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Demand-pull innovation in science: Empirical evidence from a research university's suppliers ¹

Stefano Bianchini ^{*}, Patrick Llerena ^{**} and Sofia Patsali ^{***}

^{*}*s.bianchini@unistra.fr*

BETA - Bureau of Theoretical and Applied Economics, University of Strasbourg, 61 Avenue de la Fôret Noire, Strasbourg, 67000 (France)

^{**}*pllerena@unistra.fr*

BETA - Bureau of Theoretical and Applied Economics, University of Strasbourg, 61 Avenue de la Fôret Noire, Strasbourg, 67000 (France)

^{***}*sofia.patsali@iusspavia.it*

Scuola Universitaria Superiore IUSS Pavia, Piazza della Vittoria n.15, Pavia, 27100 (Italy)

Abstract: The paths via which university-generated knowledge reaches final users and creates value are traditionally considered to be the supply-side channels of the commercialisation of inventions, consultancy, and R&D contracts. Yet, this focus limits universities to being “providers” of knowledge and technology for industrial applications and fails to account for the diversity of mechanisms responsible for the diffusion of academic activities. This paper aims to complete the existing understanding of the contribution made by universities to the corporate innovation process by recognising the impact of university demand on the innovative performance of firms in the scientific value chain. We study the impact of a large French public university on the innovative performance of its suppliers of scientific equipment. We perform micro-econometric analyses in a quasi-experimental setting, showing that university suppliers have a higher propensity to introduce new-to-the-market product innovations than do other firms belonging to the same sectors and with similar characteristics. Our results provide support to the conjecture that innovations and technological changes are the result not only of scientific and technical discoveries, but also of a complex chain reaction triggered by the interplay between specific demands and solutions designed to overcome technology bottlenecks.

Keywords: University-industry interactions; Demand-pull innovation; User innovation; Scientific equipment; Public procurement; Propensity score matching.

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Introduction

In the 1920s, Philipp Ellinger, a professor of pharmacology at Heidelberg University, was performing cutting-edge research on the functions of human organs and the detection of bacteria in living tissues. At that time, existing fluorescence microscopes were of little use for observing and studying samples from opaque living organs, so Ellinger decided to develop his own intravital fluorochroming prototype. A few years later, inspired by Ellinger's work, the German manufacturer Carl Zeiss was able to produce a new fluorescence microscope, a sophisticated instrument incorporating vertical illumination with a water immersion objective and filters. Between 1929 and 1931, Ellinger used the Zeiss microscope to make significant advances in our understanding of the physiology of urine formation. But the story does not end there. The use of this new instrument, intimately bound to Ellinger's methodological insights, aroused great interest among instrument manufacturers and academic researchers alike. Indeed, it was not long before other firms – most notably Bausch & Lomb, Leitz, and Reichert – were developing similar devices in close cooperation with other biomedical researchers eager to apply Ellinger's technique (Masters, 2006; Kohen, 2014). Ellinger's story is by no means an isolated case of a joint development project involving science and technology, but it is one of the first successful cases illustrating the effect of academic demand on corporate innovation.

Criticism has long been levelled at the lack of involvement of academic researchers in the activities of knowledge and technology transfer. However, the last thirty years have seen a significant shift in the perception policymakers have of universities, as they begin to acknowledge their role as central actors in the knowledge-based economy. Increasing expectations of the part universities can play in this so-called “third mission” have led to a series of policy transformations aimed at fostering links between academia and industry. The commercialisation of academic knowledge via patenting, licensing and spin-off companies has been the cornerstone of science and innovation (S&I) policies since the early '80s (Mowery et al., 2001). For instance, the Bayh-Dole Act (1980) authorised US universities to obtain intellectual property rights on inventions funded by the US federal government and enabled them to license these inventions. Similar policy actions were taken by a number of OECD governments (Mowery and Sampat, 2004). The rationale behind these initiatives was the belief that universities were producing numerous inventions of high economic value but were failing to transfer them beyond the boundaries of the academic world and so obtain the corresponding economic benefits (Kenney and Patton, 2009).

The university invention ownership model generated a large body of research focused almost exclusively on academic commercial activities as a way of forging university-industry links, and on the way these links might affect the performance of the actors involved in the process (see, among many, Bonaccorsi and Piccaluga, 1994; Scharinger et al., 2002; Cohen et al., 2002; Shane, 2004). However, these studies run the risk of providing an overly simplistic image of the interactions between universities and firms, and of failing to account for the diversity, and corresponding impact, of the mechanisms via which academic knowledge is transferred to industry (Dosi et al., 2006; Autio et al., 2014; Kenney and Mowery, 2014). More recent contributions consider a wider range of both formal and informal university-industry linkages, including collaborative R&D, contract research, consulting, and providing ad hoc advice. This involvement of academic scientists in such activities has become known as “academic engagement” (see, for example, D'Este and Patel, 2007; Perkmann and Walsh, 2007; Perkmann et al., 2013). While commercialisation implies an academic invention is exploited so as to reap financial rewards, academic engagement encompasses a broader set of activities and is pursued for manifold objectives, such as to access resources relevant for research activities via additional funds and specialised equipment, to access learning opportunities via field testing, or to obtain new insights into practical questions (Lee, 2000;

D'Este and Perkmann, 2011). Nevertheless, these recent studies are not exempt from criticism either. A common reproach is that they often limit the university-industry nexus to solely technological activities, restricting the role of the universities to that of a “provider” of knowledge and technology for industrial applications.

This paper aims to develop the usually accepted framework and does so by proposing and empirically assessing a neglected mechanism of university-industry knowledge exchange. We present an original perspective according to which these exchanges, and their corresponding benefits, materialise as a result of the demand for customized goods and services. In line with the traditional Schumpeterian view on technological innovation, there is often a tendency to focus on the scientific/technological aspects of the innovation process and to neglect the demand-side of the story. However, economic historians and economists of innovation have long embraced the view that emerging technological paradigms can be shaped by market demand dynamics (Dosi, 1982, 1988; Mokyr, 1990; Bairoch, 1993). Seminal contributions on the role of user demand for customized goods and services with high technological content (see, among many, von Hippel, 1976; Rosenberg, 1992, Riggs and von Hippel, 1994) provide plenty of historical anecdotal evidence. While such anecdotes are interesting insofar as they demonstrate the importance of user involvement in the innovation processes that led to the emergence of certain technologies in specific industries, they are uninformative about the direct effects these technologies had on firm performance.

This study therefore seeks to empirically assess and quantify the impact of university demand on the innovative performance of firms that constitute part of the scientific value chain – i.e., firms that supply goods and services to research universities. It is our conjecture that the demands universities make to firms are quite unique, since academic scientists often encounter a specific need long before the majority of firms in the marketplace encounter it, and, moreover, universities are better positioned to benefit significantly by obtaining a solution to that need. As a result, scientists may act as “lead-users” of technologies and indirectly support the costs of learning and refining associated with the development of new products (von Hippel, 2005; Stephan, 2012). In short, the demand of academic scientists for custom goods and services may provide a stimulus for firms to introduce novel products and organisational concepts, thus contributing to the shaping of technological trajectories and fostering product and process innovations.

Here, we perform micro-econometric analyses in a quasi-experimental setting to assess the impact of a large French public university on the innovative performance of its suppliers of research equipment and materials. The quantitative approach is possible because of an original and unique dataset containing fine-grained information on university purchases and associated suppliers. These data are complemented by accurate details on various aspects of the innovation process and by the financial statements of the university's suppliers and a representative sample of French businesses. The data infrastructure allows us to exploit a wide set of innovation-related variables to benchmark suppliers and other businesses in terms of their innovative performance, while controlling for a large number of firm-level attributes and contextual factors. We show that firms supplying university laboratories have a significantly higher propensity to introduce new-to-the-market product innovations and to enjoy higher sales from these products, all other things being equal. In contrast, we do not observe any significant effect on process innovation. All these findings are very robust to different econometric methods and alternative proxies of technological innovations.

The contributions made by this paper build on and extend the previous literature in several ways. From a theoretical perspective, our results indicate that public universities may also have a considerable economic impact on innovation via the demand side. As such, the study makes a unique contribution to the existing literature on university-industry interactions which to date has focused mainly on supply-side factors. Furthermore, our results contribute

to the rich literature analysing the scale and breadth of the economic contribution made by universities (see, for example, Drucker and Goldstein, 2007; Lane and Bertuzzi, 2011; Valero and van Reenen, 2016). Indeed, universities have far-reaching impacts on the economy, effects that are often interrelated. The purchase of goods and services is just one of these impacts, as it increases turnover, and supports employment, in the companies that supply them (Lane et al., 2018). Our findings suggest that the actual contribution made by research universities could be much larger than what is typically estimated, since it also includes dynamic effects in the economy associated with demand-pull innovations. Finally, this study provides the first robust evaluation of a phenomenon that has been invoked extensively in historical accounts as anecdotal evidence (von Hippel, 1976; Rosenberg, 1992; Riggs and von Hippel, 1994; Stephan, 2012), but which has never been inferred quantitatively on a larger scale.

The rest of the article proceeds as follows. In Section 2, we identify some of the theoretical roots of our study. We describe the data infrastructure in Section 3 and the methodology we employ in our analysis in Section 4. Empirical results are presented in Section 5. Robustness checks are discussed in Section 6. Finally, Section 7 discusses the implications of our results in light of the existing literature and concludes.

Conceptual framework

Understanding the impact of university demand on corporate innovation first requires a clear understanding of how this demand is created. This in turn calls for a careful consideration of the complex patterns of co-development formed by science and technology throughout history. Take for instance what is considered the first scientific instrument – Galileo’s telescope. In the 16th century, the telescope could be designed thanks to the development of thick concave lenses, which made it possible to see distant objects. Once the Galilean telescope has been introduced, it had a tremendous impact on how scientists undertook their research, but it also became an object of constant development and refinement, motivated precisely by inquiries into the daily research activities of academics. Later, in the 17th century, scientists were interested in determining just how the instrument worked, which in turn stimulated further developments in the field of optics, leading, eventually, to the development of modern microscopes (de Solla Price, 1968).

This desire to broaden the domain of observation has been one of the main driving forces behind the development of new scientific instrumentation and methodologies in academia (Masters, 2006; Franzoni, 2009; Stephan, 2012). New tools are adopted to observe natural phenomena, study them in detail, measure them and collect novel data. The simple act of reporting fresh evidence about previously unknown (invisible) facts is sufficient justification to pursue further research in a specific direction. But academic scientists require highly efficient scientific equipment, the performance of which is critical inasmuch as it determines how far they can advance with respect to existing knowledge. The research process is a highly uncertain undertaking, its results are highly unpredictable; hence, it is always better to be able to conduct observations that offer finer granularity and a broader scope. Researchers using high-performance instruments are more likely to provide unexpected findings and new data that can lead them down novel scientific avenues (Stephan and Levin, 1992). The reward system governing academia is a peculiar one, since what is prioritised is reputation, and reputation provides a mechanism for capturing the externalities associated with a given discovery (Merton, 1957; Dasgupta and David, 1994).

An additional scientific endeavour that obliges academics to develop new tools is the testing of existing theories. Franzoni (2009), for instance, reports an insightful example from the field of high energy physics. Here, elementary particles are studied at very high temperatures,

which requires large, costly instruments, such as spectrometers. Scientific instruments are central to the field of particle physics, making the development, supply and support of new tools an essential part of a researcher's work in that discipline. Once more, the success of the research, indeed of the scientists themselves, is critically dependent on the performance of their lab equipment.

New scientific instruments and methodologies are not always inspired by the desire to do something completely novel, but also by the need to apply standard procedures at a larger scale. Many scientific tools were originally developed in seeking to execute a common task faster and more efficiently. Equipment that can save time, manpower and energy facilitates the performance of familiar tasks at a new scale and so changes the focus of analysis to a broader dimension. Automating a time-consuming procedure provides not only efficiency gains but also the possibility of tackling entirely new types of research question. A good example of this is provided by DNA sequencing methods in the biological sciences. Here, the transformation of the whole field of biotechnology went hand in hand with the constant progress made in the efficiency of equipment for undertaking DNA analysis and manipulation (Stephan, 2012). The significant improvements achieved in the performance of new instruments allowed scientists to engage in ambitious, large-scale studies that otherwise would have been unimaginable in a researcher's lifetime.

In short, a vital part of an academic's work is to develop new instruments, methodologies and processes for conducting their research (Rosenberg, 1992; Rosenberg and Nelson, 1994). The locus of innovation theory (von Hippel, 2005) claims that the persistent use of a given item (instrument, tool or equipment) in a specific context results in users developing a certain amount of tacit knowledge. The acquisition of this knowledge and related capabilities is attributable to the learning effect in challenging environments of use, as typified by scientific research. What is important for our study here is that this tacit innovation-related knowledge enables scientists to visualise and develop future extensions of existing products. However, researchers may lack the resources or in-house expertise to change the functionalities of existing tools and design "exactly the right product", while firms may be equipped to build custom products faster, better and cheaper than the researchers are able to do themselves. Although many mass manufacturers may well be unwilling to accommodate "out of the ordinary" requests, there are firms that specialise in developing products for a limited number of users. The rationale for this specialisation is that such businesses can gain a competitive advantage from their innovative capabilities in one or a few specific solution types, in the expectation that these solutions will be transformed into higher profits either when used in the development of other products (i.e., through economies of scope) or when they become common in the marketplace (von Hippel, 2005; Bogers et al., 2010; Di Stefano et al., 2012).

According to theories advanced in the existing literature, we can expect university demand to affect firms' innovation performance via two channels. On the one hand, in an intrinsically uncertain environment (as is that of scientific research), the needs driving demand provide a guideline for change. As Witt (2009) pointed out, these needs and wants are themselves adaptive to novelty; indeed, the extent to which they can be adapted to novelty is necessary for markets to emerge and develop. By providing producers with knowledge and detailed information about their needs, academic scientists can contribute to the emergence of new concepts and/or ideas, reducing in turn the uncertainty and risk of failure that inherently characterise the innovation process (Malerba et al., 2007, Fontana and Guerzoni, 2008; Guerzoni, 2010; Di Stefano et al., 2012). Scientists can also act as users of technologies that are not yet demanded by industry (e.g. prototypes, proofs of concept), and by so doing can indirectly support the costs of learning and refining associated with the development of these technologies (von Hippel, 1977; Clark, 1985; Bogers et al. 2010). Stimulating firms' innovative performance by reducing the uncertainty associated with product innovation has

been labelled the “uncertainty effect”. On the other hand, public spending on equipment and research materials (which are typically the outcome of public procurement bids) ensures a minimal market size in the early stages of innovation, as the university and its associated supplier frequently enter into a binding contract for a certain period of time. This minimum market size provides firms with an incentive to improve their production practices given that lower production costs would imply higher profits, all other things being equal (Malerba et al., 2007). In this way, demand acts as a multiplier of a firm’s mark up and should trigger process innovation in what is known as the “incentive effect” (see, for example, the seminal discussion in Schmookler, 1962; or more recent debates in Fontana and Guerzoni, 2008).

In the light of the above discussion, we expect university demand to have a positive and significant effect on the innovation performance of its suppliers, all other factors being equal. This conceptual framework is tested in our empirical analysis.

Data and measurement

The context

We focus our study on one of the largest research-oriented universities in France: the University of Strasbourg (henceforth, UNISTRA). This public university has a long-standing tradition of excellence in both basic and applied research conducted in three major fields: the life sciences, engineering, and the social sciences and humanities.

UNISTRA constitutes a vibrant ecosystem formed by a network of researchers, high-tech industrial firms, and technology transfer activities. Since 2009, UNISTRA has implemented a research policy based on openness and the pursuit of research excellence. To this end, it boasts the second largest, and most diverse, student community among French universities (around 20% of its student body are foreigners). Rated among the top 100 universities in the Shanghai ranking, UNISTRA stands 19th in the 2015 ARWU global rankings in chemistry and 16th worldwide according to Nature’s 2017 Lens score. UNISTRA’s scientific excellence is further attested to by the fact that its research staff have received various prizes, including the Kavli prize in nanosciences (2014) and three Nobel prizes for medicine (2011) and chemistry (2013 and 2016), the recipients of which are still active researchers.

The university’s unique know-how is built around its massive scientific facilities at the cutting-edge of research, permitting, for instance, physico-chemical and chemical analyses of known molecules and new molecules synthesised in its laboratories. Given its profile, UNISTRA represents an ideal environment for our study.

Data sources

This section describes in detail the process by which the data used in the econometric analysis were assembled. Our study draws on three data sources: (i) fine-grained data on university expenditure and its associated suppliers, (ii) innovation-related data from the non-anonymised French Community Innovation Survey (CIS), and (iii) firm-level accounting, financial and employment data from the FARE (*Fichier Approché des Résultats d’Esane*) dataset.

University expenditure

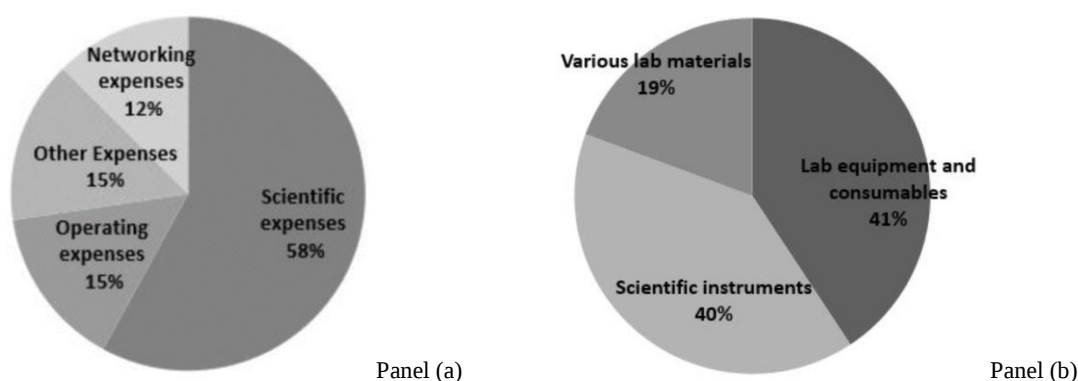
Under strict confidentiality protocols, we manually downloaded from UNISTRA’s Information System granular information about all input purchases made by all the

university's research laboratories for the period 2011–2014.² Our data include spending originating from all the funding sources available to UNISTRA's researchers during the period considered, that is, public competitive grants (regional, national, EU), private grants, and university block funding.

Initially, we mapped 57,124 economic transactions, corresponding to a total volume of about €50 million, involving 2,961 suppliers. We performed a manual cleaning to remove duplicates and other inconsistencies.³ The resulting dataset consists of 47,373 transactions and 1,908 suppliers, for a value of about €40 million. The distribution of the value of these transactions is skewed, since most are small and correspond to scale purchases, such as office supplies and trips of short duration. However, the dataset also includes several large-scale transactions (> €1 million) for major scientific supplies and research infrastructure. The mean value per transaction is about 900€. Although a few suppliers are associated with thousands of transactions, the average number of transactions per supplier is about 20, with many suppliers of dedicated scientific equipment responsible for just one.

The peculiarity of our data is that each transaction is classified by UNISTRA's Information System using different object codes that reflect the nature of the purchase, and which we aggregate into four macro categories: namely, scientific expenses, networking expenses, operating expenses, and other expenses.⁴ This grouping allows us to isolate all the supplies related to research materials, which represent the highest share in terms of their economic value (Figure 1, panel a). The category "scientific expenses" can be disaggregated to a finer level of granularity, giving three additional subcategories of supplies, namely: lab equipment and consumables, scientific instruments, and various lab materials (Figure 1, panel b).

Figure 1. Distribution of expenses broken down by category (Panel a) and by subcategory within "scientific expenses" (Panel b)



For illustrative purposes, Table 1 presents examples of the scientific supplies included in our dataset. They include small and medium-sized lab equipment and products, such as filters, thermometers, synthetic antibodies, and chemical reagents. The supplies also include

² Before 2011 the university employed a different Information System. Despite attempts to migrate the old accounting records into the new Information System, the type of information stored before 2011 is substantially different and not suitable for our study.

³ For example, the initial dataset contained many entities that are not relevant to our study, including liberal professionals (translators, doctors, web designers, etc.), non-profit organizations and foundations.

⁴ UNISTRA's Information System contains 71 distinct object codes which are univocally assigned to each purchase; details about this classification and our grouping are available upon request. Note also that for most expenses we have a precise description of the good purchased.

scientific instruments, such as a dual-beam microscope, mass spectrometer, DNA sequencer, odontological pre-clinical simulator, magnetic resonance imaging scanner for small animals, to name just a few. And, finally, there are a variety of items related to research activity, including specific workwear and technical documentation.

Table 1: Examples of supplies broken down by subcategories

<i>Category</i>	<i>Subcategory</i>	<i>Example of supplies</i>
Scientific expenses	Lab equipment and consumables	Mini-protean short plates Membranes for filtration Reagent for detection of biomolecules DNA sequencing reagent Synthetic antibodies
	Scientific instruments	Double-beam microscope Next-generation DNA sequencer Femtosecond laser Confocal microscope Multi-station magnetic stirrer
	Various lab materials	Anti-static lab coats Technical documentation

Each transaction is associated with a given supplier, and each French supplier is identified in our data by means of a univocal firm-level code provided by the French national statistics office (INSEE). This code allows us to match university expenditure data to the non-anonymized Community Innovation Survey (CIS) and FARE datasets, both made available to us under confidentiality protocols by INSEE. In conclusion, here, we focus on 682 French suppliers, accounting for around 5,000 supplies of research materials for a total volume of about €18 million.⁵

CIS and FARE datasets

We exploit the latest two waves of the French Community Innovation Survey (CIS 2012 and 2014) to provide accurate information on various aspects of firms' innovation activities, including the introduction of new product and process innovations, investment in R&D activities, forms of cooperation to develop innovations, among others. Albeit with certain limitations, the CIS has served as the empirical foundation for many innovation-related studies and proved to be a reliable source of data (Mairesse and Monhen, 2010).⁶ Innovation surveys, however, contain only a limited set of firm-level attributes related to a firm's operating capabilities. Thus, we also exploit the structural business registers contained in the FARE (*Fichier Approché des Résultats d'Esane*) dataset. FARE assembles accounting and performance data (i.e., year of foundation, sectoral affiliation, turnover, value added,

⁵ To be more accurate, our focus is, in fact, on businesses located in France. A manual check confirmed that a high share of the suppliers are French-based entities of foreign companies. Unfortunately, our dataset does not contain any meaningful firm-level identifier for companies located outside France; hence, we have been obliged to discard these firms from the analysis.

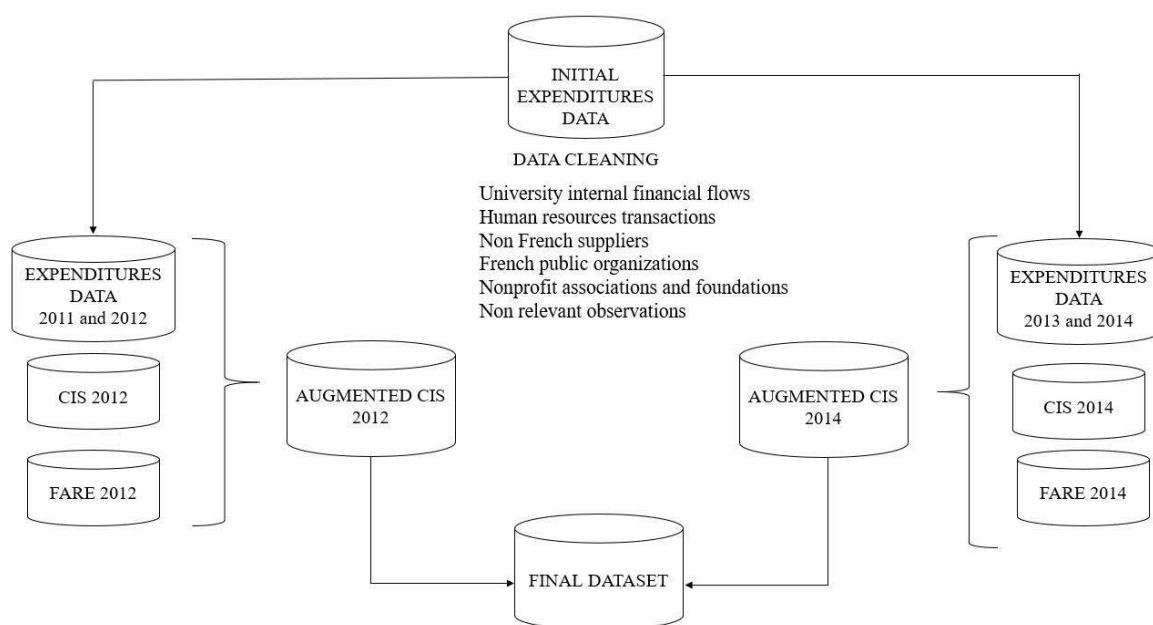
⁶ In conducting the robustness checks, we also consider patent data drawn from PATSAT, an alternative proxy of firms' innovation capabilities, and replicate the main analysis. For more details, see Section 6.

profitability measures, etc.) for the totality of French businesses, except firms with no employees, or those belonging to the agricultural or banking and financing sectors.

The final dataset

We merge the three data sources described above by means of the univocal firm-level code, common to all sources. Figure 2 shows the details of this procedure. The resulting dataset consists of an augmented CIS. In short, in the two original innovation surveys we identify those firms that supplied UNISTRA's research laboratories and we include other operating performance variables. Finally, we pool the two augmented datasets.

Figure 2. The merging procedure



We match 199 firms supplying lab equipment and scientific instruments out of the 682 in the initial dataset. These firms, representing 30% of the total, account for more than 40% of the total economic value. Although the final sample is relatively small in terms of size, we are confident it is representative. As shown in Figure 3, the distribution of spending across the subcategories associated with the matched firms closely mimics that associated with all the firms in the parent data (panel a). A further concern is that we are only matching suppliers located in certain geographical areas. However, as shown in Figure 3 (panel b), the geographical spread of input purchases pre- and post-merging remains essentially the same. With various caveats (for a discussion see the following sections), we are now in a position to exploit a rich set of innovation-related variables linked to benchmark suppliers and other businesses included in the survey in terms of their innovative performance, while controlling for a large number of firm-level attributes.

Measures

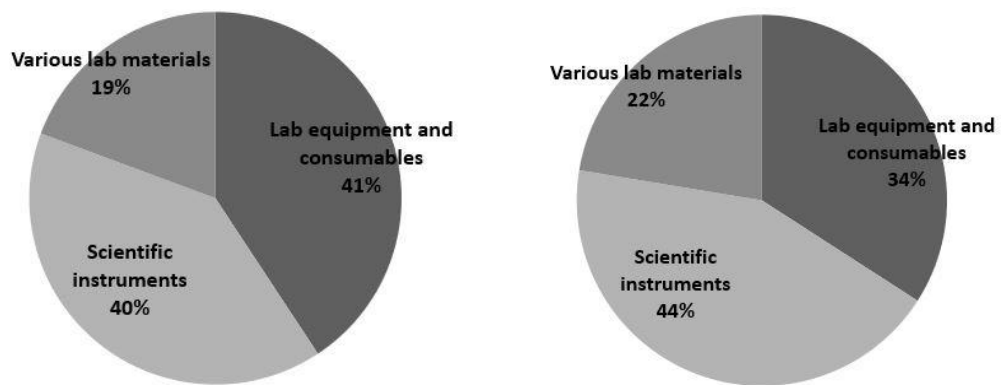
Dependent variable

We use different variables to reflect various aspects of a firm's innovative performance. First, we consider two proxies that capture a firm's ability to achieve product innovations: (i) a dummy indicating if the firm has introduced "new-to-the-market" products (*New Mkt*), and

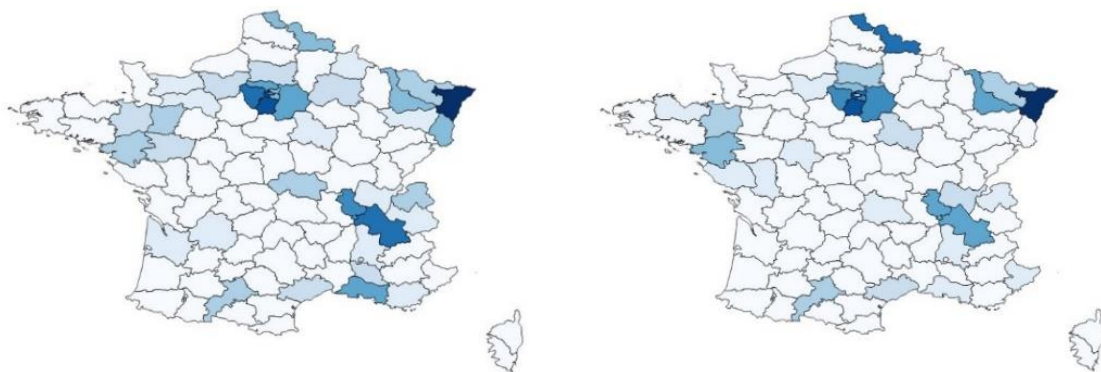
(ii) a continuous variable measuring the volume of sales (in logs) stemming from those products (*New Mkt Volume*). Second, we consider a standard dummy of process innovation (*Iproc*), measuring whether the firm has re-organized its production practices or whether it has implemented new or significantly improved production processes.

The three variables considered here seek to capture the mechanisms via which university demand might effect the firms' innovation outcomes, as described in Section 2. Thus, while *New Mkt* and *New Mkt Volume* capture the “uncertainty effect”, *Iproc* captures the “incentive effect”.

Figure 3. Distribution of expenses broken down by category (panel a) and geographical spread of input purchases (panel b) [left: Expenditure data; right: Final dataset]



Panel (a)



Panel (b)

Other variables

We need to rely on a set of observable characteristics so as to create viable control groups and to isolate the net impact of university demand on corporate innovation. Hence, we first build an exhaustive vector of firm-level attributes that include the following: a proxy for firm size based on the number of employees (*Empl_log*); firm age computed by year of foundation (*Age*); a proxy for a firm's financial status in terms of return on sales (*ROS*); a labor productivity index (*LabProd_log*) calculated as the ratio between total value added and number of employees; R&D intensity (*R&D*) as a traditional proxy of innovation inputs, obtained by dividing total R&D expenditure by firm turnover; and, finally, three dummy variables, respectively, taking a value of 1 if the firm belongs to an industrial group (*Group*), receives public financial support for innovation (*PubFund*), or has an internal R&D department (*R&DDep*), and zero otherwise.

Second, we introduce additional variables reflecting a firm's external collaboration strategies. We consider a proxy for the breadth (*Breadth*) of the firm's cooperation with other enterprises or organisations on innovation activities (Salter and Laursen, 2006). The CIS asks firms to indicate whether or not firms have formal innovation collaboration links with eight different external sources (e.g., suppliers, clients or customers, competitors, etc.). Each of these eight sources is, therefore, encoded as a binary variable, 0 indicating that they do not use them and 1 indicating that they use the given source. Subsequently, the eight sources are combined so that a firm obtains a 0 when it does not cooperate with any external partners, while it obtains the maximum value of 8 when it has links with all eight partners. Finally, to capture the existence of university-industry links more effectively, we build a binary indicator taking a value of 1 if the firm has formal R&D collaboration agreements with French universities or other higher education institutions in France (*UniColl*).⁷ Concise definitions and the labels of the variables used in this paper are reported in Table 2.

Table 2. The variables for this study

<i>Variable</i>	<i>Description</i>	<i>Source</i>
New Mkt	Product innovations (goods or services) new-to-the-market (dummy)	CIS
New Mkt Volume	Sales stemming from new-to-the-market products (in log)	CIS
Iproc	Process innovations (dummy)	CIS
Empl_log	Number of employees (in log)	FARE
Age_log	Date of incorporation (in log)	FARE
Group	Part of an enterprise group (dummy)	CIS
R&D	R&D expenditures over sales	CIS
R&DDep	Presence of R&D laboratory within the firm (dummy)	CIS
PubFund	Public financial support for innovation activities (dummy)	CIS
Breadth	Number of cooperation partners on innovation activities	CIS
ROS	Net revenue over sales	FARE
LabProd_log	Labor prod. (in log) computed as value added over number of employees	FARE
UniColl	Cooperation with French universities or other HEI (dummy)	CIS
Sector	Industry dummies (2-digit NACE classification)	CIS
Region	Regional dummies at the department level	CIS

Descriptive statistics

Table 3 reports the basic descriptive statistics for the set of variables considered. Substantial differences between university suppliers and other companies are found in relation to almost all characteristics. For instance, the former are found to be significantly larger and older. Furthermore, 67% of university suppliers belong to an enterprise group compared to 60% of other firms, and the former also benefit more from public financial support. University suppliers present a higher degree of openness, using on average more than one collaboration partner and collaborating more frequently with universities or other higher education institutions (30% maintain collaborations with French universities compared to 14% in the population of other firms). Finally, suppliers tend to invest more in internal R&D activities and to produce “radical” product innovations (90% of them introduce new-to-the-market

⁷ Note that this additional variable is especially relevant to our study as it allows us to detect the “net” effect of the university as a customer (and, therefore, user), isolating the effect of the university in its role as a collaboration partner. Yet, it should be stressed that the R&D collaboration variable considered here is quite uninformative about the specific university the firm collaborates with, be it UNISTRA or not. In Section 6 we exploit other UNISTRA administrative data on university-firm collaborations to tackle this issue more thoroughly.

products, compared to 69% in the overall sample of French businesses) whilst, in contrast, they seem less likely to introduce process innovations.

Taken together, these descriptive statistics show that university suppliers and the population of other companies present very heterogeneous profiles; hence, the need to use appropriate statistical techniques to build a reliable counterfactual. This is the argument developed in the next Section.

Table 3. Descriptive statistics of the variables

Variable	All Firms		Suppliers (1)		Other firms (2)		(1) – (2)
	Mean	SD	Mean	SD	Mean	SD	t-test
New Mkt	0.6945	0.4607	0.9036	0.2969	0.6927	0.4614	4.1574***
New Mkt Vol.	4.9788	4.0053	7.7455	3.7522	4.9552	3.9994	6.3326***
Iproc	0.6394	0.4802	0.6145	0.4896	0.6397	0.4801	-0.4761
Empl_log	4.5051	1.6038	6.0676	1.9158	4.4917	1.5944	8.9495***
Age_log	3.0893	0.7333	3.3772	0.6060	3.0868	0.7339	3.5942***
Group	0.6120	0.4873	0.7711	0.4227	0.6106	0.4876	2.9882***
R&D	5.0267	11.6206	5.2153	11.3547	5.0251	11.6234	0.1485
R&DDep	0.7869	0.4096	0.8675	0.3411	0.7862	0.4100	1.8012*
PubFund	0.3023	0.4593	0.4578	0.5012	0.3009	0.4587	3.1005***
Breadth	1.4711	2.0347	2.2892	2.4070	1.4641	2.0210	3.6807***
ROS	0.0308	0.1804	0.1075	0.5473	0.0302	0.1739	3.8898***
LabProd_log	10.9993	0.5756	11.2554	0.4804	10.9972	0.5758	4.0728***
UniColl	0.1431	0.3502	0.3012	0.4616	0.1418	0.3488	4.1334***
Obs	9 796		199		9 597		

Note: Significance level: *** p<0.01, ** p<0.05, * p<0.1

Econometric approach

Our empirical strategy is to consider university supplier status as the “*treatment*”.⁸ According to the conceptual framework outlined in Section 2, this treatment should affect different aspects of the firms’ innovative behaviour, namely their product and process innovations. We proceed in two complementary steps: first, we estimate the effect of “being a university supplier” on the set of innovation variables using standard regression techniques; and, second, we adopt a quasi-experimental framework and employ propensity score matching (PSM) to obtain the impact of the treatment.

Regression analysis

We start by applying a standard regression model:

$$Inno_i = \alpha Supplier_i + \mathbf{X}_i\beta + \varepsilon_i \quad (1)$$

where the dependent variable *Inno* represents the three innovation proxies considered (*New Mkt*; *New Mkt Volume*; *Iproc*), the main regressor *Supplier* is a binary variable taking a value of 1 if firm *i* is a university supplier, *X* is a vector of firm-level controls (as described in

⁸ Note that some firms included in the overall sample might also be considered “treated” if, for example, they supply other universities. Unfortunately, we are not able to test this hypothesis but, as discussed in Section 5, our estimates would nevertheless reflect the lower bound of the treatment effect. In other words, we are confident that if a bias exists, it would not run counter to our conjectures.

Section 3.3), and ε_i is an idiosyncratic error term. The model is estimated using Ordinary Least Squares (OLS) and the coefficient of interest in Equation (1) is α , representing the effect of the treatment on the innovative performance of firms.

Sources of selection bias

Although easily interpretable, the above econometric approach embeds an important assumption: namely, that the data come from randomised trials – i.e., the assignment of the treatment to firms (that is, being a supplier of the university or not) is completely random. However, here, we are dealing with non-randomized observational data as the university chooses its own suppliers and the latter are likely to differ substantially from other firms in many respects (see Table 3). This absence of randomly assigned treatment to firms introduces a bias in the regression estimates.

Indeed, there are two primary sources of bias. First, a university typically plays a “picking the best” strategy. As the university organises public procurement bids to choose its suppliers, it is reasonable to assume that it will pick “good companies”, essentially those characterized by the soundness of their financial conditions and a high degree of innovativeness. Second, it is also possible that firms self-select themselves to become suppliers. For instance, some companies may have better search capabilities, or other types of competitive advantage, that allow them to detect, and thus strategically apply for, a public procurement competition. In short, university suppliers are likely to be intrinsically different from non-suppliers even in the absence of the treatment, and we need to account for this possibility.

Propensity score matching

The goal is to estimate the expected value of the average treatment effect on the treated (ATT), defined as the difference between the expected outcome values with and without treatment for those who actually participated in the treatment. Formally:

$$\tau_{ATT} = E(\tau|T = 1) = E[Y(1)|T = 1] - E[Y(0)|T = 1] \quad (2)$$

where $E[Y(1)|T = 1]$ is the expected value of the outcome variable of the treated units and $E[Y(0)|T = 1]$ is the expected value of this variable when the units are not treated. As the counterfactual mean for the units treated is not observed, we have to choose a substitute for this value in order to estimate the ATT. We apply propensity score matching (PSM) to construct the pseudo-counterfactual or the control. Matching estimators are based on a comparison of the outcomes obtained by the treated units (i.e., university suppliers) and those obtained by a “comparable” control group (i.e., a subsample of other companies), conditional on a set of defined characteristics. Under certain assumptions, the difference in mean outcomes between the two groups can be attributed exclusively to the treatment.⁹

The matching procedure requires the definition of a set of characteristics X , which leaves the estimate prone to the well-known “curse of dimensionality”. In short, this problem requires the estimation of a high-dimensional vector of exogenous covariates to find an exact twin for each treated unit. Rosenbaum and Rubin (1983) suggest it is possible to compress this vector into a single scalar index – that is, the propensity score – and to use this index to search for similar (in statistical terms) units. In our framework, the propensity score measures the

⁹ Two identifying conditions must be fulfilled: unconfoundedness and common support. Unconfoundedness, or the conditional independence assumption, states that the outcome should be statistically independent of the treatment. For this condition to hold, all the variables likely to affect simultaneously the probability of receiving the treatment and the potential outcomes should be known and taken into consideration. The common support condition states that the control group should contain at least one sufficiently similar observation for each treated unit.

probability of a firm becoming a supplier of scientific materials and equipment to UNISTRA based on a set of observable characteristics.

PSM requires three important methodological choices: i) the model to be estimated; ii) the variables to be included in the model; and iii) the matching algorithm to be applied. In the case of the first choice, because our treatment is a binary variable, we estimate a probit regression. Caliendo and Kopeinig (2008) show that, in the case of binary treatments, probit and logit regressions generate very similar results. As regards the choice of variables, we exploit the entire set described in Section 3.3 to determine the probability of firms receiving the treatment. This choice was dictated by existing empirical evidence but, above all, by the idea of mimicking the practices adopted by UNISTRA's public procurement office when selecting suppliers. As pointed out above, the university's suppliers are selected via public procurement bids, a procedure that has a dual objective – to uphold competition and transparency during the selection process and to guarantee the effective spending of public money. Hence, we conducted three semi-structured interviews with the university's public procurement managers to understand the implementation of the selection procedure, its various stages, selection criteria, and the role played by researchers in the process. The managers confirmed the appropriateness of our set of variables.¹⁰ Finally, regarding the choice of the matching algorithm, we opt for the bias-corrected nearest-neighbour (NN) matching estimator proposed by Abadie and Imbens (2006). Given the large sample and the similar distribution of propensity scores between treated and control units, we apply a NN search without replacement and with oversampling – i.e., we match each treated unit with three untreated observations. As the results may be sensitive to these implementation choices (Caliendo and Kopeinig, 2008), in Section 6 we perform a series of robustness checks implementing alternative specifications.

Thus, we proceed as follows. First, we obtain the propensity scores associated with the binary treatment via the estimation of the probit model (or selection equation) containing the original set of variables. Next, we apply the NN algorithm and use the estimated propensity scores to match the subsample of suppliers with the most similar group of firms in the sample. Finally, we compute the ATT to draw conclusions about the effect of university demand on the innovativeness of its suppliers.

Results

Regression analysis

Table 4 presents the results of the regression analysis. Two major findings merit discussion. First, the coefficients of the regressor *Supplier* associated with the two product innovation proxies (*New Mkt* and *New Mkt Volume*) are positive and statistically significant at the 1% level. These estimates imply that university suppliers exhibit a higher propensity to introduce new-to-the-market products and to enjoy higher sales from these products. Taken together, these results support our conjecture that university demand for goods and services affects the innovative performance of suppliers, and that this effect is positive in the case of product innovations. Indeed, as discussed in Section 2, university demand seems to act in two complementary ways: on the one hand, because of their quite specific needs, scientists can

¹⁰ The interviews took place in September 2017 at UNISTRA's public procurement office, and lasted about one hour each. Specifically, the managers ranked the firms' financial status and their receiving public support for innovation (acting as "reputation effect") as being among the most important criteria for assessing candidates. Other important criteria were identified as the firms' fiscal status and whether they respect the codes of ethics governing labour law. As it is the applicants themselves that provide the information related to these last two criteria, it proves quite challenging to include a reliable proxy for them in our estimation.

contribute to the emergence of new concepts and ideas, reducing the uncertainty and risk of failure that is inherent to the innovation process; while, on the other, scientists can act as lead-users of technologies, thus indirectly bearing the costs of learning and refining associated with their development.

Table 4: Regression analysis, OLS estimates

Variable	New Mkt (1)	New Mkt Volume (2)	Iproc (3)
Supplier	0.1498*** (0.0329)	1.3121*** (0.3710)	-0.0797 (0.0520)
Empl_log	0.0044 (0.0036)	0.5872*** (0.0328)	0.0164*** (0.0037)
Age_log	-0.0089 (0.0065)	-0.1744*** (0.0540)	-0.0020 (0.0070)
Group	0.0101 (0.0110)	0.2204*** (0.0842)	-0.0098* (0.0116)
R&D	0.0026*** (0.0004)	0.0189*** (0.0033)	-0.0010** (0.0005)
R&DDep	0.2197*** (0.0128)	1.4543*** (0.0986)	-0.0639*** (0.0129)
PubFund	0.0378*** (0.0104)	0.2754*** (0.0874)	0.0342*** (0.0113)
Breadth	0.0278*** (0.0028)	0.2487*** (0.0256)	0.0443*** (0.0031)
ROS	-0.0216 (0.0201)	-0.5839** (0.2505)	0.0431 (0.0259)
LabProd_log	0.0389*** (0.0085)	0.6740*** (0.0793)	-0.0412*** (0.0091)
UniColl	-0.0208 (0.0152)	0.1188 (0.1438)	-0.0273* (0.0172)
Sectors	yes	yes	yes
Regions	yes	yes	yes
Obs	9 796	9 796	9 796
R ²	0.1022	0.1989	0.0518

Note: Robust standard errors in parenthesis. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Second, we observe that the regressor *Supplier* does not have any relevant effect on process innovations. In our conceptual framework, we argued that university demand might provide firms with a minimal market size, hence, providing incentives to improve production practices and achieve scale economies. A tentative explanation for the lack of effect found might be that scientists' needs are highly specific and, as such, represent needs that are not yet common in the marketplace. This is especially true of high-tech instrumentation that only serves very specific research aims. While idiosyncratic demand grants firms competitive advantages in specific solution types and fosters the development of new products, it may prevent the exploitation of economies of scale, at least in the short-term. In other words, since this demand is unlikely to be experienced by users outside academia or by researchers in other fields, firms face no incentives to achieve process innovations and reduce production costs. The coefficients of the control variables conform, by and large, with those reported in previous studies (i.e., Laursen and Salter, 2006; Cohen, 2010; Beck et al., 2016; Scandura, 2016). The intensity of R&D investments (*R&D*) and public support for innovation (*PubFund*) positively affect the propensity to achieve product innovations. The breadth of

openness of firms' innovative cooperation (*Breadth*) also appears to be an important factor in explaining innovative performance. More efficient companies (*LabProd_log*) tend to innovate more in terms of new products, though not in terms of new processes. The lack of significance of the role of universities and PROs as collaboration partners in innovation (*UniColl*) is surprising yet consistent with the fact that the breadth measure could absorb this effect. Finally, it seems that large (*Empl_log*) but young (*Age_log*) companies belonging to industrial groups (*Group*) enjoy higher sales from their product innovations, whilst these demographic features do not present robust patterns across the other specifications.

Propensity score matching

We now turn to examine the results of the matching estimates. We first discuss the process of selection and the reliability of the control group. Next, we present the paper's main findings. The results of the estimation are reported in Table 5 (left panel). The estimated coefficients represent the influence that each variable has on the probability of a firm becoming a university supplier. Note that the percentage of correctly predicted zeroes and ones implies a satisfactory goodness of fit. It emerges that larger firms have a higher probability of becoming suppliers of scientific material and equipment to UNISTRA. Moreover, we find that firms benefiting from public support for innovation and with a higher labour productivity index are also more likely to be selected as university suppliers. Firm profitability affects positively and significantly the probability of receiving the treatment, although at a low significance level. The other variables do not play any relevant role. Overall, these estimates suggest that a selection process is actually in place and that financial conditions and reputation are the most relevant factors.

Before discussing the final results, in Table 6 (right panel), we report a *t*-test for equality of means between treated and untreated units before and after the matching. Pre-matching comparisons (unmatched) show that the two groups present statistically significant differences in almost all the variables considered. If the matching procedure is effective, the sample of untreated firms should not differ in statistical terms from the sample of treated firms in any dimension. We find equality of means in the treated and control groups post-matching (matched), indicating that the matching procedure has generated a reliable counterfactual.

Finally, Table 6 shows the results of the propensity score matching. The first column reports the mean value of the outcome variables for the suppliers, the second column the mean values for the control group, while the third column represents the main parameter of interest, namely the ATT.

In line with the results presented in Table 4 above, we confirm the positive and statistically significant effect of the treatment in the case of product innovation. University suppliers are more innovative compared to other firms insofar as they show a higher propensity to introduce "radical" product innovations and to reap greater revenues from the sales of these products. It is worth stressing the actual magnitude of these effects. First, 90% of suppliers achieve product innovations compared to about 75% of firms operating in the same industries and with similar characteristics. Second, the sales of suppliers' market novelties are much higher (1.5 times) than those of other firms. Again, we do not find any significant effect on process innovations.

All in all, the above findings confirm that university demand exerts a very strong effect on the innovative performance of its suppliers. It was our conjecture that the persistent use of a given item (tool, equipment, or more generally, a given technology) in the challenging environment of scientific research induces scientists to develop some tacit knowledge. This knowledge enables scientists to visualise future extensions of existing technologies or completely new

solutions. According to our results, it seems that university-firm interactions via such demand allow suppliers to increase their innovation potential.

Table 5: Selection equation estimates (left panel) and balance checking (right panel)

<i>Selection equation</i>		<i>Balance checking</i>			
Variable	Supplier	Status	Treated	Control	t-test
Empl_log	0.2054*** (0.0335)	Unmatched	6.0676	4.4917	8.95***
		Matched	6.0676	5.8787	0.65
Age_log	0.0587 (0.0545)	Unmatched	3.3772	3.0868	3.59***
		Matched	3.3689	3.3535	0.15
Group	-0.1761* (0.1069)	Unmatched	0.7711	0.6106	2.99***
		Matched	0.7683	0.7520	0.24
R&D	0.0033 (0.0038)	Unmatched	5.2153	5.0251	0.15
		Matched	4.7128	4.2838	0.27
R&DDep	0.0952 (0.1276)	Unmatched	0.8675	0.7862	1.80*
		Matched	0.8659	0.8943	-0.56
PubFund	0.2008** (0.0908)	Unmatched	0.45783	0.30094	3.10***
		Matched	0.45122	0.4187	0.42
Breadth	-0.0499* (0.0266)	Unmatched	2.2892	1.4641	3.68***
		Matched	2.2317	2.0569	0.48
ROS	0.2919* (0.1497)	Unmatched	0.1075	0.0302	3.89***
		Matched	0.0482	0.0430	-1.11
LabProd_log	0.2245*** (0.0759)	Unmatched	11.255	10.997	4.07***
		Matched	11.24	11.284	-0.57
UniColl	0.1326 (0.1343)	Unmatched	0.3012	0.1418	4.13***
		Matched	0.2927	0.2642	0.40
Sectors	yes				
Regions	yes				
Obs	9 796				
Correctly Classified	99,15%				
Pseudo R ²	0.1307				

Note: Robust standard errors in parenthesis. Significance level *** p<0.01, ** p<0.05, * p<0.1

Table 6: Average Treatment Effect on the Treated (ATT), main results

Variable	Treated	Controls	ATT	t-test
New Mkt	0.9024	0.7561	0.1463***	3.22
New Mkt Volume	7.8399	6.3702	1.4698***	2.80
Iproc	0.6098	0.6707	-0.0610	-0.92
Obs	199	9 597		
Off support	1	0		

Note: Significance level *** p<0.01, ** p<0.05, * p<0.1

Robustness checks

Our finding that university suppliers are systematically more innovative than other companies of similar characteristics is robust to a variety of specifications and alternative proxies of innovation (i.e., patents).

Sensitivity analysis

The first exercise introduces a more accurate control variable in the selection equation that specifically accounts for R&D collaboration agreements with UNISTRA, as opposed to universities in general, as in the main analysis. To this end, the university's technology transfer office (TTO) gave us access to a complete list of research contracts entered into jointly by researchers and industrial partners in the period 2011–2014. This list enables us to define a finer grained dummy variable to control for more traditional university-industry linkages, and so to isolate the net effect of university demand on firm performance. The ATT estimates reported in column 1 (Table 7) indicate that the results are unaffected insofar as we observe similar patterns in terms of magnitudes and levels of significance.

The second exercise, “trimming” the selection equation (modelling the probability of becoming a university supplier) raises the question as to whether it is better to include too many variables as opposed to too few. It has been shown that overspecifying the probit model can result in inconsistent estimates of the propensity scores and, in turn, to misleading conclusions (Caliendo and Kopeinig, 2008). Accordingly, we re-estimate the selection equation retaining only those covariates that were significant at the 1% and 5% level in the original specification, and so obtain what is known as a parsimonious equation. The ATT estimates reported in column 2 (Table 7) show that our main findings hold.

Table 7: Average Treatment Effect on the Treated (ATT), robustness check analysis

Variable	UNISTRA (1)	Parsimon. (2)	Scient. Inst. (3)	NN1 (4)	NN5 (5)	Kernel (6)	Caliper (7)	Radius (8)
New Mkt	0.1260***	0.1825***	0.1389***	0.1341***	0.1390***	0.1479***	0.1463***	0.1514***
New Mkt Volume	1.0255**	1.4165***	1.0372*	1.0499*	1.3862***	1.3896***	1.4698***	1.4254***
Iproc	-0.0691	-0.0635	-0.1556**	-0.0976	-0.0610	-0.0866	-0.0610	-0.0867
Treated	199	199	143	199	199	199	199	199
Off support	1	0	1	1	1	1	1	1
Controls	9 597	9 597	9 597	9 597	9 597	9 597	9 597	9 597
Off support	0	570	0	0	0	0	0	0

Note: Significance level *** p<0.01, ** p<0.05, * p<0.1

In the main analysis proposed in Section 5, we considered supplies of research materials ranging from small purchases to high cost research infrastructure. To verify whether the results are sensitive to supply type, we replicate the analysis with a sub-sample of companies that supplied goods with high technological content (or, more precisely, we consider only those purchases in the subcategory “scientific instruments”, as reported in Table 1). Thus, we do not consider here supplies related to general lab equipment and consumables that might simply represent off-the-shelf products. The number of treated units falls (143 firms) but the sample is large enough to obtain meaningful statistical inference. Here, also, the estimates reported in column 3 point to a statistically significant difference in terms of innovation outcomes between university suppliers and other companies, although the magnitude of the effect tends to decrease slightly.

Finally, in the case of the matching algorithm, it is well established that there is no best option. Different algorithms involve different trade-offs between estimate variance and bias (Caliendo and Kopeinig, 2008). Therefore, we replicate the analysis by changing the number of matching partners for each treated individual. More precisely, we match every treated firm with one nearest neighbour (NN1) and again with five neighbours (NN5). Next, we apply three alternative matching algorithms, namely caliper, radius, and kernel matching. While caliper and radius matching use only a limited number of observations from the untreated units to build the final counterfactual group, the kernel algorithm uses weighted averages of nearly all the population. As we can see from columns 4-8 (Table 7), the results are highly persistent across the different alternatives.

Patent analysis

Although widely used, innovation survey data are known to suffer certain limitations. For instance, among the most critical are the cross-sectional nature of the data, the representativeness of the sample, the lack of financial and accounting variables, and the subjectivity of the information reported (Archibugi and Pianta 1996; Mairesse and Mohnen 2010).

Here we propose a supplementary analysis that relies on two alternative sources: BvD AMADEUS and PATSTAT. The analysis aims at partially addressing some of the criticisms concerning CIS data. We retrieve financial and accounting information for all French businesses from the AMADEUS database, for the period 2011–2014. This database does not include, however, complete and precise information on the innovation activities of firms; thus, we retrieve additional patent data from the European Patent Office (EPO) – Worldwide Patent Statistical Database (PATSTAT). We implement the matching of firm-level and patent data via a semantic matching procedure based on the firms’ names. The method is carried out in three steps: harmonization, matching and filtering (for details, see Tarasconi 2014).

We succeeded in identifying all of UNISTRA’s suppliers in the AMADEUS-PATSTAT dataset (i.e., 682 companies). However, given the extent of the missing information, the sample of suppliers that can be exploited for the empirical analysis falls substantially and we end up with 121 firms.

Our variable of interest is the number of patent applications by firm (*Patents*). To be consistent with our main analysis, we select (wherever possible) the same group of control variables. Thus, we include the size of the company (*Empl_log*), the age (*Age_log*), an index of profitability (*ROS*) and labour productivity (*LabProd_log*), a dummy to account for R&D collaboration agreements with UNISTRA (*UniColl_Unistra*), and a full set of industry (NACE 2 digits) and regional dummies. We also control for the firms’ previous innovation

efforts and propensity to patent by including the stock of patents (*PatStock*). Finally, we proxy the firms' innovation capabilities by considering their intangible assets (*IntAss_log*).¹¹

Table 8: OLS and ZINB estimates, robustness check analysis

Variable	OLS (1)	ZINB (2)
Supplier	0.3539** (0.1511)	1.9739*** (0.4367)
PatStock	0.0017*** (0.0002)	0.0023** (0.0009)
Empl_log	0.0141*** (0.0016)	0.9504*** (0.0842)
Age_log	-0.0094*** (0.0023)	-0.1368 (0.1233)
ROS	0.0074*** (0.0016)	0.2472 (0.3989)
LabProd_log	0.0081*** (0.0013)	0.5671*** (0.1299)
UniColl_Unistra	0.8074* (0.4131)	-0.3401 (0.4214)
IntAss_log	0.0036*** (0.0008)	
<i>Inflation:</i>		
IntAss_log		-0.6282*** (0.0988)
Sectors	yes	yes
Regions	yes	yes
Obs	155 963	155 963
R ²	0.6250	

Note: Robust standard errors in parenthesis. Significance level *** p<0.01, ** p<0.05, * p<0.1

To complete the econometric analysis, we first estimate an OLS regression, where the dependent variable is *Patents*, the main regressor *Supplier* is the binary variable taking a value of 1 if the firm is a UNISTRA supplier, while we also include a vector of firm-level controls, as discussed above. However, the patent applications variable presents a skewed distribution with the presence of many zeroes. Furthermore, in our data we observe that the conditional variance of *Patents* exceeds its conditional mean. Thus, it seems appropriate to complement the OLS setting with a zero-inflated negative binomial model (ZINB). Such models estimate two equations simultaneously, one to describe the relationship between the response variable and the set of covariates and one to model the excess of zeroes. We use intangible assets as an inflator since we expect firms with lower assets to exhibit a lower propensity to patent.

Table 8 reports the results. The coefficients of *Supplier* are positive and statistically significant (at the 5% level) in both regressions, implying that university suppliers exhibit a higher propensity to patent, all other things being equal. Overall, these estimates further corroborate the main findings discussed in Section 5.

¹¹ In this context, too, we find substantial differences between university suppliers and other companies with respect to the characteristics considered. Descriptive statistics for the sample are not reported in the text but are available upon request.

Conclusions

Innovation theories generally consider the innovation process as being generated by advances in scientific and technical knowledge that lead to discoveries and their technological and economic applications. And in the generation of these discoveries universities are accredited with playing a central role. Yet, there is much less consensus regarding the mechanisms by which university-generated knowledge reaches final users and creates value. Innovation theories in economics often assume the existence of pure externalities, supposing that academic knowledge spills over the economy and reaches all private agents (especially business companies) at no, or at quite a low, cost. These externalities benefit both the economic sectors and the regional activities centred upon the sources of technological change. More recent theories, however, have stressed the presence of transaction costs (i.e., the costs incurred in order to acquire knowledge and benefit from it) and the importance of market-mediated mechanisms. This new emphasis has led to a series of policy transformations aimed at encouraging and fostering knowledge and technology transfer from research universities and PROs to private businesses.

While research on university-industry interactions has focused almost exclusively on supply-side factors, and, in so doing, emphasized the role of academic commercialization and technology transfer activities, here we have proposed a complementary approach by focusing on the impacts emanating from the demand created by the university itself. In this study, we have empirically examined the impact of a large French public university on the innovative performance of its suppliers of research equipment and materials, and to do so we have employed a unique university expenditure dataset. Our results point to the fact that university suppliers have a higher propensity to introduce more “radical” product innovations, which we attribute to the special role played by academic scientists as knowledge brokers, bringing to firms insights about the evolution of technologies and needs that are not yet common in the marketplace. In this sense, we embrace the conjecture forward by economic historians that innovations and technological changes are the result not only of scientific and technical discoveries, but also of a complex chain reaction triggered by the interplay of quite specific demands and solutions designed to overcome technology bottlenecks.

The results presented in this paper serve to enrich the literature on the scale and breadth of the economic contribution made by universities. Indeed, since most of the purchases in our data are funded by public money, this study delivers new empirical evidence about the positive return of public investment in science. This question is particularly important in the context of the increasing pressure being exerted by the institutions to evaluate the economic benefit of academia. As Salter and Martin acknowledge (2001, p. 528) “[t]hese benefits are often subtle, heterogeneous, difficult to track or measure, and mostly indirect”. In this respect, our results bolster traditional justifications for the continuing public support of the research universities. Indeed, we show that governments and funding agencies need to devote sufficient funding for the purchase and maintenance of the latest tools and equipment requested by researchers to complete their projects.

The results proposed in this paper could be extended in various ways. First, we have focused on one of the largest French research-oriented universities. This university stands out in terms of the impressive research achievements of its members, which owe much to the use of sophisticated research equipment. However, it would be interesting to broaden the analysis to other contexts. In this way, it would be possible to perform comparative studies across universities and countries, and so gain a greater understanding of the characteristics of the eco-systems that are conducive for demand-pull innovation. Second, it would be interesting to complement the econometric analysis reported here with qualitative studies. The strength of qualitative research methods resides in their ability to provide a fuller description of the

mechanisms involved and so to understand better the complex reality of the phenomenon under investigation and its implications. Among the aspects that deserve closer attention would be the negotiation process for intellectual property rights in the case of the joint-development of new technologies, the role of procurement practices and the degree of freedom in that process, and the impact of the new technologies demanded by the university on the overall organization of the firm (e.g. marketing and pricing strategies). Third, more sophisticated work could usefully be conducted on patent data and over longer time horizons, for instance, considering the impact of university demand on patent quality (e.g. number of citations received or the generality index), patent characteristics (e.g. patent scope), and network of inventors. All these suggestions for extending the field of study will guide our own future research.

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