Healthcare Procurement and Firm Innovation:

Evidence from AI-powered Equipment

Sofia Patsali[1] Michele Pezzoni[1,2,3,4] Jackie Krafft[1]

[1]Université Côte d'Azur, CNRS, GREDEG, France
[2]Observatoire des Sciences et Techniques, HCERES, France
[3]OFCE, Sciences Po, France
[4]ICRIOS, Bocconi University, Italy

Abstract

In line with the innovation procurement literature, this work investigates the impact of becoming a supplier of a national network of excellence regrouping French hospitals on the supplier's innovative performance. It investigates whether a higher information flow from hospitals to suppliers, proxied by the supply of AI-powered medical equipment, is associated with higher innovative performance. Our empirical analysis relies on a dataset combining unprecedented granular data on procurement bids and equipment with patent data to measure the firm's innovative performance. To identify the firm's innovative activities relevant to the bid, we use an advanced neural network algorithm for text analysis linking firms' equipment descriptions with relevant patent documents. Our results show that firms becoming hospital suppliers have a significantly higher propensity to innovate. About the mechanism, we show that supplying AI-powered equipment further boosts the suppliers' innovative performance, and this raises potential important policy implications.

JEL Classification: H57, D22, O31, C81
Keywords: Innovation performance, public procurement, medical equipment, hospitals, artificial intelligence

1. Introduction

The effect of procurement on innovation has been a topic of interest for decades (Chicot and Matt 2018; Rolfstam, Phillips, and Bakker 2011, Askfors and Fornstedt 2018; Uyarra et al. 2014; Uyarra and Flanagan 2010a; Rolfstam, Phillips, and Bakker 2011). The procurement literature generally converges in identifying a positive effect of procurement on supplier firms' innovation (Belenzon and Cioaca 2021; Miller and Lehoux 2020; Guerzoni and Raiteri 2015; Lichtenberg 1988). In the case of equipment procurement, the positive relationship is explained by the flow of valuable technological information from organizations asking for procurement to firms supplying equipment (Patsali 2021; Autio, Hameri, and Vuola 2004; Rosenberg 1992). Indeed, the information flow is expected to provide firms with novel technological ideas to improve existing equipment or develop new equipment (Fontana and Guerzoni 2008; Myers and Marquis 1969). Among the procured equipment, the one embedding Artificial Intelligence (AI) is expected to be particularly effective in facilitating the information flow to firms and, therefore, fostering firms' innovation performance (Esteva et al. 2019). Indeed, the general purpose of AI technologies in medicine is to analyze large amounts of data with computer algorithms to uncover relevant information to support clinical decision-making (Hamamoto et al. 2020; Topol 2019; He et al. 2019; Yu, Beam, and Kohane 2018). The abundance of data that hospitals provide to firms to train their algorithms provide firms with useful information, favoring innovation. Another characteristic of AI technologies is that they can be applied in any healthcare domain, including diagnostics and therapeutics (Esteva et al. 2021). This wide range of applications of AI technologies allows us to distinguish between equipment characterized by high and low information flow in different healthcare domains.

The effect of procurement has been studied in several contexts, such as the military sector (Mowery 2012), research institutes (Autio, Hameri, and Vuola 2004; Castelnovo et al. 2018), universities (Bianchini, Llerena, and Patsali 2019; Patsali 2021), public agency investments (Bonvillian 2018; Fuchs 2010; Mazzucato 2011), and healthcare sector (García-Altés et al. 2023; Miller and Lehoux 2020; Askfors and Fornstedt 2018; Meehan, Menzies, and Michaelides 2017). Studying the effect of procurement of the healthcare sector is crucial for policymakers due to its relevance in the national economies and due to the large amount of taxpayer money invested (Askfors and Fornstedt 2018; Boon and Edler 2018; Dalpé 1994; Georghiou et al. 2014).

This paper studies and quantifies the impact of procurement on firms' innovation in the context of the healthcare sector. Using unique data, we investigate whether hospitals' procurement affects the innovation performance of firms supplying medical equipment. Moreover, we explore if the supply of equipment embedding Artificial Intelligence (AI) moderates the procurement effect.

Although the procurement literature has advanced our knowledge of the relationship between procurement and innovation, we identify two significant gaps. The first gap is the lack of econometric studies using micro-level data to assess the relationship between healthcare procurement and innovation. The extant empirical evidence about healthcare procurement's effect on innovation is mostly qualitative. Literature in healthcare includes detailed case studies on specific hospitals and technologies, but these case studies can hardly be generalized to other hospitals and technologies. Other studies take a macro perspective at the national level, missing the opportunity to investigate the mechanisms linking procurement to innovation, which is possible only using procurement micro-level data (Uyarra et al. 2020). Finally, a few quantitative studies (Aschhoff and Sofka 2009; Guerzoni and Raiteri 2015) use firm-level data (i.e., CIS survey data) but lack fine-grained administrative data describing the hospitals' procurement bids and the equipment supplied. The second literature gap is the lack of empirical studies aiming to understand the "underlying mechanism" through which procurement affects firms' innovation (Uyarra et al. 2017). The information flow between organizations asking for procurement and supplying firms is often considered a potential mechanism, although it has rarely been tested empirically (Bianchini, Llerena, and Patsali 2019; Autio, Hameri, and Vuola 2004).

We fill these two literature gaps using an unprecedented dataset of hospital procurement bids to address two research questions: How does hospital procurement affect firms' innovation? Does the intensity of information flow from hospitals to suppliers, as proxied by the supply of AI-powered equipment, moderate the procurement effect?

We conduct our analysis in the empirical context of healthcare procurement by the French Unicancer network of oncological hospitals. The data provided by Unicancer include detailed information on the equipment, the complete list of firms competing for the procurement (whether or not they obtain the procurement), a description of the selection criteria applied by Unicancer's evaluation committees, and the evaluation scores assigned to each piece of equipment. We analyzed 68 procurement bids for hospital equipment from 2011 to 2017. We rely on patent application documents at the European Patent Office to assess the innovation performance of firms supplying equipment. We link equipment procured to firms' relevant patents using an advanced neural network algorithm for text analysis.

We find that becoming a hospital supplier increases the number of patent applications by one patent per year in the three years after winning the bid. Conditional on becoming a hospital supplier, we find that supplying equipment embedding AI technologies further increases the suppliers' innovative performance. This latter finding supports the hypothesis that the flow of information from hospitals to suppliers fosters supplier firms' innovation. Moreover, analyzing two additional cases in which we expect a high flow of information from hospitals to suppliers, we confirm that information flow is associated with firms' innovative performance. Specifically, we observe that large-size bids and bids in which equipment technology is highly valued further enhance supplier firms' innovation.

Our paper provides three main contributions to the literature. First, different from previous quantitative studies on public procurement, we benefitted from detailed information on the hospitals' procurement procedure and the supplied equipment. For instance, one of the main advantages of our data is that we obtained the complete list of firms competing in procurement bids. Therefore, unique to our study, we can compare firms that obtained the procurement with firms that competed for the procurement but did not succeed. Second, we shed light on the mechanism linking procurement to innovation. Specifically, we test that information flow is the mechanism linking procurement to innovation using a reliable proxy for information flow from hospitals to suppliers, i.e., the supply of AI-powered equipment. In doing so, we provide empirical evidence on how AI affects innovation in healthcare and complement the extant studies investigating other uses of AI (e.g., the possible applications of AI in oncology). Third, we consider AI not only a subject of study but also a methodological tool that allows us to match procurement with innovation data. In this way, we contribute to the emerging discussion in the innovation community about the identification of AI technologies (Iori, Martinelli, and Mina 2021; WIPO 2019).

Our results inform policymakers that hospital public procurement represents an effective way to foster firms' innovation, especially when AI technologies are involved.

The rest of the paper proceeds as follows. Section 2 presents the background literature in procurement and healthcare innovation studies. Section 3 describes the empirical context in which we conducted our study. Section 4 discusses the three types of datasets we draw upon and the variables we calculated. Section 5 describes the methodology applied to identify the procurement effect on innovation. Section 6 presents the main results and a set of further analyses. Finally, Section 7 concludes discussing possible policy implications of our findings.

2. Related literature

Procurement in the healthcare sector

Several works studying procurement illustrated the positive impact of procurement on firms' innovation (Dalpé 1994; Geroski 1990; Lichtenberg 1988; Langrish et al. 1972; Myers and Marquis 1969; Sherwin and Isenson 1967). The evidence of a positive effect of procurement on innovation has led scholars and policymakers to consider procurement as a relevant demand-pool policy tool that can be used to foster firms' innovation (Slavtchev and Wiederhold 2016; Rolfstam 2012; Uyarra and Flanagan 2010a; Edler and Georghiou 2007; Georghiou 2006; Edquist, Hommen, and Tsipouri 2000). The relevance of procurement as a tool for industrial policies has oriented the scientific debate on comparing the effectiveness of procurement versus other supply-side policy tools to promote firms' innovation (Guerzoni and Raiteri 2015; Aschhoff and Sofka 2009).

However, only a handful of studies performed empirical analyses focused on procurement contracts. Among the first contributions in the domain, Lichtenberg (1988) found that the effect of competitive public procurement on firms' propensity to engage in R&D is significantly higher than that of non-competitive private procurement contracts. Geroski (1990) found that public procurement provides more incentives for industrial innovation than R&D subsidies. Specifically, Geroski's results suggest that public procurement fosters innovation by creating demand for new products or processes and ensuring a minimal market size in the initial phase of the innovation process. Slavtchev and Wiederhold (2016) show that the technological intensity of government procurement increases the aggregate level of private R&D investments. Specifically, they find that one dollar increase in high-tech public demand is associated with 0.21 dollar additional R&D private expenditures. Using data on federal procurement contracts and US publicly traded firms, Belenzon and Cioaca (2021) find that firms' publication activity is positively affected by obtaining non-competitive procurement contracts, while their patenting activity is not affected.

The procurement effect has been evaluated in different domains such as the military sector (Mowery 2010), big science infrastructure (Florio 2021; Castelnovo et al. 2018; Florio et al. 2018), space agencies (Robinson and Mazzucato 2019; Petrou 2007) and universities (Bianchini, Llerena, and Patsali 2019). Despite the importance of the health sector, there is a lack of empirical studies assessing the effect of healthcare procurement. Extant studies on the health sector have adopted a qualitative approach focusing on particular cases. For instance, through documents and interviews, Sorenson and Kanavos (2011) studied equipment procurement in the health sector across five countries. Kastanioti et al. (2013) provided an overview of the effect of austerity in Greece on procuring medical equipment and pharmaceuticals. Mudyarabikwa and Regmi (2016) conducted a qualitative analysis of how public-private partnerships increase efficiency in the public procurement of primary healthcare facilities in the UK. Meehan et al., 2017 investigated the antecedents of adopting a price-based or value-based procurement approach in the UK. Miller and Lehoux (2020) conducted a case study across four provinces in Canada exploring the role of procurement offices as intermediaries in healthcare innovation.

AI equipment in the health sector

Previous literature has documented the positive effect of procurement on firms' innovation. This effect has been attributed to technological learning due to the flow of information from procurement agencies to suppliers (Autio et al. 2004). Although the previous literature has embraced this explanation, there is a lack of studies testing it empirically. Among the procured equipment, equipment embedding AI is expected to be particularly effective in facilitating the information flow. AI medical equipment significantly differs from "ordinary" medical equipment as AI imitates human cognition and learning. Developing AI equipment requires training AI algorithms on a large amount of data (Food and Drug Administration 2019). Unicancer hospitals provide their suppliers with this data. We expect that becoming a supplier to Unicancer hospitals with equipment embedding AI is associated with a significant data and information flow between hospitals and firms, leading firms to become more innovative. In other words, firms that supply AI-powered equipment are expected to benefit more from hospital procurement than suppliers of non-AI equipment.

3. Empirical context

We study the relationship between procurement and firms' innovation performance in the French context. Our empirical context concerns the Unicancer network of hospitals, including all the French Comprehensive Cancer Centres (FCCCs). Unicancer hospitals are private non-profit health establishments exclusively devoted to treatment, research, and teaching in oncology. Unicancer hospitals are present throughout France. They are crucial actors in contributing to French healthcare excellence in cancer treatment. Indeed, the French national healthcare system has adopted many of Unicancer's innovative approaches to treat cancer. Most French oncology hospitals (15 out of 24) are associated with the Unicancer network.

One aspect crucial for Unicancer hospitals is to use up-to-date equipment at the technological frontier. Hospitals purchase equipment through procurement bids participated by firms. For 2010-2020 the procurement contracts reflect a value of 323,692,991 euros. In 2020, Unicancer signed the first contract for radiotherapy and proton therapy equipment at the European level, and bought over 45 particle accelerators. Since 2010, ten years after the launch of the Unicancer purchasing group, the amount of pooled purchases has almost tripled. The procurement bids at Unicancer are organized every 3 to 4 years for each field of activity: radiotherapy (linear accelerators), medical imaging (Magnetic resonance imaging Scans, Computed tomography Scans), nuclear medicine (Positron Emission Tomography Scans), interventional radiology, molecular biology, and radiation safety training programs. Purchases related to radiotherapy represent the most significant share of procurement, accounting for 56% of the total value, followed by medical imaging equipment (22%) and nuclear medicine (19%).

At the national level, cancer research and treatment have become a priority for France. In 2021, President Macron launched a ten-year national strategy for fighting cancer. The development of medical innovation, such as AI-Powered equipment, is one of the central actions of this strategy. Regarding public funding, the plan amounts to 1.7 billion euros until 2026. A significant part of this public investment is dedicated to hospital procurement and new cancer treatment technologies. The conduct of public procurement is also one of the axes within the report Villani that significantly influenced the French national strategy around AI.

4. Data and variables

4.1 Data sources

To study the impact of equipment procurement on firm innovation, we build an original dataset by merging three data sources: procurement, patent, and equipment data.

Procurement data

We use procurement administrative data provided by the Unicancer network of hospitals for 2010 - 2020. Our analysis focuses on radiotherapy, medical imaging, and radiology, covering 97% of the economic value of the Unicancer procurement. We obtained data on 68 Unicancers' procurement bids participated by 14 firms offering 57 pieces of equipment. Compared to existing studies on procurement and innovation, Unicancer provided us with unique information on the complete list of selected and non-selected firms competing in procurement bids. Each procurement bid is structured in batches according to the various types of technologies included in each call. For instance, a bid in medical imaging is organized in separate batches, in which firms compete to become suppliers of different scanner models. Unicancer's evaluators apply a set of selection criteria specific to each batch, and each criterion is weighted differently in the final evaluation of equipment the firms offer. The list of criteria includes technical characteristics of the device, financial plan of the purchase, business analysis, price, clinical quality, training programs associated with the equipment, maintenance, and physical testing. In our sample, Unicancer's evaluators use, on average, 3.56 selection criteria for each batch, with a minimum of 1 and a maximum of 5 criteria. Each firm receives a score on a scale from 1 to 5 for each selection criteria and a final score that is the sum of the partial scores. A firm can be a candidate for supplying equipment in different batches of the same procurement bid, and more than one firm can be selected based on the final ranking. Finally, there is no deterministic threshold score above which candidates are automatically selected, Unicancer's evaluators in each batch decide the selected equipment for procurement according to the equipment ranking and hospitals' needs. On average, 66.17% of the equipment the firms offer is selected.

Patent data

To measure suppliers' innovation performance, we retrieve firms' patent applications from the European Patent Office's Statistical Database (PATSTAT[1]). We manually attribute the corresponding patent applications to each firm by searching the firm's name among the applicants in the patent documents. We retrieved 62,264 patent applications for the 14 firms in our sample over the period 1978 - 2020. Unicancer suppliers are both small specialized firms and large multiproduct firms. Among the large firms in our study sample, we find some of the top 30 patent applicants worldwide (WIPO 2019). Large firms are active in multiple sectors developing technologies other than medical equipment. Therefore, we classify patents in technology fields according to the International Patent Classification (IPC) hierarchical codes to isolate technologies relevant to our analysis.

Equipment data

We retrieve the description for each supplied piece of equipment from the Global Medical Device Nomenclature (GMDN). The GMDN is an internationally agreed standard way of naming and describing medical equipment created by the Food and Drug Administration. Over 60 national Medical Device Regulators use the GMDN standard. GMDN offers a detailed and homogenous description of each piece of equipment. Differently from patient brochures, leaflets, user manuals, and videotapes, GMDN's description is neither patient-oriented (and therefore not indicating enough information about the technology) nor practitioners oriented (highly detailed such as in users' manuals). These characteristics of the GMDN's equipment

[1] Academic researchers and policymakers consider PATSTAT as the reference database for patent analysis as the calculation of patent indicators and the production of technical indicators.

description are ideal for our study, providing a standardized and homogeneous technical description of the equipment close to the language used in patent applications.

4.2 Retrieving firms' technological fields relevant to the procurement bids

Several firms in our sample are large firms developing technologies in various technological domains, such as consumer electronics, telecommunications, and software. Therefore, measuring the impact of procurement of medical equipment considering all the firms' patent applications across different technological domains would bias our analysis. To identify technological domains relevant to the procurement bids, we proceed in three steps. First, we assess the similarity of the GMDN equipment description with the abstracts of the patents attributed to the supplier firm. To do so, we use the Word2vec neural network algorithm for text analysis that transforms documents into vectors according to the semantic meaning of the words appearing in their texts (Mikolov et al. 2013). The logic behind Word2vec algorithm is that words sharing common contexts end up close to one another in a vectorial space representing the semantic meaning of the words. We trained Word2vec on a large corpus of 1,000,000 patent abstracts in English. To obtain the vectorial representation of each document, i.e., the GMDN equipment descriptions and the suppliers' patent applications, we calculate the centroid of the vectorial representation of all the words included in each document. Then, to calculate a similarity index between the GMDN equipment descriptions and the suppliers' patent documents, we calculate the cosine similarity for each GMDN description-patent document pair. By doing so, we obtain a cosine similarity value for each GMDN description-patent application pair. Second, among all the pairs, we selected those with high values of cosine similarity in order to identify the supplier's patent documents similar to the piece of supplied equipment. We define a high cosine similarity value as a value higher than 0.85[2]. Third, once we identified patents highly similar to the equipment description, we retrieved the IPC codes at the group level[3] of those patents. We consider these IPC codes as the ones in which the outcome of the procurement bid potentially influences firms' innovation performance. We selected 279 distinct IPC codes identifying technological domains relevant to the equipment in our study sample. Table 1 shows the three most frequent IPC codes.

Table 1: Three most frequent relevant IPC codes.

[2] The threshold 0.85 has been selected by manually valuating the similarity between documents.
[3] See https://www.wipo.int/edocs/pubdocs/en/wipo_guide_ipc_2019.pdf for a detailed description of the IPC code hierarchical structure.

IPC code	IPC description	N. of products to which the IPC is associated*
A61B6	Apparatus for radiation diagnosis, e.g. combined with radiation therapy equipment	53
A61N5	Magnetotherapy	51
A61B5	Measuring for diagnostic purposes	45

NOTE: *Overall, we have 57 products offered by the firms in the procurement bids in our database.

4.3 Study sample

Our empirical analysis aims to assess how becoming a hospital supplier affects the yearly innovative performance of firms in relevant IPC classes for the equipment supplied. Therefore, we aim to measure the patenting activity for each firm that offered a piece of equipment in a relevant IPC class for 2,755 Firm-Equipment-IPC triplets. We observe each Firm-Equipment-IPC triplet for six years, three before and three after applying to become a supplier. Specifically, the period considered in our analysis ranges from *t-3* to *t+2*, where *t* is the procurement application year. Overall, our data includes 16,530 Firm-Equipment-IPC-Year observations (2,755*6).

4.4 Variables

To measure the firms' innovation performance, we define the variable *Number of Patents* as the firm's number of patents in the relevant IPC classes in year *t*. The average number of patents per year equals 5.09 (*Number of Patents*). We also calculate another proxy for the firms' innovation performance defining the variable *At least one patent* as a binary variable that equals 1 if the firm has at least one patent application in the relevant IPC class in year *t*, 0 otherwise. Firms file at least one patent in 62% of the Firm-Equipment-IPC observations in our sample.

Concerning the explanatory variables, we define *Supplier* as a binary variable that equals 1 if the firm is selected to supply equipment to Unicancer, 0 otherwise. The variable *Supplier* equals 1 for 46% of the Firm-Equipment-IPC pairs in our sample. Conditional on becoming a supplier, we define *AI-Powered* as a binary variable that equals 1 if the firm supplies AI-powered equipment, 0 otherwise. The variable *AI-Powered* equals 1 in 30.85% of the Firm-Equipment-IPC pairs in our sample. Table 2 reports the descriptive statistics of the variables.

Table 2: Dependent and independent variables.

	Observations	Average	Standard deviation
Number of Patents	16,530	5.09	16.14
At least one patent	16,530	0.62	0.49
Supplier	16,530	0.46	0.50
AI-Powered	7,644*	0.31	0.46

NOTE: We calculate the variable AI-Powered only for the subset of observations in which the firm becomes a supplier.

5. Methodology

We perform our analysis in two steps. First, we use a difference-in-differences approach to estimate the effect of becoming a Unicancer supplier on firms' innovation. Second, conditional on becoming a supplier, we analyze if suppliers of AI-powered equipment are more innovative compared to the suppliers of non-AI-powered equipment.

Effect of becoming a supplier

Equation 1 represents the model used to estimate the effect of becoming a Unicancer supplier. We used, in turn, the variables *Number of Patents* and *At least one patent* as dependent variables measuring the firm's innovative performance in year *t*. As independent variables, we include in our model the variable *Supplier* identifying firms becoming a Unicancer supplier and a dummy variable *After-market* that equals one after the procurement date, i.e., in the years from *t* to *t*+2. Finally, to account for unobserved Firm-Equipment unobserved time-invariant characteristics, we include Firm-Equipment fixed effects (γ). Our goal is to provide a reliable estimate of the coefficient β_1 measuring the effect of becoming a supplier on firms' propensity to patent after competing in the procurement bid. Finally, we estimate the coefficients with Ordinary Least Squares (OLS).

$$Firm's\ innovative\ performance_t =$$
$$\beta_0 + \beta_1 Supplier*After\text{-}market_t + \beta_2 After\text{-}market_t + \gamma$$

Equation 1

Effect of supplying AI-powered equipment

Once we have established the effect of becoming a Unicancer supplier on firms' innovation, we aim to estimate whether there is a significant difference between AI-powered equipment suppliers and non-AI-powered equipment suppliers. We select the subsample of 7,644 observations, including only firms that become suppliers in our sample, and we identify AI suppliers as defined by the *AI-Powered* variable. Using a difference-in-differences approach, we estimate the effect of becoming a supplier of AI-powered equipment as represented by α_1 in Equation 2. We estimate the coefficients with Ordinary Least Squares (OLS).

$$Firm's\ innovative\ performance_t = \alpha_0 + \alpha_1 AI\text{-}Powered{*}After\text{-}market_t + \alpha_2 After\text{-}market_t + \gamma$$

Equation 2

6. Results

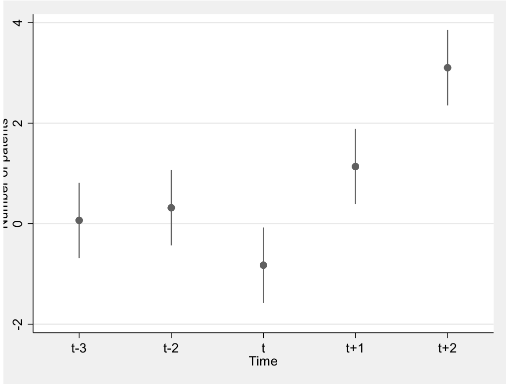
Our results show that firms selected as Unicancer suppliers have a significantly higher propensity to innovate than non-selected firms. Table 3, Column 1, shows that Unicancer suppliers file one patent application more per year in the three years after the procured contract is signed than firms that participated in the bid but were not selected. Coherently with Column 1, the regression exercise reported in Column 2 that explains the probability of observing *At least one patent* application in year *t* shows that suppliers' probability of applying for a patent is 8.4 percentage points higher than firms that participated in the bid but were not selected.

Table 3: Regression estimating the relationship between procurement and firms' innovative performance.

	(1) OLS Number of Patents	(2) LPM At least one patent
Supplier*After-market	1.01***	0.084***
	(0.22)	(0.011)
After-market	-1.07***	-0.12***
	(0.15)	(0.0072)
Constant	5.39***	0.52***
	(0.078)	(0.0037)
Observations	16,530	16,530
R-squared	0.836	0.613
Firm-Equipment-IPC fixed effects	Yes	Yes
Number of Firm-Equipment-IPC triplets	2,755	2,755

Figure 1 shows the marginal effects of becoming a supplier calculated separately for each of the six years from *t-3* to *t+2*. To calculate Figure 1, we estimated an econometric model in which we interact the variable *Supplier* with each of the six dummy variables identifying the six time periods from *t-3* to *t+2*. The year before the procurement competition, i.e., *t-1*, is considered as the reference year. Coherently with our expectations, we observe no impact of becoming a supplier before year *t*, the year of the procurement bid, while we observe a positive impact after winning the bid increases over time, in *t+1* and *t+2*.

Figure 1: Marginal effect of becoming a supplier estimated for each time period, from *t-3* to *t+2*.



NOTE: Bars represent 95% confidence intervals. The reference year that does not appear in the graph is *t-1*, the year preceding the procurement bid.

Once we have documented the effect of becoming a supplier on the firms' innovation performance, we test whether the flow of information from hospitals to suppliers is a possible mechanism explaining our results. If it is the case, we expect to observe a stronger effect of becoming a supplier on innovation when the information flow between hospitals and suppliers is higher, i.e., when firms supply AI-powered equipment to hospitals. We distinguish AI and non-AI-powered equipment according to the variable *AI-Powered*. We estimate the effect of supplying AI-powered equipment conditional on being a Unicancer supplier, using a subsample of 7,644 observations. Table 4, Columns 1 and 2, show that suppliers of AI-Powered equipment do not show a higher number of patent applications per year (although the estimated coefficient suggests a positive relationship between becoming a supplier and the firms' innovation performance) and a higher probability of filing a patent application (+3.9 percentage points) than suppliers of non-AI powered equipment.

Table 4: Regression estimating the relationship between supplying AI-powered equipment and the firms' innovative performance.

	(1) OLS Number of Patents	(2) LPM At least one patent
AI-Powered*After-market	0.20	0.039**
	(0.27)	(0.016)
After-market	-0.12	-0.043***
	(0.15)	(0.0089)
Constant	3.54***	0.40***
	(0.087)	(0.0053)
Observations	7,644	7,644
R-squared	0.868	0.686
Firm-Equipment-IPC fixed effects	Yes	Yes
Number of Firm-Equipment-IPC triplets	1,274	1,274

7. Further analyses

In this section, we conduct three additional analyses. First, we estimate the model presented in Equation 1 using the firms' number of medical publications as an alternative dependent variable. Second, we consider an alternative estimation strategy of the procurement effect using a regression discontinuity design approach. Third, we further test our hypothesis that the flow of information between hospitals and suppliers is the mechanism at the base of the observed procurement effect. To do so, we consider two cases (in addition to the supply of AI-Powered equipment) in which we expect a high information flow from hospitals to suppliers and, consequently, a stronger procurement effect.

7.1 Using firms' scientific publications as dependent variable

In Table 3 we measure firms' innovative performance as the *Number of patents* the probability of observing *At least one patent* in year *t*. However, firms either publish or patent the technological knowledge they produce (Dasgupta and David 1994). Therefore, publishing is another possible outcome of the firm innovative effort. To include the publications in our analysis, we estimate Equation 1 using as dependent variable the number of publications written by authors affiliated with the firm offering the equipment. Specifically, we calculate the variable firms' *Number of publications* by counting all the publications reporting the names of the firms in our sample as affiliations of at least one of the authors. We use the SCOPUS bibliometric dataset as the source of publication data, and we consider only publications that are classified in the field of medicine according to the SCOPUS classification and have at least one French author. We also define the dummy variable *At least one publication* as equal to one if, in year *t,* we find at least one firm's publication. The estimates of the econometric model are reported in Table 5. The sample on which the model is estimated includes 408 observations (instead of 16,530 as in Table 3) because the level of observation in Table 5 is Firm-Equipment-year (instead of Firm-Equipment-IPC-year as in Table 4). The average *Number of publications* per year in our study sample is 3.29, and the unconditional probability of observing *At least one publication* equals 36%. Table 5 shows that firms becoming Unicancer suppliers have 1.50 more publications per year than non-selected firms. These outcomes are coherent with Table 4, where we use patent data to calculate proxies for firms' innovative performance. Our results on publications also add evidence to recent procurement studies that find that procurement is associated with significantly higher scientific publications and hiring additional scientists (Belenzon and Cioaca 2021).

Table 5: Regression estimating the relationship between procurement and firms' innovative performance. Firms' innovation is proxied by the number of scientific articles.

	(1)	(2)
	OLS	LPM
	Number of publications	At least one publication
Supplier*After-market	1.50***	0.25***
	(0.55)	(0.073)
After-market	-1.67***	-0.19***
	(0.45)	(0.060)
Constant	3.63***	0.37***
	(0.18)	(0.024)
Observations	408	408
R-squared	0.877	0.560
Firm-Equipment fixed effects	Yes	Yes
Number of Firm-Equipment pairs	68	68

7.2 Regression discontinuity estimation

A high score assigned by Unicancer evaluators to equipment increases the firm's probability of becoming a supplier but does not completely determine it. In other words, firms offering equipment that obtain high scores have a high probability of winning the procurement bid but there is no specific score threshold above which firms are automatically selected to become suppliers. In this context, we apply an alternative approach to the estimate of Equation 1, implementing a regression discontinuity design approach that uses the scores assigned by Unicancer evaluators to each piece of equipment. Specifically, we apply a two-step estimate (Angrist and Pischke, 2008). First, we use a parametric polynomial regression to predict the probability of becoming a supplier with the score obtained by the equipment offered by the firm (Equation 3). The variable *Score* is calculated as the average value of the scores assigned to each characteristic of the equipment offered. It is a continuous variable that ranges from 0 to 5. Second, we use the predicted probability of becoming a supplier as an explanatory variable in a difference-in-differences model specification as reported in Equation 4.

$$\widehat{Supplier} = \boldsymbol{\delta_2} Score \quad + \boldsymbol{\delta}_3 Score^{\,2} + \boldsymbol{\delta}_4 Score^{\,3}$$
Equation 3

$$Firm's\ innovative\ performance_t = \\ \beta_0 + \boldsymbol{\beta_1} \widehat{Supplier} \text{*} After\text{-}market_t + \beta_2 After\text{-}market_t + \gamma$$
Equation 4

Table 6 confirms a positive and significant effect of becoming a supplier on Firms' innovation performance, in line with the results reported in Table 3. As an additional robustness check of our results, following the idea behind regression discontinuity design, we estimate Equation 1 excluding Firm-Equipment pairs characterized by very low and very high scores. The rationale is to include in our sample only pieces of equipment that are qualitatively similar according to the Unicancer evaluators and that differ only because some are selected and others are not. We define very high scores as the ones above the 75th percentile and very low scores as the ones below the 25th percentile. Table 7 shows that the results of this second robustness check are in line with our results presented in Table 4.

Table 6: Regression estimating the relationship between procurement and firms' innovative performance using the regression discontinuity design approach.

	(1) OLS Supplier	(2) Random effects estimates Number of Patents	(3) Random effects estimates At least one patent
$\widehat{Supplier}$*After-market		1.28**	0.10***
		(0.59)	(0.028)
After-market		-1.19***	-0.12***
		(0.29)	(0.014)
$\widehat{Supplier}$		1.26	0.053
		(1.51)	(0.041)
Score	-5.06***		
	(0.34)		
$Score^2$	1.18***		
	(0.097)		
$Score^3$	-0.081***		
	(0.0089)		
Constant	6.95***	4.80***	0.49***
	(0.39)	(0.47)	(0.014)
Observations	16,530	16,530	16,530
R-squared	0.145	-	-

Table 7: Regression estimating the relationship between procurement and firms' innovative performance. The sample used for the estimates excludes Firm-Equipment pairs with very high or very low scores assigned by Unicancer's evaluators.

	(1) OLS Number of Patents	(2) LPM At least one patent
Supplier*After-market	0.91**	0.11***
	(0.40)	(0.016)
After-market	-1.38***	-0.14***
	(0.22)	(0.0089)
Constant	5.54***	0.51***
	(0.13)	(0.0053)
Observations	9,030	9,030
R-squared	0.783	0.572
Firm-Equipment fixed effects	Yes	Yes
Number of Firm-Equipment pairs	1,408	1,408

7.3 Testing the mechanism at the base of the procurement effect

We explained the observed positive effect of procurement on firms' innovation with the information flow between hospitals and suppliers. In the analyses reported in Table 4, we use the supply of *AI-powered* equipment as a proxy for a high information flow. However, there are other cases in which we expect a high information flow from hospitals to suppliers. We identified two of these cases. The first case is when firms are suppliers of a market of large size. In this case, the probability of having information feedback from hospitals is higher due to the high number of equipment users that can provide firms with useful feedback on the equipment technology. The second case in which we expect a higher flow of useful information for firms' innovation activities is when equipment is selected by Unicancer evaluators mainly for its technological characteristics. In this case, the equipment technology is crucial for the users, who are expected to become a source of technology-related feedback for the firms.

Size of the market

Following earlier studies, we expect to find a larger effect of hospital procurement on firms' innovation in larger markets (Schmookler 1962; Mowery 2012). We consider two proxies of market size. First, we calculate the number of Unicancer hospitals associated with each procurement bid. We define the dummy variable *Many-hospitals* as equal to one if the number of hospitals involved in the bid is higher than the average number of hospitals in the bid in our sample, i.e., 9 hospitals. As second proxy for market size, we calculate the number of pieces of equipment provided to the hospitals by the firms. We define the dummy variable *High-volume* as equal to one if the volume is higher than the average in our sample, i.e., 10 pieces of equipment.

Conditional on becoming a Unicancer supplier, we estimate the model described in Equation 2 but substituting the variable *AI-powered* equipment with the variable *Many-hospitals* (Table 7) and with the variable *High-volume* (Table 8). Table 7 and Table 8 show that market size boosts the effect of procurement. Based on our assumption that larger markets increase the flow of information between hospitals and firms, these results further support our hypothesis that the effect of procurement on firms' innovation is due to information flow.

Table 7: Regression estimating the relationship between procurement and firms' innovative performance in large and small markets. The market size is defined according to the number of hospitals supplied.

	(1) OLS Number of Patents	(2) LPM At least one patent
Many-hospitals*After-market	0.66***	0.082***
	(0.25)	(0.015)
After-market	-0.34**	-0.066***
	(0.16)	(0.0098)
Constant	3.54***	0.40***
	(0.087)	(0.0053)
Observations	7,644	7,644
R-squared	0.756	0.548
Firm-Equipment-IPC fixed effects	Yes	Yes
Number of Firm-Equipment-IPC triplets	1,274	1,274

Table 8: Regression estimating the relationship between procurement and firms' innovative performance in large and small markets. The market size is defined according to the number of pieces of equipment supplied.

	(1) OLS Number of Patents	(2) LPM At least one patent
High-volume*After-market	1.15***	0.076***
	(0.25)	(0.015)
After-market	-0.74***	-0.076***
	(0.19)	(0.012)
Constant	3.54***	0.40***
	(0.087)	(0.0053)
Observations	7,644	7,644
R-squared	0.756	0.550
Firm-Equipment-IPC fixed effects	Yes	Yes
Number of Firm-Equipment-IPC triplets	1,274	1,274

Technology based selection

We expect the effect of procurement on innovation to be reinforced by the supply of equipment at the frontier of technology than off-the-shelf products (Florio et al, 2017; Aiutio et al. 2004; CERN 2018; Cozzi and Impullitti 2010). When the technology of the procured equipment plays a crucial role for hospitals, we expect the information flow from hospitals to firms to be on the technological aspects of the equipment, favoring equipment technological improvement and, consequently, firms' innovation. We assess the technological content of the supplied equipment with two proxies. First, we define the dummy variable *High-tech* as equal to 1 if the Unicancers' evaluators weigh the technology embedded in the equipment more the 50% of all the selection criteria. Second, we consider the number of criteria used by the Unicancers' evaluators in the selection process. The rationale for this proxy for the high technological content of the equipment is that if a large number of selection criteria are considered in the selection, less weight is attributed to the equipment technology. We define the variable *Many-criteria* as equal to 1 if the Unicancer evaluators apply more than 3 selection criteria, where 3 is the average number of selection criteria applied in our sample.

Conditional on becoming a Unicancer supplier, we estimate the model described in Equation 2 but substituting the variable *AI-powered* equipment with the variable *High-tech* (Table 9) and *Many-criteria* (Table 10). Table 9 shows that firms selected with technology as the main selection criterion innovate significantly more than firms selected according to other criteria. We observe a positive effect of the interaction *High-tech*After-market* on the variable *Number of patents* but no effect on the variable *At least one patent*. Similarly, Table 10 shows that when Unicancer evaluators apply many criteria to select equipment, weighting other characteristics than the technology, the effect of procurement on firms' innovation performance is lower. We observe a negative effect of the interaction *Many-criteria*After-market* on the variable *Number of patents* but no effect on the variable *At least one patent*.

Table 9: Regression estimating the relationship between procurement and firms' innovative performance for high-tech and low-tech equipment. High-tech equipment is the one selected by evaluators based on the technology embedded.

	(1) OLS Number of Patents	(2) LPM At least one patent
High-tech*After-market	0.54**	-0.0067
	(0.25)	(0.015)
After-market	-0.38**	-0.027**
	(0.19)	(0.012)
Constant	3.54***	0.40***
	(0.087)	(0.0053)
Observations	7,644	7,644
R-squared	0.868	0.629
Firm-Equipment-IPC fixed effects	Yes	Yes
Number of Firm-Equipment-IPC pairs	1,274	1,274

Table 10: Regression estimating the relationship between procurement and firms' innovative performance using many or few selection criteria.

	(1) OLS Number of Patents	(2) LPM At least one patent
Many-criteria*After-market	-0.51**	0.0063
	(0.26)	(0.016)
After-market	0.28	-0.035***
	(0.21)	(0.013)
Constant	3.54***	0.40***
	(0.087)	(0.0053)
Observations	7,644	7,644
R-squared	0.755	0.541
Firm-Equipment-IPC fixed effects	Yes	Yes
Number of Firm-Equipment-IPC triplets	1,274	1,274

8. Conclusion

This paper contributes to a better understanding of how hospital procurement in oncology can boost industrial innovation in the health sector. Our work investigates the impact of becoming a supplier of the French national network of excellence hospitals -Unicancer- on the supplier's innovative performance. Moreover, we test whether a higher information flow from hospitals to suppliers, proxied by the supply of AI-Powered medical equipment, is associated with higher innovative performance. The rationale for using AI-Powered equipment as a proxy for a high information flow is that, through AI-Powered medical equipment, hospitals provide data, information, and knowledge to firms that use this information to innovate.

Our results show that firms becoming hospital suppliers have a significantly higher propensity to innovate. About the mechanism, we show that supplying AI-powered equipment further boosts the supplier's innovative performance.

We conduct a series of robustness checks on our results. Having data on the grades assigned by the hospital to each product, we apply a fuzzy regression discontinuity design to obtain estimates as close as possible to the causal effect of becoming a supplier to Unicancer. Our discontinuity design regression exercise confirms our main results. Finally, we run a number of additional analyses to confirm that the information flow from hospitals to supplier firms is the mechanism driving our results. We show that firms selected in procurement bids focusing the selection on technological criteria are more innovative than those selected weighing less technological criteria. Furthermore, suppliers selected in large bids involving many hospitals and a high equipment volume also benefited from becoming suppliers.

These results inform policymakers on the design of procurement bids to encourage firms' innovation. Our result on the positive effect of AI-Powered equipment on firms' innovation is coherent with the view that hospitals represent an appropriate environment for developing AI technologies due to the volume of data they produce. Moreover, we show that large procurement bids focusing on technological selection criteria positively affect supplier firms' innovation.

References

Aschhoff, Birgit, and Wolfgang Sofka. 2009. "Innovation on Demand—Can Public Procurement Drive Market Success of Innovations?" *Research Policy,* 13.

Askfors, Ylva, and Helena Fornstedt. 2018. "The Clash of Managerial and Professional Logics in Public Procurement: Implications for Innovation in the Health-Care Sector." *Scandinavian Journal of Management* 34 (1): 78–90. https://doi.org/10.1016/j.scaman.2018.01.001.

Autio, Erkko, Ari-Pekka Hameri, and Olli Vuola. 2004. "A Framework of Industrial Knowledge Spillovers in Big-Science Centers." *Research Policy* 33 (1): 107–26. https://doi.org/10.1016/S0048-7333(03)00105-7.

Belenzon, Sharon, and Larisa C. Cioaca. 2021. "Guaranteed Markets and Corporate Scientific Research." *National Bureau of Economic Research.* No. w28644. https://www.nber.org/system/files/working_papers/w28644/w28644.pdf.

Bianchini, Stefano, Patrick Llerena, and Sofia Patsali. 2019. "Demand-Pull Innovation in Science: Empirical Evidence from a Research University's Suppliers." *Research Policy* 48: 100005.

Bonvillian, William B. 2018. "DARPA and Its ARPA-E and IARPA Clones: A Unique Innovation Organization Model." *Industrial and Corporate Change* 27 (5): 897–914. https://doi.org/10.1093/icc/dty026.

Boon, Wouter, and Jakob Edler. 2018. "Demand, Challenges, and Innovation. Making Sense of New Trends in Innovation Policy." *Science and Public Policy* 45 (4): 435–47. https://doi.org/10.1093/scipol/scy014.

Castelnovo, Paolo, Massimo Florio, Stefano Forte, Lucio Rossi, and Emanuela Sirtori. 2018. "The Economic Impact of Technological Procurement for Large-Scale Research Infrastructures: Evidence from the Large Hadron Collider at CERN." *Research Policy* 47 (9): 1853–67. https://doi.org/10.1016/j.respol.2018.06.018.

Chicot, Julien, and Mireille Matt. 2018. "Public Procurement of Innovation: A Review of Rationales, Designs, and Contributions to Grand Challenges." *Science and Public Policy* 45 (4): 480–92. https://doi.org/10.1093/scipol/scy012.

Dalpé, Robert. 1994. "Effects of Government Procurement on Industrial Innovation." *Technology in Society* 16 (1): 65–83. https://doi.org/10.1016/0160-791X(94)90021-3.

Edler, Jakob, and Luke Georghiou. 2007. "Public Procurement and Innovation—Resurrecting the Demand Side." *Research Policy* 36 (7): 949–63.

Edquist, Charles, Leif Hommen, and Lena Tsipouri. 2000. "Policy Implications." *Public Technology Procurement and Innovation*, 301–11.

Esteva, Andre, Katherine Chou, Serena Yeung, Nikhil Naik, Ali Madani, Ali Mottaghi, Yun Liu, Eric Topol, Jeff Dean, and Richard Socher. 2021. "Deep Learning-Enabled Medical Computer Vision." *NPJ Digital Medicine* 4 (1): 5.

Esteva, Andre, Alexandre Robicquet, Bharath Ramsundar, Volodymyr Kuleshov, Mark DePristo, Katherine Chou, Claire Cui, Greg Corrado, Sebastian Thrun, and Jeff Dean. 2019. "A Guide to Deep Learning in Healthcare." *Nature Medicine* 25 (1): 24–29. https://doi.org/10.1038/s41591-018-0316-z.

Florio, Massimo. 2021. "Large-Scale Investment in Science: Economic Impact and Social Justice." *The Economics of Big Science: Essays by Leading Scientists and Policymakers*, 105–12.

Florio, Massimo, Francesco Giffoni, Anna Giunta, and Emanuela Sirtori. 2018. "Big Science, Learning, and Innovation: Evidence from CERN Procurement." *Industrial and Corporate Change* 27 (5): 915–36.

Fontana, Roberto, and Marco Guerzoni. 2008. “Incentives and Uncertainty: An Empirical Analysis of the Impact of Demand on Innovation.” *Cambridge Journal of Economics* 32 (6): 927–46. https://doi.org/10.1093/cje/ben021.

Food and Drug Administration. 2019. “Proposed Regulatory Framework for Modifications to Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD).”

Fuchs, Erica RH. 2010. “Rethinking the Role of the State in Technology Development: DARPA and the Case for Embedded Network Governance.” *Research Policy* 39 (9): 1133–47.

García-Altés, Anna, Martin McKee, Luigi Siciliani, Pedro Pita Barros, Lasse Lehtonen, Heather Rogers, Dionne Kringos, Jelka Zaletel, and Jan De Maeseneer. 2023. “Understanding Public Procurement within the Health Sector: A Priority in a Post-COVID-19 World.” *Health Economics, Policy and Law* 18 (2): 172–85. https://doi.org/10.1017/S1744133122000184.

Georghiou, Luke. 2006. “Effective Innovation Policies for Europe–the Missing Demand-Side.” *Report for the Prime Minister’s Office of Finland, Economic Council of Finland*.

Georghiou, Luke, Jakob Edler, Elvira Uyarra, and Jillian Yeow. 2014. “Policy Instruments for Public Procurement of Innovation: Choice, Design and Assessment.” *Technological Forecasting and Social Change* 86 (C): 1–12.

Geroski, Paul A. 1990. “Procurement Policy as a Tool of Industrial Policy.” *International Review of Applied Economics* 4 (2): 182–98.

Guerzoni, Marco, and Emilio Raiteri. 2015. “Demand-Side vs. Supply-Side Technology Policies: Hidden Treatment and New Empirical Evidence on the Policy Mix.” *Research Policy* 44 (3): 726–47. https://doi.org/10.1016/j.respol.2014.10.009.

Hamamoto, Ryuji, Kruthi Suvarna, Masayoshi Yamada, Kazuma Kobayashi, Norio Shinkai, Mototaka Miyake, Masamichi Takahashi, Shunichi Jinnai, Ryo Shimoyama, and Akira Sakai. 2020. “Application of Artificial Intelligence Technology in Oncology: Towards the Establishment of Precision Medicine.” *Cancers* 12 (12): 3532.

He, Jianxing, Sally L. Baxter, Jie Xu, Jiming Xu, Xingtao Zhou, and Kang Zhang. 2019. “The Practical Implementation of Artificial Intelligence Technologies in Medicine.” *Nature Medicine* 25 (1): 30–36. https://doi.org/10.1038/s41591-018-0307-0.

Iori, Martina, Arianna Martinelli, and Andrea Mina. 2021. “The Direction of Technical Change in AI and the Trajectory Effects of Government Funding.” *LEM Working Paper Series*, 74.

Kastanioti, Catherine, Nick Kontodimopoulos, Dionysis Stasinopoulos, Nikolaos Kapetaneas, and Nikolaos Polyzos. 2013. “Public Procurement of Health Technologies in Greece in an Era of Economic Crisis.” *Health Policy* 109 (1): 7–13. https://doi.org/10.1016/j.healthpol.2012.03.015.

Langrish, John, Michael Gibbons, William G. Evans, and Frederic Raphael Jevons. 1972. *Wealth from Knowledge: Studies of Innovation in Industry*. Springer.

Lichtenberg, Frank R. 1988. “The Private R and D Investment Response to Federal Design and Technical Competitions.” *The American Economic Review* 78 (3): 550–59.

Mazzucato, Mariana. n.d. “THE ENTREPRENEURIAL STATE.”

Meehan, Joanne, Laura Menzies, and Roula Michaelides. 2017. “The Long Shadow of Public Policy; Barriers to a Value-Based Approach in Healthcare Procurement.” *Journal of Purchasing and Supply Management* 23 (4): 229–41. https://doi.org/10.1016/j.pursup.2017.05.003.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. “Efficient Estimation of Word Representations in Vector Space.” arXiv. http://arxiv.org/abs/1301.3781.

Miller, Fiona A., and Pascale Lehoux. 2020. “The Innovation Impacts of Public Procurement Offices: The Case of Healthcare Procurement.” *Research Policy* 49 (7): 104075.
Mowery, David C. 2010. “Military R&D and Innovation.” In *Handbook of the Economics of Innovation*, 2:1219–56. Elsevier.
———. 2012. “Defense-Related R&D as a Model for ‘Grand Challenges’ Technology Policies.” *Research Policy* 41 (10): 1703–15. https://doi.org/10.1016/j.respol.2012.03.027.
Mudyarabikwa, Oliver, and Krishna Regmi. 2016. “Public-Private Partnerships and Efficiency in Public Procurement of Primary Healthcare Infrastructure: A Qualitative Research in the NHS UK.” *Journal of Public Health* 24: 91–100.
Myers, S., and D. G. Marquis. 1969. “Successful Industrial Innovations. A Study of Factors Underlying Innovation in Selected Firms.” PB211097. Institute of Public Administration, Washington, D.C. https://ntrl.ntis.gov/NTRL/dashboard/searchResults/titleDetail/PB211097.xhtml.
Patsali, Sofia. 2021. “University Procurement-Led Innovation.” *GREDEG Working Papers*, GREDEG Working Papers, March. https://ideas.repec.org/p/gre/wpaper/2021-13.html.
Petrou, Ioannis. 2007. “The European Space Agency’s Procurement System: A Critical Assessment.” *Pub. Cont. LJ* 37: 141.
Robinson, Douglas K. R., and Mariana Mazzucato. 2019. “The Evolution of Mission-Oriented Policies: Exploring Changing Market Creating Policies in the US and European Space Sector.” *Research Policy*, New Frontiers in Science, Technology and Innovation Research from SPRU’s 50th Anniversary Conference, 48 (4): 936–48. https://doi.org/10.1016/j.respol.2018.10.005.
Rolfstam, Max. 2012. “Understanding Public Procurement of Innovation: Definitions, Innovation Types and Interaction Modes.” *Innovation Types and Interaction Modes (February 26, 2012)*.
Rolfstam, Max, Wendy Phillips, and Elmer Bakker. 2011. “Public Procurement of Innovations, Diffusion and Endogenous Institutions.” *International Journal of Public Sector Management* 24 (5): 452.
———. n.d. “Public Procurement and the Diffusion of Innovations: Exploring the Role of Institutions and Institutional Coordination,” 22.
Rosenberg, Nathan. 1992. “Scientific Instrumentation and University Research.” *Research Policy* 21 (4): 381–90. https://doi.org/10.1016/0048-7333(92)90035-3.
Sherwin, Chalmers W., and Raymond S. Isenson. 1967. “Project Hindsight: A Defense Department Study of the Utility of Research.” *Science* 156 (3782): 1571–77.
Slavtchev, Viktor, and Simon Wiederhold. 2016. “Does the Technological Content of Government Demand Matter for Private R&D? Evidence from US States.” *American Economic Journal: Macroeconomics* 8 (2): 45–84.
Sorenson, Corinna, and Panos Kanavos. 2011. “Medical Technology Procurement in Europe: A Cross-Country Comparison of Current Practice and Policy.” *Health Policy* 100 (1): 43–50. https://doi.org/10.1016/j.healthpol.2010.08.001.
Topol, Eric. 2019. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. Hachette UK.
Uyarra, Elvira, Jakob Edler, Javier Garcia-Estevez, Luke Georghiou, and Jillian Yeow. 2014. “Barriers to Innovation through Public Procurement: A Supplier Perspective.” *Technovation* 34 (10): 631–45. https://doi.org/10.1016/j.technovation.2014.04.003.
Uyarra, Elvira, and Kieron Flanagan. 2010a. “Understanding the Innovation Impacts of Public Procurement.” *European Planning Studies* 18 (1): 123–43. https://doi.org/10.1080/09654310903343567.

———. 2010b. “Understanding the Innovation Impacts of Public Procurement.” *European Planning Studies* 18 (1): 123–43. https://doi.org/10.1080/09654310903343567.

Uyarra, Elvira, Kieron Flanagan, Edurne Magro, and Jon Mikel Zabala-Iturriagagoitia. 2017. “Anchoring the Innovation Impacts of Public Procurement to Place: The Role of Conversations.” *Environment and Planning C: Politics and Space* 35 (5): 828–48. https://doi.org/10.1177/2399654417694620.

Uyarra, Elvira, Jon Mikel Zabala-Iturriagagoitia, Kieron Flanagan, and Edurne Magro. 2020. “Public Procurement, Innovation and Industrial Policy: Rationales, Roles, Capabilities and Implementation.” *Research Policy* 49 (1): 103844. https://doi.org/10.1016/j.respol.2019.103844.

WIPO, World Intellectual Property. 2019. *WIPO Technology Trends 2019: Artificial Intelligence*. Geneva: World Intellectual Property Organization.

Yu, Kun-Hsing, Andrew L. Beam, and Isaac S. Kohane. 2018. “Artificial Intelligence in Healthcare.” *Nature Biomedical Engineering* 2 (10): 719–31. https://doi.org/10.1038/s41551-018-0305-z.