



Supply-side and demand-side innovation policies and their combination into policy mixes: New evidence from Italian microdata

JUNE 6, 2018 • ESIEE, PARIS

Serenella Caravella^a

Francesco Crespi^{a, b}

^a Department of Economics, Roma Tre University

^b BRICK, Collegio Carlo Alberto

Introduction

- A new approach to innovation policies
- The regained role of demand-side policies
- Evaluation & Confounding factors
- Literature Gaps & Paper objective

Theoretical Background

- Supply-push policies & confounding factors
- Potential and limits of public procurement
- The Italian case

Empirical analysis

- Dataset & Focus variables
- Methodology
- Results

Conclusions & Policy implications

In recent years, we are seeing a shift in emphasis in the “driving vision” of innovation policy discourse, where the **policy mix concept** seems to have found its way.

The novel approach claims a more **systemic view** of innovation policies (Edquist, 2014) and a more **proactive role** of the public sector as innovator in its own right (Flanagan et al., 2011).

It aims to deal with two challenges:

- i. facing the **increasing complexity** attached to the innovation policy agenda in a systemic world
- ii. counteracting the relative failures of two decades of traditional *supply-push* policies efforts consisting in *linear* and *R&D-centred* measures (Cunningham et al., 2013).

INTRODUCTION (2/5). **The regained role of demand-side tools**

In this vein, the rigid divide between supply-side and demand-side approaches is leaving room for a more comprehensive view, where both instruments are intended in a **complementary** way (Di Stefano et al., 2012) to be maximally effective (Mohnen and Röller, 2005).

As regard to demand-side tools, the spotlight is put on the potential of **public procurement** in supporting competitiveness and innovation by ensuring sufficient critical mass of demand to encourage innovative investments.

In recent years, procurement practices have regained a relevant role mainly in the form of “policy mix”, thus representing **complementary solutions** to *supply-push* policies (Lember et al 2014).

In general, in order to provide unbiased estimates, the evaluation-related literature stresses the importance to account for the **confounding factors** when a “given treatment” is scrutinized.

In particular, within a policy mix context, the evaluation of a “single innovation policy” requires to control for other policies (**confounding factors**) which could represent a source of bias.

In fact, the same treated unit could be involved in more than one policy program :

- ✓ the “picking the winner” bias, which takes place when governments select firms that are already more innovative than others with the aim to maximize the probability of success of their innovation policies ([Almus & Czarnitzki, 2003](#); [Antonelli & Crespi, 2013](#))
- ✓ the bias affecting those firms able to apply for supply-push programs as well as win a regular and/or innovative public procurement tender (it is very likely for firms involved in innovation policy programs to possess capability advantage over firms that fail to spot the opportunities)

- While the **effectiveness of supply push (SP)** instruments (grants and R&D tax credits) has been extensively scrutinized (Cerulli, 2010), few studies account for the presence of **demand instruments as potential sources of bias** (Guerzoni and Raiteri, 2017).
- However, this aspect is particularly relevant given that **public procurement (PP) practices are regaining room** in the policy agenda of developed and emerging economies (Georghiou et al., 2010; OECD, 2011; Uyarra, 2013; Lember et al., 2013; Vecchiato and Roveda, 2014).
- PP is currently under scrutiny for its potential as innovation policy tool.
- However, the “quantitative” evidence focusing on the link between PP policies and innovation is to date in its **infancy** (Ghisetti, 2017; Raiteri, 2018).

To provide a contribution to the literature by developing a quasi-experimental analysis at the firm level based on a **two-stage Propensity Score Matching strategy**.

The contribution of the analysis is fourfold:

1 stage
MAIN
ANALYSIS

1. The investigation of the impact of **SP policies** by accounting for *PP policies as confounding factors*
2. The investigation of the impact **PP policies** by accounting for *SP policies as confounding factors*
3. The investigation of the impact of SP and PP tools when combined into a **policy mix**.

2 stage
SENSITIVITY
ANALYSIS

4. The investigation of the **impact PP policies** in a reduced sample of firms involving in SP policies by controlling for other potential sources of bias

THEORETICAL BACKGROUND (1/6). **The effectiveness of S**
polici

Most of empirical innovation studies focus on the impact of single SP instruments which still dominates the content of actual innovation policies in Europe (Edquist, 2014).

The mixed and heterogenous empirical evidences are influenced by several factors ranging from the policy measure of interest, firms' characteristics, the choice of the target variable to the **methodology exploited** (Capron et de la Potterie, 1988; David al, 2000).

Findings are **less mixed when quasi-experimental analyses are performed** (Cerul 2010). The literature usually rejects the presence of a crowding-out effect and support under certain conditions, the positive impact of R&D policies upon innovation activities (Almus and Czarnitzki, 2003; Czarnitzki and Licht, 2006; Bérubé and Mohnen, 2009; Corchuelo Martínez-Azúa and Martínez-Ros, 2009; Carboni, 2011; Bronzini and Iachini, 2014).

The last decade sees an increasing awareness among researchers and policy makers about the key role of PP in pursuing, among others, innovative policy goals.

In this renovated framework, PP has been recognized as a key industrial and innovation policy instruments (Crespi and Guarascio, 2017; Crespi and Quatraro, 2013; Edquist, 2015; Mazzucato, 2016) as well as a key sustenance in the diffusion (Raiteri, 2018) and standardization (Blind, 2013) of the innovation process.

From a theoretical perspective, PP is supposed to counteract innovation-related market and systemic failures by means of three channels (Cave & Frinking, 2007):

1. By enlarging the absorptive capacity of *new* product by markets and, thus, stimulating positive expectations of profitability from returns.
2. By resizing the appropriability problem usually linked to the engage of R&D investments thanks to the PP-led demand
3. By signaling and articulating market needs upstream.

However, the current role of PP in leading, or hindering, innovation is not clear enough from the empirical point of view given the still scarce, anecdotal and case-study based empirical evidence.

The success of PP depends on “contextual” aspects reflecting **national differences** in the design, governance and implementation of PP as well as different objectives at country and sectoral level.

In this respect, a recent stream of literature points out the existence of the country-specific breakdowns ([Mourão and Cantu 2014](#), [Uyarra et al. 2014b](#), [Li et al., 2015](#), [Rolfstam and Petersen 2011](#), [Cepilovs 2013](#); [Lember et al., 2014b](#)) and systemic hindrances ([Amann and Essig 2015](#); [Georghiou et al. 2013](#); [Rolfstam, 2012](#)) affecting P

Different and contradictory ideas, especially in regard to the **trade-off between short-term efficiency and long-term projects** (Nyiri et al. 2007)

Barriers at administrative level since PP is seen as a time consuming and an extremely complex procedure (Amann and Essig, 2015).

- i. Lack of institutional capacities especially in the implementation stage (Georghiou et al, 2013)
- ii. Lack of a proper communication along the institutional chain of procurement (Georghiou et al, 2013)
- iii. Lack of coordination practices (Lember et al. 2015,(Kattel and Lember, 2015)
- iv. Lack of co-determination of outcomes between endogenous and exogenous institutions (Rolfstam, 2002)
- v. Lack of a proper degree of centralization (Albano and Sparro , 2010)

- In the general framework of the EU2020 strategy, since 2011 Italy has set the scene the procurement of innovation by including *innovation-inducing* procurement into its R&D policy framework. However, to date, the finished cases of success are **three**, all concentrated in the healthcare sector ([EC, 2014](#); [Fedesantità, 2015](#))
- The Italian normative framework of the public procurement of innovation has been recently updated (Law Decree 50/2016 and the three-year plan AgID , Agenzia per l'Italia Digitale) .
- In this new context, the public purchasing of innovative goods has been largely enhanced by new instruments as, for example, the possibility of partnerships between public and private actors.

The scarce exploitation of the new procurement-related tools has been currently claimed by AgID which signals serious deficiencies affecting the “uploaded” version of the Italian PP.

1. Low degree of clearness and applicability of procurement contracts
2. Weak level of expertise at institutional level
3. Short-term and static-efficiency vision of the tree-year plan AgID,
4. Inefficient organization along the procurement chain
5. Low propensity to innovate (rationalization of public spending in goods and services)

The empirical analysis is based on firm-level data drawn from the 6th and 7th waves of the Italian Community Innovation Survey referring to the tree-year periods 2010-2012 and 2012-2014, respectively.

The survey sampled 18.697 and 17.532 firms belonging to manufacturing and service sectors for the 2010-2012 and 2012-2014 respectively, by recording a response rate higher than 60% for both periods.

To properly implement our empirical strategy, the CIS dataset has been integrated with balance-sheet data extracted from the AIDA-Bureau VanDijk database which provides information on firms' financial structure.

After dropping not innovative firms (excluded from innovation-related questions “by construction”) and those operating in not manufacturing sectors, and cleaning for missing information, the final **pooled sample** consists of **4.215** observations.

With respect to previous waves, in CIS6 and CIS7 a special section on public procurement (PP) and innovative public procurement (IPP) has been added. We exploited the following questions:

➤ **PUBLIC FUNDING IN THE ENTERPRISES**

Question **5.3**. *During the three years, did your enterprise receive any public financial support for innovation activities from the following levels of government? (financial support via credits or deductions, grants, subsidized loans, and loan guarantees)*

➤ **PUBLIC SECTOR PROCUREMENT AND INNOVATION IN THE ENTERPRISES**

Question **10.1**. *During the three years, did your enterprise have any procurement contracts to provide goods or services for domestic/foreign public sector organisation (Yes/Not)*

Question **10.2**. *Did your enterprise undertake any innovation activities as part of a procurement contract to provide goods or services to a public sector organisation? (Include activities for product, process, organisational and marketing innovation)*

Yes but innovation not required as part of the contract

Yes and innovation required as part of the contract

No

The dichotomic core variables used in the analysis have been designed as follows:

1 stage
**MAIN
ANALYSIS**
(4.215 firms)

- **SP (SUPPLY-PUSH)**: whether or not the innovative firm has received same kind of financial support from national and/or European governments
- **PS (PUBLIC-PROCUREMENT)** whether or not the innovative firm has been involved in a contract of public furniture

*Reduced
sample*
(3.639 firms)

- **IPP (INNOVATIVE PUBLIC-PROCUREMENT)** whether or not the public contract explicitly required the engagement in innovation activities

2 stage
**SENSITIVITY
ANALYSIS**
(1.492 firms)

The sample is reduced to innovative firms involving in PS programs

- **PS (PUBLIC-PROCUREMENT)** whether or not the innovative firm has been involved in a contract of public furniture

The empirical strategy is based on a **counter-factual analysis**. The basic idea is to compare the same unit in both states of the world, i.e. with or without treatment, by creating a hypothetical situation where the treated unit is untreated and then testing if there are significant differences in the mean of the variable of interest.

Being the “counterfactual” situation not directly observable for the same unit, a “twin” unit is used as control. In this case, the average treatment effect on treated firms (ATT) is estimated by comparing differences on the mean of the target variable between the groups of treated and control, which are assumed to be identical to each other, except for the treatment. Formally:

$$ATT = E(Y_{i1} | T=1) - E(Y_{i0} | T=0) = E(Y_{i1} - Y_{i0})$$

where Y_{i1} represents the outcome variable of the individual i under the treatment T ($T=1$) and Y_{i0} is referring to the outcome variable of the same individual i (its twin) in absence of treatment ($T=0$).

This procedure works if, and only if, the two groups are **perfectly randomized**, which means that the probability of taking part to a policy program must be not correlated with individual characteristics of the firm. Formally:

$$Y_{i1} \perp T_i ; Y_{i0} \perp T_i$$

The not randomly assignment assumption difficulty holds, because of:

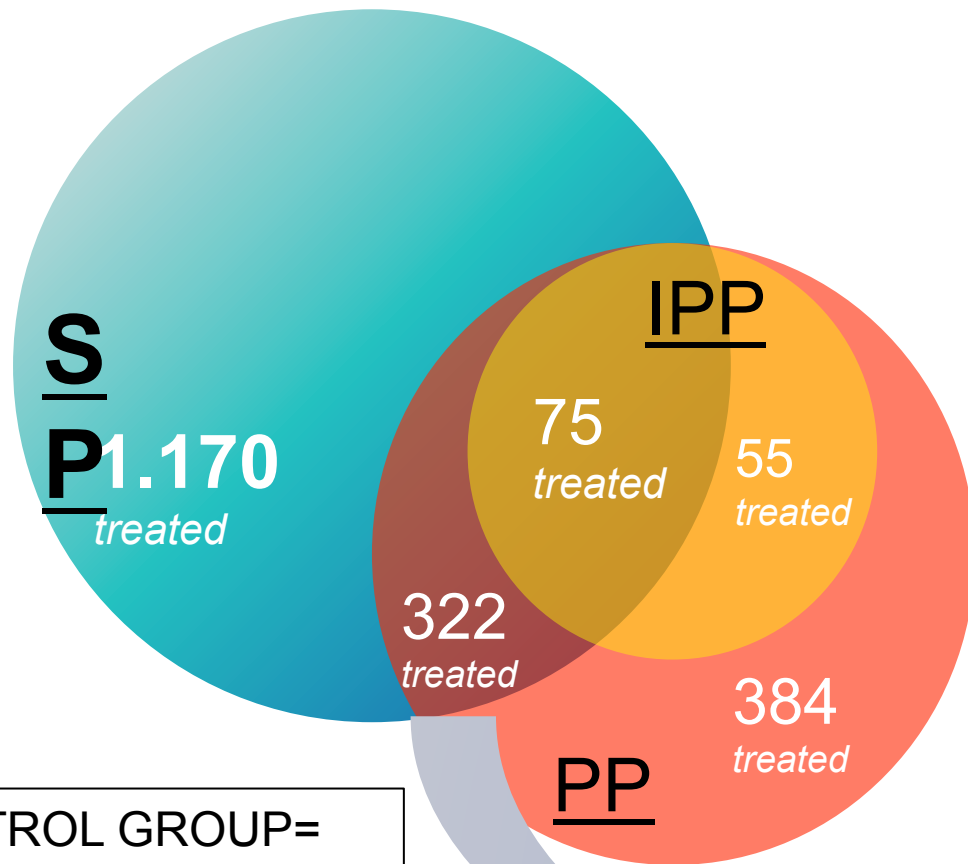
1. **SELF-SELECTION** → Firms receiving treatments are “**self-selected**” on the basis of same characteristics that drive selection of who gets or not the treatment (the “picking the winner” bias & the **capabilities bias**)

which is correlated to the:

2. **HIDDEN TREATMENT EFFECT** → Confounding effect arising when the effect of a treatment is estimated not taking into account its potential interactions **with other treatments aimed at the same goal and active in the same environment.**

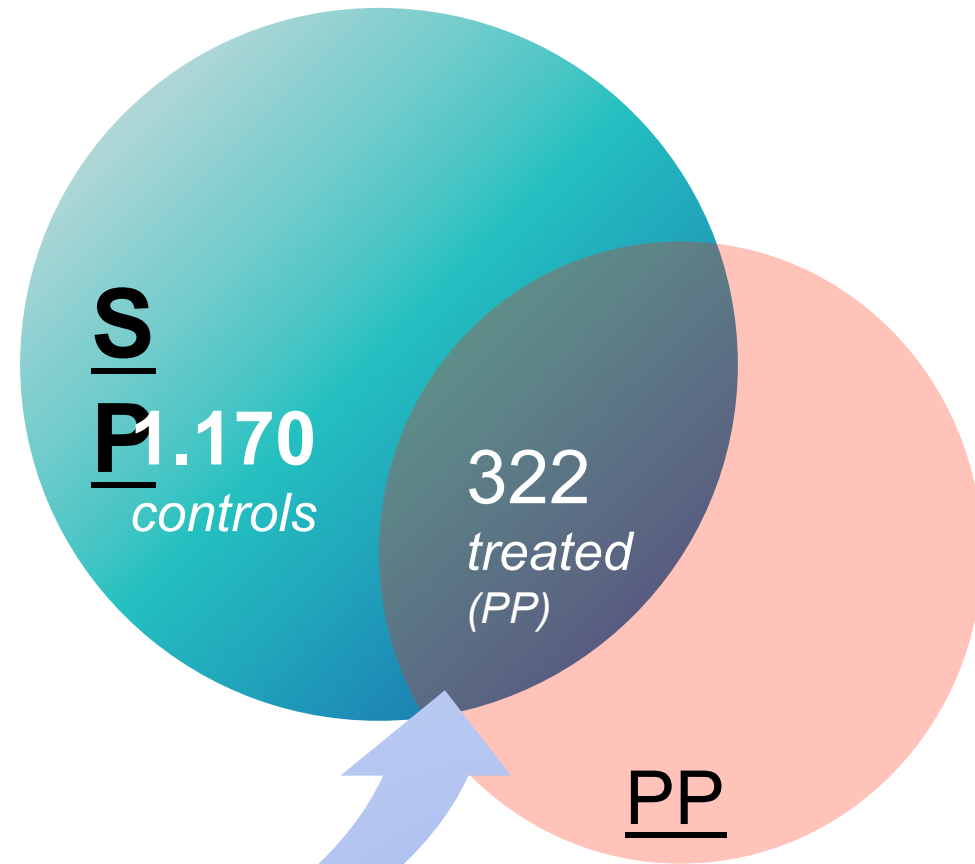
As a consequence, the probability for the same firm of being involved in a double treatment scenario is highly feasible as well the presence of same hidden effect if each policy is not properly taken into account.

MAIN ANALYSIS



CONTROL GROUP=
9 FIRMS (not SP
not PP, and not

SENSITIVITY ANALYSIS



We compare the average treatment (ATT) effect on the outcome variable (Y) deriving from different m treatments with the same baseline scenario characterized by the absence of any treatment. Formally, for a given treatment m :

$$ATT = E(Y_{11} - Y_{10} | m=1) + E(Y_{10} | m=1) - E(Y_{10} | m=0)$$

where

$$E(Y_{10} | m=1) - E(Y_{10} | m=0) \neq 0$$

where Y_{11} represents the outcome variable under the treatment program of interest (m) and Y_{10} is referring to the outcome variable in the absence of any type of treatment.

In order to artificially create the contrafactual situation $E(Y_{10} | m=1)$ depicting the outcome of the treated under the untreated condition, the best pairs of treated and control firms have been identified by exploiting the propensity score matching **for each treatment on the basis of the pretreatment characteristics (χ) believed to affect both the treatment and the target variable.**

The covariates of PSM have been identified according to those aspects influencing both the participation to *SP* and *PP* policies as well as stimulating private R&D expenditures.

- ✓ A measure of financial constraints proxied by the **bank interest** paid by firms on their bank loans (**DEBT**) → to control for firms' potentiality in founding R&D expenditures
- ✓ A regressor (**SIZE**) (log. of turnover) → to capture the influence of firms' dimension.
- ✓ The variable EMPUD (share on graduated employees) → represent the relevance of specialized **human capital** in firms' innovation capabilities and the ability of assimilating knowledge
- ✓ An export dummy EXPORT has also been included
- ✓ Finally, **regional dummies** and **seven sectoral dummies** have been included.

The outcome variable capturing the “input additionality” is represented by the total expenditures in internal and external R&D activities over the three-year period (**RDTURN**). This amount has been divided by the mean of turnover referring to the period.

Descriptive statistics

Variables	Untreated	<i>Reduced sample</i>				
		(PS_Only)	(PP_Only)	(PS&PP)	(IPP_Only)	(PS&IPP)
DEB	2.27	2.45*	2.00*	2.29 (NS)	1.78*	2.25 (NS)
SIZE	16.95	17.25*	17.21*	17.77*	17.22(NS)	18.12*
EMPUD	2.40	2.65*	3.02*	3.34*	3.45*	3.74*
EXP	0.89	0.94*	0.80*	0.90 (NS)	0.83(NS)	0.90 (NS)
R&D/TURNOVER	1.84	3.23*	1.57 (NS)	4.21*	2.37(NS)	6.15*
N	2.339	1.170	383	322	55	75

Variable mean differences between different groups of treated and control group (2.229 untreated firms) are statistically different from zero (t-test p-value < 0.05); NS, the difference between the groups is not statistically different

EMPIRICAL ANALYSIS (10/17). Propensity score matching stage

Propensity scores estimates: results from logit regressions

	Reduced sample				
	SP_Only	PP_Only	SP&PP	IPP_Only	SP&IPP
B	0.0660*** (4.30)	-0.0302 (-1.45)	0.0723** (3.13)	-0.0456 (-1.13)	0.0892* (2.24)
E	0.0439** (2.85)	0.0429* (2.02)	0.137*** (5.97)	0.00872 (0.25)	0.182*** (4.65)
PUD	0.0422** (2.58)	0.125*** (5.87)	0.148*** (6.29)	0.153*** (3.79)	0.193*** (4.88)
PORT	0.238** (2.76)	-0.450*** (-4.86)	-0.261* (-2.21)	-0.447* (-2.39)	-0.362 (-1.76)
sectoral dummies	yes	yes	yes	yes	yes
geographical dummies	yes	yes	yes	yes	yes
constant	-1.707*** (-6.61)	-1.903*** (-5.29)	-3.950*** (-10.13)	-2.510*** (-4.17)	-5.346*** (-7.94)
observation	3509	2722	2661	2128	2414

The balancing property of the propensity score tested using the Becker and Ichimura (2002) user-written Stata command *pscore* and it is satisfied for each of the four computations

*Standard errors in parentheses. ***, **, denote 1%, 5% and 10% levels of significance, respectively*

The **5NNM method** has been selected but results are robust ([Caliendo & Kopeinig, 2006](#)).

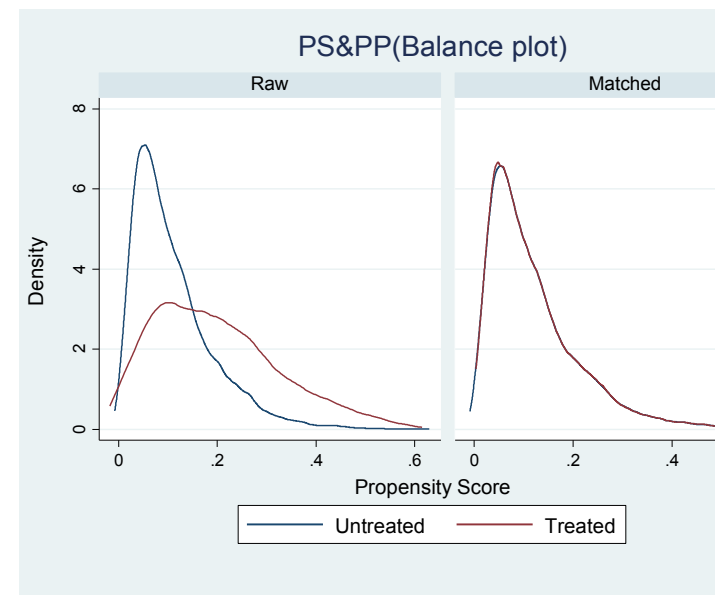
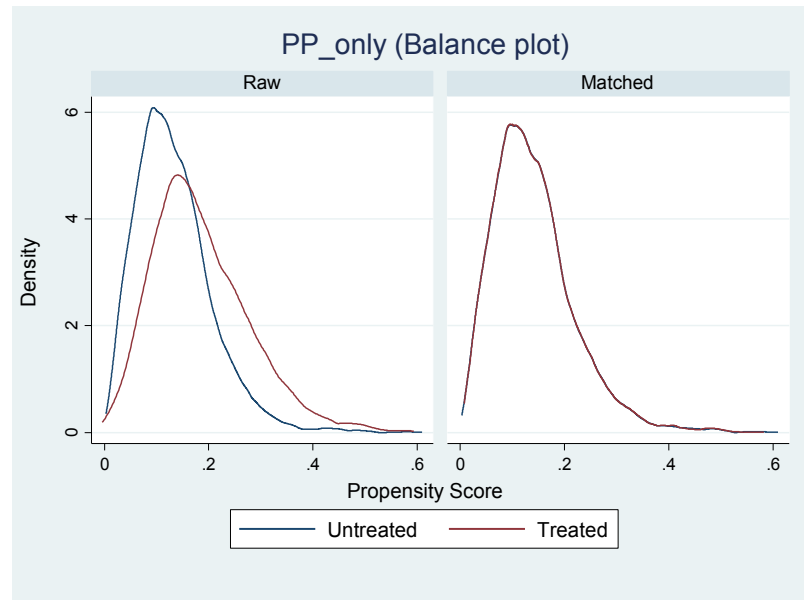
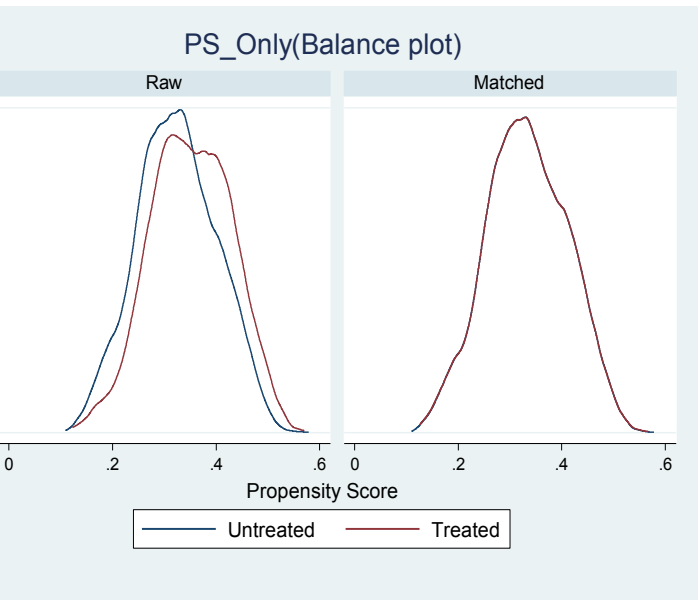
The estimated propensity score before and after the pairing procedure, signals the good quality of the procedure in reason of a significant reduction of the dissimilarities between treated and controls after the matching.

The overlap assumption is not violated since the estimated densities have most of their respective masses in regions in which they overlap.

The validity of the matching procedure is supported by all tests for matching quality

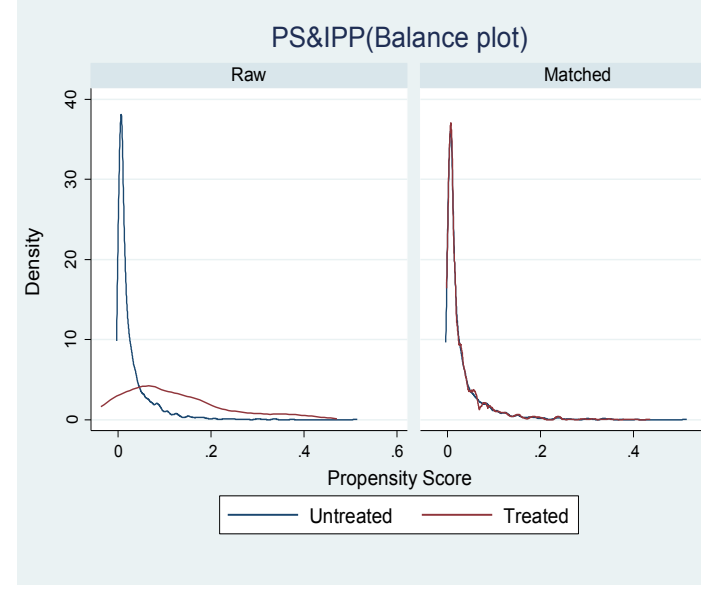
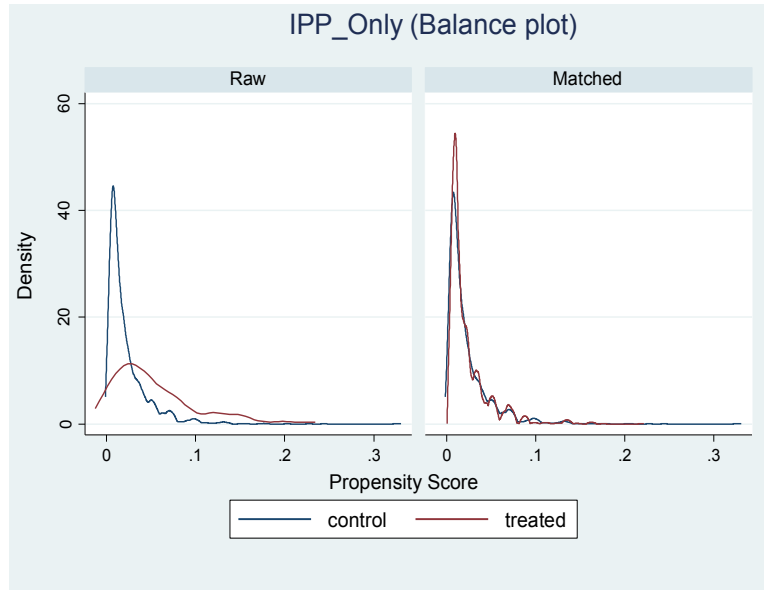
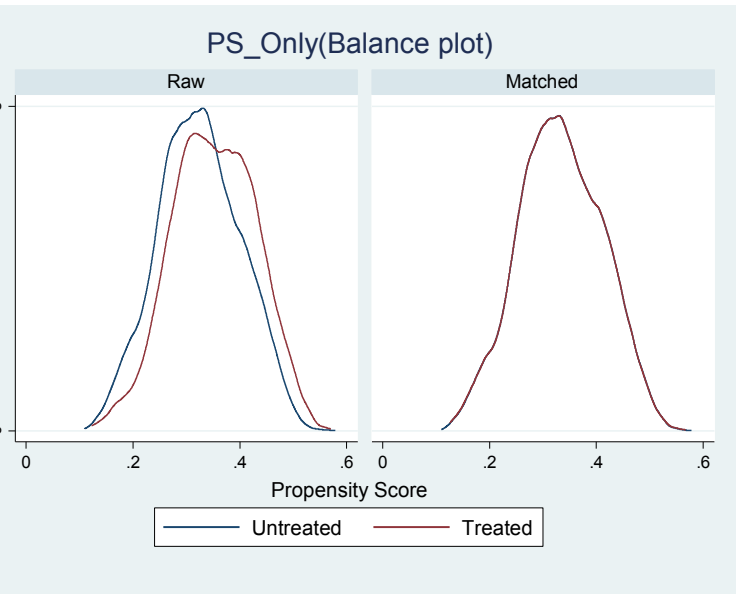
1. The reduction of the mean standardized bias falls below 5% threshold ([Rosenbaum and Rubin, 1985](#)).
2. The pseudo R-square values are lower for matched firms when compared with unmatched ([Sianesi, 2004](#)).
3. Thirdly, the log-likelihood ratio tests on differences in covariates means is rejected before the matching and not rejected after the matching, showing that all *p-values* are lower than 0.05 ([Ghisetti, 2017](#))

MAIN ANALYSIS (WHOLE SAMPLE)



Algorithm	Ps R2	LR chi2	p>chi2	MeanBias	MedBias
PS_Only	0.001	1.85	1.000	1.4	1.5
PP_Only	0.002	2.22	0.998	2.9	2.5
PS&PP	0.004	3.66	0.989	3.3	2.8

MAIN ANALYSIS (REDUCED SAMPLE)



Algorithm	Ps R2	LR chi2	p>chi2	MeanBias	MedBias
PS_Only	0.001	1.85	1.000	1.4	1.5
IPP_Only	0.007	1.00	1.000	4.7	4.5
PS&IPP	0.007	1.39	1.000	4.9	3.6

MAIN ANALYSIS (WHOLE SAMPLE)

Results from 5NNM

SP_Only /SP&PP difference test	
Coeff	SE
-0.4550283***	.1619395

Treatment	Coef. ATT	S.E.	Z	P> z
P_Only	1.026791***	.1921766	5.34	0.000
P_Only	-.277552	.2151881	-1.29	0.197
P&PP	1.504409***	.4390531	3.43	0.001

Robustness

Treatment	1NNM	3NNM(a)	KERNEL (Bootstrapped SE, 1000 repetitions)
P_Only	1.29345***	1.097929 ***	1.510717 ***
P_Only	-.3226154	-.3226154	-.7760685
P&PP	1.671447 ***	1.635461 ***	1.771294 ***

***, **, * denote 1%, 5% and 10% levels of significance, respectively

) The same algorithm (3NNM) has been implemented by imposing the “caliper” threshold (0.25 times the standard deviation of the propensity scores uncovered with the multinomial logit models) which imposes a tolerance level on the maximum propensity score distance to avoid bad matches. **Results remain unchanged.**

MAIN ANALYSIS (REDUCED SAMPLE)

Results from 5NNM

Treatment	Coef. ATT	S.E.	Z	P> z
SP_Only	1.026791***	.1921766	5.34	0.000
PP_Only	.4572425	.4556725	1.00	0.316
SP&IPP	3.914337**	1.70761	2.29	0.022

Robustness

Treatment	1NNM	3NNMa)	KERNEL (Bootstrapped SE, 1000 repetitions)
SP_Only	1.29345***	1.097929 ***	1.510717 ***
PP_Only	.810576**	.6356891	.8576806
SP&IPP	3.304866***	3.013017***	3.67365 ***

***, **, * denote 1%, 5% and 10% levels of significance, respectively

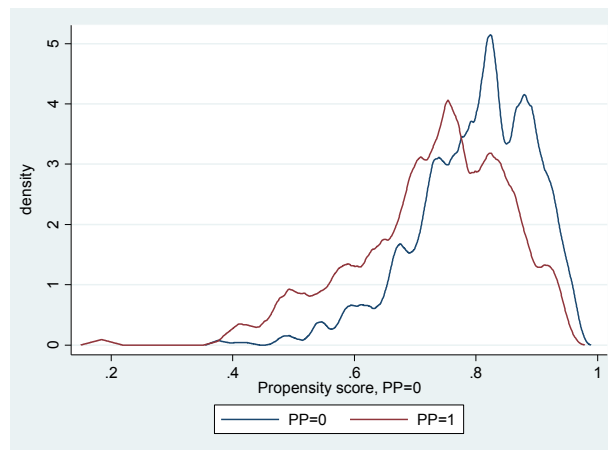
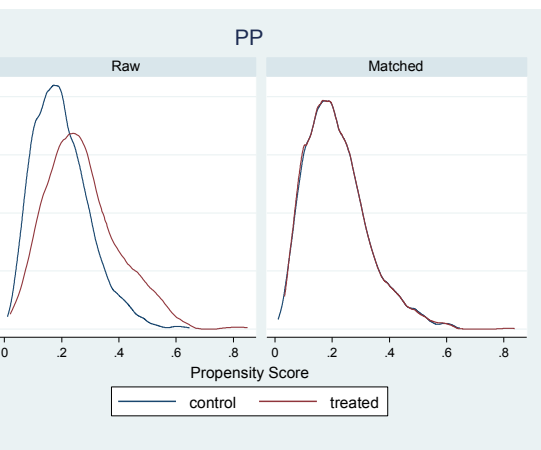
) The same algorithm (3NNM) has been implemented by imposing the “caliper” threshold (0.25 times the standard deviation of the propensity scores uncovered with the multinomial logit models) which imposes a tolerance level on the maximum propensity score distance to avoid bad matches. **Results remain unchanged.**

WHY A SENSITIVITY ANALYSIS IS NEEDED?

- In stage 1, PP has been found to exert a positive and significant effect on R&D investment **only if in combination with SP policies.**
- The positive impact arising from the double treatment SP&PP could be essentially driven by the selection bias affecting firms involved in both measures instead of the influence of PP by its own.
- In order to better control for this potential bias, the new matching is performed on a more homogenous sample exclusively composed by firms receiving SP sustain.

SENSITIVITY ANALYSIS

Goodness of matching



Treatment	PS R2	LR chi2	p>chi2	Mean Bias
PP	0.001	1.09	1.000	1.9

Results

Treatment	Algorithm	Coef. ATT	S.E.	Z	P> z
	5NNM	.1748546	.3953385	0.44	0.658
	1NNM	.2079075	.5395482	0.39	0.700
	3NNM	.1512797	.4019571	0.38	0.707
	KERNEL	.2079075	.5099057	0.41	0.683

Results **confirm previous results on additionality of SP innovation policies**, when hidden treatment effects are accounted for.

Demand pull policies appear to be able to enhance innovation activities when technological capabilities are **jointly stimulated** by suggesting that firms benefiting only from public contracts have less incentives to compete on markets through innovative investments (high capabilities for firms involving in the double treatment, already developed innovations)

However, by controlling for selection bias in a reduced sample of firms benefiting from SP policies, Public Procurement seems not influence **additional R&D expenditures**.

Possible interpretations of the **ineffectiveness of PP**

1. Short-term and static-efficiency vision → Focus on cost-efficiency programs
2. Lack of capabilities at institutional level

Our empirical evidence show that PP has been affected by inefficiencies even before the recent modifies.

- Need to shift from a static and cost-efficiency vision of PP to a dynamic-efficiency and innovation-oriented approach
- Need to take into account the **inner complexity** associated with PP schemes
- Need to adopt a **skill-building-capability approach** (learning and skill development at institutional level (national and subnational) to make procuring entities able to acknowledge and manage PP
- MAJOR LIMITS OF THE STUDY:
 - i. Need to distinguish between different SP instruments
 - ii. Lack of cross-country comparisons



Thank you

Serenella Caravella
serenella.caravella@uniroma3.it