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research paper series

Globalisation, Productivity and Technology

Research Paper 2019/13

Do university technology transfers increase firms' innovation?

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Acknowledgements
We acknowledge Loles Añón, Simon Gaechter and Joel Stiebale for their helpful comments.

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JEL classification: L25, D22, L24, O31

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We would like to thank Loles Añón, Simon Gaechter and Joel Stiebale for their helpful comments.

1. Introduction

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 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 try to fill this gap.

We investigate the effect on firm innovativeness of knowledge transfers from universities to private firms. 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

[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 Mark Schankerman (2009) and Caldera and Debande (2010) study the performance of university technology transfer offices.
[3] For instance, farmers producing strawberries hire agricultural engineers and chemistry services from universities in order to increase expiry dates. This is a known technology in the agricultural industry but it is difficult to implement by small farmers.

competitors and to reduce their costs. These large firms also often acquire basic research from universities to obtain radical innovations.[4] Therefore studying university technology transfers help 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, for example, because 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 identifying 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 contains 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 baseline empirical approach is a combination of matching techniques and DiD estimations. As 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

[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 Azoulai et al. (2019) 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.

[5] Medda et al. (2005), 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.

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 all over the business cycle but particularly in less financially constrained periods.

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 that we find evidence that technology transfers from universities also enhance firms' internal capabilities and their internal R&D resources, which implies that knowledge transfers are complements to internal research.

Our paper contributes to the literature that tries to identify the contribution of public research on industrial innovativeness. In his seminal paper Mansfield (1991) used survey data from top R&D executives to study the effects of academic research on firms' innovation performance.[6] Similarly, Beise and Stahl (1999) analyse 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. One major difference between these papers and our research is that we do not use self-reported data about the

[6] The information used to measure the importance of academic research on the firm innovation performance came from the answer to the question about the innovation that could not have been developed (without substantial delay) in the absence of academic research.

importance of academic research. Moreover, 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 impacts 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 industry. Arvanitis et al. (2008) use Swiss survey data to study how different types of university knowledge 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 firm understanding. More recently, Fudickar and Hottenrott (2019) analyze the importance of formal and informal interactions with universities on new-technology based firms. An important difference in our approach with respect to these papers is that our measure of technology transfer is contractual R&D that firms acquire from universities. The advantage of this measure is that we can account for the direction of the technology transfer, which facilitates identification. Moreover, we use the panel structure of our data to account for potential selection bias.

Our paper is most closely related to Medda et al. (2005), who study the effect of R&D acquisitions from universities and other types of external R&D on firm productivity. Vega-Jurado et al. (2017) investigate the effects of both contractual and cooperative relationships between universities and private firms on innovative performance. In contrast to previous research, we use matching techniques and instrumental variable specifications in order to control for causality. A further novelty of our analysis is that we provide evidence on the role of technology transfers over the business cycle.

Finally, our paper contributes to the literature on spillover effects from universities (e.g. Jaffe (1989), Jaffe et al. (1993), Anselin et al. (1997), Belenzon and Schankerman (2013) and Toivanen and Väänänen (2016)) and to the more general literature that investigates the contribution of universities to economic growth (e.g. Cantoni and Yuchtman (2014), Hausman (2012), and Valero and Van Reenen (2016)).

This paper proceeds as follows: Section 2 presents the data and the description of the main variables; Section 3 discusses our econometric specification; Section 4 presents our main results; Section 5 shows additional empirical evidence, investigating heterogenous effects, spillovers and crowding-out effects. Section 6 concludes.

2. The 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 2004-2013. PITEC represents the contribution of Spain to the Europe-wide Community Innovation Survey (CIS) and 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 with the aim of providing data to the CIS.[7] This is an

[7] PITEC applies the methodological rules defined in the *Oslo Manual* OECD's (2005a). Details on PITEC and data access guidelines can be obtained at: http://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176755&menu=resultados&secc=1254736195616&idp=1254735576669.

unique dataset that includes a representative sample of the universe of Spanish firms. The dataset 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 of 58,306 observations corresponding to 11,314 firms.

2.1. The 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 by firms operating in Spain from Spanish Universities. In the survey, each company indicates its *R&D acquisitions,* that is, its purchases of R&D services.[8] *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 Medda et al. (2004) and Vega-Jurado et al. (2017). 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.

[8] 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).[9] 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 use so often by small firms as they require high-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.

2.2. The 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:

[9] 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 hold by six research-oriented US universities.

having product innovation, having process innovation and having patents.[10] 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.[11] 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 (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 differentiating by technology transfers from universities' status. The percentage of firms with technology transfers from universities is 6.7%. These firms 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 patents. More than 30% of

[10] 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.
[11] 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.

firms with technology transfers reported at least a patent during the current or previous two years while this percentage is less than 10% for companies without technology transfers. 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.

3. Econometric specification

We aim to study the effect of university technology transfers on firm innovativeness. To face this objective, in our main specification, we estimate an empirical model that combines propensity score matching with a difference-in-differences (DID) estimator.[12] 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. 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.

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

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. 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 identification 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. An important assumption for our identification strategy is that the technology transfers from universities do not have an indirect effect through spillovers into the control group, as this would be a violation of the Stable Unit Treatment Value Assumption (SUTVA assumption). We initially rule out this possibility and investigate this assumption in Section 5.

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. 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:

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

where y_{it+2} denotes firm innovation output and β is the DiD parameter of interest and it measures the ATT effect.[13]

4. The 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 and we show robustness checks including our IV specification. Third, we exclude from our sample firms without any type of technology transfers. 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.

4.1. Results from the whole sample

Before we report our results from the matching sample, we first show evidence based on the whole sample without controlling for the potential selection bias or endogeneity issues. We

[13] 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.

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.[14] 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 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

[14] 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.

conservative estimations, in columns 4b or 5b, we observe that university technology transfers increase process innovation by 2.2 percentage points. Finally, the results in panel C, in the most conservative estimations, indicate that having university technology transfers increases the likelihood to patent to 1.8 percentage points (column 5c).

4.2. Results from the matched sample. Main results

Before turning to the effect of technology transfers from universities on firm innovativeness with the matched sample, 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 add product, process and patent dummy variables. To avoid reverse causality problems, we lag our explanatory variables one period.

The results from the probit specification are reported in Table A1 in the Appendix. Our estimates suggest that firms that innovate 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 are 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 and also with Santoro and Gopalakrishnan (2001) who find that size is an important determinant of university technology transfers.

Based on the results from equation (2), we pair each treated firm with the closest untreated firm by caliper matching with replacement. The matching procedure works well. In Table 4, we report balancing tests after matching. Our matching specification generates well-balanced samples, which implies that control and treatment groups are equivalent in their overall observable characteristics before treatment.

In Table 5, 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 4.1 percentage points, process innovations by 2.2 percentage points and patenting by 7.2 percentage points.

4.3. Robustness checks

We perform several sensitivity tests of our main specification results that we present in the Appendix, including alternative matching estimators, longer pre-treatment trends, alternative definitions of our innovation output variables, a placebo test and an IV specification.

First, we test the sensitivity of our matching procedure by using alternative matching estimators. In Tables A2 and A4 in the Appendix, we replicate the analysis using alternative matching techniques. In Table A2, we estimate the ATT effect with a reweighted estimation, where we include firm fixed effects. In Table A4, we report ATT effects after matching with a matched sample calculated with caliper matching with the closest neighborhood with replacement with firm fixed effects.[15] These robustness tests yield results that are very similar to those of Table 5.

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. The results reported in Table A6 are, again, similar to those of previous specifications.[16] In all cases, we observe that technology transfers from universities lead to an increase in firm innovation. This suggests that our results are not biased by different 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 capturing, well, innovation output for continuous successful innovators. For example, in a given year, a very innovative company and a company with just one innovation are treated the same using dummy variables as innovation output measures. For this reason, in Table A7, 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 intensity. Our variable is the logarithm of the number of patents plus one, to

[15] The balancing test is reported in Table A3 in the Appendix.
[16] Balancing tests are shown in Table A5.

deal with zeros.[17] The results show that the ATT effect for sales from new products to the market and number of patents are positive and statistically significant. The effect is also positive for sales from new products to the firm but it is not significant at standard statistical levels. This suggests that university technology transfers lead on average to innovations that firms consider radical and highly valuable (instead of incremental type of innovations, as it is in the case of innovations new to the firm). 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 A8 and from the ATT effect in Table A9. The results from these placebo regressions are significantly very different from previous estimations. We now find no differences between control and treatment groups in terms of product innovation, process innovation, and patenting.

The DiD model combined with the matching estimator described above controls 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 variant unobservable 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.[18] 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

[17] See for example Haucap et al. (2019) or Stiebale (2016).
[18] This measure is constructed for the year 2004.

university scientists,[19] but it is exogenous to unobservable time-variant firm 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 A10 in the Appendix. In the bottom part of table, we show the first stage regression of the 2SLS estimations as well as the Kleibergen-Paap F-statistics. The instrument is statistically and 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.[21] The IV point estimates presented in the top part of Table A10 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.

4.4. 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).[22] In this way, we can assess the differential contribution of transfers from universities and transfers from other providers. If

[19] 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.
[20] See for example Appleyard (1996) for types of knowledge flows in Japanese firms or Monteiro and Birkinshaw (2015) for different types of technology sourcing.
[21] The critical value for a maximum IV bias of 10% of the weak identification test is 16.38 (Stock and Yogo 2002).
[22] Technology transfers from other sources are acquisitions of R&D from other private companies or research associations (not including universities).

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 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 in Table 6 and the balancing test in Table A11 in the Appendix. The estimated coefficients for product and process innovations, shown in columns 1 and 2, are negative but not significant at statistical levels. This suggests that the contribution of university technology transfers to product and process firm innovativeness is very similar to the effect of technology transfers coming from other providers. The estimation in column 3, where we show the effect for patents, is positive and strongly statistically significant. This result suggests that technology transfers from universities increase patents by 3.2 percentage points more than the increase in patenting when firms obtain technology transfers coming from other providers. This confirms the importance of the contribution of universities for highly valuable innovations. We provide evidence to the Rosenberg and Nelson (1994) idea that universities play an important role in the development of radical innovations, which are those that are likely to be patented.

5. 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 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.

5.*1. Heterogeneous effects*

5.1.1. 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).[23] 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.[24] 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 in Table A12 in the 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 in columns 1, 2, 3, and 6. In the specifications in columns 4 and 5, for product and process innovations of non-SMEs, 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 product

[23] 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.
[24] See among others Aghion et al. (2015); Audretsch et al. (1999); Autio et al. (2014); Decker et al. (2014) and Haltiwanger et al. (2013).

and process innovations. Both large and small firms benefit from the technology generated by the universities in terms of patents. The estimates for patents suggest that the effects of technology transfers from universities are larger for SMEs than for non-SMEs. Overall, the results suggest that the effect of technology transfers from universities on firm innovativeness is more important for SMEs than for non-SMEs.

5.1.2. 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.[25] These were times of severe financial constraints, which allow 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.[26] 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,

[25] For a description of the Spanish economy during the financial crisis and Great Recession period, see for example Almunia et al. (2018).
[26] See also López-García et al. (2013) and Beneito et al. (2015).

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 constraints the contribution of the university technology declines. From an empirical point of view, this is an open question. For this reason, we next analyze whether there are significant differences between the non-recession and the recession period.

We present the balancing test for the non-recession and recession period in Table A13 in the 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. For product and process innovations, the estimated ATT effect is only statistically significant during the non-recession period. The estimated ATT effect for patents is statistically significant and very similar in both periods. This suggests that the contribution of technology from universities to firm innovativeness is important for very valuable innovations, which are those that are typically patented, independently on the macroeconomic environment.[27] However, the contribution of technology transfers is more sensitive during financially constrained periods for less

[27] This result may also be the consequence of a strong commitment between university and firm to develop and patent radical innovations (Hall et al., 2001). If a company is close to obtaining a patent, it will do as much as possible to finalize the research project and patent it, instead of abandoning it and losing the costs that it has incurred so far.

commercially competitive innovations such as product or process innovations than for innovations linked to patents.

5.2. The contribution of technology transfers beyond the direct effect on innovation

5.2.1. 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 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. In our analysis, we establish 32 industry-region clusters with an average of 5.4% 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.[28]

[28] 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 9.

We present the estimated ATT effects in Table 9 and the balancing test in Table A14 in the Appendix. We do not find any statistically significant effect for product and process innovation in columns 1 and 2, respectively. However, we find a positive and statistically significant effect for patents, in column 3. This result suggests that there are positive spillovers but they are only statistically significant for patents. Therefore, technology transfers from universities seem to have an important contribution to firm patent 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 if they are located in regions and in industries with high concentration 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.

5.2.2. 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.[29] 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

[29] See Barge-Gil et al. (2018) for a review and Mohnen and Röller (2005) for an analysis of the complementarity of the obstacles to innovation in both the probability of becoming an innovator and the intensity of the innovation.

of scale and experience with the license process. More recently, Añón et al. (2018) analyze whether intramural and external R&D are complementary innovation strategies for increasing total factor 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 in Table 10. In column 1, we analyze 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 suggest that having technology transfers from universities increases total innovation expenditures by 31.4%, internal R&D expenditures by 16.1% and researchers in R&D by 23.2%. 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.

6. 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 over different macroeconomic cycles, but 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 knowledge, which cannot be easily obtained internally. We show that this frontier knowledge benefits both small and large firms but our results imply that universities play a significant role in the innovation of small firms and, thus, for local job creation. Typical of SMEs, liquidity constraints and difficulties on attracting high skill 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 might 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. It would be interesting to extend the analysis to other countries. Second, we do not have information about informal contacts between firms and universities, which are also part of the knowledge transferred. This could lead to a downward bias, which would mean that our results are obtained using a very conservative measure of technology transfers. Finally, 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.

References

Aghion, P., Akcigit, U., and P. Howitt (2015). The Schumpeterian Growth Paradigm. *Annual Review of Economics*, 7: 557-575.

Aghion, P., Askenazy, P., Berman, N., Cette, G. and L. Eymard (2012). Credit constraints and the cyclicality of R&D investment: Evidence from France. *Journal of the European Economic Association*, 10(5): 1001-1024.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., and S. Prantl (2009). The effects of entry on incumbent innovation and productivity. *The Review of Economics and Statistics*, 91(1): 20-32.

Aghion, P., Van Reenen, J., and L. Zingales (2013). Innovation and institutional ownership. *American Economic Review*, 103(1): 277-304.

Agrawal, A., Galasso, A. and A. Oettl (2017). Roads and innovation. *The Review of Economics and Statistics*, 99(3): 417-434.

Almunia, M., Antràs, P., Lopez-Rodriguez, D., and E. Morales (2018). Venting Out: Exports during a Domestic Slump. Available at https://scholar.harvard.edu/antras/publications/venting-out-exports-during-domestic-slump

Anselin, L., Varga, A., and Z. Acs (1997). Local geographic spillovers between university research and high technology innovations. *Journal of urban economics*, 42(3): 422-448.

Añón Higón, D., Máñez, J.A. and J.A. Sanchis-Llopis (2018). Intramural and external R&D: evidence for complementarity or substitutability. *Economia Politica*, 35(2): 555–577.

Appleyard, M (1996). How does knowledge flow? Interfirm patterns in the semiconductor industry. *Strategic management journal*, 17(S2): 137-154.

Arvanitis, S., Kubli, U., and M. Woerter (2008). University-industry knowledge and technology transfer in Switzerland: What university scientists think about co-operation with private enterprises. *Research Policy*, 37(10): 1865-1883.

Audretsch, D., Segarra, A., and M. Teruel (2014). Why not all Young Firms Invest in R&D?. Working Paper Collecció "Documents de Treball del Departament d'Economia- CREIP" No. 01-2014.

Autio, E., Kenney, M., Mustar, P., Siegel, D., and M. Wright (2014). Entrepreneurial Innovation: The Importance of the Context. *Research Policy*, 43: 1097-1108.

Aw, B. Y., M. J. Roberts and D. Y. Xu (2011). R&D investment, exporting and productivity dynamics, *American Economic Review*, 101, 1312–1344.

Azoulay, P., Graff Zivin, J. S., Li, D., and B. Sampat (2018). Public R&D investments and private-sector patenting: evidence from NIH funding rules. *The Review of Economic Studies*, 86(1): 117-152.

Barge-Gil, A., Huergo, E., López, A. and L. Moreno (2018). Empirical models of firms' R&D, in L. C. Corchón and M. A. Marini (ed.): *Handbook of Game Theory and Industrial Organization*, Edward Elgar. Cheltenham, UK and Northampton, MA.

Beise, M., and H. Stahl (1999). Public research and industrial innovations in Germany. *Research policy*, 28(4): 397-422.

Belenzon, S., and M. Schankerman (2009). University knowledge transfer: private ownership, incentives, and local development objectives. *The Journal of Law and Economics*, 52(1): 111-144.

Belenzon, S., and M. Schankerman (2013). Spreading the word: Geography, policy, and knowledge spillovers. *Review of Economics and Statistics*, 95(3): 884-903.

Bena, J., and K. Li (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, 69(5): 1923-1960.

Beneito, P., Rochina-Barrachina, M.E., and A. Sanchis-Llopis (2015). Ownership and the cyclicality of firms' R&D investment. *International entrepreneurship and management Journal*, 11(2): 343-359.

Bercovitz, J., and M. Feldman (2007). Fishing upstream: Firm innovation strategy and university research alliances. *Research policy*, 36(7): 930-948.

Bishop, K., D'Este, P., and A. Neely (2011). Gaining from interactions with universities: Multiple methods for nurturing absorptive capacity. *Research Policy*, 40(1): 30-40.

Caldera, A., and O. Debande (2010). Performance of Spanish universities in technology transfer: An empirical analysis. *Research policy*, 39(9): 1160-1173.

Cantoni, D., and N. Yuchtman, N. (2014). Medieval universities, legal institutions, and the commercial revolution. *The Quarterly Journal of Economics*, 129(2): 823-887.

Cassiman, B. and R. Veugelers (2006). In Search of Complementarity in Innovation Strategy: Internal R&D and External Technology Acquisition. *Management Science*, 52(1): 68–82.

Ceccagnoli, M., Higgins, M. and V. Palermo (2014). Behind the scenes: Sources of complementarity in R&D. *Journal of Economics & Management Strategy*, 23 (1): 125-148.

Cefis, E., and L. Orsenigo (2001). The persistence of innovative activities: a cross-countries and cross-sectors comparative analysis. *Research Policy*, 30(7): 1139–1158.

Cefis, E. (2003). Is there persistence in innovative activities?. *International Journal of Industrial Organization*, 21: 489–515.

Chapple, W., Lockett, A., Siegel, D., and M. Wright (2005). Assessing the relative performance of UK university technology transfer offices: parametric and non-parametric evidence. *Research Policy*, 34(3): 369-384.

Clausen, T., Pohjola, M., Sapprasert, K., and B. Verspagen (2011). Innovation strategies as a source of persistent innovation. *Industry and Corporate Change*, 21 (3): 553–585.

Cohen, W. M., Nelson, R. R., and J. Walsh (2002). Links and impacts: The influence of public research on industrial R&D. *Management Science*, 48(1): 1–23.

Cosh, A., Hughes, A., and R. Lester (2006). *UK plc: Just How Innovative Are We?* Cambridge, UK, Cambridge–MIT Institute.

Decker, R., Haltiwanger, J., Jarmin, R., and J. Miranda (2014). The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives*, 28(3): 3-24.

D'Este, P., and P. Patel (2007). University–industry linkages in the UK: What are the factors underlying the variety of interactions with industry?. *Research policy*, 36(9): 1295-1313.

Fudickar, R., and H. Hottenrott (2019). Public research and the innovation performance of new technology based firms. *The Journal of Technology Transfer*, *44*(2): 326-358.

Ganter, A., and A. Hecker (2013). Deciphering antecedents of organizational innovation. *Journal of Business Research*, 66(5): 575-584.

García-Vega, M., P. Hofmann and R. Kneller (2019). The internationalisation of R&D and the knowledge production function. *International Journal of Industrial Organization*, 63: 583-614.

Geroski, P., Van Renen, J., and C. Walters (1997). How persistently do firms innovate?. *Research Policy*, 26: 33–48.

Girma, S., Gong, Y., Görg, H. and S. Lancheros (2015). Estimating Direct and Indirect Effects of Foreign Direct Investment on Firm Productivity in the Presence of Interactions between Firms. *Journal of International Economics,* 95(1): 157-169.

Griffith, R., Huergo, E., Mairesse, J., and B. Peters (2006). Innovation and productivity across four European countries. *Oxford review of economic policy,* 22(4): 483-498.

Griliches, Z. (1992). The Search for R&D spillovers. *Scandinavian Journal of Economics,* 94: 29-47.

Guadalupe, M., Kuzmina, O., and C. Thomas (2012). Innovation and foreign ownership. *American Economic Review, 102*(7): 3594-3627.

Hall, B. H., Link, A. N., and J. Scott (2001). Barriers inhibiting industry from partnering with universities: evidence from the advanced technology program. *The Journal of Technology Transfer*, 26(1-2), 87-98.

Haltiwanger, J., Jarmin, R., and J. Miranda (2013). Who Creates Jobs?: Small versus Large versus Young. *The Review of Economics and Statistics,* Vol. XCV, No. 2: 347-361.

Haucap, J., Rasch, A., and J. Stiebale (2019). How mergers affect innovation: Theory and evidence. *International Journal of Industrial Organization,* 63: 283-325.

Hausman, N. University Innovation, Local Economic Growth, and Entrepreneurship, US Census Bureau Centre for Economic Studies Paper No. CES-WP- 12-10.

Jabbour, L., Tao, Z., Vanino, E., and Y. Zhang (2019). The good, the bad and the ugly: Chinese imports, European Union anti-dumping measures and firm performance. *Journal of International Economics,* 117: 1-20.

Jaffe, A. (1989). Real effects of academic research. *American economic review*, 79(5): 957-970.

Jaffe, A. B., M. Trajtenberg, and R. Henderson (1993). Geographical Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics,* 108: 577-98.

Javorcik, B., and S. Poelhekke (2017). Former foreign affiliates: Cast out and outperformed?. *Journal of the European Economic Association,* 15(3): 501-539.

Lach, S., Neaman, Z., and M. Schankerman (2017). Government Financing of R&D: A Mechanism Design Approach. CEPR Discussion Paper 12199.

López-García, P., Montero, J. M., and E. Moral-Benito (2013). Business cycles and investment in productivity-enhancing activities: evidence from Spanish firms. *Industry and Innovation,* 20(7): 611-636.

Macho-Stadler, I., Pérez-Castrillo, D., and R. Veugelers (2007). Licensing of university inventions: The role of a technology transfer office. *International Journal of Industrial Organization*, 25(3): 483-510.

Mansfield, E. (1991). Academic research and industrial innovation. *Research policy*, 20(1): 1-12.

Mairesse, J. and P. Mohnen. (2005). The importance of R&D for innovation: A reassessment using French survey data. *Journal of Technology Transfer,* 30(1-2) 183-197.

Martínez ‐ Ros, E., and J. Labeaga (2009). Product and process innovation: Persistence and complementarities. *European Management Review,* 6(1): 64-75.

Medda, G., Piga, C. and D. Siegel (2004). University R&D and firm productivity: evidence from Italy. *The Journal of Technology Transfer,* 30(1-2): 199-205.

Monteiro, F. and J. Birkinshaw (2017). The external knowledge sourcing process in multinational corporations. *Strategic Management Journal,* 38(2): 342-362.

Mohnen, P. and L. Röller (2005). Complementarities in innovation policy. *European Economic Review,* 49(6): 1431-1450.

Novartis, (2017). Annual report, available at: https://www.novartis.com/sites/www.novartis.com/files/novartis-annual-report-2017-en.pdf).

OECD (2005a). Oslo Manual. Guidelines for Collecting and Interpreting Innovation Data. *OECD Publishing,* Paris.

OECD (2005b). OECD SME and Entrepreneurship Outlook: 2005, OECD Paris.

OECD (2018). Strengthening SMEs and entrepreneurship for productivity and inclusive growth. Available at https://www.oecd.org/cfe/smes/ministerial/documents/2018-SME-Ministerial-Conference-Key-Issues.pdf

Parmigiani, A. (2007). Why do firms both make and buy? An investigation of concurrent sourcing. *Strategic Management Journal,* 28(3): 285-311.

Perkmann, M., and K. Walsh (2007). University–industry relationships and open innovation: Towards a research agenda. *International Journal of Management Reviews,* 9(4): 259-280.

Piga, C. and M. Vivarelli (2004). Internal and external R&D: a sample selection approach. *Oxford Bulletin of Economics and Statistics,* 66(4): 457-482.

Rosenberg, N. and R. Nelson (1994). American universities and technical advance in industry. *Research Policy*, 23: 323–348.

Russell Group (2010). *The Economic Impact of Research Conducted in Russell Group Universities.* Russell Group Papers, 1/2010.

Sacristán, V. (2017). ¿Quién financia la universidad? Comparación entre comunidades autónomas en España, Europa y la OCDE, 2009-2015. OSU: Observatorio Sistema Universitario.

Santoro, M., and S. Gopalakrishnan (2001). Relationship dynamics between university research centers and industrial firms: Their impact on technology transfer activities. *The Journal of Technology Transfer*, 26(1-2): 163-171.

Scherer, F. M., and D. Harhoff (2000). Technology Policy for a World of Skew-distributed Outcomes. *Research Policy*, 29(4–5): 559–66.

Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics*, 111(2): 381-405.

Siegel, D. S., Waldman, D., and A. Link (2003a). Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study. *Research policy*, 32(1): 27-48.

Siegel, D., Waldman, D., Atwater, L., and A. Link (2003b). Commercial knowledge transfers from universities to firms: improving the effectiveness of university–industry collaboration. *The Journal of High Technology Management Research*, 14(1): 111-133.

Siegel, D., Waldman, D., Atwater, L. and A. Link (2004). Toward a model of the effective transfer of scientific knowledge from academicians to practitioners: qualitative evidence from the commercialization of university technologies. *Journal of engineering and technology management*, 21(1-2): 115-142.

Siegel, D. S., Veugelers, R., and M. Wright (2007). Technology transfer offices and commercialization of university intellectual property: performance and policy implications. *Oxford review of economic policy*, 23(4): 640-660.

Siemer, M. (2019). Employment effects of financial constraints during the Great Recession. *Review of Economics and Statistics*, 101(1): 16-29.

Stephan, P. (1996): The Economics of Science. *Journal of Economic Literature*, 34, 1199-1235.

Stiebale, J. (2016). Cross-border M&As and innovative activity of acquiring and target firms. *Journal of International Economics*, 99: 1-15.

Stock, J. H. and Yogo, M. (2002). Testing for Weak Instruments in Linear IV Regression, NBER Technical Working Paper no 284.

Tavassoli, S., and C. Karlsson (2015). Persistence of various types of innovation analyzed and explained. *Research Policy*, 44(10): 1887-1901.

Teirlinck, P., and Spithoven, A. (2013). Research collaboration and R&D outsourcing: Different R&D personnel requirements in SMEs. *Technovation*, *33*(4-5), 142-153.

Toivanen, O., and L. Väänänen, L. (2016). Education and invention. *Review of Economics and Statistics*, 98(2): 382-396.

Valero, A., and J. Van Reenen (2019). The economic impact of universities: Evidence from across the globe. *Economics of Education Review*, 68: 53-67.

Vega-Jurado, J., Kask, S., and L. Manjarrés-Henriquez (2017). University industry links and product innovation: cooperate or contract?. *Journal of Technology Management & Innovation, 12*(3): 1-8.

Veugelers, R. (2016). The embodiment of knowledge: universities as engines of growth. *Oxford Review of Economic Policy*, *32*(4): 615-631.

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of applied econometrics*, 20(1): 39-54.

TABLES

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Observations
Technology transfers from universities	0.067	0.251	113,850
Employment	4.122	1.721	113,850
Physical investment	7.825	2.457	78,954
Internal R&D expenditures	7.750	1.574	55,203
Product innovation	0.471	0.499	113,855
Process innovation	0.485	0.500	113,855
Patents	0.102	0.303	113,855
Sales	15.800	2.140	113,753
Sales from products new to the market	3.762	6.307	113,855
Sales from products new to the firm	5.009	6.867	113,855
Number of patents	0.123	0.440	103,777
Innovation expenditures	12.355	1.764	66,753
Employment in R&D	1.873	1.173	55,204

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. Employees 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). 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 is the natural logarithm of the sales of the company. 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. Innovation expenditures is the natural logarithm of the total innovation expenditures. Employment in R&D is the natural logarithm of the number of employees working in R&D units.

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

	With technology transfers			Without technology transfers		
Variable	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations
Employment	4.429	1.657	6,533	4.051	1.727	90,181
Physical investment	8.440	2.509	5,908	7.727	2.449	60,181
Internal R&D expenditures	8.624	1.578	6,158	7.624	1.522	39,929
Product innovation	0.754	0. 430	6,533	0. 451	0. 497	90,181
Process innovation	0. 719	0. 449	6,533	0. 474	0. 499	90,181
Patents	0. 302	0. 459	6,533	0. 083	0. 276	90,181
Sales	11.802	2.319	6,533	11.192	2.128	90,181
Sales from products new to the market	7.690	7.390	6,533	3.543	6.167	90,181
Sales from products new to the firm	8.064	7.423	6,533	4.797	6.771	90,181
Number of patents	0. 425	0. 796	6,533	0. 101	0. 393	90,181
Innovation expenditures	13.446	1.657	6,533	12.224	1.720	49,474
Employment in R&D	2.534	1.207	6,158	1.774	1.133	39,930

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.

Table 3: The effect of technology transfers from universities on firms' innovation

Panel A: Dependent variable product innovation					
	(1a)	(2a)	(3a)	(4a)	(5a)
University technology transfers	0.242***	0.185***	0.074***	0.028***	0.028***
	(0.009)	(0.010)	(0.008)	(0.008)	(0.008)
Observations	83,738	58,306	50,675	58,306	58,306
R-squared	0.120	0.116		0.045	0.049
Number of id			10,806	11,314	11,314
Panel B: Dependent variable process innovation					
	(1b)	(2b)	(3b)	(4b)	(5b)
University technology transfers	0.204***	0.131***	0.052***	0.022***	0.022***
	(0.010)	(0.010)	(0.008)	(0.009)	(0.009)
Observations	83,738	58,306	50,675	58,306	58,306
R-squared	0.068	0.075		0.051	0.055
Number of id			10,806	11,314	11,314
Panel C: Dependent variable patents					
	(1c)	(2c)	(3c)	(4c)	(5c)
University technology transfers	0.179***	0.160***	0.035***	0.019***	0.018***
	(0.010)	(0.010)	(0.004)	(0.007)	(0.007)
Observations	83,738	58,306	50,339	58,306	58,306
R-squared	0.064	0.078		0.005	0.008
Number of id			10,795	11,314	11,314
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 Table A1 in the Appendix. Estimated robust standard errors clustered at the firm level are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.

Table 4: Balancing property

Variable	Treated	Control	t-test	p-value
Product innovation	0.779	0.784	-0.600	0.550
Process innovation	0.746	0.750	-0.490	0.621
Patents	0.275	0.282	-0.720	0.473
Employment	4.389	4.415	-0.740	0.458
Capital investment	8.361	8.472	-2.200	0.028
Researchers	-0.855	-0.868	0.760	0.447
Internal R&D	8.487	8.452	1.080	0.280

Note: The table shows mean differences between treated and control observations for the matched sample based on the propensity score. All variables are in lags. The variables' employment, capital investment, researchers and internal R&D are in logarithms.

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

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	0.041**	0.022*	0.072***
	(0.013)	(0.012)	(0.011)
Observations	7,540	7,540	7,540

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped 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

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	-0.019	-0.026	0.032**
	(0.014)	(0.016)	(0.014)
Observations	5,983	5,983	5,983
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 is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish Universities. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped 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

Dependent variable	SMEs			Non-SMEs		
	Product innovation	Process innovation	Patents	Product innovation	Process innovation	Patents
	(1)	(2)	(3)	(4)	(5)	(6)
University technology transfers	0.041**	0.050**	0.068***	0.002	0.015	0.056*
	(0.015)	(0.017)	(0.013)	(0.026)	(0.031)	(0.033)
Observations	5,761	5,761	5,761	1,512	1,512	1,512

Notes: SMEs are firms with at most 250 employees. University technology transfers is a dummy variable that takes the value one if a firm has expenditures in R&D services from Spanish universities. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped 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

Dependent variable	Non- recession period			Recession period		
	Product innovation	Process innovation	Patents	Product innovation	Process innovation	Patents
	(1)	(2)	(3)	(4)	(5)	(6)
University technology transfers	0.031*	0.046*	0.058***	0.027	0.001	0.049**
	(0.018)	(0.024)	(0.016)	(0.019)	(0.022)	(0.018)
Observations	3,296	3,296	3,296	3,927	3,927	3,927

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped standard errors between parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.

Table 9: Spillover effect. Average treatment effect on the treated after matching

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
Spillover	-0.007	0.002	0.045**
	(0.031)	(0.023)	(0.015)
Observations	2,160	2,160	2,160

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 Table A1 in the Appendix. Bootstrapped standard errors between parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.

Table 10: Effect of technology transfers from universities on firms' internal R&D capabilities. Average treatment effect on the treated after matching

Dependent variable:	Total R&D expenditures	Internal R&D expenditures	Researchers
	(1)	(2)	(3)
University technology transfers	0.273***	0.150***	0.209***
	(0.038)	(0.036)	(0.031)
Observations	7,065	7,065	7,065

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped standard errors between parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.

Appendix

Table A1: Estimation of the propensity score

$Patents_{t-1}$	0.233***
	(0.031)
Product $innovation_{t-1}$	-0.041
	(0.030)
Process $innovation_{t-1}$	0.098***
	(0.028)
$Employment_{t-1}$	-0.049***
	(0.013)
Physical $capital_{t-1}$	0.025***
	(0.007)
Researchers in $R\&D_{t-1}$	0.091***
	(0.018)
Internal $R\&D_{t-1}$	0.217***
	(0.011)
Observations	40,016

Notes: Results from Probit regression. Dependent variable takes the value one in the case of technology transfers from universities. All regressors are lagged one year. Time 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. Matched sample Reweighted estimation

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	0.053***	0.025**	0.028***
	(0.012)	(0.011)	(0.008)
Observations	53,667	53,667	53,667
R-squared	0.070	0.068	0.009
Number of id	7,478	7,478	7,478
Sector x year and year FEs in all regressions			

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Estimated robust standard errors clustered at the firm level are in parentheses. * Significant at 10%;** Significant at 5%; *** significant at 1%.

Table A3: Balancing property for caliper matching closest neighborhood with replacement.

Variable	Treated	Control	t-test	p-value
Product innovation	0.783	0.784	-0.18	0.855
Process innovation	0.752	0.742	1.22	0.223
Patents	0.321	0.318	0.4	0.691
Employment	4.529	4.522	0.25	0.805
Capital investment	8.530	8.506	0.50	0.614
Researchers	-0.848	-0.867	1.17	0.240
Internal R&D	8.702	8.730	-0.90	0.369

Note: Mean differences between treated and control observations for the matched sample based on the propensity score. All variables are in lags. The variables employment, capital investment, researchers and internal R&D are in logarithms.

Table A4: Effect of technology transfers from universities on firms' innovation. Matched sample caliper matching closest neighborhood with replacement

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	0.048***	0.031***	0.026***
	(0.008)	(0.009)	(0.007)
Observations	30,500	30,500	30,500
R-squared	0.067	0.073	0.012
Number of id	4,169	4,169	4,169
Sector x year and year FEs in all regressions			

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Estimated robust standard errors clustered at the firm level are in parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A5: Balancing property for matching with longer pre-treatment trend

Variable	Treated	Control	t-test	p-value
Product innovation	0.778	0.793	-1.530	0.126
Process innovation	0.743	0.755	-1.180	0.240
Patents	0.278	0.286	-0.680	0.494
Employment	4.401	4.408	-0.180	0.856
Capital investment	8.400	8.432	-0.560	0.575
Researchers	-0.841	-0.865	1.200	0.229
Internal R&D	8.471	8.483	-0.340	0.735

Note: Mean differences between treated and control observations for the matched sample based on the propensity score. All variables are with two year lags. The variables employment, capital investment, researchers and internal R&D are in logarithms.

Table A6: Effect of technology transfers from universities on firms' innovation with longer pre-treatment trend. Average treatment effect on the treated after matching

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	0.054***	0.056***	0.082***
	(0.014)	(0.014)	(0.012)
Observations	6,298	6,298	6,298

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A7: Effect of technology transfers from universities on continuous measures of firm innovativeness. Average treatment effect on the treated after matching

Dependent variable:	Sales from new products to		Number of patents
	the market	the firm	
	(1)	(2)	(3)
University technology transfers	0.703***	0.278	0.081***
	(0.203)	(0.207)	(0.020)
Observations	7,540	7,540	7,065

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. For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A8: Balancing property for placebo test

Variable	Treated	Control	t-test	p-value
Product innovation	0.766	0.766	0.040	0.967
Process innovation	0.747	0.739	0.520	0.601
Patents	0.194	0.189	0.360	0.721
Employment	4.090	4.131	-0.790	0.428
Capital investment	7.814	7.854	-0.480	0.629
Researchers	-0.857	-0.856	-0.040	0.965
Internal R&D	7.731	7.717	0.270	0.791

Note: Mean differences between treated and control observations for the matched sample based on the propensity score. All variables are in lags. The variables employment, capital investment.

Table A9: Placebo test: Random assignment of university technology transfers. Average treatment effect on the treated after matching

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
Random university technology transfers	0.025	0.003	-0.017
	(0.019)	(0.022)	(0.013)
Observations	3,150	3,150	3,150

Notes: For exact definitions and sources of all variables see Table A1 in the Appendix. Bootstrapped standard errors between parentheses. * Significant at 10%; ** Significant at 5%; *** significant at 1%.

Table A10: Effect of technology transfers from universities on firms' innovation. IV specification

Dependent variable	Product innovation	Process innovation	Patents
	(1)	(2)	(3)
University technology transfers	0.521***	0.204*	0.484***
	(0.162)	(0.122)	(0.154)
Observations	31,897	31,897	31,897
R-squared	0.334	0.507	0.377
First stage results:			
Weighted regional researchers	0.158***	0.157***	0.146***
	(0.033)	(0.033)	(0.033)
Kleibergen-Paap F-Statistic	22.843	22.943	19.817

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 Table A1 in the Appendix. 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%.

Table A11: Balancing property for companies with technology transfers from universities (treated) and companies with technology transfers from other providers (control)

Variable	Treated	Control	t-test	p-value
Product innovation	0.786	0.802	-1.790	0.074
Process innovation	0.743	0.743	-0.030	0.980
Patents	0.268	0.281	-1.280	0.202
Employment	4.370	4.361	0.250	0.799
Capital investment	8.359	8.323	0.690	0.488
Researchers	-0.874	-0.887	0.730	0.468
Internal R&D	8.463	8.459	0.130	0.899

Note: Mean differences between treated and control observations for the matched sample based on the propensity score. All variables are in lags. The variables employment, capital investment.

Table A12: Balancing property for heterogeneous effects: SMEs and non-SMEs

	SMEs				Non-SMEs			
Variable	Treated	Control	t-test	p-value	Treated	Control	t-test	p-value
Product innovation	0.771	0.766	0.410	0.679	0.793	0.827	-1.790	0.073
Process innovation	0.706	0.693	1.170	0.242	0.851	0.862	-0.690	0.489
Patents	0.245	0.251	-0.610	0.544	0.295	0.321	-1.160	0.248
Employment	3.698	3.707	-0.300	0.763	6.469	6.475	-0.120	0.904
Capital investment	7.621	7.637	-0.340	0.731	10.522	10.572	-0.510	0.613
Researchers	-0.786	-0.796	0.520	0.601	-1.096	-1.115	0.380	0.701
Internal R&D	8.113	8.129	-0.490	0.624	9.428	9.415	0.170	0.863

Note: Mean differences between treated and control observations for the matched sample based on the propensity score.
All variables are in lags.

Table A13: Balancing property for heterogeneous effects: Non-recession and recession

	Non-recession				Recession			
Variable	Treated	Control	t-test	p-value	Treated	Control	t-test	p-value
Product innovation	0.760	0.760	0.000	1.000	0.783	0.787	-0.290	0.771
Process innovation	0.720	0.708	0.840	0.403	0.748	0.749	-0.030	0.973
Patents	0.256	0.267	-0.790	0.432	0.255	0.267	-0.950	0.341
Employment	4.111	4.095	0.300	0.766	4.508	4.521	-0.290	0.775
Capital investment	8.226	8.177	0.650	0.517	8.315	8.362	-0.670	0.501
Researchers	-0.787	-0.770	-0.620	0.533	-0.923	-0.936	0.500	0.618
Internal R&D	8.134	8.113	0.440	0.658	8.611	8.569	0.960	0.337

NoteMean differences between treated and control observations for the matched sample based on the propensity score.
All variables are in lags.

Table A14: Balancing property for companies without technology transfers from universities located in regions and sectors with high technology transfers from universities (treated) and companies without technology transfers from universities located in regions and sectors with low technology transfers from universities (control)

Variable	Treated	Control	t-test	p-value
Product innovation	0.770	0.780	-1.330	0.183
Process innovation	0.712	0.687	2.860	0.004
Patents	0.170	0.166	0.660	0.512
Employment	4.082	4.035	1.630	0.104
Capital investment	7.716	7.742	-0.590	0.558
Researchers	-0.917	-0.920	0.170	0.865
Internal R&D	7.662	7.651	0.420	0.672

Note: Mean differences between treated and control observations for the matched sample based on the propensity score.
All variables are in lags. The variables employment, capital investment.