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

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ABSTRACT

International research interactions, specifically interpersonal collaboration, institutional collaboration and within multinational corporation (MNC) collaboration, have been increasing since the 2000s as a result of globalization and rising technological complexity. Yet the impact of international research interactions (IRIs) on national innovation performance is ambiguous. In this study patent-based bibliometric indicators are developed to investigate the influence of different types of IRI on innovation performance using bibliometric data covering eight knowledge intensive manufacturing sectors and 32 countries during the 2003–2008 period. This sector-based approach avoids some of the problems of using patents as innovation indicators, like varying patenting propensities across sectors by comparing the same sectors across countries. In the study a knowledge production function is estimated for each sector, with patents serving as an indicator of knowledge output. The overall results suggest an absence of positive influence of IRI on innovation performance, and sometimes even a negative influence pointing to 'reversed knowledge flows'. But the pattern is nuanced and differs per sector and type of collaboration. For example, interpersonal collaboration has a negative or no effect on innovation performance depending on the sector, and institutional collaboration has no effect on innovation performance. Within MNC collaboration has a positive influence on innovation performance in the chemicals and pharmaceuticals sectors, but a negative effect or no effect in other sectors. Computers are an exceptional sector in that the influence of IRI depends on the absolute size of the sector in the domestic economy. The paper concludes with the theoretical relevance of these findings and some policy implications are also discussed.

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1. Introduction

International research interactions, specifically 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 et al. 2014; Locke and Wellhausen 2014; OECD 2012). This leads to increased competition between firms and to a growing global division of labor 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 et al. 2009; Awate et al. 2014; Castellani et al. 2013; OECD 2007). International research interactions are especially prevalent in knowledge intensive sectors (Asheim and 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 et al. 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 et al. 2004; Freeman et al. 2010; Gertler 2003) and several empirical studies (Grossman and Helpman 1991; Guan and Chen 2012; Guellec and Van Pottelsberghe de la Potterie 2001; Hottenrott and Lopes-Bento 2014; OECD 2009; Simmie 2003). On the other hand, international research interactions have been found to weaken local research activity and interaction under particular circumstances (Kwon et al. 2012; Leydesdorff and Sun 2009; Van Geenhuizen and Nijkamp 2012a, 2012b; Ye et al. 2013) and also weaken overall innovation performance in clusters (Chang et al. 2013; Propris and Driffield 2005).

In studying innovation, patents can be regarded as a "paper trail" (Jaffe et al. 1993), containing information about the inventors, assignees, technology and institutional and interpersonal links. This makes them a versatile and widely used data source for innovation studies (Lei et al. 2011; Shapiro 2015). While there are limitations and drawbacks to using patent data as an innovation indicator (Kleinknecht, Montfort, and Brouwer, 2002), patents do contain "clues" which can expand our understanding of the innovation process. Furthermore, patent output has been found to correlate fairly well with

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other innovation activity indicators (Acs et al. 2002). These 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 and Kabla 1998; Malerba and 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 and Nepelski 2014; De Rassenfosse and 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 and McCann 2006; Malerba 2002).

This study addresses the basic question: *To what extent does international research interaction influence national innovation performance according to patent-based indicators, and which differences in influence exist between sectors*?

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). Analysis of the model estimation, results and validation (Section 4) comes before a brief discussion and the conclusion (Section 5).

2. International research interaction: theory and hypotheses

International research interaction can be understood from a variety of theoretical domains, including inter-organizational learning and various concepts of non-geographic proximity, including the competitive and technological pressures that are the drivers of increasing international research interaction.

International research interaction (IRI) exists in many forms, however this study considers two important ones: international research collaboration (both institutional and interpersonal) and the global network of research activities of knowledge intensive firms (especially MNCs) and other knowledge using and creating actors such as universities and public research institutions. While international research interaction does occur through other mechanisms, such as the trade in high technology goods and services, technology licensing, contract manufacturing and international labor mobility, international research collaboration appears to be rapidly growing in both developed and developing economies (Awate et al., 2014; Enkel et al., 2009; Locke and 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 firms to seek out the best knowledge, wherever it may be (Archibugi and Iammarino 2002; Asheim and Gertler 2005; Bathelt et al. 2004; Chesbrough 2006; Doz et al. 2001).

International research collaboration and the global network of research activities within firms enable the access and use of new knowledge. While innovation is facilitated by proximity, this proximity is not necessarily geographical or spatial (Boschma 2005). In recent approaches of 'relational economies' non-spatial proximity is seen as an important factor in the innovation process (Asheim et al. 2007; Birch 2007; Ponds et al. 2007). It 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 (Fazio and Lavecchia 2013; 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 creation of 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 et al. 2010). An illustration of this tendency is the fact that collaboration in innovation 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 et al. 1994; Anselin et al. 1997; Fischer and Varga 2003; Jaffe 1989). In addition, knowledge exchanges also occur in long-distance collaborative networks of social and institutional relationships (Autant-Bernard et al. 2007; Breschi et al. 2003; Huber 2012; Knoben 2009; Ponds et al. 2010; Wilhelmsson 2009).

Research collaboration is generally assumed to be beneficial for all participants involved (Dosi et al. 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 and Mazzucato 2013). In fact, power inequalities between partners within research networks tend to reduce research collaboration overall (Liu 2014).

MNCs and other globally distributed organizations have a unique advantage in that they provide an organizational structure and standard culture that reduces the aforementioned cognitive distance and thus facilitates the transfer of tacit knowledge over large distances within the organization (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 and Iammarino 2002; NCSES 2014). At the same time, increased participation by MNCs in local innovation systems (regional or national), be it through research collaboration or commercially driven, can weaken research interactions among local actors by reorienting them towards external collaborations (Kwon et al. 2012; Van Geenhuizen and Nijkamp 2012a, 2012b; 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 and Lee 2014; Tödtling and 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 et al. 2012). Thus, while innovation systems can potentially benefit significantly from IRI (Bathelt et al. 2004), the interaction does not appear to "automatically" improve innovation performance.

The factors that influence innovation performance are summarized in a simplified model in Fig. 1. Accordingly, innovation performance is

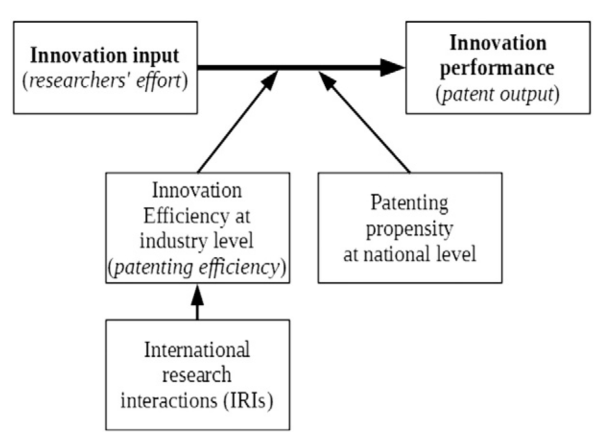

Fig. 1. Simple model of innovation performance.

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 is seen as being dependent upon the patenting propensity (which is nation and sector-dependent) and the innovation (or patenting) efficiency, which in this study, depends on IRI. The knowledge production function that underlies this conceptual model is provided in Section 3.1.

Given the ambiguity in the literature about the influence of IRI on innovation performance, we formulate six hypotheses which cover the three types of relationships: international interpersonal research collaboration, international institutional research collaboration and international appropriation, the last signals local presence of international research organizations, which are separated into a hypothesis that posits a positive influence on innovation performance (*a*-hypotheses) and a hypothesis that posits the lack of such influence (*b*-hypotheses).

H1a. : International interpersonal research collaboration correlates positively with innovation performance.

H1b. : International interpersonal research collaboration does not correlate positively with innovation performance.

H2a. : International institutional research collaboration correlates positively with innovation performance.

H2b. : International institutional research collaboration does not correlate positively 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 positively with innovation performance.

The above hypotheses will be tested using a knowledge production function, the estimation results of which are presented in Section 4.1. In the next section (Section 3) the knowledge production function, indicators, dataset and methodology are discussed.

3. Model, indicators, data and methodology

3.1. Knowledge production function

The knowledge production function relates innovation input to output, and allows additional terms to be introduced, either as separate inputs or as moderating variables. Because knowledge is a very abstract concept, De Rassenfosse and van Pottelsberghe de la Potterie (2009) propose a *patent* production function, which makes a 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, see the conceptual model in Fig. 1. This relationship can also be expressed mathematically in the form of a patent production function, see 1. The equation is derived by De Rassenfosse and van Pottelsberghe de la Potterie (2009) from the "original" knowledge production function (Jones 1995; Romer 1990).

$$P_{ij} = \quad \delta L_{ij}{}^{\lambda} \tag{1}$$

Here i represents a country and j represents a particular sector or industry. The propensity to patent (δ) is understood to be determined by inherent characteristics of the technology and the market as well as IP regulations, or more broadly, by the policy environment (De Rassenfosse and van Pottelsberghe de la Potterie 2009).

In addition, Arundel and 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. Therefore it can be argued that the national context and the sector have an influence on innovation propensity (Tidd and Bessant 2013).

In addition to these theory-grounded arguments, a differentiation at the national and sector level is also merited from a methodological perspective. The main focus of this research lies in research productivity (λ) and so we seek to control the patenting propensity in such a way that differences in patent output can be attributed to research productivity only. This can be achieved by using multilevel regression analysis, whereby the national level and industry level are allowed to vary when estimating patenting propensity and patenting efficiency, respectively. This approach allows for differences in the industry composition of the national economy to be accounted for (Malerba and Orsenigo 1996). Including the national level also allows data for the US to be used in the study. Normally the US should be excluded as the USPTO data suffers from a US "home bias", but if a correction can be made at the country level, the US can be included in the analysis.

Returning to the original patent production function in 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:

$$\ln\ P_{ij} = \ \ln\ \delta_{ij} + \lambda_j \ln L_{ij} + \varepsilon_{ij} \tag{2}$$

Here, ε_{ij} is an error term which varies depending on each country and sector, while patenting propensity δ_{ij} varies at both the country level and sectoral level, and patenting efficiency (λ_j) only at the sector level. Therefore variation in patenting output relative to input should be caused by various institutional factors, including IRI.

The question that then remains is whether IRIs influence patenting propensity, patenting efficiency, or both. This question is fundamental in the sense that it determines how IRIs should be implemented in the model, but to solve it we take a pragmatic approach of seeking a model that best fits the data based on an analysis of variance (ANOVA). This pragmatic approach is also taken with the inclusion of the country level. Although there is a theoretical justification for including the country level, the dataset has at most 6 observations per country per sector (see Section 3.3), which makes it difficult to ensure a robust multilevel estimation. Therefore the country level is not implemented in the model but instead the US, which is included in the primary data set, is excluded from the validation dataset, as it is a likely source of bias (see Section 4.2).

Therefore, although there are good theoretical reasons for a multilevel regression model, separate standard regression models are used to estimate coefficients for each sector. The model is estimated using the "lm" (linear model) function in R (R Core Team 2015).

3.2. Bibliometric and statistical indicators

The estimation of the patent production function relies on bibliometric and statistical indicators. In total this study considers six bibliometric indicators, which are described in Table 1. The first four indicators are used in the model estimation, while the fifth, the number of patent claims (*CLM*) is used for validation purposes, see Section 4.2. The descriptions of the two statistical indicators, researchers and business R&D expenditure, is given in Table 2.

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

Table 1
USPTO patent grant-based bibliometric indicators.

Indicator	Description	Formula
P_{ij}	Total number of patents in a particular country's sector.	not applicable
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_{ij}
AS	International institutional research collaboration as evidenced by the number of patents with assignees from two or more countries: "international co-assigned patents" (P_{AS}).	P_{AS}/P_{ij}
AP	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_{ij}
CLM	Number of patent claims listed on the patent records of a particular country's sector in a particular year based on the patent's application or priority date.	not applicable

Table 2
OECD statistical indicators.

Indicator	Description
RES	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.

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 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.

In this study data is used for the 2003–2008 period, however it is possible to extend the dataset from 1975 to a more recent year, as both USPTO and OECD data are available. However such an extended time period would require some adjustments, as statistical standards such as industry categories and patenting rules undergo changes.

The 2003–2008 period is marked by a period of worldwide economic growth, which was followed by a slowdown or economic recession in most advanced economies, starting in 2008. While these developments had a significant impact on financial markets in the US and elsewhere, their impact on innovation output appears limited, as is evident from the graph in Fig.2 The authors therefore consider the 2003–2008 period as "relatively normal", including both fortuitous and challenging economic conditions.

On average, over the six year period around 120 country data points are available per sector. The statistical data include a number of low tech sectors, such as agriculture, forestry and fisheries. The study therefore limits itself to eight knowledge intensive manufacturing sectors (Eurostat 2014) for which a large number of observations are available. They are listed in Table 3 along with their International Standard Industrial Classification (ISIC) code (revision 4), and the top five patent owners. Sector descriptions are the official descriptions from the United Nations statistics division, which produces the ISIC. Values are the total or average for the 2003–2008 period.

The overlap in top assignees in Table 3 is remarkable because it suggests that a small number of large corporations (e.g. Samsung Electronics, General Electric, Canon, Denso, etc.), play a very dominant role in the global manufacturing 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 (26, 27 & 28) where there is significant overlap in top patent assignees, including with the "chemicals" sector (20), which presumably reflects research in new materials. It is also interesting to note the presence of Toyota in "electrical equipment" (27) which could be related to the car maker's development of electric vehicles. Denso Corporation, which is considered to be a car parts company is also listed in "electrical equipment" (27) and "air and spacecraft" (303), in addition to "motor vehicles" (29). Similarly "pharmaceuticals" (21) encompasses medical device makers Boston Scientific SciMed and Medtronics as top 5 patent assignees.

In addition, the sectors also show significant variation in assignee concentration, with "computers" (26), "motor vehicles" (29) and "air and spacecraft" (303) all having 10% or more of patents assigned to the largest five entities.

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 Spain (48). The country with the least observations is Mexico (5). Because countries voluntarily collect and submit data to the OECD, data coverage is not consistent for all countries and years.

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 (26–28), 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.

The OECD data set of research expenditure, which is used for validation in Section 4.2, is similar to the researchers database in terms of sectors covered and the total number of observations. It notably includes Israel and China.

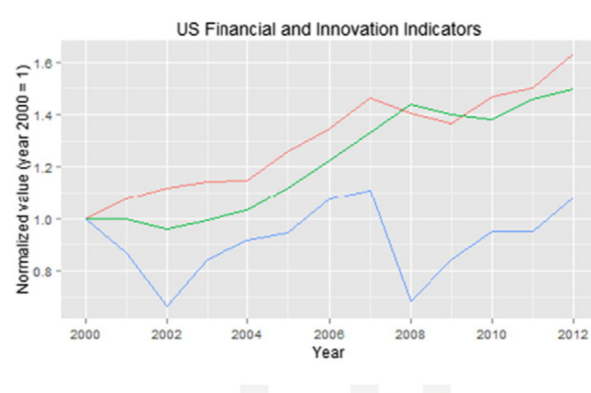

Fig. 2. USPTO patent applications, US Business Expenditure on R&D (BERD) and the S&P 500 stock index, 2000–2012.

[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

Table 3
Overview of sectors.

ISIC	Researcher data points	Sector description	Top 5 patent owners	Share of top 5 owners
20	188	Manufacture of chemicals and chemical products	1. Samsung Electronics Co., Ltd. 2. Canon Kabushiki Kaisha 3. Kabushiki KaishaToshiba 4. International Business Machines Corp. 5. Seiko Epson Corporation	5.4%
21	184	Manufacture of basic pharmaceutical products and pharmaceutical preparations	1. Monsanto Technology LLC 2. Pioneer Hi-Bred International, Inc. 3. Boston Scientific SciMed, Inc. 4. Meditronics, Inc. 5. Bristol-Myers Squibb Company	4.0%
26	207	Manufacture of computer, electronic and optical products	1. International Business Machines Corp. 2. Samsung Electronics Co., Ltd. 3. Canon Kabushiki Kaisha 4. Microsoft Corporation 5. Sony Corporation	10.3%
27	185	Manufacture of electrical equipment	1. Samsung Electronics Co., Ltd. 2. General Electric Company 3. Toyota Jidosha Kabushiki Kaisha 4. Denso Corporation 5. International Business Machines Corp.	5.9%
28	204	Manufacture of machinery and equipment n.e.c.	1. International Business Machines Corp. 2. Canon Kabushiki Kaisha 3. Samsung Electronics Co., Ltd. 4. Microsoft Corporation 5. Sony Corporation	9.3%
29	147	Manufacture of motor vehicles, trailers and semi-trailers	1. Toyota Jidosha Kabushiki Kaisha 2. Honda Motor Co., Ltd. 3. Denso Corporation 4. Robert Bosch GmbH 5. Ford Global Technologies, LLC	15.3%
303	101	Manufacture of air and spacecraft and related machinery	1. The Boeing Company 2. General Electric Company 3. Honeywell International Inc. 4. Denso Corporation 5. Robert Bosch GmbH	12.1%
325	92	Manufacture of medical and dental instruments and supplies	1. Boston Scientific SciMed, Inc. 2. Siemens Aktiengesellschaft 3. General Electric Company 4. Ethicon Endo-Surgery, Inc. 5. Medtronics, Inc.	6.9%

3.4. Methodology

In addition to the choice of model, indicators and dataset, results of the study are influenced by three other important methodological choices: the performance of a sector 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 sector comparison is primarily driven by methodological considerations, i.e. the desire to control patenting propensity. However this raises the prospect of sector differentiation of 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 protection by patents (Arundel and Kabla 1998; Iammarino and McCann 2006). This situation 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 (Asheim et al. 2007; Iammarino and McCann 2006; Ponds et al. 2010). At the same time most sectors incorporate multiple technologies (Pavitt 1984), which would 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. Thus it is ambiguous whether the influence of IRI varies across the sectors defined in this study.

The second choice 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 and 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, which is the subject of the next section. All estimations are carried out by using linear least squares regression.

And a third choice is to assign patents to countries based on their inventors' stated place of residence, as this is the most likely indicator of where the research was carried out.

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

Country	*Data points by sector (ISIC)*								
	20	21	26	27	28	29	303	325	Sum total
Australia	6	6	6	6	6	6	6	3	45
Austria	3	3	3	3	3	3	1	3	22
Belgium	6	6	6	6	6	6	6	6	48
Canada	6	6	6	6	6	6	0	0	36
Chile	2	2	2	0	0	0	0	0	6
Czech Rep.	6	6	6	6	6	4	3	3	40
Germany	3	3	3	3	3	3	3	3	24
Denmark	4	4	5	5	5	4	0	4	31
Spain	6	6	6	6	6	6	6	6	48
Estonia	3	3	4	3	4	0	0	2	19
Finland	0	0	5	5	5	0	0	0	15
France	5	5	5	5	5	5	5	5	40
UK	6	6	6	6	6	6	6	0	42
Hungary	6	6	6	5	6	2	0	4	35
Ireland	5	5	5	5	5	3	3	3	34
Italy	5	5	5	5	5	5	4	5	39
Japan	6	6	6	6	6	6	6	0	42
Korea Rep.	6	6	6	6	6	6	6	5	47
Mexico	1	1	1	1	1	0	0	0	5
Netherlands	5	5	5	5	5	5	3	5	38
Norway	5	5	6	6	6	6	5	2	41
Poland	6	6	6	5	6	2	4	5	40
Portugal	5	5	6	4	6	2	0	1	29
Romania	2	0	2	0	3	0	0	0	7
Singapore	5	5	5	5	5	5	5	5	40
Slovakia	1	1	6	3	6	0	0	0	17
Slovenia	6	6	6	6	6	1	0	1	32
Sweden	3	3	2	0	2	3	0	0	13
Turkey	0	0	4	4	4	2	0	0	14
Taiwan	6	6	6	6	6	6	0	6	42
USA	5	5	5	5	5	1	5	0	31
# of countries	134	132	151	137	150	104	77	77	

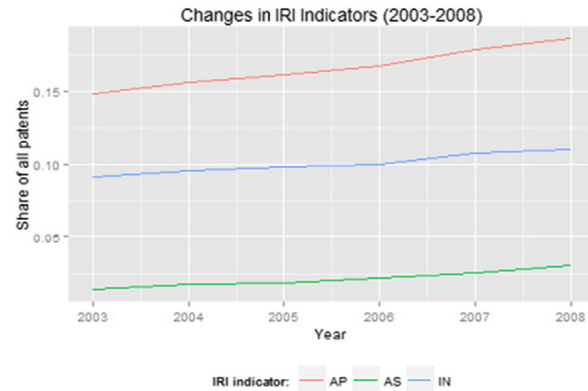

Fig. 3. Changes in IRI, 2003–2008, all-country average for eight sectors. Note: AP = internationally appropriated patent %, AS = internationally co-assigned patent%, IN = internationally co-invented patent%.

4. Model estimation and validation

4.1. Model estimation

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 international research interaction (IRI) is provided in Fig. 3. First, the indicators suggest that the local presence of international entities (*AP*) is the most common type of IRI, accounting for 18.6% of all patents in 2008. Next are internationally co-invented (*IN*) patents at 11.0% in 2008 and internationally co-assigned patents (*AS*) at 3.0% in 2008. All three types of IRI have been increasing steadily since 2003. Clearly international research interactions are growing in importance.

The model estimation serves to explore whether IRI can be shown to influence innovation performance. We use two models: Model 1 includes IRI as simple linear components; from a theoretical point of view, IRIs are conceived as influencing patenting propensity.[3] In contrast, Model 2 includes IRI as a component that interacts with innovation inputs, in this case researchers (*RES*); from a theoretical perspective IRI influence patenting efficiency.[4] Based on ANOVA, most sectors have a better or similar model fit with Model 1 with the exception of computers (26), which has a much better fit ($p < 0.001$) for Model 2. An overview of the Model 1 estimation coefficients is provided in Table 5.

As assumed, the results of Model 1 suggest in all sectors a positive influence of number of researchers on patent output, on a high level of significance. Further, interpersonal collaboration (*IN*) has a negative effect or no effect on innovation performance, and institutional collaboration (AS) has no effect at all. International appropriation (AP) has a positive effect in the chemicals (20) and pharmaceuticals (21) sectors, but a negative effect or no effect in other sectors. Based on these results hypotheses *H1b* and *H2b* can be accepted while *H3a* can be accepted for chemicals and pharmaceuticals (20 and 21) and *H3b* for other sectors.

It is useful to note that for chemicals and pharmaceuticals (20 and 21) a university assignee, the Regents of the University of California, is listed among the 20 largest assignees for the sector: they are 17th and 6th, respectively for chemicals and pharmaceuticals. This suggests that in these sectors universities and fundamental research institutes perform a relatively strong role in the innovation process.

Computers (26), which does not reveal any significant influence of IRI in the Model 1 estimation (Table 5), does show a significant influence of IRI in the Model 2 estimation, see Table 6 and Annex A. The result suggests that in countries in which the computer sector is small, interpersonal collaboration (IN) plays a positive role, while international appropriation (AP) acts as a barrier to innovation performance. However, as the sector becomes larger, this changes to a reverse situation and interpersonal collaboration becomes less beneficial, while international appropriation becomes more beneficial.

In a more detailed analysis of the computer sector, taking the estimated coefficients and the size of the sector (researchers) into account, the "inflection point" of the size of the sector is approximately 73,000 researchers for interpersonal collaboration (IN) and 26,100 researchers for international appropriation (AP). This means that increased international appropriation (AP) has a negative influence on all countries computer sectors except Korea, Japan, Taiwan and the US, which have very large sectors. It also means that increased interpersonal collaboration (IN) has a mild negative effect on Japan and the US but is likely to very significantly benefit countries with very small computer sectors such as Estonia, Slovakia, Slovenia and Mexico.

Table 5
Model 1 estimation coefficients

Industry	*ln RES*	*IN*	*AS*	AP
chemicals (20)	1.279***	−3.765***	1.946	2.240**
pharmaceuticals (21)	1.017***	−1.985*	0.091	1.508*
computers (26)	1.029***	−1.212	−0.950	0.281
electrical equipment (27)	1.015***	−0.156	0.254	−2.909***
machinery (28)	0.929***	−3.720***	−0.445	−0.790
motor vehicles (29)	0.763***	0.349	−1.132	−1.863**
air and spacecraft (303)	0.555***	0.018	−0.563	−2.83*
medical instruments (325)	1.005***	−2.500**	2.033	0.589

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

[3] $P_{ij} = \beta_0 + \beta_1 \ln RES + \beta_2 IN + \beta_3 AS + \beta_4 AP$
[4] $P_{ij} = \beta_0 + \beta_1 \ln RES + (\beta_2 + \beta_{12} \ln RES) IN + (\beta_3 + \beta_{13} \ln RES) AS + (\beta_4 + \beta_{14} \ln RES) AP$

Table 6
Model 2 estimation coefficients for computers (sector 26), see Annex A for further results.

ln *RES*						
IN	*AS*	*AP*	ln *RES*:*IN*	ln *RES*:*AS*	ln *RES*:*AP*	
1.142***	8.418**	−0.559*	−2.905~	−1.725***	−0.006	0.658**

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.
~ $p < 0.1$.

The computer sector (26), along with motor vehicles (29) and air and spacecraft (303) all have a high patent ownership concentration, see Table 3. In these sectors international appropriation (AP) tends to have a negative effect on innovation performance.

In the medical instruments sector (325) the result of the Model 1 estimation is also supported by the Model 2 estimation (see Annex A). The Model 2 estimation suggests that interpersonal collaboration (IN) is generally negative except for a country with a (unrealistically) large medical instrument sectors with more than 586,000 researchers. Thus Model 2 estimation adds to the insight of Model 1 by suggesting that in countries with a larger medical instrument sector the negative effect of interpersonal collaboration is less.

4.2. Validation

The results of this study are validated by estimating the models with an alternative indicator generated from the same sources. The OECD database also contains business expenditure on R&D (BERD), *EXP*, for the same industries, time period and mostly the same countries.[5] The USPTO dataset contains the number of patent claims, *CLM*, which, although closely correlated to the number of patents (Hagedoorn and Cloodt 2003), has also been found to be a predictor of patent value (Lanjouw and Schankerman 2004), and thus of innovation performance.

By using *EXP* and *CLM* as model indicators instead of *RES* and P_{ij}, and by excluding the USA to remove the "home bias" (mentioned in Section 3.1), the same model coefficients as in Section 4.1 can be estimated. Although the estimation result is not identical, there are no contradictory estimations. That is to say: there are no coefficients with different signs that are also statistically significant. Hence the results are validated. Annex A has tables with the validation estimation results for Model 1 and Model 2.

5. Discussion and conclusion

This study provides a quantitative exploration of the impact of international research interaction (IRI) on national innovation performance using eight different sectors and novel patent-based bibliometric indicators for this interaction. In doing so the study contributes to the current academic discourse on the influence of various types of international collaboration, like interpersonal collaboration and institutional collaboration and collaboration within organizations such as MNCs and other large actors on the innovation performance of a country. The study offers an approach that is shown to be sufficiently robust and which offers clear quantitative evidence for the research findings. Thus, the paper contributes to two types of literature. First, it contributes to the emerging literature on globally distributed innovation and its management, which occurs mainly through collaborative relations within multinational corporations (MNCs), and secondly, it contributes to the methodological literature concerning the use of patent-based bibliometric indicators.

The research question addressed was the following: *To what extent does international research interaction influence national innovation performance according to patent-based indicators, and which differences in influence exist between sectors*? Using a simplified innovation model, the estimation outcomes suggest a lack of positive influence on national innovation performance.

The three kinds of IRI explored in this paper, interpersonal collaboration, institutional collaboration and collaboration within MNCs (or other multinational research organizations) tend to not enhance national innovation performance, with the chemicals and pharmaceuticals sectors as notable exceptions on the basis of collaboration within MNCs/large research organizations. This pattern contradicts the 'euphoria' on benefits from global research collaboration, at least for the years 2003–2008. The pattern is clearly more nuanced than straightforward benefits, and differs per sector and type of collaboration: interpersonal collaboration tends to cause negative impacts in chemicals, pharmaceuticals, machinery, and medical instruments, while inter-organizational collaboration tends to be indifferent for innovation performance.

Furthermore, collaboration within MNCs tends to negatively influence innovation performance for electrical equipment, automotive, and aerospace, which as previously noted are linked by several large companies, including parts makers Denso and Bosch and car maker Toyota, who are active in two or more of these sectors. These sectors also tend to have a high concentration of patent ownership among a few leading firms. In general, these are manufacturing industries which have stable products and are therefore likely to undertake incremental innovation (Iammarino and McCann 2006). The results of this study appear to confirm that a large presence of MNCs can lead to 'reverse knowledge integration', whereby new knowledge originating in a foreign subsidiary is 'distracted' to be utilized by the headquarter organization elsewhere (Ambos et al. 2006; Frost and 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.

In contrast, within MNC or large research organization collaboration tends to exert a positive influence on innovation performance in the chemicals and pharmaceuticals sectors. This result complies with the character of these sectors as "science based" sectors (Asheim and Coenen 2005; Carlsson 2013), and the strong position of universities among the sectors' leading patent owners. It is possible that in these sectors universities and the surrounding innovation network serve as 'anchors' of innovation, perhaps through their role in raising local absorptive capacity (Fu 2008; Furman et al. 2013).

Furthermore, the computer sector shows a weak positive influence of within MNC collaboration on innovation performance, this is related to a positive influence only in countries with very large sectors, which effectively would mean that international appropriation is beneficial for Korea, Japan, Taiwan and the US, having the scale to generate sufficient absorptive capacity to benefit from multinational corporations' presence, something that is lacking in other countries with smaller computer sectors.

To fully understand the previous outcomes, studies of specific innovation systems may be required, both national and regional (Tödtling and Trippl 2005).

Despite various interesting insights the IRI approach faces some serious limitations. Although collaboration is an important indicator in itself, signaling research performance or the maturity of an innovation system (Choi et al. 2014; Kim et al. 2014), quantifying that collaboration, or knowledge flows in general, can help to characterize an innovation system in a more relevant and richer way (Kwon 2013). Furthermore, the specific positioning of a country or sector within an international network, which is not captured by the present IRI analysis, may offer further insights. Such structural network studies have been used to understand changes in global research collaboration (Choi 2011) and human knowledge flows (Jiang 2014), to give just two examples.

[5] Compared to the researchers dataset, the BERD data includes China and Israel but excludes Denmark, Ireland and the UK.

In addition, a significant limitation of the study is that it uses only patent data as innovation output and to construct IRI indicators, although innovation inputs have been validated with a second R&D expenditure dataset. Adding other sources of bibliometric data, such as scientific publications, could help to establish whether the results of this study can be generalized beyond patent-based collaboration. It is possible that there are significant differences because patents are commercial and legal documents while scientific publications primarily serve as tools of (scientific) communication. However similarities would make the findings more meaningful. 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.

Connected with this is another measurement issue: a relatively low or high 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 and Riedel 2012), and so further research should be carried out to confirm this study's findings.

Despite these concerns, the findings are also 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. The chance for 'reversed knowledge flows' certainly does not justify the offering of tax and other incentives to attract international research activities (Wellhausen 2013). Instead, a more reluctant approach, accounting for different nuances in local–global MNC relations seems to be more appropriate.

Appendix A. Annex

Table 7
Model 2 estimation coefficients using researchers and patents.

Industry	ln RES	IN	AS	AP	ln RES:IN	ln RES:AS	lnRES:AP
chem. (20)	1.183***	−0.918	9.494	−3.166	−0.474	−1.342	0.835
phar. (21)	1.166***	−1.508	−1.361	3.977*	−0.011	0.247	−0.405
comp. (26)	1.142***	8.418**	−0.559	−2.905$^{\sim}$	−1.725***	−0.006	0.658**
elect. (27)	1.118***	2.977	−21.49	−0.951	−0.525	3.628	−0.291
mach. (28)	1.042***	6.688	−16.34	−4.051	−1.780*	2.575	0.653
m.v. (29)	0.949***	−3.489	1.196	4.495	0.582	−0.427	−0.958*
a.s. (303)	0.714***	−4.458	21.74	4.470	0.832	−3.909	−1.368
m.d. (325)	0.815***	−13.75***	23.06	1.792	2.384**	−4.102	−0.435

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.
$^{\sim}$ $p < 0.1$.

Table 8
Model 1 estimation coefficients using business expenditure on research and development and patent claims (for validation).

Industry	ln RES	IN	AS	AP
chemicals (20)	1.043***	−2.249*	1.311	0.951
pharmaceuticals (21)	0.949***	0.304	1.356	−0.475
computers (26)	0.976***	−1.014	−0.628	0.818
electrical equipment (27)	0.836***	−0.911	0.193	−2.927***
machinery (28)	0.872***	−2.442**	−0.800	−0.927
motor vehicles (29)	0.819***	0.835	−0.950	−2.142***
air and spacecraft (303)	0.457***	1.719	0.423	−2.360*
medical instruments (325)	0.927***	−2.502$^{\sim}$	2.752	1.057

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.
$^{\sim}$ $p < 0.1$.

Table 9
Model 2 estimation coefficients using business expenditure on research and development and patent claims (for validation).

Industry	ln EXP	IN	AS	AP	ln EXP:IN	ln EXP:AS	ln EXP:AP
chem. (20)	1.065***	−3.510	38.69**	−2.396	0.065	−2.122**	0.196
phar. (21)	0.837***	71.95*	−21.22	−62.12*	−3.743*	1.169	3.207*
comp. (26)	1.272***	46.24***	12.14	−13.25**	−2.558***	−0.663$^{\sim}$	0.810**
elect. (27)	1.203***	10.43	−7.574	9.849	−0.596	0.449	−0.704$^{\sim}$
mach. (28)	1.003***	0.085	4.393	3.684	−0.157	−0.273	−0.226
m.v. (29)	0.897***	−20.40$^{\sim}$	5.911	17.57$^{\sim}$	1.147$^{\sim}$	−0.361	−1.062
a.s. (303)	0.565**	−0.582	25.67	5.739	0.111	−1.418	0.450
m.d. (325)	0.793***	−19.43	61.50	−3.711	1.041	−3.388	0.256

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.
$^{\sim}$ $p < 0.1$.

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