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Article

# The Impact of University–Industry Relationships on Firms' Performance: A Meta-Regression Analysis

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## Abstract

The University–Industry (U–I) relationship is a fundamental part of innovation systems. A wide spread of public resources has been given to promote this relationship and a large number of studies has evaluated the results. However, while innovation theory identifies this relationship as a positive instrument to increase firms' performance, evaluation literature reports a wide range of findings. The lack of conclusiveness results in theory and evaluation literature motivates this meta-regression analysis (MRA), built on fifty-one micro-level studies published since 1995. After controlling for publication selection bias, sample, and study heterogeneities, our results show a small effect on firms' performance. Specifically, the size of the effect is more significant for technical outcomes than economic ones. These findings have a lot of relevance for universities, firms, and policymakers for determining open-innovation strategies and public policies.

**Key words:** university–industry collaboration; meta-regression analysis; STI; firm performance

## 1. Introduction

Since the early literature on technological change (Allen and Cohen 1969; Arrow 1974), academics and practitioners reckon that firms cannot only rely on their internal resources; but rather that acquisition of external knowledge is a key determinant for their innovation and performance (Cohen et al. 2002). Collaboration with different types of organizations such as customers, suppliers, and research partners is considered to be the primary source of external knowledge (Belderbos et al. 2004; Jensen et al. 2007; Nieto and Santamaría 2010). Specifically, collaboration between universities and industries is a driver of knowledge-transfer related to research, science, and technology (Metcalfe 1995; Hagedoorn et al. 2000; Hall et al. 2003).

Literature on university–industry (U–I) collaboration has identified an extensive set of interactions between partners aimed at transferring scientific knowledge to businesses (Rosenberg and Nelson 1994; Mansfield and Lee 1996; Argyres and Liebeskind 1998). In particular, relationship-based mechanisms are a specific mode of inter-organizational cooperation orientated to pursue an R&D assignment together with or without a commercial orientation (Hall et al. 2003; Arranz and Fdez de Arroyabe 2008; Belderbos et al. 2015).

U–I relationships include a broad type of formal agreement such as collaborative research, joint R&D, contract research, and consulting (Perkmann and Walsh 2007). The relevance of these relationships is mirrored by the fact that they represent one of the most frequent policy instruments put in place by policymakers to foster firms' innovation (Barajas et al. 2012). The effects of these relationships have been widely analysed at different levels (Jaffe 1989; Adams 2002; Boschma 2005), and they are an important part of the foundations of evolutionary growth theories based on innovation models (Etzkowitz and Leydesdorff 2000; Leydesdorff 2012).

But, for macro-economic effects to be generated, collaboration between companies and universities has to be successful at an organizational level (Grillitsch and Trippl 2018; Grillitsch et al. 2019). Most academic literature and practical guides tend to point to the existence of a positive impact on firms' performance (OCDE 2018). However, primary studies, in their attempt to investigate the existence of a causal relationship between U–I collaboration and company's results, yield conflicting findings. U–I are found to impact positively on firm's performance; to have no effect at all, or even to produce a negative impact. All three possible research outcomes are well-reported in the literature.

This paper aims to shed light on this topic by doing the first meta-regression analysis (MRA) of the quantitative microeconomic literature on the impact of U–I relationships on firms' performance. So, in line with meta-regression studies of other innovation topics (Dimos and Pugh 2016; Neves and Sequeira 2018; Ugur et al. 2020), we investigate this literature to determine the extent to which

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heterogeneous findings can be explained by the heterogeneity of samples and empirical methodologies. The degree—if any—to which this literature suffers from publication selection bias, and the genuine representative effect—if any—established by this literature—after controlling for possible publication bias and sources of heterogeneity on average—and firms' technical and economic specific performance measures—will likewise be investigated.

Our results show that the main variables which explain the heterogeneity and estimated effect size of the primary estimates are: the types of output measurements, research partners, relationships, and firms' sample and estimation characteristics. They also point out the existence of publication bias and, on average, a small positive effect on firms' performance after accommodating and correcting for publication bias. Furthermore, our research revealed that there is a verifiable medium-size effect on patent generation and a small negative effect on innovative sales growth.

This paper has been organized as follows: In Section 2, we dissect the theoretical framework of the U–I relationship and the main causes of heterogeneity in their results; in Section 3, we explain the methodology used; in Section 4, we present the results obtained from the literature search and for the MRA; in Section 5, we discuss the implications of these results; and finally, in Section 6, we present the main conclusions, limitations of our work, and our future lines of research.

## 2. Theoretical framework and heterogeneity causes

In the previous decade, Perkmann and Walsh (2007) pointed out that to offer a general conclusion about U–I relationships is difficult due to the wide variety of analyses in terms of outputs, partners, contractual arrangements, and firms involved. Since then, several literature reviews have tried to provide a general conclusion (Vivas and Barge-Gil 2015; Mascarenhas et al. 2018; Sjöö and Hellström 2019; Skute et al. 2019). However, none of them has offered a quantitative estimation of the impact of the U–I relationship on firms' performance as reported in the literature. Thus, their conclusions have to be interpreted with caution.

In this section, we first review the theoretical framework behind the U–I relationships focusing on the motivations of firms to engage in this type of relationship. Second, we analysed different factors which the literature has pointed to as the main causes of heterogeneity in the reported effects of U–I relationships' impact on firms' performance. This enables us to identify a group of studies within the heterogeneous literature that are sufficiently homogeneous for valid investigation by MRA. We focus our analysis on types of output measurements, research partners, relationships, and firms.

### 2.1 Theoretical framework

During the lasts 25 years, universities and other types of research and technology organizations (RTOs) have orientated the greater part of their efforts on their "third mission" (Mansfield 1995 D'Este and Patel 2007). This third mission seeks the generation and transmission of knowledge outside academics to increase social-economic development based on technology and knowledge spillovers (Hall et al. 2003). One of the most-used mechanisms to achieve this goal is the collaboration between universities and industry on R&D projects (Beise and Stahl 1999; Adams et al. 2003). In the past, firms did R&D in-house; they only had contact with the universities during the recruitment process (Perkmann and Walsh 2007). However, as the importance of introducing new technical product and process increases to firms' results grew, the relationship between firms and research partners also grew (Nieto and Santamaría 2010). Today there is a vast panoply of U–I relationships (Perkmann and Walsh 2007). Different types of firms (e.g., High-Techs and SMEs (Small and Medium Enterprises)) collaborate with different types of research partners (e.g., Universities and Research institutes (RIs)) searching for different results (e.g., patents and productivity growth) under several types of relationships (e.g., joint R&D projects and outsourcing). But, through all of them, firms pursue the generation of a competitive advantage over their competitors (Philbin 2008).

From an economic perspective, U–I relationships have been explained through the lens of transaction cost theory (Williamson 1981). Transaction cost theory assumes that firms' '*make* versus *buy*' decisions are driven by their willingness to reduce both production and transaction costs while protecting from opportunistic behaviour (Hagedorn et al. 2000). Specifically, relationships with the university are seen as one of the leading ways to avoid the high cost of internalizing intangible assets (Hall et al. 2003), scientific personnel (Perkmann et al. 2013), and R&D facilities (Becker and Dietz 2004). The cost reduction of the technological advance knowledge can have a direct effect on firms' results, increasing efficiency and financial results (Medda et al. 2004; Belderbos et al. 2006; Aschhoff and Schmidt 2008). Moreover, by establishing formal relationships, both agents could avoid opportunistic behaviours focused on exploiting the knowledge (Vega-Jurado et al. 2009; Barge-Gil 2010; Nieto and Santamaría 2010).

From a strategic management perspective, these relationships have been explained through the resource-based view (Barney 1991; Das and Teng 2000) and stakeholder theory (Freeman and Reed 1983; Siegel et al. 2003). The resource-based view considers that firms are boundlessly rational and undertake decisions based on the needs of their technological capabilities (Hall et al. 2003). Through relationships with universities, firms can access complementary resources and knowledge, use collaboration as a learning vehicle to accumulate and deploy new skills and capabilities, share R&D cost and generate the opportunity to develop innovations to satisfy market failures. From the stakeholder perspective, firms' engagement with universities could be regarded as a CSR practice (Christensen et al. 2020). Universities and firms strive to satisfy social needs, and their cooperation in this respect can improve the level of economic development in a region, of innovation, and of educational development in society (e.g., promoting R&D joint project orientated to responsible research and innovation). Taking these advantages of the opportunities proposed by both strategic management perspectives, firms could develop a range of competencies and capabilities that lets them be more competitive in the market than their competitors (Arvanitis et al. 2008; Fey and Birkinshaw 2005; Di Maria et al. 2019).

Both theoretical approaches claim that the existence of positive effects at firm-level empirical literature has shown contradictory results. For example, some authors, such as Arvanitis and Woerter (2009), who analysed a sample of 2,428 Swiss firms, found that consulting R&D activities has a positive impact on firms' patent generation and innovative sales. Howells et al. (2012) found a positive relationship between cooperation with higher education institutions (HEIs) and the introduction of innovation and firms' innovative sales revenue, in a sample of 371 UK firms. Furthermore, Medda et al. (2004) showed in a sample of 2,222 Italian firms how collaborative research with RIs has a positive effect on firms' productivity. However, the same work showed how collaborative research also

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has a negative effect on firms' innovative sales. Others, like Kanama and Nishikawa, who examined 1,001 Japanese manufacturing firms, found the same results. Access to university knowledge could increase firm innovation, but it is unlikely to result in profitable innovation. Furthermore, Tsai and Hsieh (2009), who analysed a sample of 1,346 Chinese manufacturing firms, found that joint R&D with RTOs has negative results on innovative product sales. These authors explain that the relationship between both agents could suffer different types of dissimilarities such as operational (i.e., organizational procedures) and cultural ones (i.e., goals and objectives) (Sarkar et al., 2001).

All the above-mentioned studies analysed UIR (University-Industry Relationships), although they address it from different perspectives. That is what other quantitative works and previous literature reviews have pointed out as the cause of the heterogeneity of results (Perkmann and Walsh 2007; Vivas and Barge-Gil 2015; Mascarenhas et al. 2018; Sjöö and Hellström 2019; Skute et al. 2019). Specifically, they have pointed out the differences in the main characteristics of every U–I relationship: the output analysed, the research partner involved, the type of relationship, and the firm involved. We will use this same framework to address in detail the heterogeneity of results reported in the literature based on these characteristics.

## 2.2 Types of output measurements

Different types of measurement could find the result of the same U–I relationship fruitful for both parts, only for one, or negative for both (Perkmann and Walsh 2007). However, one of the companies' main motivation for engaging U–I collaboration is to use it as a 'window' of scientific knowledge rather than for developing marketable innovations (Caloghirou et al. 2001; Volpi 2017). In recent times, this trend has changed due to the need for both partners to increase the finalization degree of collaborative projects (Weingart 1997; Zapp and Powell 2017). For universities, the evolution of performance-based research-funding systems (e.g., UK REF or Nordic FOKUS) increased the need to measure their impact on society as with, for example, measuring patent generation (Hicks 2012; Bellucci and Pennacchio 2016). For firms, the need to improve financial and economic results has increased the orientation towards developing innovations from science-based relationships, for example, developing new-to-market products (Faems et al. 2005; Parrilli Alcalde-Heras 2016). That is why it is important to take into account how the literature has measured the output of the U–I relationship. Based on Barge-Gil and Modrego (2011)'s work, it can be addressed from technical and economic perspectives.

Technical outputs consider the generation of any type of short-term output capable of being considered an innovation. This measurement includes new products and processes (Becker and Dietz 2004; Fey and Birkinshaw 2005; Nieto and Santamaría 2010), and patents (Arranz and Fdez de Arroyabe 2008; Fabrizio 2009; Hall et al. 2003). Most of the innovation literature tends to accept the positive effect of this type of formal collaboration on these outcome indicators (Arranz and Fdez de Arroyabe 2008; Arvanitis and Woerter 2009; Nieto and Santamaría 2010). For example, Nieto and Santamaría (2010) found a positive association between U–I cooperation and product innovation in Spanish firms. The literature which found a negative impact is residual (Adams et al. 2003; Fabrizio 2009). However, there exists a sample of studies which do not find strong evidence in one direction or another (Fey and Birkinshaw 2005; Arvanitis et al. 2008; Barge-Gil 2010).

Economic output considers the impact of medium- to long-term effects on economic results, measured by total sales growth (Barge-Gil and Modrego 2011; Fu and Li 2016; Di Maria et al. 2019), sales growth of new products (Belderbos et al. 2004; Arranz and Fdez de Arroyabe 2008; Frenz and Ietto-Gillies 2009), and added value or productivity growth (Belderbos et al. 2004, 2006; Aschhoff and Schmidt 2008; Harris et al. 2013). The consensus on the effect on these outcomes is weaker in comparison with the technical outcome. Some studies found a positive impact (Belderbos et al. 2004; Arranz and Fdez de Arroyabe 2008; Aschhoff and Schmidt 2008). However, others, such as Tsai and Hsieh (2009) found a negative association between the U–I relationship and the share of new-to-market innovative product sales and improved products in Taiwanese firms (Hall et al. 2003; Kanama and Nishikawa 2017). Besides, the literature which points to non-clear evidence is larger (Belderbos et al. 2006, 2015; Frenz and Ietto-Gillies 2009).

## 2.3 Types of research partners

In the U–I relationships, the 'University' includes the traditional view of 'Academia', but also encompass other types of modern research organizations, such as RIs and public or private research centres (Vivas and Barge-Gil 2015). Although all these research partners pursue the same objective of increasing the scientific and technological stock of knowledge of society (Jaffe 1989), they could address society in different forms. Different types of research partners could influence the result of the UIR so as to be patent-orientated or to develop product or process innovations (Yaşar and Paul 2012). As Perkmann and Walsh (2007) reviewed, under the 'university' or 'research partners', there are three main types of organizations: higher education institutions (HEIs), RIs, and RTOs.

HEIs refer to the traditional meaning of Universities. These institutions play various roles in innovation systems (Teirlinck and Spithoven 2012). Such roles include the education of students, advances in the limits of the frontiers of knowledge, and collaboration with society, known as the 'third-mission'. In the last decade, this third role has gained much relevance (Hou et al. 2019). HEIs can be orientated to collaborate in creating new knowledge but also to consult and guide in the introduction of innovations related to new materials and technologies for reducing energy and materials waste (Albahari et al. 2017; Biedenbach et al. 2018; Aiello et al. 2019). For example, Biedenbach et al. (2018) found a positive association between U–I cooperation and product and process innovation in a sample of Swedish firms. The literature which found a negative impact is residual (Fabrizio 2009). However, there is a sample of studies which does not find strong evidence in one direction or another (Fey and Birkinshaw 2005; Arvanitis et al. 2008; Barge-Gil 2010).

RIs can carry out activities mostly related to applied scientific knowledge for developing innovations or patents (Hall et al. 2003). That is due to the fact that RIs' funds come from private sources related to a specific industry (Huang and Yu 2011; Yaşar and Paul 2012) or from public administration, which understands the need to establish strong research relationships between these organizations and companies. Furthermore, the objectives of these organizations are often project-oriented (Adams et al. 2003) and related to new scientific fields such as microelectronics, biotechnology and materials science (Hou et al. 2019). For example, Hou et al. (2019) find a

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positive impact of this partner on Chinese firms' new-product-sales revenue per employee. The literature which analyses this partner is smaller than previous categories, and its effect is not clear (Brouwer and Kleinknecht 1996; Medda et al. 2004; Arvanitis et al. 2008).

Finally, other scholars have referred to the organizations above and to other types (e.g., public–private laboratories, public research organizations) under the term: RTOs. Scholars using this category do that because they consider that the common objective of increasing the scientific and technological stock of knowledge of society is enough to treat them as the same type of research partner. That is why this is the leading category used in the literature (Becker and Dietz 2004; Belderbos et al. 2004; Robin and Schubert 2013), and the results are contradictory. Some of them found positive results (Brouwer and Kleinknecht 1996; Belderbos et al. 2015). In contrast, others addressed negative results or non-significant results with this type of partner (Vega-Jurado et al. 2009; Barge-Gil and Modrego 2011; Nuñez-Sánchez et al. 2012).

## 2.4 Types of U–I relationships

One of the main types of U–I collaboration is the inter-organizational agreements which imply formal relationships such as research partnerships, contract research, and consulting. On an organizational level, this type of cooperation can be motivated to reduce transactional costs of scientific knowledge and to use it as sources of competitive advantage (Lai and Chang 2010). Perkmann and Walsh (2007) pointed out that firms value these relationships over the whole innovation cycle, not only for the initial supply of scientific knowledge and inventions. However, in some cases, research partnerships or collaborative research are more orientated to basic research than consulting or contract research. Based on the degree to which the inter-organization is orientated to obtain a specific output, two types of contractual forms can be established: research partnership and service research.

Research partnership includes collaborative research and joint-research ventures between universities and firms. This type of collaboration is usually conditional on public funding, but it could also be funded by private institutions (Adams et al. 2003; Caloffi et al. 2018). This relationship is the most complex since it implies that both types of organizations pool their R&D resources, infrastructures, and personnel in a form of joint work to achieve the general objectives of the project, as well as the specific goals of both organizations (Fabrizio 2009). Using firm-level evidence, Radicic and Pinto (2019) find a positive effect on product and process-innovation in Spanish low- and medium-low-technology industries, although others like Medda et al. (2004) do not find strong evidence of positive returns on collaborative research with universities in enhancing productivity in Italian firms.

Service research implies an externalization of the company's R&D activities in the facilities and laboratories of the research organization (Darby et al. 2004; Hou et al. 2019) and consulting activities (Brouwer and Kleinknecht 1996; Arvanitis and Woerter 2009). The relationship could be less complicated than research partnerships, since it is not necessary to combine resources, but rather establish a contractual relationship which is linked to achieving the objectives set by the company that is financing the project. Moreover, consulting implies a formal agreement based on the possibility of the university advising the company on R&D activities for new products (Perkmann and Walsh 2008). Consulting usually happens in the initial stages of launching new products or implementing new organizational processes in a company (Brouwer and Kleinknecht 1996; Arvanitis and Woerter 2009; Di Maria et al. 2019). In this case, the collaboration can be more flexible and developed in different ways, always based on mutual adaptation. On an organizational level, some authors like Grimpe and Kaiser (2010) find a positive relationship between R&D outsourcing and German firms' innovative performance.

## 2.5 Types of firms

Since Laursen and Salter (2004)'s works some part of the scholar's studies have focused on what types of firms may benefit more from a relationship with research partners. Some of them have analysed firms' internal resources and capabilities (Escribano et al. 2009; Grimpe and Kaiser 2010), while others have focused on the environment in which the UIR is developed (Buerger et al. 2012; Caloffi et al. 2020). However, the most important topic could be the firms' attributes; this research topic has been addressed from two main perspectives: the industrial perspective, focusing on high-tech companies (Hall et al. 2003; Kim 2012), and manufacturing firms (Becker and Dietz 2004; Hewitt-Dundas et al. 2019), and from a Schumpeterian approach, focusing on small and more dynamic firms (Belderbos et al. 2006; Neyens et al. 2010; Hewitt-Dundas et al. 2019), and those which are innovative because they have developed R&D activities and innovative routines (Barge-Gil 2010; Yu and Lee 2017).

Companies based on high technologies include aerospace, software, and biotech firms, among others (OCDE 2018). These firms tend to be knowledge-intensive (Cosh and Hughes 2010), and due to this, the relationship with universities can be essential for high-tech firms to overcome their constraints and boost innovation and patent generation. Specifically, the relationship between research organizations and biotech companies has been deeply analysed (Hall et al. 2003; Fabrizio 2009; Wang et al. 2013). However, the effects of collaboration between this type of firm and universities are not clear. For example, Kim (2012) does not find a positive influence on the developing of new products in a sample of US biotech firms.

Sector and industry differences have also been taken into account in the literature as control variables (Aschhoff and Schmidt 2008; Belderbos et al. 2015). However, other studies delve deeper into the differences between specific sectors (Ukpabio et al. 2016). The main classification done here is between manufacturing and service firms (Becker and Dietz 2004; Belderbos et al. 2004; Hewitt-Dundas et al. 2019). Manufacturing firms orientate their collaboration to introduce new products or techniques which increase economic results and productivity. For example, Zhang et al. (2019) find a positive relationship between U–I relationships and innovation in a sample of listed Chinese manufacturing firms.

Since Schumpeter's work (Malerba and Orsenigo 1996), firm size has also been an important topic in the discussions of what firms innovate (Cohen 2010). Some researchers have focused their analyses on the SME firms, which can be more innovative due to their capacity to assimilate new knowledge and routines faster (Belderbos et al. 2006; Neyens et al. 2010; Hewitt-Dundas et al. 2019). For example, Nieto and Santamaría (2010) find a more positive interaction between small companies and Spanish manufacturing firms than the effect produced in technological collaboration in medium and big firms. However, Neyens et al. (2010) found non-significant results in a sample of 217 German firms.

Finally, the consideration of "innovative firms" as also been studied (Cohen 2010). These firms are those which develop R&D activities and those which introduce a kind of innovation, and are

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the most studied category. Innovation surveys have created a vast amount of data regarding this type of firm (Hong et al. 2012). The scholars argue that this type of firm could suffer fewer operational dissimilarities with research partners and would obtain better results than others. Some studies, such as Inauen and Schenker-Wicki (2011), find a positive causality between university collaboration and product innovation in a sample of stock-listed companies from Germany, Switzerland, and Austria. However, others do not find positive results (Barge-Gil 2010; Yu and Lee 2017).

## 3. Methodology

### 3.1 Data collection and literature search

Our search for studies and data selection meets the MAER-NET guidelines (Stanley et al. 2013). The starting point of this technique is a systematic literature review to track down every academic paper that studies the impact of U–I collaboration on firms' performance.

First, adapting Perkmann and Walsh (2007) and Vivas and Barge-Gil (2015)'s search protocols, we started establishing a group of keywords that were representative of the main concepts used in the previous literature. The chosen keywords were grouped into five categories, presented in Table A.1 (see Appendix 1). The first category was used for grouping keywords referring to universities and research partners (University). The second category contains collected terminology for firms (Industry). The third group included terms to describe the collaboration (Collaboration). The fourth group collected keywords addressing the type of interaction (Relationship). The fifth and final group collected keyword terminology for impact evaluation of performance (Impact).

Second, we chose the Web of Knowledge and Scopus databases for this review. The first search string returned a total of 16,891 publications from both databases. The list of publications was then narrowed to those articles (both published and unpublished but available before our cut-off date of 26 November 2019) related to social science and science and technology areas (see Appendix 1, Table A.2) in which the evaluation of U–I relationships could be analysed from our same perspective. The total number decreased to 5,954, results after duplicates were removed. This is a considerable number of documents, the main explanation for it being that the keyword 'University' covers a vast number of topics. (For comparison, Vivas and Barge-Gil (2015) obtain similar results). So, we did a screening process to include only those studies which analyse the quantitative evidence of the impact of the U–I relationship on firms' performance.

Accordingly, we established exclusion criteria based on the limitation of the MRA analysis: (1) the article must use empirical quantitative regressive methods (semi-parametric and non-parametric approaches were excluded), (2) the effect must be analyses from the firm's output perspective (analyses of inputs or pure spillovers were excluded), and (3) there must be an inter-organizational agreement (informal relationships were excluded).

Finally, the dataset consisted of 173 estimates from fifty-one studies directly related to U–I relationships, featuring results and data, and examining a measure of firm performance. The studies are listed and summarized in Table A.3 (see Appendix 1). Finally, to achieve the highest standards demanded of scientific rigour, we contrasted our final set with the sets of Vivas and Barge-Gil (2015) and Perkmann and Walsh (2007). We corroborate that all papers listed in their analyses address our inclusion criteria.

### 3.2 Coding methodology

In order to develop a MRA (Stanley and Doucouliagos 2012; Stanley et al. 2013), we needed to quantify and classify the relevant information from each study. We recorded the following article information: author's name, year, title, method of data collection, effect size of interest and standard error (based the author's report), number of observations, time period that the analysis involved, country in which the observations were studied, type of collaboration, partner and outcome, among other studies' main characteristics—see Table 4 for the complete list of the studies' coding dimensions.

### 3.3 Conversion to a common effect size

As pointed out in the background theory, there are specific characteristics of the U–I studies which could influence the output. Moreover, the existence of different measures for each type of impact complicates the analysis because although they are related, they are not equal. However, a similar problem has already been overcome by Stanley and Doucouliagos (2012). These authors recommend converting each estimated coefficient to the partial correlation coefficient (PCC) as a standard metric. This enabled us to compare the connection between U–I relationship and firm performance through different specifications and alternative measures. To include as many estimations as possible, U–I relationship impact on firm performance was measured via the PCC.

PCC is a unit-free measure of the magnitude and direction of the association between an independent variable over a dependent variable, arrived at by holding others included in the model constant (Dimos and Pugh 2016). In this case, we used them to isolate the effect of U–I relationship on the firm's performance. Using PCC in MRA has several advantages compared with other potential-effect size measures such as correlations or Fisher's *Z*-transformation (Stanley et al. 2018). PCC and its standard error calculation formula are as follows:

$$\mathrm{PCC}_i = {}^{t}\Big/_{\sqrt{(t^2+\mathrm{df})}} \tag{1}$$

$$\mathrm{SEpcc}_i = \sqrt{{}^{(1-\mathrm{PCC}^2)}\Big/_{\mathrm{df}}} \tag{2}$$

where $t$ stands for the $t$-statistic on the estimated U–I relationship effect and df for the degrees of freedom extracted from the respective estimate in the primary literature.

## 4. Results

### 4.1 Characteristics of included studies

In order to ascertain the main attributes of the studies analysed, we account for the study's publishing year, journals, and countries, and the specific characteristic of the U–I relationships.

A descriptive analysis of our results shows us that half of the studies were published after 2011. The literature suffers a reduction in number of papers in the period of 2013–2016; however, in the last year of the decade, this relationship grabbed the attention of academics and practitioners as the role of science-driven innovation had become a key concern for firms' performance. Furthermore, the three most interesting journals dealing with this relationship are *Journal of Research Policy* (15.69% of the studies), *Technology Transfer* (15.69%), and *International Journal of Technology*

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*Management* (7.84%). To determine countries with the most research regarding U–I collaboration, a simple counting of papers was conducted. The most-analysed countries are Spain (23.52%), the USA (13.73%), and Germany (13.73%).

As we reported in the theoretical discussion, there is a natural difference between the different characteristics of U–I relationships which are the cause of the heterogeneity. Focusing on the output measurement, we differentiated between *technical outcome* (67.63% of the observations), which includes the studies which measure this impact in terms of product or process innovation and patent generation, and *economic outcome* (32.37% of the observations), which includes studies which analysed the increase in sales, innovative product sales, and the firm's added value or productivity. The classification based on the types of relationships was between *research partnerships* (88.44%) and *service research* (11.56%). The former includes joint R&D and cooperation agreements, the latter, contract or outsourcing research inter-organizations. The final category was based on the types of research partners. We differentiate between research and technology organizations (43.35% of the observations), which is the most used category because it does not distinguish between *Higher Education Institutes* (47.40%) and RIs (9.25%).

## 4.2 Meta-regression analysis

In this section, we first measure the existence of a real effect between U–I relationships using the weighted averages of the estimated results. Second, we study the degree of a potential publication selection bias through the FAT-PET-PEESE approach. Third, an estimation of the real effect of U–I relationships on the new patent generation and innovative sales growth is made. Finally, the sources of heterogeneity effect size established by this literature after controlling for possible publication bias are evaluated.

### 4.2.1 Basic MRA

Beginning with our meta-analysis, Table 1 shows overall weighted averages of PCCs of the U–I relationship effect on firm performance. The inverse of its variance weights each PCC. The fixed effect estimates (FEEs) weights each effect estimation by the inverse of its squared standard error $(1/\mathrm{SE}_i^2)$. The random effect estimates (REEs) use more complex weights that allow for excess between-study heterogeneity $(\tau^2)$, as well as individual estimation error, $\left(1/(\mathrm{SE}_i^2+\tau^2)\right)$. However, according to Stanley and Doucouliagos (2015), the FEE and REE estimator provides estimates inferior to unrestricted weighted least square (WLS), especially when there is publication selection bias and heterogeneity, as here.

In Table 1, average estimates of the PCCs are reported; all of them are greater than zero. Analysing WLS results, it appears that the partial correlation between U–I relationship and firm performance is 0.024. As per Doucouliagos (2011), economic guidelines for assessing the strength of a correlation coefficient, U–I collaboration, have a small effect on firm performance. This effect size could be a result of the non-existence of a real impact, or due to the existence of heterogeneity. The Cochran's $Q$-test indicates clear evidence of excess heterogeneity beyond what is measured by random sampling alone ($P < 0.001$). To account for this heterogeneity, we identify a group of moderator variables, in the relationship between U–I cooperation and firm performance, which can produce it (see Table 4). However, before we turn to analysing them through a multiple meta-regression, we need to explore whether there is publication selection bias and how it might affect the reported output estimates in the literature.

**Table 1.** Unweighted and weighted averages of PCCs.

| Ba | (1)FEE | (2)REE | (3)WLS |
|---|---|---|---|
| Asverage | 0.024 | 0.041 | 0.024 |
| 95% CI | 0.022–0.027 | 0.033–0.050 | 0.17–0.031 |
| *N* | 173 | 173 | 173 |
| *K* | 51 | 51 | 51 |

*Notes*: Columns (1–3) report the overall weighted average for PCCs. FEE, REE, and WLS denote fixed effects, random effects, and unrestricted WLSs, respectively. *N* is the number of estimates. *k* is the number of studies.

## 4.3 Publication selection bias

Publication bias occurs whenever the research that appears in the published literature is systematically unrepresentative of the population of completed studies (Rothstein et al. 2006). It can be the result of a specification search to obtain estimates of a particular sign or—especially in small sample studies—to get more significant estimates to offset more significant standard errors. The usual way to analyse the existence of publication bias is through a funnel graph (Schmidt and Hunter 2015).

Figure 1 shows a funnel graph of the effect of U–I collaboration on firms' performances. On the horizontal axis, the estimated effect derived from each study's PCC is displayed; and on the vertical axis, the precision of the estimate measured by the inverse of its standard error. More precise estimates will be close to the real underlying effect, while the imprecise estimates will be more dispersed at the bottom of the figure. Therefore, in the absence of publication selection, the figure should resemble a symmetrical inverted funnel plot. The dashed line represents the median and the solid the average reported effect. A visual inspection of Fig. 1 suggests an imbalance in the reported impact of U–I relationships, as the right side of the funnel appears to be heavier. This finding indicates that positive estimates above zero may be preferably selected in the published studies.

However, visual methods are subjective, so we test for publication bias statistically. To carry out this test, we follow an approach well-known in the meta-analysis literature, namely the basic meta-regression or Egger's regression (Equation 3) (Egger et al. 1997; Stanley and Doucouliagos 2012; Schmidt and Hunter 2015).

$$r_i = \alpha_0 + \alpha_i \mathrm{SE}_i + \varepsilon_i \tag{3}$$

where $r_i$ is the estimated effect (in this case, PCC), $\mathrm{SE}_i$ is its standard error, and $\varepsilon_i$ the conventional random sampling (or estimation) error. The term $\alpha_i$ is used to test for publication bias.

Through this regression, we contrast two hypotheses. First, the null hypothesis that $\alpha_1 = 0$: this test provides statistical evidence whether or not there is any publication selection bias and is known as the *funnel asymmetry test*, or 'FAT'. Second, Egger's regression also tests the null hypothesis that $\alpha_0 = 0$: this test identifies whether there is any underlying empirical effect remaining after potential publication, and is known as the Precision Effect Test, 'PET'.

If the PET fails to reject the null hypothesis of no effect, then $\alpha_0$ is taken as the estimate of overall effect with the understanding that it is statistically insignificant from zero. If the PET rejects the null, then a new specification is estimated, and the associated estimate of $\gamma_0$ represents the best estimate of the overall effect, known as the precision effect estimate with standard error, PEESE test. (Stanley and Doucouliagos 2012; Alinaghi and Reed 2018). According to

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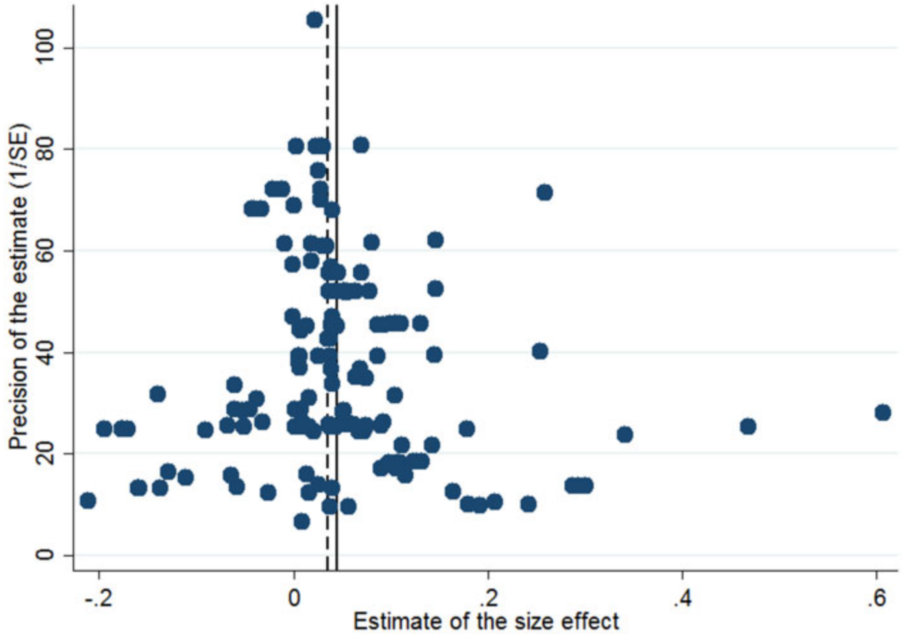


**Figure 1.** Funnel plot, partial correlations of U–I relationship impact.

**Table 2.** FAT–PET–PEESE.

| | (1)FAT ($\alpha_1 = 0$)WLS | (2)PET ($\alpha_0 = 0$)WLS | (3)PEESE ($\gamma_0 = 0$)WLS | (4)FAT ($\alpha_1 = 0$) Cluster Robust | (5)PET ($\alpha_0 = 0$) Cluster Robust |
|---|---|---|---|---|---|
| Coef. | 1.083*** | 0.013** | 0.022*** | 1.083* | 0.012 |
| 95% CI | 0.386 to 1.780 | 0.003 to 0.023 | −0.740 to 2.520 | −0.897 to 2.255 | −0.008 to 0.033 |
| *t*-value | 3.07 | 2.40 | 5.56 | 1.85 | 1.24 |

*Notes*: The dependent variable is partial correlations. Coef. is the estimated coefficient. 95% CI offers the interval confidence at 95%. *t*-value is the *t*-statistic of the estimate. FAT–PET estimates (columns 1–2 and 4–5) are based in Equation (4) using unrestricted WLSs (columns 1 and 2) and cluster-robust standard errors (columns 4 and 5). PEESE estimate (column 3) are based in Equation (5) using unrestricted WLSs. FAT tests the presence of publication selection bias, PET and PEESE estimates, and tests the effect of U–I relationship on firm's performance corrected for publication selection bias. *P < 0.1; **P < 0.05; ***P < 0.01.

Stanley et al. (2018), instead of using the standard error of the PEESE test, we use the variance of the estimated coefficient ($SE_i^2$), which gives a better estimate of the size of the genuine effect, corrected for publication bias (Equation 4).

$$r_i = \gamma_0 + \gamma_i SE_i^2 + \upsilon_i \quad (4)$$

The FAT–PET–PEESE model for PCCs of all 173 estimates is reported in Table 2. Columns 1 and 2 report use FAT–PET using unrestricted the WLS approach. As stated before, we preferred this approach rather than FEE or REE, because both meta-regression models (1) and (2) suffer heteroskedasticity resulting from the reported effects' widely different standard errors. MRA regression coefficients from the unrestricted WLS-MRA models can be used to test for the presence of publication selection bias ($H_0$: $\alpha_1 = 0$), and a genuine effect beyond publication selection bias ($H_0$: $\alpha_0 = 0$). However, due to several estimates reported by most studies and in order to offer a robust analysis, we also report results corrected for potential within-study-dependence as well as calculated robust standard errors (Columns 5 and 6).

It must be noted that estimates provide evidence of publication bias ($\hat{\alpha}_1 = 1.083$). However, there is a possibility that this bias is due to other moderating factors (e.g., study characteristics and sample characteristics). Besides, as a result of the rejection of the null hypothesis ($\hat{\alpha}_0 = 0.013$), we can assume there is clear evidence of a positive effect of U–I collaboration on firms' performance: a PEESE test confirms this effect ($\hat{\gamma}_0 = 0.022$).

However, according to Stanley and Doucouliagos (2014), these analyses show that the U–I relationships have a small-size effect on firms' performance, so we will analyse two subsamples to address specific effect size on different outcomes and, after that, account for other explanatory variables which can be a source of heterogeneity.

### 4.4 Patents and innovative sales as effect size

To gain further insight into the size of the U–I relationship effect on firms' performance, we analyse the impact of the collaboration in technical and economic subsamples as well as the implications for patent generation (twenty-eight observations) and innovative sales growth (forty-four observations). The former is selected as the representative for technical outcome and the latter for an economic one. Using these comparable dependent variables between primary studies, we analyse the effect size without primary studies of both subsamples are plotted against their inverse standard error in Fig. 2.

To check for the existence of a real effect on patent generation and innovative sales, we use the FAT-PET-PEESE approach by

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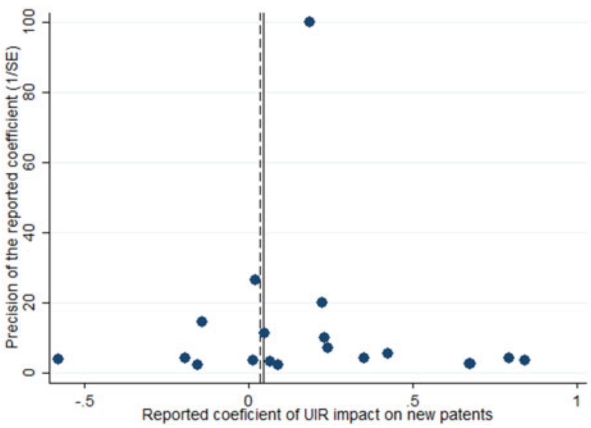


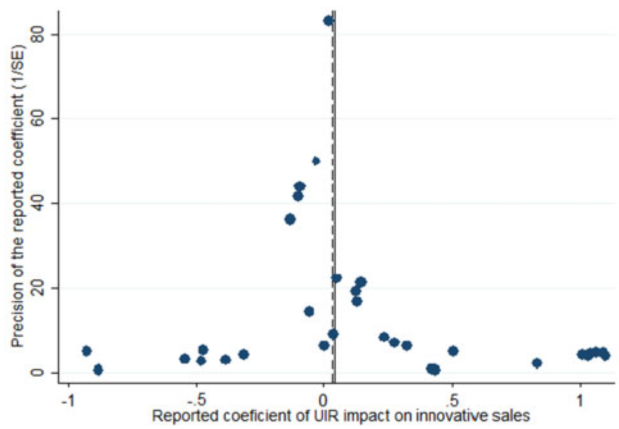


**Figure 2.** Funnel plot, reported coefficients of U–I relationship impact on firm's new patents and innovative sales.

**Table 3.** FAT–PET–PEESE—new patents and innovative sales as effect sizes.

| | (1)FAT ($\alpha_1 = 0$) WLS | (2)PET ($\alpha_0 = 0$)WLS | (3)PEESE ($\gamma_0 = 0$) WLS | (4)FAT ($\alpha_1 = 0$) Cluster Robust | (5)PET ($\alpha_0 = 0$) Cluster Robust |
|---|---|---|---|---|---|
| New patents | 0.907* | 0.153*** | 0.170*** | 0.907 | 0.153*** |
| ($k = 28$) | [−0.160 to 1.975] | [0.100 to 0.204] | [0.134 to 0.206] | [−1.211 to 3.026] | [0.834 to 0.221] |
| | $t = 1.75$ | $t = 6.01$ | $t = 9.72$ | $t = 0.95$ | $t = 4.96$ |
| Innovative | 1.538*** | −0.055** | −0.139 | 1.538 | −0.055 |
| sales ($k = 44$) | [0.501 to 2.574] | [−0.105 to −0.006] | [−0.058 to 0.030] | [−0.869 to 3.944] | [−0.163 to 0.052] |
| | $t = 2.99$ | $t = -2.25$ | $t = -0.63$ | $t = 1.35$ | $t = -1.09$ |

*Notes*: The dependent variable is the reported coefficient by the primary study. The 'New Patents' subsample is formed by twenty-eight observations from eleven studies and the 'Innovative Sales' subsample is formed by forty-four observations from seventeen studies. First the estimated coefficient is reported, between brackets are the interval confidence at 95% and finally, $t=$ is the $t$-statistic of the estimate. FAT–PET Estimates (columns 1–2 and 4–5) are based in Equation (4) using unrestricted WLSs (columns 1 and 2) and cluster-robust standard errors (columns 4 and 5). PEESE estimate (column 3) are based in Equation (5) using unrestricted WLSs. FAT tests the presence of publication selection bias, PET, and PEESE estimates and tests the effect of U–I relationship on firm's performance corrected for publication selection bias. *P < 0.1; **P < 0.05; ***P < 0.01.

estimating Equations (3) and (4). Here, $r$ stands for the coefficient reported in the literature and $SE_i$ for its standard error. In this model, the estimated size directly gives the impact representative of each subsample. Table 3 reports the estimates.

Compared with the full-sample estimates for effect estimates reported in Table 2, these subsample estimates of the FAT test provide weaker evidence of publication bias on patent subsample and a relatively high bias regarding the innovative sales subsamples. Moreover, in Table 2, the estimated impact of U–I cooperation on firm's performances was lower compared with the one reported on patent generation in Table 3 ($\hat{\alpha} = 0.153$) and higher compared with the impact on innovative sales ($\hat{\alpha} = -0.055$). PET and PEESE estimations let us conclude the existence of the robust real medium-size effect of U–I collaboration on firms' patent generation and a negative or non-significant effect on the sales growth of innovative products.

### 4.5 Multiple MRA

Several researchers who analyse U–I relationships and firm's performances emphasize that the estimated effect depends on the study attributes such as output measure, data span, type of firms analysed, and even information source (Perkmann and Walsh 2007; Vivas and Barge-Gil 2015). The characteristics of each study generate an intrinsic heterogeneity in our basic MRA. To determine whether the research context influences the practical effect, we conducted a multivariate regression analysis. The hypothesized sources of this excess heterogeneity are incorporated into Equation (5) as 'moderator variables', in order to obtain a better understanding of the variation of the estimated effects size. However, only those research dimensions present in at least five primary studies are specified in our MRA model, which can be expanded as follows:

$$r_i = \beta_0 + \sum \beta_k Z_{ki} + \beta_1 SE_i + \sum \delta_{ji} SE_i K_{ki} + \varepsilon_i \qquad (5)$$

In this model (Equation 5), $\alpha_0$ from Equation (3) is replaced by $\beta_0 + \beta_k Z_{ki}$, where the $Z$ variables represent heterogeneity. The $SE_i K_{ki}$ terms constitute any factor related to publication bias or the researches' inclination to report a statistically significant positive U–I collaboration effect. The classification into $Z$- and $K$-variables is not exempt from the debate, as Dimos and Pugh (2016) and Valickova et al. (2015) point out; the classification done by Stanley and Doucouliagos (2012: 91) is to some degree arbitrary. Stanley et al. (2018) noticed that, and in recent articles, they relaxed their point of view, considering that some methodological study characteristics could be related to the publication bias.

We consider as $Z$-variables those related with the primary study characteristics like the type of U–I relationship studied or the

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**Table 4.** Variables, *Z*/*K* moderators, means, and standard deviations

| | Variable | Description | Z/K | Mean | SD |
|---|---|---|---|---|---|
| | PCC | is the PCC of U–I collaboration and firm performance | | 0.044 | 0.104 |
| | SEpcc | is the standard error of the estimated partial correlation | | 0.035 | 0.025 |
| Type of impact | Technical impact | =1, if estimate comes from technical impact, 0 otherwise | Z | 0.665 | 0.473 |
| | Economic impact | =1, if estimate comes from economic impact, 0 otherwise | Z | 0.335 | 0.473 |
| Type of relationship | Research partnership | =1, if estimate comes from U–I collaboration research, 0 otherwise | Z | 0.884 | 0.321 |
| | Service research | =1, if estimate comes from U–I contract research, 0 otherwise | Z | 0.116 | 0.321 |
| Type of research partner | HEI | =1, if estimate uses data from a relationship with HEIs. | Z | 0.474 | 0.501 |
| | RI | =1, if estimate uses data from a relationship with RIs, 0 otherwise | Z | 0.092 | 0.291 |
| | Research and technology org. | =1, if estimate uses data from a relationship with RTOs, 0 otherwise | Z | 0.434 | 0.497 |
| Regional effects | European Union | =1, if estimate uses data from European Union, 0 otherwise | Z | 0.578 | 0.495 |
| | USA | =1, if estimate uses data from USA, 0 otherwise | Z | 0.127 | 0.334 |
| | UK | =1, if estimate uses data from UK, 0 otherwise | Z | 0.087 | 0.282 |
| | China | =1, if estimate uses data from China, 0 otherwise | Z | 0.162 | 0.369 |
| | Japan | =1, if estimate uses data from Japan, 0 otherwise | Z | 0.012 | 0.107 |
| | South Korea | =1, if estimate uses data from South Korea, 0 otherwise | Z | 0.023 | 0.151 |
| Estimation characteristics | Control sector | =1, if estimate controls for firm sector, 0 otherwise | Z | 0.532 | 0.500 |
| | Control size | =1, if estimate controls for firm size, 0 otherwise | Z | 0.555 | 0.498 |
| | Control R&D | =1, if estimate controls for firm R&D activities, 0 otherwise | Z | 0.711 | 0.455 |
| | Control age | =1, if estimate controls for firm age, 0 otherwise | Z | 0.434 | 0.497 |
| | Control gov. support | =1, if estimate controls for government supported projects, 0 otherwise | Z | 0.035 | 0.184 |
| | Homogeneity | =1, if estimate comes from a homogeneity firm sample, 0 otherwise | Z | 0.116 | 0.321 |
| | Endogeneity | =1, if estimate controls for endogeneity problems, 0 otherwise | Z | 0.081 | 0.274 |
| | OLS | =1, if OLS method is used for the estimation, 0 otherwise | Z | 0.445 | 0.498 |
| | Probit | =1, if Probit method is used for the estimation, 0 otherwise | Z | 0.179 | 0.385 |
| | Logit | =1, if Logit method is used for the estimation, 0 otherwise | Z | 0.145 | 0.353 |
| | Other methods | =1, if other methods are used for the estimation, 0 otherwise | Z | 0.254 | 0.437 |
| | Cross sectional | =1, if study uses cross sectional data to estimate, 0 otherwise | Z | 0.474 | 0.501 |
| | Panel | =1, if study uses panel data to estimate, 0 otherwise | Z | 0.289 | 0.455 |
| | Pooled cross sectional | =1, if study uses pooled cross-sectional data to estimate, 0 otherwise | Z | 0.237 | 0.426 |
| | Log | =1, if Log. transformation is applied for the dependent variable, 0 otherwise | Z | 0.353 | 0.479 |
| | CIS data | = if estimate uses data from CIS based survey, 0 otherwise | Z/K | 0.434 | 0.497 |
| Type of firms | Manufacturing firms | = if estimate uses data from manufacturing firms only, 0 otherwise | Z/K | 0.162 | 0.369 |
| | High-tech firms | = if estimate uses data from high tech. sector firms only, 0 otherwise | Z/K | 0.370 | 0.484 |
| | Innovative firms | = if estimate uses data from innovative firms only, 0 otherwise | Z/K | 0.046 | 0.211 |
| | SME firms | = if estimate uses data from small or medium firms only, 0 otherwise | Z/K | 0.162 | 0.369 |

methodological characteristics. These variables have a direct influence on the effect size, *ceteris paribus*. *K*-variables are those which address special attributes of the sample and not all the primary studies have focused on them (types of firms: *Innovative*, *High Tech*., *Manufacturing*, and *SME*) and which we used as control variables—with caution (Dimos and Pugh 2016: 808). Due to its relevance, we also consider whether the source of the data is the Community Innovation Survey or other CIS-based questionnaire as a *K*-moderator variable (*CIS Data*). *Z*- and *K*-variables could influence the research towards reporting a statistically significant positive effect due to '*a priori*' bias influence based on the sample characteristics or in '*posteriori*' bias due to the interest in publishing it.

Table 4 lists all the *Z*/*K* moderators that are coded and investigated in this study. Specifically, we examined differences in the type of U–I relationship by means of dummy variables coded *Partnership Research* as the omitted variable in our MRA model. The second type of moderator variable concerned is the kind of research partner: *Research and Technology Organizations* category is used as the reference variable. The third type of moderator variable involved is related to the sort of impact. *Economic outcome* is used as the reference variable among other moderator variables driven by the parametric method, and regional effects are also taken into account.

According to Stanley et al. (2018), we follow the general-to-specific modelling approach in our model WLS-MRA (Columns 1–3), validated through a robust-standard estimation (Columns 2–4). Table 5 shows the results of our WLS-MRA model for a *holdout*-(Columns 1 and 2) and a *within*-sample (Columns 2–4). This table presents the set of moderator variables that were included in the final sample of the general-to-specific model WLS approach.

We now focus on the previously analysed variables selected by the theoretical framework related to the collaboration characteristic. We show that there is a publication bias in the literature based on the outcome, the research partner, and the type of relationship. *Technical outcome* (0.080) has a statistically significant positive effect. If we focus on the kind of research partner, we demonstrate that single collaboration with *HEI*s (−0.035) or *RI*s (−0.037) have a negative influence compared with the general group research and

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**Table 5.** Multiple WLS-MRA of U–I collaboration effects MRA—Equation (5).

| Variables | Holdout sample | | Within Sample | |
|---|---|---|---|---|
| | (1)WLS | (2)Cluster robust | (3)WLS | (4) Cluster Robust |
| Technical output | 0.080*** (0.011) | 0.058*** (0.011) | 0.116*** (0.016) | 0.090*** (0.019) |
| HEIs | −0.035*** (0.011) | −0.018** (0.008) | −0.048*** (0.012) | −0.021* (0.012) |
| RIs | −0.037** (0.014) | | −0.058*** (0.016) | −0.030* (0.015) |
| Service research | 0.044** (0.022) | | | |
| Innovative firms | −0.025** (0.011) | −0.016* (0.009) | −0.021* (0.011) | |
| European Union | 0.021* (0.011) | | | |
| USA | −0.031* (0.017) | −0.022* (0.011) | −0.053*** (0.015) | −0.042*** (0.013) |
| Control age | −0.039*** (0.012) | −0.051*** (0.014) | −0.072*** (0.014) | −0.070*** (0.019) |
| Control R&D | −0.048*** (0.013) | −0.056*** (0.017) | −0.057*** (0.012) | −0.048*** (0.014) |
| Control sector | −0.066*** (0.013) | −0.027** (0.012) | −0.048*** (0.010) | −0.037** (0.017) |
| Control gov. support | 0.066* (0.034) | | | |
| Endogeneity | 0.041*** (0.014) | 0.027*** (0.009) | | |
| Log | −0.038*** (0.014) | −0.041*** (0.015) | −0.046*** (0.012) | −0.047*** (0.013) |
| Logit | −0.031** (0.014) | | −0.056*** (0.015) | −0.043* (0.024) |
| Manufacturing firms * SEpcc | 0.038*** (0.010) | | | |
| SEpcc | 1.166*** (0.402) | | | |
| Intercept | 0.048** (0.024) | 0.104*** (0.018) | 0.156*** (0.020) | 0.142*** (0.036) |
| Number of observations | 173 | 173 | 171 | 171 |
| Number of studies (clusters) | | 51 | | 50 |
| $R^2$ | 0.491 | 0.418 | 0.518 | 0.503 |
| AIC | −646.613 | −644.012 | −646.613 | −644.012 |
| BIC | −599.488 | −603.171 | −599.488 | −603.171 |

*Notes*: The dependent variable is PCCs. Standard errors are reported in parenthesis. See Table 4 for variable definitions. *P < 0.1; **P < 0.05; ***P < 0.01.

technology organizations. *Service Research* (0.044) is positive, significant in WLS estimation. Being cautious, we can assert that university consulting or contract research activity for firms has a positive effect (0.044) on firm performance compared with research partnerships.

Following Dimos and Pugh (2016), we also analyse the effect produced by the firm characteristic. This specific effect influences the PCC and even the publication bias. If primary studies samples are formed only by innovative firms (*Innovative Firms*, −0.025), the MRA analysis shows a negative effect on the PCC. And, samples only formed by Manufacturing firms interact with the standard error *SEppc* (*Manufacturing Firms * Sepcc*, 0.038), resulting in authors having more possibility of publishing when they analyse this type of firm.

Moderator variables of regional effects are significant for the *European Union* and the *USA*. The former shows a positive impact (0.021) and the latter, a negative one (−0.031). Moderator variables of firm control such as *Age* (−0.039), *R&D* activities (−0.048), and *Sector* (−0.066), provide a small partial correlation effect which implies little practical value. In this estimation, only controlling for *Government support* (0.066) has a positive impact on effect size. In short, we can affirm that controlling for firms' age and R&D activities and industry has a negative practical value in the studies' regressions, and controlling for government support of the collaboration increased the partial correlation effect estimates.

Moderator variables of the primary studies estimation method show that the primary studies control for *Endogeneity* has statistically significant positive effects (0.041). Based on this last result, we can assert that controlling for the endogeneity problem (i.e., mostly used lag variables) increases the U–I collaboration effect reported. Also, analysing the estimation method used in the primary studies results show the *log* base (−0.038) has a significant adverse impact on the estimation as does also the use of the *Logit* (−0.038) estimation method.

Finally, our omission of Barge-Gil and Modrego (2011) provides an opportunity to see if our MRA model provides accurate predictive or explanatory ability. If a meta-regression model is genuinely explanatory, it captures some true relationship to the underlying effect investigated, which can be used to forecast future performance. Unfortunately, this is not the case for the multiple WLS-MRA model reported in Column 1, Table 5. The mean absolute deviation (MAD) for the holdout sample of fifty-one studies of U–I collaboration on economic growth is 24% larger than the within-sample MAD (0.058 versus 0.047) and the RMSE is quite similar (0.036 versus 0.035). However, as the adjusted $R^2$ is near 0.50, the above results regarding the causes of heterogeneity should be interpreted cautiously.

## 5. Discussion

Our MRA serves to review the reported effects of U–I relationship on firms' performance, analysing the parametric quantitative literature on the subject over the past quarter of the century. Our basic MRA and multiple MRA offer essential findings of the literature that need to be analysed carefully.

First, the analysis of the weighted average shows that the real effects of this collaboration on the company's performance are positive, though small. This effect has been statistically proven through the FAT-PET-PEESE approach. These tests confirm that there is a publication bias in the primary studies and that this heterogeneity in the reported effects should be deepened. Moreover, analysis of the effect size measured as new patent and innovative sales confirms

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that there is a real medium effect on companies' technical and negative or no significant impact on economic performance.

Second, an analysis of the causes of heterogeneity confirms that the works which analyse the relationship between research and technology organizations and firms report more significant results than those which examine the relationship only with HEIs or RIs. The existence of a small number of papers in the sample that focus on RIs could be the cause of that negative effect. Even so, being cautious, we can interpret the variable that partially collects them as a proxy for the real impact generated by this type of organization. RTO are more oriented towards applied science projects with market orientation (Teirlinck and Spithoven, 2012).

The idea, that primary works which analyse more finalization-orientated relationships report higher results, is not accepted. Research partnership has often been pointed out as difficult cooperation between two different cultures which can generate problems of adaptation. However, in modern times inter-organizational cooperation has solved these problems, establishing clear objectives (Estrada et al. 2016). Also, it should also be noted that innovative firms are often analysed as the main important firm partner. However, our results show that non-innovative firms could benefit the most, more than those which use the collaboration only as a window to scientific knowledge and scientific personal. Collaborative outcomes are fully exploited by established companies and universities (Almeida et al. 2011).

## 6. Conclusion

The broad interest in U–I collaboration is understandable. Innovation literature is based on models that give this relationship a prominent place (Bozeman et al. 2013). However, none of the research yields unambiguous conclusions to the effect of U–I relationship on firms' performance. We conducted a MRA of the literature since 1995—comprising fifty-one primary studies—to identify the genuine representative effect established by this literature, after controlling for publication bias and sources of heterogeneity.

In this MRA, we analyse a group of studies which evaluates the impact of the U–I relationship on firms' performance. The heterogeneity between them is reflected in our literature review and meta-regression variables. Moreover, as there is no standard effect measurement in the literature, we transform the heterogeneous reported coefficients into PCCs. Using this effect-size standard measure and applying MRA, we can affirm that there is a genuine empirical effect beyond publication bias. This result is a contribution that complements previous literature reviews, which do not check for publication bias nor could estimate a genuine representative effect beyond publication bias.

Table 2 shows that positive publication bias exists, which may reflect the asymmetric weight of theory in this literature in reporting positive outcomes. In any case, estimation by meta-regression of the genuine effect identified a 'small' positive effect after accommodating for publication bias. However, PCC is a standard measure yet not one of economic effect.

To provide a direct measure of impact on firms' performance, we analyse two subsamples of studies which analyse patent generation and innovative sales growth as examples of technical and economic outcomes. As both outcome measures are commonly used in the literature, the estimation of a genuine effect does not require any transformation, and the results can be interpreted from an impact perspective. Although the samples are small, the models diagnose satisfactorily and show that U–I cooperation has a significant medium-size effect on patent generation and small negative effect on innovative sales.

In sum, our MRA findings reject the negative effect of this cooperation on firms' performance, although the average effect is small. While the lack of evidence for substantial results might be disappointing for policymakers, this suggests that this may be typical of innovation policies. U–I collaboration is an important part of the innovative process, but it depends on the capacity that the firms have to absorb external knowledge. This conclusion contributes to the policy debate by identifying a representative U–I collaboration effect from the large and complex open-innovation literature.

U–I relationships contribute to companies' performance through technical outcomes rather than economic ones. We find that the U–I relationships need to orientate the analysis to the qualitative aspects which can address the individual differences for increasing outcome performance. This analysis could be especially important when collaborative research is implemented as part of a broader open-innovation policy to achieve projects which produce not only positive effects for firms, but also positive spillovers for all of society (Jaeger and Kopper 2014).

Our results also have implications for research practice and the interpretation of findings in this literature. Multiple MRA contradicts main-stream thought. They reveal that finalization-orientated relationships and innovative firms do not increase the impact on the estimated effect size. Now it is accepted that the 'third mission' must be a fundamental part of a research organizations' future activities. Our findings suggest that non-innovative firms could benefit the most if the relationship is boosted with public funds.

In any case, the overall impact of a U–I relationship is underestimated by this evaluation literature because a knowledge spillover effect is not accounted for. Firms might benefit from U–I relationships in a way that cannot be captured by traditional measurements. If so, the lack of substantial effect identified in this MRA may not fully capture the quality of the outcome (Zahringer et al. 2017). This possibility is consistent with the negative influence on the estimated effect size of using logit models to evaluate collaboration effects, because the logit model is only used to measure binary outcomes.

Furthermore, this work also faced certain limitations, such as the fact that the sample of quantitative parametric enterprise-level studies is smaller than that of qualitative studies or semi-parametric ones. First, studies carried out in the past tend not to report the coefficient of effect or standard error, and, to be strict regarding the meta-analysis, they have not been counted so as not to introduce any type of bias on the part of the researcher when it comes to quantifying them. Second, the extended use of a CIS-based survey limited the analysis of the effects of each type of scientific partner; we suffered a certain heterogeneity on our classifications because there is no unified perspective of what collaboration with universities or scientific partners is. Third, the standard 'general-to-specific' approach (Stanley and Doucouliagos 2012: 90) could generate some false certainty about the 'best model' selected (Steel 2020).

To address these limitations, we propose that future works move towards mixed-analyses which can simultaneously address quantitative and qualitative aspects. These approaches have an opportunity to analyse the heterogeneity produced by different scientific partners beyond our classification. For example, it would be interesting to know how the RTOs differ among them or how the Technical Universities differ from other HEIs. Also, a quantitative approach would permit addressing specific time and subnational effects in those regions which have recently modified their scientific institutional frame (e.g., UK REF or

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Nordic FOKUS). In addition, we encourage future MRA studies of approaches to continue developing other types of model selection, such as Bayesian model averaging approaches (Steel 2020) or other non-parametric approaches (Havranek and Sokolova 2020).

Finally, taking these caveats into account, our results provide food for thought about the role played by the U–I interactions on a firm's performance. We offer a measurement of the effect size and an explanation about what variables increase the effect size estimate. Science-based innovation is an important factor for economic growth. Firms engaging in scientific partnerships innovate more. However, our results raise questions about how firms' internal dynamic or characteristics could improve the results of cooperation to maximize their performance and create more value. These results represent a challenge for academics, practitioners, and decision-makers in their quest to design policies and strategies that would create more adequate conditions and environments for firms to perform better and be more competitive.

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## References (references denoted with * are those also included in the MRA)

Adams, J. D. (2002) 'Comparative Localisation of Academic and Industrial Spillovers', *Journal of Economic Geography*, 2/3: 253–78.

*——, Chiang, E. P., and Jensen, J. L. (2003) 'The Influence of Federal Laboratory R&D on Industrial Research', *Review of Economics and Statistics*, 85/4: 1003–20.

*Aiello, F., Cardamone, P., and Pupo, V. (2019) 'New Evidence on the Firm-University Linkages in Europe. The Role of Meritocratic Management Practices', *International Review of Applied Economics*, 33/6: 813–28.

*Albahari, A., Pérez-Canto, S., Barge-Gil, A. et al. (2017) 'Technology Parks versus Science Parks: Does the University Make the Difference?', *Technological Forecasting and Social Change*, 116: 13–28.

Alinaghi, N. and Reed, W. R. (2018) 'Meta-analysis and Publication Bias: How Well Does the FAT-PET-PEESE Procedure Work?', *Research Synthesis Methods*, 9/2: 285–311.

Allen, T. J. and Cohen, S. I. (1969) 'Information Flow in Research and Development Laboratories', *Administrative Science Quarterly*, 14/1: 12.

*Almeida, P., Hohberger, J., and Parada, P. (2011) 'Individual Scientific Collaborations and Firm-Level Innovation', *Industrial and Corporate Change*, 20/6: 1571–99.

Argyres, N. S. and Liebeskind, J. P. (1998) 'Privatising the Intellectual Commons: Universities and the Commercialisation of Biotechnology', *Journal of Economic Behavior & Organization*, 35/4: 427–54.

*Arranz, N. and Fdez de Arroyabe, J. C. (2008) 'The Choice of Partners in R&D Cooperation: An Empirical Analysis of Spanish Firms', *Technovation*, 28/12: 88–100.

Arrow, K. J. (1974) *The Limits of Organisation*. London (UK): Norton & Company.

*Arvanitis, S., Sydow, N., and Woerter, M. (2008) 'Is There Any Impact of University–Industry Knowledge Transfer on Innovation and Productivity? An Empirical Analysis Based on Swiss Firm Data', *Review of Industrial Organization*, 32/2: 77–94.

*—— and Woerter, M. (2009) 'Firms' Transfer Strategies with Universities and the Relationship with Firms' Innovation Performance', *Industrial and Corporate Change*, 18/6: 1067–106.

*Aschhoff, B. and Schmidt, T. (2008) 'Empirical Evidence on the Success of R&D Cooperation—Happy Together?', *Review of Industrial Organization*, 33/1: 41–62.

Barajas, A., Huergo, E., and Moreno, L. (2012) 'Measuring the Economic Impact of Research Joint Ventures Supported by the EU Framework Programme', *The Journal of Technology Transfer*, 37/6: 917–42.

Barney, J. (1991) 'Firm Resources and Sustained Competitive Advantage', *Journal of Management*, 17/1: 99–120.

*Barge-Gil, A. (2010) 'Cooperation-Based Innovators and Peripheral Cooperators: An Empirical Analysis of Their Characteristics and Behavior', *Technovation*, 30/3: 195–206.

*—— and Modrego, A. (2011) 'The Impact of Research and Technology Organisations on Firm Competitiveness. Measurement and Determinants', *The Journal of Technology Transfer*, 36/1: 61–83.

*Becker, W. and Dietz, J. (2004) 'R&D Cooperation and Innovation Activities of Firms—Evidence for the German Manufacturing Industry', *Research Policy*, 33/2: 209–23.

*Beise, M. and Stahl, H. (1999) 'Public Research and Industrial Innovations in Germany', *Research Policy*, 28/4: 397–422.

*Belderbos, R., Carree, M., and Lokshin, B. (2004) 'Cooperative R&D and Firm Performance', *Research Policy*, 33/10: 1477–92.

*——, ——, and —— (2006) 'Complementarity in R&D Cooperation Strategies', *Review of Industrial Organization*, 28/4: 401–26.

*——, ——, ——, and Fernández Sastre, J. (2015) 'Inter-temporal Patterns of R&D Collaboration and Innovative Performance', *The Journal of Technology Transfer*, 40/1: 123–37.

Bellucci, A. and Pennacchio, L. (2016) 'University Knowledge and Firm Innovation: Evidence from European Countries', *The Journal of Technology Transfer*, 41/4: 730–52.

*Biedenbach, T., Marell, A., and Vanyushyn, V. (2018) 'Industry–University Collaboration and Absorptive Capacity: An Empirical Study in a Swedish Context', *International Journal of Technology Management*, 76/1/2: 81.

Boschma, R. A. (2005) 'Proximity and Innovation: A Critical Assessment', *Regional Studies*, 39/1: 61–74.

Bozeman, B., Fay, D., and Slade, C. P. (2013) 'Research Collaboration in Universities and Academic Entrepreneurship: The-State-of-the-Art', *The Journal of Technology Transfer*, 38/1: 1–67.

*Brouwer, E. and Kleinknecht, A. (1996) 'Firm Size, Small Business Presence and Sales of Innovative Products: A Micro-econometric Analysis', *Small Business Economics*, 8/3: 189–201.

Buerger, M., Broekel, T., and Coad, A. (2012) 'Regional Dynamics of Innovation: Investigating the Co-evolution of Patents, Research and Development (R&D), and Employment', *Regional Studies*, 46/5: 565–82.

Caloffi, A., Mariani, M., Mattei, A., and Mealli, F. (2020) 'What Kinds of R&D Consortia Enhance SMEs Productivity? A Hierarchical Bayesian Approach for the Analysis of a Regional Innovation Policy', *Papers in Regional Science*, 99/1: 25–53.

——, ——, Rossi, F., and Russo, M. (2018) 'A Comparative Evaluation of Regional Subsidies for Collaborative and Individual R&D in Small and Medium-Sized Enterprises', *Research Policy*, 47/8: 1437–47.

Caloghirou, Y., Tsakanikas, A., and Vonortas, N. S. (2001) 'University–Industry Cooperation in the Context of the European Framework Programmes', *The Journal of Technology Transfer*, 26/1–2: 153–61.

*Cardamone, P., Pupo, V., and Ricotta, F. (2018) 'Exploring the Relationship between University and Innovation: Evidence from the Italian Food Industry', *International Review of Applied Economics*, 32/5: 673–96.

*Chen, Y., Vanhaverbeke, W., and Du, J. (2016) 'The Interaction between Internal R&D and Different Types of External Knowledge Sourcing: An Empirical Study of Chinese Innovative Firms', *R&D Management*, 46/S3: 1006–23.

Christensen, M. V., Nieminen, M., Altenhofer, M. et al. (2020) 'What's in a Name? Perceptions and Promotion of Responsible Research and Innovation Practices Across', *Science and Public Policy*, 47/3: 360–70.

Cohen, W. M. (2010) 'Fifty Years of Empirical Studies of Innovative Activity and Performance'. In: *Handbook of the Economics of Innovation*, 1st ed., Vol. 1, pp. 129–213.

Downloaded from https://academic.oup.com/spp/advance-article/doi/10.1093/scipol/scab025/6215148 by e.acebo@unileon.es on 08 April 2021

———, Nelson, R. R., and Walsh, J. P. (2002) 'Links and Impacts: The Influence of Public Research on Industrial R&D', *Management Science*, 48/1: 1–23.

Cosh, A. and Hughes, A. (2010) 'Never Mind the Quality Feel the Width: University–Industry Links and Government Financial Support for Innovation in Small High-Technology Businesses in the UK and the USA', *The Journal of Technology Transfer*, 35/1: 66–91.

*Darby, M. R., Zucker, L. G., and Wang, A. (2004) 'Joint Ventures, Universities, and Success in the Advanced Technology Program', *Contemporary Economic Policy*, 22/2: 145–61.

Das, T. K. and Teng, B.-S. (2000) 'A Resource-Based Theory of Strategic Alliances', *Journal of Management*, 26/1: 31–61.

*De Marchi, V. (2012) 'Environmental Innovation and R&D Cooperation: Empirical Evidence from Spanish Manufacturing Firms', *Research Policy*, 41/3: 614–23.

D'Este, P., and Patel, P. (2007) 'University–Industry Iinkages in the UK: What are the Factors Underlying the Variety of Interactions with Industry?', *Research Policy*, 36/9: 1295–313.

*Di Maria, E., De Marchi, V., and Spraul, K. (2019) 'Who Benefits from University–Industry Collaboration for Environmental Sustainability?', *International Journal of Sustainability in Higher Education*, 20/6: 1022–41.

Dimos, C. and Pugh, G. (2016) 'The Effectiveness of R&D Subsidies: A Meta-Regression Analysis of the Evaluation Literature', *Research Policy*, 45/4: 797–815.

Doucouliagos, H. (2011) How Large Is Large? Preliminary and Relative Guidelines for Interpreting Partial Correlations in Economics (No. 5). Deakin (AU).

Egger, M., Smith, G. D., Schneider, M. et al. (1997) 'Bias in Meta-Analysis Detected by a Simple, Graphical Test', *BMJ*, 315/7109: 629–34.

*Ehrenberger, M., Koudelková, P., and Strielkowski, W. (2015) 'Factors Influencing Innovation in Small and Medium Enterprises in the Czech Republic', *Periodica Polytechnica Social and Management Sciences*, 23/2: 73–83.

Escribano, A., Fosfuri, A., and Tribó, J. A. (2009) 'Managing External Knowledge Flows: The Moderating Role of Absorptive Capacity', *Research Policy*, 38/1: 96–105.

Estrada, I., Faems, D., Martin Cruz, N. et al. (2016) 'The Role of Interpartner Dissimilarities in Industry–University Alliances: Insights from a Comparative Case Study', *Research Policy*, 45/10: 2008–22.

Etzkowitz, H. and Leydesdorff, L. (2000) 'The Dynamics of Innovation: From National Systems and "Mode 2" to a Triple Helix of University–Industry–Government Relations', *Research Policy*, 29/2: 109–23.

*Fabrizio, K. R. (2009) 'Absorptive Capacity and the Search for Innovation', *Research Policy*, 38/2: 255–67.

*Faems, D., Van Looy, B., and Debackere, K. (2005) 'Interorganizational Collaboration and Innovation: Toward a Portfolio Approach', *Journal of Product Innovation Management*, 22/3: 238–50.

*Fernandes, C. I. and Ferreira, J. J. M. (2013) 'Knowledge Spillovers: Cooperation between Universities and KIBS', *R&D Management*, 43/5: 461–72.

*Fey, C. F. and Birkinshaw, J. (2005) 'External Sources of Knowledge, Governance Mode, and R&D Performance', *Journal of Management*, 31/4: 597–621.

Freeman, R. E. and Reed, D. L. (1983) 'Stockholders and Stakeholders: A New Perspective on Corporate Governance', *California Management Review*, 25/3: 88–106.

*Frenz, M. and Ietto-Gillies, G. (2009) 'The Impact on Innovation Performance of Different Sources of Knowledge: Evidence from the UK Community Innovation Survey', *Research Policy*, 38/7: 1125–35.

*Fu, X. and Li, J. (2016) 'Collaboration with Foreign Universities for Innovation: Evidence from Chinese Manufacturing Firms', *International Journal of Technology Management*, 70/2: 3: 193–217.

*González-Pernía, J. L., Parrilli, M. D., and Peña-Legazkue, I. (2015) 'STI–DUI Learning Modes, Firm–University Collaboration and Innovation', *The Journal of Technology Transfer*, 40/3: 475–92.

Grillitsch, M., Hansen, T., Coenen, L. et al. (2019) 'Innovation Policy for System-Wide Transformation: The Case of Strategic Innovation Programmes (SIPs) in Sweden', *Research Policy*, 48/4: 1048–61.

——— and Trippl, M. (2018) 'Innovation Policies and New Regional Growth Paths: A Place-Based System Failure Framework'. In: J., Niosi (ed.) *Innovation Systems, Policy and Management*, pp. 329–358. Cambridge (UK): Cambridge University Press

Grimpe, C. and Kaiser, U. (2010) 'Balancing Internal and External Knowledge Acquisition: The Gains and Pains from R & D Outsourcing', *Journal of Management Studies*, 47/8: 1483–509.

Hagedoorn, J., Link, A. N., and Vonortas, N. S. (2000) 'Research Partnerships', *Research Policy*, 29/4: 5: 567–586.

*Hall, B. H., ———, and Scott, J. T. (2003) 'Universities as Research Partners', *Review of Economics and Statistics*, 85/2: 485–91.

*Harris, R., Li, Q. C., and Moffat, J. (2013) 'The Impact of Higher Education Institution-Firm Knowledge Links on Establishment-Level Productivity in British Regions', *The Manchester School*, 81/2: 143–62.

Havranek, T. and Sokolova, A. (2020) 'Do Consumers Really Follow a Rule of Thumb? Three Thousand Estimates from 144 Studies Say "Probably Not', *Review of Economic Dynamics*, 35: 97–122.

*Hewitt-Dundas, N., Gkypali, A., and Roper, S. (2019) 'Does Learning from Prior Collaboration Help Firms to Overcome the 'Two-Worlds' Paradox in University–Business Collaboration?', *Research Policy*, 48/5: 1310–22.

Hicks, D. (2012) 'Performance-Based University Research Funding Systems', *Research Policy*, 41/2: 251–61.

Hong, S., Oxley, L., and Mccann, P. (2012) 'A Survey of the Innovation Surveys', *Journal of Economic Surveys*, 26/3: 420–44.

*Hou, B., Hong, J., Chen, Q. et al. (2019) 'Do Academia–Industry R&D Collaborations Necessarily Facilitate Industrial Innovation in China?: The Role of Technology Transfer Institutions', *European Journal of Innovation Management*, 22/5: 717–46.

*Howells, J., Ramlogan, R., and Cheng, S. (2012) 'Universities in an Open Innovation System: A UK Perspective', *International Journal of Entrepreneurial Behavior & Research*, 18/4: 440–56.

*Huang, K.-F. and Yu, C.-M. J. (2011) 'The Effect of Competitive and Non-competitive R&D Collaboration on Firm Innovation', *The Journal of Technology Transfer*, 36/4: 383–403.

*Inauen, M. and Schenker-Wicki, A. (2011) 'The Impact of Outside-in Open Innovation on Innovation Performance', *European Journal of Innovation Management*, 14/4: 496–520.

Jaeger, A. and Kopper, J. (2014) 'Third Mission Potential in Higher Education: Measuring the Regional Focus of Different Types of HEIs', *Review of Regional Research*, 34/2: 95–118.

Jaffe, A. (1989) 'Real Effects of Academic Research', *The American Economic Review*, 79/5: 957–70.

Jensen, M. B., Johnson, B., Lorenz, E. et al. (2007) 'Forms of Knowledge and Modes of Innovation', *Research Policy*, 36/5: 680–93.

*Kanama, D. and Nishikawa, K. (2017) 'What Type of Obstacles in Innovation Activities Make Firms Access University Knowledge? An Empirical Study of the Use of University Knowledge on Innovation Outcomes', *The Journal of Technology Transfer*, 42/1: 141–57.

*Kim, K. Y. (2012) 'Strategic R&D Alliance Factors that Impact Innovation Success in the Biotechnology Industry', *International Journal of Technology Management*, 59/1/2: 116.

*Kobarg, S., Stumpf-Wollersheim, J., and Welpe, I. M. (2018) 'University–Industry Collaborations and Product Innovation Performance: The Moderating Effects of Absorptive Capacity and Innovation Competencies', *The Journal of Technology Transfer*, 43/6: 1696–724.

Lai, W. H. and Chang, P. L. (2010) 'Corporate Motivation and Performance in R&D Alliances', *Journal of Business Research*, 63/5: 490–6.

Laursen, K. and Salter, A. (2004) 'Searching High and Low: What Types of Firms Use Universities as a Source of Innovation?', *Research Policy*, 33/8: 1201–15.

Leydesdorff, L. (2012) 'The Triple Helix, Quadruple Helix, …, and an N-Tuple of Helices: Explanatory Models for Analysing the Knowledge-Based Economy?', *Journal of the Knowledge Economy*, 3/1: 25–35.

Malerba, F. and Orsenigo, L. (1996) 'Schumpeterian Patterns of Innovation Are Technology-Specific', *Research Policy*, 25/3: 451–78.

Mansfield, E. (1995) 'Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing', *The Review of Economics and Statistics*, 77/1: 55.

Downloaded from https://academic.oup.com/spp/advance-article/doi/10.1093/scipol/scab025/6215148 by e.acebo@unileon.es on 08 April 2021

—— and Lee, J.-Y. (1996) 'The Modern University: Contributor to Industrial Innovation and Recipient of Industrial R&D Support', *Research Policy*, 25/7: 1047–58.

Mascarenhas, C., Ferreira, J. J., and Marques, C. (2018) 'University–Industry Cooperation: A Systematic Literature Review and Research Agenda', *Science and Public Policy*, 45/5: 708–18.

*Medda, G., Piga, C., and Siegel, D. S. (2004) 'University R&D and Firm Productivity: Evidence from Italy', *The Journal of Technology Transfer*, 30/1–2: 199–205.

Metcalfe, J. S. (1995) 'Technology Systems and Technology Policy in an Evolutionary Framework', *Cambridge Journal of Economics*, 19/1: 25–46.

Neves, P. C. and Sequeira, T. N. (2018) 'Spillovers in the Production of Knowledge: A Meta-Regression Analysis', *Research Policy*, 47/4: 750–67.

*Neyens, I., Faems, D., and Sels, L. (2010) 'The Impact of Continuous and Discontinuous Alliance Strategies on Startup Innovation Performance', *International Journal of Technology Management*, 52/3–4: 392–410.

*Nieto, M. J. and Santamaría, L. (2010) 'Technological Collaboration: Bridging the Innovation Gap between Small and Large Firms', *Journal of Small Business Management*, 48/1: 44–69.

*Nuñez-Sánchez, R., Barge-Gil, A., and Modrego-Rico, A. (2012) 'Performance of Knowledge Interactions between Public Research Centres and Industrial Firms in Spain: A Project-Level Analysis', *The Journal of Technology Transfer*, 37/3: 330–54.

OCDE. (2018) *Guidelines for Collecting, Reporting and Using Data on Innovation*. 4th edn. Oslo Manual 2018.

Parrilli, M. D. and Alcalde-Heras, H. (2016) 'STI and DUI Innovation Modes: Scientific-Technological and Context-Specific Nuances', *Research Policy*, 45/4: 747–56.

Perkmann, M., and Walsh, K. (2008) 'Engaging the Scholar: Three Types of Academic Consulting and Their Impact on Universities and Industry', *Research Policy*, 37/10: 1884–91.

——, Tartari, V., McKelvey, M., Autio, E. et al. (2013) 'Academic Engagement and Commercialisation: A Review of the Literature on University–Industry Relations', *Research Policy*, 42/2: 423–42.

—— and Walsh, K. (2007) 'University–Industry Relationships and Open Innovation: Towards a Research Agenda', *International Journal of Management Reviews*, 9/4: 259–80.

Philbin, S. (2008) 'Process Model for University-Industry Research Collaboration', *European Journal of Innovation Management*, 11/4: 488–521.

*Radicic, D. and Pinto, J. (2019) 'Collaboration with External Organisations and Technological Innovations: Evidence from Spanish Manufacturing Firms', *Sustainability*, 11/9: 2479.

*Robin, S. and Schubert, T. (2013) 'Cooperation with Public Research Institutions and Success in Innovation: Evidence from France and Germany', *Research Policy*, 42/1: 149–66.

Rosenberg, N. and Nelson, R. R. (1994) 'American Universities and Technical Advance in Industry', *Research Policy*, 23/3: 323–48.

Rothstein, H. R., Sutton, A. J., and Borenstein, M. (2006) *Publication Bias in Meta-Analysis*, London, UK: SAGE Publications.

Sarkar, M., Echambadi, R., Cavusgil, S. T. et al. (2001) 'The Influence of Complementarity, Compatibility, and Relationship Capital on Alliance Performance', *Journal of the Academy of Marketing Science*, 29/4: 358–73.

Schmidt, F. L. and Hunter, J. E. (2015) *Methods of Meta-Analysis: Correcting Error and Bias in Research Findings*. 3rd edn. London, UK: SAGE Publications (https://doi.org/10.4135/9781483398105).

Siegel, D. S., Waldman, D. A., Atwater, L. E. et al. (2003) 'Commercial Knowledge Transfers from Universities to Firms: Improving the Effectiveness of University–Industry Collaboration', *The Journal of High Technology Management Research*, 14/3: 111–33.

Sjöö, K. and Hellström, T. (2019) 'University–Industry Collaboration: A Literature Review and Synthesis', *Industry and Higher Education*, 33/4: 275–85.

Skute, I., Zalewska-Kurek, K., Hatak, I. et al. (2019) 'Mapping the Field: A Bibliometric Analysis of the Literature on University–Industry Collaborations', *The Journal of Technology Transfer*, 44/3: 916–47.

Stanley, T. D. and Doucouliagos, H. (2012) *Meta-Regression Analysis in Economics and Business*. New York (US): Routledge.

—— and —— (2014) 'Meta-Regression Approximations to Reduce Publication Selection Bias', *Research Synthesis Methods*, 5/1: 60–78.

—— and —— (2015) 'Neither Fixed nor Random: Weighted Least Squares Meta-Analysis', *Statistics in Medicine*, 34/13: 2116–27.

——, ——, Giles, M. et al. (2013) 'Meta-Analysis of Economics Research Reporting Guidelines', *Journal of Economic Surveys*, 27/2: 390–4.

——, ——, and Steel, P. (2018) 'Does ICT Generate Economic Growth? A Meta-Regression Analysis', *Journal of Economic Surveys*, 32/3: 705–26.

Steel, M. F. J. (2020) 'Model Averaging and Its Use in Economics', *Journal of Economic Literature*, 58/3: 644–719.

Teirlinck, P. and Spithoven, A. (2012) 'Fostering Industry-Science Cooperation through Public Funding: Differences between Universities and Public Research Centres', *The Journal of Technology Transfer*, 37/5: 676–95.

*Tsai, K. H. and Hsieh, M. H. (2009) 'How Different Types of Partners Influence Innovative Product Sales: Does Technological Capacity Matter?', *Journal of Business Research*, 62/12: 1321–8.

*Turkina, E., Oreshkin, B., and Kali, R. (2019) 'Regional Innovation Clusters and Firm Innovation Performance: An Interactionist Approach', *Regional Studies*, 53/8: 1193–206.

Ugur, M., Churchill, S. A., and Luong, H. M. (2020) 'What Do We Know about R&D Spillovers and Productivity? Meta-Analysis Evidence on Heterogeneity and Statistical Power', *Research Policy*, 49/1.

Ukpabio, M. G., Adeyeye, A. D., and Oluwatope, O. B. (2016) 'Absorptive Capacity and Product Innovation: New Evidence from Nigeria', *Innovation and Development*, 6/2: 213–33.

*Un, C. A., Cuervo-Cazurra, A., and Asakawa, K. (2010) 'R&D Collaborations and Product Innovation', *Journal of Product Innovation Management*, 27/5: 673–89.

Valickova, P., Havranek, T., and Horvath, R. (2015) 'Financial Development and Economic Growth: A Meta-Analysis', *Journal of Economic Surveys*, 29/3: 506–26.

*Vega-Jurado, J., Gutiérrez-Gracia, A., and Fernández-De-Lucio, I. (2009) 'Does External Knowledge Sourcing Matter for Innovation? Evidence from the Spanish Manufacturing Industry', *Industrial and Corporate Change*, 18/4: 637–70.

Vivas, C. and Barge-Gil, A. (2015) 'Impact on Firms of the Use of Knowledge External Sources: A Systematic Review of the Literature', *Journal of Economic Surveys*, 29/5: 943–64.

Volpi, M. (2017) 'Sources of Information for Innovation: The Role of Companies' Motivations', *Industry and Innovation*, 24/8: 817–36.

*Wang, Y., Huang, J., Chen, Y. et al. (2013) 'Have Chinese Universities Embraced Their Third Mission? New Insight from a Business Perspective', *Scientometrics*, 97/2: 207–22.

Weingart, P. (1997) 'From "Finalization" to "Mode 2": Old Wine in New Bottles?', *Social Science Information*, 36/4: 591–613.

Williamson, O. E. (1981) 'The Economics of Organization: The Transaction Cost Approach', *American Journal of Sociology*, 87/3: 548–77.

*Yaşar, M. and Paul, C. J. M. (2012) 'Firm Performance and Knowledge Spillovers from Academic, Industrial and Foreign Linkages: the Case of China', *Journal of Productivity Analysis*, 38/3: 237–53.

*Yu, G. J. and Lee, J. (2017) 'When Should a Firm Collaborate with Research Organisations for Innovation Performance? The Moderating Role of Innovation Orientation, Size, and Age', *The Journal of Technology Transfer*, 42/6: 1451–65.

Zahringer, K., Christos, K., and Nicholas, K. (2017) 'Academic Knowledge Quality Differentials and the Quality of Firm Innovation', *Industrial and Corporate Change*, 26/5: 1–23.

Zapp, M. and Powell, J. J. W. (2017) 'Moving towards Mode 2? Evidence-Based Policy-Making and the Changing Conditions for Educational Research in Germany', *Science and Public Policy*, 44/5: 645–655.

Zhang, X., Shi, M., and Xu, B. (2019) 'Do Government R&D Subsidies Cultivate Enterprises' Voluntary National/Industry Standard-Setting for Sustainable Development?', *Sustainability*, 11/19: 20.

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## Appendix 1

**Table A1.** Keywords and search strings.

| Category | Keywords |
|---|---|
| University | Universit* OR HEI* OR Higher Education OR Academ* OR Research* |
| Industry | Firm* OR Enterprise* OR 'Private Sector' OR Industr* OR SME* OR Compan* |
| Relationship | Link* OR Relation* OR Cooperat* OR Collaborat* OR External OR Partner* OR Alliance |
| Activity | Innovat* OR R&D OR research OR transfer* OR support OR consultan* |
| Impact | Effect* OR impact* OR assess* OR evaluat* |
| • Search String 1: 26 November 2019<br>• Web of Science: 14.344 Results<br>• Scopus: 2.547 Results | • TOPIC: (Effect* OR impact* OR assess* OR evaluat*) AND TOPIC: (Firm* OR Enterprise* OR 'Private Sector' OR Industr* OR SME* OR Compan*) AND TOPIC: (Link* OR Relation* OR Cooperat* OR Collaborat* OR External OR Partner* OR Alliance) AND TOPIC: (Innovat* OR R&D OR research OR transfer* OR support OR consultan*) AND TOPIC: (Universit* OR HEI* OR Higher Education OR Academ*)<br>• Index = SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC TIME PERIOD = ALL YEARS |
| • Search String 2: 26 November 2019<br>• Web of Science: 6.585 Results<br>• Scopus: 1.584 Results | • TOPIC: (Effect* OR impact* OR assess* OR evaluat*) AND TOPIC: (Firm* OR Enterprise* OR 'Private Sector' OR Industr* OR SME* OR Compan*) AND TOPIC: (Link* OR Relation* OR Cooperat* OR Collaborat* OR External OR Partner* OR Alliance) AND TOPIC: (Innovat* OR R&D OR research OR transfer* OR support OR consultan*) AND TOPIC: (Universit* OR HEI* OR Higher Education OR Academ*)<br>• Refined by: WEB OF SCIENCE INDEX: (WOS.SSCI OR WOS.SCI) AND TYPE OF DOCUMENTS: (ARTICLE) AND LANGUAGE: (ENGLISH)<br>• INDEX = SCI-EXPANDED, SSCI. TIME PERIOD = ALL YEARS |
| • Search String 3: 26 November 2019<br>• Web of Science: 5.214 Results<br>• Scopus: 1.327 Results | • TOPIC: (Effect* OR impact* OR assess* OR evaluat*) AND TOPIC: (Firm* OR Enterprise* OR Private Sector OR Industr* OR SME* OR Compan*) AND TOPIC: (Link* OR Relation* OR Cooperat* OR Collaborat* OR External OR Partner* OR Alliance) AND TOPIC: (Innovat* OR R&D OR research OR transfer* OR support OR consultan*) AND TOPIC: (Universit* OR HEI* OR Higher Education OR Academ*)<br>• Refined by: LANGUAGE: (ENGLISH) AND TYPE OF DOCUMENTS: (ARTICLE) AND (32 Sub Area)<br>• INDEX = SCI-EXPANDED, SSCI. TIME PERIOD = ALL YEARS |

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**Table A.2.** List of search string subareas.

1. Agriculture;
2. Automation and Control Systems;
3. Biotechnology and Applied Microbiology;
4. Business and Economics; Chemistry;
5. Communication; Computer Science;
6. Construction and Building Technology;
7. Demography;
8. Education and Educational Research;
9. Energy and Fuels;
10. Engineering;
11. Environmental Sciences and Ecology;
12. Fisheries;
13. Food Science and Technology;
14. Government and Law;
15. Information Science and Library Science;
16. International Relations;
17. Instruments and Instrumentation;
18. Materials Science;
19. Medical Laboratory Technology;
20. Nuclear Science and Technology;
21. Operations Research and Management Science;
22. Physics;
23. Public Administration;
24. Science and Technology—Other Topics;
25. Social Issues or Geography;
26. Social Sciences—Other Topics;
27. Sociology;
28. Sport Sciences;
29. Telecommunications;
30. Urban Studies.

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**Table A3.** Articles analysed (Denoted with * in the References Section).

| Study | Dependent Variable | Coeff. (S.E.) | Period | Sample | Relation | Research partner | Region |
|---|---|---|---|---|---|---|---|
| Adams et al. (2003) | Patents | 0.48 (0.253) | 1996–1998 | 274 | Service | Res. Institute | USA |
| Albahari et al. (2017) | Innovative sales | −0.315 (0.241) | 2007–2009 | 849 | Partnership | Higher Educ. Inst. | Spain |
| | Patents | 0.014 (0.293) | | | | | |
| Almeida et al. (2011) | Patents | 0.019 (0.038) | 1990–2003 | 149 | Partnership | Higher Educ. Inst. | USA and EU |
| Arranz and Fdez de Arroyabe (2008) | Patents | 0.185 (0.000) | 1997–1998 | 4,763 | Partnership | Higher Educ. Inst. | Spain |
| | Innovative Sales | 0.003 (0.164) | | | | | |
| Arvanitis and Woerter (2009) | Patents | 0.422 (0.183) | 2001 | 2,428 | Service | Higher Educ. Inst. | Switzerland |
| | Innovative Sales | 0.275 (0.146) | | | | | |
| Arvanitis et al. (2008) | Patents | −0.154 (0.481) | 2001 | 241 | Service | Higher Educ. Inst. | Switzerland |
| | | −0.991 (0.664) | | | | Res. Institute | |
| Aschhoff and Schmidt (2008) | Productivity | 0.064 (0.292) | 2001–2004 | 699 | Partnership | Res. Tech. Org. | Germany |
| | Innovative sales | 8.460 (3.490) | | | | | |
| Barge-Gil (2010) | Innovative product | 0.347 (0.322) | 2004 | 3,549 | Partnership | Res. Tech. Org. | Spain |
| | Innovative process | −0.002 (0.036) | | | | | |
| Barge-Gil and Modrego (2011) | Tech. performance | −0.293 (0.292) | 2003–2005 | 257 | Partnership | Res. Tech. Org. | Spain |
| | Econ. performance | 0.072 (0.039) | | | | | |
| Becker and Dietz (2004) | Innovative product | 0.544 (0.209) | 1990–1993 | 2,048 | Partnership | Res. Tech. Org. | Germany |
| Beise and Stahl (1999) | Innovative sales | −0.471 (0.195) | 1993–1996 | 9,782 | Partnership | Higher Educ. Inst. | Germany |
| | | −0.482 (0.370) | | | | Res. Institute | |
| Belderbos et al. (2004) | Added value | 0.507 (0.200) | 1996–1998 | 1,360 | Partnership | Res. Tech. Org. | Netherlands |
| Belderbos et al. (2006) | Productivity | 0.016 (0.061) | 1996–1998 | 1,992 | Partnership | Res. Tech. Org. | Netherlands |
| Belderbos et al. (2015) | Innovative sales | 0.053 (0.045) | 2004–2011 | 9,782 | Partnership | Res. Tech. Org. | Spain |
| Biedenbach et al. (2018) | Innovative product | 1.530 (0.150) | 2010–2013 | 1,532 | Partnership | Higher Educ. Inst. | Sweden |
| Brouwer and Kleinknecht (1996) | Innovative product | 0.820 (0.090) | 1990–1992 | 3,784 | Service | Res. Institute | EU |
| | Innovative sales | 2.080 (1.825) | | | Partnership | Res. Tech. Org. | |
| Cardamone et al. (2018) | Innovative sales | 0.010 (0.006) | 2004–2006 | 3,719 | Partnership | Higher Educ. Inst. | Italy |
| | Innovative sales | 0.006 (0.003) | | | Partnership | | |
| Chen et al. (2016) | Innovative sales | 0.146 (0.047) | 2006–2013 | 478 | Partnership | Res. Tech. Org. | China |
| Darby et al. (2004) | Patents | 31.973 (11.208) | 1988–1996 | 350 | Service | Higher Educ. Inst. | USA |
| | Patents | 30.554 (11.254) | | | | | |
| De Marchi (2012) | Innovative product | 0.244 (0.091) | 2007–2007 | 6,047 | Partnership | Res. Tech. Org. | Spain |
| Di Maria et al. (2019) | Patents | 0.89 (0.404) | 2008–2012 | 350 | Service | Higher Educ. Inst. | Italy |
| Ehrenberger et al. (2015) | Patents | −0.140 (0.069) | 2011 | 1,144 | Partnership | Higher Educ. Inst. | Czech Rep. |
| Fabrizio (2009) | Patents | 0.216 (0.112) | 1976–1999 | 83 | Partnership | Higher Educ. Inst. | USA |
| Fernandes and Ferreira (2013) | Innovative product | 0.400 (0.034) | 2012 | 500 | Partnership | Higher Educ. Inst. | EU |
| | Innovative process | 3.830 (0.224) | | | | | |
| Fey and Birkinshaw (2005) | Innovative product | 0.060 (0.110) | 2003 | 107 | Partnership | Higher Educ. Inst. | UK and Sweden |
| Frenz and Ietto-Gillies (2009) | Sales | 0.419 (1.420) | 1997–2002 | 786 | Partnership | Higher Educ. Inst. | EU |
| Fu and Li (2016) | Sales | 2.111 (1.414) | 2005–2007 | 1,408 | Partnership | Higher Educ. Inst. | China |
| | Innovative product | 3.967 (2.786) | | | | | |
| González-Pernía et al. (2015) | Innovative product | 0.025 (0.091) | 2003–2011 | 4,257 | Partnership | Higher Educ. Inst. | Spain |
| | Innovative process | 0.317 (0.058) | | 4,969 | | | |
| Hall et al. (2003) | Patents | 0.020 (0.340) | 2004–2006 | 313 | Service | Higher Educ. Inst. | USA |
| Harris et al. (2013) | Added value | 0.151 (0.055) | 2004–2006 | 7,580 | Partnership | Higher Educ. Inst. | UK |

(continued)

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**Table .** (continued)

| Study | Dependent Variable | Coeff. (S.E.) | Period | Sample | Relation | Research partner | Region |
|---|---|---|---|---|---|---|---|
| Hewitt-Dundas et al. (2019) | Innovative product | 0.280 (0.060) | 2004–2014 | 7,580 | Partnership | Higher Educ. Inst. | UK |
| Hou et al. (2019) | Innovative product | 0.363 (0.088) | 2009–2014 | 180 | Service | Res. Institute | China |
| Howells et al. (2012) | Innovative product | 2.900 (1.270) | 2008–2009 | 371 | Partnership | Higher Educ. Inst. | UK |
| | Innovative process | 2.900 (1.190) | | | | | |
| | Innovative sales | 1.500 (0.640) | | | | | |
| Huang and Yu (2011) | Patents | 0.413 (0.199) | 1996–2005 | 165 | Partnership | Res. Institute | China |
| Inauen and Schenker-Wicki (2011) | Innovative product | 0.109 (0.050) | 2006–2008 | 141 | Partnership | Higher Educ. Inst. | Germany, Switzerland and Austria |
| | Innovative process | 0.118 (0.048) | | | | | |
| | Innovative sales | 0.022 (0.012) | | | | | |
| Kanama and Nishikawa (2017) | Innovative product | 0.900 (0.274) | 2006–2008 | 1,001 | Partnership | Higher Educ. Inst. | Japan |
| | Innovative sales | −0.927 (0.209) | | | | | |
| Kim (2012) | Innovative product | 0.052 (0.241) | 2003–2011 | 265 | Partnership | Res. Tech. Org. | USA |
| Kobarg et al. (2018) | Innovative sales | 1.060 (0.210) | 2003–2011 | 2,061 | Partnership | Res. Tech. Org. | Germany |
| Medda et al. (2004) | Productivity | −0.066 (1.119) | 1998 | 2,222 | Partnership | Higher Educ. Inst. | Italy |
| | Productivity | 0.542 (0.289) | | | | Res. Institute | |
| Neyens et al. (2010) | Innovative sales | 0.040 (0.110) | 2001–2002 | 217 | Partnership | Res. Tech. Org. | Germany |
| Nieto and Santamaría (2010) | Innovative product | 0.722 (0.129) | 1998–2002 | 1,300 | Partnership | Res. Tech. Org. | Spain |
| | Innovative process | 0.208 (0.084) | | | | | |
| Nuñez-Sánchez et al. (2012) | Patents | −0.192 (0.245) | 1989–1995 | 262 | Partnership | Res. Tech. Org. | Spain |
| | Innovative product | 0.098 (0.184) | | | | | |
| Radicic and Pinto (2019) | Innovative product | 0.132 (0.057) | 2001–2011 | 11,141 | Partnership | Res. Tech. Org. | Spain |
| | Innovative product | 0.221 (0.100) | 1998–2000 | 3,241 | | | |
| | Innovative product | 0.195 (0.100) | | 4,931 | | | |
| Robin and Schubert (2013) | Innovative product | 0.240 (0.120) | 2002–2004 | 5,200 | Partnership | Res. Tech. Org. | Germany and France |
| | Innovative process | −0.030 (0.020) | | | | | |
| Tsai and Hsieh (2009) | Innovative sales | −0.105 (0.024) | 2005–2005 | 1,346 | Partnership | Res. Tech. Org. | China |
| Turkina et al. (2019) | Patents | 0.195 (0.100) | 2000–2009 | 5,780 | Partnership | Res. Tech. Org. | EU |
| Un et al. (2010) | Innovative product | 0.410 (0.159) | 2000–2009 | 781 | Partnership | Higher Educ. Inst. | Spain |
| Vega-Jurado et al. (2009) | Innovative process | 0.510 (0.530) | 2002–2004 | 4,445 | Partnership | Res. Tech. Org. | Spain |
| | Innovative product | 0.520 (0.470) | | | | | |
| Wang et al. (2013) | Patents | 0.673 (0.380) | 2000–2005 | 100 | Partnership | Higher Educ. Inst. | China |
| Yaşar and Paul (2012) | Innovative product | 0.686 (0.203) | 2000–2002 | 1,566 | Partnership | Higher Educ. Inst. | China |
| | Innovative process | 0.206 (0.210) | | | | | |
| | Patents | 0.350 (0.238) | | | | | |
| Yu and Lee (2017) | Patents | 0.242 (0.140) | 2013 | 601 | Partnership | Res. Tech. Org. | South Korea |

*Note*: Coefficients and standard error in bold implies a statistically significant.

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