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Space policy drives innovation through technological procurement: evidence from Italy

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Abstract

To what extent public procurement for mission-oriented policies drives innovation? Space policy is a particularly interesting case study, and we investigate the impact of technological procurement of the Italian Space Agency (ASI) on suppliers' innovation output. We have built an empirical model that takes advantage of unique data on ASI orders merged with patent and company data of more than 460 firms involved in a procurement relationship with ASI over the period 2004-2018. We combine matching techniques with a diff-in-diff approach with heterogeneous timing in treatment to assess whether becoming a space agency technological supplier has an impact on the extent and quality of firms' patenting activity. Our findings, that are novel for space policy studies, suggest a statistically significant effect of space agency procurement. The effect is stronger for high-tech suppliers. These results are robust to several alternative specifications and estimation methods and provide evidence about the importance of space policy in enhancing firms' innovation capacity through the procurement pathway.

Keywords: Public procurement, space industry, space policy, innovation.
JEL Codes: C25, H57, O32, O38

1. Introduction

Space policy is increasingly studied as an example of mission-oriented policies, as it needs to solve new technological challenges and create new market opportunities. Mazzucato and Robinson (2018; 2019) study the evolving role of NASA and ESA, respectively the US and European space agencies. Worldwide, expenditure in space activities has recently reached 75 billion dollars (62.8 billion euros), the highest figure so far, with an upward trend (OECD, 2019). Governments remain key performers and customers of innovation in the space industry. Government spending accounted for around 23% of the global space economy (OECD, 2016). The space industry in Europe reached its maximum commercial value in recent years, combining more than 8 billion in sales and 40 thousand employees; public buyers are responsible for around 60% of total sales, with the European Space Agency (ESA) above all (ASD, 2019). In terms of investments, France is the first European space economy with expenditures equal to 0.1% of the GDP, followed by Italy at 0.05% and Germany at 0.047% (OECD, 2019).

Established in 1988, the Italian Space Agency (ASI) is a national public body supervised by the Ministry of Education, University and Research Its yearly budget sharply raised from €350 million in 2015 to more than €1 million in 2019 and 2020[1].

As stated in its statute, one of the ASI primary mandate is to promote technological development and scientific research. To this aim ASI develops programs and projects with high technological value[2]. This is reached mainly by financing applied research, by awarding contracts, selecting projects, and choosing the suppliers for their realization. Therefore, the ASI can be described mainly as a technological contracting authority.

The lines of action by the ASI include initiatives such as: i) the transfer of technical-scientific knowledge to/in favour of enterprises, universities, and research centres; ii) initiatives to support start-ups; iii) promotion of public and private additional investments (such as venture capital, risk finance, etc.) with a leverage effect; iv) transfer mechanisms of technologies and methods from other productive sectors; v) management and safeguard of the patent portfolio. Moreover, the ASI defines the technical and quality standards of space products and services, and carries out certification, authorization, and control tasks for the national space activities.

Altogether this highlights the ASI procurement capabilities, as well as its technical and scientific expertise and know-how it can make available to its industrial partners.

In this paper we explore to what extent procurement by ASI has been instrumental in promoting innovation. Our case study is relevant because public procurement in general is an important feature of the European economy, and increasingly of interest in the context of the public discourse on mission-oriented policies (Kattel and Mazzuccato 2018).

In the EU, public authorities spent around 14% of GDP on public procurement to purchase goods or services[3]. It has been widely argued that if part of this budget was dedicated to purchase innovative products, public procurement would generate a powerful stimulus for innovation (Aschoff and Sofka,

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[1] Source: ASI website

[2] According to the last Decree Law enforced (128/2003), the ASI is "*a national public authority with the aim to promote, develop and spread, by means of agency activities, the scientific and technological research applied to the space and aerospace sectors (…), develop innovative services, (…), coordinate and managing national, European, and international programs (…), safeguarding the competitiveness of the Italian industrial sector*".

[3] Source: https://ec.europa.eu/info/sites/info/files/file_import/european-semester_thematic-factsheet_public-procurement_en_0.pdf

2009; Edler et al. 2006, OECD, 2011). Through the request of new products, Public Procurement for Innovation (PPI, hereafter)[4] can lower the uncertainty linked to the innovative process, contributing to overcome the related market failures. By highlighting unmet needs and by favouring the interaction between users and potential suppliers PPI can stimulate the research and development of the firms receiving the orders (Edquist et al., 2105; Edler and Georghiou, 2007; OECD, 2017); it can foster technological progress and strengthen firms' innovation capacity (Edquist and Zabala-Iturriagagoitia, 2012; Ghisetti, 2017) through different channels, such as: increasing the firm's know-how, improving its ability to develop new equipment and methodologies; enhancing problem-solving ability; developing new networks and social relations (Salter and Martin, 2001).

Nevertheless, the capacity of public procurement to support innovation should not be taken for granted. Uyarra et al. (2014) discussed several conditions that should be satisfied for public procurement to be an effective stimulus to innovation. According to authors, numerous barriers can inhibit the potential role of PPI in spurring the suppliers' ability to innovate. A variety of professional skills is required on behalf of the procurer to overcome potential problems, such as the capacity to: design adequate contracts; properly evaluate tenders; interact effectively with the supplying firms in the post-procurement phase in order to overcome potential technical problems that may arise in the development of new products. In the lack of internal competences, the procurer may face problems in monitoring and evaluating the performance of the supplying party, thus creating potential room for a moral hazard behaviour that could result in raising the procurement's costs and timing (Edler et al. 2006). Internal competences are required also to be able to assess and to manage potential risks associated to the procurement process. A risk-adverse attitude of the procurer can represent another barrier as the contracting agency may be reluctant to use the public procurement as instrument to invest in R&D activities that do not guarantee a given market return (Tsipouri et al. 2010). Public procurers should act as risk-takers in R&D and innovation investments. Indeed, the risks due to the uncertainty of future demand and to the results of new products development often discourage private companies from bearing innovation costs (Mazzucato, 2016), leading to a socially sub-optimal level of innovation. Moreover, since the lack of market demand represents an obstacle for innovation (Gallup, 2011), public procurement may result ineffective in supporting innovation if it was a sporadic activity which does not manage to ensure a critical mass that firms require to undertake R&D investments.

Our research focuses on the space industry sector to empirically test the role of the Italian Space Agency in stimulating innovation among its suppliers through the public procurement tool.

Space activities have historically required large upfront investments and long-term funding commitments. This is still very much the case for many space programmes: although there is an increasing role for business enterprises, market, and technology risks (system failures) still justify public intervention in funding space innovation.

This paper investigates the impact of the procurement placed by ASI on the firms involved in its supply chain by carrying out a quantitative analysis based on procurement data. For each contract issued by the agency in the period 2004-2018 we gathered balance-sheet and patent data of more than 460 firms involved in a procurement relationship with the space agency.

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[4] PPI has been defined to take place when public authorities act as a launch-customer by placing an order for a product or a service that still do not exist on the market or is not commercially available on a large scale, but which could be developed within a reasonable timeframe (Edquist, Hommen and Tsipouri, 2000)

Count data models are applied to estimate the impact of the procurement collaboration on the number of patents filed by ASI suppliers. The analysis is performed following different approaches. First, we take a simple before/after approach that exploits the heterogeneity in the year when firms receive the order. Then, a matching technique is applied to expand the analysis by including a control group of non-ASI suppliers and a diff-in-diff approach which exploits firms' heterogeneity in the beginning of the procurement is applied to assess whether becoming a space agency technological supplier had a differential impact on the extent and quality of firms' patenting activity. Lastly, we take an event-study approach to grasp the timing of the impact.

Various estimation strategies provide consistent evidence that firms have benefit from the procurement relationship with ASI, resulting in an increase of their patenting activity with respect to both their pre-procurement level and the patents registered by the non-ASI firms belonging to the control group.

The paper is organized as follows. Section 2 reviews the relevant literature on PPI and technological spill-overs from the space industry. Section 3 presents the data and section 4 the describes the empirical strategy and presents the estimation results, while in Section 5 several robustness checks are entertained. In Section 6, we draw conclusions and discuss policy implications.

2. Literature review

Our research contributes to the empirical economic literature which investigate the impact of PPI on firms' innovation output. Within this literature, from a methodological standpoint it is possible to distinguish two approaches: 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 database including balance-sheet and patent data.

Analyses based on case-studies mainly focus on large public research infrastructures and provide a first qualitative insight on how the procurement placed by these entities can play a crucial role to support firms' economic performance and innovative activities. Evidence suggests that the impact is particularly strong for suppliers operating in high-tech sectors (Aberg and Bengston 2015; Autio et al. 1996; Autio et al. 2004; CSIL 2019; Martin and Tang 2007; Edquist et al. 2000).

Studies based on surveys to the suppliers of a specific public customer make it possible investigating the experience of a larger sample of companies, even if with a less in-depth detail level, allowing a superior generalization of the results. Among the studies that opted for this research strategy there are Autio et al. (2003) and Florio et al. (2018), which focused on the case of the CERN. They evaluate the impact of CERN procurement using multi-dimensional surveys to its suppliers, which allow identifying the benefits generated by the procurement relationship in different areas.

A survey methodology based on direct interviews with contracting firms has been adopted also by studies focusing specifically on the space industry. A comprehensive evaluation of the indirect industrial effects generated by the European space programs was conducted by B.E.T.A.[5] (1980, 1988, 1996) and then analysed and discussed by Cohendet (1997) and Bach et al. (2003). Findings suggest 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.

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

More recently, the Danish Agency for Science (2008) has 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 the direct turnover for ESA contractors and the indirect effects resulting from the development of new technologies and competencies. In a survey addressed to enterprises involved in the provision of technological products and services to the Italian and European Space Agencies, Castelnovo et al. (2021) showed that firms benefited from the procurement relationship with the space agency, resulting in the achievement of product and process innovation outputs. Interviewed firms argued that the collaboration with the space agencies helped them to enhance their technical know-how, with significant improvement in their production processes, R&D capabilities, and management/organizational skills.

Most of the studies performing quantitative analysis rely on the data collected through national or international surveys, such as the Community Innovation Survey (CIS), and often implement non-parametric matching techniques using PPI as the treatment variable.

Some of these analyses investigated the effectiveness of PPI as a demand-side innovation policy compared to, or in combination with, other innovation measures. A recent study by Stojcic et al. (2020) used CIS data from in eight Central and Eastern European countries to evaluate the effectiveness of both public funding and PPI on firm-level innovation output and test whether the two measures complement each other in their effects on firm innovation and performance. Applying matching techniques, they found that PPI has a large effect on innovation and output, and the stronger impact is achieved when firms receive both PPI and financial support. Caravella and Crespi (2020) investigated the impact of public procurement on firms' R&D investments when taken in combination or insolation with supply-push measures. Exploiting CIS data from Italy, they distinguished between regular procurement contracts (RP) and PPI, and then used balance-sheet information extracted from the AIDA-Bureau Van Dijk database to implement propensity score matching. Their results showed that, while supply-pushing policies (like soft loans, tax deduction and grants) alone can foster firms' R&D expenditures, the ability of public procurement activities in shaping innovative investments depends on the inclusion of innovative demand in the procurement contracts and the adoption of contemporaneous supply side measures. Specifically, RP is not able to trigger a significant rise of R&D, while PPI achieves this goal when jointly implemented with supply-side instruments, suggesting that the design of the policy mix matters.

Different conclusions are drawn by Guerzoni and Raiteri (2015). Using data from the Innobarometer survey and implementing matching techniques, they suggested that the impact of PPI on firms' expenditure in innovative activities may be even stronger than R&D subsidies and tax credits. When controlling for the interaction with other policies, supply-side subsidies turn out to be not as effective as reported in previous studies, while PPI achieves the stronger impact.

Similarly, Aschoff and Sofka (2009), who compared the effectiveness of regulations, R&D subsidies, and basic research at universities in driving the market success of innovation. Exploiting data from the "Mannheim Innovation Panel" survey, which includes information on over 1,100 German companies, they showed that PPI is as effective as knowledge spill-overs from universities in propelling innovation success, while neither regulation nor public R&D subsidies seems to have a significant impact on market success. However, the effectiveness of public procurement varies according to firms, industry, and area: it is especially effective for smaller firms in regions under economic stress and in distributive or technological services.

Czarnitzki et al. (2020) investigated whether PPI can stimulate innovation in the business sector by exploiting a legal change in the procurement framework implemented in Germany in 2009, which allowed government agencies to specify innovative aspects of procured products as selection criteria in calls for tender. Using data from the CIS and implementing a wide range of econometric models which include nearest-neighbour matching, they showed a significant effect of PPI on revenues from new products and services. Moreover, they demonstrated that PPI mainly stimulates incremental innovation rather than true market novelties.

The use of PPI as a tool to stimulate innovation find application in different fields, as shown by Ghisetti (2017) who investigated the role of governmental demand in driving the adoption and diffusion of sustainable manufacturing technologies. Using data from the Innobarometer survey database and implementing non-parametric matching techniques, the author suggested that PPI plays a crucial role in the uptake of environmental innovations.

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 public procurement on the CERN supply-chain. Their analysis showed that becoming a CERN supplier has a positive impact on company R&D investment, probability to patent new products, productivity, and economic performance. These results are driven by suppliers operating in high-tech sectors, while the impact on low-tech companies is smaller and often not statistically significant. We build on these previous results with a further improvement of the econometric approach.

3. Sampling strategy and descriptive statistics

ASI granted us access to its procurement database, including information on 15,208 technological contracts/orders placed by ASI to 739 suppliers over the period 2004-2018[6]. The database includes information about contracts (subject, signing year, the related programme and project) and the awarding suppliers.

Since the aim of the present paper is to study the impact on ASI industrial partners, we exclude from the sample universities and public agencies and authorities. This leaves us with a sample of 676 firms.

Exploiting the online databases maintained by Bureau Van Djik (BVD) - namely Aida, Orbis and Orbis Intellectual property - we retrieved balance sheet and patent data over the period 2003-2018.

Specifically, the data we extracted from the Orbis and Aida databases include information about company assets (tangible fixed assets and intangible fixed assets), operating revenues, number of employees, listing status, incorporation year, activity sector (based on NACE codes) and geographical location. From the Orbis IP database we obtained company patent data, including the patent application number, the year of the application, the patent office where patents, and the number of forward citations.

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 7.150 observations over the period 2003-2018.

After matching the cross-sectional dataset on ASI contracts with the longitudinal dataset on firms' data we can create a dichotomic variable named *Post Procurement (PP)* which equals 0 in the year preceding the award of the first contract and 1 after the company became an ASI supplier. Figure 1 reports the partition into suppliers and non-supplier firms across years. We can observe that firms

[6] 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.

composing 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 contractual relation with ASI. Between 2004 and 2017, in each year some firms shift their status from not-yet-supplier to suppliers in different years.

Figure 1 – Change in suppliers' status over time.

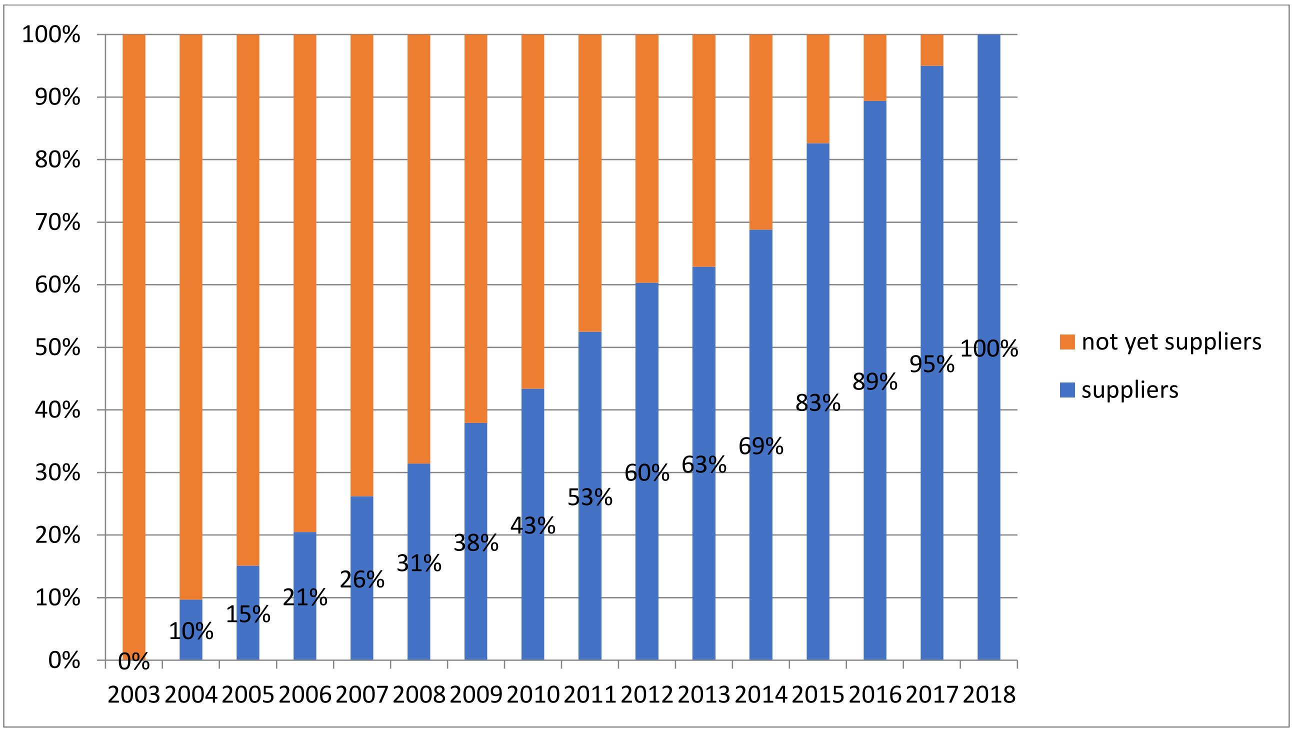
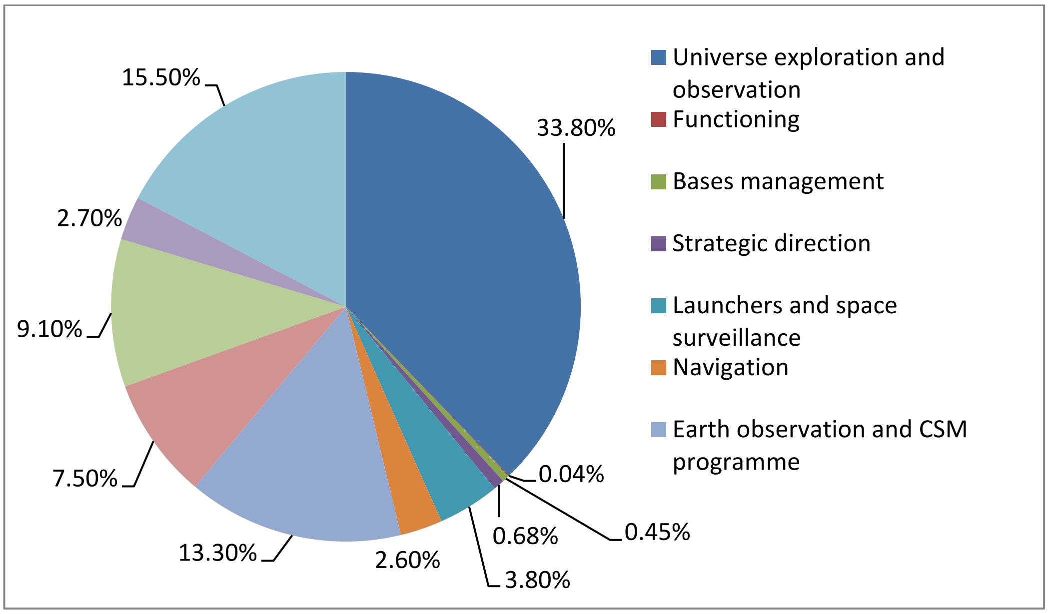


Figure 2 shows the distribution of projects financed through the ASI public procurement across activity sectors, as classified by the space agency when placing the order. Most of the orders are included in the three categories: i) universe exploration and observation, ii) human space flight and microgravity, and iii) earth observation and Cosmo SkyMed satellite programs[7].

Figure 2 – Distribution of contracts by activity sector

[7] Cosmo SkyMed represents one of the most significant projects financed entirely by ASI. It is the world first Earth satellite observation system designed for dual purposes, civil and military, for national security, but also for the prevention of environmental disasters, for the study of the Earth's surface. COSMO SkyMed is based on a constellation of four identical satellites, equipped with synthetic aperture radar (SAR) working in the X band.



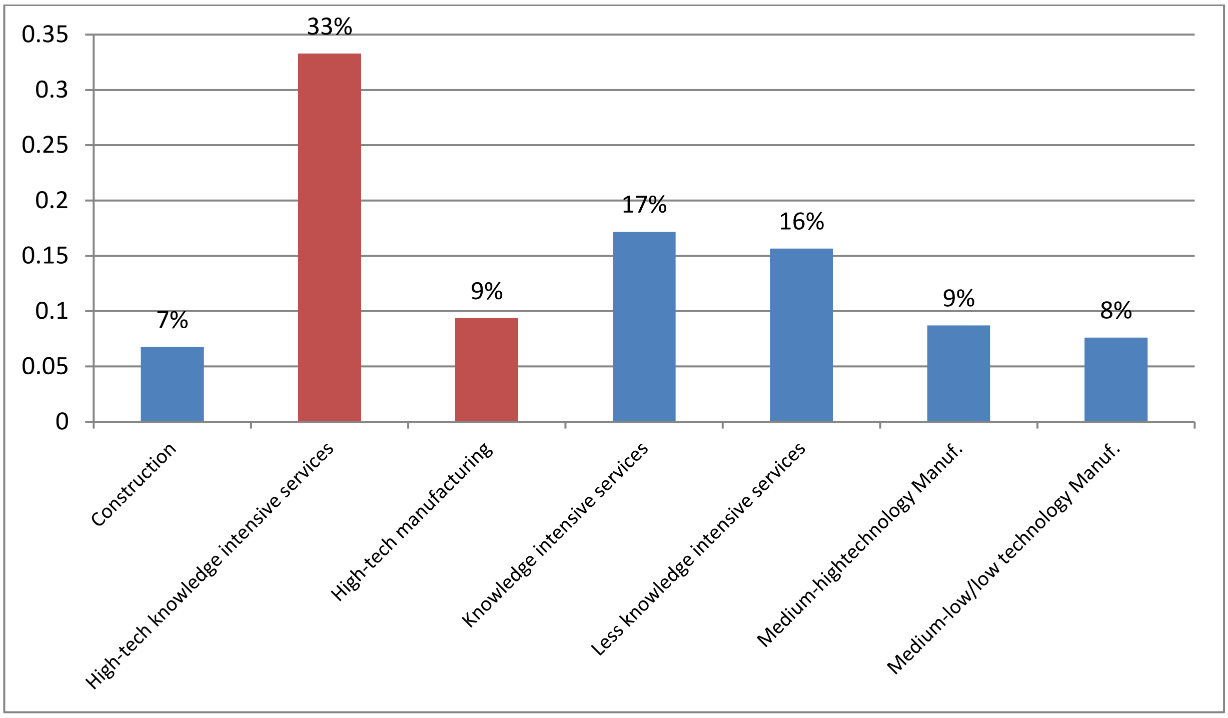
Most of the firms composing our sample operates in the ICT and Manufacturing sectors (27% and 25% of the sample respectively), while almost 20% undertake professional, scientific, and technical activities. Table 1 below provides the full distribution of suppliers according to the NACE classification.

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**

As shown in Figure 3, built according to the OECD sector classification into technological classes, 42% of suppliers are active in high-tech manufacturing or knowledge intensive services, 9% of them belongs to medium-high-tech manufacturing sectors and an additional 17% operates in knowledge intensive services, providing evidence of the high technological and knowledge content of the orders delivered by firms involved in the space procurement.

Figure 3 – Firm sectorial distribution based on Eurostat High-tech aggregation by NACE rev.2



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 companies emerges also from the summary statistics for suppliers' balance-sheet presented in Table 3, which exhibit a heavily skewed distribution (as it is often the case with accounting data) as it can be noticed comparing the mean and median values.

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%

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

Variable	Obs	Mean	Std. Dev.	Median
Total assest (€ , thd)	459	473.548	2.940.950	3087
Tangible fixed assets (€ , thd)	459	182.504	1.818.316	117
Intangible fixed assets (€ , thd)	459	69.667	538.611	51
Turnover (€ , thd)	459	271.938	1.635.772	2.630
Employees	459	2485	28.737	20

Concerning the firms' patenting activity, almost three quarters of the companies did not file any patent over the period 2003-2018, as usual in many industrial sectors (REFERENCE). As it can be noticed, however, the average number of patent applications per firm and the stock of patents in the post-procurement period significantly increased compared to its pre-procurement level. We want to test in a multivariate context if this simple descriptive statistics is confirmed, as it would provide evidence that public procurement actually is an innovation pathway of space policy, confirming the qualitative evidence of the above mentioned previous literature.

Table 4 - Patent application per firm (2003-2018)

Patent applications	N° of firms	%	Patent stock	N° of firms	%
0	349	75.6	0	333	72.1
1-5	58	12.6	1-50	89	19.4
6-10	16	3.5	51-100	11	2.4
>10	38	8.3	>100	28	6.1
	Mean			**Mean**	
Avg. 2003-2018	0.78		Avg. 2003-2018	4.30	
Avg. pre-procurement	0.51		Avg. pre-procurement	1.53	
Avg. post-procurement	1.06		Avg. post-procurement	7	

4. Empirical strategy

With the present analysis we intend to contribute to the literature which has investigated the role of public procurement as a potential demand-pull instrument for triggering technological innovation (Aschoff and Sofka, 2009; Salter and Martin, 2001). Specifically, we are interested in assessing whether the Italian Space Agency, through the order of particularly tailored niche high-tech products that still do not exist on the market or that are not commercially available on a large scale, acts as driving player in supporting the innovation process within the space industry.

A variety of empirical strategy is developed in this paper to test the impact of space technological procurement on suppliers' innovation output. We first use a before-after approach to analyse how the firms' patents have varied before and after the beginning of its procurement relationship with a space agency and, thus, to infer what is the role played by ASI in supporting the firm's patenting activity through the public procurement tool, while controlling for other factors which contribute to explain the firm's propensity to innovate.

To this aim we exploit the heterogeneity across firms in the year of the first contract signed with (we recall that firms composing our sample became ASI suppliers in different years). This approach entails that, in each year, firms that are not-yet-suppliers act as a control group. The advantage of this empirical strategy is that, given the highly specialized nature of firms involved in the space industry and the characteristics of goods and services they provide, it allows to have a control group that is structurally similar to the treated group.

However, we are aware that this strategy suffers from some possible drawbacks. The possibility of inferring a clear effect of public procurement on patenting activity by simply comparing the average level of patents before and after the treatment takes place is threatened by a potential endogeneity issue and, in particular, by a potential selection bias. Indeed, the treatment (awarding a public procurement) is not exogenous, and our dataset includes only firms that have been selected by the ASI itself according to some observable characteristics, including their pre-procurement technological skills and possibly their innovation capability, which is likely to persist after the beginning of the procurement relationship. If this is the case, the lack of a counterfactual would not allow to identify the impact of space procurement on innovation, as it would not be possible to

determine with certainty whether the possible increase of patents in the post-procurement period shall be attributed to the treatment itself or rather to the idiosyncratic characteristics of the ASI suppliers.
Since an experimental randomized strategy is not a feasible option because of the nature of the industry, to address this potential endogeneity issue, we developed a quasi-experimental design where a propensity score matching (PSM) procedure is combined with a diff-in-diff approach.

4.1 Propensity Score Matching

To address the potential selection bias issue, we used a PSM technique to create a counterfactual control group. This approach consists in selecting a sample of firms whose characteristics in the pre-treatment period are not statistically different from the ASI suppliers (our "treatment group").
To estimate the propensity score – that is the probability of being treated given a vector X of observable characteristics – we first select a very large sample on non-treated companies to be matched with the treated ones. Specifically, we select from the Orbis database around 2 million active firms operating in the same NACE sectors (defined according to the 4-digit NACE rev. 2 classification) of the space agency suppliers and located in the EU15 Member States. Then, we extract from Orbis a randomly selected subsample of 250.000 firms, with the related balance-sheet and patent data.
Then, a logit model is adopted to estimate the probability of being treated conditionally on observable firms' characteristics. Specifically, we considered both variables that are fixed over time – the sector where they operate, their year of incorporation and their listing status – and variables measured in the pre-treatment period. We used the mean value of firms' tangible and intangible assets, operating revenues and number of employees calculated in the years before the treatment.
Since the time of the treatment is not unique – treated companies become ASI suppliers in different years – it would be questionable to match companies across different years, thus we replicated the matching procedure several times to match companies 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 are then excluded from this latter group to avoid double counting).
After sorting the dataset according to a randomized order, for each treated company, we selected up to three companies from the non-treated group according to the closest propensity scores obtained from the corresponding logit estimation.
The table below shows the good quality of the adopted matching procedure. The pre-treatment mean value of some variables of interest is reported for both the treated and the control group. Then, the t-tests for equality of means in the two samples is performed both before and after the matching procedure. The results of the two-sample t-test shows that, for almost the variables, the significant differences in the means among the unmatched groups do not persist after the propensity score matching procedure. The null hypothesis (H0) is that the difference between the averages of the two groups is zero. When looking at the unmatched group, for all the variables analysed, except for the age of the firm, 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 allows to reject the null hypothesis, allowing us to exclude the persistence of statistically significant differences between the groups in the pre-treatment period. Interestingly, this result holds not only for the control variables that have been used in the matching procedure but is verified for the patent variable as well.

Having constructed a control group whose mean outcome in the pre-treatment period does not differ compared to the treated group, we face a lower risk of our results being affected by selection issue, and possible patent differences among the two groups in the post-treatment period can be attributed to the treatment with a higher degree of confidence.

Table 5. Two-sample t test - balancing property for unmatched and matched groups

		Mean	St. Dev.	Control group	Treated group	Tstat	(p-value)
Tangible Assets	unmatched	8,717.47	362,816.92	8,348.94	113,619.69	6.22	0
	matched	119,706.28	1,381,564.30	121,825.51	113,538.31	-0.11	0.91
Intangible Assets	unmatched	3,830.97	199,951.97	3,629.69	61,124.94	6.16	0
	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
	matched	275,640.06	2,441,702.44	303,722.70	193,906.09	-0.83	0.41
Number of employees	unmatched	97.4	2,497.38	92.29	1,551.94	12.53	0
	matched	1,776.10	17,941.17	1,851.96	1,555.32	-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
Patent stock	unmatched	0.01	1.86	0	2.55	29.46	0
	matched	3.49	38.58	3.81	2.56	-0.6	0.55
Patents	unmatched	0	0.72	0	0.89	26.65	0
	matched	0.86	10.8	0.85	0.9	0.08	0.94

4.2 Empirical models and results

In the following, we present the empirical models adopted to analyse the role of public procurement in supporting innovation for the firms which become ASI suppliers. We present several model specifications, discuss the rationale behind their choice and for each of them we present and discuss the results of our empirical analysis.

In our main specification, firms' innovation output is proxied by their stock of patent applications in the year t[8], which is defined by the following equation:

$$patent\ stock_t = patent\ stock_{t-1}(1-\rho) + patent_t$$

where $patent_t$ is the number of patents filed by each company 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).

As acknowledged by previous literature, patents are an imperfect proxy of firms' innovation. Patents are not always embedded into innovative products which are commercialized in the marketplace. In this case, patents can better measure the firms' invention rather than their innovativeness since they may not be commercially exploited. Moreover, the number of filed patents can potentially under-represent innovation – this is the case when firms strategically opt not to patent their inventions in order to avoid any disclosure requirement – or alternatively over-represent innovation, especially

[8] Previous research has already used the stock of patents as main dependent variable (Guadalupe et al. 2012; Bertoni and Tykvová 2015). However, this choice is not detrimental, as our main results are confirmed when the yearly number of patents is used as main dependent variable.

when patents are filed for strategic reasons different from the genuine protection of an innovation, for instance to create some market barriers against potential new entrants or to increase the costs that competitors must support to use a given technology (Archibugi and Pianta 1996; Griliches 1990; Langinier 2004; Kleinknecht et al. 2002).

Despite the shortcomings, patent applications are usually considered an output of the firm inventive process and have been widely used in the literature to measure firm-level innovation (among others Mann and Stager 2007; Hall and Lerner 2010; Arqué-Castells 2012; Marin 2014; Marin and Lotti 2017; Clò et al. 2020) and particularly to measure the role of public procurement in supporting innovation (Castelnovo et al. 2018, Raiteri 2018). Indeed, patent data are publicly available documents, they represent a measurable source of information about the research and development process, they are regularly collected worldwide and present long time series, thus allowing for international comparison on the path of technological change and the firm process of innovation (Griliches 1990). Moreover, patent counts highly correlate with other potential measures of innovative activity, such as R&D spending or new products (Kortum 1997, Hagedoorn and Cloodt 2003). They can be considered a reliable proxy of innovation activity especially in manufacturing industries (Kleinknecht et al. 2002; Hipp and Grupp 2005).

According to previous research (Castelnovo et al. 2018; Clò et al. 2020) also in this work we decided to restrict out 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 of representing an appropriate proxy of the firm's innovation in the space industry.

Negative binomial models

Our analysis assesses whether becoming an ASI supplier is associated with an increase in the firm's patenting activity. Given the positive-skewed distribution with a long right tail of our dependent variable, following other papers (Choi et al. 2011; Furman and Stern 2011; Castelnovo et al. 2018), we adopt a negative binomial model with standard errors being robust to heteroskedasticity. This model generalizes the Poisson regression model by introducing an unobserved heterogeneity term which is independent on the vector of regressors X_i (Blundell et al., 1995). This choice is driven by the overdispersion of our data compared to the Poisson distribution[9], which assumes the sample variance of the patent variables being equal to the sample mean ($E[Y] = var[Y] = \vartheta$). The negative binomial is thus robust to several misspecifications such as over-dispersion, the presence of an excessive number of zeros, as well as cross-sectional dependence.

The first specification of the negative binomial regression model with standard errors being robust to heteroscedasticity is given by:

$$E\left[PAT_{i,t}\right] = exp(\alpha + \beta PostProcurement_{i,t} + X'_{i,t}\gamma + \vartheta PAT\_PSA_i + Z'_i\delta + \theta Y_t) \quad (1)$$

where the dependent variable $PAT_{i,t}$ is the expected number of the stock patents filed by the firm *i* in year t. $PostProcurement_{i,t}$ is a dichotomy variable that for the treated companies takes the value of 0 in the pre-procurement period – in the year before the first order a company received from ASI –

[9] This is indicated by the significance of the goodness-of-fit $\chi 2$

and 1 thereafter. For the control group, the variable $PostProcurement_{i,t}$ equals zero, as this latter group is composed by companies which have never entered in a contractual relationship with ASI.
The vector $X_{i,t}$ includes the set of firm-level variables recognized as relevant to explain the firm's innovative activity and that are introduced to control for potential confounding factors. The size of the company is proxied by its operating revenues, tangible assets are included to measure the firm's capital expenditures, and intangible assets are used as a proxy for internal R&D effort, R&D expenditures are usually not specified in the firms' balance sheets (Leoncini et al 2018; Marin 2014). All these financial characteristics are log-transformed for estimation purposes. We also include the age of the firm among the explanatory variables and a dummy variable equal to 1 if the firm is listed on the stock market and zero otherwise.
We also include in our main estimation model the variable PAT_PSA_i (patent pre-sample average), that is the mean level of patent filed by the company before 2003. This pre-sample mean captures the firm's patent capability prior to our considered period and proxies for the unobserved difference among firms in their ability to patent, allowing us to control for possibly correlated, time-invariant heterogeneity (Blundell et al. 2002).
The vector Z_i includes country and sector fixed effects that capture time-invariant differences in patenting activities across geographical areas and industries. They have been added to control for potential confounding factors and for correlated unobserved heterogeneity, while the yearly fixed effect Y_t is included to control for time-dependent common shocks, including macroeconomic exogenous shocks.
In a second specification of the model, we investigate whether the impact of procurement on the patenting activity is differentiated across sectors depending on their technological intensity. For this purpose, we modelled the interaction between the PP_{it} dummy variable and a $Low\ Tech_{it}$ dummy variable which equals 1 only for firms belonging to low tech sectors, as defined by the Eurostat indicators on High-tech industry and Knowledge – intensive services

$$E\left[PAT_{i,t}\right] = exp(\alpha + \beta PostProcurement_{i,t} + \varphi PostProcurement_{i,t} * Low\ Tech_{it} + X'_{i,t}\gamma + \vartheta PAT\_PSA_i + Z'_i\delta + \theta Y_t) \quad (2)$$

Results of this analysis are reported in Table 6. Initially only the ASI suppliers have been considered (Columns 1-3 of Table 6), then the analysis has been extended to the enlarged sample obtained through the propensity score matching (PSM) procedure (Columns 4-6 of Table 6).
Column 1 reports an extended knowledge production function which includes the award of a public procurement by ASI. Results show that the number of patents is positively and significantly associated to the size of the firm (measured by the log of the number of employees), the intensity of R&D internal effort (proxied by the log of intangible assets) and negatively correlated with the firm age. Operating revenues has a negative coefficient, while tangible fixed assets have a positive coefficient, both being significant at a 10%. Being listed on a stock market is significant in explaining the firms' patenting activity. Our main variable of interest – the public procurement variable – has a positive and significant coefficient, implying that after awarding a procurement and becoming an ASI supplier, firms experience an increase in their patenting activity. This suggests that the public procurement promoted by the Italian Space Agency contributes to support innovation for the firms active in the upstream sector of the space industry.
In Column 2 we add the patent pre-sample mean among the explanatory variables to control for firm-specific not observable factors that might be relevant in explaining their patenting activity. As

expected, the coefficient of the patent pre-sample mean is positive and significant. More importantly, our main result is confirmed even after controlling for the pre-sample. The coefficient of the public procurement variable is still positive and significant at a 1% level, though its size is reduced significantly. This suggests that endogenous non-observable firms' characteristics are relevant in explaining their innovative performance and that omitting to consider them would bring to bias results. Other coefficients change in size or significance after the inclusion of the pre-sample mean. Both coefficients of the Operating Revenues and tangible fixed assets are now negative and not significant. Also being listed on the stock market is not significant anymore in explaining the firms' patenting activity. In Column 3 we further extend our analysis by introducing an interaction term between the Public Procurement dummy and the Low Tech dummy that identifies firms operating in low-tech sectors. Results show that the impact of public procurement is differentiated among sectors. Firms operating in high-tech sectors experience an increase in their patenting activity after becoming an ASI supplier. This is indicated by the positive and highly significant coefficient of the Public Procurement dummy whose size slightly increased after differentiating between high-tech and low-tech sector. Conversely, the coefficient of the interaction term is negative and significant, pointing that becoming an ASI supplier is negative associated with the patenting activity of firms operating in low-tech sectors.

In Columns 4-6 we show that our main findings continue to hold when the analysis is conducted on the enlarged sample determined through the PSM procedure. In all the three specifications of the model reported in Column 4-6, the coefficient of the public procurement dummy continues to be positive and significant. The impact of public procurement continues to be differentiated among high-tech and low-tech, though both the size of the coefficient and its significance are now lower. Among the other results, we report that, employees, tangible and intangible fixed assets have a positive and significant coefficient.

Table 6 - The role of ASI public procurement in firms' patenting activity: negative binomial model specification

	(1)	(2)	(3)	(4)	(5)	(6)
	ASI suppliers' sample			Enlarged sample after PSM		
Post Procurement (PP)	1.040***	0.441***	0.668***	1.248***	1.234***	1.295***
	(0.145)	(0.108)	(0.125)	(0.118)	(0.084)	(0.097)
Low Tech			0.489***			-0.033
			(0.173)			(0.125)
PP*Low Tech			-0.978***			-0.312*
			(0.203)			(0.189)
patent pre-sample mean		8.241***	8.161***		4.492***	4.497***
		(0.641)	(0.626)		(0.192)	(0.194)
Operating Revenues	-0.092*	-0.061	-0.066	0.186***	0.056	0.054
	(0.052)	(0.044)	(0.044)	(0.035)	(0.035)	(0.035)
Tangible Fixed Assets	0.087*	-0.007	-0.001	0.065***	0.043**	0.046**
	(0.045)	(0.032)	(0.032)	(0.022)	(0.022)	(0.022)
Intangible Fixed Assets	0.176***	0.149***	0.146***	0.221***	0.136***	0.137***
	(0.030)	(0.024)	(0.024)	(0.020)	(0.017)	(0.017)

Number of Employees	0.617***	0.287***	0.289***	0.335***	0.171***	0.173***
	(0.083)	(0.066)	(0.063)	(0.059)	(0.050)	(0.051)
Age	-0.261***	-0.214***	-0.199***	-0.073**	-0.030	-0.025
	(0.046)	(0.037)	(0.036)	(0.034)	(0.027)	(0.026)
Listed	1.853***	0.409	0.487	1.536***	-0.885***	-0.851***
	(0.607)	(0.294)	(0.309)	(0.226)	(0.180)	(0.180)
Constant	-3.568***	-3.335***	-3.496***	-6.258***	-4.924***	-4.878***
	(0.496)	(0.364)	(0.358)	(0.371)	(0.275)	(0.287)
Observations	7,150	7,150	7,150	19,745	19,745	19,745
Year Sector and Country FE	YES	YES	YES	YES	YES	YES
Vcetype	Robust	Robust	Robust	Robust	Robust	Robust

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Fixed Effect Model

The major limitation of the PSM procedure is that it can control only for the observable characteristics of the matched firms. Therefore, we further adopt an OLS fixed effect estimator, which allows to control for time-invariant differences across firms, thus avoiding a potential bias to arise from omission of fixed but unobservable firm-specific characteristics. This specification of the model reported in the equation below allows us to control for the unobserved heterogeneity between companies that might affect our estimates.

$$Y_{it} = \alpha + \mu_i + \gamma_t + X_{it}^{'}\theta + \beta PostProcurement_{i,t} + \varepsilon_{it}$$

Where μ_i and γ_t are respectevely individual and time fixed effects. $PostProcurement_{i,t}$ takes the value of 1 in the years after the treatment takes place and 0 otherwise. Being this variable equal to zero for the control group, its coefficient captures the impact of the public procurement on the treated group.

We first focus on the ASI suppliers only. After controlling for fixed effects, most of the variables is no longer significant in explaining the firms' patenting activity. The only variables that are still significant are the intangible fixed assets and the $PostProcurement$ dummy (Column 1 of Table 7). Therefore, these new results mainly confirm our previous finding about the positive role played by the ASI public procurement in stimulating firms' innovativeness. We also confirm that this impact is not uniform across sectors, being positive only for the firms belonging to the medium or high-tech sectors (Column 2). Columns 3 and 4 of Table 7 report the results of the analysis developed on the enlarged sample determined through the PSM.

In our regression, this is captured by the positive and significant coefficient of the variable $PostProcurement$ reported in Columns 3 and 4. This implies that, after becoming an ASI supplier, the change in the patenting activity of the firms belonging to the treated group increases with respect to the change in the patenting activity of the firms belonging to the control group. Results of the fixed effect estimator confirm also that the impact of public procurement is differentiated across sectors.

Table 7 - The role of ASI public procurement on firms' patenting activity: Fixed Effects model and two-way fixed effects model

	(1)	(2)	(3)	(4)

	ASI suppliers' sample		Enlarged sample after PSM	
Post Procurement (PP)	0.080***	0.112***	0.108***	0.139***
	(0.013)	(0.015)	(0.008)	(0.009)
PP *Low Tech		-0.102***		-0.098***
		(0.020)		(0.014)
Operating Revenues	-0.001	-0.002	0.003	0.003
	(0.005)	(0.005)	(0.003)	(0.003)
Tangible Fixed Assets	0.003	0.002	0.007***	0.006***
	(0.005)	(0.005)	(0.002)	(0.002)
Intangible Fixed Assets	0.016***	0.016***	0.012***	0.012***
	(0.004)	(0.004)	(0.002)	(0.002)
Number of Employees	-0.002	-0.004	0.002	0.000
	(0.009)	(0.009)	(0.005)	(0.005)
Age	0.023	0.015	0.022	0.021
	(0.050)	(0.050)	(0.014)	(0.014)
Listed	0.038	0.040	-0.176***	-0.176***
	(0.149)	(0.149)	(0.051)	(0.051)
Constant	0.014	0.067	-0.004	0.015
	(0.221)	(0.221)	(0.066)	(0.066)
Observations	7,150	7,150	19,745	19,745
Number of id	461	461	1,791	1,791
Year and Area	YES	YES	YES	YES

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Diff-in-diff with heterogenous timing in treatment

In the empirical model specification presented in this section, we exploit heterogeneity in the year companies receive the first order from ASI to develop a difference in differences approach with heterogeneous timing in the treatment. Recent literature has highlighted the limits of the traditional two-way fixed effect when the treatment is not unique but varies across groups or time periods (Callaway and Sant'Anna 2020; de Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2019). Goodman-Bacon (2019) shows that, when the time of the treatment varies across groups, the treatment effects are heterogeneous in time and the the unbiased DiD estimator is a weighted average of the multiple groups/periods DiD estimators. The intuition behind this result is that, when multiple treatment periods are in place, the late-treated group acts as a control group for the early-treated group and vice versa.

We are interested in estimating the impact of an event (becoming an ASI supplier) which occurs in different time periods across different units, while controlling for firms that never become a space agency supplier. Since ASI suppliers enter in a contractual relationship with the space agency in different years (the year of the procurement differs among firms), we adopt a panel event study model (Clarke and Schythe 2020). By using as counterfactuals both untreated units and units that have not been treated yet (that receive the treatment in a following year), panel event study models are designed to estimate the impact of an event affecting units in different time periods (Athey and Imbens 2018). By denoting as $Event_i$ a variable which record the time period t when the event takes place for the unit i, the specification of the panel event study can be written as:

$$y_{it} = \alpha + \sum_{j=2}^{J} \beta_j (LAG\ j)_{it} + \sum_{k=1}^{K} \gamma_k (LEAD\ k)_{it} + \mu_i + \gamma_t + X'_{it}\theta + \varepsilon_{it}$$

Lags and leads are defined as follows:

$$(LAG\ J)_{it} = 1[\mathrm{t} \leq\ Event_i - J]$$

$$(LAG\ j)_{it} = 1[\mathrm{t} =\ Event_i - j]\ \ for\ j\ \epsilon\ \{1, \dots, J-1\}$$

$$(LEAD\ k)_{it} = 1[\mathrm{t} =\ Event_i + k]\ \ for\ k\ \epsilon\ \{1, \dots, K-1\}$$

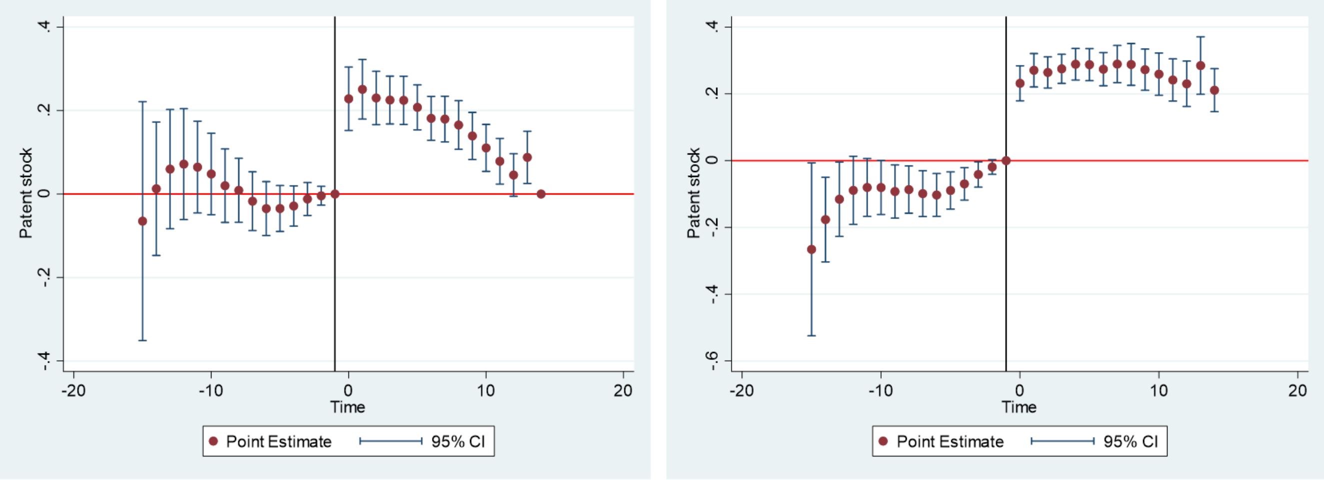
$$(LEAD\ K)_{it} = 1[\mathrm{t} \geq\ Event_i + K]$$

Lags and leads are binary variables capturing the distance across the year of the observation and the year when the event takes place. They indicate that each unit of observation *i* is a given number of periods away from the event. Firms that never become ASI suppliers have null lags and leads and represent the pure counterfactual. Ultimately, the inclusion of lags and leads allows to estimate a treatment effect which is heterogeneous in time and to assess its temporal dynamic, for instance whether it is increasing or decreasing in time, whether it is stable or volatile, whether it is permanent or temporary.

Below we report only the main results referred to the public procurement variable, while the whole set of coefficients are reported in Table A.1 in the Appendix. The related lag and lead coefficients along with their confidence intervals are plotted in Figure x, where panel (a) refers to the ASI sample only, while panel (b) refers to the enlarged sample after PSM. Both figures provide evidence of an increase in the patent activity in the years following the award of a procurement. It is also possible to observe that the effect is not constant, and it tends to decline with time.

We can conclude that the positive effect of the ASI public procurement in the upstream space industry is robust to alternative model specification and is confirmed even when matching techniques are combined with fixed effects and with a diff-in-diff approach, which is designed to address potential endogeneity issues when randomization is not feasible.

Figure 4 - The role of ASI public procurement in firms' patenting activity: Diff in diff with heterogeneous timing in treatment



(a) ASI suppliers (b) Enlarged sample after PSM

5. Other Robustness Checks

In this section, we present a variety of further robustness checks showing that our main findings do not depend on depend on the chosen empirical strategy and are robust to alternative specifications of the dependent and explanatory variables, as well as to alternative estimation methods and matching techniques.

Zero-Inflated binomial models

Although the negative binomial model is appropriate when the dependent is characterized by a positive-skewed distribution and is robust to several misspecifications such as overdispersion and the presence of an excessive number of zeros, we adopt also a more stringent model - the Zero-Inflated negative binomial (ZIB) - to test whether our results are still valid when explicitly accounting for the high prevalence of zero in the dependent variable. Among the 461 ASI suppliers, 349 have never applied for a patent during the considered period, while the percentage of non-patenting firms raises to 82% when we considered the enlarged sample selected through the PSM procedure. To account for the prevalence of zero counts in the dependent variable we use a ZIB model, which is robust to zero outcomes as well as over-dispersion of the count data (Mullahey 1986, Greene 1997). The ZIB is based on a zero-inflated probability distribution, that allows for frequent zero-valued observations. It is structured in two parts: a logit model, which predicts the probability of not patenting, is fitted into a negative binomial model. Results are shown in Table 8. Results of the logit model for ASI suppliers suggest that the probability of belonging to the zero-patenting group decreases with the firm intangible fixed assets and with their patent pre-sample mean. The other inflate coefficients are not significant, suggesting that the odds of an inflated zero are not affected by other variables, including the public procurement one (Column 1). The results of the negative binomial model show that the award of an ASI public procurement is significant in explaining the firms' patenting activity, and this holds even when accounting for the firms' patent pre-sample mean which continue to have a positive and significant coefficient (Column 2). Results are widely confirmed when we look at the enlarged sample determined with the PSM. Results of the logit model (Column 3) indicate that, like before, the probability of never patenting decreases with the firm's intangible assets and its patent pre-sample mean. Moreover, also the coefficient of the Public Procurement variable is negative and significant, suggesting that the probability of belonging to the zero-patenting group decreases when a firm becomes an ASI supplier. Like before, the result of the negative binomial regression (Column 4) indicate that the firm's patenting activity increases after the award of a public procurement. The ZIB regression also confirms that the positive effect of the public procurement of the firms patenting activity is differentiated among low-tech and high-tech sectors (results have not been reported due to space constraint but are available upon request).

Table 8 - The role of ASI public procurement in firms' patenting activity: Zero-Inflated negative binomial model specification

	(1)	(2)	(3)	(4)
	Logit (inflate)	negative binomial	Logit (inflate)	negative binomial
	ASI suppliers' sample		Enlarged sample after PSM	
Public Procurement	-0.146	0.385***	-1.153***	0.417***
	(0.146)	(0.102)	(0.093)	(0.077)
Operating Revenues	0.029	-0.019	0.127***	0.149***
	(0.048)	(0.055)	(0.033)	(0.029)
Tangible Fixed Assets	0.038	0.030	0.003	0.013
	(0.044)	(0.040)	(0.026)	(0.019)
Intangible Fixed Assets	-0.301***	-0.048*	-0.268***	0.014
	(0.043)	(0.025)	(0.025)	(0.014)
Number of Employees	0.007	0.261***	-0.060	-0.031
	(0.082)	(0.067)	(0.047)	(0.041)
Age	-0.015	-0.038	0.008	0.106***
	(0.056)	(0.035)	(0.038)	(0.020)
patent pre-sample mean	-504.994***	2.226***	-573.378***	1.613***
	(12.629)	(0.120)	(14.222)	(0.047)
Constant	6.975***	-0.387	7.773***	-1.319***
	(1.065)	(0.384)	(1.046)	(0.260)
Observations	7,150	7,150	19,745	19,745
Year Sector and Country FE	YES	YES	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Generalized Method of Moments

The choice of using the patent stock as dependent variable could rise a problem of spurious correlation. As a first strategy to address this issue, we consider a Generalized Method of Moments (GMM) estimator to account for unobserved heterogeneity and tackle possible endogeneity concerns. As shown in Table 9, our main findings continue to hold when we use a first-difference GMM estimator, which includes the lagged dependent variable among the regressors (Arellano and Bond, 1991).

Table 9 - The role of ASI public procurement in firms' patenting activity: GMM

	(1)	(2)	(3)	(4)
	ASI suppliers' sample		Enlarged sample after PSM	

Post Procurement (PP)	0.024***	0.028***	0.030***	0.035***
	(0.007)	(0.009)	(0.005)	(0.006)
PP * Low Tech		-0.011		-0.015*
		(0.011)		(0.009)
Lagged dependent variable	0.737***	0.736***	0.696***	0.695***
	(0.030)	(0.030)	(0.023)	(0.023)
Operating Revenues	0.005**	0.005*	0.004**	0.004**
	(0.003)	(0.003)	(0.002)	(0.002)
Tangible Fixed Assets	-0.001	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Intangible Fixed Assets	0.005***	0.005***	0.003***	0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Number of Employees	0.010*	0.009*	0.006*	0.005*
	(0.005)	(0.005)	(0.003)	(0.003)
Age	-0.011	-0.012	0.004	0.004
	(0.043)	(0.043)	(0.010)	(0.010)
Listed	0.014	0.015	-0.022	-0.022
	(0.088)	(0.088)	(0.029)	(0.029)
Observations	6,228	6,228	15,253	15,253
R-squared				
Number of id	461	461	1,676	1,676
Fixed Effects	YES	YES	YES	YES

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Alternative definition of the dependent variable: yearly number of patent application

As a second strategy to support the evidence that our findings are not driven by the choice of the dependent variable, we show that estimation results are confirmed when the yearly amount of patent applications is used as main dependent variable instead of its stock level[10]. See Table 10 below.

Table 10 - The role of ASI public procurement on firms' patenting activity: Fixed Effects model and yearly patent application as dependent variable

	(1)	(2)	(3)	(4)
VARIABLES	ASI suppliers' sample		Enlarged sample after PSM	
Post Procurement (PP)	0.035***	0.040***	0.024***	0.029***
	(0.013)	(0.014)	(0.008)	(0.009)
PP * Low Tech		-0.016		-0.016
		(0.019)		(0.015)
Operating Revenues	0.011**	0.010**	0.009***	0.009***
	(0.005)	(0.005)	(0.003)	(0.003)
Tangible Fixed Assets	-0.005	-0.005	0.004	0.004
	(0.004)	(0.004)	(0.003)	(0.003)
Intangible Fixed Assets	0.010***	0.010***	0.001	0.001
	(0.004)	(0.004)	(0.002)	(0.002)

[10] Hereby we report the results of the fixed effects estimator. Nevertheless, our main results are valid also under the alternative model specifications adopted in the paper

Number of Employees	0.023**	0.023**	0.017***	0.017***
	(0.009)	(0.009)	(0.006)	(0.006)
Age	0.035	0.034	0.009	0.009
	(0.048)	(0.048)	(0.015)	(0.015)
Listed	-0.033	-0.033	-0.095*	-0.095*
	(0.144)	(0.144)	(0.054)	(0.054)
Constant	-0.219	-0.211	-0.061	-0.058
	(0.213)	(0.214)	(0.069)	(0.069)
Observations	7,150	7,150	19,745	19,745
Number of id	461	461	1,791	1,791
Fixed Effects	YES	YES	YES	YES

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Alternative definition of the dependent variable: forward citation-weighted patent grants
Results based on the use of patent application as dependent variable confirmed the validity of our findings. However, another criticism may concern the choice of patent applications as dependent variable: since not all patent applications are granted, it can be argued that this variable is not a good proxy for the quality of innovation. Against this potential issue, results reported in table A.2 in the Appendix show that our main findings still hold when the yearly number of forward citation-weighted patent grants are used as dependent variable[11].

Alternative matching technique: Coaserned Exact Matching (CEM)
Finally, we show that our results do not depend on the strategy adopted to build a control group. Instead of the PSM procedure, we have selected a control group through the "Coarsened exact matching" (CEM) strategy.
CEM belongs to the generalized class of matching methods known as ''Monotonic Imbalance Bounding'' introduced by Iacus et al. (2011), which have been shown to produce superior covariate balance between exposure groups than other matching methods like PSM and Mahalanobis matching. As a result, CEM allows reducing the impact of confounding in observational causal inference. Also, CEM dominates commonly used matching methods in its ability to reduce model dependence, estimation error, bias, variance, mean square error (see Iacus et al., 2012). The strategy is simply matching simultaneously by a set of potential confounders that have been "coarsened", reducing the number of potential matching values for a given covariate to increase the number of matches achieved.
Tables A.3-A5 in the Appendix show that our results are robust to the use of this alternative matching procedure: the coefficient of the PP variable remains positive and highly significant both in the negative binomial and zero-inflated negative binomial models, as well as in the fixed effect model[12].

6. Conclusions

Public procurement can represent a strong stimulus for innovation though, to be effective, some conditions need to be satisfied. The procurer must have some internal competences that are required to design adequate contracts; properly evaluate tenders or to interact effectively with the supplying

[11] Hereby we report the results of the fixed effects estimator. Nevertheless, it can be show that our main results are valid also under the alternative model specifications adopted in the paper.
[12] Our main results are valid also under the alternative model specifications adopted in the paper

firms in the post-procurement phase to overcome potential technical problems that may arise in the development of new products. Not only, a risk-oriented attitude is required to support uncertain R&D activities that do not guarantee a certain market return.

In the light of the potential obstacles that can inhibit the public procurement effectiveness, our research aims at assessing empirically the impact of public procurement on innovation by focusing on a peculiar type of PPI, that is space procurement, where the above-mentioned barriers are not likely to be detrimental. Indeed, space agencies are specialized procurement agencies with internal technical and scientific expertise and know-how that can be made available to its industrial partners. Our research shows that in the context of space policy, public procurement can stimulate the patenting activity of the firms receiving the order.

We gathered balance sheet and patent data of 461 suppliers included in the ASI procurement database over the period 2004-2018 and built a suitable control group of firms operating in the same industries. The various estimation strategies adopted provide consistent evidence that firms benefited from the procurement collaboration with the ASI, resulting in an increased patenting activity with respect to both their pre-procurement level and firms belonging to the control group of non-ASI suppliers.

This finding suggests a twofold mechanism for positive externality: first, the technological content of the asset required by the ASI generates learning effects for the firms delivering the order. Second, ASI deliberate lack of interest in appropriating possible rents 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 it 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 not seek compensation for the knowledge spillovers that may occur.

Our results bring about policy and managerial implications. At the policy level, they provide further evidence that PPI is an effective demand-side policy tool to foster companies' innovation and suggest that policy incentives should be introduced to support the collaborations between firms and public agencies/research infrastructures. Moreover, they suggest that the positive impact of PPI on suppliers' innovation capacity is particularly relevant when the order is placed by a competent procurer, characterized by internal technical skills and know-how.

At the managerial level, our findings have implications on 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.

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Appendix

Table A.1 - The role of ASI public procurement in firms' patenting activity: Diff in diff with heterogeneous timing in treatment

VARIABLES	(1) ASI suppliers' sample (treated group)	(2)	(1) Sample after propensity score matching (treated and control group)	(2)
Post Procurement (PP)	-0.214***	-0.186***	-0.203***	-0.180***
	(0.041)	(0.042)	(0.028)	(0.032)
PP * Low Tech		-0.130***		-0.103**
		(0.048)		(0.047)
lag10	0.048	0.052	-0.080*	-0.083**
	(0.050)	(0.050)	(0.041)	(0.041)
lag9	0.020	0.023	-0.093**	-0.094**
	(0.045)	(0.045)	(0.041)	(0.041)
lag8	0.009	0.010	-0.087**	-0.089**
	(0.039)	(0.039)	(0.036)	(0.036)
lag7	-0.017	-0.017	-0.099***	-0.101***
	(0.036)	(0.036)	(0.035)	(0.035)
lag6	-0.035	-0.035	-0.103***	-0.105***
	(0.033)	(0.033)	(0.033)	(0.033)
lag5	-0.035	-0.035	-0.089***	-0.091***
	(0.028)	(0.028)	(0.028)	(0.029)
lag4	-0.029	-0.028	-0.070***	-0.070***
	(0.025)	(0.025)	(0.025)	(0.025)
lag3	-0.012	-0.013	-0.042**	-0.043**
	(0.020)	(0.020)	(0.019)	(0.019)
lag2	-0.004	-0.005	-0.019*	-0.021*
	(0.011)	(0.012)	(0.011)	(0.011)
lead0	0.228***	0.236***	0.231***	0.237***
	(0.039)	(0.039)	(0.027)	(0.027)
lead1	0.251***	0.259***	0.271***	0.277***
	(0.036)	(0.036)	(0.026)	(0.025)
lead2	0.230***	0.238***	0.264***	0.270***
	(0.032)	(0.033)	(0.024)	(0.024)
lead3	0.225***	0.232***	0.275***	0.281***
	(0.029)	(0.029)	(0.022)	(0.022)
lead4	0.224***	0.230***	0.289***	0.294***
	(0.029)	(0.029)	(0.024)	(0.025)
lead5	0.208***	0.214***	0.287***	0.295***
	(0.027)	(0.028)	(0.024)	(0.025)
lead6	0.181***	0.187***	0.274***	0.281***
	(0.027)	(0.027)	(0.025)	(0.026)
lead7	0.180***	0.185***	0.289***	0.297***
	(0.028)	(0.028)	(0.028)	(0.029)
lead8	0.165***	0.168***	0.288***	0.295***
	(0.030)	(0.030)	(0.032)	(0.033)

lead9	0.139***	0.141***	0.272***	0.279***
	(0.029)	(0.028)	(0.031)	(0.032)
lead10	0.110***	0.112***	0.259***	0.266***
	(0.029)	(0.029)	(0.032)	(0.033)
Operating Revenues	-0.003	-0.003	0.002	0.002
	(0.008)	(0.008)	(0.005)	(0.005)
Tangible Fixed Assets	0.006	0.005	0.007	0.006
	(0.011)	(0.011)	(0.006)	(0.006)
Intangible Fixed Assets	0.011	0.011	0.011**	0.011**
	(0.010)	(0.010)	(0.005)	(0.005)
Number of Employees	-0.006	-0.008	0.002	0.001
	(0.026)	(0.026)	(0.017)	(0.017)
Age	0.010	0.001	0.011	0.010
	(0.050)	(0.046)	(0.008)	(0.008)
Constant	0.050	0.075	0.070	0.072
	(0.241)	(0.226)	(0.080)	(0.081)
Observations	7,150	7,150	19,745	19,745
Number of id	461	461	1,791	1,791
Time Fixed Effects	YES	YES	YES	YES

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.2 - The role of ASI public procurement in firms' patenting activity: Fixed effects and citation-weighted patent grants as dependent variable

	(1)	(2)	(3)	(4)
VARIABLES	ASI suppliers' sample		Enlarged sample after PSM	
Post Procurement (PP)	0.100***	0.167***	0.125***	0.190***
	(0.018)	(0.020)	(0.011)	(0.013)
PP * Low Tech		-0.211***		-0.203***
		(0.027)		(0.020)
Operating Revenues	0.018***	0.017***	0.016***	0.015***
	(0.006)	(0.006)	(0.004)	(0.004)
Tangible Fixed Assets	-0.005	-0.006	0.005	0.005
	(0.006)	(0.006)	(0.003)	(0.003)
Intangible Fixed Assets	0.024***	0.024***	0.014***	0.014***
	(0.005)	(0.005)	(0.003)	(0.003)
Number of Employees	-0.053***	-0.058***	-0.020***	-0.023***
	(0.013)	(0.013)	(0.008)	(0.008)
Age	0.028	0.011	0.033*	0.031
	(0.068)	(0.068)	(0.020)	(0.020)
Listed	0.048	0.052	-0.084	-0.084
	(0.204)	(0.203)	(0.072)	(0.072)
Constant	0.232	0.344	0.086	0.125
	(0.302)	(0.301)	(0.093)	(0.093)
Observations	7,150	7,150	19,745	19,745

Number of id	461	461	1,791	1,791

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.3 - The role of ASI public procurement in firms' patenting activity: Negative Binomial model and sample selected with CEM procedure

	(1)	(2)
	Enlarged sample after CEM	
Post Procurement (PP)	1.086***	1.296***
	(0.103)	(0.116)
Low Tech		-0.035
		(0.124)
PP * Low Tech		-1.284***
		(0.222)
Operating Revenues	-0.186***	-0.190***
	(0.055)	(0.053)
Tangible Fixed Assets	0.066*	0.058*
	(0.035)	(0.034)
Intangible Fixed Assets	0.235***	0.233***
	(0.025)	(0.025)
Number of Employees	0.241**	0.257**
	(0.106)	(0.100)
Age	-0.263***	-0.272***
	(0.043)	(0.042)
Listed	-1.414***	-1.304***
	(0.411)	(0.406)
patent pre-sample mean	13.246***	13.131***
	(0.816)	(0.802)
Constant	-3.901***	-3.618***
	(0.423)	(0.410)
Observations	9,244	9,244
Year, Sector and Country FE	YES	YES

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.4 - The role of ASI public procurement in firms' patenting activity: Zero Inflated Negative Binomial model and sample selected with CEM procedure

	(1)	(2)	(3)	(4)
	Enlarged sample after CEM			
VARIABLES	Negative Binomial	Logit	Negative Binomial	Logit
Post Procurement (PP)	0.765***	-0.462***	1.182***	-0.134
	(0.141)	(0.153)	(0.151)	(0.165)
Low Tech			0.667***	0.759***
			(0.186)	(0.246)
PP * Low Tech			-2.236***	-2.264***
			(0.274)	(0.552)

Operating Revenues	-0.083	0.039	-0.050	0.059
	(0.077)	(0.065)	(0.071)	(0.066)
Tangible Fixed Assets	0.120**	-0.005	0.135***	-0.005
	(0.052)	(0.054)	(0.046)	(0.051)
Intangible Fixed Assets	0.040	-0.188***	0.051*	-0.182***
	(0.030)	(0.046)	(0.029)	(0.043)
Number of Employees	0.036	-0.100	-0.055	-0.148
	(0.090)	(0.120)	(0.085)	(0.109)
Age	-0.141*	0.150*	-0.260***	0.058
	(0.077)	(0.081)	(0.073)	(0.079)
patent pre-sample mean	3.198***	-578.292***	3.226***	-575.540***
	(0.426)	(9.183)	(0.445)	(10.296)
Constant	0.685	8.192***	0.627	8.755***
	(0.576)	(1.244)	(0.536)	(1.330)
Observations	9,244	9,244	9,244	9,244
Year, Sector and Country FE	YES	YES	YES	YES

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.5 The role of ASI public procurement in firms' patenting activity: Fixed-effect model and sample selected with CEM procedure

	(1)	(2)
	Enlarged sample after CEM	
Post Procurement (PP)	0.068***	0.105***
	(0.009)	(0.010)
PP * Low Tech		-0.122***
		(0.016)
Operating Revenues	-0.002	-0.003
	(0.003)	(0.003)
Tangible Fixed Assets	0.010***	0.011***
	(0.003)	(0.003)
Intangible Fixed Assets	0.006**	0.005**
	(0.003)	(0.003)
Number of Employees	-0.011	-0.015**
	(0.008)	(0.008)
Age	-0.018	-0.022
	(0.039)	(0.039)
Listed	-0.034	-0.025
	(0.095)	(0.095)
Constant	0.106	0.148
	(0.172)	(0.172)
Observations	9,244	9,244
R-squared	0.050	0.057
Number of id	694	694
Year and Area	YES	YES

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1