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Effectiveness of public procurement of innovation versus supply-side innovation measures in manufacturing and service sectors

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Abstract

Most quantitative evaluations report positive but small effects of supply-side innovation measures. Although the literature suggests that demand-side measures, in particular, public procurement of innovation, might be more effective in stimulating innovation than supply-side measures, empirical evidence on this proposition is scarce. To empirically test this proposition, we utilize the Eurobarometer 2014 survey to estimate the effects from public procurement of innovation as well as from the supply-side innovation measures on product and process innovations in manufacturing and service firms in the USA and Europe. Our findings suggest that the treatment effects of public procurement of innovation are indeed larger than the effects of supply-side public support on product innovation in both manufacturing and service sectors. This finding also holds for process innovation, but only in the service sector. In contrast, in manufacturing firms, the estimated effects on process innovation are only positive and significant in firms receiving public support.

Key words: public procurement of innovation; product and process innovations; quantitative evaluation; supply-side innovation measures

1. Introduction

This study uses data from the Flash Eurobarometer 2014 survey, covering Europe and the USA, to estimate the effects of public procurement of innovation and supply-side policy measures on product and process innovations in manufacturing and service firms. The aim of the study is to empirically investigate the theoretical argument that the demand-side policy measures, in particular, public procurement, might be more effective in fostering innovation than the supply-side measures (Aschhoff and Sofka, 2009; Geroski, 1990; Guerzoni and Raiteri, 2015). Due to market and system failures, R&D and innovation policy have been an integral component of a country's industry policy. Until recently, the main policy instruments for promoting innovation were supply-side instruments, such as R&D subsidies, R&D tax credits, the protection of intellectual property rights and support for collaborative innovation activities (Edler et al., 2012; Edquist et al., 2015). However, an extensive evaluation of these instruments, in particular, R&D subsidies and R&D tax credits, revealed positive, but rather small additional effects (OECD, 2014; Radicic and Pugh, 2017). To tackle this issue, policy-makers and innovation scholars began exploring the potential of demand-side policy measures, in particular public procurement, which has recently appeared high on policy agendas in many countries as well as at the EU level (Boon and Edler, 2018; Edler et al., 2012; Edquist and Zabala-Iturriagagoitia, 2012; Uyarra and Flanagan, 2010). This policy instrument has a potential to induce a large effect on firms' innovation activities, given that the proportion of public procurement in gross domestic product (GDP) is estimated to be approximately 12.8 per cent in the OECD countries (Loader, 2015; OECD, 2013) and between 15 and 20 per cent across the twenty-eight EU Member States (Amann and Essig, 2015; EU COM, 2012; Edquist, 2015; Stake, 2017). Yet the main challenge in using public procurement as an innovation policy instrument is that public procurement contracts are assigned based on the key criterion of value for money. This creates a major impediment in facilitating innovation, given that the innovation often entails large costs, thus consequently, puts innovative firms in a disadvantaged position when applying for procurement grants, relative to those firms that focus on minimizing costs to meet value-for-money criterion (Loader, 2007, 2013). To tackle this issue, policy-makers and scholars introduced public procurement of innovation, for example procurement contracts that purposefully facilitate innovation.

The importance of public procurement of innovation is reflected in the Lead Market Initiative (European Commission, 2007), for which public procurement is considered to be a critical policy instrument (Davis and Brady, 2015; Uyarra and Flanagan, 2010).[1] This growing emphasis on public procurement as a means of promoting innovation calls for a quantitative evaluation of its effectiveness, especially since current evidence is based on case studies with little quantitative content (Aschhoff and Sofka, 2009; Guerzoni and Raiteri, 2015). This study addresses the lack of quantitative evidence on the effectiveness of public procurement of innovation and its comparison with the effectiveness of supply-side measures. Moreover, by evaluating both supply and demand-side innovation policy instruments, we contribute to empirical evidence on the effectiveness of a 'holistic innovation policy', defined as 'a policy that integrates all public actions that influence or may influence innovation processes' (Edquist, 2014: 4).

Previous empirical evidence (e.g. Aschhoff and Sofka, 2009; Guerzoni and Raiteri, 2015), although scarce, indicates that innovative procurement is effective in promoting firms' innovation inputs and market success. However, still absent is the empirical evidence on the impact of public procurement on innovation outputs. In this regard, a further contribution of this study is to estimate procurement effects on product and process innovations.

Finally, our study provides first exploratory results on the impact of public procurement of innovation in manufacturing and service firms separately. Martin (2016), in his paper on twenty challenges for innovation studies, calls for more studies on innovation in services, given that nowadays in many advanced economics the share of the manufacturing sector is below 20 per cent of GDP. We adopt two approaches with regards to defining and studying innovation in the service sector. First is the synthesis approach (Coombs and Miles, 2000), which aims to create an integrated theoretical framework to innovation that would be able to incorporate innovation activities in both sectors, without favouring one sector over the other (Tether, 2005). We adopt this approach by analysing the full sample consisting of both manufacturing and service firms. Second is the demarcation approach, which considers innovation in services as a distinct activity from innovation in manufacturing (Coombs and Miles, 2000). Thus, we follow this approach by analysing the effectiveness of innovation policy in the subsamples of manufacturing and service sectors. Furthermore, besides exploring the effectiveness of innovation policy on product innovation in goods, we also use product innovation in services as a measure of innovation output. Therefore, we explore both aspects—innovation in the service sector and product innovation in services (as a type of innovation).

The remainder of the article discusses public procurement as a demand-side innovation policy, its impact of innovation and previous empirical evidence (Section 2). Section 3 reviews the dataset and empirical strategy employed in the study. In Section 4, we present and discuss empirical findings. Finally, Section 5 concludes with policy implications, as well as limitations of the study and suggestions for further research.

2. Literature review

2.1 Public procurement as demand-side innovation policy

Instruments in support of innovation are divided into two categories—technology push and demand (market) pull. The first generation of innovation models were linear, technology-push models focused on the supply-side innovation policies. The second generation shifted the focus to the demand side of the innovation process (Nemet, 2009). Demand-side public measures were designed after the formalization of the third-generation interactive or coupling innovation models, which brought together the technology-push and the demand-pull arguments and emphasised the role in the innovation process played by demand (Boon and Edler, 2018; Edquist and Hommen, 2000).

Although there is no commonly accepted definition of the demand-side innovation policies, OECD (2011) adopts the definition proposed by Edler and Georghiou (2007: 952): 'demand-side innovation policies are defined as all public measures to induce innovations and/or speed up diffusion of innovations through increasing the demand for innovations, defining new functional requirement for products and services or better articulating demand'. Examples of demand-side innovation policies include: tax credits and rebates for consumers of new technologies; technology mandates; innovation-specific regulations standards; and technology-oriented public procurement (OECD, 2011).

From the perspective of firms' innovation activities, there are two types of public procurement. The first is public technology procurement, which occurs when a public sector organisation purchases products or services that demand innovation by a supplier, such as R&D activities (Aschhoff and Sofka, 2009; Edquist and Hommen, 2000; Guerzoni and Raiteri, 2015; Uyarra and Flanagan, 2010). To extend this concept beyond R&D, scholars have recently introduced other terms, such as public procurement of innovation, innovative public procurement, and public innovation procurement (Edler and Georghiou, 2007; Edquist et al., 2015; Edquist and Zabala-Iturriagagoitia, 2012; Ghisetti, 2017; Uyarra and Flanagan, 2010). Accordingly, Edquist et al. (2015: 6–7) offer the following definition: 'public procurement for innovation (PPI) occurs when a public organization places an order for the fulfilment of certain functions (that are not met at the moment of the order or call) within a reasonable period of time through a new or improved product'. In contrast, regular or normal procurement refers to the purchase of ready-made products where contracts do not require any additional R&D or even broader innovative activities.

Several qualitative and quantitative studies in the 1970s and 1980s pointed out that public demand for innovation is an effective policy tool, perhaps even more so than R&D subsidies (Geroski, 1990). Although demand-side policy measures have been used in parallel with traditional supply-side measures in a few strategic sectors, such as construction, health care, and transport (Edler and Georghiou, 2007), their wider diffusion was absent until recent years. Renewed interest from policy-makers at both national and EU levels during the last decade is a consequence of the realization that supply-side measures alone are not sufficient to promote innovation and enhance competitiveness and that, instead, supply- and demand-side policy measures are complementary (Edler and Georghiou, 2007; OECD, 2011; Pickernell et al., 2011; Uyarra et al., 2014). OECD (2014) identifies three potential reasons as to why demand-side measures in innovation policy have attracted renewed interest from policy-makers. First, demand-side innovation policy might stimulate innovation to meet societal needs. Secondly, demand-side measures might be more cost effective than the traditional supply-side measures. This is particularly relevant argument after the global financial crisis and the consequent austerity policy, with limited governments' budgets and fiscal consolidation (Dosso et al., 2018). Finally, the renewed interest might be motivated by the rather disappointing effects of the supply-side measures (or they were insufficient alone to foster innovation; Pickernell et al., 2011). Consistent with this trend, Edler and Georghiou (2007) recognized the importance of public procurement in innovation policy, which is echoed in OECD (2011: 11): '... public procurement is at the heart of demand-side innovation policy initiatives'. Consequently, the UK, Germany, the Netherlands, Finland, and Spain have put in place legislation and programmes for integrating innovation into public procurement.

2.2 Public procurement and innovation

The procurement effect on market size and expected demand gives rise to an 'incentive effect' on both product and process innovations (Fontana and Guerzoni, 2008; Schmookler, 1962). Consistent with this, Uyarra (2016) argues that public procurement for products with insufficient private demand may induce firms to invest in R&D. In particular, public procurement can help firms to recover the sunk costs of large and sometime risky investments in innovation (OECD, 2011).

Edler and Georghiou (2007) and Boon and Edler (2018) identify asymmetric information as one of the main sources of market failures, and poor interaction between potential suppliers and users of innovative products as the main source of systemic failures, while Georghiou et al. (2014) argue that both of these can be overcome by public procurement. Similarly, Uyarra et al. (2014) argue that public procurement reduces information and interaction barriers to innovation. Regarding the former, lack of information is pertinent at both ends of the value chain. Both private and public customers might not be aware of innovative goods and services that are available in the marketplace or that could be supplied if sufficient demand were to occur. On the other hand, innovating firms might not have timely information about future trends in demand, which would enable them to meet that demand with new products and services. Accordingly, the provision of relevant information and knowledge about market needs and users' requirements reduce the effects of uncertainty on innovation (Fontana and Guerzoni, 2008). This may apply with particular force to SMEs (OECD, 2014).

Poor interaction between suppliers and customers occurs, for instance, when dispersed demand hampers suppliers in identifying customers' needs and from timely offering of new products to meet these needs (Edler and Georghiou, 2007). Consequently, any improved interaction between suppliers and users via public procurement mitigates systemic failures (Uyarra et al., 2014).[2] By purchasing innovative goods and service, government as the lead user can signal the usefulness of new products and services to the market and private users and thus facilitate the diffusion of innovation (Boon and Edler, 2018; Chicot and Matt, 2018; OECD, 2011; Uyarra and Flanagan, 2010).

According to Cabral et al. (2006), public procurement can enlarge the market for new goods up to a critical level that will provide incentives for firms to invest in innovation. Moreover, domestic procurement may enhance productivity and, hence, market power of domestic producers and/or give them a first mover advantage in international markets. If such firms operate in industries that give rise to learning effects and productivity spillovers, then this may induce product and process innovations (i.e. such innovation arises indirectly; Cabral et al., 2006; Uyarra and Flanagan, 2010).

To date, only few studies report empirical findings on the effectiveness of public procurement in promoting innovation.[3] Aschhoff and Sofka (2009) find that public procurement increases German firms' market success, especially for smaller firms located in regions under economic stress. In turn, this may suggest that public procurement is particularly effective for firms with limited internal resources. Pickernell et al. (2011) explore local and regional economic consequences for SMEs of public procurement in the UK. Their findings indicate that public procurement at local and regional levels does not induce innovation in SMEs although it might stimulate demand for firms with a future capacity to absorb innovation. Guerzoni and Raiteri (2015) investigate how interaction between public procurement of innovation, R&D tax credits, and R&D subsidies affects innovation expenditure. The data utilized in their study is the Innobarometer data on 'Strategic Trends in Innovation 2006–8', which was conducted in 2007 in twenty-seven EU Member States, Norway, and Switzerland. Their results suggest that public procurement of innovation has a positive impact on innovation inputs when this policy tool is considered separately, as well as when analysed in combination with R&D subsidies and R&D tax credits. Saastamoinen et al. (2018) investigate whether public procurement of innovation mediates the impact of interorganizational networks on innovation performance in Finish SMEs. Empirical findings point out that the demand from both private and public sectors customers mediates the effectiveness of networking on radical and incremental innovations, but the effect of public procurement of innovation is larger than the effect of demand originating from private sector customers.

3. Methodology

3.1 Data

We use the Flash Eurobarometer 394—'The role of public support in the commercialisation of innovations' survey—which includes firms from 28 EU Member States, Switzerland, and the USA and covers the period from January 2011 to February 2014 (European Commission, 2014). The survey was requested by the Directorate-General for Enterprise and Industry and carried out by the TNS Political & Social network. The sample was selected from an international business database and stratified by size, sector, and country.[4] Different Eurobarometer surveys have been explored in, for example Guerzoni and Raiteri (2015), who used Innobarometer 2009 data and Ghisetti (2017), who used Innobarometer 2015 data.

In total, 12,108 firms were interviewed. However, our analysis includes only firms that were innovators. Following Aschhoff and Sofka (2009), in order to mitigate potential selection bias arising from a non-random selection of firms in the sample, we excluded non-innovating firms (defined in a broad sense, as firms that introduce neither technological nor non-technological innovations), so the final sample amounted to 6,719 innovative firms in the full sample, out of which the manufacturing sector includes 1,955 firms and the service sector 4,764 firms. The definition of innovation adopted in the survey is as follows: 'Innovation occurs when a company introduces a new or significantly improved good, service, process, marketing strategy, or organisational method. A company can develop the innovation itself or acquire it from other companies or organisations'. This broad definition of innovation is in accordance with the *Oslo Manual* (OECD, 2005), thus encompassing both technological (product and process) innovations and non-technological (organizational and marketing) innovations.

Table A.1 shows share of firms that participated in public procurement of innovation as well as those that received public support. Out of the total number of innovative firms, only 13.3 per cent of firms have participated in public procurement of innovation, while the share is slightly higher for public support (15.6 per cent). In the manufacturing sector, slightly less than a fifth of firms received public support (23.9 per cent), whereas the share of firms that participated in public procurement of innovation is significantly lower (11 per cent). As expected, a larger share of service firms participated in public procurement of innovation (14.1 per cent) than those that received public support (12 per cent). We should bear in mind that firms that received public support as well as participated in public procurement of innovation at the same time are excluded from the analysis, and thus from Table A.1 too.[5]

3.2 Empirical strategy

In the evaluation of traditional supply-side measures, quantitative evaluation of public procurement has to take into account its potential endogeneity (Cerulli 2010; Guerzoni and Raiteri, 2015). Likewise, in evaluating the effectiveness of public procurement of innovation, OECD (2014) notes that firms might self-select themselves into a public procurement tender; for example, those firms that are more likely to innovate have higher propensity to apply for a tender. In addition, public agencies might adopt a 'picking-the-winner' strategy, whereby firms might be selected on the basis of their observable innovation capabilities (such as, a proven track record) (Radicic et al., 2016).

To address the selection bias arising from firms' self-selection as well as from public agencies favouring firms with the successful innovation record, we implement a propensity score matching methodology, which is the most commonly applied evaluation method in innovation studies (Cerulli, 2010). This approach entails two identifying assumptions. The first is the conditional independence assumption or selection on observables, which posits that the outcome in the case of no treatment (Y_0) is independent of treatment assignment, conditional on covariates X (Imbens, 2004; Imbens and Wooldridge, 2009). That is

$$Y_0 \coprod D|X, \tag{1}$$

where X represents a vector of covariates and D is the treatment assignment.

The second assumption is associated with the overlap or common support condition, where the estimated propensity scores take values between zero and one (see Equation (2)) (Heckman and Vytilacil, 2007). The overlap condition implies that both treated and non-treated firms have a positive probability (P) of receiving a treatment ($D = 1$) or not receiving a treatment ($D = 0$).

$$0 < P(D = 1\, X) < 1. \tag{2}$$

The treatment of interest is the average treatment effect on the treated (ATT), which indicates the difference in outcomes of the treated firms with and without treatment and can be written as:

$$\text{ATT} = E[Y_1\, D = 1] - E[Y_0\, D = 1]. \tag{3}$$

The first term on the right-hand side of Equation (3), $E[Y_1|D = 1]$, is the expected outcome for treated firms, while the second term $E[Y_0|D = 1]$ is the expected outcome had treated firms not received the treatment. This second term refers to a counterfactual outcome that is not observed but needs to be estimated.

Concerning the choice of covariates X, the literature suggests that all observed variables that simultaneously affect treatment assignment and the outcome should be included. After the selection of matching variables, the next step in the matching protocol is the estimation of the propensity score model using either probit or logit models as they usually yield similar results (Caliendo and Kopeinig, 2008).

Next, we select the matching algorithm. The main estimator is kernel matching on the estimated propensity score, which uses weighted averages of most units in the control group to estimate a counterfactual outcome. The major advantage of this non-parametric estimator is the reduction in variance as the entire sample of the control group is used in matching algorithm (Caliendo and Kopeinig, 2008). As a robustness check, we use the Inverse Probability Weighing Regression Adjustment (IPWRA) estimator because it has a double robust property. If either the propensity score model (the outcome model) or the treatment model is correctly specified, then this estimator will yield treatment effects with a lower bias than will other estimators that are not characterized by the double robustness property. The estimator consists of three steps: first, the propensity score model—the treatment model—is estimated. Secondly, the inverse of the estimated propensity scores (probabilities of receiving a certain level of treatment) are used as weights in the regression analysis. Thirdly, the ATT is computed as the difference in the weighted averages of the predicted outcomes (for technical details, see Wooldridge, 2010).

The purpose of matching estimators is to balance the observed covariates X between treated and untreated units. Therefore, after the estimation of the propensity score, but prior to applying a chosen matching estimator, a balancing test should be conducted. The purpose of a balancing test *before matching* (or the stratification test) is to check how well the estimated propensity score has succeeded in balancing covariates. This approach requires the division of the sample into strata conditional on the propensity score and checking whether there are no statistically significant differences between the means of the propensity score of the treated and non-treated firms. If the difference in means is statistically insignificant, then covariates are well balanced between matched pairs (Caliendo and Kopeinig, 2008). This balancing property is satisfied in all models reported below.

The literature identifies several approaches for assessing the matching quality *after matching*. The first approach consists of comparing the standardized bias before and after matching (the mean and the median bias in Table A.2). The rule of thumb adopted in most empirical studies is that a standardized bias below 3 or 5 per cent is acceptable (Caliendo and Kopeinig, 2008). The matching quality can also be assessed by checking the joint significance of all covariates in the selection equation based on the likelihood-ratio test. All variables should be jointly significant before matching and jointly insignificant after matching. Furthermore, one can estimate the propensity score only for matched treated and non-treated firms and compare the pseudo-R^2 before and after matching. Low pseudo-R^2 after matching indicates a good matching quality (Caliendo and Kopeinig, 2008). Finally, we also utilize the following two criteria: Rubin's B, which is the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group; and Rubin's R, which is the ratio of treated to (matched) non-treated variances of the propensity score index. Rubin (2001) recommends that B be <25 and that R be between 0.5 and 2 for the sample to be considered sufficiently balanced. Table A.2 shows matching criteria for kernel matching.[6] All criteria uniformly show that kernel matching satisfies the matching quality in each model.

Treatment effects of any matching estimator based on the propensity score are only estimated in the region of common support (see Equation (2)). Thus, it is necessary to check the overlap of the propensity score between treated and non-treated firms after matching. The method applied in this study is based on identifying a minimum and a maximum propensity score and then deleting those observations for which the propensity scores in the treatment group are smaller than the minimum, and larger than the maximum propensity score in the comparison group (Morgan and Harding, 2006).[7] In this case, causal estimates are narrower treatment effects than estimates of the ATT: the common support treatment effect for the treated, which are reported in the tables with results below.

3.3 Model specification

We estimate models with two treatment variables. The first treatment variable is *Procurement of innovation*, defined as a binary indicator equal to 1 if the firm sold innovative goods or services innovation as a part of a public procurement contract or if the firm participated in the public procurement of innovative solutions, and zero otherwise.[8] To take into account the hidden bias, for example, that firms have received both treatments—public support for innovation (the supply-side innovation measures) and public procurement of innovation, we excluded from the analysis firms that received the supply-side measures. That is, both treated and control firms do not include those firms that received public support for their innovation activities. The second treatment variable is *Public support*, defined as a binary indicator equal to 1 if the firm received any public financial support for research and development or other innovation activities from either local, regional, national, or EU administration since January 2011, and zero otherwise (see Tables A.1 and A.3 for variable description and descriptive statistics, respectively). To account for the hidden bias in the case of the supply-side innovation measures, we excluded firms that participated in public procurement of innovation.

The three outcome variables are binary indicators for: (1) the introduction of product innovation in goods; (2) the introduction of product innovation in services; and (3) the introduction of process innovation. Reijonen et al. (2016) note that procurement of services is likely to involve innovative approaches because services are more complex than products, customer needs are specific and determining the quality of services is difficult. We also want to explore how both types of innovation measures affect the introduction of process innovation, given that product and process innovations are considered as complementary activities. Namely, implementing new products or upgrading existing ones might render process innovation necessary. Likewise, process innovation might allow firms to enhance the quality of their existing products or to manufacture new products (Flaig and Stadler, 1998). In summing up, if produce and process innovations are indeed complementary, then the supply and demand-side policy measures aimed at facilitating product innovation will simultaneously induce process innovation as well.

To account for firm and market characteristics, we include the following control variables. We control for the firm's business experience by including the binary variable *Young* equal to 1 if a firm was established after January 2008 and zero otherwise, given that older firms have more experience in bidding for public tenders than their younger counterparts (Guerzoni and Raiteri, 2015). However, Reis and Cabral (2015) found that younger firms are more likely to win a tender. They interpret this result in relation to the selection process, whereby if value for money is the main criterion then experience is not a significant factor in the process. Regarding absorptive capacity, the models include a binary variable *R&D activity* equal to 1 if a firm carried out R&D either in-house or by subcontracting in the period January 2011 to February 2014 and zero otherwise (Guerzoni and Raiteri, 2015). We also controlled for patent applications as a measure of an intermediate innovation output. The variable *Patents* is equal to 1 if a firm applied for one or more patents or trademarks and zero otherwise.

Firm size is modelled by including three dummy variables: *Small firms* (for firms with more than ten and fewer than fifty employees); *Medium firms* (for firms with more than 50 and fewer than 250 employees); and *Large firms* (for firms with more than 250 employees) (the base category is *Micro firms* for firms with more than zero and fewer than ten employees) (Guerzoni and Raiteri, 2015). Each firm's *exporting* activities is measured as the percentage of its total revenues accounted for by sales in foreign markets (Aschhoff and Sofka 2009). Competition in the main market is modelled by including three dummy variables in the model: *Monopoly* if a firm reported no competition or one competitor in the main market (zero otherwise); *Monopolistic competition* if a firm reported 'Tens' as the number of competitors (zero otherwise); and *Perfect competition* if a firm reported 'Hundreds' or 'Too many to count' as the number of competitors (zero otherwise) (the base category is *Oligopoly* if a firm reported 'A few' as the number of competitors; zero otherwise). Finally, the models include binary indicators for three country groups: *Innovation leaders*; *Innovation followers*; and *Modest innovators* (*Moderate innovators* is the base category) (according to the European Innovation Scoreboard, European Commission 2015) (see Table A.1 for the list of countries in each group).[9] Finally, after estimating treatment effects for the whole sample, we split it into two subsamples—manufacturing and services. In the manufacturing subsample, we created four dummies by grouping sectors based on their technology intensity using NACE Rev.2 classification: high technology sectors; medium high technology sectors; medium low technology sectors; and low technology sectors (the base category). In the service subsample, sectors are grouped into knowledge-intensive services (KIS) (the base category), and less knowledge-intensive services (LKIS) (see Table A.1 for the list of sectors in each category).

Given that the dataset used in the study is cross-sectional, we assume that control (matching) variables are constant over time and unaffected by the treatment assignments. According to Guerzoni and Raiteri (2015), this assumption is not problematic for some control variables, such as firm age, a country, and an industry in which a firm operates. However, the problem of endogeneity might arise in the case of variables such as firm size, R&D activities and patent applications. Concerning firm size, it is measured by binary indicators, which means that it is unlikely that participating in public procurement of innovation or receiving public support would have such an impact on firm size to move from one category to another (e.g. from small to medium-sized firms) (Guerzoni and Raiteri, 2015). Likewise, both R&D activities and patent applications are binary indicators, and as such, to not measure the magnitude of R&D expenditures or patent counts. Consequently, it is unlikely that a firm did not conduct any R&D activities or apply for patents before participating in public procurement of innovation or receiving public support (Guerzoni and Raiteri, 2015). This implies that the problem of endogeneity in the case of these measures of innovation activities should not be large enough to invalidate our results. Finally, dummies for the market structure should also be regarded as fixed over time, as the number of competitors over the period of three years covered by the survey (2011–4) can increase, but not to a degree to change the nature of the market structure.

4. Results and discussion

Before proceeding with the interpretation of our results, we check for the overlap condition. The plots depicted in Figs A.1–A.3 show that the overlap or the common support condition is satisfied in all

Table 1. The estimated ATTs in the full sample

Outcome variable	Treatment = Procurement of innovation			Treatment = Public support		
	Kernel	IPWRA	Number of observations	Kernel	IPWRA	Number of observations
Product innovation in goods	0.106***	0.105***	5114	0.015	0.019	5255
	(0.020)	(0.019)		(0.016)	(0.018)	
Product innovation in services	0.124***	0.118***	5148	0.034	0.027	5286
	(0.021)	(0.019)		(0.021)	(0.019)	
Process innovation	0.063***	0.053***	5140	0.072***	0.063***	5281
	(0.021)	(0.020)		(0.015)	(0.019)	

Note: Bootstrapped standard errors are reported for kernel matching, the number of replications is 100. Robust standard errors are reported for the IPWRA estimator.

$*P<0.10$; $**\ P<0.05$; $***\ P<0.01$.

Table 2. The estimated ATTs in the manufacturing sector

Outcome variable	Treatment = Procurement of innovation			Treatment = Public support		
	Kernel	IPWRA	Number of observations	Kernel	IPWRA	Number of observations
Product innovation in goods	0.134***	0.126***	1353	−0.013	−0.013	1582
	(0.032)	(0.033)		(0.026)	(0.024)	
Product innovation in services	0.118**	0.114***	1349	0.046	0.040	1577
	(0.046)	(0.044)		(0.031)	(0.031)	
Process innovation	0.020	0.012	1354	0.110***	0.107***	1582
	(0.042)	(0.042)		(0.029)	(0.028)	

Note: Bootstrapped standard errors are reported for kernel matching, the number of replications is 100. Robust standard errors are reported for the IPWRA estimator.

$***P<0.01$; $**\ P<0.05$; $*\ P<0.10$.

reported models, given that the probabilities of receiving treatment (either procurement of innovation or public support; treatment = 1) or not receiving treatment (treatment = 0) are between zero and one (and not too close to the boundary values) (Cattaneo et al., 2013).

Table A.5 reports results from logit models that are used in estimating propensity scores for both treatment variables in the full sample as well as in the subsamples of manufacturing and services firms. The logit models show the effects of covariates on the probabilities of receiving a treatment. The coefficients in the models are not of interest in themselves, as the purpose of specifying the model is to facilitate the estimation of treatment effects by estimating a propensity score needed for the matching procedure (Cattaneo et al., 2013).

The estimated treatment effects for the full sample are reported in Table 1. The treatment effects of public procurement of innovation suggest that the probability of the introduction of product innovation in goods is higher by 10.6 percentage points (p.p.) ($P<0.01$) in firms that participated in public procurement of innovation (without receiving the supply-side support). A slightly higher effect is reported for product innovation in services. Namely, the participation in public procurement of innovation increases the likelihood of this type of innovation by 12.4 p.p. ($P<0.01$). Concerning process innovation, participating in public procurement of innovation increases the probability of its adoption by 6.3 p.p. ($P<0.01$). Therefore, our results uniformly suggest positive and significant policy effects of public procurement of innovation on both product and process innovations in the full sample of manufacturing and service sectors.

To empirically test our hypothesis on the larger impact of public procurement of innovation than public support, we need to look at the estimated treatment effects from the second set of models, in which the treatment variable is *Public support*, and then compare these results with the previous results on public procurement on innovation. Accordingly, the treatment effects in Table 1 show that public support, or the supply-side policy measures, have no effect on product innovation in both goods and services, but the effect on process innovation is positive and significant ($P<0.01$). Namely, receiving public support increases the likelihood of process innovation by 7.2 p.p.

The comparison of treatment effects in Table 1 reveals not only that public procurement of innovation has larger effects than the supply-side public support on product innovation in both goods and services, but also that once we take into account the hidden bias, we find no effects of the supply-side measures. Therefore, we find support for our hypothesis in the case of product innovation. This finding reinforces the potential role that public procurement could have in facilitating product innovation as well as the fact that previous quantitative evaluations of the supply-side measures could be overestimated, because of the hidden bias that was not accounted for (Guerzoni and Raiteri, 2015). In the case of process innovation, however, there is no statistical difference at any conventional statistical level between treatment effects of public procurement of innovation and the supply-side public support. Accordingly, we find no support for our hypothesis in the case of process innovation. In other words, the impact of both types of policy measures on process innovation is positive, and no measure is superior to the other.

Table 3. The estimated ATTs in the service sector

Outcome variable	Treatment = Procurement of innovation			Treatment = Public support		
	Kernel	IPWRA	Number of observations	Kernel	IPWRA	Number of observations
Product innovation in goods	0.102***	0.101***	3761	0.044	0.048*	3673
	(0.022)	(0.023)		(0.027)	(0.025)	
Product innovation in services	0.122***	0.115***	3799	0.026	0.015	3709
	(0.020)	(0.021)		(0.027)	(0.025)	
Process innovation	0.075***	0.062***	3786	0.030	0.023	3699
	(0.023)	(0.023)		(0.025)	(0.026)	

Note: Bootstrapped standard errors are reported for kernel matching, the number of replications is 100. Robust standard errors are reported for the IPWRA estimator.

***$P < 0.01$; ** $P < 0.05$; * $P < 0.10$.

Policy implications of this finding will be discussed in the next section.

We proceed by analysing manufacturing and service sectors separately to explore whether the results for the full sample will be confirmed when the full sample is split into manufacturing and service subsamples. The treatment effects in the subsample of manufacturing firms are shown in Table 2. The effects of public procurement of innovation are positive and significance ($P < 0.01$) in the case of product innovation in both goods and services, but insignificant ($P > 0.10$) in the case of process innovation. The opposite pattern is found for the treatment effects of public support. Namely, the estimated ATTs are statistically insignificant for product innovation in both goods and services, but significant ($P < 0.01$) and positive ($\text{ATT} = 0.11$) in the case of process innovation. Therefore, our hypothesis of larger treatment effects of innovative public procurement than public support is confirmed for product innovation, but not for process innovation. Furthermore, our results suggest interesting complementary effects of the demand- and supply-side policy measures. These complementary effects are not found for the same type of innovation, but rather for different types. Namely, our results imply that the supply- and the demand-side policy measures promote different types of innovation; while public procurement of innovation induces new products, public support increases the likelihood of process innovation. The implications of these findings can be associated with the distinct features of products and process innovations. Namely, while product innovation is market-driven type of innovation adopted for the purpose of revenue generation, process innovation is an internally driven type of innovation, aimed at cost reduction and productivity increase. Therefore, a policy mix of both supply and demand innovation measures could have a synergistic effect on profitability of manufacturing firms.

Finally, Table 3 presents the estimated treatment effects for the service subsample. The results reveal a clear pattern of policy effects, while innovative procurement induces both product and process innovations, we find no significant effects of public support on either type of innovation. Therefore, the formulated hypothesis on the larger effects of innovative procurement than public support is fully supported in the service sector for both product and process innovations. This finding echoes our discussion concerning the results for the full sample. Namely, once the hidden bias is taken into account, not only the impact of the supply-side measures is small (in line with OECD, 2014) but it is even insignificant. As noted above for the case of the full sample, previous empirical findings on the effectiveness of supply-side policy measures in the service sector could be overestimated. If this is indeed the case, then the previously reported small policy effects might even be rendered insignificant had the hidden bias been accounted for.

Looking at the results for the whole sample, we found positive effects of the same magnitude of innovative procurement and public support on process innovation. But when full sample is split into manufacturing and service sectors, a different pattern is revealed. In the manufacturing sector, innovative procurement has no impact on process innovation, but public support has a positive effect. The opposite is reported in the service sector; innovative procurement has a positive impact on process innovation, but public support has no effect. In the next section, we discuss policy implications of our findings.

5. Conclusions and policy implications

Our study addresses the scarcity of quantitative evidence on the impact of public procurement of innovation on innovation outputs and of the comparative analysis of the effectiveness of public procurement of innovation versus the effectiveness of the supply-side policy measures. Accordingly, our objective is to support policy makers with empirical evidence on two research questions: Is public procurement of innovation more effective policy instrument than the supply-side measures in facilitating firms' adoption of product and process innovations? Are the effects of public procurement of innovation versus the supply-side policy measures homogenous among manufacturing and service firms? To empirically explore these research questions, we utilize the dataset from the Flash Eurobarometer 2014 survey to estimate the treatment effects of both public procurement of innovation and the supply-side measures on product and process innovations in the whole sample, as well as in manufacturing and service sectors separately.

With respect to the first research question, our findings from the full sample of manufacturing and service firms indicate that public procurement of innovation is indeed more effective in stimulating product innovation than the supply-side policy measures. These findings have two-fold implications, if we consider that the previous empirical evidence suggests positive, but small additional effects from the latter (OECD, 2014) and that our empirical strategy accounts for the presence of a hidden treatment. The first implication is in relation to the best practice in the quantitative policy evaluation, such that evaluators should consider potential hidden treatments when estimating the effectiveness of innovation policy. This implication is consistent with Guerzoni and Raiteri (2015), who were the first to point out to the problem of overestimation of previous findings because hidden treatments were not considered. The second is a policy implication with respect to the provision of the demand versus supply policy measures. If policy makers want to stimulate the adoption of product innovation, then public procurement of innovation has a much larger potential for additional innovation effects than the supply-side measures. This implication is particularly relevant in the period of austerity measures in the aftermath of the global financial crisis, because, from the perspective of government spending, public procurement of innovation could be more cost effective than the supply-side measures (OECD, 2014). However, if the government objective is to induce cost effectiveness and firm productivity arising from the adoption of process innovation, then policy makers can consider either demand or supply measures given that our findings imply qualitatively the same additional effects from either measure. A similar innovation effect of demand and supply measures, in turn, could allow policy makers to focus on the cost effectiveness of these measures, rather than on their innovation effects.

Concerning the second research question, we focus on the findings from the subsamples of manufacturing and service firms. In this second step of the analysis, empirical evidence points out to similarities as well as differences between manufacturing and service sectors. With respect to similarities, we find no effect of the supply-side measures on product innovation, while the effect of public procurement of innovation is positive and significant. In other words, not only the effect of public procurement is larger than the effect of public support, but we find no additional effects of the latter. As noted above for the full sample, this finding points out to the potential substitutability of demand versus supply policy measures. Another similarity between manufacturing and service firms is found for product innovation in goods and services. Namely, we find support for the argument that both demand- and supply-side measures have a homogeneous influence on product innovation in goods and product innovation in services. Consequently, our findings support the synthesis approach given the lack of differences between the policy effects on product innovation in goods and product innovation in services in both manufacturing and service firms.

Finally, we comment and draw policy implications with respect to differences between manufacturing and service sectors. In manufacturing firms, public procurement of innovation does not seem to induce any effects on process innovation, while the supply-side measures do. This finding has a straightforward policy implication. If innovation policy is to be targeted towards cost efficiency and firm productivity in the manufacturing sector, then the effective innovation policy is the one encompassing supply-side measures. However, this implication does not hold for the service sector. Here, policy makers should focus on removing barriers to public procurement so that service firms can be more innovative (with respect to both product and process innovations), and consider reducing the provision of the supply-side measures, as our results suggest that they do not induce service firms to innovate.

Our study suffers from limitations that can also serve as suggestions for further research on assessing the effectiveness of public procurement of innovation. First, the data on the amount of a public procurement contract are unavailable, which prevents us from investigating how the scale of public procurement affects firm innovation performance. Secondly, public procurement is likely to affect firms' innovation output in the medium and longer run (Edler et al., 2012). However, this impact cannot be explored in a cross-sectional setting. Longitudinal data would allow evaluators to assess the effectiveness of public procurement of innovation over time (Flynn et al., 2015; Uyarra, 2016). Finally, a more fined-grained analysis at the individual country level would enable comparison of findings between countries. In addition, with a greater number of observations, the analysis could be conducted at the country group level (Leaders, Followers, Moderate, and Modest innovators).

Notes

1. A lead market is a market with particular characteristics favourable to the introduction of a certain innovation (Edler et al., 2012).
2. However, it should be considered that public procurement as innovation policy from the demand side can also suffer from this problem or barrier. In particular, it is not easy to get good interaction at least in the initial stages. We would like to thank the anonymous referee for this point.
3. For qualitative evaluations, see e.g. Edler (2016) and Uyarra (2016).
4. The database is publicly available at https://www.gesis.org/en/home/. The full sample includes four sector categories: Manufacturing, Retail, Services, and Industry. We have excluded the category 'Industry' from the analysis. The service sector analysed in this study includes the category 'Retail'. For more details on sampling, see European Commission (2014). For the details on each sector category, see Appendix Table A.1.
5. In total, 228 innovative firms received public support as well as participated in public procurement of innovation at the same time, out of which 77 firms are from the manufacturing sector and 151 firms are from the service sector. With respect to the firm size, the disaggregation is as follows: 34 micro firms, 73 small firms, 76 medium-sized firms, and 45 large firms.
6. Appendix Table A.4 shows the matching quality for the IPWRA estimator. The standardized differences for all treatment levels and firm size categories are very close to zero, and the variance ratios are all very close to one, which suggests that covariates are well balanced (Austin, 2009).
7. In each model, very few observations were outside of the common support region.
8. Public procurement of innovative solutions is defined in the questionnaire as 'a specific type of public procurement, different from regular public procurement, where contracting authorities purchase innovative goods or services which are not yet available on a large-scale commercial basis'.
9. The European Innovation Scoreboard publishes the average innovation performance based on a composite indicator, encompassing twenty-five individual indicators. The innovation performance of each Member State is then compared with the average innovation performance of twenty-eight EU Member States.

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Appendix

Table A.1. Variable description

	Variable description
Treatment variables	
Procurement of innovation	=1 if the firm responded 'Yes' to either 'Did your company sell an innovative good or service as part of any public procurement contract that you won?' or 'Has your company been involved in the Public Procurement of Innovative Solutions since January 2011?', and zero otherwise
Public support	=1 if the firm responded 'Yes' to 'Has your company received any public financial support for research and development or other innovation activities from any of the following since January 2011?' from either local/regional, national, or EU administration and zero otherwise
Outcome variables	
Product innovation in goods	=1 if a firm introduced new or significantly improved goods since January 2011; zero otherwise
Product innovation in services	=1 if a firm introduced new or significantly improved services since January 2011; zero otherwise
Process innovation	=1 if a firm introduced new or significantly improved processes (e.g. production processes or distribution methods) since January 2011; zero otherwise
Independent variables	
Micro firms (base category)	= 1 if a firm has less than 10 employees in 2014, zero otherwise
Small firms	= 1 if a firm has more than 9 and less than 50 employees in 2014, zero otherwise
Medium firms	= 1 if a firm has more than 50 and less than 250 employees in 2014, zero otherwise
Large firms	= 1 if a firm has more than 250 employees in 2014, zero otherwise
Young	= 1 if a firm was founded after January 2008; zero otherwise
Exports	Percentage of firms' total revenues from selling goods and services abroad in 2013
R&D activity	= 1 if a firm carried out R&D either in-house or by subcontracting since January 2011, zero otherwise
Patents	= 1 if a firm applied for one or more patents or trademarks since January 2011, zero otherwise
Monopoly	= 1 if a firm reported no competition or one competitor in the main market in 2014, zero otherwise
Oligopoly (base category)	= 1 if a firm reported 'A few' as the number of competitors in the main market in 2014, zero otherwise
Monopolistic competition	= 1 if a firm reported 'Tens' as the number of competitors in the main market in 2014, zero otherwise
Perfect competition	= 1 if a firm reported either 'Hundreds' or 'Too many to count' as the number of competitors in the main market in 2014, zero otherwise
Leaders	=1 if a firm is located in Denmark, Finland, Germany, Sweden, Switzerland and USA; zero otherwise
Followers	=1 if a firm is located in Austria, Belgium, Cyprus, Estonia, France, Ireland, Luxembourg, Netherlands, Slovenia, and UK; zero otherwise
Moderate innovators (base category)	=1 if a firm is located in Croatia, Czech Republic, Greece, Hungary, Italy, Lithuania, Malta, Poland, Portugal, Slovakia, and Spain; zero otherwise
Modest innovators	=1 if a firm is located in Bulgaria, Latvia, and Romania; zero otherwise
High tech industries	=1 if a firm operates in NACE 21: Manufacture of basic pharmaceutical products and pharmaceutical preparations; 26: Manufacture of computer, electronic, and optical products; zero otherwise
Medium–high tech industries	=1 if a firm operates in NACE 20: Manufacture of chemicals and chemical products; 27: Manufacture of electrical equipment; 28: Manufacture of machinery and equipment; 29: Manufacture of motor vehicles, trailers, and semi-trailers; or 30: Manufacture of other transport equipment; zero otherwise
Medium–low tech industries (base category in the manufacturing subsample)	=1 if a firm operates in NACE 19: Manufacture of coke and refined petroleum products; 22: Manufacture of rubber and plastic products; 23: Manufacture of other non-metallic mineral products; 24: Manufacture of basic metals; 25: Manufacture of fabricated metals products, excepts machinery, and equipment; 33: Repair and installation of machinery and equipment; zero otherwise
Low tech industries	=1 if a firm operates in NACE 10: Manufacture of food products; 11: Beverages; 12: Tobacco products; 13: Textile; 14: Wearing apparel; 15: Leather and related products; 16: Wood and of products of wood; 17: Paper and paper products; 18: Printing and reproduction of recorded media; 31: Manufacture of furniture; 32: Other manufacturing; zero otherwise
KIS (the base category in the full sample and in the service subsample)	=1 if a firm operates in NACE 50: Water transport; 51: Air transport; 58: Publishing activities; 59: Motion picture, video and television programme production, sound recording, and music publish activities; 60: Programming and broadcasting activities;
	61: Telecommunications; 62: Computer programming, consultancy and related activities; 63: Information service activities; 64: Financial activities; 66: Insurance activities; 69: Legal and accounting activities; 70: Activities of head offices, management consultancy activities; 71: Architectural and engineering activities, technical testing, and analysis; 72: Scientific research and development; 73: Advertising and market research; 74: Other professional, scientific, and technical activities; 75: Veterinary activities; 78: Employment activities; 91–93: Arts, entertainment, and recreation (section R); zero otherwise
LKIS	=1 if a firm operates in NACE 45: Wholesale trade; 46: Retail trade; 47: Repair of motor vehicles and motorcycles; 49: Land transport and transport via pipelines; 52: Warehousing and support activities for transportation; 53: Postal and courier activities; 55: Accommodation; 56: Food service activities; 68: Real estate activities; 77: Rental and leasing activities; 79: Travel agency, tour operator reservation service, and related activities; 81: Services to buildings and landscape activities; 82: Office administrative, office support, and other business support activities; zero otherwise

Table A.2. Balance or matching quality after kernel matching

Treatment	Sample	Pseudo R^2	Likelihood-ratio chi-square	P chi-square	Mean bias	Median bias	Rubin's *B*	Rubin's *R*
Procurement of innovation—full sample								
	Raw	0.030	120.61	0.000	8.8	7.9	45.7	0.99
	Matched	0.002	3.07	1.000	1.8	1.6	9.5	1.12
Public support—full sample								
	Raw	0.105	478.82	0.000	20.9	15.5	84.9	1.36
	Matched	0.001	2.28	1.000	1.2	0.9	7.5	1.06
Procurement of innovation—manufacturing								
	Raw	0.041	38.46	0.001	10.4	9.6	53.2	1.28
	Matched	0.002	1.01	1.000	2.5	2.4	11.6	1.23
Public support—manufacturing								
	Raw	0.094	163.20	0.000	17.5	11.0	77.9	1.04
	Matched	0.001	1.05	1.000	1.5	1.4	7.6	1.03
Procurement of innovation—services								
	Raw	0.028	84.1	0.000	10.4	8.9	43.6	0.99
	Matched	0.002	3.01	0.999	2.2	1.7	10.7	1.09
Public support—services								
	Raw	0.080	216.61	0.000	18.5	13.8	73.9	1.55
	Matched	0.002	2.14	1.000	2.1	1.6	9.9	0.97

Notes: B should be <25 and that *R* should be between 0.5 and 2 for the sample to be considered sufficiently balanced.

Table A.3. Summary statistics

Variables	Full sample, mean (standard deviation)	Manufacturing sector, mean (standard deviation)	Service sector, mean (standard deviation)
Treatment variables			
Procurement of innovation	0.133 (0.339)	0.110 (0.313)	0.141 (0.348)
Public support	0.156 (0.363)	0.239 (0.427)	0.120 (0.325)
Outcome variables			
Product innovation in goods	0.565 (0.496)	0.710 (0.454)	0.512 (0.500)
Product innovation in services	0.559 (0.497)	0.408 (0.492)	0.614 (0.487)
Process innovation	0.491 (0.500)	0.589 (0.492)	0.456 (0.498)
Independent variables			
Micro firms	0.420 (0.494)	0.287 (0.452)	0.468 (0.499)
Small firms	0.327 (0.469)	0.350 (0.477)	0.318 (0.466)
Medium firms	0.192 (0.394)	0.271 (0.444)	0.164 (0.370)
Large firms	0.061 (0.239)	0.092 (0.290)	0.050 (0.217)
Young	0.124 (0.330)	0.086 (0.280)	0.138 (0.345)
Exports	14.240 (27.765)	28.587 (35.517)	9.078 (22.225)
R&D activity	0.320 (0.466)	0.432 (0.496)	0.279 (0.449)
Patents	0.108 (0.311)	0.172 (0.378)	0.085 (0.279)
Monopoly	0.030 (0.372)	0.038 (0.192)	0.027 (0.163)
Oligopoly	0.372 (0.483)	0.417 (0.493)	0.355 (0.479)
Monopolistic competition	0.360 (0.480)	0.359 (0.480)	0.361 (0.480)
Perfect competition	0.238 (0.426)	0.186 (0.389)	0.267 (0.437)
Leaders	0.224 (0.417)	0.223 (0.416)	0.225 (0.418)
Followers	0.304 (0.460)	0.301 (0.459)	0.305 (0.461)
Moderate innovators	0.372 (0.483)	0.367 (0.482)	0.373 (0.484)
Modest innovators	0.100 (0.300)	0.109 (0.482)	0.097 (0.295)
High tech industries	0.012 (0.110)	0.047 (0.211)	–
Medium–high tech industries	0.052 (0.221)	0.195 (0.396)	–
Medium–low tech industries	0.083 (0.276)	0.315 (0.465)	–
Low tech industries	0.118 (0.323)	0.443 (0.497)	–
KIS	0.214 (0.410)	–	0.291 (0.454)
LKIS	0.521 (0.500)	–	0.709 (0.454)

Table A.4. Balance or matching quality of the IPRWA estimator

Variables	Full sample				Manufacturing sector				Service sector			
	Standardized differences		Variance ratio		Standardized differences		Variance ratio		Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted
Young	−0.087	−0.002	0.809	0.995	−0.021	−0.013	0.944	0.962	−0.114	−0.000	0.771	0.999
Patents	0.102	−0.003	1.273	0.995	0.177	0.024	1.316	1.031	0.096	−0.008	1.308	0.981
R&D activity	0.218	−0.002	1.140	0.999	0.191	0.006	1.030	1.000	0.252	−0.006	1.217	0.997
Exports	−0.119	0.004	0.658	0.872	−0.177	0.015	0.683	0.860	−0.045	0.003	0.742	0.885
Monopoly	−0.047	−0.003	0.760	0.983	−0.072	−0.005	0.687	0.861	−0.035	−0.002	0.811	0.986
Monopolistic competition	0.073	0.002	1.040	1.001	0.101	0.015	1.058	1.006	0.064	0.001	1.036	1.000
Perfect competition	−0.150	−0.003	0.812	0.995	−0.032	−0.012	0.954	0.981	−0.194	−0.001	0.777	0.998
Small firms	0.052	0.002	1.038	1.001	−0.035	0.008	0.983	1.006	0.082	−0.001	1.062	1.000
Medium firms	0.062	0.003	1.099	1.004	0.012	0.006	1.018	1.006	0.099	0.003	1.185	1.005
Large firms	1.134	−0.004	1.564	0.988	0.127	0.001	1.394	1.003	0.152	−0.007	1.757	0.980
Leaders	0.088	−0.000	1.116	1.000	0.155	−0.014	1.206	0.986	0.067	0.001	1.090	1.001
Followers	−0.079	0.002	0.931	1.003	−1.114	−0.001	0.899	0.999	−0.070	0.003	0.940	1.003
Modest innovators	−0.016	0.001	0.960	1.003	0.040	0.008	1.109	1.109	−0.031	0.002	0.919	1.006
High tech industries	0.100	0.001	2.201	1.001	0.264	−0.011	2.570	0.972	–	–	–	–
Medium–high tech industries	−0.008	0.002	0.970	1.010	0.091	0.015	1.146	1.019	–	–	–	–
Medium–low tech industries	−0.041	−0.001	0.882	0.998	0.050	−0.002	1.044	0.998	–	–	–	–
Low tech industries	−0.175	−0.002	0.617	0.993	–	–	–	–	–	–	–	–
LKIS	−0.036	0.004	1.003	1.000	–	–	–	–	−0.152	−0.002	1.130	0.998

Table A.5. Logit models for estimating propensity scores for both treatment variables in full sample and manufacturing and service sectors

Independent variables	Full sample		Manufacturing sector		Service sector	
	Procurement of innovation	Public support	Procurement of innovation	Public support	Procurement of innovation	Public support
Young	−0.171 (0.138)	0.100 (0.133)	−0.042 (0.331)	−0.060 (0.266)	−0.203 (0.152)	0.167 (0.154)
Patents	0.122 (0.130)	0.511***(0.104)	0.284 (0.227)	0.588***(0.146)	0.082 (0.160)	0.399***(0.152)
R&D activity	0.432***(0.090)	0.834***(0.086)	0.325*(0.190)	0.733***(0.138)	0.462***(0.102)	0.891***(0.110)
Exports	−0.007***(0.002)	0.005***(0.001)	−0.010***(0.003)	0.005**(0.002)	−0.004*(0.002)	0.006***(0.002)
Monopoly	−0.317 (0.275)	0.439**(0.195)	−0.188 (0.548)	0.317 (0.308)	−0.393 (0.320)	0.549**(0.251)
Monopolistic competition	−0.012 (0.094)	−0.047 (0.092)	0.194 (0.198)	−0.076 (0.143)	−0.073 (0.107)	−0.022 (0.121)
Perfect competition	−0.280**(0.116)	−0.120 (0.112)	0.199 (0.256)	0.204 (0.181)	−0.419***(0.130)	−0.292**(0.144)
Small firms	0.289***(0.100)	0.525***(0.105)	0.089 (0.231)	0.685***(0.201)	0.345***(0.112)	0.471***(0.126)
Medium firms	0.345***(0.118)	0.641***(0.116)	0.240 (0.260)	0.914***(0.211)	0.395***(0.134)	0.499***(0.149)
Large firms	0.648***(0.166)	0.803***(0.154)	0.524 (0.335)	1.050***(0.255)	0.705***(0.196)	0.709***(0.211)
Leaders	0.018 (0.109)	−0.300***(0.112)	0.048 (0.230)	−0.139 (0.177)	−0.015 (0.124)	−0.394***(0.146)
Followers	−0.195*(0.104)	0.050 (0.094)	−0.241 (0.229)	0.194 (0.150)	−0.188 (0.118)	−0.031 (0.122)
Modest	0.020 (0.150)	−0.351**(0.161)	0.189 (0.298)	−0.261 (0.237)	−0.040 (0.174)	−0.438**(0.222)
High tech	0.766**0.305)	0.106 (0.293)	1.474***(0.326)	0.160 (0.298)	–	–
Medium high	−0.307 (0.207)	−0.063 (0.156)	0.526**(0.235)	0.002 (0.162)	–	–
Medium low	−0.146 (0.202)	0.014 (0.165)	0.615***(0.228)	0.080 (0.170)	–	–
Low tech	−0.706***(0.169)	−0.101 (0.126)	–	–	–	–
LKIS	−0.198**(0.098)	−0.567***(0.101)	–	–	−0.288***(0.102)	−0.529***(0.109)
Constant	−1.833***(0.130)	−2.331***(0.134)	−2.574***(0.266)	−2.610***(0.223)	−1.742***(0.143)	−2.259***(0.162)

Notes: For the industry dummies, the base category is medium–low industries in the manufacturing subsample and KIS in the full sample and the service subsample. For the firm size dummies, the base category is micro firms. For the country group dummies, the base category is Moderate innovators country group. For the market structure dummies, the base category is oligopoly.

***$P < 0.01$; ** $P < 0.05$, * $P < 0.10$.

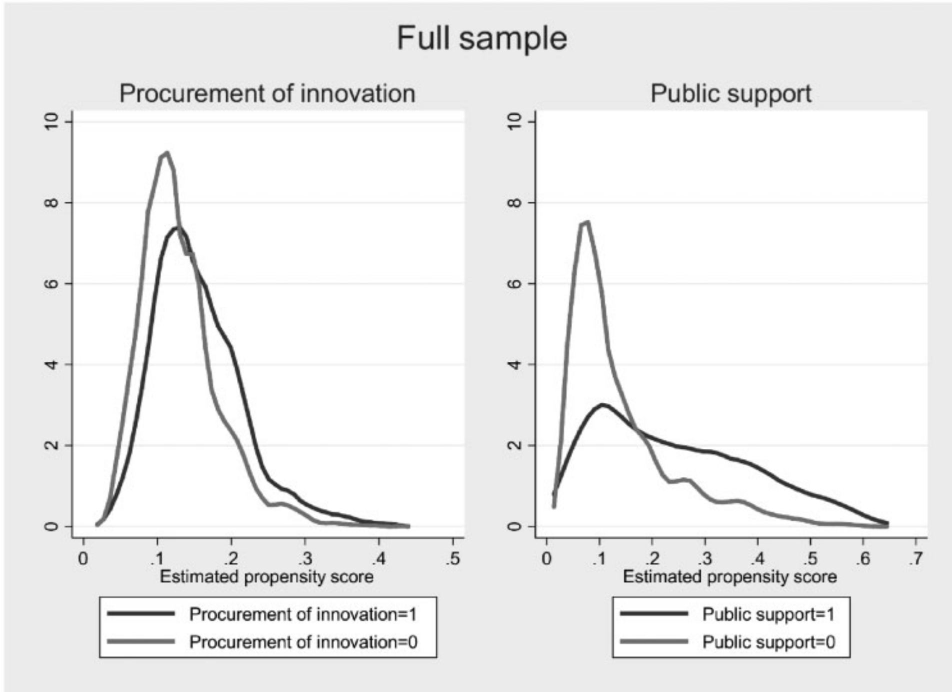

Figure A.1. Checking the overlap condition in the full sample.

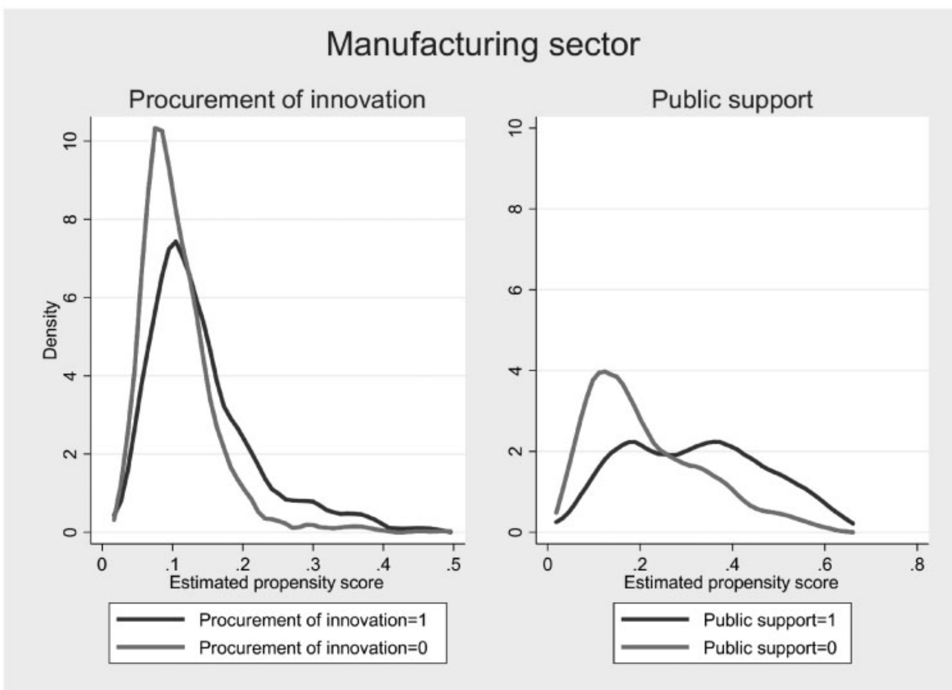

Figure A.2. Checking the overlap condition in the manufacturing sector.

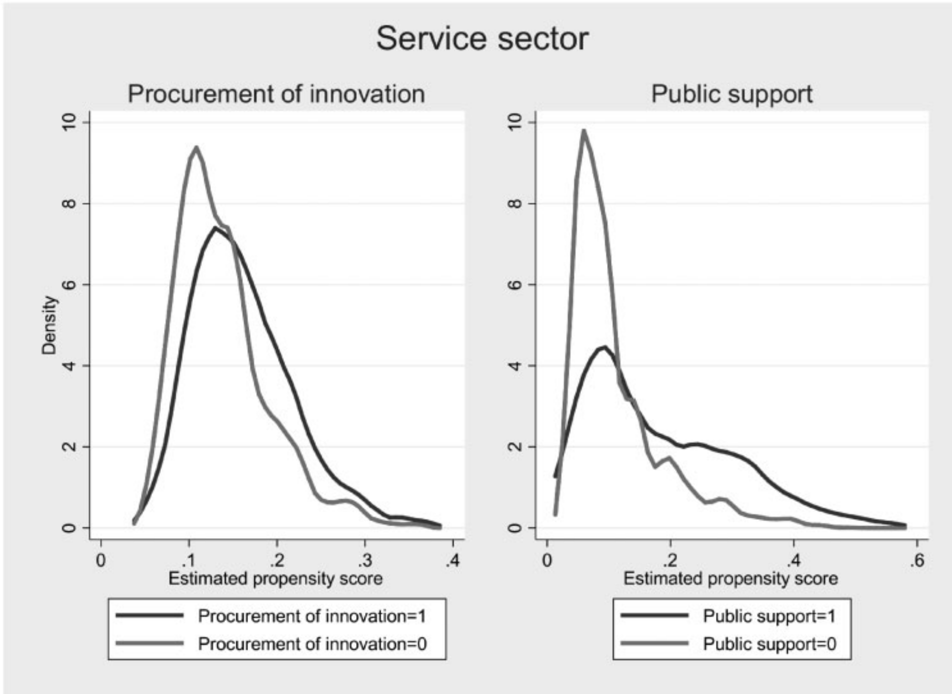

Figure A.3. Checking the overlap condition in the service sector.