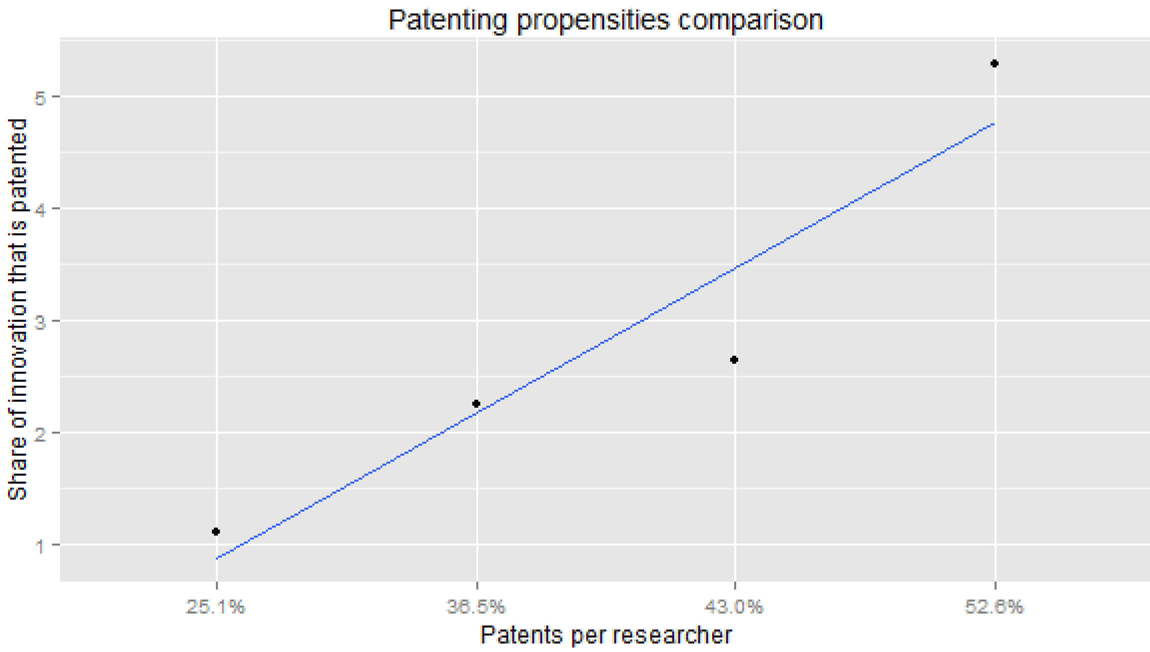


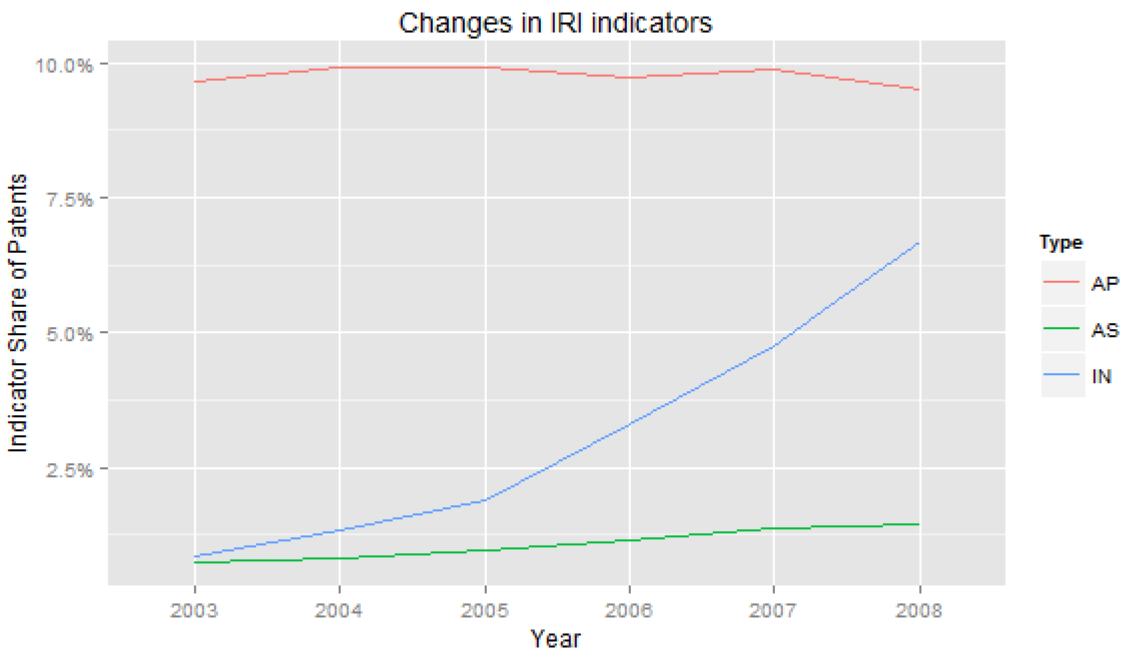
Figure 4: Scatter plot of patents per researcher (RES) and share of patented innovations with linear least-squares fitted line.

The consistency in relative patenting propensity supports both the use of bibliometric patenting propensity indicators and the view that, in order to use patent data as an innovation indicator, a sector-based approach is very important.

4.2 Results and Analysis

The estimation of the patent production function is based on the patent data and bibliometric indicators described in section 3. Prior to presenting these estimation results a brief overview of the bibliometric indicators for IRIs are provided in figure 5. These indicators provide a number of insights. First, they suggest that the local presence of international entities (*AP*) is the most common type of research interaction, accounting for approximately 9.5% to 9.9% of all patents with foreign inventors filed at the USPTO. This figure includes foreign-invented patents with American assignees, and therefore may have a slight "home bias", as many American corporations may choose to file patents at the USPTO. It is nevertheless a high share.

The share of *AP* is also relatively stable during the 2003-2008 period. However the share of internationally co-invented (*IN*) and internationally co-assigned patents (*AS*) is rising, with *AS* patents rising from below 1% in 2003 to 6.7% in 2008. Naturally these are aggregate statistics, but this trend is generally visible in all of the six sectors and in every country. This suggests that international research interactions are indeed growing in importance.



Note: AP = internationally appropriated patent %, AS = internationally co-assigned patent%, IN = internationally co-invented patent%

Figure 5: Changes in bibliometric indicators for IRIs, 2003-2008, average for 6 sectors for all countries except the United States.

ADJUST VERTICAL SCALE TO %

The estimation results of the patent production function are given in table 7. Overall, there is a significant negative correlation between patent output and *AP* (indicator for the local presence of international entities). The only sector where this is not the case, 23, has some outlier countries. If Taiwan is removed from the dataset then *AP* there too has a negative correlation at a 5% significance threshold. The other two international research interactions only occasionally have a statistically significant negative correlations, but there is no positive correlation that is significant.

Industry	11	22	23	31	32	33
ln(*RES*)	1.20***	1.17***	0.69***	1.13***	1.05***	1.23***
$IN \cdot \ln(RES)$	-0.015	-0.55	-0.15	-0.46	-1.10**	-0.45

$AS \cdot \ln(RES)$	-0.69*	-1.11	3.09	1.84	1.49	-1.20
$AP \cdot \ln(RES)$	-0.26*	-0.80***	-0.56	-1.51***	-1.02***	-1.14***
n	99	84	86	116	111	120

*, ** and *** denotes significance at respectively the 5%, 1% and 0.1% significance threshold

Table 7: Patent production function estimation results.

Therefore hypotheses *H1a*, *H2a* and *H3a* are rejected, while hypotheses *H1b*, *H2b*, *H3b* are accepted. The implications of this outcome are discussed in the next section. It is useful to note that there is no clear differentiation between sectors in terms of the impact of the various IRIs. However there are significant differences between the estimated coefficients for each sector. The similarity in outcomes in all 6 sectors may be because patents reflect innovations that are clearly codified, which is not the case for every innovation (Arundel & Kabla, 1998). However even if the lack of positive correlation with any IRI indicators can only be confirmed from patent-based bibliometric indicators, the fact that it occurs across all 6 sectors suggests that it is a widespread phenomenon.

5 DISCUSSION AND CONCLUSION

This study provided a quantitative exploration of the impact of IRIs on national innovation using six different sectoral comparisons and novel patent-based bibliometric indicators to quantify IRIs. In doing so the study contributes to the current academic discourse on the influence co-invention, co-assignment and the appropriation of inventions by international organisations on local innovation performance. The study also offers a methodology that allows differences in patenting propensity to be controlled, thus removing an important draw-back of using patents as innovation indicators.

The outcomes of the patent production function estimation raise some important questions about the role of IRIs in the innovation process, and by extension, their influence on innovation performance. The results suggest that the three kinds of IRIs explored in this paper, co-invention, co-assignment and appropriation, do not enhance national innovation performance. To the contrary, the appropriation of innovation by international actors (*AP*) has a significant negative correlation with innovation performance. The largest negative impact appears to be in the electronics related sectors (31-33), with a relatively large negative coefficient is estimated. *AP* also appears to accounts for a relatively large share of IRIs, and for roughly 10% of all patents in the dataset.

However it is not immediately clear why such a negative relationship manifests itself. From a theoretical perspective, the result can be interpreted as suggesting that there are relational power imbalances or a lack of local absorptive capacity in countries where international organisations have a relatively large local presence (Fu, 2008; Lazonick & Mazzucato, 2013). Indications for power imbalances are also found in studies on multinationals in which knowledge originating in a foreign subsidiary appeared to be utilized by the headquarter organization elsewhere, labelled as 'reverse knowledge integration' (Ambos, Ambos, & Schlegelmilch, 2006; Frost & Zhou, 2005). Such relationships which are beneficial for the headquarter location, tend to 'weaken' the place (cluster or country) where the actual research is performed. Connected with this, but partly being a measurement issue: the low innovation performance could be due to innovation that is hidden and in fact recorded elsewhere in the global innovation supply chain (Audretsch et al., 2014). For example, there are signs that multinationals register in patent location with lowest corporate taxation (Karkinsky & Riedel, 2012).

To fully understand the outcomes studies of specific innovation systems may be required (Tödtling

& Trippl, 2005). All these are not only intriguing theoretical questions but also highly relevant from a policy perspective. If the local presence of international organizations such as multinational corporations has a potentially negative impact on national innovation performance, then this should be reflected in innovation policies. And it certainly does not justify the offering of tax and other incentives to attract international research activities (Wellhausen, 2013).

Aside from raising theoretical questions, the research also shows some of the merits of conducting an international sectoral comparison using patent data, rather than using national aggregates. The results from the validation of the number of inventors relative to researchers and patenting propensities support the use of patents as an innovation indicator, provided that patenting propensity is carefully controlled for. This provides useful avenues for researching sectors, countries and regions for which statistical data is unavailable: patent-based bibliometric indicators appear to be able to fill some of these gaps.

Returning then to the research questions. (1) *Does international research interaction influence national innovation performance according to patent-based indicators?* And (2): *Is there significant variation between sectors?* The statistically significant estimation results suggest that patent-based indicators do provide valuable information about the influence of IRIs on innovation performance. Although patents are only a partial indicator of innovation output, the information they contain does appear to be representative of the sectors, as is evident from the strong linear correlation between the number of inventors and the number of researchers.

The results also suggest that the international appropriation of innovation, measured using the share of patents invented but assigned to a foreign organisation, correlates negatively to innovation performance. This could be a sign of 'reversed' knowledge flows within multinational firms including integration of knowledge created in subsidiaries in various countries in the headquarter organization. In this regard there does not appear to be significant variation between sectors.

It would be interesting to replicate this research with other bibliometric sources, such as scientific publications, to ascertain whether the negative correlation is also evident from those sources and not only from patent data. It may also be worthwhile to consider the effects of international research interactions on a smaller geographical scale, e.g. that of regions or clusters.

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