Revista Galega de ECONOMÍA | Galician Journal of ECONOMICS

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
https://doi.org/10.15304/rge.33.3.9514

Articles

Does Cooperation with Universities and Knowledge Intensive Business Services Matter? Firm-level Evidence from Spain

É importante a cooperación coas universidades e os KIBS? Evidencia de España a nivel de empresa

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Received: 07/11/2023; Accepted: 24/06/2024

Abstract

This manuscript contributes to the literature on firm cooperation with universities and Knowledge Intensive Business Services (KIBS) by framing the analysis according to the literature on causal effects, comparing the effect of each of the agents and exploring which firms benefit the most from cooperation with a specific partner. The results have shown that the bias-adjusted effect is around a 27-30% increase in sales from new products for both types of partners. After covariates and fixed effects are used, it is considered unlikely that this effect is driven by time-varying unobservable factors. Moreover, we have seen that firms that benefit the most from cooperation with universities are different from those firms that benefit the most from cooperation with KIBS.

Keywords: Firm cooperation; Universities; KIBS; Treatment effects; Heterogeneity; Policy matching.

Resumo

Este manuscrito contribúe á literatura sobre a cooperación de empresas con universidades e Knowledge Intensive Business Services (KIBS) enmarcando a análise segundo a literatura sobre efectos causais, comparando o efecto de cada un dos axentes e explorando qué empresas se benefician máis da cooperación cun socio específico. Os resultados mostraron que o efecto axustado polo sesgo provoca ao redor dun 27-30% de aumento das vendas de novos produtos para ambos os tipos de socios. Unha vez utilizadas as covariables e os efectos fixos, considérase pouco probable que este efecto sexa debido a factores inobservables que varían co tempo. Ademais, temos mostrado que as empresas que máis se benefician da cooperación coas universidades son diferentes das que máis se benefician da cooperación cos KIBS.

Palabras chave: Cooperación empresarial; Universidades; KIBS; Efectos do tratamento; Heteroxeneidade; Emparellamento de políticas.

JEL: O32; O33; L24.

1. INTRODUCTION

Cooperation between firms and external knowledge sources for innovation activities has grown considerably in recent decades (Meeus et al, 2004; Amara & Landry, 2005), followed by public initiatives aimed at facilitating these partnerships and a growing interest in analysing their determinants and outcomes (Perkmann & Walsh, 2007; Jaffe, 2008)[1]. In this regard, three research questions have been addressed by previous studies: (i) Which firms are most likely to collaborate with these knowledge providers? (ii) Do these linkages achieve any type of impact? and (iii) What are the determinants of the impacts achieved (if any)?

Vivas-Augier and Barge-Gil (2015) conducted a systematic review of the empirical literature and concluded that the stylised facts that had been developed were that the larger, more R&D-intensive and high-tech firms were, the more likely they were to use knowledge providers and that firms that made use of them achieved greater technical results than those that did not.

However, we have little knowledge about the third question highlighted above: 'What are the determinants of impact?' This would be useful to identify, because firms that would benefit the most would be those that are least likely to use them, which is concerning (Barge-Gil, 2010). In addition, comparisons between external knowledge sources have seldom been made, so the best matchings between potential customers and knowledge providers are open to speculation. Both managers and policy makers would be able to reap benefits from this information; managers may need assistance in choosing the most suitable partner among those available, while policy makers may require guidance about the complementarity or substitutability among different external knowledge providers and about the partners that would best fit with each firm, as the 'one size fits all' approach has proved unsuccessful (Tödtling & Trippl, 2005) and collaboration projects are more likely to fail than individual projects (Guzzini et al, 2018).

The main goals of this work are to provide a comparative analysis of the economic impact of firm cooperation with universities and Knowledge Intensive Business Services (KIBS)[2], with an exploration of the role played by unobservable firm characteristics in the estimation of the impact, and to analyse which types of firms achieve the most impact from collaboration projects with each specific partner. We contribute to the literature in four ways:

Firstly, to our knowledge, this is the first study on the impact of cooperation with knowledge providers that has controlled for unobserved firm-specific time-invariant effects using a large sample of firms from different manufacturing industries and also the first to provide an evaluation of the amount of bias that there could be from other unobservable factors. What is rather important is that after controlling for firm fixed effects, the role played by unobserved characteristics has been negligible[3].

Secondly, although knowledge providers include different types of agents like universities, public research centres, research and technology organisations and KIBs, previous studies have focused on just one type of agent (usually universities). In this study, we provide a comparative

[1] Cooperation for innovation is understood as 'active participation in joint innovation projects' (pure contracting out of work, where there is no active collaboration, is not regarded as cooperation) (OECD, 2005)

[2] KIBs are firms whose primary value-added activities consist of the accumulation, creation or dissemination of knowledge for the purpose of developing a customised service or product solution to satisfy clients' needs (Bettencourt et al, 2002).

[3] García-Vega and Vicente-Chirivella (2020) is a related study that focuses on external R&D supplied by universities only (rather than by collaborations and KIBS).

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
https://doi.org/10.15304/rge.33.3.9514

analysis for the two types of knowledge providers most frequently used by firms as cooperation partners: universities and KIBs[4].

Thirdly, we offer evidence on the economic impacts of these collaborations. While some evidence exists on a positive technical impact, previous studies on the economic impact have provided controversial evidence, thus indicating that more studies were required to develop stylised facts (Vivas-Augier & Barge-Gil, 2015).

Fourth, we explicitly move to a world of heterogeneous effects in order to explore the best matchings between firm characteristics and types of partners, which is very relevant for practitioners and policy makers.

The main results show that the effect of cooperating with universities and KIBS was considerable in magnitude: the bias-adjusted estimate for the effects was around a 27-30% increase in sales of new-to-the-market products as a consequence of cooperation. After covariates and fixed effects were used, it was found that this effect was likely not to have been driven by time-varying unobservable factors. In addition, the average effect of the two knowledge providers was quite similar. However, when an exploratory analysis of heterogeneous effects was developed, we found notable differences between them. The effect of KIBS focuses on small, very R&D-intensive firms and large firms that outsource R&D entirely, while the effect of universities focuses on large, R&D-intensive firms and small firms that outsource R&D entirely. Although the latter results were mainly exploratory, they suggest huge potential benefits from improving the matching between firms and knowledge providers.

The rest of the paper is organised as follows: section 2 summarises the key findings from academic literature that have addressed the impact of collaboration with knowledge providers; section 3 discusses the methodology employed; section 4 presents the data and variables; section 5 explains the results of the analysis; last of all, section 6 provides the discussion and conclusions.

2. LITERATURE REVIEW

The importance of collaboration between firms and knowledge providers has been addressed in the scientific literature, arising from the realisation of the need to innovate for economic growth and competitiveness. Arora et al. (2016) stated that if firms lacked access to external sources of knowledge, the overall rate of innovation would drop significantly. It is, therefore, no surprise that cooperation between external sources of knowledge and industry has intensified over time (Chen et al., 2016), as has the interest from policy makers and R&D managers to identify the best mechanisms for successful collaborations to be formed.

2.1. The determinants and impacts of collaboration

The determinants of collaboration with knowledge providers and its impact on firms are of great interest to researchers. However, the literature has been more interested in studying technical impacts of collaboration between them rather than economic ones: These collaborations with knowledge providers have been found to help firms in many ways, including developing new or improved products or services, filing patents and publishing scientific papers (Almeida et al, 2016; Antonelli & Fassio, 2016; Pippel & Seefeld, 2016).

[4] García-Vega and Vicente-Chirivella (2024) is a related contribution that focus on external R&D bought from universities and from public research institutes (rather than collaboration and KIBS)

Despite the importance of innovation for economic growth, economic impacts of collaboration between firms and knowledge providers have received far less attention than technical ones, and most importantly, stylised facts about these impacts cannot be stated (Vivas-Augier & Barge-Gil, 2015). Some studies have supported the positive effect of collaboration between firms and knowledge providers on economic indicators like sales of new products (innovation sales), overall sales, productivity and sales growth (Barge-Gil & Modrego, 2011; Bishop et al., 2011; Chen et al., 2016; Harris et al., 2011; Mole et al., 2008, 2009; Tsai & Hseih, 2009). However, several other studies have reported otherwise, finding either no effect or a negative effect (Aschhoff & Schmidt, 2008; Belderbos et al., 2006; Eom & Lee, 2010; Hall et al., 2003; Lambrecht & Pirnay, 2005; Miotti & Sachwald, 2003).

Regarding the determinants of collaboration, the literature has found that size and R&D intensity are amongst the most relevant drivers of collaboration with knowledge providers (Adams et al., 2003; Arvanitis et al., 2008; González-Pernía et al., 2013). Size and R&D intensity are often considered to be indicators for the absorptive capacity of firms (Vega-Jurado et al., 2009), yet their roles as determinants not only of utilisation but also of the impact of the collaboration between firms and knowledge providers has not received enough attention, with the direction of the effect being theoretically unclear.

On this topic, the size of firms is generally accepted as a determinant of collaboration, as it encourages more of their resources to be allocated to innovation activities (Nieto & Santamaria, 2010) and it should help them better absorb and benefit from external knowledge, thus making collaboration more successful (Drejer & Østergaar, 2017). However, Eom and Lee (2010) stated that the impact of collaboration is more noticeable for small firms due to their lack of internal resources, especially financial, R&D capacity and facility ones. The smaller the R&D capacity is in these firms, the more active they are when it comes to cooperating with partners in an attempt to overcome their barriers to R&D. In addition, it has been shown that when external knowledge is not easily accessed, small firms are affected more than large ones because the former rely more on external sources for innovation than the latter (Hewitt-Dundas, 2006) and because their resources are more limited than those of their large counterparts (Nieto & Santamaria, 2010).

Barge-Gil (2010) qualified these results in relation to the use of external knowledge sources, showing that the smaller and less R&D-intensive firms are, the less likely they are to use external knowledge sources in their innovation processes, but if they do use them, the more notably they rely on them than large firms or the most R&D-intensive firms do.

To summarize, regarding the determinants of the impact of collaboration, the scientific literature has not provided conclusive evidence on the effect of size and R&D intensity. Accordingly, it is not clear if the firms which are the most likely to collaborate are the same as those benefiting the most from cooperation. Hence, there could be room for an innovation policy to be drawn up to maximize the impact.

2.2. About the type of partner and the impact of collaboration

While the importance of different partners for innovation has been widely studied (Becker & Dietz, 2004), there are a lack of studies comparing the impact of collaborating with different types of knowledge providers. Among the latter, universities have received far more attention than any other group, while KIBS have received the least (Tether & Tajar, 2008). The evident dissimilarities between universities and KIBS[5] would suggest varying motives for firms collaborating, impacts on firms and determinants of these impacts from collaboration with universities and with KIBS. However, the scientific literature has not addressed these

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
https://doi.org/10.15304/rge.33.3.9514

disparities extensively enough to give advice to R&D managers or policy makers on how the type of partner influences the impact of collaboration for different firms.

Analysing firm collaboration with universities, Un et al. (2010) highlighted that firms choose to collaborate with universities because they possess a broader knowledge base and face fewer barriers to accessing knowledge than other providers do. According to Bishop et al. (2011), firms are also eager to collaborate with universities to have access to the outputs of their scientific research. For these reasons, large and R&D-intensive firms are more likely to work with universities (Belderbos et al., 2004). In addition to the impacts mentioned earlier in this section, companies that go into partnerships with universities seem to improve their in-house R&D capacities and increase their R&D investments (Becker and Dietz, 2004).

However, other studies have reported non-significant or negative impacts from collaborating with universities. Vega-Jurado et al. (2009), Kim and Park (2008) and Freel and Harrison (2006) found no significant impact of these collaborations on product innovation. Regarding process innovation, some studies have supported similar non-significant findings (Kim & Park, 2008, Nieto & Santamaria, 2007; Vega-Jurado et al., 2009) and even a negative effect for manufacturing companies (Freel and Harrison, 2006). Fabrizio (2009), Tsai and Hsieh (2009) and Hall et al. (2003) also stated that there is a negative and significant effect of collaboration with universities for the time it takes to file patents, poor innovation sales and the early termination of R&D projects, respectively.

This set of results is coherent with other findings which have stated that the culture and the mismatch of research interests between firms and universities are often motives for firms to seek other types of partners (Freel & Harrison, 2006). Regarding the important topic of which types of firms benefit the most from collaboration with universities, the academic literature has not provided clear insights yet.

KIBS, on the other hand, are expert companies that provide services such as business advice and consultancy (Johnson et al., 2007) to firms who are in need of their specialist services and know-how (Bennett & Robson., 2003). According to Johnson et al. (2007), companies work with KIBS because of a perceived gap between their existing internal resources and those required in order to achieve current and future business objectives. In other words, one of the main reasons for firms collaborating with KIBS is their interest in achieving business growth (Lambrecht & Pirnay, 2005).

Some studies have supported a positive impact of collaboration with KIBS on patents (Ciriaci et al., 2015), sales (Mole et al., 2008; Robson & Bennett, 2000) and employment (Mole et al., 2009). However, others have not found any significant impact from KIBS on product innovation (Vega-Jurado et al., 2009) or on economic firm growth indicators (Mole et al., 2009, 2008) and Tsai and Hsieh (2009) even discovered a significant and negative impact of these partnerships on innovation sales indicators.

Again, as for the types of firms which benefit the most from collaboration with universities, the scientific literature has not provided clear insights on which types of firms would benefit more from collaborating with KIBs instead. While Johnson et al. (2007) and Lambrecht and Pirnay (2005) argued that size is also a determinant for collaboration with KIBS because large organisations, in general, are highly complex and likely to require a higher level of external support than their smaller, less complex organizations, Robson and Bennett (2000) stated that KIBS are good partners for smaller firms because of their experience in dealing with SME clients.

[5] Some of these are legal formation, goals and aims, services and resources and staff profiles.

To sum up, previous studies have achieved contrasting results on the economic impact of collaboration with external sources of knowledge and they have not provided comparative analyses of universities and KIBs, meaning that they have not offered insights into which firms benefit the most from either of these collaborations. The remainder of the paper will try to shed light on these issues.

3. METHODOLOGY

The main challenge when analysing the effect of cooperation with knowledge providers is not to confound the effect of cooperation with the effect of other firms' characteristics. For example, it has been shown that more R&D-intensive firms are more likely to cooperate. If we observe that cooperating firms show higher innovation output that non-cooperating firms, we do not know if this higher innovation output is due to the cooperation or if it is due to the fact that cooperating firms are more R&D-intensive than non-cooperation firms.

This problem has tended to be addressed in previous literature by using multiple regression models, which are useful tools for studying causal effects (Angrist & Pischke, 2009)[6]. This is done to try to control for observable confounding factors, not only R&D intensity but also other firm characteristics such as size, industry, and so on. In this sense, multiple regression is regarded as an 'automated matchmaker', meaning that it only compares the firms that are equal in these observable characteristics, using EQ1.

$$\text{EQ1: } Y_i = \alpha + \beta D_i + \gamma X_i + u_i$$

where Y_i is the output to be analysed (usually new products, processes or patents), D_i is an indicator for cooperation with knowledge providers, X_i is a vector of observable confounding factors and u_i is the error term, which should be independent of D_i for β to be interpreted as the causal effect.

However, it could well be that some potential confounding factors are not observable. For example, 'managerial quality' may be a factor that affects innovation results as well as the likelihood of cooperation and no indicator of 'managerial quality' is usually available. When this is the case, u_i is not independent of D_i, causing the results from the multiple regression to be biased. In this study, we have moved away from EQ1 in two ways[7].

Firstly, we have employed a panel database, each firm having been observed over several years. This means that there is an additional way of addressing the problem of comparing 'similar' firms. Instead of comparing different firms, the effect of cooperating with knowledge providers for each firm across time can be compared (e.g. innovation results beforehand and afterwards). This is called the 'within' or 'fixed effects' (FE) estimator. The idea is that the error term in EQ1 can be decomposed in two different components: a_i, which is time-invariant, and e_{it}, which is time-variant (EQ2, including sub-index for t).

$$\text{EQ2: } Y_{it} = \alpha + \beta D_{it-1} + \gamma X_{it-1} + a_i + e_{it}$$

[6] Randomised controlled trials (RCTs) are usually considered to be the best methodology to address this problem. Unfortunately, empirical studies using RCTs in this research area are scarce (exceptions being Bloom et al. (2013) and Bruhn et al. (2017), who focus only on managerial consultancy).

[7] We also tried to instrument the endogenous variable in different ways. These (unsuccessful) attempts have been reported in the Appendix.

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The fixed effects estimator allows causal effects to be estimated, even when there is correlation between D_{it} and a_i. In the example above, 'managerial ability' is usually considered a firm characteristic that changes very slowly, so it can be included in the time-invariant error term. Accordingly, the fixed effect estimator does not confound the effect of managerial ability on innovation output with our effect of interest, that is, the effect of cooperation with knowledge providers. It is important to note, however, that correlation between D_{it} and e_{it} still needs to be absent to adequately estimate this effect[8]. Despite its wide utilisation in many empirical applications, to our knowledge, this is the first study to use fixed effects methods in the estimation of the effect of cooperation with knowledge providers in a large sample of manufacturing industries[9].

Secondly, we have applied Oster's method (Oster, 2019) to evaluate the amount of bias. This method is based on the analysis of the stability of the estimated coefficient when observed confounding factors are included, with the movement of the estimation scaled by the change in the R^2. When there is just one covariate and under the assumption that selection in unobservables is proportional to selection in observables, the following formula is used[10].

$$\beta^* = \tilde{\beta} - [\dot{\beta} - \tilde{\beta}]\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}}$$

where:

$\tilde{\beta}$ is the coefficient in the regression with full controls
$\tilde{R}$ is the R^2 in the regression with full controls
$\dot{\beta}$ is the coefficient in the regression without controls
$\dot{R}$ is the R^2 in the regression without controls
$R_{\max}$ is $1.3\tilde{R}$ (according to Oster's estimation)

Alternatively, one can calculate the parameter δ, which is the ratio between selection in unobservables relative to selection in observables needed for the coefficient to be zero. To our knowledge, this is the first study to evaluate the amount of bias in multiple regression models when estimating the effect of cooperation with knowledge providers.

[8] An alternative estimator used with panel data is the random effects estimator (RE), which is the Generalised Least Squares (GLS) estimator of EQ2. The assumptions required for this model to consistently estimate the effects of knowledge providers are the same required by OLS but it has the advantage of taking into account the autocorrelation of the error term.

[9] Almeida et al (2011) did one for biotechnology firms and Chen et al (2016) for electronic firms. Fabrizio (2009) reported a robustness check with fixed effects in an analysis of biotechnology and pharmaceutical firms

[10] With more covariates there are multiple solutions for β^*. The Stata program psacalc that accompanies the paper (Oster, 2019) provides a single solution under the additional assumption that the bias from the unobservables is not so large that it biases the direction of the covariance between the observable index and the treatment.

4. ECONOMETRIC ANALYSIS

4.1. Description of the dataset

We have used information from the Technological Innovation Panel (PITEC). The PITEC is a statistical instrument for studying the innovation activities of Spanish firms over time. The database has been developed by the INE (The National Statistics Institute of Spain). The data comes from the Spanish Community Innovation Survey (CIS) and the R&D Survey. The CIS questionnaire follows guidelines in the Oslo Manual (OECD, 2005). In addition, the Spanish version of the CIS is administered together with the R&D Survey, so it includes a much more detailed questionnaire in some aspects of firms' innovation processes, following guidelines in the Frascati Manual (OECD, 2002). The database is available for researchers upon request to INE. The PITEC contains information for a panel of more than 12,000 firms since 2003. The PITEC consists of several subsamples, the most important of which are a sample of firms with intramural R&D expenditures and a sample of firms with 200 or more employees. Both subsamples can be considered census-based. A more detailed description can be found on the INE web site[11].

For this study, data from the years 2004 to 2013 were used. The year 2003 was excluded because relevant questions from the questionnaire were framed in a different way in 2003 and for the years after 2013, there was a methodological change (a rotation system of firms) that may have affected results, so were also excluded. In addition, we restricted the analysis to firms in manufacturing industries that were active in innovation, that is, with positive expenditures in any innovation activity. On the one hand, manufacturing and services show different features in their innovation behaviour (Hipp & Grupp, 2005) [12]. On the other, our population of interest is that of firms active in innovation. In total, 36,922 observations from a 10-year time period were analysed.

4.2. Definition of variables.

4.2.1. Dependent variable.

Our dependent variable was sales from new-to-the-market products, in logs, (LNINNOSALES). This indicator has been widely used in innovation studies and includes radical and incremental product innovation but not pure imitations[13]. Its main advantages are that it is an accurate measure of the level of economic success of firm innovation activities, its applicability to all sectors and is a continuous variable, which is an advantage for the

[11] Data downloaded in October 2015 from http://icono.fecyt.es/PITEC/Paginas/descarga_bbdd.aspx, where they were available at that time.

[12] In addition, KIBS were included in service sectors (EU, 2012). Therefore, if firms from the service sector were included in the sample, these organisations would enter both customers (dependent variable) and knowledge providers (independent variable), perhaps influencing the results. We believe the issue that knowledge providers are also customers is an interesting line of future research, but it is outside the scope of this paper.

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
https://doi.org/10.15304/rge.33.3.9514

econometric analysis (Kleinknecht et al. 2002, Negassi 2004)[14]. Table 1 provides labels, definitions and descriptive statistics of all the variables.

4.2.2. Independent variables.

One limitation identified from previous literature was the lack of studies comparinge the performance of different knowledge providers. With the aim of shedding some light on this issue, one goal of this study is to analyse the effects of cooperation with both universities and KIBS. Accordingly, we used two main independent variables: collaboration with national universities (COOPUNI) and collaboration with national KIBS (COOPKIB)[15,16]. Both were measured in the period from t to t-2 to avoid reverse causality[17].

4.2.3. Control variables.

As explained in the methodology section, the crucial issue for multiple regression to give unbiased estimates of the parameters of interest lies in adequately controlling for the potential confounding factors.

Firstly, we controlled for cooperation with other agents (COOPOTHER). Doing this is very important because cooperation usually takes place with several partners at the same time, and our goal is to distinguish between the effect of cooperation with universities and KIBS and that of other agents whose main activity is not focused on the provision of knowledge or innovation services (e.g., customers, regular providers and competitors).

Secondly, we controlled for firm size (LNSIZE). Larger firms show, on average, more innovation sales and are more likely to cooperate with knowledge providers. Accordingly, controlling for size is crucial to disentangle the effects of cooperation with knowledge providers from the effects of size.

Thirdly, we controlled for the internal R&D intensity of firms (LNRDINTENSITY). Holding all else equal, the higher the investment a firm has in internal R&D, the more innovation sales can be seen and the more likely it is to cooperate with knowledge providers. As for size, this variable must be included in the equation so that the effect of cooperation is not confused with the effect of R&D intensity.

Fourthly, we controlled for the technological level of the industry in which each firm was

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[13] Chen and Roth (2024) have highlighted that when log-transforming variables with zeros, the results may be sensitive to the units of measurement. Results shown here are the log-transformation of INNOSALES in thousands of euros. The log-transformation of INNOSALES in euros yielded similar results (available upon request from the authors).

[14] Its main limitation is the dependence on the economic cycle, which may be different depending on the firm under study, like an exporter or a non-exporter, for example (Kleinknecht, 2002). However, this can be controlled adequately with regression methods.

[15] Unfortunately, the data does not provide any information on the characteristics of universities and KIBS, so a more detailed analysis considering different types of universities or KIBs cannot be performed.

[16] The reason for focusing on national partners was that, in addition to attempting to deal with endogeneity, instrumental variables were employed. International cooperation also showed distinctive features (Miotti & Sachwald, 2003).

[17] Results (available upon request) were robust to the consideration of cooperation between t-1 and t-3.

located. Firms located in high tech industries achieved, all else equal, more innovation sales and were more likely to use external knowledge providers. Again, it is essential to control for this not to confound different effects.

Fifthly, we added four dummy variables for the following firm characteristics: exporting (ITEXPORTS), being part of a group (INGROUP), new creation (ISNEW) and foreign equity (ISFOREIGN). All these factors were likely to be positively related to both innovation sales and cooperation with knowledge providers (see, for example, Mohnen et al., 2006, de Faria et al., 2010).

Table 1. Summary of variables.

VARIABLE	DESCRIPTION	MEAN	SD	MIN	MAX
LNINNOSALES	Log of total innovation sales (sales of new-to-the-market products)18	3.151	3.886	0	11.756
COOPUNI	Binary that takes the value 1 if the firm cooperates with national universities	0.148	0.356	0	1
COOPKIB	Binary that takes the value 1 if the firm cooperates with national KIBS	0.108	0.311	0	1
COOPOTHER	Binary that takes the value 1 if the firm cooperates with any other type of partner	0.347	0.476	0	1
LNSIZE	Log of the total sales of the firm	9.336	1.727	12.025	20.542
LNRDINTENSITY	Log of the internal R&D investment per employee	1.044	1.274	0	10.795
ISLOWTECH	Binary that takes the value 1 if the firm is from a low-tech sector according to the OECD classification[19]	0.273	0.445	0	1
ISLOWMTECH	Binary that takes the value 1 if the firm is from a low-mid tech sector according to the OECD classification	0.240	0.427	0	1
ISMHIGHTECH	Binary that takes the value 1 if the firm is from a mid-high tech sector according to the OECD classification	0.369	0.483	0	1
ISHIGHTECH	Binary that takes the value 1 if the firm is from a high-tech sector according to the OECD classification	0.119	0.323	0	1
ITEXPORTS	Binary that takes the value 1 if the firm has exporting activity: EU or other countries	0.853	0.354	0	1
ISNEW	Binary that takes the value 1 if the firm is new	0.008	0.089	0	1
INGROUP	Binary that takes the value 1 if the firm belongs to a corporate holding	0.427	0.495	0	1
ISFOREIGN	Binary that takes the value 1 if the firm's capital is 51% foreign or higher	0.002	0.047	0	1

Note. Year dummies have also been included. The total number of observations was 36,922.

Source: Own elaboration from PITEC

[19] Source: OECD Data Portal: https://data.oecd.org/

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
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5. RESULTS

5.1. Average effect of cooperation with universities and KIBS

5.1.1. Baseline results

Baseline results are shown in Table 2. Column I shows results from the regression using only cooperation variables, column II includes the rest of the covariates, column III comprises the fixed effects regression and column IV contains the random effects regression.

The coefficients from Column I were positive and very large in magnitude for our variables of interest. Cooperation with universities is associated with an increase of 131.6% in sales from new-to-the-market products while cooperation with KIBS is associated with a 98.97% increase in this same indicator [20]. This is clearly a naïve comparison, as there are many potential confounding factors (e.g., firm size, R&D intensity and industry). Column II includes these covariates, with the estimated effect being around 50% lower, albeit still rather high. Cooperation with universities is associated with a 57.6% increase in sales from new-to-the-market products while cooperation with KIBS is associated with an increase of 57.3%. Notably, both knowledge providers were affected in this regression in a similar way, suggesting that the role played by the covariates was slightly different between the partners; that is, the selection in observables was higher for cooperation with universities [21].

However, there may have been firm-specific unobservables that drive this result. In the third column, we used within-firm variation only, thus eliminating time-constant unobservables (e.g., managerial ability). This caused an additional reduction in the coefficients but the effects were still very high in magnitude: cooperation with universities and KIBS are associated, respectively, with 32.18% and 28.79% increases in sales from new-to-the-market products.

The last column shows the results from the random effects regression. By definition, they lie between the OLS and FE estimations. The Hausman test clearly rejected the null hypothesis that RE was consistent (Chi-Square=201.6, p-value=0.0000), suggesting that the time-invariant fixed unobservables of firms were an important confounding factor.

To summarise, a naïve comparison of sales of new-to-the-market products between firms that cooperated and that did not cooperate with knowledge providers gave us implausibly large estimates of the effect. Around 50% of these estimates were due to firm observables and another 25% could have been attributed to firm-specific, time-invariant unobservables.

There are several concerns that should be addressed. Firstly, the latter estimates could still have been contaminated by firm-specific, time-varying unobservables. Secondly, the dependent variable was censored (i.e., there were firms active in innovation that did not show sales of new-to-the-market products).

[20] Percentages were calculated as , where betahat was the estimated coefficient.

[21] An analysis using the Gelbach (2016) method suggests that this is mainly because of the role played by size in cooperation with universities.

Table 2. Main results

	(1) Simple OLS	(2) Multiple OLS	(3) Fixed effects	(4) Random effects
COOPUNI	0.840*** [0.114]	0.455*** [0.106]	0.279*** [0.091]	0.380*** [0.082]
COOPCTKIB	0.688*** [0.122]	0.453*** [0.114]	0.253** [0.099]	0.337*** [0.091]
COOPOTHER	0.943*** [0.078]	0.641*** [0.074]	0.437*** [0.065]	0.528*** [0.059]
LN_SIZE		0.479*** [0.027]	0.488*** [0.062]	0.436*** [0.024]
ISMLOWTECH		-0.133 [0.099]	0.048 [0.290]	-0.070 [0.086]
ISMHIGHTECH		0.197** [0.092]	0.281 [0.284]	0.331*** [0.083]
ISHIGHTECH		0.277** [0.130]	0.259 [0.228]	0.455*** [0.108]
LN_RDINTENSITY		0.193*** [0.010]	0.078*** [0.010]	0.131*** [0.008]
ITEXPORTS		0.217*** [0.082]	0.103 [0.101]	0.225*** [0.069]
ISNEW		0.498** [0.203]	0.251 [0.239]	0.328* [0.186]
INGROUP		-0.081 [0.085]	0.222* [0.114]	0.065 [0.073]
ISFOREIGN		0.163 [0.604]	0.520 [0.503]	0.314 [0.449]
_CONS	2.625*** [0.043]	-6.996*** [0.427]	-6.297*** [1.020]	-6.034*** [0.365]
N	36,922	36,922	36,922	36,922

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors in brackets. Year dummies included.

5.1.2. Analysis of coefficient stability

The main concern is that FE estimates could still be contaminated by firm-specific, time-varying unobservables. Ideally, we would like to use instrumental variable methods. Although we used them, the results were unfruitful, as can be seen in the Appendix. An alternative way to explore this issue was following Oster's method (Oster, 2019), the results of which are shown in Table 3.

When this method was applied to the multiple OLS, the bias-adjusted estimate for the coefficient was 0.271 for universities and 0.342 for KIBS (the effects reaching 31.1% and 40%, respectively). That is, in both cases, the effects were still very large in magnitude [22]. The δs were well above 1, indicating that selection in unobservables should be much more important than selection in observables for the effect to be zero (δ=2.4 for universities and δ=3.98 for KIBS).

Oster's method can also be applied to the FE estimator. Interestingly, when it was applied, the bias-adjusted effect was very close to the actual FE estimates. More precisely, the bias-adjusted effect is 0.269 for universities and 0.244 for KIBS (effects of 30.86% and 27.6%, respectively). As a consequence, the corresponding δs were extremely high: 24.9 for universities and 27.0 for KIBS.

This is a very important result, as it suggests that firm-varying unobservables play a minor role when the within variation is the only one used and, accordingly, that the upward bias

[22] The reason for the bias-adjusted effect being higher for KIBS is that selection in unobservables is assumed to be proportional to selection in observables, which, as we have seen, is higher in the case of universities.

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https://doi.org/10.15304/rge.33.3.9514

observed in OLS was almost entirely due to the firm time-invariant unobservables that did not contaminate the fixed-effect estimation.

Table 3. The analysis of the stability of effects according to Oster's method

	OLS		FE	
Variable	Bias-adjusted β	Delta	Bias-adjusted β	Delta
COOPUNI	0.271	2.4	0.269	24.9
COOPKIB	0.342	3.98	0.244	27.0

5.1.3. Tobit analysis

An additional concern is that our dependent variable was censored (whereby 58% of firms active in innovation did not sell new-to-the-market products). Although OLS is still the best Minimum Mean Squared Error (MMSE) linear approximation to the conditional expectation function and, in practice, average marginal effects from Tobit models are usually very close to OLS coefficients, we wanted to check whether this was the case in our study (Angrist & Pischke, 2009)[23].

Tobit results are reported in Table 4. Computing average marginal effects for cooperation with universities yielded an effect of 43.76% in the pooled Tobit and 32.7% in the random effects Tobit, while these effects for cooperation with KIBS were 46.67% in the pooled Tobit and 31.13% in the random effects Tobit. This means that the magnitude of the effects was close to that provided by OLS.

Table 4. Tobit regression models

	(1) Multiple OLS	(2) Random effects
COOPUNI	0.767*** [0.207]	0.632*** [0.138]
COOPCTKIB	0.810*** [0.219]	0.602*** [0.144]
COOPOTHER	1.545*** [0.161]	1.203*** [0.104]
LN_SIZE	0.710*** [0.058]	0.617*** [0.050]
ISMLOWTECH	-0.240 [0.234]	-0.081 [0.218]
ISMHIGHTECH	0.403* [0.210]	0.860*** [0.201]
ISHIGHTECH	0.531* [0.281]	1.109*** [0.254]
LN_RDINTENSITY	0.497*** [0.026]	0.310*** [0.017]
ITEXPORTS	0.794*** [0.214]	0.707*** [0.162]
ISNEW	1.270*** [0.487]	0.871* [0.451]
INGROUP	-0.179 [0.194]	0.176 [0.146]
ISFOREIGN	-0.075 [1.268]	0.293 [0.918]

[23] We chose to report the baseline analysis using OLS because it allowed us to address different complications in a way that non-linear models (e.g., Tobit) do not. For example, within estimation and the analysis of coefficient stability proposed by Oster encounter a number of important complications when Tobit models are used.

	(1) Multiple OLS	(2) Random effects
_CONS	-17.989*** [0.922]	-15.706*** [0.810]
N	36,922	36,922

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Coefficients provided. Standard errors in brackets. Year dummies included.

5.2. Heterogeneous effects according to firm characteristics

In this section, we explore the important issue of which firms benefit the most from cooperating with each partner. We focus on the role played by firm size and R&D intensity. We define three size groups according to their annual turnover (European Commission, 2016): (i) small: less than €10M, (ii) medium: between €10M and €50M and (iii) large: more than €50M. We also define three groups according to internal R&D intensity groups: (i) no internal R&D[24], (ii) internal R&D intensity being positive but lower than €5,000/employee, (iii) internal R&D intensity higher than €5,000/employee[25]. These groups are interacted with the COOPUNI and COOPCTKIB variables following the partition approach (Yip & Tsang, 2007) for simplicity of interpretation (the coefficients directly reporting the effect of cooperation with universities/KIBS for these particular groups of firms, that is, the difference in the expected value of the dependent variable for two firms that belong to a specific group when one of them cooperates with universities/KIBS and the other does not, holding all other covariates equal). Table 5 reports the results for the interactions with size and R&D intensity. Multiple OLS estimations are reported in columns 1 and 4, RE in columns 2 and 5 and FE in columns 3 and 6.

This analysis was mainly explorative, so we do not claim that these effects should be interpreted as causal. Our preferred specification in this analysis was the RE regression. The reason is that, first of all, FE estimation is not very suitable for estimating these heterogeneous effects since it uses within-firm variation only and the amount of within variation in size and R&D intensity that takes place together with a different choice in cooperating with universities or KIBS is too low for the effects to be estimated with an acceptable degree of precision [26]. Secondly, RE estimation is preferred over OLS because RE accounts for the autocorrelation of error terms for each firm, while OLS does not.

Column II shows that universities achieved a higher impact with the larger firms and a lower impact with the medium-sized firms, while the impact of KIBS was more uniformly distributed, albeit slightly higher for small and medium-sized firms than for large firms. In Column V, it can be seen that universities obtained a higher impact with firms that did not

[24] These firms have shown positive investments in other innovation activities, such as design, training for innovation, the acquisition of licenses and marketing activities related to new products.

[25] This threshold was chosen so that the two groups (firms that cooperated with universities or KIBS with ‘low’ internal R&D intensity and firms that cooperated with universities or KIBS with ‘high’ R&D intensity) would have a similar sample size. We also tried to use the continuous indicators for size and R&D. However, as we will see in the results, some non-linear effects were hidden in those attempts, even when squared terms were introduced. We decided to report the results using these categorical variables so as to reveal these non-linear effects. Results from interaction with linear and squared terms are available upon request.

[26] Accordingly, as can be seen in table 5, FE standard errors were higher. However, the magnitude of the effects was not far from that provided by multiple OLS and RE.

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https://doi.org/10.15304/rge.33.3.9514

perform internal R&D, while KIBS had a very high effect with both firms that did not perform internal R&D and those that did.

Table 5. Heterogeneous effects according to firm size and internal R&D intensity

	Size			R&D intensity		
	(1) Multiple OLS	(2) Random effects	(3) Within	(4) Multiple OLS	(5) Random effects	(6) Within
COOPUNI1	0.191 [0.118]	0.180* [0.099]	0.138 [0.114]	0.611** [0.290]	0.527** [0.248]	0.318 [0.265]
COOPUNI2	0.107 [0.179]	0.170 [0.133]	0.147 [0.142]	0.444*** [0.146]	0.381*** [0.112]	0.322*** [0.121]
COOPUNI3	1.113*** [0.231]	0.911*** [0.178]	0.664*** [0.197]	0.417*** [0.141]	0.331*** [0.109]	0.202* [0.120]
COOPCTKIB1	0.164 [0.135]	0.289** [0.113]	0.318** [0.126]	1.029*** [0.306]	0.741*** [0.236]	0.556** [0.247]
COOPCTKIB2	0.484*** [0.185]	0.373** [0.146]	0.313** [0.155]	0.199 [0.147]	0.105 [0.118]	0.042 [0.126]
COOPCTKIB3	0.603** [0.253]	0.278 [0.204]	0.046 [0.220]	0.701*** [0.174]	0.589*** [0.132]	0.504*** [0.141]
COOPOTHER	0.646*** [0.074]	0.524*** [0.059]	0.432*** [0.065]	0.644*** [0.074]	0.531*** [0.059]	0.441*** [0.065]
LN_SIZE	0.433*** [0.028]	0.413*** [0.024]	0.478*** [0.062]	0.484*** [0.028]	0.439*** [0.024]	0.488*** [0.061]
ISMLOWTECH	-0.127 [0.099]	-0.069 [0.086]	0.048 [0.290]	-0.135 [0.099]	-0.071 [0.086]	0.047 [0.290]
ISMHIGHTECH	0.193** [0.092]	0.328*** [0.083]	0.279 [0.284]	0.190** [0.092]	0.326*** [0.083]	0.283 [0.283]
ISHIGHTECH	0.262** [0.129]	0.447*** [0.108]	0.251 [0.228]	0.254** [0.129]	0.441*** [0.108]	0.261 [0.228]
LN_RDINTENSITY	0.192*** [0.010]	0.131*** [0.008]	0.077*** [0.010]	0.197*** [0.010]	0.134*** [0.008]	0.080*** [0.010]
ITEXPORTS	0.249*** [0.082]	0.237*** [0.069]	0.105 [0.100]	0.214*** [0.082]	0.223*** [0.069]	0.102 [0.101]
ISNEW	0.471** [0.202]	0.318* [0.186]	0.250 [0.239]	0.480** [0.202]	0.320* [0.186]	0.248 [0.239]
INGROUP	-0.079 [0.085]	0.066 [0.073]	0.222* [0.114]	-0.085 [0.085]	0.063 [0.073]	0.221* [0.114]
ISFOREIGN	0.046 [0.576]	0.297 [0.447]	0.534 [0.505]	0.188 [0.610]	0.338 [0.451]	0.540 [0.502]
_CONS	-6.268*** [0.437]	-5.671*** [0.373]	-6.141*** [1.020]	-7.086*** [0.429]	-6.103*** [0.367]	-6.328*** [1.018]
N	36,922	36,922	36,922	36,922	36,922	36,922

Note:*p < 0.10, **p < 0.05, ***p < 0.01. Standard errors in brackets. Year dummies included.

Because size and R&D intensity are negatively correlated when only innovation-active firms are considered (Cohen & Klepper, 1996)[27], we decided to define six different groups of firms to further explore these results: SMEs without internal R&D, SMES with low internal R&D, SMEs with high internal R&D, large firms without internal R&D, large firms with low internal R&D and large firms with high internal R&D, where the small and medium groups from the previous table were collapsed and the three different groups were maintained[28]. Table 6 shows the sample distribution of the different groups:

[27] The correlation was -0.06 (p-value=0.000) in our sample.

[28] The reason for collapsing small and medium-sized firms together is that coefficients for them were quite close and estimations gain in precision if the total number of groups under consideration is reduced.

Table 6. Distribution of firms by group

	Total sample	UNIs	KIBS
Small without internal R&D (SN)	11.75%	4.16%	5.3%
Small with low internal R&D (SM)	44.32%	28.54%	33.47%
Small with high internal R&D (SH)	24.66%	33.08%	27.52%
Large without internal R&D (LN)	2.98%	1.33%	1.95%
Large with low internal R&D (LM)	12.17%	20.6%	20.57%
Large with high internal R&D (LH)	4.11%	12.28%	11.20%

The results are reported in Table 7, again following the partition approach. COOPUNISN is the interaction term between COOPUNI and small firms without internal R&D, COOPUNISM is the interaction term between COOPUNI and small firms with low internal R&D, COOPUNISH is the interaction term between COOPUNI and small firms with high internal R&D, COOPUNILN is the interaction term between COOPUNI and large firms without internal R&D, COOPUNILM is the interaction term between COOPUNI and large firms with low internal R&D and COOPUNILH is the interaction term between COOPUNI and large firms with high internal R&D. The same way of defining the labels has been used for the interaction with COOPCTKIB.

As seen with Table 5, and as already explained, our preferred specification was the RE regression. This regression shows that firms that achieve a higher impact from collaboration with universities are either small firms that outsource R&D or large firms that do perform internal R&D. On the other hand, the firms that achieve a higher impact when collaborating with KIBS are either firms without internal R&D (especially large firms) or small firms with high internal R&D intensity. The results are summarised in Figure 1.

Table 7. Heterogeneous effects of size and internal R&D intensity

	(1) Simple OLS	(2) Multiple OLS	(3) Within	(4) Random effects
COOPUNISN	0.504* [0.286]	0.782*** [0.290]	0.579** [0.253]	0.755*** [0.241]
COOPUNISM	-0.025 [0.161]	-0.009 [0.156]	0.100 [0.129]	0.067 [0.120]
COOPUNISH	-0.097 [0.149]	0.197 [0.143]	0.101 [0.124]	0.175 [0.112]
COOPUNILN	0.790 [0.780]	0.122 [0.749]	-0.492 [0.688]	-0.206 [0.646]
COOPUNILM	2.035*** [0.294]	1.194*** [0.285]	0.801*** [0.238]	1.008*** [0.219]
COOPUNILH	2.107*** [0.359]	1.082*** [0.359]	0.617** [0.304]	0.903*** [0.276]
COOPCTKIBSN	0.304 [0.297]	0.682** [0.291]	0.301 [0.223]	0.466** [0.216]
COOPCTKIBSM	0.057 [0.156]	0.094 [0.152]	0.158 [0.135]	0.149 [0.125]
COOPCTKIBSH	0.489*** [0.184]	0.539*** [0.176]	0.529*** [0.147]	0.534*** [0.137]
COOPCTKIBLN	2.823*** [0.788]	1.967*** [0.749]	1.266* [0.654]	1.504** [0.619]
COOPCTKIBLM	0.811*** [0.313]	0.267 [0.302]	-0.243 [0.255]	-0.052 [0.240]
COOPCTKIBLH	1.218*** [0.452]	0.890** [0.451]	0.328 [0.369]	0.609* [0.346]
LN_RDINTENSITY	0.181*** [0.010]	0.196*** [0.010]	0.080*** [0.010]	0.135*** [0.008]

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
https://doi.org/10.15304/rge.33.3.9514

	(1) Simple OLS	(2) Multiple OLS	(3) Within	(4) Random effects
COOPOTHER	0.833*** [0.077]	0.649*** [0.074]	0.436*** [0.065]	0.527*** [0.059]
LN_SIZE		0.440*** [0.028]	0.474*** [0.061]	0.415*** [0.024]
ISMLOWTECH		-0.132 [0.099]	0.055 [0.289]	-0.072 [0.086]
ISMHIGHTECH		0.184** [0.092]	0.289 [0.283]	0.322*** [0.083]
ISHIGHTECH		0.232* [0.128]	0.263 [0.228]	0.429*** [0.108]
ITEXPORTS		0.248*** [0.082]	0.107 [0.100]	0.237*** [0.069]
ISNEW		0.448** [0.201]	0.239 [0.239]	0.306* [0.185]
INGROUP		-0.080 [0.085]	0.219* [0.114]	0.064 [0.073]
ISFOREIGN		0.076 [0.577]	0.549 [0.507]	0.323 [0.450]
_CONS	1.476*** [0.067]	-6.393*** [0.431]	-6.099*** [1.016]	-5.729*** [0.370]
N	36,922	36,922	36,922	36,922

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors in brackets. Year dummies included.

Figure 1. Heterogeneous effects of cooperation with universities and KIBS

High R&D Intensity	KIBS	UNIS
Low R&D Intensity		UNIS
No R&D Intensity	UNIS/KIBS	KIBS
	Small firms	Large firms

6. DISCUSSION, CONCLUSIONS AND IMPLICATIONS

The importance of firm cooperation with universities and KIBS has grown in recent decades, as has interest from academics and policy makers on this topic. This literature has been very valuable in developing some stylised facts but has left several questions unanswered. This study aimed to shed light on some of these questions, especially considering the economic impact of firm collaboration with knowledge providers.

On the one hand, studies that have evaluated the effect of a firm's cooperation with universities and KIBS have not usually reflected on the unobservable factors that may bias the results achieved. We have found that most of the bias from naïve comparisons can be accounted for by using observable firm characteristics such as size, R&D intensity, industry and so on and, more importantly, that the remaining biases were almost entirely due to firm-specific, time-invariant unobservables, which we were able to control by using the within estimator. As in previous studies, one limitation of this body of work is that the several attempts we made to use instrumental variables were not successful. Finding suitable instruments is very difficult, especially with observational data from anonymised surveys. The good news is that our results suggest that, after observed covariates are included and within estimation is performed, the role played by unobserved characteristics is negligible.

On the other hand, contrary to the analysis of the technical results for firms, previous studies that have evaluated the economic effect of cooperation with knowledge providers have failed to reach a consensus, so more evidence was needed. Our results are quite clear on this issue. Cooperation with universities and KIBS shows a positive effect on sales from new-to-the-market products. This effect is large in magnitude. The bias-adjusted effect means that sales are around 27%-30% higher for those that cooperate with either of these types of partners, holding all else equal.

In addition, previous literature has tended to focus on a single knowledge provider, especially if the analysis was not merely descriptive. In this study, we simultaneously analysed two types of knowledge providers: universities and KIBS. Although this is not methodologically challenging, it is highly useful from a practical point of view, particularly if heterogeneous effects are allowed for. More precisely, we addressed the issue of which firms benefit the most from cooperation with each knowledge provider. This question is very important for managers and policy makers because there are potential significant benefits to be made if the matching for collaboration between firms and knowledge providers is improved. Results show that, although average effects of cooperation with universities or KIBS were very similar, several differences could be found for different types of firms.

Firstly, universities had their highest effect over small firms without internal R&D intensity and over large firms with internal R&D intensity. Previous literature has not dealt with the heterogeneous effects of these links, but the preference of university teams for working with large, R&D-intensive firms (which can enhance one's reputation and future job prospects) has already been documented (Beise & Stahl, 2001). In addition, some studies (Bruneel et al., 2010) have highlighted the barriers encountered by small firms and those with low internal capabilities when interacting with universities. However, the impact on SMEs without internal R&D was an unexpected finding. These firms may have been founded within universities and, after separation, may have outsourced their entire R&D function to them. More research is needed to understand the mechanisms driving this result.

Secondly, KIBS achieved their largest impact in SMEs with high R&D intensity and in large firms with low R&D intensity. Literature on KIBS has not addressed this issue empirically, but these results are consistent with previous views from the literature. The key role played by KIBS in interactions with SMEs has been highlighted by previous studies (Muller & Zenker, 2001), as has been their role with large non-high-tech firms (Tödtling et al, 2009).

To sum up, this study has provided evidence on the effect of the cooperation of firms with universities and KIBS on their (innovation-related) economic results. In addition, it has provided an exploratory view on the very important issue of matching between firms and knowledge providers. There are some limitations of this study which open avenues for future research: other identification strategies should be employed, specially devoted to a more in-depth analysis of the best matching between knowledge providers and firms. In addition, the use of better proxies of collaboration that go beyond a dummy variable and the utilisation of different measures of performance would improve our knowledge on the collaboration between firms and knowledge providers. Another area of focus should be on extending the analysis to service firms. Finally, this study is not able to provide a better understanding of why certain knowledge providers match better with certain types of clients. The analysis of project-level data and the case studies could be very insightful to address these concerns.

Acknowledgments

We thank for the valuable comments received on an earlier version of this article at the *Workshop on Economics of Science and Innovation*. Barcelona Graduate School of Economics. Andrés Barge Gil acknowledges funding from projects S2015/HUM-3417 (Comunidad de Madrid), ECO2017-82445-R and PID2020-112984GB-C21 (Ministerio de Ciencia e Inovación, Spain).

Authors contribution

Conceptualization, A. B.-G. and C. V.-A.; Methodology, A. B.-G. and C. V.-A..; Software, A. B.-G. and Carlos Vivas-Augie.; Data acquisition, A. B.-G. and C. V.-A.; Analysis and interpretation, A. B.-G. and C. V.-A.; Writing- Preparation of the draft, A. B.-G. and C. V.-A..; Writing-Revision & Editing, A. B.-G.. All authors read and agree with the published version of the manuscript.

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Appendix

Appendix. Instrumental variables (IV)

An ideal instrument for firms' cooperation with universities and KIBS could be the 'exogenous' supply of universities and KIBS[29]. That is, for two firms equal in all characteristics (observables and unobservables), cooperation with universities is expected to be more likely, the more universities the firm has at its disposal, the same being true for KIBS. In the IV language, this means that the instruments satisfy the inclusion restriction. However, the instruments should also satisfy the exclusion restriction, meaning that in our example, if the firm can choose from a high number of universities but decides not to cooperate with any, its sales from new-to-the-market products should not be affected. This restriction could be quite problematic, as a consolidated stream of the literature has documented knowledge spillovers from universities to firms (see, for example, Trajtenberg et al., 1993). This exclusion can be tested if we have over-identification (more instruments than right-hand endogenous variables).

Based on this idea, we used data from EUROSTAT[30] to estimate the supply of universities and KIBS. For universities, the share of total R&D expenditure from the higher education sector out of gross domestic product of each region was chosen[31]. For KIBS, the share of employees from the R&D industry of each region out of the total number of employees of each region was chosen[32].

In addition, we used a typical instrument that is standard with CIS data, the industry-year average of the endogenous variable (see, for example, Cassiman & Veugelers, 2002), so that the exclusion restriction could be tested. As suspected, we clearly rejected the null hypotheses of the instruments satisfying the exclusion restriction[33] so that we cannot use those instruments.

As we had panel data at our disposal, we were able to search for instruments using lags (Arellano & Bond, 1991). However, once again, the null hypotheses of the instruments satisfying the exclusion restriction were clearly rejected[34].

These attempts highlight the difficulty in implementing instrumental variable methods to analyse the effect of cooperation with universities and may partially explain why previous studies did not usually try to use them. Fortunately, our results suggest that most of the confounding factors in the naïve regression are either observable or time-invariant, so they can be controlled for with panel data.

[29] This is the idea followed by Robin and Schubert (2013), among others. Their instruments satisfy the Sargan test for France but not for Germany.

[30] http://ec.europa.eu/eurostat/web/science-technology-innovation/data/database

[31] Eurostart Indicators of total intramural R&D expenditure (GERD) by sectors of performance and NUTS 2 regions from the database of R&D expenditures at national and regional levels: SECTPERF (Higher education sector).

[32] Eurostart Indicators of SBS data by NUTS 2 regions from the database of Human Resources in Science and Technology: NACE_R1 (Research and development), NACE_R2 (Scientific research and development) and INDIC_SB (Number of persons employed). NACE Rev 1.1. Sector 73 (1998 – 2007) and NACE Rev 2 Sector 72 (2008 onwards).

[33] Hansen's J Chi-Square(2)=14.47 (p-value=0.0007),

[34] Chi-Square (106)=195.87 (p-value=0.000. When the closest lags were eliminated, it was the inclusion restriction that was not satisfied.

Revista Galega de Economía, 33(3) (2024). ISSN-e: 2255-5951
https://doi.org/10.15304/rge.33.3.9514