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12 November 2019

Online at https://mpra.ub.uni-muenchen.de/96949/
MPRA Paper No. 96949, posted 23 Nov 2019 00:38 UTC

Does Cooperation with Universities and KIBS Matter? Firm-level Evidence from Spain

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Abstract

This manuscript contributes to the literature on firm cooperation with universities and KIBS by framing the analysis according to the literature on causal effects, comparing the effect of the two different agents and exploring which firms benefit more from cooperation with a specific partner. Results shows that the lower bound for the effect is around 27-30% increase in sales from new products for both types of partners. After covariates and fixed effects are used, it is found that this effect is not likely driven by time-varying unobservable factors. Moreover, we show 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.

JEL: O32; O33, L24

1. Introduction

Firms' cooperation with universities and Knowledge Intensive Business Services (KIBS) has grown remarkably in recent decades (Amara and Landry, 2005), followed by public initiatives aimed at facilitating those links and a growing interest in analyzing the determinants and outcomes of these partnerships (Perkmann and Walsh, 2007; Jaffe, 2008). More precisely, three different research questions have been addressed: (i) Which firms are most likely to collaborate with these knowledge providers? (ii) Do they achieve any type of impact? and (iii) What are the determinants of collaboration impacts?

Vivas and Barge-Gil (2015) conduct a systematic review of the empirical literature and conclude that the stylized facts developed so far are that larger, more R&D-intensive and high-tech firms are more likely to use knowledge providers and that firms that make use of knowledge providers achieve greater technical results. However, this previous literature also shows some methodological caveats and leaves several questions open.

On the one hand, from a methodological point of view, previous literature usually does not frame the evaluation in a causal framework, and as such, little attention has been paid to the crucial issue of the difference between firms that collaborate with external providers and those that do not, so that most results from previous impact evaluations may be biased (Pippel and Seefeld, 2016).

On the other hand, regarding open questions, we have little knowledge about the third question highlighted above: 'What are the determinants of impact?' This is important because the concern exists that firms that potentially benefit the most are those less likely to use them (Barge-Gil, 2010). In addition, comparisons across different external knowledge sources have seldom been made, so the best 'matchings' between potential customers and knowledge providers are open to debate. This is of great practical importance for both managers and policy makers: managers need assistance in choosing the most suitable partner among those available, while policy makers require guidance about the complementarity or substitutability among different external knowledge providers and about the partners that best fit with each firm, as the 'one size fits all' approach has proved unsuccessful (Tödtling and Trippl, 2005) and collaborations projects are more likely to fail (Guzzini et al, 2018)

This work contributes to the literature in four different ways:

First, we structure the evaluation in a causal framework. This methodology makes it easier to think about the potential biases existing in any method and forces researchers to explicitly reflect on potential confounding factors and techniques to address them. More precisely this study is, to our knowledge, the first one to control by unobserved firm-specific time-invariant effects[1] in a large sample of manufacturing industries dealing with this topic and also the first in providing an evaluation of the amount of bias that could be due to other unobservable factors.

Second, we consider two different types of knowledge providers: universities and Knowledge Intensive Business Services (KIBs) and compare the impact achieved by both of them.

Third, we provide evidence on the economic impacts of these collaborations. While some evidence exist on a positive technical impact, evidence on the economic impact is still controversial (Vivas and Barge-Gil, 2015).

Fourth, we explicitly move to a world of heterogeneous effects 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 is large in magnitude: the lower bound estimate for the effects is around a 27-30% increase in sales from new-to-the-market products as a consequence of cooperation. After covariates and fixed effects are used, it is found that this effect is not likely driven by time-varying unobservable factors, so it can be interpreted in a causal way. In addition, the average effect of the two knowledge providers is quite similar. However, when an exploratory analysis of heterogeneous effects is developed, we find important 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 are mainly exploratory, they suggest huge potential benefits from improving the matching between firms and knowledge providers.

The rest of the paper is organized as follows. Section 2 summarizes key findings from academic literature that addresses the impact from collaboration with knowledge providers. Section 3

[1] Almeida et al (2011) did it for biotechnology firms, Chen et al (2016) did it for electronic firms and Fabrizio (2009) reports a robustness check with fixed effects in their analysis of biotechnology and pharmaceutical firms.

discusses the methodology employed. Section 4 presents data and variables. Section 5 shows results of the analysis and Section 5 provides discussion and conclusions.

2. Literature Review

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

2.1. About the Determinants and the Impact of Collaboration

The determinants of collaboration with knowledge providers and its impact on firms are of great interest for researchers. However, the literature has taken greater interest in studying the technical impacts of collaboration between firms and knowledge providers, rather than economic impacts (Vivas-Augier and Barge-Gil, 2015). These impacts have been found to be positive and relevant: Collaboration with knowledge providers helps firms to develop new or improved products or processes (Antonelli & Fassio, 2016; Pippel and Seefeld, 2016), to patent (Almeida et al, 2016), and to publish scientific papers, among other relevant outcomes.

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, more importantly, it is not yet possible to state stylized facts about the economic impact of collaboration between firms and knowledge providers (Vivas and Barge-Gil, 2015). Some studies support the positive effect of collaboration between firms and knowledge providers on economic indicators of firms like sales from new products (innovation sales), overall sales, productivity and sales growth (Chen et al., 2016, Barge-Gil and Modrego, 2011, Bishop et al., 2011, Harris et al., 2011, Tsai and Hseih, 2009, Mole et al. 2008, 2009). However, several other studies report differently, finding no effect or a negative effect (Eom and Lee, 2010, Hseuh et al., 2010, Aschhoff and Schmidt, 2008, Belderbos et al., 2006, Lambrecht and Pirnay, 2005, Hall et al., 2003, Miotti and Sachwald, 2003).

Regarding the determinants of collaboration, the literature supports that size and R&D intensity are amongst the most relevant drivers of collaboration with knowledge providers (Adams et al., 2003), Arvanitis el al., 2008, Gonzalez-Pernia et al., 2013). Size and R&D intensity are often considered as indicators for the absorptive capacity of firms (Vega-Jurado et al., 2009), yet their role as determinants not only of utilization but also of the impact of collaboration between firms and knowledge providers has not received enough attention (Vivas and Barge-Gil, 2015) with the direction of the effect being theoretically unclear.

For example, size is generally accepted as a determinant of collaboration as it favors the allocation of more resources to firms' innovation activities (Nieto and Santamaria, 2010) and it should help to better absorb and benefit from external knowledge, thus making collaboration more successful (Drejer and Østergaar, 2017). However, Eom and Lee (2010) state that the impact of collaboration is larger on smaller firms due to because of their lack of internal resources, especially financial, R&D capacity, or facility. The smaller the R&D capacity, the more active the firm is in cooperating with partners in order to overcome its barriers to R&D. In addition, it has been shown that lack of supply of external knowledge providers is more harmful for smaller firms than for larger firms because smaller firms rely more on external sources for innovation than larger firms (Hewitt-Dundas, 2006) and because their resources are more limited than large firms' (Nieto and Santamaria, 2010).

Barge-Gil (2010) qualifies these results in relation to the use of external knowledge sources, showing that smaller and less R&D-intensive firms are less likely to use external knowledge sources in their innovation process but, conditional on doing so, they rely much more on them than large firms or than more R&D-intensive firms.

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 those firms more likely to cooperate are also those benefiting the most from cooperation so that it could be room for innovation policy to take actions in order to maximize the impact.

2.2. About the Partner and the Impact of Collaboration

While the importance of different partners for innovation has been widely studied (Becker and Dietz, 2004), there is a lack of studies comparing the impact of collaborating with different types of knowledge providers (Vivas and Barge-Gil, 2015). Among knowledge providers, universities have received far more attention than any other, while KIBS have received the least (Tether and Tajar, 2008). The evident differences between universities and KIBS[2] would suggest differences in the motives for firms to collaborate, the impact on firms from collaboration and the firms' determinants of the impact of collaboration with universities and KIBS. However, the scientific literature has not addressed these differences extensively enough to give advice to R&D managers and policy makers on how the type of partner influences the impact of collaboration for different firms (Vivas and Barge-Gil, 2015).

Analyzing firm collaboration with universities, Un et al. (2010) highlight that some of the motives for firms to collaborate with universities relate to the facts that universities possess a broader knowledge base and face fewer barriers to accessing knowledge than other providers. 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 such reasons, larger and R&D-intensive firms are more likely to choose collaborating with universities (Belderbos et al., 2004). In addition to the impacts mentioned earlier in this section, firms that collaborate with universities

2 Legal formation, goals and aim, services and resources, profile of staff, etc.

seem to improve their in-house R&D capacities and increase their R&D investments (Becker and Dietz, 2004).

Despite studies that support the positive impacts of collaboration with universities, there are studies that report non-significant or negative impact from collaborating with them. Vega-Jurado et al. (2009), Kim and Park (2008) and Freel and Harrison (2006) report no significant impact of collaboration with universities on product innovation. Regarding process innovation, some studies support similar non-significant findings (Vega-Jurado et al., 2009, Kim and Park, 2008, Nieto and Santamaria, 2007) and even a negative effect for manufacturing companies (Freel and Harrison, 2006). Fabrizio (2009), Tsai and Hsieh (2009) and Hall et al. (2003) also report a negative and significant effect of collaboration with universities for time to patent, innovation sales and early-termination of R&D projects , respectively.

The latter conclusions are coherent with findings that report that the culture and the mismatch of research interests between firms and universities are often motives for firms to seek other types of partners (Harrison and Freel, 2006). Regarding the important topic of which types of firms will benefit more 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 the increasing need of firms for specialist services and knowledge skills (Bennett and Robson., 2003). According to Johnson et al. (2007), firms seek and use KIBS because of a perceived gap between their existing internal resources and the resources required in order to achieve current and future business objectives. In other words, one of the main reasons for firms to collaborate with KIBS is their interest in seeking business growth (Lambrecht and Pirnay, 2005).

Johnson et al. (2007) and Lambrecht and Pirnay (2005) argue that size is also a determinant for collaboration with KIBS. Larger organizations, in general, are highly complex and likely to require a higher level of external support than smaller, less complex organizations. Few studies support, for example, their positive impact for patents (Ciriaci et al., 2015), sales (Robson and Bennett, 2000; Mole et al., 2008) or employment (Mole et al., 2009). Robson and Bennett (2000) state that KIBS are a good partner for smaller firms because of their experience in dealing with SME clients. However, some authors report no significant impact from KIBS for product innovation (Vega-Jurado et al., 2009) or economic growth indicators of the firm (Mole et al., 2009, 2008). Tsai and Hsieh (2009) report a significant and negative impact of KIBS on innovation sales indicators. Again, as for which types of firms will benefit more from collaboration with universities, the scientific literature has not provided clear insights on which types of firms will benefit more from collaboration with KIBs.

Considering that the literature lacks stylized facts for choosing the best partner in terms of impact of collaboration, and given the importance of choosing the correct partner for innovation and collaboration success, in what follows, we will address these open questions from the previous literature.

3. Methodology

The starting point for addressing the causal effect of cooperation with knowledge providers is the *potential outcomes model* with homogeneous effects (Angrist and Pischke 2009)[3]. In our study, this model states that for each firm i a binary indicator D is employed to control for whether individual i cooperated with a knowledge provider ($D_i = 1$ if the firm cooperates and $D_i = 0$ if it does not).

If we denote innovation output by Y, two potential innovation outputs exist: Y_1, which is the output achieved by the firm if it does cooperate and Y_0, which is the output achieved by the firm when it does not cooperate. If we could observe every firm in both states of the world, evaluation of the causal effect would be straightforward.

[3] As a starting point, we can consider homogeneous effects (if the effects are heterogeneous, the model provides the average effect among those that cooperated). Then, we will move to a world of heterogeneous effects according to different firms' characteristics.

However, this is not the case. For the firms that do cooperate, we observe Y_1 but not Y_0, while for firms that do not cooperate, we observe Y_0 but not Y_1. In other words, we do not observe the innovation result of a specific firm (at a specific point in time) when the firm cooperates *and* when the firm does not. We only observe one of the two potential outcomes. EQ1 shows this fact: the output we observe is Y_0 if the firm does not cooperate and is $Y_0 + (Y_1 - Y_0)$, that is, Y_1, if the firm does cooperate. Accordingly, the term $(Y_{1i} - Y_{0i})$ is the causal effect of D_i.[4].

EQ1: $Y_i = Y_{0i} + (Y_{1i} - Y_{0i}) D_i$

As it is unfeasible to compare both states for any one individual, we have to approach the causal effect analysis by comparing those firms that cooperate with those that do not. As EQ2 shows, this comparison adds a *selection bias*[5]*:* the difference in the outputs of cooperating and non-cooperating firms if none of them had cooperated: $E\,[Y_{0i} \mid D_i = 1] - E\,[Y_{0i} \mid D_i = 0)$.

EQ2: $E\,[Y_i \mid D_i = 1] - E\,[Y_i \mid D_i = 0] = E\,[Y_{1i} - Y_{0i} \mid D_i = 1] + E\,[Y_{0i} \mid D_i = 1] - E\,[Y_{0i} \mid D_i = 0]$

In other words, the crucial problem is that we are comparing firms that are different in some characteristic (confounding factor) that affects both the innovation output and the decision to cooperate. For example, it has been shown that more R&D-intensive firms are more likely to cooperate (Vivas and Barge-Gil 2015). If we observe that cooperating firms show higher output that non-cooperating firms, is this because of cooperation or the fact that cooperating firms are more R&D-intensive? We don't know and we can't know if we do not move a step forward. All the methods to evaluate casual effects share the purpose of aiming to compare firms that are equal in those potential confounding factors[6].

[4] For simplicity, we explain the methodology with a single cooperation variable. In the empirics, we will use two different variables (cooperation with universities and cooperation with KIBS). This does not add any important methodological issue to the analysis.

[5] The difference in average Y_{0i} between those individuals with and without the treatment.

[6] The ideal methodology would be a 'randomized controlled trial' (RCT). Unfortunately, empirical studies using RCTs in this are scarce (exceptions are Bloom et al., 2013, and Bruhn et al., 2017, who focus only on managerial consultancy).

Multiple regression models are a useful tool for studying causal effects (Angrist and Pischke 2009, Wooldridge 2002). The idea is to control for observable confounding factors: for example, 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'. That is, it compares only those firms that are equal in these observable characteristics[7]. This has been the strategy usually employed by previous studies analyzing the effect of cooperation with knowledge providers on firms' innovative output, thus estimating EQ3.

EQ3: $Y_i = \alpha + \beta D_i + \gamma X_i + u_i$

However, a concern still exists. It could well be that some potential confounding factors are not observable. If this is the case, the results from multiple regressions are still biased. For example, it could be that 'managerial quality' is a factor that affects innovation results but it also affects the likelihood of cooperation. However, no indicator of 'managerial quality' is usually available. Following the notation from EQ3, it means that D and u are related, so β is a biased estimator of the 'true' effect we would like to know. In this study, we move further in two ways[8].

First, we employ a panel database (each firm is observed several times). This means that we have an additional way of addressing the problem of comparing 'similar' firms. Instead of comparing between different firms, we can compare the effect of cooperating with knowledge providers for each firm across time (comparing innovation results before and after the cooperation). This is called the 'within' or 'fixed effects' estimator. The idea is that the error term in EQ3 can be decomposed in two different components: a_i, which is time-invariant, and e_{it} ,which is time-variant (EQ4, including sub-index for t).

EQ4: $Y_{it} = \alpha + \beta D_{it-1} + \gamma X_{it-1} + a_i + e_{it}$

[7] It is important to distinguish between good and bad controls. Bad controls are those also caused by the variable of interest. For example, if one output of cooperation is more patents, and patents favo~~ur~~ further innovation result, then patents should not be included as a control in the regression.

[8] We also tried different ways of instrumenting the endogenous variable. These (unsuccessful) attempts are reported in Appendix A.

The fixed effects estimator allows estimating causal effects even in the presence of correlation between D_{it} and a_i. In the example above, 'managerial ability' has usually been 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 the absence of correlation between D_{it} and e_{it} is still needed to adequately estimate this effect[9].

Second, we apply Oster's method (Oster, 2019) to evaluate the amount of the bias. This method allows for the calculation of the lower bound of the coefficient under the assumption that selection in unobservables is proportional to selection in observables, using the following formula:

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

where:

$\tilde{\beta}$ is the coefficient in the regression with full controls

$\tilde{R}$ is the R^2 in the corresponding regression

$\dot{\beta}$ is the coefficient in the regression without controls

$\dot{R}$ is the R^2 in the corresponding regression

$R_{\max}$ is $1.3\tilde{R}$ (according to Osters' 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.

[9] An alternative estimator to be used with panel data is the random effects estimator (RE), which is the Generalized Least Square (GLS) estimator of EQ4. The assumptions required for this model to consistently estimate the effects of knowledge providers are the same required by OLS but it provides the advantage of taking into account the issues of autocorrelation of errors to achieve efficiency.

4. Econometric Analysis

4.1. Description of the dataset.

We use 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 is developed by the INE (The National Statistics Institute). The data come 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 placed at the disposal of researchers on the FECYT web site. 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 within intramural R&D expenditures and a sample of firms with 200 or more employees. Both subsamples enter on a census basis. A more detailed description can be found on the FECYT web site[10].

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 years after 2013 are not used because there was a methodological change that may affect results[11]. In addition, we restrict the analysis to firms with *internal expenditures in innovation* (GTINN) from manufacturing sectors. On the one hand, our population of interest is that of firms active in innovation. On the other, manufacturing and services show different features in

[10] Data downloaded in October 2015 from http://icono.fecyt.es/PITEC/Paginas/descarga_bbdd.aspx.
[11] A rotation system of firms was implemented. Further details can be found in: https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176755&menu=metodologia&idp=1254735576669.

their innovation behavior (Hipp and Grupp, 2005)[12]. In total, 36,922 observations from a 10-year time period were analyzed.

4.2. Definition of variables.

4.2.1. Dependent variable.

There are several types of impacts of the use of knowledge providers: economic, technical, investment and intangible (Barge-Gil and Modrego, 2011). The aim of this study is to focus on economic impact, like in Robin and Schubert (2013), Cumming and Fischer (2012) and Knudsen (2007)[13], which achieve contrasting results. As a consequence, no stylized facts have yet been developed regarding the influence of knowledge providers on economic results (Vivas and Barge-Gil, 2015). The main goal of this study is to shed new light on this issue. For this reason, our dependent variable is sales from new-to-the- market products, in logs, (LNINNOSALES). This indicator has been widely used in recent innovation studies (for a review see, for example, Barge-Gil, 2013). Its main advantages are being an accurate measure of the level of economic success of the innovation activities of the firm, its applicability to all sectors, and being a continuous variable, which is an advantage for the econometric analysis (Kleinknecht et al. 2002, Negassi 2004)[14]. Table 3 provides labels, definitions and descriptive statistics of all variables.

4.2.2. Independent variables.

One limitation identified from previous literature was the lack of studies that compare the performance of different knowledge providers. With the aim of shedding some light on this

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

[13] For a review on different types of impacts when collaborating with knowledge providers, see, for example, Bishop et al. (2011).

[14] Its main limitation is the dependence on the economic cycle, which may be different for different firms, for example, exporters and non-exporters (Kleinknecht, 2002). However, this can be controlled adequately with regression methods.

issue, one goal of this study is to analyze the effects of cooperation with both universities and KIBS. Accordingly, we use two main independent variables: collaboration with national universities (COOPUNI) and collaboration with national KIBS (COOPKIB)[15]. Both are measured in the period from t to t-2 to avoid reverse causality[16].

4.2.3. Control variables.

As explained in the methodological 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.

First, we control for cooperation with other agents (COOPOTHER). Controlling for cooperation with other agents is very important because cooperation usually takes place with several partners at the same time, and our goal is to distinguish the effect from cooperation with universities and KIBS from the cooperation with other agents (like customers, regular providers or competitors).

Second, we control 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 separate the effects of cooperation with knowledge providers from those of size.

Third, we control for firms' internal R&D intensity (LNRDINTENSITY). Holding all else equal, those firms with higher investment in internal R&D show more innovation sales and are also more likely to cooperate with knowledge providers. As for size, it is crucial to include this variable in the equation not to confound the effect of knowledge providers and cooperation.

[15] The reason to focus on national partners is that, in an additional attempt to deal with endogeneity, instrumental variables were employed. In addition, international cooperation shows some distinctive features (Miotti and Sachwald, 2003)

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

Fourth, we control for technological level of the industry in which the firm is located. Firms located in high tech industries achieve, all else equal, more sales from new-to-the-market products and are more likely to use external knowledge providers. Again, it is crucial to control for this not to confound different effects.

Fifth, we add 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 are likely to be positively related to both sales from new-to-the-market products and cooperation with knowledge providers (see, for example, Mohnen et al., 2006, de Faria et al., 2010).

Table 3 – Summary of variables.

VARIABLE	DESCRIPTION	MEAN	SD
LNINNOSALES	Log of total innovation sales (sales from new-to-the-market products, in thousands of euros)	3.151	3.886
COOPUNI	Binary that takes the value 1 if the firm cooperates with national universities	0.148	0.356
COOPKIB	Binary that takes the value 1 if the firm cooperates with national KIBS	0.108	0.311
COOPOTHER	Binary that takes the value 1 if the firm cooperates with any other type of partner	0.347	0.476
LNSIZE	Log of the total sales of the firm	16.238	1.793
LNRDINTENSITY	Log of the internal R&D investment per employee	6.779	3.065
ISLOWTECH	Binary that takes the value 1 if the firm is from a low-tech sector according to the OECD classification (see Appendix B)~~.~~	0.273	0.445
ISLOWMTECH	Binary that takes the value 1 if the firm is from a low-mid tech sector according to the OECD classification (see Appendix B)~~.~~	0.240	0.427
ISMHIGHTECH	Binary that takes the value 1 if the firm is from a mid-high tech sector according to the OECD classification (see Appendix B)~~.~~	0.369	0.483
ISHIGHTECH	Binary that takes the value 1 if the firm is from a high-tech sector according to the OECD classification (see Appendix B)~~.~~	0.119	0.323
ITEXPORTS	Binary that takes the value 1 if the firm has exporting activity in EU or other countries	0.853	0.354
ISNEW	Binary that takes the value 1 if the firm is a newborn~~.~~	0.008	0.089
INGROUP	Binary that takes the value 1 if the firm belongs to a corporate holding~~.~~	0.427	0.495
ISFOREIGN	Binary that takes the value 1 if the firm's capital is 51% or more foreign~~.~~	0.002	0.047
YEAR DUMMIES	10 binary variables (one for each year of the sample) that take the value 1 if the data from the observation correspond with the year of the variable		

5. Results

5.1. Average effect of cooperation with universities and KIBS

5.1.1. Baseline results

Results are shown in Table 4. Column I shows results from a simple regression using only cooperation variables. Column II includes the rest of the covariates. Column III shows fixed effects regression and Column IV shows random effects regression.

Coefficients from Column I are 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[17]. Of course, this is a naïve comparison, as there are many potential confounding factors, e.g., firm size, R&D intensity or industry. Column II includes these covariates and the estimated effect is around 50% lower, but still very 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%. Remarkably, both knowledge providers show a similar effect in this regression, suggesting that the role played by the covariates is a bit different between the partners; that is, selection in observables is higher for cooperation with universities[18].

However, there can be firm-specific unobservables that drive this result. In the third column, we make use of within-firm variation only, thus eliminating time-constant unobservables (e.g., managerial ability). This causes an additional reduction in the coefficients but the effects are 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.

[17] Percentages are calculated as (exp(betahat)-1)*100, where betahat is the estimated coefficient.
[18] An analysis using the Gelbach (2016) method~~,~~ suggests that this is mainly because of the role played by size in cooperation with universities.

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

To summarize, a naïve comparison of sales from new-to-the-market products between firms that cooperate with knowledge providers and firms that do not~~,~~ give us implausibly large estimates. Around 50% of these estimates were due to firm observables and another 25% can be attributed to firm-specific, time-invariant unobservables.

There are several concerns that should be addressed. First, these latter estimates could still be contaminated by firm-specific, time-varying unobservables. Second, the dependent variable is censored.

Table 4 – Main results

	(1) Simple OLS	(2) Multiple OLS	(3) Within	(4) Random Effects
COOPUNI	0.840***	0.455***	0.279***	0.380***
	[0.114]	[0.106]	[0.091]	[0.082]
COOPCTKIB	0.688***	0.453***	0.253**	0.337***
	[0.122]	[0.114]	[0.099]	[0.091]
COOPOTHER	0.943***	0.641***	0.437***	0.528***
	[0.078]	[0.074]	[0.065]	[0.059]
LN_SIZE		0.479***	0.488***	0.436***
		[0.027]	[0.062]	[0.024]
ISMLOWTECH		-0.133	0.048	-0.070
		[0.099]	[0.290]	[0.086]
ISMHIGHTECH		0.197**	0.281	0.331***
		[0.092]	[0.284]	[0.083]
ISHIGHTECH		0.277**	0.259	0.455***
		[0.130]	[0.228]	[0.108]
LN_RDINTENSITY		0.193***	0.078***	0.131***
		[0.010]	[0.010]	[0.008]
ITEXPORTS		0.217***	0.103	0.225***
		[0.082]	[0.101]	[0.069]
ISNEW		0.498**	0.251	0.328*
		[0.203]	[0.239]	[0.186]
INGROUP		-0.081	0.222*	0.065
		[0.085]	[0.114]	[0.073]
ISFOREIGN		0.163	0.520	0.314
		[0.604]	[0.503]	[0.449]
_CONS	2.625***	-6.996***	-6.297***	-6.034***
	[0.043]	[0.427]	[1.020]	[0.365]
N	36922	36922	36922	36922

* 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 these last estimates are still contaminated by firm-specific, time-varying unobservables. Ideally, we would like to use instrumental variable methods. We tried them and the (unsuccessful) attempts are reported in Appendix A. An alternative way to explore this issue is to follow Oster's method (Oster, 2019). The results are provided in Table 7.

When this method is applied to the multiple OLS, the lower bound estimated for the coefficient is 0.271 for universities and 0.342 for KIBS (effects of 31.1% and 40%, respectively). That is, in both cases, the effects are still very large in magnitude[19]. The δs are 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. Remarkably, the lower bound of the effect in this case is very close to the actual FE estimates. More precisely, the lower bound of the estimates is 0.269 for universities and 0.244 for KIBS (effects of 30.86%% and 27.6%, respectively). As a consequence, the corresponding δs are 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 only the within variation is used and, accordingly, that the upward bias observed in OLS was almost entirely due to the firm time-invariant unobservables that are not contaminating the fixed-effect estimation.

Table 5 – Analysis of stability of effects according to Oster's method

	OLS		**FE**	
VARIABLE	Lower Bound for β	Delta	Lower Bound for 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 is censored (58% of firms active in innovation do not achieve 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

[19] The reason the lower bound is higher for KIBS is that selection in unobservables is assumed to be proportional to selections in observables, which, as we have seen, are higher in the case of universities.

OLS coefficients, we want to check whether this is the case in our study (Angrist and Pischke, 2008)[20].

Tobit results are reported in Table 6. Computing average marginal effects for cooperation with universities yields an effect of 43.76% in the pooled Tobit and 32.7% in the random effects Tobit, while these effects for cooperation with KIBS are 46.67% in the pooled Tobit and 31.13% in the random effects Tobit. That is, the magnitude of the effects is close to that provided by OLS.

Table 6. Tobit regression models

	(1) Multiple OLS	(2) Random Effects
COOPUNI	0.767***	0.632***
	[0.207]	[0.138]
COOPCTKIB	0.810***	0.602***
	[0.219]	[0.144]
COOPOTHER	1.545***	1.203***
	[0.161]	[0.104]
LN_SIZE	0.710***	0.617***
	[0.058]	[0.050]
ISMLOWTECH	-0.240	-0.081
	[0.234]	[0.218]
ISMHIGHTECH	0.403*	0.860***
	[0.210]	[0.201]
ISHIGHTECH	0.531*	1.109***
	[0.281]	[0.254]
LN_RDINTENSITY	0.497***	0.310***
	[0.026]	[0.017]
ITEXPORTS	0.794***	0.707***
	[0.214]	[0.162]
ISNEW	1.270***	0.871*
	[0.487]	[0.451]
INGROUP	-0.179	0.176
	[0.194]	[0.146]
ISFOREIGN	-0.075	0.293
	[1.268]	[0.918]
_CONS	-17.989***	-15.706***
	[0.922]	[0.810]
N	36922	36922

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

[20] We chose to report the baseline analysis using OLS because it allows 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 different important complications when Tobit models are used.

5.2. Heterogeneous effects according to firms' characteristics

In this section, we explore the important issue of which firms benefit most from cooperating with each partner. We will focus on the role played by firm size and R&D intensity. We will define three size groups according to their annual turnover (EC, 2016): (i) small: less than 10M€, (ii) medium: between 10M€ and 50M€ and (iii) large: more than 50M€ and three groups according to internal R&D intensity groups~~:~~ (i) no internal R&D, (ii) internal R&D intensity positive but lower than 5,000€/employee, (iii) internal R&D intensity higher than 5,000€/employee[21]. These groups are interacted with the COOPUNI and COOPCTKIB variables following the partition approach (Yip and Tsang, 2007) for simplicity of interpretation (coefficients directly report 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 7 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 is mainly explorative, so we do not claim that these effects should be interpreted as causal. Our preferred specification in this analysis is the RE regression. The reason is that, first of all, FE estimation is not very suitable for estimating these heterogeneous effects because it uses only within-firm variation, and the amount of variation in size and R&D intensity that takes place together with a different choice in cooperating with universities or KIBS is very low to estimate the effects with some degree of precision[22]. Secondly, RE estimation is preferred

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

[22] However, as can be seen in the table, FE standard errors are higher, but the magnitude of the effects is not far from that provided by multiple OLS and RE.

over OLS because RE is efficient, while OLS is not because of autocorrelation of error terms for each firm.

Column II shows that universities achieve a higher impact with the larger firms and a lower impact with the medium-sized firms, while KIBS' impact is more uniformly distributed, although a bit higher for small and medium-sized firms than for large firms. Column V shows that universities achieve a higher impact with firms that do not perform internal R&D, while KIBS do achieve a very high impact with both firms that do not perform internal R&D and firms that do.

Because size and R&D intensity are negatively correlated when only innovation-active firms are considered (Cohen and Klepper, 1996)[23], 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 previous small and medium groups are collapsed and the three different groups are maintained[24]. Table 8 shows the sample distribution of the different groups:

[23] Correlation of -0.06 (p-value=0.000) in our sample.

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

Table 7 – Heterogeneous effects according to firm size and internal R&D intensity

	SIZE			R&D intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
	Multiple OLS	Random Effects	Within	Multiple OLS	Random Effects	Within
COOPUNI1	0.191	0.180*	0.138	0.611**	0.527**	0.318
	[0.118]	[0.099]	[0.114]	[0.290]	[0.248]	[0.265]
COOPUNI2	0.107	0.170	0.147	0.444***	0.381***	0.322***
	[0.179]	[0.133]	[0.142]	[0.146]	[0.112]	[0.121]
COOPUNI3	1.113***	0.911***	0.664***	0.417***	0.331***	0.202*
	[0.231]	[0.178]	[0.197]	[0.141]	[0.109]	[0.120]
COOPCTKIB1	0.164	0.289**	0.318**	1.029***	0.741***	0.556**
	[0.135]	[0.113]	[0.126]	[0.306]	[0.236]	[0.247]
COOPCTKIB2	0.484***	0.373**	0.313**	0.199	0.105	0.042
	[0.185]	[0.146]	[0.155]	[0.147]	[0.118]	[0.126]
COOPCTKIB3	0.603**	0.278	0.046	0.701***	0.589***	0.504***
	[0.253]	[0.204]	[0.220]	[0.174]	[0.132]	[0.141]
COOPOTHER	0.646***	0.524***	0.432***	0.644***	0.531***	0.441***
	[0.074]	[0.059]	[0.065]	[0.074]	[0.059]	[0.065]
LN_SIZE	0.433***	0.413***	0.478***	0.484***	0.439***	0.488***
	[0.028]	[0.024]	[0.062]	[0.028]	[0.024]	[0.061]
ISMLOWTECH	-0.127	-0.069	0.048	-0.135	-0.071	0.047
	[0.099]	[0.086]	[0.290]	[0.099]	[0.086]	[0.290]
ISMHIGHTECH	0.193**	0.328***	0.279	0.190**	0.326***	0.283
	[0.092]	[0.083]	[0.284]	[0.092]	[0.083]	[0.283]
ISHIGHTECH	0.262**	0.447***	0.251	0.254**	0.441***	0.261
	[0.129]	[0.108]	[0.228]	[0.129]	[0.108]	[0.228]
LN_RDINTENSITY	0.192***	0.131***	0.077***	0.197***	0.134***	0.080***
	[0.010]	[0.008]	[0.010]	[0.010]	[0.008]	[0.010]
ITEXPORTS	0.249***	0.237***	0.105	0.214***	0.223***	0.102
	[0.082]	[0.069]	[0.100]	[0.082]	[0.069]	[0.101]
ISNEW	0.471**	0.318*	0.250	0.480**	0.320*	0.248
	[0.202]	[0.186]	[0.239]	[0.202]	[0.186]	[0.239]
INGROUP	-0.079	0.066	0.222*	-0.085	0.063	0.221*
	[0.085]	[0.073]	[0.114]	[0.085]	[0.073]	[0.114]
ISFOREIGN	0.046	0.297	0.534	0.188	0.338	0.540
	[0.576]	[0.447]	[0.505]	[0.610]	[0.451]	[0.502]
_CONS	-6.268***	-5.671***	-6.141***	-7.086***	-6.103***	-6.328***
	[0.437]	[0.373]	[1.020]	[0.429]	[0.367]	[1.018]
N	36922	36922	36922	36922	36922	36922

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

Table 8. 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%

Results are reported in Table 9, 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 is used for the interaction with COOPCTKIB

As in the previous table and, for the same reasons, our preferred specification is 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. Results are summarized in Figure 1.

Table 9 – Heterogeneous effects of size and internal R&D intensity

	(1) Simple OLS	(2) Multiple OLS	(3) Within	(4) Random Effects
COOPUNISN	0.504*	0.782***	0.579**	0.755***
	[0.286]	[0.290]	[0.253]	[0.241]
COOPUNISM	-0.025	-0.009	0.100	0.067
	[0.161]	[0.156]	[0.129]	[0.120]
COOPUNISH	-0.097	0.197	0.101	0.175
	[0.149]	[0.143]	[0.124]	[0.112]
COOPUNILN	0.790	0.122	-0.492	-0.206
	[0.780]	[0.749]	[0.688]	[0.646]
COOPUNILM	2.035***	1.194***	0.801***	1.008***
	[0.294]	[0.285]	[0.238]	[0.219]
COOPUNILH	2.107***	1.082***	0.617**	0.903***
	[0.359]	[0.359]	[0.304]	[0.276]
COOPCTKIBSN	0.304	0.682**	0.301	0.466**
	[0.297]	[0.291]	[0.223]	[0.216]
COOPCTKIBSM	0.057	0.094	0.158	0.149
	[0.156]	[0.152]	[0.135]	[0.125]
COOPCTKIBSH	0.489***	0.539***	0.529***	0.534***
	[0.184]	[0.176]	[0.147]	[0.137]
COOPCTKIBLN	2.823***	1.967***	1.266*	1.504**
	[0.788]	[0.749]	[0.654]	[0.619]
COOPCTKIBLM	0.811***	0.267	-0.243	-0.052
	[0.313]	[0.302]	[0.255]	[0.240]
COOPCTKIBLH	1.218***	0.890**	0.328	0.609*
	[0.452]	[0.451]	[0.369]	[0.346]
LN_RDINTENSITY	0.181***	0.196***	0.080***	0.135***
	[0.010]	[0.010]	[0.010]	[0.008]
COOPOTHER	0.833***	0.649***	0.436***	0.527***
	[0.077]	[0.074]	[0.065]	[0.059]
LN_SIZE		0.440***	0.474***	0.415***
		[0.028]	[0.061]	[0.024]
ISMLOWTECH		-0.132	0.055	-0.072
		[0.099]	[0.289]	[0.086]
ISMHIGHTECH		0.184**	0.289	0.322***
		[0.092]	[0.283]	[0.083]
ISHIGHTECH		0.232*	0.263	0.429***
		[0.128]	[0.228]	[0.108]
ITEXPORTS		0.248***	0.107	0.237***
		[0.082]	[0.100]	[0.069]
ISNEW		0.448**	0.239	0.306*
		[0.201]	[0.239]	[0.185]
INGROUP		-0.080	0.219*	0.064
		[0.085]	[0.114]	[0.073]
ISFOREIGN		0.076	0.549	0.323
		[0.577]	[0.507]	[0.450]
_CONS	1.476***	-6.393***	-6.099***	-5.729***
	[0.067]	[0.431]	[1.016]	[0.370]
N	36922	36922	36922	36922

* 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 firms' 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 stylized facts but has left several questions open. This study aimed to shed light on some of these questions, especially considering the economic impact of firms' collaboration with knowledge providers.

On the one hand, studies that evaluate the effect of a firm's cooperation with universities and KIBS have not usually been framed according to the literature of evaluation of causal effects. In this study, we have structured the evaluation in a casual framework, which made us reflect on the potential unobservables that were biasing our results. We have found that most of the biases can be accounted for by using observable firm characteristics such as size, R&D intensity, industry and so on and, very 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 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 anonymized surveys. The good news is that, if most of the unobservables are either observed or time-invariant, we can achieve consistent estimates without the use of instruments if we have longitudinal data at our disposal.

On the other hand, contrary to the analysis of firms' technical results, previous studies that evaluate 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-market products. This effect is large in magnitude. The lower bound estimated for the effect is around 27%-30% higher sales from those that cooperate with any of these partners, holding all else equal.

In addition, previous literature has usually focused on a single knowledge provider, especially if the analysis was not merely descriptive. In this study, we simultaneously analyze two different knowledge providers: universities and KIBS. Although this is not methodically challenging, it is quite important from a practical point of view, especially if heterogeneous effects are allowed for. More precisely, from an exploratory point of view, we address the issue of which firms benefit more from cooperation with each knowledge provider. This question is very important for managers and policy makers because huge potential benefits exist if the matching for collaboration between firms and knowledge providers is improved.

Our exploratory results show that, although average effects of cooperation with universities or KIBS are very similar, important differences can be found for different types of firms.

First, universities achieve their higher effect on small firms without internal R&D intensity and in large firms with internal R&D intensity. Previous literature has not dealt with heterogeneous effects of these links, but the preference of university teams for working with large, R&D-intensive firms (which give reputation and possibilities of future job offers) has already been documented (Beise and Stahl, 2001). In addition, some studies (Bruneel et al., 2010) have highlighted the barriers encountered by small firms and firms with low internal capabilities when interacting with universities. However, the impact on SMEs without internal R&D is an unexpected finding. It could be that small universities implement some initiatives to support these firms or that they were born in the university and, after separation, outsource their entire R&D function to the university. More research is needed to understand why this is happening.

Second, KIBS achieve their higher impact in SME~~s~~ firms 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 and Zenker, 2001), as has 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 for cooperation between firms and knowledge providers. There are some limitations of this study that also constitute opportunities for future research: other identification strategies should be employed, specially to devoted to a more in depth analysis of the best matching between knowledge providers and firms. In addition, the utilization of better proxies of collaboration that go beyond a dummy variable and the utilization of different measures of performance would improve our knowledge on the collaboration between firms and knowledge providers. Another important issue would be the extension of the analysis to service firms. Finally, this study is not able to provide a better understanding of why some knowledge providers match better with some types of clients. The analysis of project-level data and the case studies could be very helpful on this regard.

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Annexes

Appendix A – Instrumental variables (IV)

An ideal instrument for firms' cooperation with universities and KIBS would be the 'exogenous' supply of universities and KIBS[25]. That is, for two firms equal in all characteristics (observables and unobservables), it would be expected that cooperation with universities is more likely if the firm is exposed to a higher supply of universities and the same will happen for KIBS. In the IV language, this would mean that the instruments satisfy the inclusion restriction. But the instruments should also satisfy the exclusion restriction, meaning in our example that, if the firm is exposed to a higher supply of universities but does not cooperate, then 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[26] for estimating 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[27]. 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[28].

In addition, we used a typical instrument used with CIS data: the industry-year average of the endogenous variable (see, for example, Cassiman and Veugelers, 2002) so that the exclusion

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

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

[27] 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).

[28] 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).

restriction could be tested. As suspected, we clearly rejected the null hypotheses of instruments that satisfy exclusion restriction: Hansen's J Chi-Square(2)=14.47 (p-value=0.0007), so we cannot use those instruments.

As we have panel data at our disposal, we can search for instruments using lags (Arellano and Bond, 1991; Arellano and Bover, 1995). However, again, the null hypotheses of instruments that satisfy exclusion restriction are clearly rejected: Chi-Square (106)=195.87 (p-value=0.000)[29].

These attempts highlight the difficulty in implementing instrumental variable methods to analyze the effect of cooperation with universities and perhaps may partially explain why previous studies usually did not attempt 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 using within multiple estimation.

[29] If we discard the closer lags, then it was the inclusion restriction that was not satisfied.

Appendix B – OECD Sectorial Classification

SECTORIAL CORRESPONDENCE (3-digit level)		
VARIABLE	NACE 93	NACE 2009
LOW TECH	o Manufacture of food products, beverages and tobacco o Textiles and textile products o Leather and leather products o Wood and wood products o Pulp, paper and paper products o Publishing and printing o Manufacturing n.e.c.	o Manufacture of food products o Manufacture of beverages o Manufacture of tobacco products o Manufacture of textiles o Manufacture of wearing apparel o Manufacture of leather and related products o Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials o Manufacture of paper and paper products o Printing and reproduction of recorded media excluding reproduction of recorded media o Manufacture of furniture o Other manufacturing excluding manufacture of medical and dental instruments and supplies
LOW-MID TECH	o Manufacture of coke, refined petroleum products and nuclear fuel o Manufacture of rubber and plastic products o Basic metals and fabricated metal products o Other non-metallic mineral products o Building and repairing of ships and boats	o Reproduction of recorded media o Manufacture of coke and refined petroleum products o Manufacture of rubber and plastic products o Manufacture of other non-metallic mineral products o Manufacture of basic metals o Manufacture of fabricated metal products, except machinery and equipment excluding manufacture of weapons and ammunition o Building of ships and boats o Repair and installation of machinery and equipment
MID-HIGH	o Manufacture of chemicals and chemical products, excluding 24.4	o Manufacture of chemicals and chemical products

TECH	manufacture of pharmaceuticals, medicinal chemicals and botanical products o Manufacture of machinery and equipment n.e.c. o Manufacture of electrical machinery and apparatus n.e.c. o Manufacture of motor vehicles, trailers and semi-trailers o Manufacture of other transport equipment, excluding 35.1 Building and repairing of ships and boats and excluding 35.3 Manufacture of aircraft and spacecraft.	o Manufacture of weapons and ammunition o Manufacture of electrical equipment o Manufacture of machinery and equipment n.e.c. o Manufacture of motor vehicles, trailers and semi-trailers o Manufacture of other transport equipment excluding building of ships and boats and excluding manufacture of air and spacecraft and related machinery o Manufacture of medical and dental instruments and supplies
HIGH TECH	o Manufacture of pharmaceuticals, medicinal chemicals and botanical products o Manufacture of office machinery and computers o Manufacture of radio, television and communication equipment and apparatus o Manufacture of medical, precision and optical instruments, watches and clocks o Manufacture of aircraft and spacecraft	o Manufacture of basic pharmaceutical products and pharmaceutical preparations o Manufacture of computer, electronic and optical products o Manufacture of air and spacecraft and related machinery

Source: OECD Data Portal: https://data.oecd.org/