Technovation 121 (2023) 102683

Contents lists available at ScienceDirect

Technovation

journal homepage: www.elsevier.com/locate/technovation

A quasi-experimental design to assess the innovative impact of public procurement: An application to the Italian space industry

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ARTICLE INFO

JEL classification:
C25
H57
O32
O38

Keywords:
Public procurement
Innovation
Patent
Space industry
Staggered diff-in-diff
Multiple treatments

ABSTRACT

A growing number of empirical studies have shown that public procurement can be a relevant demand-side innovation policy. We assess the impact of public procurement on firms' innovation in the space industry. This is an important field of application because it widely uses public procurement and the procuring space agencies have distinctive characteristics, namely innovation-oriented mandate, relevant internal competences and professional skills. Specifically, we focus on the procurement activity of the Italian Space Agency over a 15-years period. We assess the causal impact of public procurement on suppliers' patenting activity by implementing a novel *quasi-experimental* design. Our approach allows addressing the endogeneity issues and potential estimation biases stemming from both the procurement selection process and its time heterogeneity. By combining matching techniques with a staggered diff-in-diff approach, we find that, after the beginning of the procurement collaboration, the supplier firms have increased on average their patent applications by roughly 10% compared to the control group. Such effect is increasing in time and persists for several years after the beginning of the procurement relationship.

1. Introduction

The space industry plays a strategic role in our society. Space-related infrastructures and satellite data have increasingly found applications in several fields, ranging from transportation to telecommunications, from the management of natural disasters to the monitoring of the evolution of environmental phenomena, such as marine acidification, terrestrial desertification, deforestation, concentration of greenhouse gases, the thinning of the stratospheric ozone layer (Onoda and Young 2017). Space technologies, particularly Earth Observation by satellites, represent a formidable tool to address contemporary societal challenges such as the ecological transition, sustainable development, and social well-being in the vision of a Knowledge Economy and Society (European Commission 2016).

Economic data confirm the space industry's growing importance. According to OECD (2019) worldwide expenditures in space activities were estimated USD 62.8 billion, while the upstream space industry (particularly launchers and other hardware) was valued USD 20 billion. Space agencies are key actors in this market. Their innovation-oriented missions are aimed at discovering as much as possible about the Earth, the surrounding space environment, the Solar System, and the Universe in general. For this purpose, they design and manage space infrastructures and satellite technologies and services. Public procurement represents the most relevant tool used so far to purchase specific and dedicated products in the market. While it is widely recognized that this activity supported the development of the upstream space industry, with an important stimulus to the related R&D and innovative activity (OECD, 2016; ESPI 2019; OECD 2021), a rigorous empirical analysis of the impact of their procurement activity is still lacking.

Considering this background, we investigate whether the public procurement activity effectively supports innovation in the upstream space industry, with an application to the Italian case. Specifically, the main goal of our research is to assess the causal impact of the procurement placed by the Italian Space Agency (ASI) on the supplying firms' patenting activity, which is used as a (objective though imperfect) proxy of their innovation output. We contribute to the related literature by developing a novel quasi-experimental design which addresses the procurement endogeneity issue.

Public procurement (PP) is the most adopted demand-side policy to correct the market failures deriving from the public nature of innovation

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https://doi.org/10.1016/j.technovation.2022.102683
Received 15 February 2022; Received in revised form 2 November 2022; Accepted 11 December 2022
Available online 21 December 2022

and the uncertainty of the related economic returns (Arrow 1962; Griliches 1979; Grossman and Helpman 1991). In particular, public procurement of innovation (PPI, hereafter) has been defined as a specific type of procurement where the procuring authority acts as a launch customer for specialized or dedicated products or services that are not yet commercially available on a large-scale but can be developed within a reasonable timeframe (Edquist et al., 2000). The economic literature has recognized that PPI can foster innovation via multiple channels, such as increasing demand predictability, lowering the uncertainty of the innovative process or reducing the financial constraints associated to innovation (Edquist et al., 2015; Edler and Georghiou, 2007; OECD, 2017; Bleda and Chicot, 2020). However, other research stressed that several barriers could limit the PPI capacity to effectively support innovation (Geroski, 1990). For instance, innovation can be hindered by the existence of information asymmetries between the contracting parties, specifically by the procurer's difficulty to observe ex-ante the suppliers' innovation capability, monitor its R&D effort and verify ex-post the value of its innovation (Edler et al., 2006; Guerzoni 2010; Uyarra et al., 2014). To overcome these barriers, the procuring agency should exhibit a clear innovation-oriented mission, a risk-oriented attitude, and specific internal competences (Georghiou et al., 2014).

Considering this literature, our decision to focus on the procurement activity of a major space agency can be motivated on several grounds. First, in light of the size of the European space industry and the role played by the space agencies within this sector, the European space policy is increasingly studied as a relevant case of mission-oriented policy towards the development of new technological challenges and market opportunities (Mazzucato and Robinson, 2018). It has been argued that: "*unlike all the other space faring nations for which strategic autonomy and prestige considerations have been the primary justifications for public expenditures, European public investments in space have been primarily subject to the logic of economic return, being conceived as an enabler of economic growth and job creation in Europe, fostering its innovation potential,* supporting *scientific progress and responding to public policy objectives*" (see ESPI 2020, n75).

Within this context, our research focuses on the ASI, one of the major space agencies in Europe, which was established in 1988 and whose yearly budget sharply increased from €350 million in 2015 to more than €1 billion in 2020. Further considerations clarify why the potential obstacles that can inhibit the PP effectiveness in supporting innovation are likely to be less relevant within this context, mainly because of the ASI internal mission and competences.

As stated in its statute, one of the ASI primary mandates is "*to promote, develop and spread (…) the scientific and technological research applied to the space and aerospace sectors*" (DL 128/2003), this resulting in an innovation-oriented procurement strategy. With this respect, ASI can be described as a technological contracting agency which finances applied research, programs, and projects with high technological value. To develop its space missions, ASI purchases very specialized and dedicated products that are not readily available in the market and, thanks to its internal competences, it can manage potential risks associated with the procurement process. Submitted projects are not evaluated on the cheapest bid basis but according to technological and performance standards, which are clearly specified in the call for tenders. Moreover, in the post-procurement phase, ASI interacts effectively with the supplying firms to overcome potential technical problems that may arise in the development of new products.

Previous research has recognized that specific sectors, including the defense and the aerospace, have been forerunners in the use of the PPI tool to purchase highly specialized technological products that were not available on the market (OECD 2011; Raiteri 2018; Geroski, 1990). We further investigate this field exploiting a unique dataset provided directly by ASI, which reports the orders ASI placed to purchase the technologies needed to develop and manage space missions and programs over the period 2004–2018. This dataset disregards the regular procurements of off-the-shelf products which ASI purchases for its routine activity, and thus includes only the subset of orders specifically aimed at purchasing high-tech products or services. We extend this dataset with the yearly balance-sheets and patent applications, extracted respectively from the Orbis and Orbis Intellectual Property databases, both managed by Bureau Van Dick. Indeed, ORBIS also reports relevant information relating to the patenting activity of companies. Bureau Van Dijk has extended the OECD HAN database (Harmonised Applicants' Names) (Thoma et al., 2010) and provides a reliable matching of patent assignee names (and the corresponding publication numbers) with ORBIS firms. After having extracted from Orbis IP all the patents globally filed by each firm, following previous studies, we restrict the analysis only to those patents filed in the world main patent offices - USPTO, EPO, JPO and WIPO – which, on top of granting a wider geographical intellectual property protection in the most relevant markets, are acknowledged for presenting a rigorous and transparent patent evaluation procedure. This choice is aimed at increasing the patents' likelihood to represent a valid proxy of firms' innovation.

Our major contribution to the PPI literature is the design of a novel quasi-experimental empirical strategy which addresses the endogeneity issues of the procurement activity, allowing to assess its causal impact on firms' innovation.

The first issue is that PPI (our treatment) is not exogenous, nor it is randomly assigned across firms. The procurer selects the supplying firms according to some observable characteristics. Due to this selection issue, we cannot in principle assess whether, in the post-procurement period, the firms' innovative activity varies because of the procurement itself or because of their intrinsic superior innovative capacity. Apart from some notable exceptions (Dai et al., 2021), previous studies failed to address this endogeneity issue, thus providing a biased evaluation of the real impact of procurement on innovation. To address it, we develop a conditional difference-in-differences (diff-in-diff) estimation model based on a propensity score matching technique.

The second issue is the potential estimation bias arising from the heterogeneity of the procurement timing (firms enter the procurement collaboration in different years), which has not been properly addressed by any research so far. Recent advances in the econometric literature have highlighted that the application of the standard diff-in-diff model can lead to biased estimates when multiple treatments take place at different times (Goodman-Bacon 2021; Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfoeuille 2020). Building on Deshpande and Li (2019) and Fadlon and Nielsen (2021), we apply a staggered diff-in-diff design, which allows to causally assess the impact of procurement on firms' patenting activity by exploiting the heterogeneity in the treatment time. This approach also allows to tackle possible issues related to the endogenous selection of suppliers, since it does not require the procurement to be an exogenous event, but only its timing to be random. We also investigate the dynamics of the PPI effect using the novel estimators developed by Callaway and Sant'Anna (2020), and de Chaisemartin and D'Haultfoeuille (2020), which are robust to heterogeneous and dynamic treatment effects.

The estimation strategies provide consistent evidence that firms benefited from the procurement relationship with ASI. Accordingly, their patenting activity increased compared to the pre-procurement level and was higher than that of the control group of non-ASI suppliers.

Beyond the methodological approach, our research contributes to the PPI literature in several ways.

First, we bring some empirical evidence supporting the theoretical literature on the PPI's barriers. Notably, we show that the presence of a public procurer with high and specific skills allows overcoming the barriers that can limit the effective ability of procurement to support innovation. We also show the temporal dynamics of the PPI impact on firms'patenting activity. We show that, in the post-procurement period, the patenting activity is not constant, and it evolves in a non-linear way. This is consistent with the idea that innovation needs time to materialize. Finally, this represents one of the first studies on the PPI impact on the space industry. Despite being under-analyzed, this represents a crucial sector from a socio-economic perspective. This can be understood considering the European Commission policy agenda within the space economy field, whose future main actions to supporting research and innovation will include, among others, the strengthening of the use of innovative procurement schemes to stimulate the demand-side of innovation (see ESPI, 2019). This looks particularly relevant within the current macroeconomic and geopolitical context that may reduce the propensity to innovate on behalf of the private sector, thus requiring public institutions like space agencies to play an active role.

The paper is organized as follows. Building on the relevant literature, section 2 presents the conceptual framework on PPI. Section 3 presents the data. In section 4, we describe the empirical strategy, while the estimation results are presented in section 5. Several robustness checks are introduced in section 6. In Section 7, we draw conclusions and discuss policy implications.

2. Theoretical background and literature review

It is well recognized that sub-optimal investments in R&D-based innovation can originate from multiple factors related to the intrinsic nature of the innovation process (Arrow 1962). Difficulties in financing innovation due to the uncertainty of R&D returns and their imperfect appropriability stemming from the public nature of knowledge can be acknowledged among the main arguments calling for innovation-supporting public policies and legislation (Griliches 1979; Grossman and Helpman 1991; Martin and Scott 2000; Foray 2004; Hall and Lerner, 2010).

Government intervention within this field has traditionally been supply-side oriented, including measures as intellectual property right protection (Scotchmer 1991; Landes and Posner 2003), R&D subsidies and R&D tax credits (Busom 2000; Salter and Martin 2001; Dimos et al., 2022) or support to collaboration between universities and firms (Richter Østergaard and Dreier, 2022).

Nevertheless, as increasingly recognized, demand-side factors can inhibit investments in innovation as well. Potential demand for innovation can be fragmented and uncertain, or even unknown to the firms; consumers can be locked-in into existing technologies presenting network externalities; information asymmetries may limit the potential users' capacity to verify R&D effort and the value of the innovation output, thus lowering their propensity to purchase and finance it (Iossa et al., 2018). These arguments support the rationale for complementing the traditional supply-side oriented innovation policies with demand-side instruments. Among these, PP represents the most investigated tool (Edler and Georghiou 2007; Edquist and Zabala-Iturriagagoitia 2012; Crespi and Guarascio 2019).

2.1. Public procurement as demand-side innovation policy

Different types of PP have been defined depending, among others, on the type of procured products, its degree of innovativeness, and the competences of the contracting authority.

Regular PP takes place when the public sector demands standardized and ready-made products with easily verifiable information on price, quality, and performance, and for which no R&D effort is required. According to Uyarra and Flanagan (2010), innovation can arise as side effect of the regular PP, as this can generate indirect demand-pull impacts and bring to adaptive or incremental innovation (Edquist and Zabala-Iturriagagoitia 2012).

In other cases, innovation can be stimulated more directly through the procurement of specialized or dedicated products. PPI takes place when the procuring authority acts as a launch customer, or early adopter, for innovative products or services that are not yet available on a large-scale commercial basis but can be developed within a reasonable timeframe (Edquist et al., 2000).

Previous literature recognized that PPI can support directly a radical-oriented type of innovation via multiple channels. First, through the request of dedicated innovative products, PPI can favour the signalling of unmet needs, increasing demand predictability and allowing to overcome potential asymmetric information problems among the contracting parties (OECD 2011). By acting as an "experimental customer" (Malerba et al., 2007, p. 676), the procuring agency bears part of the risk associated to R&D activity, thus contributing to lower the uncertainty of the innovative process (Edquist et al., 2015; OECD, 2017; Bleda and Chicot, 2020). Second, by guaranteeing the purchase of a certain level of the contracted product, PPI can allow reducing the financial constraints associated to innovation and promote cost reduction through the exploitation of economies of scale. Moreover, through the specification of complex requirements and high technical standards that can be met only by developing new solutions, PPI can allow overcoming lock-in effects generated by network externalities.

Previous empirical analyses found evidence on the effectiveness of PPI as a demand-side innovation policy compared to, or in combination with, other innovation measures (Stojcic et al., 2020; Caravella and Crespi 2021; Guerzoni and Raiteri 2015; Czarnitzki et al., 2020; Castelnovo et al., 2018).

Overall, this literature stressed the PPI capacity to foster technological progress and to strengthen firms' innovation capacity by increasing their know-how, improving their ability to develop new equipment and methodologies, enhancing their problem-solving ability, and favouring the development of new networks and social relations (Salter and Martin, 2001; Edquist and Zabala-Iturriagagoitia, 2012; Ghisetti, 2017).

2.2. Barriers to innovations and limits of the procurement approach

Despite the multiple benefits stemming from PPI, its capacity to effectively support innovation should not be taken for granted, as it can be inhibited by some barriers which crucially depend on the procuring agency' quality and internal competences.

It has been observed that, to avoid potential failures, the procuring agency must clearly identify its needs, and specify and communicate them through adequate procurement contracts (Guerzoni 2010). This implies that the procurer must own a variety of professional skills and technological competencies to design adequate contracts, properly evaluate tenders and interact with the supplying firms in the post-procurement phase, to overcome potential technical problems (Uyarra et al., 2014). Conversely, when there is a lack of internal competences, the procurer may face selecting, monitoring, and evaluating problems, thus creating potential room for adverse selection or moral hazard behaviours, which increase the procurement's costs and timing (Edler et al., 2006).

Georghiou et al. (2014) highlight how the PPI success crucially depends on the procurer's internal mission and attitude. The procurer should be committed to an innovation goal and inclined to support new ideas by taking adequate risks. A risk-adverse attitude might bring to the purchase of standardized goods through procurement contracts which emphasize price over quality, thus bringing rebating competition logic to prevail on innovation logic (Mazzucato, 2016). Moreover, since the lack of market demand represents an obstacle for innovation, public procurement may be ineffective in supporting innovation if it is a sporadic activity which does not ensure the critical mass required by firms to undertake R&D investments. It has been argued that, given the large variety of public procurers with different missions and competences,[1] it is quite unrealistic to expect all of them to contribute to innovation through the PPI tool (Uyarra and Flanagan, 2010). These arguments

[1] Public procurers range from decentralised public administration offices to centralised governmental departments, from dedicated executive agencies to generalized organizations. These are likely to have different missions and competencies, and use the procurement tool to purchase products with different nature and complexity.

motivated our choice to focus on a space agency to assess the impact of public procurement on innovation. Thanks to a clear mandate and internal competences of space agencies like the ASI, the barriers that can hinder the capacity of public agencies to support innovation via the procurement tool are likely to be less relevant in the space industry setting.

2.3. Methodological approaches to study PPI

The PPI literature can be distinguished in two broad classes: i) qualitative research based on case-studies and small sample-size surveys addressed to firms involved in the supply chain of public organizations, institutes, and agencies, and ii) quantitative studies that develop econometric analysis based on the information collected through surveys with national or international coverage or "secondary" data sources, such as online databases including balance-sheet and patent data.

Analyses based on case-studies (see e.g., Aberg and Bengston, 2015; Autio et al., 2004; CERN and CSIL, 2019; Martin and Tang, 2007; Edquist et al., 2000) mainly focused on large public research infrastructures and provide a first qualitative insight on how the procurement placed by these entities play a crucial role in supporting firms' economic performance and innovative activities (e.g., the development of new products and technological innovations).

Studies based on surveys to the suppliers of a specific public customer make it possible to investigate the experience of a larger sample of companies. Among them, there are Autio et al. (2003) and Florio et al. (2018) which, focusing on the case of CERN, identified the benefits generated by the procurement relationship in different areas, like product and process innovation, market penetration, revenues from sales, and cost reduction.

Most of the studies performing quantitative analysis rely on the data collected through national or international surveys, such as the Community Innovation Survey (CIS), the "Mannheim Innovation Panel" or the Innobarometer survey, and often implement non-parametric matching techniques using PPI as the treatment variable. Among them, Stojcic et al. (2020), Czarnitzki et al. (2020) and Aschoff and Sofka (2009) assessed the effectiveness of PPI in enhancing firms' turnover from new products and services, while Caravella and Crespi (2021) and Guerzoni and Raiteri (2015) investigated its impact on firms' expenditure in R&D and innovative activities.

None of these studies addressed the possibility that firm's participation into PPI programs may not be a fully random process, therefore they cannot rule out a potential selection bias.

Dai et al. (2021) were among the first to use a conditional difference-in-differences (diff-in-diff) to address potential selection bias issues and identify the causal impact of PPI on firms' innovation outcomes. Conversely, they did not address the potential biases stemming from the heterogeneity in the treatment timing.

Crespi and Guarascio (2019) took an industry-level perspective and used Poisson regression models to investigate the correlation between patent applications and different innovation policies, providing evidence of a demand-pull effect of PPI. To the best of our knowledge, Castelnovo et al. (2018) was the first paper that applied econometric techniques to firms' balance-sheet data collected from online databases with international coverage to study the effect of PPI on firms' R&D investment, number of patent applications, productivity, and economic performance, focusing on the CERN supply-chain.

We build on this previous research to further improve the quantitative approach to the study of the PPI impact, with a specific application to the space industry.

2.4. Public procurement in the space industry

The extant empirical evidence on the role of public procurement for space policies is scarce, have mainly focused on aggregate returns and relied on a survey methodology based on direct interviews with contracting firms. A comprehensive evaluation of the indirect industrial effects generated by the European space programs was conducted by B.E.T.A.[2] (1980, 1988, 1996) and then analyzed and discussed by Cohendet (1997) and Bach et al. (2002). Findings suggested that, on average, every euro paid by the European Space Agency (ESA) to the industry resulted in a three-times higher indirect economic benefit through ESA contracting firms. More recently, the Danish Agency for Science (2008) surveyed Danish companies involved in the ESA supply chain over the years 2000–2007, finding that every million euros of Danish contributions to ESA generated a total benefit of 4.5 million euros, through direct turnover for ESA contractors and indirect effects resulting from the development of new technologies and competencies.

A firm-level perspective, with focus on both economic and innovative outcomes, was adopted by Castelnovo et al. (2021). Taking advantage of a survey addressed to the enterprises involved in the provision of technological products and services to the ASI, they showed that firms benefited from the procurement relationship, achieving product and process innovation outputs. Interviewed firms argued that the collaboration with the ASI helped them to enhance their technical know-how, with a significant improvement in their production processes, R&D capabilities, and management/organizational skills.

3. Sampling strategy and descriptive statistics

ASI granted us access to its technological procurement database (named Archimede), including information on the technological contracts placed by ASI to purchase the space technologies required to develop and manage space missions and programs.[3] This dataset disregards the regular procurements of off-the-shelf products which ASI purchases for its ordinary activity. ASI itself selected the technological orders aimed at purchasing specific and detailed high-tech products or services. For each order, the database includes information about the contract (subject, signing year, the related programme and project) and the supplier. We exploit this information to distinguish firms from universities, public agencies, public authorities, and other non-enterprise institutions that were assigned ASI contracts. Universities and other research institutions play a non-neglectable role in the innovation process, particularly when they proficiently interact with firms and other research stakeholders. The Triple Helix model (Etzkowitz and Leydesdorff, 1996) describes these interactions building on the concept of innovation system (Lundvall, 1992; Edquist and Johnson, 1997) and recognises them a prominent role in the generation and transfer of knowledge. Despite the relevance of this issue, we preferred to exclude universities and other research institutions from our sample and focus our analysis on firms. This allows us to work with a homogeneous sample composed by comparable units. Moreover, firm-level data are not available for research institutions, and academic research is typically measured by indicators different from patents, such as published research articles, cross-reference citations, and impact factor. Academic institutions and their relations with the procuring authority and industrial partners represent the focus of a separated research.

We expanded our contract database with specific firm-level financial and patent data extracted respectively from the Orbis and Orbis Intellectual Property databases. Specifically, we included information about company assets (tangible and intangible fixed assets), operating revenues, number of employees, listing status, incorporation year, NACE activity sector and geographical location. From the Orbis IP database we obtained company patent data, including the patent application

[2] Bureau d'Économie Théorique et Appliquée of the University of Strasbourg (B.E.T.A.).

[3] Part of these contracts were directly published by ASI. Another part was published by the European Space Agency and reserved to Italian firms in proportion to the budget that ASI addresses to finance the European Space Agency projects.

number, the year of the application, and the relevant patent office.

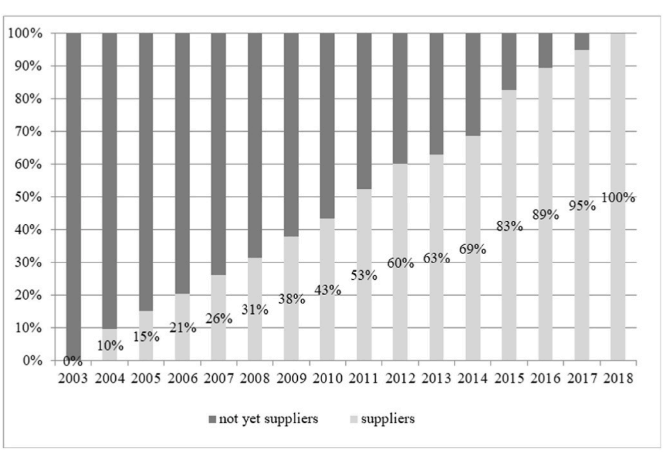
The final longitudinal sample, obtained after merging and cleaning the data, by excluding firms for which either financial or patent information is not available, is composed by 461 suppliers and 7150 observations over the period 2003–2018. These suppliers were awarded a total of 3134 orders over the considered period, that is, on average, 6.8 orders per firm. This average is driven by a small share of suppliers with more than 10 orders (13% of the sample), as more than 70% of firms received less than 5 orders.

Around 95% of suppliers are Italian firms, while the remaining 5% is in other European countries.

After matching the cross-sectional dataset on ASI contracts with the longitudinal dataset including firms' information, we created a dichotomic variable (named *Post*) which equals 0 in the years preceding the assignment of the first contract and 1 after the company became an ASI supplier. Fig. 1 reports the partition into supplier and non-supplier firms across years. We can observe that firms in our sample became ASI suppliers in different years. None of them was an ASI supplier in 2003, while at the end of the period, in 2018, all the firms established a procurement relation with ASI. In each year between 2004 and 2017, some firms shifted their status from not-yet-supplier to suppliers.

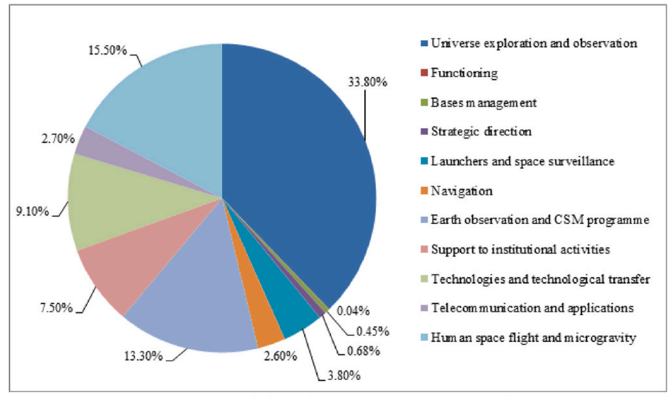
Fig. 2 shows the distribution of projects financed through ASI public procurement across activity sectors, as classified by the space agency when placing the order. Most of the orders are included in the three categories: i) universe exploration and observation, ii) human space flight and microgravity, and iii) earth observation and Cosmo SkyMed satellite programs.[4]

Most of the firms composing our sample operate in the ICT and Manufacturing sectors (27% and 25% respectively), while almost 20% undertake professional, scientific, and technical activities. Table 1 below provides the full distribution of suppliers according to the NACE classification. As shown in Fig. 3, according to the OECD sector classification into technological classes, 42% of suppliers are active in high-tech manufacturing or knowledge intensive services, 9% belong to medium-high-tech manufacturing sectors and an additional 17% operate in knowledge intensive services. This provides evidence of the high technological and knowledge content of the orders delivered by firms involved in space procurement.



Source: own elaboration on ASI procurement data

Fig. 1. Change in suppliers' status over time.
Source: own elaboration on ASI procurement data



Source: own elaboration on ASI procurement data

Fig. 2. Distribution of contracts by activity sector.
Source: own elaboration on ASI procurement data

Table 1
Suppliers industrial classification (based on one-digit NACE codes).

Sector	N° of firms	%
C – Manufacturing	115	25
F – Construction	30	6,5
G - Wholesale and retail trade; repair of motor vehicles	31	6,74
H - Transportation and storage	16	3,48
J - Information and communication	125	27,18
M – Professional, scientific, and technical activities	90	19,57
N - Administrative and support services	23	5
Other	31	6,53
Total	**461**	**100**

Source: own elaboration on ASI procurement data

According to the number of employees recorded in 2018, most of suppliers can be classified as SMEs (81.3%), while 18.7% are large firms (see Table 2). The presence of few very large firms also emerges from the summary statistics for suppliers' balance-sheet data presented in Table 3, which show a heavily skewed distribution (often the case with accounting data) as suggested by the comparison of the mean and median values.

Concerning the firms' patenting activity, almost three quarters of the companies did not file any patent over the period 2003–2018 (see Table 4), as it is usual in many industrial sectors (see e.g., Castelnovo et al., 2018; Bastianin et al., 2021). However, the average number of patent applications per firm in the post-procurement period significantly increased compared to its pre-procurement level. To assess whether this change was caused by the ASI procurement we use a Propensity Score Matching technique to build a control group of non-ASI suppliers.

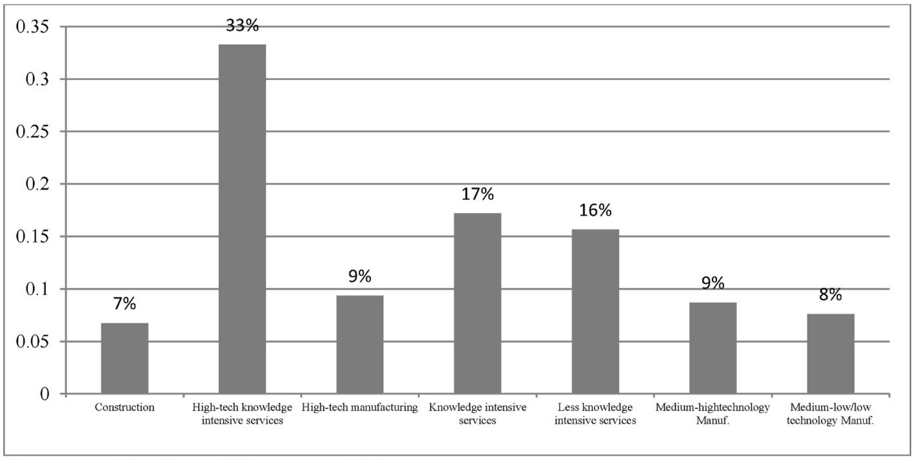
Table 5 shows the main technology classes of the patents filed by ASI suppliers, classified according to the International Patent Classification (IPC). As it can be noticed, most of patents are included in the following IPC classes: B64 (Aircraft aviation; cosmonautics); F01, F02, F016 (Mechanical engineering); G01, G02, G06, G08 (Physics), and H01, H04 (Electricity).

4. Empirical strategy

This section introduces the empirical models we developed to address potential endogeneity issues arising from the procurement activity and which we used to determine the causal impact of ASI procurement on the supplier firms' patenting activity.

The Archimede dataset includes firms that have been selected by the ASI according to some observable characteristics, including their pre-procurement technological skills and possibly their innovation capability, which likely persist after the beginning of the procurement relationship. If this is the case, the treatment (i.e., the assignment of a PPI

[4] Cosmo SkyMed is one of the most significant projects financed entirely by ASI. It is the world's first Earth satellite observation system designed for dual purposes, civil and military, i.e., national security, but also the prevention of environmental disasters and the study of the Earth's surface.



Source: own elaboration on ASI procurement data

Fig. 3. Firm sectorial distribution based on Eurostat High-tech aggregation by NACE rev.2.
Source: own elaboration on ASI procurement data

Table 2
Suppliers' size classification.

Firm Size	N° of employees	(%)
Small	less than 50	66%
Medium	50 ≤ and <250	15.3%
Large	≥250	18.7%

Source: own elaboration on ASI procurement data

Table 3
Balance-sheet data summary statistics, year 2018.

Variable	Mean	Std. Dev.	Median
Total assest (€, thd)	473,548	2,940,950	3087
Tangible fixed assets (€, thd)	182,504	1,818,316	117
Intangible fixed assets (€, thd)	69,667	538,611	51
Turnover (€, thd)	271,938	1,635,772	2.630
Employees	2485	28,737	20

Source: own elaboration on ASI procurement data

Table 4
Patent applications per firm (2003–2018).

Patent applications	N° of firms	%
0	333	72.1
1–50	89	19.4
51–100	11	2.4
>100	28	6.1
	Mean	
Avg. 2003–2018	4.30	
Avg. pre-procurement	1.53	
Avg. post-procurement	7.09	

Source: own elaboration on ASI procurement data

Table 5
Patent distributions into IPC classes.

IPC code (3 digits)	%	IPC - Class description
B64	4.0	Vehicles - Aircraft; aviation; cosmonautics
F01	4.3	Mechanical engineering; lighting; heating; weapons; blasting - Machines or engines in general; engine plants in general; steam engines
F02	6.5	Mechanical engineering; lighting; heating; weapons; blasting - Combustion engines; hot-gas or combustion-product engine plants
F16	3.4	Mechanical engineering; lighting; heating; weapons; blasting - Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
G01	15.7	Physics - Measuring; testing
G02	3.5	Physics - Optics
G06	8.3	Physics - Computing; calculating or counting
G08	3.0	Physics - Signalling
H01	8.9	Electricity - Basic electric elements
H04	10.1	Electricity - Electric communication technique
Others	32.3	Includes IPC codes with less than 3% of patents, like e.g, G05 (Physics – Controlling; Regulating); H02 (Electricity - Generation, conversion, or distribution of electric power); F23 (Mechanical engineering - combustion apparatus; combustion processes).

order) cannot be considered as exogenous, and the lack of a counterfactual would not allow the impact of space procurement on innovation to be identified. In other words, it would not be possible to determine with certainty whether the possible increase of patents in the post-procurement period should be attributed to the treatment itself or rather to the idiosyncratic characteristics of the ASI suppliers.

An experimental randomized strategy was not a feasible option because of the nature of the industry. Therefore, to address this endogeneity issue, we developed a quasi-experimental design where a propensity score matching (PSM) procedure was combined with a diff-in-diff approach. Moreover, to account for the time heterogeneity of the treatment, we expanded this approach through a staggered diff-in-diff design.

After presenting our dependent variable and discussing the pros and cons of this choice (4.1), this section introduces the PSM procedure (4.2) and our research design (4.3).

4.1. Definition of the dependent variable

Following e.g., Guadalupe et al. (2012) and Bertoni and Tykvová (2015), in our model we proxy firms' innovation output with their stock of patent applications in the year *t*, which is defined by the following equation:

$$patent\ stock_{it} = patent\ stock_{it-1}(1-\rho) + patent_{it}$$

where $patent_{it}$ is the number of patents filed by company *i* in the year *t*, while ρ is the rate at which the existing stock of patents depreciates. Consistently with the main literature, the yearly depreciation rate ρ is set equal to 15% (Griliches, 1990).

Other research has analyzed the impact of public procurement on specific measures of innovation, such as the development of new products, or the variation of sales from the new products developed thanks to procurement. These variables are more suitable for measuring the firms' innovation performance and their impact on the firms' economic activity. Unfortunately, these variables are not available from the firms' balance sheets (which are our main firm-level data source), as they are usually extrapolated from surveys. These measures of innovation have pros and cons. On one side, they allow for a deeper understanding of the results of the R&D investments on the firm innovation performance and economic activity. On the other side, they are subjective and self-reported data collected through surveys, hence they are subject to potential over-optimism and subjectivity perception biases, which might bring to overestimate the true impact of public procurement. Moreover, these data are typically collected over a short-term period and do not allow a long-term dynamic analysis.

As acknowledged by previous literature, patents are an imperfect proxy of firms' innovation, and they present some limitations. Registered patents are a measure of the firm's R&D results and do not fully capture the innovative dimension of the R&D process. Patents can better measure the firms' inventions rather than their innovativeness. Moreover, the number of filed patents may under-represent innovation when firms strategically opt not to patent their inventions to avoid any disclosure requirement. Alternatively, patents may over-represent innovation when they are filed for strategic reasons, different from the genuine protection of an innovation, for instance to create market barriers against potential new entrants or increase the costs that competitors must support to use a given technology (Archibugi and Pianta, 1996; Griliches, 1990; Langinier, 2004; Kleinknecht et al., 2002).

In the economic literature, patent applications are usually considered an output of firms' innovation process and have been widely used to measure firm-level innovation (see, among others, Hall and Lerner, 2010; Clò et al., 2020; Clò et al., 2022), particularly to assess the role of public procurement in supporting innovation (Castelnovo et al., 2018; Raiteri 2018). According to Dodgson and Hinze (2000, page 103): "*patents are the most commonly used data to construct indicators of ownership of intellectual property. Patents can provide indirect indicators of the effectiveness of investments devoted to innovation*". Indeed, patent data are publicly available documents, they represent a measurable and objective source of information about the research and development process, they are regularly collected worldwide and present long time series, thus allowing for international comparison of the technological change path and firm innovation process (Griliches 1990). Patents can be considered a reliable proxy of innovation activity especially in manufacturing industries (see e.g., Kleinknecht et al., 2002). According to Hagedoorn and Cloodt (2003) patent counts highly correlate with other measures of innovative activity, like R&D spending or the announcement of new products. Due to these considerations, we believe that our analysis based on patents can complement previous research which used innovation performance measures extracted from surveys.

4.2. Propensity score matching

To address the possible sample selection issue, we used PSM techniques to build a counterfactual control group made up of firms which are non-ASI suppliers, whose characteristics in the pre-treatment period are not statistically different from those of the ASI suppliers (treated group).

To estimate the propensity score – that is the probability of being treated given a vector X of observable characteristics – we first selected a very large sample of non-treated companies to be matched with treated ones. We selected from the Orbis database all the (around 2 million) active firms that operate in the same 4-digit NACE rev. 2 codes of the ASI suppliers and are in the EU15 Member States except for Italy. We exclude Italian firms from the control sample to avoid selection issues. Since one of the ASI's goal is promoting the technological development of the Italian industry and scientific research, more than 95% of ASI suppliers are Italian firms. Therefore, the geographical location should provide an exogenous treatment assignment between suppliers and controls. On the contrary, including Italian firms in the control group would rise issues concerning the possibility that they have not been selected as suppliers because of their characteristics.

After randomly selecting a subsample of 250,000 firms with non-missing information, we used a logit model to estimate the probability of being treated conditionally on some observable firm characteristics. Specifically, we considered both time-invariant variables – the sector where they operate and their year of incorporation – and time-variant variables measured in the pre-treatment period. We used the mean value of firms' tangible and intangible assets, operating revenues, and number of employees in the years before the treatment.

After sorting the dataset according to a randomized order, for each treated firm, we selected up to three firms from the non-treated group according to the closest propensity scores obtained from the corresponding logit estimation.[5]

Table 6 reports the results of the t-tests performed on the pre-treatment mean value of our variables of interest for both the treated and control groups, before and after the matching procedure. The fact that the significant differences in the means among the unmatched groups do not persist after the PSM procedure is informative about the good quality of the matching procedure.

The null hypothesis of the *t*-test is that the difference between the averages of the two groups is zero. When looking at the unmatched group, for all the considered variables, except for the firms' age, the p-value is zero, implying that the pre-treatment difference between the means of the two groups is statistically significant. Conversely, for the matched groups, the high p-value implies a rejection of the null hypothesis, allowing us to exclude the persistence of statistically significant differences between the treated and control groups in the pre-treatment period. Interestingly, this result holds not only for the control variables used in the matching procedure but for the dependent variable (the patent stock) as well.

Having constructed a control group whose mean outcomes in the pre-treatment period do not differ from to the treated group, we face a lower risk that our results could be affected by selection issue. Possible differences in the patenting activity among the two groups in the post-treatment period can be attributed to the treatment with a higher degree of confidence.

4.3. Research design

In the present section we describe our research design. Different subsections report the detail of each model.

4.3.1. TWFEDD

Following the framework of many empirical studies aimed at identifying the impact of a policy measure (Cameron and Trivedi, 2015; Clarke and Schythe, 2020; Avdic and Von Hinke, 2021), the average treatment effect of the procurement on firms' innovation output is initially estimated through the following two-way fixed effects diff-in-diff (TWFEDD) regression:

$$y_{it} = \gamma_i + \gamma_t + \beta(Treat_i \times Post_t) + X_{it}^{'}\theta + \varepsilon_{it} \tag{1}$$

where y_{it} is the log of the patents' stock filed by the firm i in year t, γ_i and γ_t are respectively firm and time fixed effects. $Treat_i$ is a dummy variable identifying the treated units. It takes value 1 if the firm is an ASI supplier

[5] Since treated companies became ASI suppliers at different times, we replicated the matching procedure year by year. That is, within each year of the period 2003–2018 we selected from the treated group only those companies that become ASI suppliers in that specific year and we matched them with companies from the non-treated group (these matched companies were then excluded from this latter group to avoid double counting).

Table 6
Two-sample *t*-test - balancing property for unmatched and matched groups.

		Mean	St. Dev.	Control group	Treated group	Tstat	(p-value)
Tangible Assets	Unmatched	8717.47	362,816.92	8348.94	113,619.69	6.22	0.00
	Matched	119,706.28	1,381,564.30	121,825.51	113,538.31	−0.11	0.91
Intangible Assets	Unmatched	3830.97	199,951.97	3629.69	61,124.94	6.16	0.00
	Matched	95,011.23	1,359,361.13	106,671.78	61,073.41	−0.62	0.54
Operating Revenues	Unmatched	22,731.24	484,486.78	22,119.27	196,926.04	7.74	0.00
	Matched	275,640.06	2,441,702.44	303,722.70	193,906.09	−0.83	0.41
Number of employees	Unmatched	97.4	2497.38	92.29	1551.94	12.53	0.00
	Matched	1776.10	17,941.17	1851.96	1555.32	−0.31	0.76
Age	Unmatched	4.22	1.27	4.22	4.31	1.54	0.12
	Matched	4.26	1.24	4.25	4.31	0.95	0.34
Patents	Unmatched	0.01	1.86	0	2.55	29.46	0.00
	Matched	3.49	38.58	3.81	2.56	−0.6	0.55

and zero otherwise. The variable $Post_t$ is a dichotomous variable which takes value 0 in the pre-procurement period and 1 when the year t belongs to the post-treatment period. Our coefficient of interest β captures the average treatment effect on the treated (ATT).

The vector $X_{i,t}$ includes the set of firm-level variables recognized as relevant to explaining the firm's innovative activity, which are introduced to control for potential confounding factors. The size of the company is proxied by its operating revenues and number of employees, tangible assets are included to measure the firm's capital expenditures, and intangible assets are used as a proxy for internal R&D effort, as R&D expenditures are usually not reported in the firms' balance sheets (Leoncini et al., 2019). All these financial characteristics are log-transformed for estimation purposes. The TWFEDD estimator allows for time-invariant differences across firms to be controlled, thus avoiding a potential bias from the omission of fixed but unobservable firm-specific characteristics.

We next extend this model by exploring the heterogeneity of the estimated coefficients with respect to the technological intensity of the treatment units. To do so, we augment the baseline regression as follows:

$$y_{it} = \gamma_i + \gamma_t + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times LowTech_i) + X_{it}'\theta + \varepsilon_{it} \quad (2)$$

The dummy variable $Low\ Tech_i$ equals 1 for firms belonging to low-tech sectors, as defined by the Eurostat indicators on High-tech industry and Knowledge-intensive services.

4.3.2. Goodman-Bacon decomposition

The canonical TWFEDD estimator usually applies to a setting with two (treated and control) groups and one single treatment defining two – pre and post treatment – time periods. Conversely, in our setting the treatment is not unique. Firms become ASI suppliers in different years over the 2004–2018 period, thus the time of the treatment varies across treated units. Recent development of the DD literature shows that when treatment takes place at different times, the single-coefficient TWFEDD model can misestimate the average treatment effect on the treated (ATT), since already treated units act as controls in future periods, and late-treated units act as a control group for early treated units as well. Goodman-Bacon (2021) decomposes the TWFEDD estimator into a weighted average of all possible 2 × 2 TWFEDD estimators, with the weight of each 2 × 2 estimator depending on the subsample size and the timing of the treatment. This approach highlights that the adoption of canonical TWFEDD can provide biased estimation in case of dynamic treatment effects, in particular when the size of the effect is associated with the number of the treated units or with the timing of the treatment.

Following the Goodman-Bacon approach, the second step of our research design is to decompose the single-coefficient of the TWFEDD model into its component parts: a pure "treated vs never treated" effect, and multiple effects among units treated at different points in time, which exploit the variation in the year when firms become ASI suppliers.

This approach suggests that more flexible specifications, such as a panel event-study or staggered adoption designs (Athey and Imbens, 2018; Cengiz et al., 2019; Deshpande and Li, 2019; Fadlon and Nielsen, 2021) may be more appropriate.

4.3.3. Staggered diff-in-diff

We next develop a staggered diff-in-diff design, where the treated units are categorized into groups (or cohorts) depending on the time they receive the treatment. Specifically, we rearrange our data as follows. For each treatment year t (with $t = 1, \ldots, G$), we construct a subsample where the treated group is composed only by those firms that received the order from ASI in year t and the control group includes all the firms that in the time span [t-3; $t+3$] do not change their status. This implies that the control group is made up both by never-treated firms and firms that receive the treatment (i.e., become ASI suppliers) in a year outside the window [t-3; $t+3$]: notably, early treated (treatment year prior to t-3) and late treated units (treatment year after t+3).[6] Applying this approach recursively, we construct $G = 10$ groups (corresponding to as many panel datasets), one for each year t within the period 2006–2015.[7] The resulting G panels are then stacked into a unique dataset. Accordingly, we run the following regression:

$$y_{igt} = \gamma_{ig} + \sum_{g=1}^{n}\gamma_{gt} + \beta(Treat_{ig} \times Post_{gt}) + X_{igt}'\theta + \varepsilon_{igt} \quad (3)$$

where y_{igt} is the log of the patent stock of firm i, belonging to group g, in year t; γ_{ig} are firm-level fixed effects for the firm i within the group g (notice that the same firm can appear as a control or a treated unit in different groups g), while γ_{gt} are time fixed effects referring to the year t within the group g. $Treat_{ig}$ is an indicator equal to 1 if the firm i is a treated unit (ASI supplier) within group g, while $Post_{gt}$ is a dichotomous variable that, within each group g, takes the value of 0 in the pre-procurement period and 1 thereafter. Our coefficient of interest is β, which captures the differential effect of the treatment on the treated firm i compared to the control units in the considered group g, in the post-treatment period. Since in the aggregated database there are repeated observations for each firm, standard errors are clustered at the firm level.

Our strategy is built on Fadlon and Nielsen (2021) who assessed the effect of sever health shock on family labour supply by using as counterfactuals households that experience the same shock a few years apart. Using a similar approach, Deshpande and Li (2019) estimated the effect of Social Security Administration field offices closings on the number of disability recipients, exploiting the variation in the timing of closures, with early and late treated units being compared to each other.

[6] For instance, for firms that become suppliers in 2010, the control group is made up by never-treated, "early-treated" firms (those receiving the treatment before 2007), and "late-treated" that will receive the treatment after 2013.

[7] We exclude treatments taking place in the period 2003–05 and 2016-18 because for these years we do not have a 3-years pre-treatment or post-treatment period respectively.

As shown by these authors, the exploitation of the different timing of the treatment allows addressing potential endogeneity issues stemming from the non-random assignment of treatment, being the control group composed by treated units as well, which nevertheless receive the treatment in a different time. This approach is particularly suited for our analysis since, like in Deschpande and Li (2019) and Fadlon and Nielsen (2021), our treatment might not be considered exogenous, since ASI is likely to select its suppliers according to some pre-treatment characteristics. The fact that the treatment effect is estimated by comparing treated units receiving the treatment at different moments in time (e.g., late treated are used as control for early treated) does not require the changes in the firms' status to be exogenous random events, it only requires its timing to be random.

5. Results

Estimates of equations (1) and (2) are reported in Table 7. The coefficient of the variable $Treat_i \times Post_t$ is positive and highly statistically significant, implying that after becoming an ASI supplier, the amount of patent applications of the firms belonging to the treated group increases by a magnitude of 11% with respect to the control group. This result suggests that ASI procurement plays a positive role in stimulating firms' innovativeness. Moreover, the impact is not uniform across sectors, being stronger (14%) for the firms belonging to the medium or high-tech sectors (Column 2).

In case of heterogeneous treatment effects and time-varying adoption, the TWFEED estimator (where already treated units act as controls for late-treated ones) can provide a biased estimation of our parameter of interest, particularly if the impact of the treatment varies over time.

Therefore, following Goodman-Bacon (2021), we decompose the single-coefficient of the TWFEDD estimator into its component parts: a pure "treated versus never-treated" effect, and effects owing to the variation in the timing of the treatment across treated units. The estimation displays the weights and components making up the global "single coefficient" DD estimate (see Table 8). We observe that most of the weight in the single coefficient DD estimate comes from the treated vs never-treated comparison (78.2%) and its estimated coefficient (0.125) is higher than the timing groups' one (0.082). The decomposition of the TWFEDD estimate into its components shows that the ATT is mainly driven by the "never vs timing" group, suggesting that the adoption of a canonical DD to our sample (characterized by a variation in the timing of the treatment) is not likely to bring to biased results. Nevertheless, to further address potentially endogeneity issues stemming from the non-randomness of the treatment, we adopt a staggered DD approach. Estimates of the staggered DD model (eq. (3)) are reported in Table 9 and confirm our main result: PPI has a positive effect on firms' innovation capability. Becoming an ASI supplier has a positive effect on firms' patenting activity.

Interestingly, we observe that, once we account for the treatment time heterogeneity, the size of the estimated coefficient decreases and indicates a 6% increase in the ASI suppliers' patenting activity compared to the control group (column1). The coefficient of the interaction term between the treatment and firms' technological classification is still negative, implying that the effect is stronger for firms operating in high- and medium-tech sectors (column 2).

Table 7
Impact of PPI on firms' patenting activity: TWFEDD.

	(1)	(2)
Treat*Post	0.109***	0.141***
	(0.025)	(0.033)
Treat *Post*Low Tech		−0.098*
		(0.054)
Operating Revenues	0.003	0.003
	(0.005)	(0.005)
Tangible Fixed Assets	0.007	0.006
	(0.006)	(0.006)
Intangible Fixed Assets	0.011**	0.012**
	(0.005)	(0.005)
Number of Employees	0.002	0.001
	(0.017)	(0.017)
Constant	0.065	0.075
	(0.078)	(0.080)
Observations	19,745	19,745
R-squared	0.052	0.054

Robust standard errors clustered at firm level in parentheses; Time and firm fixed effects are included in the regressions; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 8
Impact of PPI on firms' patenting activity: Goodman-Bacon decomposition.

	Weight	Estimate
Timing groups	0.207	0.082
Never vs timing	0.782	0.125
Within	0.011	−0.494
Diff-in-diff estimate	0.107***	

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 9
Impact of PPI on firms' patenting activity: Staggered DD.

	(1)	(2)
Treat*Post	0.060**	0.087***
	(0.025)	(0.033)
Treat*Post*Low Tech		−0.083*
		(0.044)
Operating Revenues	0.007***	0.007***
	(0.002)	(0.002)
Tangible Fixed Assets	0.003*	0.003*
	(0.002)	(0.002)
Intangible Fixed Assets	0.008***	0.008***
	(0.002)	(0.002)
Number of Employees	−0.005	−0.005
	(0.005)	(0.005)
Constant	0.196***	0.197***
	(0.023)	(0.023)
Observations	68,299	68,299
R-squared	0.022	0.023

Robust standard errors clustered at firm level in parentheses; Time and firm fixed effects are included in the regressions; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

6. Further analyses

In this section we develop some further analyses aimed at describing the dynamics of the treatment effect. Moreover, we verified the robustness of our results to alternative specifications of our main regression model or by considering a different definition of the dependent variable.

6.1. Dynamic treatment effects

Drawing from the recent econometric literature, we estimate a dynamic treatment effect, test the parallel trend assumption and assess whether the treatment effect is constant over time or changes across years. For this purpose, we exploit estimation routines recently developed within the framework of staggered adoption design. Specifically, Callaway and Sant'Anna (2020) and de Chaisemartin and D'Haultfoeuille (2020) proposed alternative estimators that are robust to arbitrary treatment effect heterogeneity and provide a casual interpretation of the treatment effect. Moreover, these model specifications allow to study the dynamic variation of the PPI effect, as well as testing the parallel trend assumption.

As a first step, they estimate group average treatment effects (ATTs) for all units first treated in g and observed in $t \geq g$. Then they appropriately aggregate the ATTs across groups and periods.

Specifically, Calloway and Sant'Anna (2020) considered a DD design with staggered adoption where there are more than two periods. Units/groups can become treated at different points in time and, once they

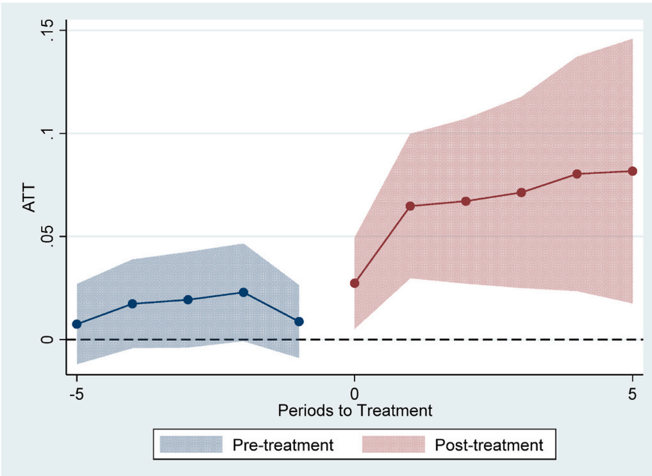


Fig. 4. Impact of PPI on firms' patenting activity: dynamic effects using the Calloway and Sant'Anna estimator.

are treated, they remain treated in the following periods.

In this setup, they suggested computing *group-time average treatment effects*, ATT(*g*, *t*), that are the average treatment effect in period *t* for the group of individuals first treated in period *g*. The main advantage of focusing on the family of ATT(*g*, *t*) is to understand treatment effect heterogeneity across different dimensions. The intuition behind Callaway and Sant'Anna (2020) estimator is that, to obtain consistent estimators for *ATT*'s, in situations when eventually all units are treated, one should use "not-yet treated" units instead of the "never treated" as controls. Otherwise, under heterogeneous treatment effects, the parallel trends assumption will be violated, resulting in biased estimations of the effects.

Fig. 4 confirms that becoming an ASI supplier has a positive and statistically significant impact on firms' patenting activity and show that such effect persists for several years after the beginning of the procurement relationship. Lead variables (T-5, …, T-1) are never statistically significant, meaning that the parallel trend assumption is satisfied. This placebo test further confirms the validity of our findings.

de Chaisemartin and d'Haultfoeuille (2020) recognize that group *g*'s treatment at period *t* may influence that group's period-*t* outcome (instantaneous effect), but it may also affect its future outcomes as well (dynamic effects). Therefore, they propose a DD estimator, DD(*k*), of instantaneous and dynamic treatment effects which rely on the standard common trend assumption but that are robust to heterogeneous and dynamic treatment effects.

Specifically, DD(*k)* is computed as a weighted average, across time periods *t* and possible values of the treatment *d*, of DDs comparing the t-*k*-1 to *t* outcome evolution, in groups with a treatment equal to *d* at the start of the panel and whose treatment changed for the first time in *t-1* (first-time switchers), and in groups with a treatment equal to *d* from period 1 to *t* (not-yet switchers). Therefore, DD(*k)* estimates the effect of having switched treatment for the first time *k* periods ago and, as the estimator developed by Callaway and Sant'Anna (2020), it uses as controls the not-yet-treated with the same treatment as the treated group at the start of the panel.[8]

The Stata routine that computes the DD(*k)* estimators, also provides placebo estimators, that can be used to test the non-anticipation, strong exogeneity, and parallel trends assumptions underlying the DD(*k)* estimators.

Results confirm once again that space procurement has a positive and statistically significant impact on suppliers' innovative output, that shows up in the first year after the beginning of the procurement collaboration and which persists and increase in magnitude in the following years (see Table 10). The placebo tests we ran are met, providing evidence that the parallel trend assumption is satisfied.

6.2. *Robustness checks*

In this section we first check the robustness of our results through a more restrictive specification of the staggered diff-in-diff model. We next consider a different definition of the dependent variable and account for contracts' value.

6.2.1. *Alternative specification of the control group*

Using "early-treated" firms as control group for "late-treated" firms may cause biased estimates because of a possible violation of the pre-treatment parallel trend assumption, which may result in case the treatment effect was not constant over time. Therefore, we re-run our regressions excluding "early-treated" firms from the control group. Specifically, within each group, we exclude from the control group firms that became suppliers before the considered time-window (i.e., before *t-3*), keeping as control group "never-treated" and "late-treated" firms.

Second, to further address potential endogeneity issues, we exclude from the control group the never-treated firms previously selected through the PSM procedure. Indeed, due to the highly specialized nature of the firms involved in the space industry and the characteristics of goods and services they provide, one could question whether the never-treated firms do effectively represent a good control for the treated units. On top of that, we cannot a priori exclude the possibility that firms classified as never-treated units have effectively never received any order from other public procurement agencies.

Having excluded never treated units, the control group is composed by late treated units. In other terms, the endogeneity issues stemming from the non-random assignment of the treatment is addressed by exploiting the heterogeneity in the timing of the treatment, that is by constructing a control group uniquely composed by treated units receiving the treatment in a different time. Results reported in the online Appendix (Table A1) provide evidence that our findings are robust to the exclusion of both "early-treated" and "never-treated" firms.

6.2.2. *Alternative specification of the time window*

One may question whether our result depends on the chosen [t-$3/t+3$] 7-years window. Nevertheless, results reported in the online appendix (Table A2) show that our findings still hold when we construct our stacked panel dataset using a 9-year time window [t-$4; t+4$] and a 11-year time window [t-$5; t+5$]. Results are confirmed when we exclude from the control group "early-treated" and "never-treated" units.

6.2.3. *Alternative definition of the dependent variable*

We have previously discussed the limits of using patents' applications as a proxy for the firm's innovation capacity. To address this issue, we present a further analysis where citation-weighted granted patents are used as the dependent variable. Indeed, an increase in the number of patent applications does not necessarily imply an enhancement of the firm's innovative performance. Conversely, citation-weighted granted patents can better capture how relevant the patents are. Indeed, the more a patent is cited, the more it is valued by the market. Thus, to capture the quality of the firm's innovation process, we exclude from the patent counting those patents that have been filed but not (yet) granted. We focus only on granted patents and we weight them by the number of citations they received after the grant. Other papers have previously used this variable as a proxy for the quality of innovation (Hall et al.,

[8] In the special case where there are no covariates, the two estimators are numerically equivalent. However, when covariates are included in the analysis the two estimators differ: the Calloway and Sant'Anna estimator accounts for covariates non-parametrically, while the de Chaisemartin and D'Haultfoeuille (2020) estimator does it linearly. Accounting for covariates linearly needs stronger assumptions but allows to include in the estimation group-specific linear trends.

Table 10
Impact of PPI on firms' patenting activity: Dynamic treatment effect using the De Chaisemartin and D'Haultfoeuille estimator.

	Estimate	S.E.	Lower Bound	Upper Bound	N	Switchers
Effect_0	.0267279*	.0138558	−.000430	.0538853	13858	458
Effect_1	.063441***	.0212802	.0217318	.1051501	11630	435
Effect_2	.0658784***	.0227881	.0212137	.1105431	9748	409
Effect_3	.0688744***	.0241017	.0216351	.1161137	8126	377
Effect_4	.0741613***	.0284429	.0184133	.1299094	6690	314
Effect_5	.0755163**	.032916	.011001	.1400316	5509	287
Placebo_1	.0101023	.0073109	−.004227	.0244316	11605	410
Placebo_2	.0207031*	.0128684	−.001519	.0489252	9717	378
Placebo_3	.0208738	.0120485	−.002741	.0444889	8101	352
Placebo_4	.0191806	.0138731	−.008011	.0463718	6703	327
Placebo_5	.0094675	.0109514	−.011997	.0309323	5525	303

Note: * = p-value<0.1; ** = p-value<0.05; *** = p-value<0.01.

2005; Harhoff et al., 1999). We analyzed the impact of ASI procurement on this alternative dependent variable using both a standard TWFEDD estimator and a staggered diff-in-diff design. Both analyses confirm our previous findings. Results are reported in Table A3 of the online appendix.

6.2.4. Additional control variable

We finally question whether the firm's patenting activity is correlated with the contracts' monetary value. This variable has not been considered so far because it is missing for more than 50% of the suppliers. Nevertheless, limited to the subsample of firms for which this information is available, we carry out a further empirical analysis aimed at understanding whether the contracts' size may influence firms' patenting activity. Specifically, we re-estimated both the TWFEDD and the staggered diff-in-diff models adding the contracts' value among the regressors. Results are reported in Table A4 of the online appendix and show that our previous finding about the positive impact of the ASI procurement on firm's patenting activity is entirely confirmed in the considered subsample. On top of that, we find a positive correlation between the contracts' value and our proxy for firms' innovation. The estimated coefficient is positive and statistically significant, though its size is quite small.

7. Conclusions

This paper provides a novel contribution to the literature on public procurement. First, our research applies to the space industry, which is a relevant, yet under-explored economic sector. The space industry is growing in importance and size (OECD 2019, 2021) and for a long time has been using the public procurement tool to purchase highly specialized technological products not yet available in the market, thus stimulating innovation (OECD 2011; Raiteri 2018; OECD 2016; ESPI 2019). Nevertheless, no previous research has developed a rigorous micro-econometric model to assess the public procurement impact on firms' innovation in the upstream space industry. Our paper fills this gap by implementing a novel quasi-experimental design which combines a PSM technique with a difference-in-differences strategy and expands it with a staggered difference-in-differences approach. This empirical design allows to properly address the endogeneity nature of the space agency's procurement and obtain a causal estimate of its impact on the suppliers' patenting activity.

This is a major contribution to the extant literature that largely failed to estimate the causal effect of public procurement on innovation because it neglected the estimation biases arising from the non-random assignment and time heterogeneity of procurement orders.

We find that in the context of space policy, public procurement can stimulate the patenting activity of the firms receiving the order by roughly 10% compared to a control group of non-supplier firms. Our results confirm previous intuition on the positive contribution of demand-side policies in supporting innovation (Edquist et al., 2015; Edler and Georghiou, 2007; Bleda and Chicot, 2020; Stojcic et al., 2020; Caravella and Crespi 2021).

Another relevant contribution of our analysis is that, exploiting the longitudinal dimension of our data and novel econometric techniques, we investigate the dynamic dimension of the treatment effect. We find that the effect of the procurement is increasing in time and persists for several years after the beginning of the procurement relationship.

Overall, these findings suggest a twofold mechanism for positive externality: first, the technological content of the assets required by the ASI generates learning effects for the firms delivering the order. Second, ASI's deliberate lack of interest in appropriating possible benefits from invention and innovation that may arise from learning, e.g., through patent protection, creates a positive externality. Indeed, while ASI needs to be cost-effective, given its budget constraint, its fundamental objective is to promote technological development and scientific research without gaining a profit. As often happens in a procurement relationship with a public agency or research infrastructure (see Castelnovo et al., 2018), these institutions usually pay a reasonable price to the suppliers for the input and do not seek compensation for the knowledge spillovers that may occur.

Policy and managerial implications. Our results have policy and managerial implications. At the managerial level, our findings have implications for both firms' and public procurers' internal accountability. Regarding firms, they highlight the need to increase awareness about the positive impact of technological procurement on suppliers' innovation capacity, to encourage managers to develop procurement relationships. Concerning the public procurers' side, policymakers should consider the role of the public sector in shaping innovation, specifically the positive effects on firms that can return in the form of better innovation management and technological capabilities. This is crucial to fully appreciate the positive medium and long-term benefits that may stem from public procurement in the context of ambitious mission-oriented policies.

At the policy level, our findings provide further evidence that PPI is an effective demand-side policy to foster firms' innovation and suggest that policy incentives should be introduced to support the collaborations between firms and public agencies/research infrastructures. This point cannot be neglected in the current macroeconomic scenario. During the last decade the space sector increasingly attracted the attention of several private investors which have started to compete with space agencies in the building of space infrastructures. While governments still represent the main source of funding for space, over the past few years private funding has tremendously grown, "*with unprecedented private capital flows in the space sector from angel and venture capital investments*" (OECD 2019, page 18), bringing to the construction of several private satellites.[9] However, the current macroeconomic and geopolitical scenario, which combines high inflation rates, increasing interest rates,

[9] Starlink, the satellite internet constellation operated by the SpaceX company founded by Elon Musk, is probably the most famous case of these privately led initiatives.

high energy prices and relevant uncertainty due to the Ukraine war and the pandemic crisis, is likely to reduce the private sector risk-taking attitude and the related propensity to invest in a sector whose returns are uncertain and deferred in time. In this context, markets are increasingly relying on government funding to support industry and spur innovation. This calls for a future enhanced role of pivotal public players like space agencies.

Limitations and future research. We finally discuss some limitations of our paper and the related research extensions. We believe that a first issue of our analysis concerns its external validity. Previous literature has highlighted that the capacity of procurement to support innovation crucially depends on the intrinsic competences, mission, and capacity of the procuring agency (Georghiou et al., 2014; Edler et al., 2006; Guerzoni 2010; Uyarra et al., 2014). We have verified that this argument holds in our specific high-tech setting, characterized by a procuring agency with a clear innovation-oriented mandate, with relevant professional skills and competences. However, the public sector is composed by a large variety of institutions. As argued by Uyarra and Flanagan (2010) it is quite unrealistic to expect all of them to contribute to innovation through the PPI tool. Indeed, some of them may lack the required competences to govern the PPI process. This suggests that it could be more effective to limit the goal of promoting innovation via public procurement to specific procurement agencies with relevant professional skills. Another potential limitation stems from using patents as proxy for firm's innovation. We acknowledge that patents represent an imperfect proxy for firms' innovation, more tailored to measure the firms' R&D output rather than their whole innovation activity (which can be better proxied by the increase of sales from innovative goods or services, an information often available in innovation-oriented surveys).1 However, using patents allows to rely on objective data which avoid the potential self-selection, over-optimism or subjectivity biases bias associated with surveys (low compliance rate, with respondent firms being often the most efficient ones). Moreover, differently from most of the surveys, patent data are available for a long period, making it possible to build a panel dataset with a significant longitudinal dimension. This allows to inspect the dynamics of the procurement effect on firms' outcomes, an issue that has not been much investigate by previous studies.

A further limitation of our analysis is that we focus only on the direct effects of procurement on the upstream space industry, while we disregard the potential innovation spillovers that can be indirectly stimulated over the entire space industry's value chain. Over the past decades, an increasing number of high-resolution satellite services and data have become available on an open access basis (GPS enabled devices, satellite communications, weather and Earth Observation satellite data, among others). These can provide precious information, as they allow to observe global and local phenomena with elevate coverage, accuracy, and consistency (see, among others, Spreen and Kern, 2016 on sea ice extent; Kalia et al., 2016 on large scales ground instabilities and movements; Inglada et al., 2015 on precision farming; Schmidt et al., 2015 on post-eruption volcanic ashes; LeTraon et al., 2015 and Von Schuckmann et al., 2016 on, oceans' surface height, temperature and chlorophyll concentration; Duncan et al., 2014 on air pollutant fluxes). According to the OECD (2016), the availability of satellite data, combined with advances in computer processing power and analytics, is contributing to the exponential growth of innovative products and services in the downstream segment of the space sector's value chain. We believe that studying the indirect innovative impact of public procurement in the downstream sector is a promising field of future research.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.technovation.2022.102683.

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