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Do university technology transfers increase firms' innovation?

by

María García-Vega and Óscar Vicente-Chirivella*

Abstract

We investigate how technology transfers from universities to private firms influence firm innovativeness. Using data on R&D acquisitions from universities of more than 10,000 Spanish firms for the period 2005-2013 and applying propensity score matching techniques, we find that technology transfers from universities strongly increase firm innovativeness. We next explore heterogeneous effects in order to analyse whether these gains are mediated by firm size and the business cycle. Our results suggest that the contribution of universities to firm innovation is particularly important for small firms and during the whole business cycle. The contribution of universities goes beyond its direct effect on innovation: We find that technology transfers from universities generate positive spillovers and enhance firms' internal R&D capabilities. Our results suggest that the knowledge generated by universities makes an important contribution to economic growth through technology transfers, which makes firms more innovative. Hence, knowledge creation by universities provides an important public good.

Keywords: Universities, Technology Transfers, Innovation, Firms

JEL classification: L25, D22, L24, O31

1. Introduction

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Do universities provide benefits to society beyond providing higher education to the young generation? This question has been at the core of the public and political debate about the role of university in society (Veugelers, 2016). One way universities can benefit society beyond education is through the transfer of their scientific research to firms which, in turn, can enhance innovation and thereby long-run economic growth (Mansfield, 1991). A core role of universities is to generate basic knowledge at the frontier of research, which is difficult to obtain through private markets.[1] Therefore, companies have incentives to acquire some research from universities (contractual technology transfers) instead of producing it themselves to remain competitive and to increase efficiency. While there is a large amount of literature on the effects of in-house R&D on innovation, and on the productivity of technology transfers from the perspective of universities,[2] few studies analyse the effects of contractual university technology transfers on firm innovation. In this paper, we contribute to filling this gap.

We investigate the effect of knowledge transfers from universities to private firms on firm innovativeness. A fundamental feature of universities is that they generate basic and applied research in an interlinked way. As a consequence, a large variety of different firms can benefit from university knowledge. Some small and medium sized firms lack capabilities and skilled personnel to implement incremental product innovations already known in the market.[3] Some start-ups hire research university services to create and organize their own laboratories. Large firms often have incentives to develop new products and processes to stay ahead of their competitors and to reduce their costs. These large firms also often acquire basic research from universities to obtain radical innovations.[4] Therefore

[1] Basic research is a public good and therefore there is often no market for creating that type of knowledge (Stephan, 1996; Lach et al., 2017).

[2] For example, Siegel et al. (2003a), Siegel et al. (2003b), Siegel et al. (2004), Chapple et al. (2005), Siegel et al. (2007), Macho-Stadler et al. (2007), Belenzon and Schankerman (2009) and Caldera and Debande (2010) study the performance of university technology transfer offices.

[3] For instance, strawberry farmers hire agricultural engineers and chemistry services from universities in order to delay expiry dates. This is a known technology in the agricultural industry, but it is difficult to implement by small farmers. In this line, McGuik et al. (2015) show that small firms are particularly sensitive to innovative human capital in order to innovate.

[4] For example, banks hire R&D services from computer science departments at universities in order to develop customized banking based on eye tracking technology. An example provided by Azoulay et al. (2018) and Novartis (2017) is the pharmaceutical company Novartis, which funded research on gene mutation performed at the University of Pennsylvania in order to develop immunocellular therapy against cancer. Bercovitz and Feldman (2007) study the type of R&D that is performed when large multinationals collaborate with universities.

studying university technology transfers helps us to understand the economic returns to research performed at universities not only for large firms, but also for small firms, which have an important impact on local communities because, for instance, they hire predominantly from their local area.

Beyond the challenges of observing contractual technology transfers from universities to private firms from the perspective of the firms, there are selection problems, which make it hard to causally identify the effects of technology transfers. Our econometric analysis uses panel data of more than 10,000 Spanish firms for the period 2005-2013. Its panel structure permits us to treat potential selection issues and endogeneity problems. Our data contain unique information of firm acquisitions of R&D from universities. With this information, we can identify contractual technology transfers from universities to private firms.[5] To our knowledge, this dataset is the most detailed panel database worldwide for contractual technology transfers from universities and, therefore, particularly suitable for our research purposes.

Our empirical approach is a combination of matching techniques and DiD estimations. We implement a Conditional difference-in-differences (CDiD) estimator. As a robustness check, we also perform instrumental variable (IV) regressions. We find that firms with technology transfers from universities strongly increase their innovativeness compared to firms without technology transfers. We also find a positive impact of technology transfers from universities on firm innovation by comparing knowledge transfers from universities with technology transfers from other providers, such as private firms or non-university research institutions.

The effects of technology transfers on innovation we uncover are particularly sizeable for small and medium sized firms. The distinction between small and large firms is interesting because innovation by small firms is key for productivity and for reduction of inequalities (OECD, 2018). Moreover, we find that the positive impact of technology transfers occurs over the whole business cycle but particularly in less financially constrained periods.

[5] Medda et al. (2005) and Vega-Jurado et al. (2017) use a similar characterization of university technology transfers. See Perkmann and Walsh (2007) for a discussion of different types of knowledge relationships between universities and private firms.

A deeper look at the data suggests that the impact of technology transfers from universities goes beyond its direct effect on innovation. Another contribution of our paper is to show that universities generate positive spillovers on patenting in regions and sectors with high concentration of technology transfers. This suggests that our direct effects are, indeed, a lower bound for the contribution of universities on firm innovation. Our final contribution is evidence that the impact of technology transfers from universities is particularly important for firms operating in R&D intensive sectors and that technology transfers also enhance firms' internal capabilities and their internal R&D resources, which implies that knowledge transfers are complementary to internal research.

This paper proceeds as follows: Section 2 discusses the related literature and the theoretical considerations. Section 3 presents the data and the description of the main variables; Section 4 discusses our econometric specification; Section 5 contains our main results; Section 6 shows additional empirical evidence, investigating heterogeneous effects, spillovers and crowding-out effects. Section 7 discusses our results and conclusions.

2. Related literature and theoretical considerations

We might expect that technology transfers from universities increase firm innovativeness for several reasons. First, there are some innovations that firms cannot develop on their own because of the lack of basic knowledge. A prominent example provided by Mansfield (1991) is the case of silicon. The study of the organic compounds of silicon by Kipping and Staudinger at the beginning of the 20th century was essential for the development of industrial silicon. The research was motivated by the academic curiosity to find how similar silicon was to carbon and not by any commercial purpose.[6] Second, even if firms are aware of the basic knowledge, they might lack the technical capabilities to develop the innovations. Therefore, as Mansfield argues, in a practical sense, these innovations cannot be developed without academic research. For instance, firms rent university laboratories to perform

[6] Working at the University of Nottingham, Kipping published more than 57 research papers between 1899 and 1944. In 1904, Kipping called silicon polymers "sticky messes of no particular use". Silicon is now used in a broad range of sectors from pharmaceutical, electronics or automobile industry. During WWII, silicon products were used for aircraft engine isolation, which allowed allied fighter planes to fly at high altitudes and in low temperatures (Thomas, 2010).

experiments because of the high fixed costs of setting up a lab. Third, early-stage innovations require creativity, which is difficult in large firms due to their organizational bureaucracy (Williamson, 1985, Ch 6) and the routinization of their R&D investments (Baumol, 2002). As a consequence, it has been traditionally more likely that breakthrough innovations are generated in universities and then transferred to firms than being created directly in large firms.

An alternative possibility to a positive relationship between university technology transfers and firm innovation is that firms have little use of the research generated by universities, either because it is too complex or because it requires high absorptive costs. For example, firms might find that scientific knowledge is too abstract and, therefore, too disconnected from their own direct commercial purposes. Over time, research at universities is becoming more complex because more learning is required to reach and push the technological frontier (Bloom et al., 2017). Similarly, in order to use the knowledge generated by universities, firms might need to increase their investments in absorptive capacities. For some firms, particularly small firms, the costs of hiring researchers or increasing the number of researchers in their existing laboratories might be too high. Therefore, firms might prefer to focus their attention on technologies generated by close competitors or suppliers, which might be less costly to assimilate (Bikard, 2018). Moreover, these arguments suggest that there can be heterogeneous effects that mediate the relationship between technology transfers from universities and firm innovativeness. By studying a large range of heterogeneous effects, our paper contributes to a better understanding of how knowledge from universities is absorbed by private firms.

According to Perkmann and Walsh (2007) there are two main types of high-level relationships between universities and firms that can induce technology transfers: R&D contracting and cooperation. The literature suggests that these two types of relationships provide different knowledge to firms (Cassiman et al., 2010; Lucena, 2011; Vega-Jurado et al. 2017), and they involve different costs. R&D collaborations imply sharing not only codified knowledge, that is, explicit and more articulated knowledge, but also tacit sources of knowledge (Lane and Lubatkin, 1998; Almeida et al., 2003).[7] In the case of R&D contracts, typically, only codified knowledge is exchanged and, therefore, it can be more limited than cooperation. However, an advantage of contractual R&D is that it is more focused on improving problem-solving capabilities in the innovation process than on R&D cooperation. This can have important effects on firm innovativeness because problem-solving capacities expedite experiments, enhance measurements in the labs and improve the interpretation of results (Dasgupta and David 1994; Antonelli 1999). Moreover, R&D cooperation is often not used by small firms. For example, Miotti and Sachwald (2003), Negassi (2004) and López (2008), among others, find a positive relationship between firm size and the probability of R&D cooperation. Our results suggest that R&D contracting is negatively correlated with firm size. This seems to indicate that small firms are more likely to contract R&D than be involved in R&D cooperation agreements. One possible reason is that R&D cooperation requires more highly-skilled R&D personnel and research managers than R&D contracting due to the more tacit knowledge that is being transferred.[8] Another advantage of contractual R&D, instead of cooperation or more general measures such as sources of information or benefits from interactions with universities, is that we can account for the direction of the technology transfer, which facilitates identification.

How does our paper relate to the existing literature? By using a unique dataset on detailed contractual R&D from universities, we contribute to the literature on the effects of public research on industrial innovativeness. In his seminal paper, Mansfield (1991) used survey data from top R&D executives from major American firms to study the effects of academic research on firms' innovation performance. In order to measure academic research, Mansfield considered a question about the innovation that could not have been developed (without substantial delay) in the absence of academic research. Using the same variable as Mansfield (1991), Beise and Stahl (1999) analyze the impact of publicly financed funds on firm innovativeness using survey data for large German corporations. In both studies, university research has an important positive effect on firm innovation. In our study, we also find a positive effect of universities on firm innovativeness. However, in contrast to these studies,

[7] Yu and Lee (2017), Szücs (2018), Kafouros et al. (2015), Lööf and Broström (2008), Grimaldi (2002), Monjon and Waelbroeck (2003), among others study the effects of university cooperation on innovation outcomes.
[8] For example, Lucena (2011) shows for the case of R&D acquisitions from different providers that a significant number of firms that acquire R&D do not perform internal R&D, which suggests that learning from R&D acquisitions is possible even without the adoption of in-house R&D.

our paper focuses on the impact of contractual university technology transfers and we provide new evidence regarding heterogeneous effects. Another difference between our paper and these studies is that our data integrate large and small firms and, therefore, we are able to identify the contribution of universities also for medium and small sized firms.

Several studies use cross-section survey data to study the influence of university technology transfers on firm innovativeness. For example, Cohen et al. (2002) study how university public research influences industrial R&D as compared to other sources of information. Their study suggests that the effect of university research varies across industries, the pharmaceutical industry being one of the most positively affected industries. Arvanitis et al. (2008) use Swiss survey data to study how different types of university-firm relationships influence firm innovation. Their findings suggest that university research knowledge is very important for firms' sales of new products. Bishop et al. (2011) study how firms' interactions with universities enhance different types of research outputs such as problem solving, generation of patents or improvement of the firms' understanding. In contrast to Arvanitis et al. (2008) and Bishop et al. (2011) we use panel data, which allow us to address the potential selection bias problem, and we can also provide detailed determinants for firms to obtain technology transfers. Furthermore, we provide detailed evidence about contractual R&D and we discuss the intensity of technology transfers.

Our paper is most closely related to Medda et al. (2005) and Vega-Jurado et al. (2017). Medda et al. (2005) study the effect of R&D acquisitions from universities and other types of external R&D on firm productivity. They do not find a statistically significant effect on firm productivity. One possible reason for this result, as they explain in the paper, is that contractual R&D from universities might require a longer time frame to influence firm productivity than the one that they consider. In contrast, our interest is on firm innovativeness. A further novelty of our analysis is that we provide evidence on indirect effects of technology transfers testing whether they have an impact upon firms' internal capabilities and spillovers.

Vega-Jurado et al. (2017) investigate the effects of both contractual and cooperative relationships between universities and private firms on different types of product innovations. They show that contractual R&D influences incremental product innovation, while cooperation increases radical product innovation. In our study, we also find a positive relationship between contractual R&D and incremental product innovation. In contrast to them, we also investigate the effects of contractual R&D on process innovation and patents, in addition to product innovation. Another difference with Vega-Jurado et al. (2017) is that we use, among other techniques, instrumental variable procedures and matching approaches in order to control for selection. Moreover, differently from them, we compare the impact of technology transfers from universities with respect to technology transfer coming from private firms or non-university research institutions. A recent paper by Fudickar and Hottenrott (2019) investigates the impact of formal and informal interactions with universities on the innovativeness of German startups. They combine cooperative and contractual research (among other relationships) to construct their indicator of formal interactions. Differently from Fudickar and Hottenrott (2019), we focus specifically on contractual R&D. Finally, we shed light on the effects of technology transfers for the average firm and we distinguish by sectors, firm size and different macroeconomic periods.

3. Data and description of the main variables

In this section we describe the dataset and the main variables that we use for our empirical analysis. Further details are in the following sections and in Tables 1 and 2 where we present descriptive statistics and definitions of the main variables. Our goal is to analyze the effect of technology transfers from universities on firms' innovation. For this purpose, we use a dataset that comes from a survey of Spanish firms called Panel de Innovación Tecnológica (PITEC) for the period 2005-2013. PITEC represents Spain's contribution to the Europe-wide Community Innovation Survey (CIS). It is the result of the collaboration between the Spanish National Statistics Institute, the Spanish Science and Technology Foundation and the Foundation for Technological Innovation.[9] PITEC is an unique dataset that includes a representative sample of the universe of Spanish firms. The dataset

[9] PITEC applies the methodological rules defined in the *Oslo Manual* OECD's (2005a). Details on PITEC and data access guidelines can be obtained at: https://icono.fecyt.es/pitec.

contains detailed firm-level information on a number of firm characteristics such as number of employees and turnover and different measures of innovation inputs and outputs.

Our sample is an unbalanced longitudinal panel. We consider nine waves from the PITEC dataset from 2005 to 2013. On average, there are 10,760 firms during our sample period and, among these, there are 10,042 firms with four consecutive observations and 8,589 firms with nine consecutive observations. We show the distribution of firms across the different year-waves in the first column of Table 1.

3.1. Main independent variable: Technology transfers from universities

We are interested in the effects of technology transfers from universities upon firm innovativeness. Our measure of technology transfers are R&D services acquired from Spanish universities by firms operating in Spain. In the survey, each company indicates its *R&D acquisitions*, that is, its purchases of R&D services.[10] *R&D acquisitions* are defined in the survey as:

"Acquisitions of R&D services outside the firm through contracts, informal agreements, etc… Funds to finance other companies, research associations, etc… that do not directly imply purchases of R&D services are excluded".

With this information, we construct the variable *university technology transfers*, which is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish universities and zero otherwise. Measures similar to our measure of technology transfers from universities are used by Fudickar and Hottenrott (2019), Vega-Jurado et al. (2017) and Medda et al. (2005). Tests, technological support, researchers or faculty consulting are some examples of the type of R&D services that companies acquire from universities and that are embedded in our measure of technology transfers.

[10] R&D services are defined in the survey as: *"Creative work to increase the volume of knowledge and to create new or improved products and processes (including the development of software)"*.

The advantage of our measure with respect to other measures is twofold. First, it captures an intensive type of knowledge transfer from universities to companies, which is difficult to obtain using only measures of patent citations or licensing (D'Este and Patel, 2007).[11] For example, Cosh et al. (2006), using a survey of UK and US firms, report that firms consider that the most important types of university-industry interactions contributing to their innovation activities are testing and standards, problem-solving, and innovation expenditures to universities. Second, R&D acquisitions are largely used by both large and small firms, while other measures such as cooperation are not used so often by small firms as they require highly-skilled R&D personnel and research managers (Teirlinck and Spithoven, 2013). Since in our dataset there is a large number of small firms, it is likely that our estimations would suffer from a strong selection bias if we use cooperation as our measure of technology transfers because we would not be accounting for technology transfers for small firms. The disadvantage of R&D acquisitions from universities is that informal contacts between firms and universities are not included. Since many of these informal contacts are important for firm innovation and they are likely to precede the time of the formal R&D acquisition from universities, our results can be considered as a downward biased estimation of the effects of university technology transfers on firm innovation.

In our sample, the percentage of firms with technology transfers from universities is 6.8% (see Table 2). Moreover, 8.14% of firms obtain technology transfers more than twice during the sample period, although this number is reduced to 0.58% for firms with continuous technology transfers for the whole period. In Table 1, we report the number of firms with technology transfers from universities by year (column 2). We also present information on the number of firms that, in our sample period, start obtaining technology transfers in a given year for the first time (column 3), on firms that never have technology transfers (column 4) and on overlapping firms, i.e., firms that in a

[11] One disadvantage of patents citations as a measure of technology transfers is that patenting suffers from a double skewed phenomenon. Almost 40 per cent of all university patents around the world are held by 50 institutions. Moreover, within these 50 institutions, the large majority are from either the US or the UK (Veugelers, 2016). Some studies have used licenses or royalties as measures of technology transfers. However, licensing is even more concentrated than patents. For the UK, one-third of the total income generated by licenses is concentrated in two licensors (Russell Group, 2010). Scherer and Harhoff (2000) show that 93 per cent of royalties received on inventions in 1991 were held by six research-oriented US universities.

given year do not have technology transfers but had them in previous years or will have them in the future (column 5). On average, in each year, 1.5% of firms start acquiring technology from universities for the first time. Additionally, on average, 13.4% of observations correspond to firms that do not obtain technology transfers, but that either in previous years have had technology transfers or they will have them in the future. These figures indicate the importance of technology transfers from universities.

In Table OA1 in the on-line Appendix, we present the number of observations and percentage of firms with technology transfers by sectors of activity. Transfers from universities are highly concentrated in R&D-intensive sectors such as "Pharmaceutical", "Chemicals" and "R&D services" but also in the "Agricultural" sector, which is an important industry in the Spanish economy.

3.2. Dependent variables

Our dependent variables are measures of innovation output at the firm level. In particular, we consider three different measures of firm innovativeness in our baseline specifications: having product innovation, having process innovation and having patents.[12] In the robustness checks section we include additional indicators of innovation outputs. Product innovation, process innovation and patents are well-established indicators of innovation used in a large number of empirical studies.[13] We measure product (process) innovation, as a dummy variable that takes the value one if the firm reports having introduced new or significantly improved products (processes) in the current or previous two years. In the same vein, patents is a dummy variable that takes the value one if a firm reports having patents in the current or previous two years and zero otherwise.

The advantage of these measures of innovativeness is that they directly refer to the output in the context of a knowledge production function, in which technology transfer is an input. The distinction between product and process innovations allows us to differentiate between demand-based innovations

[12] See Mairesse and Mohnen (2005) for a detailed explanation of how CIS surveys are structured and the main innovation indicators in this type of survey.
[13] See Geroski et al. (1997), Griffith et al. (2006), Cefis and Orsenigo (2001), Cefis (2003), Martínez-Ros and Labeaga (2009), Clausen et al. (2011), Tavassoli and Karlsson (2015) or Ganter and Hecker (2013), among others.

(product innovations) and cost-reduction innovations (process innovations). Patents provide a good signal of the degree of novelty of firm innovativeness. Moreover, since patents are also derived from administrative data, they are likely to be more objective than other indicators of innovation output (Haucap et al., 2019). In fact, patents have been widely used in recent studies to measure innovation output (Aghion et al., 2009; 2013; Bena and Li, 2014; Seru, 2014; Haucap et al., 2019).

Table 2 shows descriptive statistics of the main variables for the whole sample and differentiating by technology transfers from universities' status. Firms with technology transfers from universities are characterized by a higher innovation profile than those without technology transfers. The percentage of firms having introduced either a product (process) innovation or a patent is higher for companies with technology transfers from universities than without technology transfers. The largest difference is for the variable product innovation. More than 70% of firms with technology transfers reported at least a product innovation during the current or previous two years while this percentage is less than 50% for companies without technology transfers. The differences in process innovation and patents are also higher than 20 percentage points. Moreover, there are also important differences on the sales from products new to the market (firm). Table 2 further shows a higher level of human capital for firms with technology transfers from universities. These results suggest that there is a positive correlation between technology transfers from universities and innovation. In the following sections, we measure these effects controlling for selection.

4. Econometric specification

We aim to study the effect of university technology transfers on firm innovativeness. To face this objective, in our main specifications, we estimate two empirical models that combine propensity score matching with difference-in-differences (DID) estimators.

The first model considers changes that happen within the same firm by examining companies that *start* for the first time to obtain technology transfers from universities. This approach allows us to determine the average treatment effect on the treated (ATT), which is the difference between the innovation outcome variable of firms with technology transfers from universities and their innovation outcome without technology transfers.[14] The ATT can be specified as follows:

$$ATT = E[y_{t+1}^{1} | T_t = 1] - E[y_{t+1}^{0} | T_t = 1] \quad (1)$$

In the expression above, the term y_{t+1}^{1} is the innovation outcome in case of technology transfers from universities, y_{t+1}^{0} is the innovation outcome without technology transfers from universities, and T_t is a dummy variable that takes the value one when there are technology transfers from universities. The evaluation problem is that the counterfactual outcome of not having technology transfers is unobserved for the treated firms.

The matching technique allows us to find a set of firms with the same observable characteristics as the treated group before having technology transfers but that did not receive the treatment. We employ a one-to-one propensity score matching within the same year with replacement (Rosenbaum and Rubin, 1983, Rosenbaum and Rubin, 1985). In each year, for each firm that will start for the first time obtaining technology transfers the following period, we identify a control firm with similar observable characteristics that never obtained transfers from universities during our sample period. In this way, we ensure that there is no overlap between treated and control group after matching. The matching procedure controls for observable firm characteristics that can influence both the probability of having technology transfers and innovating by considering a comparable sample of firms. Our identifying assumption is that, conditional on the observable characteristics that are relevant for technology transfers, the outcomes of interest for treated and control firms are orthogonal to technology transfers. In other words, we assume that, in the absence of technology transfers, the outcome of the treated group would not have been systematically different than the outcome of the control group. The DiD estimator measures the changes to innovation outcome between pre- and post-technology transfers for the treated versus the control group and, therefore, controls for time-invariant unobservable characteristics.

[14] See for example Guadalupe et al. (2012), Haucap et al. (2019), Jabbour et al. (2019), Javorcik and Poelhekke (2017), among others.

The propensity score that we use for the matching procedure comes from a Probit model where we calculate the probability of having technology transfers from universities on a set of observable firm characteristics, denoted by X_{it-1}. Formally:

$$T_{it} = \begin{cases} 1 \text{ if } \gamma + X'_{it-1}\rho + d_t + \xi_{it} > 0 \\ 0 \text{ if } \gamma + X'_{it-1}\rho + d_t + \xi_{it} \leq 0 \end{cases} \quad (2)$$

In equation (2), the vector X_{it-1} reflects pre-treatment firm characteristics that influence the likelihood to have technology transfers from universities, d_t denotes time dummies, and ξ_{it} is the error term, which we assume is normally distributed with variance σ_z^2. In all regressions, we use cluster robust standard errors at the firm level. We also control for time-specific sectoral shocks to the economy that might affect technology transfers. After we estimate the propensity score from equation (2), we pair each treated firm with the closest untreated firm by caliper matching with replacement and we obtain our DiD estimator as follows:

$$y_{it+2} = \alpha + \beta T_{it} + \varepsilon_{it}, \quad (3)$$

where y_{it+2} denotes firm innovation output and β is the DiD parameter of interest and it measures the ATT effect.[15]

Our approach, matching within the same year and considering as treated group firms that start obtaining technology transfers for the first time and considering the control group firms that never had technology transfers, has the advantage that it avoids the potential problem of overlapping treated and control firms. Moreover, it ensures that we control for time-specific confounding factors that affect firms with and without technology transfers. However, given that some treated firms receive the treatment more than once and that our panel is relatively short, it is possible that the composition of treated and control groups might change over time due to some unobservable time-variant characteristics. For example, at the beginning of our sample period, some of the firms in the control

[15] The innovation output variables are included with a two-period lead. That is, we study the probability of having innovations up to two years after receiving technology transfers from universities. The reason for the two-year lead is due to the definition of the variables in the survey. Following the usual definitions in Community Innovation Surveys, in our dataset, innovation output questions are for the current and previous two years, while innovation inputs and accounting variables are for the current period.

group might have received a treatment in the near pre-sample period, or selection into the treatment might be influenced by unobserved reasons that are not year or firm-specific but university time-variant-specific. In order to address potential concerns regarding the composition of the groups over time, we estimate a conditional difference-in-differences estimator (CDiD) with repeated cross-sections (Blundell and Costa-Dias, 2002; Aerts and Schmidt, 2008). This model allows to control for possible changes in the composition of the treated and control groups that change over time.

We estimate the average treatment effect on the treated firms using the CDiD methodology employed by Aerts and Schmidt (2008), which they apply to the effects of additionality of R&D subsidies. The approach by Aerts and Schmidt (2008) considers three different matchings. Let us call t_0 and t_1 two consecutive time periods. The first match is in period t_1 between a treated firm, denoted by *i* that receives the treatment in period t_1 and a non-treated firm, denoted by *h* that does not receive the treatment in period t_1. The second match is found in period t_0 between firm *i* and a non-treated firm in period t_0, which we denote by *k*. The third match is also in period t_0, in this case, it is between firm *h* and a non-treated firm in period t_0, which we denote by *j*. The average treatment effect on those treated is calculated as follows:

$$ATT^{CDiD} = \left(E\left[y_{i,t_1}^1 | T_{i,t_1} = 1\right] - E\left[y_{k,t_0}^0 | T_{k,t_0} = 0\right]\right) - \left(E\left[y_{h,t_1}^0 | T_{h,t_1} = 0\right] - E\left[y_{j,t_0}^0 | T_{j,t_0} = 0\right]\right) \quad (4)$$

An important assumption for our identification strategy is that technology transfers from universities do not have an indirect effect through spillovers into the control groups, as this would be a violation of the Stable Unit Treatment Value Assumption (SUTVA assumption). We initially rule out this possibility but investigate this assumption in Section 6.

5. Effect of technology transfers from universities on firm innovativeness

In this section we present evidence regarding the effect of technology transfers from universities on firm innovativeness. First, we estimate this relationship for the whole sample. Second, we estimate the impact for the matched sample using starters as treated firms and firms that never obtain technology transfers as control group. Third, we estimate the average treatment effect with the CDiD methodology and we show robustness checks including our IV specification. Fourth, we exclude from our sample firms without any type of technology transfer. In this way, we compare the effect of technology transfers from universities with the impact of technology transfers from other providers and assess its relative importance. For this analysis, we also use the CDiD methodology.

5.1. Results from the whole sample

Before we report our results from the matching samples, we first show evidence based on the whole sample without controlling for the potential selection bias or endogeneity issues. We present the results in Table 3. In panel A, the dependent variable is product innovation; in panel B, the dependent variable is process innovation; and, in panel C, the dependent variable is patents.

We report estimates including different controls and firm fixed effects. In columns 1 and 2, we do not include firm fixed effects. From column 3 to 5, we add firm fixed effects. From column 2 to 5, we include lagged control variables. In column 3, we include firm fixed effects using the Wooldridge (2005) correction methodology.[16] Following this method, the unobserved individual effect (α_i) is conditioned on the initial values of the dependent variable (y_{i0}) and the individual mean of the time-varying covariates ($\bar{x}_i$), allowing for correlation between the individual effect and the observed characteristics. In columns 1, 2 and 4, we control for sector fixed effects while in column 5 we include sector-time fixed effects. In all regressions in all panels, we include year fixed effects. All standard errors are clustered at the firm level.

In all columns, and in all panels, we show that university technology transfers are always strongly positively related to any type of innovation output. For example, the estimated coefficient of university technology transfers in column 1a suggests that having technology transfers increases the likelihood of having product innovation by 24.2 percentage points. Once we include firm fixed effects to control for time invariant firm characteristics in columns 3a to 5a, we find that this effect remains positive and highly significant, but the magnitude is lower than in previous specifications. In particular, the

[16] This methodology allows the individual effect to be correlated with the regressors and solve the 'initial conditions problem'. The initial conditions problem arises when the first observation for each firm in a panel does not coincide with the first year of this firm; that is, when we do not have information about firms from the very beginning. Since the first observation for each firm is affected by the same process that will affect the variable from the first year of the observation period, this variable would be endogenous.

estimated coefficient in column 5a suggests that having technology transfers from universities might increase the likelihood of having product innovations by 2.8 percentage points. The estimated coefficients in panel B for process innovation are of similar magnitude to those for product innovation in panel A. In the most conservative estimations, in columns 4b or 5b, we observe that university technology transfers increase process innovation by 2.3 percentage points. Finally, the results in panel C, in the most conservative estimations, indicate that having university technology transfers increases the likelihood to patent by 1.9 percentage points (column 5c).

5.2. Results using starters

Before turning to the effect of technology transfers from universities on firm innovativeness with the matched samples, we first summarize the estimates of the probability model that we use to obtain the propensity scores for our matching procedure. Our dependent variable is a dummy variable that takes the value one when there are technology transfers from universities. As control variables, we follow Cassiman and Veugelers (2006), Piga and Vivarelli (2004) and Parmigiani (2007) to consider determinants of external knowledge acquisition. We include measures of internal R&D in the regressions (measured as the natural logarithm of a firm's intramural R&D expenditures, and the natural logarithm of the number of employees working in R&D), which also control for the level of absorptive capacity of the firm. We control for firm size (with the natural logarithm of the total number of employees, and the natural logarithm of the physical investments) to account for economies of scope. We include firm exporting status and an indicator that takes the value one if the firm belongs to a business group in order to control for firm internationalization. We add product, process and patent dummy variables, as well as time and industry dummies. To avoid reverse causality problems, we lag our explanatory variables one period.

The results from the probit specification for starter firms and untreated firms that never receive the treatment during the sample period is reported in column 1 of Table A1 in the Appendix. Our estimates suggest that firms that have patents are likely to obtain technology transfers from universities in the following period. Moreover, smaller firms (in terms of employment) but with more investments in physical capital seem more likely to obtain technology transfers from universities. With respect to R&D inputs, firms with more researchers in R&D and more internal R&D expenditures are more likely to obtain technology transfers. This suggests that absorptive capacity is important in order to obtain technology transfers from universities; this is in line with Cassiman and Veugelers (2006) who find complementarity between internal and external knowledge.

Based on the results from equation (2), within the same year, we pair by caliper matching with replacement (with caliper equal to 0.0001) each treated firm with the closest untreated firm that never received the treatment.[17] We report the descriptive statistics of the matched sample in Table OA2 in the on-line Appendix. The matching procedure works well. In Table OA3 in the on-line Appendix, we report balancing tests after matching. When we compare the sample means of the variables used in the matching procedure, we find that there is no statistically significant difference in the pre-acquisition period. Our matching specification generates well-balanced samples, which implies that control (754 firms without technology transfers) and treatment groups (769 firms with technology transfers) are equivalent in their overall observable characteristics before treatment.

In Table 4, we present the ATT effect of technology transfers from universities on firm innovation after matching. In column (1) we report the estimate for product innovation; in column (2) we present the result for process innovation; and, finally, in column (3) we show the estimated coefficient for patents. In all columns, the estimates indicate a positive and statistically significant effect of technology transfers from universities on innovation outputs. The results suggest that having technology transfers from universities increases product innovations by 7.8 percentage points, process innovations by 6.9 percentage points and patenting by 9.3 percentage points.

In the last three columns of Table 4, we investigate how the impact of technology transfers from universities on firm innovation varies over different intensities of technology transfers. For this purpose, we construct four dummies that indicate the different quartiles of technology transfers intensity, where we define intensity as the ratio between technology transfers from universities over total R&D expenditures. The results show consistently for product innovation (column 4), process

[17] We use a one-to-one caliper matching with replacement, such that each starter firm, the year before it starts to obtain technology transfers from universities is matched with a firm that never obtains technology transfers. We decide for a matching with replacement in order to minimize the bias of the matching and maximize the number of observations in the final sample. As Stiebale and Woessner (2019) explain, the choice between with or without replacement involves a trade-off between bias and variance. Our results are also consistent with alternative matching algorithms such as caliper closest neighborhood and a reweighted estimator. These results are available upon request.

innovation (column 5) and patents (column 6) that as intensity increases the effect of technology transfers on innovation declines. This suggests that firms need a certain degree of absorptive capacity in order to benefit from university technology transfers. Moreover, these findings might indicate that technology transfers from universities complement the internal capabilities of the firms. We investigate this issue in more detail in Section 6.

5.3. Results using CDiD with repeated cross-section methodology

To further check the evidence presented above, we estimate the effect of technology transfers from universities using the CDiD with repeated cross-section methodology described in Section 3. We report the descriptive statistics for the different matchings in Table OA4 in the on-line Appendix. In Table OA5 in the on-line Appendix, we present the balancing test for the three different matchings required for our analysis. We show balancing tests where we aggregate across years. The matching that we employ is the nearest neighbour with replacement with caliper equal to 0.0001. The reason to use the nearest neighbour instead of one-to-one matching as in the estimations in the previous section is to avoid having to discard a large number of observations, which could reduce the estimation power (Stuart, 2010). In order to gain some insight into the general characteristics of the firms that obtain technology transfers from universities and not only of starters, in column (2) of Table A1 in the Appendix, we present the probit model that we use in our analysis. The determinants of obtaining technology transfers in column 2 are similar to those for starters in column 1. The matchings perform well across all the different variables. The comparison of sample means suggest that the different groups have statistically similar characteristics for all the observable variables. Moreover, the overall balancing tests show that the mean and median bias between groups have significantly declined after matching for the three matchings.

In Table 5, we present the ATT on the treated. The results support previous estimations. We find that technology transfers have a positive and statistically significant effect on the different measures of firm innovativeness. The findings in Table 5 suggest that technology transfers from universities increase product innovation by 4.3 percentage points (column 1), process innovation by 7.2 percentage points (column 2) and patents by 5.5 percentage points (column 3). In the next section, we present several robustness checks of our results.

5.4. Robustness checks

We perform several sensitivity tests that we present in the Appendix, including longer pre-treatment trends, alternative definitions of our innovation output variables, a placebo test. For these three robustness checks, we use the CDiD estimation methodology.[18] We also report an IV specification.

The difference-in-differences methodology is based on the assumption that the treatment and control group have statistically similar pre-treatment trends. We perform an additional test in order to control for common pre-existing trends by including two years of pre-treatment data instead of one year of the pre-treatment data. The results reported in Table A2 in the Appendix are, again, similar to those of previous specifications. Balancing tests are shown in Table OA6 in the on-line Appendix. In all cases, we observe that technology transfers from universities lead to an increase in firm product innovation and patents. This suggests that our results are not biased by longer pre-treatment trends.

We next explore the sensitivity of our results to alternative definitions of our innovation output variables. One possible concern is that our output measures in Table 5 are not properly capturing innovation output for continuous successful innovators. For example, in a given year, a very innovative company and a company with only one innovation are treated the same using dummy variables as innovation output measures. For this reason, in Table A3 in the Appendix, we present results for three continuous measures of innovation output. The first two measures capture innovative sales and are defined as the logarithm of the sales coming from products new to the market or products new to the firm, respectively, in the current or previous two years. This allows us to distinguish between radical innovations, in the case of innovations new to the market, and incremental innovations, in the case of innovations new to the firm. In addition, we include a measure of patent

[18] The different estimated results presented in the paper using the CDiD methodology are robust to the alternative specification of using starters.

intensity. Our variable is the logarithm of the number of patents plus one, to deal with zeros (see for example Haucap et al., 2019 or Stiebale, 2016). The results show that the ATT effect for sales from new products to the firm and number of patents are positive and statistically significant. The effect is also positive for sales from new products to the market, but it is not significant at conventional statistical levels. This suggests that university technology transfers lead, on average, to an increase in the intensity of firm innovativeness. Moreover, these estimations confirm our previous results with respect to patents.

In order to further assess the robustness of the results presented in Table 5, we estimate a placebo regression where we assign the treatment status randomly to the control group. We present the results from the balancing test in Table OA7 in the on-line Appendix and from the ATT effect in Table A4 in the Appendix. The results from these placebo regressions are very different from previous estimations. We now find no significant differences between control and treatment groups in terms of product innovation, process innovation, and patenting.

The DiD model combined with the matching estimators described above control for time-invariant unobservable characteristics and for time-variant observable characteristics. In order to address concerns regarding the potential bias due to the omission of unobservable time-variant characteristics that could affect both transfers of technology and innovation, such as changes in managerial practices, we use an instrumental variable approach. In these specifications, we use as instrumental variable *the importance of conferences, fairs, trade shows, or exhibitions as a source of information* measured at the average of the industry and regional level and pre-sample.[19] The validity of this instrument rests on the assumption that the pre-sample importance of conferences, fair trades, or exhibitions in a sector within a region can influence the technology transfers that a firm receives from universities as well as networking with university scientists, but it is exogenous to unobservable time-variant firm

[19] This measure is constructed for the year 2004.

characteristics.[20] The reason is that this variable is not measured at the firm level and it precedes the years of the technology transfers.

We present the results in Table A5 in the Appendix. In the bottom part of the table, we show the first stage regression of the 2SLS estimations as well as the Kleibergen-Paap F-statistics. The instrument is significantly positively related to technology transfers from universities and the Kleibergen-Paap F-statistic, which is considered an approximation of the distribution of the weak-instrument yields values above 20 (the critical value for a maximum IV bias of 10% of the weak identification test is 16.38, Stock and Yogo, 2002). The IV point estimates presented in the top part of Table A5 are positive and statistically significant, which confirms the evidence presented in previous estimations. After establishing with several robustness checks that technology transfers from universities increase firm innovativeness, in the following section we study additional empirical evidence to assess the contribution of the technology transfers from universities.

5.5. Impact of technology transfers from universities on firms' innovation versus technology transfers from other providers

In order to gain further insight into the importance of the contribution of technology transfers from universities, we compare differences in innovation outputs between firms with technology transfers from universities (treatment group) and firms with technology transfers from other sources that do not include universities (control group), where technology transfers from other sources are acquisitions of R&D from other private companies or research associations (not including universities). In this way, we can assess the differential contribution of transfers from universities and transfers from other providers. If the estimated ATT effect after matching is positive (negative) and significant, it means that the contribution of technologies coming from universities is larger (smaller) than technologies from other sources. If it is not significantly different from zero, it implies that technology transfers from universities have a similar effect than technologies from other sources. This comparison is in the

[20] See for example Siegel et al. (2004) for the importance of conference and expositions to establish relationships between business and universities and to promote technology transfers. See for example Appleyard (1996) for types of knowledge flows in Japanese firms or Monteiro and Birkinshaw (2017) for different types of technology sourcing.

spirit of Medda et al. (2005) who study private returns of research projects with universities and research projects from other external sources on firm productivity for a sample of Italian firms.

We present the estimated ATT effects using the CDiD methodology in Table 6 and the balancing test in Table OA8 in the on-line Appendix. All the estimated coefficients are positive and statistically significant at conventional levels. This suggests that the contribution of university technology transfers to product and process firm innovativeness is larger than the effect of technology transfers coming from other providers. The results suggest that technology transfers from universities increase product innovation by 13.6 percentage points; process innovation by 13.7 percentage points and patents by 12.5 percentage points more as compared with firms that obtain technology transfers coming from other providers. This confirms the importance of the contribution of universities for highly valuable innovations. We provide evidence supporting the Rosenberg and Nelson (1994) idea that universities play an important role in the development of innovations, and particularly for those that are patented.

6. Additional empirical evidence on the role of technology transfers for firm innovativeness

In this section, we first explore different heterogeneous effects differentiating firms by size and in different sample periods. Then, we study the effect of technology transfers from universities differentiating by Pavitt sectoral taxonomy. Finally, we analyse whether the contribution of technology transfers from universities goes beyond the direct effect on innovation by exploring spillover effects and the possibility of crowding-out internal R&D inputs.

6.1. Heterogeneous effects

6.1.1. Who benefits from technology transfers? SMEs vs non-SMEs

A natural question about the above estimated effects of technology transfers from universities on firm innovativeness is which particular firms benefit from the technology of the universities. In this section, we distinguish between small or medium firms (SMEs) and large firms (non-SMEs). We follow the definition of the OECD (2005b) and consider that a firm is an SME when its number of employees is less than 250. This difference is important to understand the economic contribution of universities. Small firms are fundamental for job creation, growth potential and aggregate fluctuations, as well as local growth (Aghion et al., 2015; Audretsch et al., 1999; Autio et al., 2014; Decker et al., 2014 and Haltiwanger et al., 2013, among others). They might also be subject to financial constraints, which can reduce their possibilities to innovate and to grow (Siemer, 2019). This implies that analysing the role of technology transfers from universities distinguishing by firm size provides important information about the economic contribution of universities for economic growth.

We stratify the sample by distinguishing between SMEs and non-SMEs. We present the balancing test for SMEs and non-SMEs using the CDiD methodology in Table OA9 in the on-line Appendix. In Table 7, in columns 1, 2 and 3, we show results for SMEs and in columns 4, 5 and 6 for non-SMEs (for product innovation, process innovation and patents, respectively). Our results in Table 7 show that technology transfers are positive and statistically significant for process innovations and patents. In the rest of the specifications, technology transfers are positive but not significantly different from zero. This suggests that SMEs, particularly, profit from the technology transfers from universities in terms of process innovations and number of patents. Overall, the results suggest that the effect of technology transfers from universities on firm innovativeness is more important for SMEs than for non-SMEs.

6.1.2. Recession and non-recession periods

Our sample period includes the global financial crisis and the Great Recession of the late 2000s. The Great Recession in Spain was particularly harsh and lasted from 2008 to 2013 (Almunia et al., 2018). These were times of severe financial constraints, which allows us to study the contribution of universities to innovation during two clearly differentiated periods of the business cycle. In particular, we study the differential effect of technology transfers from universities in the recession and in the non-recession period.

Aghion et al. (2012) show that internal R&D investments are pro-cyclical when firms face tighter credit constraints (see also López-García et al., 2013 and Beneito et al., 2015). Therefore, one possibility is that when firms are financially constrained, as during the times of the Great Recession, firms tend to rely on the knowledge generated by universities instead of their own research. The reason is that innovations might be cheaper to generate with knowledge from universities than if firms have to develop their own internal research. High sunk costs related to R&D investments jointly with the fixed costs to remain in the activity (Aw et al., 2011), plus the dramatic credit constraints suffered by firms during the recession period, may have hampered internal R&D investments. As a consequence, the effect of the technology transfers from universities on innovation might be more important during the recession period than during the non-recession period.

An alternative possibility is that the lack of finance reduces the productivity of the technology transfers from universities. For example, Mohnen and Röller (2005) show for a sample of four European countries that the lack of finance interacts with the productivity of several variables that affect innovation output such as internal R&D or regulations. Moreover, the public funding of Spanish universities fell by 27.7% during the recession period (Sacristán, 2017). This decline in public funding to universities might have negatively affected the productivity of the technology transfers from universities. Consequently, it is possible that during periods of financial constraint the contribution of the university technology declines. From an empirical point of view, this is an open question. For this reason, we next analyse whether there are significant differences between the non-recession and recession period.

We present the balancing test for the non-recession and recession period effects using the CDiD methodology in Table OA10 in the on-line Appendix. In Table 8, in columns 1, 2 and 3, we show results for the non-recession period and in columns 4, 5 and 6 for the recession period (for product innovation, process innovation and patents, respectively). In all cases, the estimated ATT is positive, with the exception of patents for the recession period. For process innovations, the estimated ATT effect is statistically significant during both the recession and non-recession period. The estimated ATT effect for patents is statistically significant for the non-recession period. This suggests that the contribution of technology from universities to firm innovativeness that reduce costs are independent on the macroeconomic environment. However, the contribution of technology transfers is more sensitive during financially constrained periods for innovations linked to patents.

6.1.3 Differentiating by Pavitt sectoral taxonomy

In this sub-section, we deepen our analysis by looking at whether there are differences in the effects of technology transfers from universities on firm innovativeness across sectors that might have different underlying technological appropriability and patterns of innovation. For this purpose, we follow the sectoral taxonomy purpose by Pavitt (1984) that has been broadly used in the innovation literature (Dosi, 1988). Pavitt (1984) distinguishes between four different major industries: science-based, specialized-supplier, scale-intensive and supplier-dominated sectors.

In Table 9, we present the ATT estimates using the CDiD methodology differentiating between the four sectoral groups. In panel A, we show results for *science-based* sectors. These sectors are extremely innovative and highly R&D intensive (for example, electronics, pharmaceutical or chemical industries are in this group). In panel B, we present the estimations for *specialized-supplier* sectors. These industries are typically characterized by small firms with strong links to their users. Firms operating in these sectors have opportunities to innovate although formal R&D expenditures tend to be small. For example, manufacturers of electrical machinery or mechanical engineering are included in this group. In panel C, we show estimates for *scale-intensive* sectors. These industries tend to profit from economies of scale and therefore firms in these sectors have strong incentives to innovate. Examples of these sectors are metal manufacturing or transport equipment. In panel D, we present the results for *supplier-dominated* sectors. These are traditional sectors such as agriculture or textiles where incremental innovations are more common than drastic innovations and, therefore, appropriability tends to be small. Balancing tests for the different sectors are presented in Table OA11 in the on-line Appendix.

The results suggest that the effects of technology transfers from universities are particularly important for science-based and scale and information intensive sectors. In these two sets of sectors, technology transfers from universities lead to an increase in product innovation by 8.4 percentage points and by 18.2 percentage points, respectively. The results from panel A for science-based sectors also show a positive and statistically significant effect of technology transfers on patents. For the rest of the panels and innovative indicators the estimated coefficients are positive although not significant at standard statistical levels, with the exception of panel D, column (1a) for supplier dominated sectors and product innovation, where the estimated coefficient is negative although not significantly different from zero. These findings suggest that sectors that are highly R&D intensive and with high levels of appropriability benefit relatively more from technology transfers from universities than less R&D intensive sectors. However, we believe that these results need to be taken cautiously because the stratification of the sample leads to a small number of firms in each group. Therefore, this evidence is only suggestive of the potential differential effects of university technology transfers by innovative sectors.

6.2. Contribution of technology transfers beyond the direct effect on innovation

6.2.1. Spillover effects

Our identification assumption for calculating the effects of technology transfers on innovation is that technology transfers do not generate spillovers on the control group (Stable Unit Treatment Value Assumption, SUTVA). To investigate whether there is a bias in our previous estimations, and if there is a bias in its direction, we study spillover or indirect effects. Our underlying assumption is that spillovers are regional- and industry-concentrated (Griliches, 1992; Jaffe et al., 1993; Agrawal et al., 2017). Our measure of spillovers is calculated in the spirit of Girma et al. (2015) or García-Vega et al. (2019). We measure the difference in innovation output of firms without technology transfers from universities in clusters where there is a high concentration of firms with technology transfers from universities (treated group) and firms without technology transfers from universities in clusters with low concentration of firms with technology transfers from universities (control group). In this way, we calculate the indirect effect on the non-treated firms. In our analysis, we establish 32 industry-region clusters with an average of 5.4% of firms with technology transfers from universities. We consider clusters with high concentration of technology transfers as those clusters with technology transfers above the median and we run robustness checks with thresholds at the 80th and 90th percentile of the distribution of technology transfers from universities.[21]

We present the estimated ATT effects using the CDiD methodology in Table 10 and the balancing test in Table OA12 in the on-line Appendix. We do not find any statistically significant effect for process innovation in column 2. However, we find a positive and statistically significant effect for product innovation and patents, in columns 1 and 3 respectively. This result suggests that there are positive spillovers, but they are only statistically significant for product innovation and patents. Therefore, technology transfers from universities seem to have an important contribution to firm innovation in addition to the uncovered direct effects: Firms that do not acquire technology from universities also profit from technology of universities in order to patent or to improve their products if they are located in regions and in industries with high concentrations of contractual technology transfers. Since the spillovers are positive, they imply that our estimates of the direct effects for patents are a lower bound of the technology transfers from universities' effect on firm innovation.

6.2.2. Crowding-out effects

We next turn to the question of whether technology transfers from universities is crowding-out the internal R&D of the firm. The study of complementarities or substitutability between technology sourcing and internal R&D has long been of interest to the literature on R&D governance (Barge-Gil et al., 2018, Mohnen and Röller, 2005, among others). For example, Cassiman and Veugelers (2006), using cross-sectional data on Belgian firms, find that external R&D is a complement to the R&D conducted in-house in order to generate innovations. A related paper is Ceccagnoli et al. (2014), who study the sources of complementarity between internal and external R&D. Examining a sample of pharmaceutical companies, these authors find that internal and external R&D are largely independent and that complementarity depends on a buyer's characteristics, such as absorptive capacity, economies of scale and experience with the license process. More recently, Añón et al. (2018) analyse whether intramural and external R&D are complementary innovation strategies for increasing total factor

[21] The results obtained with thresholds at the 80th and 90th percentile of technology transfers from universities (not reported) are similar to those presented in Table 10.

productivity. In our approach, we do not formally perform a test for complementarity or substitutability in order to generate innovations, which is beyond the scope of this paper; instead, we study whether technology transfers from universities lead to an increase in firm innovation inputs. The logic is that if firms reduce their innovation inputs after having technology transfers from universities, it would indicate that firms are substituting internal knowledge with external knowledge from universities. In the long run, this could damage the internal capabilities of the firms.

For our analysis, we consider as innovation input two different types of R&D expenditures and the number of researchers working in R&D. We present evidence of the effect of technology transfers from universities on R&D inputs using the CDiD methodology in Table 11. In column 1, we analyse the logarithm of total innovation expenditures (this includes internal R&D expenditures or intra-mural R&D and other expenditures such as training for workers, product alternations, market research and advertising); in column 2, we study the logarithm of internal R&D; and in column 3, the input variable is the logarithm of the number of researchers working in R&D in the firm.

In all cases, technology transfers from universities has a positive and statistically significant effect. The estimates show that having technology transfers from universities increases total innovation expenditures by 32.1%, internal R&D expenditures by 18.3% and researchers in R&D by 25.6%. These results suggest that there are no crowding-out effects and that technology transfers from universities lead to an increase in firm innovation inputs and job creation in high-skill jobs.

7. Summary and concluding remarks

To gain a better understanding of the contribution that university knowledge makes to private firms, and thus indirectly to society, this paper studies the effect of technology transfers from universities on firm innovativeness. We find that technology transfers from universities have an important positive effect on firm innovativeness. We also show that this effect holds especially during the non-recession period. Moreover, our results suggest that technology transfers induce positive spillovers and increase the internal capabilities of firms.

These results are consistent with universities providing superior technologies and, thus, allowing firms to profit from types of knowledge that cannot be easily obtained internally. We show that this frontier knowledge benefits particularly small firms. Thus, our results imply that universities play a significant role in the innovation of small firms and, consequently universities are important in an indirect way for local job creation. Typical of SMEs, liquidity constraints and difficulties on attracting highly skilled workers are barriers hampering their innovation performance. By facilitating access to specialized expert knowledge through university technology transfers, universities help to overcome these barriers and improve firm competitiveness. Furthermore, given the additionality that we find of technology transfers from universities on in-house R&D, the further promotion of university technology transfers might enhance the absorptive capacity of firms and, hence, their productivity.

The decrease of the strength of university technology transfers during the crisis period may be a consequence of the important pay cuts suffered by Spanish universities, which affected the quality of the knowledge transferred. Our results suggest that the public sector should try to maintain its support to universities, also in times of recession. Finally, the spillover effects of technology transfers found in this study make the above recommendations even more pertinent. In other words, financing universities has a private benefit, but also a benefit for the economy as a whole, through the upgrade on firm innovativeness operating in the same region and sector.

Although this study provides relevant insights, we acknowledge some limitations. First, the results are obtained based on data from a single country. Although the theoretical arguments suggests that our empirical results can be generalized to other countries, it would be interesting to extend the analysis to other countries. For example, it is possible that the impact of technology transfer on firm innovativeness varies with the type of ownership of the university, and therefore, in countries with a larger proportion of private universities than Spain, the estimated impact might be larger. Second, we do not have information about informal contacts between firms and universities, which are also part of knowledge transfers. This could lead to a downward bias, which would mean that our results are a very conservative measure of technology transfers. Moreover, we do not have information about the type of knowledge firms are getting from universities, either. Hence, we are not able to disentangle the different effects upon firms' innovativeness depending on the type of knowledge transferred. Finally, it is possible that the experience of providing knowledge to firms also provides a learning opportunity for university researchers. These are questions that are interesting avenues for future research.

The evidence we present is relevant for the understanding of the social value of universities beyond education. Our study highlights the importance of universities to contribute to the innovations in the private sector in a direct and indirect way. Hence, our results support the idea that knowledge creation by universities provides an important public good to society. Overall, our findings suggest that when policy makers are looking for policies to promote innovation and local growth, they should also consider public funding of universities.

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TABLES

Table 1: Number of firms

Years	Total	With techno. transfers from universities	First time starters	Never with transfers	Without techno. transfers but with overlap
	(1)	(2)	(3)	(4)	(5)
2005	12,098	909	457	9,806	1,383
2006	12,034	935	288	9,735	1,364
2007	11,594	915	229	9,336	1,343
2008	11,182	805	140	8,968	1,409
2009	10,796	702	106	8,632	1,462
2010	10,380	686	99	8,259	1,435
2011	9,977	597	81	7,915	1,465
2012	9,612	526	64	7,607	1,479
2013	9,172	464	67	7,240	1,468

Note: *Total* is the total number of firms in each year in the sample. *With techno. transfers from universities* is the number of firms in a given year with positive expenditures in R&D services from Spanish Universities. *First time starters* is the number of firms in a given year that start for the first time to obtain technology transfers from Universities. *Never with transfers* is the number of firms in a given year that do not have technology transfers from Universities in that year and that they never had it in the past and never will have it in the future during the sample period. *Without techno. transfers but with overlap* is the number of firms in a given year without technology transfers from Universities but with either technology transfers in the past or with technology transfers in the future (during the sample period).

Table 2: Descriptive statistics distinguishing between full sample, firms with technology transfers from universities and without technology transfers from universities

	Full sample			With technology transfers			Without technology transfers		
Variable	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations
Treatment variable									
Technology transfers from universities	0.068	0.251	114009	1.000	0.000	7714	0.000	0.000	106295
Outcome variables									
Product innovation	0.471	0.499	114009	0.749	0.433	7714	0.451	0.498	106295
Process innovation	0.485	0.500	114009	0.717	0.451	7714	0.468	0.499	106295
Patents	0.103	0.303	114009	0.309	0.462	7714	0.088	0.283	106295
Sales from products new to the market	3.764	6.308	114009	7.498	7.390	7714	3.493	6.135	106295
Sales from products new to the firm	5.011	6.867	114009	8.027	7.420	7714	4.792	6.774	106295
Number of patents	0.123	0.440	103916	0.433	0.808	6945	0.101	0.392	96971
Control variables									
Employment	4.122	1.720	114004	4.426	1.659	7714	4.100	1.723	106290
Physical investment	7.824	2.456	79069	8.449	2.501	6983	7.764	2.444	72086
Internal R&D expenditures	7.751	1.573	55292	8.615	1.595	7232	7.621	1.528	48060
Innovation expenditures	7.845	1.759	66848	8.901	1.677	7714	7.707	1.722	59134
Sales	11.282	2.141	113907	11.798	2.324	7707	11.244	2.123	106200
Exports	0.593	0.491	114009	0.754	0.430	7714	0.581	0.493	106295
Group	0.400	0.490	114009	0.496	0.500	7714	0.393	0.488	106295

Note: *Technology transfers from universities* is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish Universities. *Product (process) innovation* is a dummy variable that takes the value one if a firm reports having introduced new or significantly improved products (production processes) in the current or previous two years. *Patents* is a dummy variable that takes the value one if a firm reports having patents in the current or previous two years. *Sales from products new to the market (firm)* is the natural logarithm of the sales that come from new-to-the-market (new-to-the-firm) products in a current year. *Number of patents* is the natural logarithm of the number of patents. *Employment* is the natural logarithm of the number of employees. *Physical investment* is the natural logarithm of the physical investments of the firm. *Internal R&D expenditures* is the natural logarithm of the R&D expenditures undertaken within the enterprise or intramural (in-house). *Innovation expenditures* is the natural logarithm of the total innovation expenditures. *Sales* is the natural logarithm of the sales of the company. *Exports* is a dummy variable that takes the value one if the firm exports. *Group* is a dummy variable that takes the value one if the firm belongs to a business group.

Table 3: The effect of technology transfers from universities on firms' innovation: Effects on the unmatched sample

Panel A: Dependent variable product innovation					
	(1a)	(2a)	(3a)	(4a)	(5a)
University technology transfers	0.242***	0.184***	0.074***	0.028***	0.028***
	(0.009)	(0.010)	(0.008)	(0.008)	(0.008)
Observations	83,854	58,395	50,675	58,395	58,395
R-squared	0.120	0.117		0.045	0.049
Number of id			10,806	11,329	11,329
Panel B: Dependent variable process innovation					
	(1b)	(2b)	(3b)	(4b)	(5b)
University technology transfers	0.204***	0.131***	0.052***	0.023***	0.023***
	(0.010)	(0.010)	(0.008)	(0.009)	(0.009)
Observations	83,854	58,395	50,675	58,395	58,395
R-squared	0.068	0.075		0.051	0.055
Number of id			10,806	11,329	11,329
Panel C: Dependent variable patents					
	(1c)	(2c)	(3c)	(4c)	(5c)
University technology transfers	0.180***	0.160***	0.035***	0.020***	0.019***
	(0.010)	(0.010)	(0.004)	(0.007)	(0.007)
Observations	83,854	58,395	50,339	58,395	58,395
R-squared	0.064	0.078		0.005	0.008
Number of id			10,795	11,329	11,329
Sector FEs	Yes	Yes		Yes	
Firm FEs				Yes	Yes
Lagged control variables		Yes	Yes	Yes	Yes
Firm FEs Wooldridge correction			Yes		
Sector x time FEs			Yes		Yes
Year FEs in all regressions					

Notes: In all columns, we estimate linear probability models with the exception of column (3), where we estimate a probit model. University technology transfers is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish universities. The controls are the lagged values of the following variables: the natural logarithm of the number of employees, the natural logarithm of the physical investments. For exact definitions and sources of all variables see Tables1 and 2 and the main text. Estimated robust standard errors clustered at the firm level are in parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 4: Effect of technology transfers from universities on firms' innovation. Average treatment effect on the treated after matching for starters

Dependent variable	Product innovation	Process innovation	Patents	Product innovation	Process innovation	Patents
	(1)	(2)	(3)	(4)	(5)	(6)
University technology transfers	0.078***	0.069***	0.093***			
	(0.023)	(0.025)	(0.020)			
Quartiles of technology transfer						
1st quartile				0.126***	0.145***	0.122***
				(0.030)	(0.034)	(0.034)
2nd quartile				0.089**	0.084**	0.127***
				(0.036)	(0.041)	(0.037)
3rd quartile				0.065*	0.032	0.078**
				(0.033)	(0.038)	(0.031)
4th quartile				0.021	0.009	0.042
				(0.040)	(0.041)	(0.032)
Observations	1,416	1,416	1,416	1,416	1,416	1,416
Number of id	1,360	1,360	1,360	1,360	1,360	1,360

Notes: University technology transfers is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish Universities. The treated group are starters (firms that for the first time in our sample period have technology transfers from universities). The control group are firms that never have technology transfers from universities in our sample period. Quartiles of technology transfers are the different quartiles of university technology transfers intensity, where intensity is the ratio between R&D acquisitions and total R&D expenditures. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 5: Effect of technology transfers from universities on firms' innovation. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers^{CDiD}	0.043*	0.072**	0.055**
	(0.025)	(0.027)	(0.021)
Observations	5,841	5,841	5,841
Number of id	3,462	3,462	3,462

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 6: Technology transfers from universities on firms' innovation with respect to technology transfers from other providers. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers^{CDiD}	0.136**	0.137**	0.125*
	(0.055)	(0.063)	(0.064)
Observations	1,157	1,157	1,157
Number of id	807	807	807

Treated group: Companies with technology transfers from universities
Control group: Companies with R&D acquisitions from private companies and other institutions that are not universities

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 7: Effect of technology transfers from universities for SMEs vs non-SMEs. Average treatment effect on the treated after matching with CDiD methodology

	SMEs			Non-SMEs		
Dependent variable	Product innovation	Process innovation	Patents	Product innovation	Process innovation	Patents
	(1)	(2)	(3)	(4)	(5)	(6)
University technology transfers^{CDiD}	0.026	0.063*	0.098***	0.042	0.044	0.090
	0.030	0.032	0.023	0.071	0.075	0.083
Observations	4,208	4,208	4,208	574	574	574
Number of id	2,668	2,668	2,668	413	413	413

Notes: SMEs are firms with at most 250 employees. University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables A1 and A2 in the Appendix. Standard errors between parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.

Table 8: Effect of technology transfers from universities during the recession and non-recession period. Average treatment effect on the treated after matching with CDiD methodology

	Non- recession period			Recession period		
Dependent variable	Product innovation	Process innovation	Patents	Product innovation	Process innovation	Patents
	(1)	(2)	(3)	(4)	(5)	(6)
University technology transfers^{CDiD}	0.062	0.077*	0.133***	0.026	0.098**	0.016
	(0.040)	(0.044)	(0.034)	(0.038)	(0.041)	(0.031)
Observations	1,968	1,968	1,968	2,645	2,645	2,645
Number of id	1,775	1,775	1,775	1,978	1,978	1,978

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 9: Effect of technology transfers from universities differentiating by sectoral Pavitt taxonomy. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable	Product innovation	Process innovation	Patents
Panel A: Science based	(1a)	(2a)	(3a)
University technology transfers^{CDiD}	0.084*	0.046	0.075*
	(0.051)	(0.059)	(0.042)
Observations	1,217	1,217	1,217
Number of id	821	821	821
Panel B: Specialized suppliers	(1b)	(2b)	(3b)
University technology transfers^{CDiD}	0.066	0.147	0.132
	(0.073)	(0.091)	(0.083)
Observations	570	570	570
Number of id	374	374	374
Panel C: Scale and information intensive	(1c)	(2c)	(3c)
University technology transfers^{CDiD}	0.182***	0.007	0.009
	(0.059)	(0.058)	(0.053)
Observations	1,133	1,133	1,133
Number of id	689	689	689
Panel D: Supplier dominated	(1d)	(2d)	(3d)
University technology transfers^{CDiD}	-0.090	0.067	0.061
	(0.062)	(0.060)	(0.043)
Observations	1,067	1,067	1,067
Number of id	644	644	644

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 10: Spillover effect. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
Spillover	0.076*	-0.024	0.095**
	(0.042)	(0.048)	(0.038)
Observations	1,460	1,460	1,460
Number of id	1,008	1,008	1,008

Treated group: Companies without technology transfers from universities located in regions and sectors with **high** technology transfers from universities.
Control group: Companies without technology transfers from universities located in regions and sectors with **low** technology transfers from universities

Notes: For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table 11: Effect of technology transfers from universities on firms' internal R&D capabilities. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable:	Total R&D expenditures	Internal R&D expenditures	Researchers
	(1)	(2)	(3)
University technology transfers^{CDiD}	0.321***	0.183**	0.256***
	(0.097)	(0.091)	(0.070)
Observations	5,841	5,841	5,841
Number of id	3,462	3,462	3,462

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Appendix

Table A1: Estimation of the propensity scores

Propensity score for:	One-to-one matching	CDiD methodology
	(1)	(2)
Product innovation$_{t-1}$	-0.002	-0.002
	(0.002)	(0.004)
Process innovation$_{t-1}$	0.003	0.018***
	(0.002)	(0.003)
Patents$_{t-1}$	0.007**	0.050***
	(0.003)	(0.004)
Employment$_{t-1}$	-0.001	-0.005***
	(0.001)	(0.002)
Physical capital$_{t-1}$	0.002***	0.003***
	(0.001)	(0.001)
Researchers in R&D$_{t-1}$	0.003***	0.014***
	(0.001)	(0.002)
Internal R&D$_{t-1}$	0.010***	0.039***
	(0.001)	(0.001)
Exports$_{t-1}$	0.001	0.012***
	(0.002)	(0.004)
Group$_{t-1}$	-0.001	-0.004
	(0.002)	(0.004)
Number of id	7,345	8,518
Observations	28,056	41,767

Notes: Results from Probit regression. Dependent variable in column 1 takes the value one in the case of starter (a starter is a firm that for the first time in our sample period obtain technology transfers from universities). In column 1 the sample is restricted to firms that are either starters or that never have technology transfers over our sample period. In column 2, we do not restrict the sample and the dependent variable takes the value one in the case of technology transfers from universities. All regressors are lagged one year. Time and industry fixed effects are included in the regression. Robust standard errors in parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A2: Effect of technology transfers from universities on firms' innovation with longer pre-treatment trend. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers^{CDiD}	0.045**	0.038	0.066***
	(0.026)	(0.027)	(0.021)
Observations	6,032	6,032	6,032
Number of id	3,322	3,322	3,322

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A3: Effect of technology transfers from universities on continuous measures of firm innovativeness. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable:	Sales from new products to		Number of patents
	the market	the firm	
	(1)	(2)	(3)
University technology transfers^{CDiD}	0.534	0.763*	0.087**
	(0.406)	(0.402)	(0.031)
Observations	5,841	5,841	5,841
Number of id	3,453	3,453	3,453

Notes: University technology transfers^{CDiD} is the average treatment effect on the treated using the CDiD methodology. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A4: Placebo test: Random assignment of university technology transfers. Average treatment effect on the treated after matching with CDiD methodology

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
Random university technology transfers^{CDiD}	-0.009	-0.014	-0.011
	(0.030)	(0.031)	(0.023)
Observations	3,573	3,573	3,573
Number of id	2,542	2,542	2,542

Notes: For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A5: Effect of technology transfers from universities on firms' innovation. IV specification

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	0.523***	0.276**	0.529***
	(0.153)	(0.117)	(0.148)
Observations	33,752	33,752	33,752
Number of id	7,290	7,290	7,290
R-squared	0.335	0.474	0.345
First stage results:			
Importance of conferences	0.165***	0.163***	0.150***
	(0.031)	(0.0331	(0.031)
Kleibergen-Paap F-Statistic	27.87	27.89	23.47

Notes: University technology transfers is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish universities. Sector x year and year FEs in all regressions. For exact definitions and sources of all variables see Tables 1 and 2 and the main text. Estimated robust standard errors clustered at the firm level are in parentheses. 2SLS regressions. University technology transfers is instrumented using pre-sample values of the importance of conferences, expositions or trade fairs measured at the average of the industry and regional level. The F-statistics are reported for the Kleibergen–Paap test for weak identification. Estimations include initial values and one-year lag of the dependent variable. * Significant at 10%; ** Significant at 5%; *** significant at 1%.