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Industry-Science-Interaction in Innovation: The Role of Transfer Channels and Policy Support

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Abstract

We investigate the effects of different channels of industry-science collaboration on new product sales at the firm-level and whether government subsidies for collaboration make a difference. We distinguish four collaboration channels: joint R&D, consulting/contract research, IP licensing, human resource transfer. Employing firm-level panel data from the German Community Innovation Survey and a conditional difference-in-differences methodology, we find a positive effect of industry-science collaboration on product innovation success only for joint R&D, but not for the other three channels. The positive effect is limited to subsidized collaboration. Our results suggest that government subsidies are required to bring firms and public science into forms of collaboration that are effective in producing higher innovation output.

Keywords: Industry-science collaboration, transfer channels, product innovation, treatment effects analysis

JEL-Classification: O31, O38

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1 Introduction

Scientific findings are a major source for innovation in industry (Jaffe, 1989; Mansfield, 1991, 1995). Research results of universities, public research organizations and government research laboratories[1] provide fresh ideas for innovation, new methods for solving technological problems, or new technology (Beise & Stahl, 1999). Firms frequently exploit university knowledge for gaining an innovation advantage, by using new scientific results to develop and introduce new products or new processes (Perkmann et al., 2013; Rybnicek & Königsgruber, 2019). In order to access scientific knowledge, firms can use various ways of exchanging knowledge with universities (Perkmann & Walsh, 2007; Schmoch, 1999; Schartinger et al., 2002). When choosing knowledge exchange channels, firms have to consider both the effectiveness of obtaining relevant knowledge for innovation on the one hand, and the efficiency of interaction in terms of costs, confidentiality, and overcoming barriers such divergent incentives and 'cultures' on the other (Bruneel et al., 2010; Mora-Valentin et al., 2004). This choice is not straightforward, since some channels may be more effective, but also more costly, subject to higher knowledge leakage, and involving higher barriers of interaction. For a better understanding industry-science interactions and their role for innovation, it is important to identify the benefits of different types of relationships in terms of innovation output (Perkman and Walsh, 2007). This paper aims to contribute to this research stream by investigating the role of four different knowledge exchange channels—joint R&D, R&D services, IP licensing, human resource transfer—for product innovation output based on a representative sample of firms from Germany.

[1] In the remainder of the paper, we use 'universities' for all types of institutions that produce scientific knowledge.

Leveraging the knowledge produced at universities through industrial innovation is also a keen interest of research policy, as it allows public investment in science to be converted into economic returns. Governments therefore actively foster interactions between industry and science (Etzkowitz & Leydesdorff, 2000; Kurdve et al., 2020). A key approach in this respect is to provide financial support for joint research. In Europe, both regional and national governments as well as the European Commission run programs that fund joint R&D projects of firms and universities. By focusing on one specific channel, joint R&D, governments affect the firms' choices of knowledge exchange channels, which may have implications on the effectiveness of transferring knowledge into innovation. It is hence important to consider the role of public support when examining the innovation outcome of different types of relationships between industry and universities.

This paper aims to extend the existing empirical literature on the interplay between scientific knowledge, industrial innovation and public support in three ways. First, we provide a more detailed understanding of how industry-science interactions affect innovation output. By looking at the innovation impact of different knowledge exchange channels, we extend existing studies that usually do not separate by the type of relationship (see Hottenrott & Lopes-Bento, 2016; Maietta, 2015; Szücs, 2018; Tian et al., 2022; Un et al., 2010; Wirsich et al., 2016). In addition, we complement studies that investigate different mechanisms of knowledge exchange (see Bekkers & Bodas Freitas, 2008; Brennenraedts et al., 2006; Fabiano et al., 2020; Hu et al., 2021; van Gils et al., 2009; Vega-Jurado et al., 2017) by providing evidence on the relative innovation effectiveness of each channel. Second, we explicitly investigate the role of public subsidies for transferring university collaboration into higher innovation output of firms, providing more evidence on the effectiveness of public funding for collaboration. Third, we aim at advancing the methodology used for identifying the effects of different knowledge exchange channels by (a) focusing on the commercialization results in the market (sales with new products) and (b) using conditional difference-in-differences estimation based on panel data. Other studies in the field relied on patent data (e.g. Szücs, 2018; Wirsich et al., 2016) or binary measures of product innovation (e.g. Maietta, 2015; Un et al., 2010), and most studies used cross-section data that did not control for likely endogeneity of innovation performance and collaboration with science (e.g. Hottenrott & Lopes-Bento, 2016; Hu et al., 2021; Maietta, 2015; Tian et al., 2022; Un et al., 2010; Wirsich et al., 2016).

Our empirical findings show that entering into collaboration with universities results in product innovation success (sales generated by new products), although this positive effect is limited to joint R&D. For other types of interaction (R&D services, IP licensing, human resource transfer), we do not find a product innovation premium. The positive effect of joint R&D on product innovation is found only in case the collaboration was publicly subsidized. This result seems to indicate effectiveness of government support. Government subsidies helped firms to perform university collaboration in an effective way, which constitutes a contribution of government support to the innovation result from science collaboration.

The reminder of the paper is organized as follows. Section 2 develops the hypotheses that guide our empirical research. Section 3 presents the empirical strategy and the database. The estimation results are presented in Section 4, whereas Section 5 concludes and discusses policy implications.

2 Related Literature and Hypotheses

2.1 Types of knowledge exchange channels and innovation output

Firms can use a variety of channels to access university knowledge and to exchange with universities for innovation. The literature has identified a number of transfer channels, including licensing of academic inventions, joint R&D projects, contract research, consulting, exchange of personnel, training of company employees, reading scientific publications, citing university patents, exchanging at conferences, collaborating with university spin-offs, and various forms of informal contacts between firm employees and scientists (Arvanitis et al., 2008; Mowery & Ziedonis, 2015; Perkmann et al., 2013; Schartinger et al., 2001, 2002; Yusuf, 2008). In this paper, we focus on four types of knowledge exchange that are particularly relevant for firms aiming to incorporate university knowledge into the firms' innovation activities (Grimpe & Hussinger, 2013; Hu et al., 2021; Perkmann et al., 2013; Schmoch, 1999; Vega-Jurado et al., 2017): (1) joint R&D collaboration, (2) contract R&D and other R&D services, (3) licensing of IP or purchase of university technologies, and (4) human resource transfer, including students doing their thesis in firms, temporary exchange of personnel, and training of employees at the scientific institution.

These four transfer channels are suitable to varying degrees for exchanging knowledge relevant to innovation. From the perspective of an innovative firm, knowledge exchange with universities should enable the firm to access the knowledge it needs for developing and introducing innovations at reasonable cost, to effectively use this knowledge in its own innovation process, and to exploit the knowledge in the market. In this respect, four characteristics of knowledge channels are of particular importance:

First, a firm has to be able to appropriate the knowledge generated during the interaction, while at the same time avoid the outflow of own knowledge relevant for the innovation to others. While IP rights can be used to formally protect the knowledge generated in the exchange with universities, a more complex issue is to avoid leakage of firm knowledge that is provided to universities in the context of the relationship. This issue has frequently be mentioned as a critical challenge in innovation collaboration in general, and in industry-science interactions in particular (Frishammar et al., 2015; Henttonen et al., 2016; Rossi, 2010; Veer et al., 2016). Knowledge exchange channels that allow firms to control knowledge flows are hence better suited for securing innovation returns.

Secondly, time is a crucial factor for successful innovation. The knowledge obtained from universities should hence be 'final' in the sense that it can be directly used in industrial innovation processes, e.g., new technology should be tested and proofed to work in an industrial context. A low degree of finalization typically occurs when the main knowledge output of interaction is more on the academic side, which can easily be used for academic publications, but requires more translational work to feed into solving problems of industrial innovations (Perkmann & Walsh, 2007). Firms will hence look for knowledge channels that are associated with a high degree of finalization.

Thirdly, innovation is a highly dynamic process, and is often subject to adjustments in response to changes in the innovative environment, resulting from competitors' innovation, upcoming consumer trends, new government regulation, shift in user preferences, etc. A high degree of knowledge flexibility is therefore important for successful innovation. Flexibility indicates the degree to which knowledge exchange can be rapidly adjusted to changing knowledge needs of the firm (Ankrah & Al-Tabbaa, 2015).

Fourthly, knowledge from university should fit to the specific requirements of the firm and the firm's innovation activities. This implies a design of the knowledge exchange process that allows specifications according the particular, and often idiosyncratic, needs of the firm. Such 'specificity' is often linked to the concept of tacit knowledge, i.e., knowledge that is difficult to express to be transferred through formal ways, but often requires personal interaction and mutual learning. Tacit knowledge has been found critical for transferring new scientific findings into innovation (Goffin & Koners, 2011; Senker, 1995). Transfer channels based on face-to-face contact tend to be best suited for exchanging tacit knowledge (Perkmann & Walsh, 2007) and should hence allow firms to better communicate their specific knowledge needs in the transfer process.

In order to assess how well each of the four knowledge exchange channels is suited for serving industrial innovation process in firms, we characterize each channel in terms of the four knowledge dimensions discussed above, following the findings of prior work on characterizing industry-science relationships and transfer channels (Bekkers & Bodas Freitas, 2008; Brennenraedts et al., 2006; De Fuentes & Dutrénit, 2012; Dutrénit et al., 2010; Fabiano et al., 2020; Hu et al., 2021; Perkmann & Walsh, 2007; Schartinger et al., 2002; van Gils et al., 2009). Joint R&D, either organized through a joint R&D project or based on collaboration within a dedicated research infrastructure such as a university-industry research center, is associated with a high degree of knowledge flexibility and specificity, based on personal interaction of researchers from firms and universities and the firm's ability to design the joint work along its specific needs. Appropriability of research results is usually high since firms can directly negotiate IP rights of project results with the university. However, firms will have to share a lot of their own existing knowledge with universities in the joint research effort, including critical information about the underlying technology or the planned design of an innovation. Safeguarding this information against leakage to competitors can be challenging, particularly in case that university researchers move to other firms during the execution of the project. In terms of finalization, firms should be able to design a joint R&D activity in a way that reaches the required technology readiness level. However, as for any research, achieving the research objective is uncertain, and universities may turn out to be unable to arrive at the desired result.

With respect to R&D services provided by universities to firms through contract research or academic consulting, appropriability and finalization of knowledge are likely to be high since both can be defined by the design of the research contract. Flexibility and specificity will tend to be lower than for joint R&D, since the content of research has to be defined at the beginning of the contract, and personal interaction with university researchers is less intense than in the case of joint R&D. For IP licensing, the situation for appropriability and finalization is similar, since IP contracts can determine IP rights, and firms can choose the IP that best fits to their need. Flexibility and specificity will be low, however, since the characteristics of the technology are given and can only be adapted to a firm's specific requirements by follow-on R&D activities. Considering human resource transfer, appropriability and finalization tend to be lowest among the four knowledge exchange channels, since the knowledge remains with the individuals involved in the HR activity and needs to be transferred into the firm's innovation process. Flexibility and specificity of knowledge exchange are likely to be higher than for R&D services and IP licensing since HR-based knowledge transfer activities can be flexibly designed to the firms' needs, though depending upon the exact transfer mechanism employed.

Figure 1: A typology of science-industry knowledge exchange channels for innovation

Type	**Examples**	**Appro-priability**	**Finalization**	**Flexibility**	**Specificity / tacit knowledge**
Joint R&D	Joint R&D projects, university-industry research centers	Medium to High	Medium to high	High	High
R&D services	Contract research, academic consulting	High	High	Medium	Medium
IP licensing	Licensing of IP, selling of technology	High	High	Low	Low
Human resource transfer	Joint Ph.D. theses, temporary exchange of personnel, employee training at universities	Low	Low to medium	Medium to high	Medium to high

For transferring university knowledge into industrial innovation, it is likely that exchange channels that support all four knowledge dimensions will be most effective. From this perspective, we expect that joint R&D will produce the highest impact on innovation output, followed by R&D services, IP licensing and HR transfer. We hence derive the following hypotheses:

H1a: Firms collaborating with universities through joint R&D, R&D services, IP licensing or HR transfer will yield a higher innovation output than firms not collaborating with universities.

H1b: The innovation premium of university collaboration will be higher for joint R&D compared to R&D services, IP licensing and HR transfer.

2.2 Public support for industry-science collaboration and innovation output

By encouraging firms and universities to engage in knowledge exchange, governments try to get out most of public investment into science and spur innovation in industry (Beck et al., 2016). Policy actions include cooperative research-centers (Adams et al., 2001; Lind et al., 2013), innovation support programs (Kurdve et al., 2020) or support for personnel exchange and IP transfer (Guimón & Paunov, 2019). The by far single most important policy measure, however, is financial support for collaborative research (Veugelers, 2016). This is particularly true in the German context, which provides the empirical basis of our research. In Germany, both regional and national governments offer several funding programs for industry-university joint R&D projects, complementing similar programs by the European Commission.

For analysing the role of industry-science knowledge exchange in industrial innovation, public support for industry-science collaboration is important for two reasons: First, it provides additional financial resources for conducting knowledge exchange, helping to overcome certain 'system failures' by providing more incentives for firms and universities to engage in mutual knowledge exchange (Polt et al., 2001). The additional resources can either be used to enlarge knowledge exchange activities at both sides, or to re-direct the private money of firms that was saved by using the subsidy towards stronger commercialisation efforts (Cunningham & Gök, 2016; Vlasova, 2021). Either way is likely to increase the impact of knowledge transfer activities on innovation output. More intense knowledge exchange efforts should contribute to a better fit between the university knowledge and the firms' innovation activities. More private money available for an innovation project can be used to better design and market an innovation, contributing to higher market success.

Secondly, offering public support for particular knowledge exchange channels is likely to change the choice of channels, as the subsidy changes the relation between costs of collaboration and expected returns from collaboration, both for firms and universities. This may have adverse impacts on the transfer result, however, in case the subsidized channel is a suboptimal one and leads to a less effective knowledge transfer for the firm's innovation activity. Such a situation may occur, for instance, when a university engages in subsidized knowledge transfer primarily in order to fund additional research positions, while being less motivated to contributing to the partner's innovation objectives. Government subsidies for collaboration may also induce firms and universities to enter into collaborations they otherwise would not have attempted at all. In case the partners are not well-prepared for interacting with each other, the results of this knowledge exchange are likely to be inferior compared to other collaborations.

While the impact of public subsidies for research collaboration in general has received substantial academic attention (see, for example, Beck et al., 2016; Branstetter & Sakakibara, 2002; Czarnitzki et al., 2007; Hottenrott & Lopes-Bento, 2014; Sakakibara, 2001), fewer studies focus on the specific impact of subsidies for collaboration with universities. The existing evidence on whether subsidized and non-subsidized collaboration with universities differ in their effects on innovation performance is quite mixed. Beck et al. (2016) show for a Swiss R&D collaboration program that subsidized R&D leads to more radical innovations, but they do not find evidence of this effect being enhanced in firms collaborating with science. Szücs (2018) considers a European large-scale research subsidy program and documents substantial returns to cooperating with universities, particularly highly-ranked ones, but also shows that cooperating with public research centers has a detrimental impact on innovativeness.

Based on the mixed evidence, we hypothesize that the positive resource effect of public subsidies is likely to outperform the potential negative impact from incentivizing firms to engage in less effective knowledge exchange channels, leading to our second hypothesis:

H2: Firms receiving public financial support for knowledge exchange with universities are likely to yield higher innovation output than firms not receiving such support.

3 Data and Methodology

3.1 Data

This study makes use of unique firm-level data from the Mannheim Innovation Panel (MIP), provided by the Leibniz Centre for European Economic Research (ZEW). The MIP represents the German contribution to the Community Innovation Survey (CIS), which is supervised by the Statistical Office of the European Commission (Eurostat). The methodology and survey questionnaire follow the CIS standards and the guidelines outlined in the Oslo Manual by the OECD and Eurostat (OECD & Eurostat, 2018), which provides comprehensive instructions for collection, measurement, and analysis of data from innovation surveys. While the CIS is a biannual survey, the German CIS is conducted annually and adopts a panel approach, hence allowing to track firms' innovation behaviour over time. Each survey wave collects data of around 8,000 to 9,000 different firms every year. The survey is voluntary (25-35% response rate) and is usually completed by CEOs or innovation managers. Notably, not all variables of interest are available annually, and not all firms consistently respond to the questionnaire (as it is natural for a data collection based on non-mandatory surveys). It is based on a stratified random sample and is refreshed every second year to compensate for panel loss (Peters & Rammer, 2023). In our empirical analysis, we leverage the information regarding the distinct channels of industry-science interaction from the MIP 2018 survey wave (with the reference period for this question being the years 2015-2017). Tracking firms' behaviour in the previous and in the following survey waves, we exploit the panel dimension of the database by merging eight survey waves (2013 to 2020) and specify the treatment dummy variable of the different categories of cooperation for the 2016 to 2020 period. Our unbalanced panel is restricted to firms (i) for which we have non-missing values for all model variables (including the 17 aggregated economic sectors), (ii) that are observed at least twice in the period 2013-2020, and (iii) that are product innovators and R&D active. After taking into account only firms with full information on all model variables, we reduce the final sample size to 2,907 firm-year observations.

The regression sample is representative of the broader MIP sample of R&D active firms in term of size classes.[2] However, if compared to the estimated population of product innovators in Germany (see Rammer et al., 2023), our sample is slightly biased towards larger companies.[3] This is due to the fact that we take into consideration firms that are product innovators and R&D active.

3.2 Dependent variable

We measure innovation performance by considering market acceptance of novel products, which turns a novelty into a commercially successful product innovation. Following other CIS-based studies, we use the sales of newly introduced product innovations as our measure of innovation performance (e.g., Grimpe & Sofka, 2016; Klingebiel & Adner, 2015; Klingebiel & Rammer, 2014; Laursen & Salter, 2006; Leiponen & Helfat, 2011). This variable measures sales in the last year of the three-year survey period of product innovations that were introduced during the three-year period. It is obtained by multiplying the proportion of sales of new

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[2] In particular, in the regression sample, 15.65% of firms have less than 10 employees; 40.59% of firms have between 10 and 49 employees; 28.28% of firms have 50 to 249 employees; 5.81% of firms have between 250 and 499 employees; 9.67% have 500 or more employees. In the broader MIP sample of R&D active firms, the distribution of these size classes is similar and, respectively: 18.53%, 39.91%, 27.46%, 5.90%, and 8.20%.

[3] The distribution of the abovementioned size classes for the estimated population of German firms that are product innovators is approximately the following: 34% (less than 10 employees), 44% (10-49 employees), 16% (50-249 employees), 3% (250-499 employees), and 3% (500 or more employees) (Rammer et al., 2023).

products by total sales, in million Euros. Raw values have greater construct validity compared with new product sales normalized by a firm's total sales (Klingebiel & Adner, 2015). As this variable has a strong skew (mean, 15.54 million Euros; median, 0.87 million Euros), we use a logarithmic transformation of it, in line with the abovementioned studies using the same measure. As shown in Table 1, this measure of innovation performance largely depends on sectors, with research-intensive industries (e.g., chemicals and automobile/transport equipment) being some of the sectors characterized by average high values of sales of new products. This measure of innovation performance is influenced by firms' knowledge sourcing strategies, including collaborative innovation with science institutions, and by other firm-related characteristics (e.g., size, absorptive capacity, unobservable firm-specific characteristics). As explained in the sections below, we implement an estimation procedure and choose a set of control variables aimed at accounting for factors influencing this measure of innovation performance (see Table 5 for pairwise correlations of the model variables).

3.3 Measures for industry-science collaboration channels

In the 2018 wave of the survey, firms provide granular information on whether they engaged in different cooperation channels with scientific institutions in the reference period 2015-2017, which will be aggregated into the abovementioned four categories of cooperation, following the conceptualization described in Section 2.1: (1) joint R&D collaboration, (2) contract R&D and academic consulting, (3) licensing/purchase of technology from the scientific partner, (4) HR transfer activities (students doing their thesis, temporary exchange of personnel, training of employees at the scientific institution). In addition, the survey asks firms to rate the effectiveness of these collaboration channels with science (on a 3-level scale) and to specify whether they were publicly subsidized[4]. Given that the reference period for this question covers

[4] Firms reported to receive public support through various subsidy schemes, like Horizon 2020, Eurostar, and other German programs (e.g., ZIM, BMBF-FP).

the years 2015 to 2017, we observe the impact of the different categories of cooperation in the subsequent 2016 to 2020 period.

Table 2 shows the frequency of the four interaction channels between firms and scientific institutions in the group of 406 firms that cooperated with science (corresponding to 1,170 firm-year observations in the period 2016-2020). Between 67% and 69% of firms cooperating with science engaged in either joint R&D or HR transfer. Around 64% engaged in consulting/contract research, whereas around 12% engaged in IP licensing or acquisition of technology from scientific institutions. If we consider only firms engaging in joint R&D projects with universities (271 firms, corresponding to 809 firm-year observations in the period 2016-2020; Table 3), the proportion of firms receiving public support to collaborate with science is about 80% and the proportion of firms indicating that joint R&D with science is "highly effective" is about 54%. Around 49% of firms that engaged in joint R&D rated this channel to be highly effective and received public support for collaboration.

Subsidized firms were asked to report the name of the programs from which they received financial support for cooperating with scientific institutions (Table 4). The vast majority (approx. 63%) of firms that engaged in subsidized collaborations received support through technology programs of the German Federal Government. These programs fund joint R&D projects in specific fields of technology, covering key enabling technologies (ICT, biotechnology, nanotechnology, photonics, new materials, production technology), but also technologies relevant to specific industries (e.g., space, transport, food, textiles). Another important program for funding industry-science collaboration is the Central Innovation Program for SMEs (German abbreviation: ZIM) which focuses on firms with less than 500 employees across all industries and fields of technology. Approx. 48% of the firms in the sample with publicly funded science collaborations use ZIM. Public funding from Horizon 2020 or other EU programs (including 'Eurostars') was reported by around 21% of firms that benefitted from subsidies for collaboration with science, while around 17% of subsidized firms indicated that they received other public programs.

TABLE 1, TABLE2, TABLE 3, TABLE 4 AND TABLE 5 ABOUT HERE

3.4 Methodology

The data are used to estimate treatment effects of engaging in distinct categories of cooperation with science on innovation output performance, which is measured in this context as sales from new or significantly improved products. Differently from previous studies on the impact of cooperation with science on firms' innovation activities (e.g., Arvanitis et al., 2008b; Becker, 2003; Faems et al., 2005), we use panel data, thereby being able to assess the impact of knowledge exchange by employing (conditional) difference-in-difference methodology using fixed-effects regressions. Engaging in cooperation with science is not exogenous to innovation activities. For instance, more innovative firms may be more likely to draw from academic partners to innovate. As firms decide to cooperate with scientific institutions (i.e., they self-select), firms cooperating with science are often not comparable (without further adjustments) to other firms that do not choose to cooperate with science. This is why we address the concerns related to the endogeneity of the treatment by implementing two different matching techniques.

As a baseline model, we implement a standard difference-in-difference estimation by fixed-effects "within" regression, since the panel database has more than two periods (Wooldridge, 2010). We specify an innovation production function (e.g., M. S. Freel, 2005), defining firms that engaged in one of the four categories of cooperation with science as treatment group, and firms not engaging in such cooperation forms as control group. The dependent variable in the model (Y_{it}) is the natural logarithm of sales of new or clearly improved products (measured in million Euros). The independent variables include the four categories of collaboration with science, as well as firm size (logarithm of number of employees) and internal R&D expenditures as a proxy for knowledge assets and absorptive capacity (logarithm of total

R&D expenditures in Mio. Euro, including both internal and external R&D expenditures). We also control for a firm's collaboration history with non-scientific partners, since cooperative agreements with universities are usually embedded in a wider innovation strategy of the firm (Veugelers & Cassiman, 2005).

In the equation below, $After\_Coop_{ijt}$ indicates the treatment (based on the four categories of interaction with science) and X_{it} denotes the vector of control variables; δ_i, γ_t and ε_{it} represent firm-level fixed effects, annual time dummies and the error term, respectively.

$$Y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_{1j}(After\_Coop_{ijt}) + \beta_2 X_{it} + \delta_i + \gamma_t + \varepsilon_{it}$$

To investigate whether subsidized and non-subsidized collaboration with science have a different impact on innovation performance at the firm level, we further split the effect of the treatment between subsidized and non-subsidized collaboration. The advantage of the difference-in-difference method is that it does not require any functional form for the outcome equation. Furthermore, difference-in-difference estimations control for common macroeconomic trends and for time-invariant firm-specific unobserved effects (if the same firms are observed over time) (Wooldridge, 2010).

A crucial assumption of the difference-in-difference methodology is that the treatment group and the control group follow the same trend before the treatment takes place. In other words, the difference-in-difference method isolates the "true" effect of the treatment by assuming that both the treatment group and the control group would have evolved similarly in the absence of the treatment. We thus conduct a test on common trends by including pre-treatment variables and by checking if they are not significant in the regressions.

Another way to tackle the possible violation of the common trend assumption in the context of difference-in-difference is the combination of this method with the matching estimator (i.e., the conditional difference-in-difference estimator). This means that the control group is not simply identified based on all firms that did not receive the treatment, but based on firms that are similar to the treated ones in some observable characteristics. In this study, we condition the control and the treatment groups to be comparable on the basis of observable factors that may influence the propensity of firms to engage in cooperative agreements with academic institutions. Subsequently, the difference-in-difference regression will be conducted only on the constructed matched sample, rather than using all potential control firms.

Different balancing methods can be used to obtain comparable treatment and control groups. We first implement entropy balancing, which stochastically assigns weights to the sample observations such that the moments of the control group's variables in the pre-treatment period are the same as those in the treatment group. This weighting controls for confounding variables outside of the estimation equation and establishes the comparability of the treatment and control group (Hainmueller, 2012). We implement this balancing routine based on the set of observable characteristics used as control variables in the baseline model (firm size, R&D expenditures, past collaboration with non-scientific institutions) and by requiring that firms in the control group belong to the same industry as firms in the treatment group (following a categorization of 17 aggregate economic sectors – see Table 1).

Second, we conduct the nearest neighbor propensity score matching. This routine involves pairing each firm that engaged in cooperation with science with the single closest non-collaborating-with-science firm. The pairs are chosen based on the similarity in the estimated probability of engaging in cooperation with academic institutions, meaning the propensity score stemming from a Probit estimation on the dummy indicating cooperation. Matching on the propensity score has the advantage not to run into the "curse of dimensionality" since we use only one single index as matching argument (Rosenbaum & Rubin, 1983). In addition to matching on the propensity score, we also require the observations of firms in the selected control group to belong to the same industry as the firms in the treatment group. For this method to be implemented, it is essential that there is enough overlap between the control and the treated group (common support). The algorithm calculates the minimum and the maximum of the propensity scores of the potential control group, and deletes observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group (Czarnitzki & Lopes-Bento, 2013).

Matching routines have the advantage to require no assumptions about functional forms and error term distributions. Nevertheless, the disadvantage is that they only control for the selection on observables, and hence they rely on the (strong) assumption that all important determinants driving the self-selection into the treatment are observed (Imbens & Wooldridge, 2009). This disadvantage is mitigated in our estimation, because we combine matching techniques with the difference-in-difference method. The conditional difference-in-difference estimator controls for observable characteristics in a non-parametric way and accounts for unobserved heterogeneity by differencing out firm fixed effects.

4 Results

Table 6 presents the results of the fixed-effects "within" panel regression[5], before implementing any balancing methods. We use cluster-bootstrapped standard errors with 200 replications[6]. In the first column of the table, we regress our measure of innovation output performance on only joint R&D collaboration between firms and academic institutions, which is the mostly analyzed knowledge exchange channel in the literature (Arvanitis et al., 2008a: p. 513), and on the set of control variables described in Section 3. The coefficient of joint R&D collaboration with scientific institutions is positive and significant. In models (2)-(4), we regress the outcome

[5] An F-test for unobserved heterogeneity leads to the conclusion that firm-specific effects are not jointly zero, thus we find support for the use of Fixed Effects panel regression instead of Pooled OLS ($F(805, 2091) = 7.26$; p-Value=0.000).

[6] The modified Bhargava et al. Durbin-Watson test for autocorrelation of the error terms has the value of 1.44, thus we use cluster-bootstrapped standard errors as suggested by Bertrand et al. (2004) for difference-in-difference estimations.

variable on the other three categories of cooperation (R&D services, IP licensing, and HR transfer), while in model (5) we include all of them. Only the coefficient for joint R&D collaboration remains positive and significant. In particular, the coefficients of the other three knowledge exchange channels (R&D services, IP licensing, HR transfer) are all insignificant. As a test for the common trend assumption, we add in model (5) the pre-treatment variables associated with each of the four categories of cooperation; since their coefficients are insignificant, the common trend assumption is not rejected (joint significance test of the pre-treatment variables: $\chi^2(4) = 5.07$; p-value = 0.28). These results suggest that joint R&D collaboration is the only interaction channel between firms and public science that plays a significant role in increasing product innovation performance at the firm-level[7]. We thus confirm H1a only for joint R&D collaboration. The other three channels do not generate an innovation premium for the collaborating firm.

Although the coefficient of joint R&D has the largest magnitude, we conduct a Wald test for the equality of the coefficients of the four interaction channels, and the result indicates that we cannot reject the null ($\chi^2(3) = 3.78$; p-value = 0.29). When examining the equality of each pair of coefficients, we find that the coefficient of joint R&D is weakly significantly different from the one of R&D services ($\chi^2(1) = 3.05$; p-value = 0.08). For joint R&D and IP licensing ($\chi^2(1) = 2.32$; p-value = 0.13) and joint R&D and HR transfer, ($\chi^2(1) = 0.53$; p-value = 0.46), we find no significant differences of coefficients. Thus, our analysis does not provide support for H1b.

[7] As a robustness test, we exploit the self-reported information of the effectiveness of the distinct cooperation channels. We thus split the binary indicators of the four cooperation channels between highly effective vis-à-vis low/medium effective collaboration. Only collaboration via joint R&D exerts a significant impact on new product sales at the firm-level (Table 16, first column, Appendix). We also explore potential interaction effects between the cooperation channels (Table 17, Appendix); this additional robustness test does not point to enhanced or mitigated effects of the cooperation channels on innovation performance when we include interaction effects in the model. Moreover, as the information on the distinct cooperation channels is available in one survey wave of the MIP, we test the robustness of our results by including as control variable a dummy denoting general past collaboration with universities or PROs, regardless of the specific channel (Table 18, Appendix); we obtain consistent results to our main model.

In model (6) we split the category of joint R&D between subsidized and non-subsidized collaboration. Only publicly supported joint R&D with science positively affects firms' innovation product performance.[8] This result points to a product innovation premium only for formal collaboration via joint R&D that receives financial support through public funding. We can therefore confirm H2 in relation to joint R&D. The inclusion of the pre-treatment variables corresponding to subsidized and non-subsidized joint R&D does not reject the common trend assumption (joint significance test of the pre-treatment variables: $\chi^2(2) = 1.70$; p-value = 0.43). The coefficients of the control variables have the expected positive signs, but only the coefficients of firm size and R&D expenditures are significant.

TABLE 6 ABOUT HERE

As discussed in the previous section, the decision to engage in a collaborative agreement with scientific institutions is an endogenous treatment, and hence we complement the difference-in-difference estimation with balancing techniques. Given that joint R&D collaboration seems to be the only interaction channel that significantly affects innovation performance, we identify the treatment group as firms that engaged in joint R&D with science, while the control group is given by firms that did not engage in joint R&D[9]. Table 7 and Table 8 show the descriptive statistics for the treatment and the control group, before and after 2016. Firms in the treatment and the control group systematically differ across all the observable characteristics used in the model (firm size, R&D expenditures, past collaboration with non-scientific institutions), as well as in terms of innovation performance (sales of new products).

[8] We also explore the impact of subsidized R&D services, licensing and HR transfer by including treatment variables denoting whether these three cooperation channels occurred in combination with public support for cooperation (and public support was not related to joint R&D). The effect of subsidized joint R&D remains positive and significant (Table 16, second column, Appendix). Subsidized consulting/contract research and subsidized HR transfer do not have a significant effect on new product sales. Only the coefficient of subsidized licensing is positive and significant at 10% level. We do not interpret this result because it relates to only about 0.8% of firms cooperating with science and to only about 7% of firms cooperating via licensing.

[9] As a robustness test, we also report the results obtained with Entropy Balancing by specifying as control group firms that did not engage in any of the four interaction channels with science (Table 15, Appendix). These results are consistent with those presented in our main analysis.

After implementing entropy balancing, we restrict the sample to 2050 firm-year observations, as we establish the comparability of the treatment and the control group based on observable firm characteristics in the pre-treatment period. We replicate the main models presented in Table 6 by using the weighting obtained with entropy balancing and by clustering standard errors at the firm level. Table 9 illustrates the results, which confirm the same pattern of significance and sign of coefficients of the previous estimations (Table 6). Joint R&D is the only category of cooperation with science that significantly and positively impact product innovation performance. In addition, only subsidized joint R&D exhibits a significant and positive effect on product innovation performance.

TABLE 7, TABLE 8, TABLE 9 ABOUT HERE

We additionally implement nearest-neighbor matching and estimate the average treatment effect on the treated with a difference-in-difference approach in the sample of comparable firms (common support). The matched sample is restricted to 1411 firm-year observations, if compared to the original sample of 2907 firm-year observations. Table 10 shows the results of the Probit model on the binary indicator for joint R&D collaboration with academic institutions. R&D expenditures and past experience in collaborating with non-scientific partners positively impact the probability to engage in joint R&D with universities, while firm size decreases this probability. Table 11 reports the descriptive statistics for the matched and unmatched samples, and shows that the t-tests on mean differences for the observed firm characteristics are insignificant in the matched sample. Table 12 shows the estimates of the firm-level fixed effects panel regressions conducted on the matched sample, which confirm the results obtained after implementing entropy balancing (Table 9). The standard errors are clustered at the firm level. Among the four categories of cooperation with science, only joint R&D collaboration significantly and positively influences innovation performance at the firm level. Moreover, when we split the treatment into subsidized and non-subsidized joint R&D, we notice that only the former has a positive and statistically significant coefficient. Overall, the results obtained using the balancing techniques (entropy balancing and nearest-neighbor propensity score matching) provide support for H1a and H2 in relation to joint R&D collaboration.

TABLE 10, TABLE 11, TABLE 12 ABOUT HERE

We compute an estimate of the magnitude of the increase in sales from new or significantly improved products for firms engaging in joint R&D collaboration with science. Based on the observations of firms that did not engage in joint R&D with universities in the pre-treatment period, we derive that collaboration through this channel increases sales of new or significantly improved products by 29.3%, resulting in additional sales of around 366,000 Euros[10].

4.1 Robustness test: the impact of subsidized joint R&D on effectiveness of collaboration

To test the robustness of our findings, we further explore whether receiving a subsidy for collaborating with universities has an impact on the effectiveness of cooperation itself, based on the self-reported ratings provided by firms. While the estimations presented above show that there is a product innovation premium for subsidized joint R&D, we additionally investigate if this result is corroborated when we take into account firms' subjective evaluation of the effectiveness of collaboration channels for accessing the know-how of the science institution. We consider a sample of 434 observations in year 2017 and regress the binary indicator for highly effective joint R&D on the dummy variable denoting whether cooperation with universities was publicly subsidized. In addition, we control for employment in 2017 (log),

[10] We take into account firms that did not engage in joint R&D in the pre-treatment period. The median value of turnover from new or improved products is 1.25 Million Euros. We consider the coefficient of joint R&D collaboration obtained in model (2) after implementing Entropy Balancing (coefficient: 0.257) (Table 9). The derived percent change in turnover for firms engaging in joint R&D is obtained as: $\%\Delta y = 100\ (e^{\beta} - 1) = 100\ (e^{0.257} - 1) = 29.3\%$. This corresponds to an increase in turnover from new or significantly improved products of around 365,764 Euros.

R&D expenditure in 2017 (log), past cooperation with non-science, the proportion of employees with an academic degree in 2017, a dummy variable for continuous R&D and four aggregated sector effects. We account for the endogeneity of the variable indicating receiving a subsidy for university-industry cooperation by instrumenting it with lags of subsidy receipt in 2014 and in 2012[11]. Previous experience with receiving public subsidies is expected to positively influence the probability of obtaining new public funding, while there is no direct effect of past subsidies (in 2012 and 2014) on the effectiveness of collaboration with science in 2016. Although one might be concerned whether lagged subsidies are exogenous to this equation (as subsidies may be serially correlated), these instruments allow a rough robustness check to see whether we derive a complementary piece of analysis to our main results obtained with conditional difference-in-difference estimations. We find that these two instruments fulfil the requirements for instrumental variables: they are relevant in the first stage on the indicator for current subsidized cooperation with science, and also pass the over-identification test (Hansen J-test).[12]

TABLE 13 ABOUT HERE

Table 13 compares the regression results across OLS, IV 2SLS, Probit and IV Probit. The results indicate that subsidies for knowledge exchange exhibit a positive and significant impact on the effectiveness of collaboration, based on the subjective rating reported by firms. This finding reinforces the abovementioned results, as it confirms that promoting linkages between public science and the business sectors with public grants makes cooperation more effective.

5 Conclusions

The aim of this paper is to add new perspectives to the literature on knowledge exchange channels by assessing the effect of different modes of interaction with science on firms'

[11] Czarnitzki and Lopes-Bento (2013) implement a similar instrumental variable strategy.
[12] See Table 14 in the Appendix for the first-stage of IV 2SLS and IV Probit regressions.

innovation performance, while also investigating whether subsidized and non-subsidized collaboration with scientific institutions differ in their impact on innovation performance. Considering four different types of knowledge transfer mechanisms enables to provide a more comprehensive and nuanced picture of how firms gain from collaboration with academic institutions. Furthermore, this study aims to shed light on the aspects of knowledge exchange, based on which interaction modes are classified, that are particularly relevant for successful product innovation performance.

Our results indicate that only joint R&D collaboration significantly and positively influences innovation performance at the firm level, whereas other forms of knowledge transfer (R&D services, IP licensing, HR transfer) do not seem to have a similar impact. We can thus find support for H1a only in relation to joint R&D collaboration. This finding is not in line with previous studies that showed positive effects of both joint R&D and contract research on product innovation performance (Vega-Jurado et al., 2017), or that documented positive effects of HR transfer and IP licensing (Arvanitis et al., 2008a; De Fuentes & Dutrénit, 2012).

Since joint R&D collaboration is characterized by knowledge exchange which is particularly suited to serve a firm's innovation efforts (by providing a high degree of appropriability, finalization, flexibility, and specificity), our results indicate that these dimensions play a pivotal role in successfully translating collaboration with science into new product sales at the firm-level. Considering that R&D services and IP licensing differ from joint R&D particularly with respect to lower flexibility and specificity, we can infer from our analysis that these two knowledge dimensions are of critical relevance for innovation performance. In a similar vein, as HR transfer is characterized by a lower degree of appropriability and finalization than joint R&D, our analysis also indicates the pivotal role played by these two dimensions in transferring university knowledge into new product sales at the firm-level.

Furthermore, we find that a product innovation premium is observed for subsidized industry-science joint R&D (H2) and that public support for industry-science knowledge exchange is positively associated with the effectiveness of cooperation itself. Considering the importance of publicly funded collaborative research, this is a remarkable finding from the technology policy perspective, since governments are interested in evaluating whether public support for knowledge transfer from science to industry generates economic growth and industrial innovation (Veugelers, 2016). We thus contribute to previous studies that provide mixed evidence on whether subsidized and non-subsidized collaboration with academic institutions differ in their impact on innovation performance (Beck et al., 2016; Scandura, 2016; Szücs, 2018). In particular, our contribution is also related to the fact that we do not restrict our analysis to a specific subsidy scheme, but we take into account a sample of firms that benefitted from a variety of public support programs.

Our results suggest some important policy implications. Just creating publicly supported scientific infrastructure does not seem to be sufficient knowledge exchange among industry and the scientific institutions for successful commercialization of new products in the business sector. Our results instead suggest that direct, project-specific public support is required to make industry-science collaborations contribute to successful product introductions to the market. We believe that the project-specific funding enables the scientific institutions to focus the attention of dedicated staff on the corporate collaboration. In contrast, public support for personnel exchange, or support for consulting, such as innovation voucher programs, or incentives for IP licensing do not promise increased commercial success. Public authorities might therefore review their portfolio of support schemes for industry-science interactions and reinforce such scheme that aim at joint, mutual active knowledge creation within dedicated research projects laid out in joint grant applications by industry-science consortia.

This study has some limitations, which constitute avenues for future research. First, our findings are limited to the case of Germany. Since science systems and the institutional and regulatory set-up for industry-science collaboration differ greatly across countries (see Polt et al., 2001), cross-country data would be required in order to analyze whether our findings can be generalized across countries, or whether they are specific to the German case. In addition, the regression sample includes firms that are product innovators and R&D active in the period of interest, resulting in a sample that is slightly biased towards larger companies. As a consequence, our results and the derived implications may not be applicable to smaller firms in the general population of German companies.

Regarding the econometric specification of our model, a concern is the endogeneity of the variables indicating various categories of cooperation with science. We could expect that some unobserved characteristics affecting the likelihood of cooperating with academic institutions may also influence the outcome variable in our estimations. While we address this issue by adopting a combination of difference-in-difference and matching estimators in firm-level fixed effects regressions, it would be ideal to mitigate this concern by implementing an additional robustness check with an instrumental variable approach for the variable denoting joint R&D. For the application of an IV estimator, a valid instrument is needed for the treatment variable. However, in the present context finding valid instruments turned out to be very challenging, thus we opted to account for unobserved heterogeneity with the specifications described above.

Another limitation is related to the time structure of the data. The information on the use of knowledge exchange channels refers to a specific period in time only (2015-2017). We cannot rule out that some of our findings reflect the specific situation in the German science and industry at that time. For example, this period was characterized by a significant increase in public funding for scientific research in universities and PROs, while universities had to cope with a substantial increase in the number of students. Both developments may have limited the resources and incentives to engage in industry collaboration for some channels, e.g. R&D services or HR transfer. This may explain the weak and statistically insignificant effects for these channels. For future research, it would be good to exploit time series data on the use of different transfer channels.

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Tables

Table 1: Number of observations and average sales of new products, by sector

Sector	NACE Rev. 2	No. of observations	Mean of sales of new products (m€)
Mining, utilities, waste management	5-9, 19, 35-39	41	21.34
Manufacturing of food/tobacco	10-12	57	7.94
Manufacturing of textiles	13-15	98	4.79
Manufacturing of wood/paper product	16-17	46	11.94
Manufacturing of chemicals	20-21	251	43.57
Manufacturing of plastic products	22	93	9.10
Manufacturing of glass/ceramics	23	66	72.80
Manufacturing of metals/metal products	24-25	149	6.96
Manufacturing of electrical equipment	26-27	505	12.60
Manufacturing of machinery	28	283	14.77
Manufacturing of vehicles	29-30	97	46.66
Other manufacturing, maintenance	31-33	203	4.27
Wholesale, transport, postal services	46, 49-53, 79	76	46.91
Media services, IT/telecommunications	18, 58-63	405	10.78
Technical, R&D services	71-72	329	1.59
Consulting, advertising, financial services	64-66, 69, 70.2, 73	137	5.53
Other firm-related services	74, 78, 80-82	71	0.63
N (firm-year obs., 2013-2020)		2,907	15.54

Table 2: Different knowledge exchange channels

Cooperation channel	%
Joint R&D	69.1
R&D services (consulting/contract research)	63.8
IP licensing	11.8
HR transfer	67.2
N (firm-year obs., 2016-2020)	1,170
Number of firms	406

Source: Mannheim Innovation Panel, 2018 survey wave

Table 3: Joint R&D – subsidies for joint R&D and perceived effectiveness of joint R&D

Joint R&D	%
Subsidized joint R&D	79.7
Non-subsidized joint R&D	20.3
Highly effective joint R&D	54.4
Low/medium effective joint R&D	45.6
Subsidized, highly effective joint R&D	48.5
Non-subsidized, highly effective joint R&D	5.9
N (firm-year obs., 2016-2020)	809
Number of firms	271

Source: Mannheim Innovation Panel, 2018 survey wave

Table 4: Type of public funding for industry-science collaborations

Public funding program	%
Horizon 2020 and other EU programs	20.6
Technology programs of the Federal Government	62.8
ZIM program and similar programs run by the Federal Ministry of Economic Affairs	47.5
All other programs	16.9
N (firm-year observations, 2016-2020)	611

Source: Mannheim Innovation Panel, 2018 survey wave

Table 5: Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Sales of new products	1.000									
2. Joint R&D	0.055 (0.003)	1.000								
3. R&D services	0.094 (0.000)	0.461 (0.000)	1.000							
4. IP licensing	0.042 (0.023)	0.273 (0.000)	0.287 (0.000)	1.000						
5. HR transfer	0.087 (0.000)	0.491 (0.000)	0.598 (0.000)	0.327 (0.000)	1.000					
6. Subsidized joint R&D	0.064 (0.001)	0.860 (0.000)	0.397 (0.000)	0.231 (0.000)	0.404 (0.000)	1.000				
7. Non-subsidized joint R&D	-0.009 (0.627)	0.394 (0.000)	0.181 (0.000)	0.114 (0.000)	0.227 (0.000)	-0.131 (0.000)	1.000			
8. Employment	0.759 (0.000)	0.080 (0.000)	0.098 (0.000)	0.035 (0.059)	0.093 (0.000)	0.094 (0.000)	-0.014 (0.449)	1.000		
9. R&D expenditures	0.607 (0.000)	0.055 (0.003)	0.073 (0.000)	0.104 (0.000)	0.068 (0.000)	0.067 (0.000)	-0.014 (0.464)	0.438 (0.000)	1.000	
10. Past cooperation with non-science	0.093 (0.000)	0.268 (0.000)	0.211 (0.000)	0.130 (0.000)	0.178 (0.000)	0.295 (0.000)	-0.010 (0.600)	0.081 (0.000)	0.061 (0.001)	1.000

N *(firm-year obs., 2013-2020): 2,907. P-value in parentheses.*

Table 6: Firm-level fixed effects panel regressions

	Dependent variable: Sales of new products (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Joint R&D (1)	0.229***				0.287**	
	(0.078)				(0.132)	
R&D services (2)		-0.047			-0.112	
		(0.086)			(0.139)	
IP licensing (3)			0.134		-0.043	
			(0.143)		(0.164)	
HR transfer (4)				0.108	0.144	
				(0.081)	(0.125)	
Subsidized joint R&D (5)						0.335***
						(0.109)
Non-subsidized joint R&D (6)						0.147
						(0.275)
Employment (log)	0.452***	0.460***	0.453***	0.449***	0.444***	0.451***
	(0.087)	(0.086)	(0.085)	(0.087)	(0.086)	(0.087)
R&D expenditures (log)	0.045***	0.044**	0.045**	0.043**	0.046***	0.043**
	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
Past cooperation with non-science	0.025	0.030	0.028	0.028	0.024	0.025
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.051)
Pretreatment (1)					0.061	
					(0.141)	
Pretreatment (2)					0.161	
					(0.148)	
Pretreatment (3)					-0.173	
					(0.188)	
Pretreatment (4)					0.054	
					(0.139)	
Pretreatment (5)						0.145
						(0.113)
Pretreatment (6)						-0.004
						(0.280)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Annual time dummies	Yes	Yes	Yes	Yes	Yes	Yes
N (firm-year obs., 2013-2020)	2907	2907	2907	2907	2907	2907

Cluster-bootstrapped standard errors in parentheses; * ***p < 0.10,*** ** ***p < 0.05,*** *** ***p < 0.01***

Table 7: Descriptive statistics – control group

Pre-treatment period (2013-2015); N*T = 508				
	Mean	Sd	Min	Max
Sales of new products (m€)	12.570	58.485	0.005	818.793
Employment (no. of employees)	222.114	627.547	3	6,839
R&D expenditures (m€)	1.702	11.405	0.000	158.580
Past cooperation with non-science (0/1)	0.321	0.467	0	1
Treatment period (2016-2020); N*T = 1,243				
	Mean	Sd	Min	Max
Sales of new products (m€)	8.810	45.623	0.003	792.414
Employment (no. of employees)	167.296	493.538	3	7,606
R&D expenditures (m€)	1.467	9.801	0.001	178.293
Past cooperation with non-science (0/1)	0.277	0.448	0	1

Table 8: Descriptive statistics – firms engaging in joint R&D with scientific institutions

Pre-treatment period (2013-2015); N*T = 347				
Variables	Mean	Sd	Min	Max
Sales of new products (m€)	25.567	117.419	0.008	1,500.000
Employment (no. of employees)	947.320	5,209.872	3	53,163
R&D expenditures (m€)	4.087	21.120	0.000	190.786
Past cooperation with non-science (0/1)	0.594	0.492	0	1
Treatment period (2016-2020); N*T = 809				
Variables	Mean	Sd	Min	Max
Sales of new products (m€)	23.428	130.499	0.004	1,614.391
Employment (no. of employees)	1,000.472	6,454.056	3	76,000
R&D expenditures (m€)	6.691	69.641	0.000	1,369.732
Past cooperation with non-science (0/1)	0.635	0.482	0	1
Subsidized joint R&D (0/1)	0.797	0.402	0	1
Non-subsidized joint R&D (0/1)	0.203	0.402	0	1
Subsidized, highly effective joint R&D (0/1)	0.485	0.500	0	1
Non-subsidized, highly effective joint R&D (0/1)	0.059	0.236	0	1

Table 9: Firm-level fixed effects panel regressions with entropy balancing

	Dependent variable: Sales of new products (log)		
	(1)	(2)	(3)
Joint R&D	0.287***	0.257**	
	(0.100)	(0.102)	
R&D services		-0.125	
		(0.113)	
IP licensing		0.118	
		(0.145)	
HR transfer		0.150	
		(0.112)	
Subsidized joint R&D			0.308***
			(0.104)
Non-subsidized joint R&D			0.175
			(0.155)
Employment (log)	0.517***	0.489***	0.511***
	(0.128)	(0.128)	(0.125)
R&D expenditures (log)	0.062***	0.065***	0.062***
	(0.021)	(0.021)	(0.021)
Past cooperation with non-science	-0.020	-0.023	-0.022
	(0.057)	(0.057)	(0.057)
Firm FE	Yes	Yes	Yes
Annual time dummies	Yes	Yes	Yes
N (firm-year obs., 2013-2020)	2050	2050	2050

Clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Propensity score matching - Probit model

	Dependent variable: Joint R&D
Employment (log)	-0.171***
	(0.037)
R&D expenditures (log)	0.217***
	(0.032)
Past cooperation with non-science	0.698***
	(0.097)
Constant	0.059
	(0.306)
17 sector dummies	Yes
N (firm obs., pre-treatment period)	1171
Pseudo-R-sq.	0.147

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Propensity score matching results – T-tests on mean differences

	Unmatched	Mean		t-test	
Variables	Matched	Treated	Control	t	p>|t|
Employment (log)	U	3.983	3.764	1.98	0.048
	M	3.884	3.959	-0.54	0.590
R&D expenditures (log)	U	-1.478	-2.720	9.49	0.000
	M	-1.589	-1.634	0.30	0.768
Past cooperation with non-science	U	0.622	0.324	10.77	0.000
	M	0.618	0.616	0.05	0.964

Samples are also balanced based on 17 sector dummies.

Table 12: Firm-level fixed effects panel regressions with propensity score matching

	Dependent variable: Sales of new products (log)		
	(1)	(2)	(3)
Joint R&D	0.230**	0.204*	
	(0.106)	(0.108)	
R&D services		-0.144	
		(0.116)	
IP licensing		0.112	
		(0.144)	
HR transfer		0.146	
		(0.114)	
Subsidized joint R&D			0.251**
			(0.109)
Non-subsidized joint R&D			0.119
			(0.159)
Employment (log)	0.523***	0.498***	0.517***
	(0.139)	(0.141)	(0.136)
R&D expenditures (log)	0.066***	0.070***	0.066***
	(0.022)	(0.023)	(0.022)
Past cooperation with non-science	-0.019	-0.021	-0.021
	(0.061)	(0.061)	(0.061)
Firm FE	Yes	Yes	Yes
Annual time dummies	Yes	Yes	Yes
N (firm-year obs., 2013-2020)	1411	1411	1411

Clustered standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01

Table 13: Subsidized university-industry cooperation and effectiveness of cooperation

	Dependent variable: Highly effective joint R&D (0/1)			
	OLS	IV 2SLS	Probit	IV Probit
	(1)	(2)	(3)	(4)
Subsidized cooperation with science (0/1)	0.506***	0.501***	1.830***	1.812***
	(0.047)	(0.086)	(0.193)	(0.418)
Employment in 2017 (log)	0.006	0.005	0.051	0.051
	(0.014)	(0.014)	(0.068)	(0.069)
R&D expenditure in 2017 (log)	0.002	0.002	-0.011	-0.011
	(0.012)	(0.012)	(0.056)	(0.057)
Past cooperation with non-science	0.093**	0.095**	0.528***	0.533***
	(0.039)	(0.041)	(0.172)	(0.190)
Employees with an academic degree (%)	0.001*	0.001*	0.007**	0.007*
	(0.001)	(0.001)	(0.004)	(0.004)
Continuous R&D (0/1)	-0.011	-0.010	-0.004	-0.001
	(0.036)	(0.038)	(0.217)	(0.227)
Constant	-0.032	-0.031	-2.417***	-2.413***
	(0.089)	(0.090)	(0.465)	(0.475)
4 aggregated sector dummies	Yes	Yes	Yes	Yes
N	434	434	434	434
R-sq.	0.40	0.38		
Pseudo R-sq.			0.39	
Test of overidentifying restrictions		Chi-sq. = 0.08 (p = 0.78)		
First-stage robust F statistic		F(2,423) = 47.86		

Robust standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01

Appendix

Table 14: First-stage IV 2SLS and IV Probit regressions

	Dependent variable: Subsidized cooperation with science (0/1)	
	IV 2SLS	IV Probit
	(1)	(2)
Public subsidies in 2014 (0/1)	0.352***	0.352***
	(0.065)	(0.064)
Public subsidies in 2012 (0/1)	0.186***	0.186***
	(0.059)	(0.058)
Employment in 2017 (log)	-0.000	-0.000
	(0.016)	(0.016)
R&D expenditure in 2017 (log)	0.010	0.010
	(0.013)	(0.012)
Past cooperation with non-science	0.012	0.012
	(0.049)	(0.049)
Employees with an academic degree (%)	0.001	0.001
	(0.001)	(0.001)
Continuous R&D (0/1)	0.118**	0.118***
	(0.046)	(0.045)
Constant	0.047	0.047
	(0.109)	(0.108)
4 aggregated sector dummies	Yes	Yes
N	434	434
R-sq.	0.38	0.38

Robust standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01

Table 15: Firm-level fixed effects panel regressions with entropy balancing– robustness check (treatment group: firms that engaged in at least one of the four collaboration channels with science)

	Dependent variable: Sales of new products (log)		
	(1)	(2)	(3)
Joint R&D	0.319***	0.309***	
	(0.098)	(0.098)	
R&D services		-0.176	
		(0.107)	
IP licensing		0.063	
		(0.148)	
HR transfer		0.150	
		(0.106)	
Subsidized joint R&D			0.340***
			(0.102)
Non-subsidized joint R&D			0.208
			(0.154)
Employment (log)	0.532***	0.511***	0.527***
	(0.140)	(0.140)	(0.138)
R&D expenditures (log)	0.068***	0.071***	0.067***
	(0.021)	(0.021)	(0.021)
Past cooperation with non-science	0.021	0.020	0.019
	(0.062)	(0.062)	(0.062)
Firm FE	Yes	Yes	Yes
Annual time dummies	Yes	Yes	Yes
N (firm-year obs., 2013-2020)	2050	2050	2050

Clustered standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01

Table 16: Firm-level fixed effects panel regressions – robustness check (A)

	Dependent variable: Sales of new products (log)	
	(1)	(2)
Highly effective joint R&D	0.328***	
	(0.124)	
Low/medium effective joint R&D	0.298**	
	(0.142)	
Low/medium effective IP licensing	0.041	
	(0.210)	
Highly effective IP licensing	0.013	
	(0.293)	
Low/medium effective R&D services	-0.181	
	(0.133)	
Highly effective R&D services	0.089	
	(0.141)	
Low/medium effective HR transfer	0.114	
	(0.118)	
Highly effective HR transfer	-0.077	
	(0.124)	
Subsidized joint R&D		0.336***
		(0.123)
Non-subsidized joint R&D		0.267
		(0.349)
Subsidized R&D services		-0.202
		(0.223)
Non-subsidized R&D services		0.090
		(0.266)
Subsidized IP licensing		0.533*
		(0.285)
Non-subsidized IP licensing		-0.387
		(0.406)
Subsidized HR transfer		0.373
		(0.240)
Non-subsidized HR transfer		-0.165
		(0.251)
Employment (log)	0.443***	0.448***
	(0.095)	(0.093)
R&D expenditure (log)	0.047***	0.044**
	(0.018)	(0.018)
Past cooperation with non-science	0.026	0.025
	(0.045)	(0.045)
Firm FE	Yes	Yes
Annual time dummies	Yes	Yes
Pretreatment dummies	Yes	Yes
N (firm-year obs., 2013-2020)	2907	2907

Cluster-bootstrapped standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Firm-level fixed effects panel regressions – robustness check (B)

	(1)	(2)	(3)	(4)	(5)	(6)
Joint R&D	0.284**	0.182	0.221***			
	(0.118)	(0.111)	(0.081)			
R&D services	-0.152			-0.192	-0.077	
	(0.137)			(0.130)	(0.087)	
IP licensing			0.003		0.031	0.461**
			(0.341)		(0.279)	(0.205)
HR transfer		-0.028		0.161		0.111
		(0.128)		(0.129)		(0.084)
Joint R&D # R&D services	-0.000					
	(0.179)					
Joint R&D # HR transfer		0.090				
		(0.172)				
Joint R&D # IP Licensing			0.052			
			(0.369)			
R&D services # HR transfer				0.074		
				(0.174)		
R&D services # IP Licensing					0.172	
					(0.311)	
HR transfer # IP Licensing						-0.434*
						(0.261)
Employment (log)	0.456***	0.451***	0.451***	0.449***	0.456***	0.445***
	(0.087)	(0.089)	(0.087)	(0.087)	(0.085)	(0.088)
R&D expenditures (log)	0.047***	0.045***	0.046***	0.045***	0.045***	0.044**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)
Past cooperation with non-science	0.026	0.025	0.025	0.029	0.029	0.027
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Annual time dummies	Yes	Yes	Yes	Yes	Yes	Yes
N (firm-year obs., 2013-2020)	2907	2907	2907	2907	2907	2907

Cluster-bootstrapped standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Firm-level fixed effects panel regressions – robustness check (C)

	Dependent variable: Sales of new products (log)		
	(1)	(2)	(3)
Joint R&D (1)	0.232***	0.288**	
	(0.079)	(0.132)	
R&D services (2)		-0.116	
		(0.139)	
IP licensing (3)		-0.041	
		(0.165)	
HR transfer (4)		0.151	
		(0.125)	
Subsidized joint R&D (5)			0.338***
			(0.109)
Non-subsidized joint R&D (6)			0.147
			(0.275)
Employment (log)	0.453***	0.446***	0.452***
	(0.088)	(0.086)	(0.087)
R&D expenditures (log)	0.045***	0.047***	0.043**
	(0.017)	(0.017)	(0.017)
Past cooperation with non-science	0.038	0.038	0.038
	(0.050)	(0.050)	(0.050)
Past cooperation with science	-0.045	-0.051	-0.046
	(0.060)	(0.060)	(0.061)
Pretreatment (1)		0.056	
		(0.140)	
Pretreatment (2)		0.156	
		(0.148)	
Pretreatment (3)		-0.176	
		(0.189)	
Pretreatment (4)		0.066	
		(0.138)	
Pretreatment (5)			0.143
			(0.112)
Pretreatment (6)			-0.001
			(0.279)
Firm FE	Yes	Yes	Yes
Annual time dummies	Yes	Yes	Yes
Observations	2907	2907	2907

Cluster-bootstrapped standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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