Istituto Regionale Programmazione Economica della Toscana

R&D collaboration policies: Are they really able to promote networking?

New title:

Better together? A comparative evaluation of firm subsidies to individual and collaborative R&D projects

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Setting the scene

- R&D collaboration policies extensively used by policymakers around the world in order to promote R&D and stimulate networking (OECD, 2001; Tsipouri et al., 2009)

- However, there is scanty evidence that supports their ability to modify in a non-transitory way the behavior of funded organizations

- No evidence on the relative effectiveness of R&D collaboration vs other types of (simpler) innovation policies, such as R&D subsidies to individual firms
  - Same goal with same instrument, but different unit of intervention
  - The latter can support networking! (Busom and Fernández-Ribas, 2008; Antonioli et al., 2014; Roper and Hewitt-Dundas, 2014; Marzucchi et al., 2015)

Our contribution

- We compare the ex-post effects of R&D collaboration policies with that of R&D subsidies to individual firms

- We focus on input and network effects

Network effect / additionality?

- "Network additionality" refers to the possible increased cooperation and networking resulting from public intervention (Falk, 2004, 2007; Autio et al., 2008; Clarysse et al., 2009)

- Network additionality is a specific type of behavioural additionality of a policy (Buisseret et al., 1995; Georghiou, 2002) → BA refers to the possible *learning effects* of a policy on an organization's behaviour during and/or after the project's implementation. This approach considers a policy as successful when it increases the participants' cognitive capacities, competencies and networking in a non-transitory way (Georghiou, 2002)

- The theoretical context is that of capability and adoption failures, as well as the system failures (see Edler and Gok, 2011)

Our hypotheses

- **H1**: Ex-post R&D additionality effects are higher for firms receiving subsidies for a collaborative R&D project than for firms receiving an individual R&D subsidy

- **H2**: Ex-post networking effects are higher for firms receiving subsidies for a collaborative R&D project than for firms receiving an individual R&D subsidy

Our hypotheses: input additionality

- Internalisation of spillovers supports larger investments in R&D than individual projects (Katz, 1986; d'Aspremont and Jacquemin, 1989; Kamien et al., 1992)

- Once the subsidised project is over, new and improved prospects, knowledge, skills and, possibly, equipment and infrastructures, can stimulate the firm to continue to perform R&D (Clarysse et al., 2009; Roper and Hewitt-Dundas, 2014)

- The post-project effect of an investment that is larger due to resource pooling could be considerable!

Our hypothesis: network additionality

As R&D collaboration policies have many features that are designed specifically to promote networking – more than those of other R&D policies – we believe that they are able to produce a larger network additionality than other policies (namely R&D subsidies to individual firms)

R&D collaboration policies	**R&D incentives to individual firms**
✓Agents perform R&D	✓Agents perform R&D
✓Collaboration with external organisations is required by design	
✓Specific rules of the game may require agents to collaborate with some particular type of agent	

Two main mechanisms underlying network additionality:
*Organisational learning - by experience / interaction / absorptive capacity (Cyert and March, 1963; Cohen and Levinthal, 1989; Amin and Cohendet, 2000; Asheim et al., 2007)
*Cumulative effect of learning and of networking (Gulati, 1995; Powell et al., 1996; Van den Bosch et al. 1999)

Data from regional policies

- Same policymaker: Tuscany Region
- Same funds: ERDF funds
- Same programming period: 2000-2006 (2002-2008)
- Same policy goal: supporting R&D and innovation
- Same policy instrument: R&D grants

Policy	Final beneficiaries	Tech/ sectoral target	Individual incentive	N. of funded SMEs	
				Total	Of which: receiving a single grant
R&D collaboration policy (C)	Consortia or temporary associations including SMEs	Wide	About 70,000 €	677	535
R&D grants to individual firms (I)	Individual SMEs	Wide	About 60,000 €	336	120

Overview of our empirical strategy

1. **Matched sampling**: estimation of a preliminary propensity score, one for each programme, from a number of basic background characteristics available on the full population of eligible regional enterprises. Based on these preliminary propensity scores, we selected a pool of untreated firms by matching each beneficiary to its five nearest neighbours, without replacement.
2. **Questionnaire** to collect information on relevant outcome and pre-treatment variables. The survey suffers from some non-response, therefore...
3. **Inverse probability weighting**, to account for missing responses (e.g. Wooldridge, 2007). Let $R_{i,}$ be a binary indicator equal to 1 if firm *i* responds to the survey. We have, for each treatment level other than *U:*

$$w_{i,\,T=t,}=1/Pr(R_i = 1 \mid \boldsymbol{X}_i,\, T_i=t),$$

where $\boldsymbol{X}_i$ contains the covariates that are available for all treated firms, be they respondent or not

4. **(Weighted) Propensity Score Matching** within a multiple-treatment framework (Lechner 2001, 2002). Using the powerful covariate-balancing propensity score estimator by Imai and Ratkovic (2014), we perform nearest-neighbor matching. We also impose an exact matching with respect to the pre-treatment level of outcome variable

Quantities of interest

There are 3 treatment levels: **C** collab. Subsidy; **I** individual subsidy; **U** nothing
Each firm has three potential outcomes for each outcome variable,

$Y_i(C)$, $Y_i(I)$, $Y_i(U)$ only one is observable for each i

Need to resort to **assumptions** to identify causal effects. Our choice: **strong ignorability**

For each pair of treatments l and m, the causal estimands of interest include

- the average treatment effect for the subpopulation of firms receiving l rather than m, known as average treatment effect on the treated (ATT)

$$ATT_{l,m}=E[Y_i(l)-Y_i(m)|T=l,\boldsymbol{X}_i=\boldsymbol{x}], \qquad [1]$$

- and also the average treatment effect for the subpopulation of firms receiving m had they received l, known as average treatment effect on the untreated (ATU)

$$ATU_{l,m}=E[Y_i(l)-Y_i(m)|T=m,\boldsymbol{X}_i=\boldsymbol{x}]. \qquad [2]$$

Interpretation of [1] and [2] depends on what types of treatments *l* and *m* are

Descriptive statistics on selected pre-treatment variables

Firms participating in R&D ***collaboration policies*** *(C-type firms) are more outward-looking than I-type firms*

Firms benefiting from ***individual incentives*** *to R&D (I-type firms) are more internal innovator than C-type firms*

Respondent firms Variable	T=C Proportion / Mean	T=I Proportion / Mean
Had collaborations with universities$_{t-1}$ (1/0)	0.376	0.183
Had collaborations with other firms$_{t-1}$ (1/0)	0.396	0.192
Performed R&D activities$_{t-1}$ (1/0)	0.528	0.833
R&D expenditures$_{t-1}$ (€)	169,038	193,617

Other variables used in the matching procedure: sector, employees, legal form, province

Variables used in the matched sampling: sector, employees, legal form, province
Variables used in the calculation of weights: sector, employees, legal form, province, respondent

Descriptive statistics on post-treatment outcomes

For the sake of consistency between the two surveys, almost all post-treatment outcomes are expressed in a binary fashion

Respondent firms

Variable	T=C Proportion / Mean	T=I Proportion / Mean
Had collaborations with universities$_{post}$ (1/0)	0.445	0.242
Had collaborations with other firms$_{post}$ (1/0)	0.412	0.250
Performed R&D activities$_{post}$ (1/0)	0.654	0.817
R&D gain (€)	21,608	29,532

Matching is weighted and we impose an exact matching with respect to the pre-treatment outcome variables

Treatment I or C vs. no treatment U

Estimand of interest	l = I; m = U	l = C; m =U
$ATT_{l,m} = E[Y_i(l)- Y_i(m) \mid T=l, \boldsymbol{X}_i=\boldsymbol{x}]$ Contrast between: - observed outcome of firms receiving *l* - outcome that these firms would achieve with no treatment at all (m = U)	Average causal effect of the I subsidy the firms that actually take it 5.7% university (1/0) -0.8% other firms (1/0) -0.4% R&D (1/0) **39.438** *** € R&D gain	Average causal effect of the C subsidy the firms that actually take it **20.3%** *** university (1/0) 2.9% other firms (1/0) **24.2%** *** R&D (1/0) 1.309 € R&D gain
$ATU_{l,m} = E[Y_i(l)- Y_i(m) \mid T=m, \boldsymbol{X}_i=\boldsymbol{x}]$ *Contrast between:* *- observed outcome of untreated firms* *- outcome that these firms would achieve after receiving l*	Average effect of the I subsidy on untreated-type firms *Does not make sense after matched sampling*	Average effect of the C subsidy on untreated-type firms

With a binary outcome, these are differences in probability!

Differential effects of alternative treatments I and C

Estimand of interest	l = I; m = C	l = C; m = I
$ATT_{l,m} = E[Y_i(l) - Y_i(m) \mid T=l, \mathbf{X}_i=\mathbf{x}]$ Contrast between: - observed outcome of firms receiving *l* - outcome that these firms would achieve after alternative treatment *m*	Average differential causal effect of the I subsidy on the firms that actually take it **-30.6%*** universities (1/0) **-27%*** other firms (1/0) -4.5% R&D (1/0) 28,590 € R&D gain	Average differential causal effect of the C subsidy on the firms that actually take it 2.7% universities (1/0) -4.3% other firms (1/0) **18.3%**** R&D (1/0) 24,860 € R&D gain
$ATU_{l,m} = E[Y_i(l) - Y_i(m) \mid T=m, \mathbf{X}_i=\mathbf{x}]$ Contrast between: - observed outcome of firms receiving *m* - outcome that these firms would achieve after receiving *l*	Average differential effect of the I subsidy on the firms that actually take C -2.7% universities (1/0) 4.3% other firms (1/0) **-18.3%**** R&D (1/0) -24,860 € R&D gain	Average differential effect of the C subsidy on the firms that actually take I **30.6%*** universities (1/0) **27%*** other firms (1/0) 4.5% R&D (1/0) -28,590 € R&D gain

Multiple testing

When one performs multiple tests on the same data, some of these tests may appear statistically significant purely by chance.

To address this issue, we take the approach by Benjamini and Hochberg (1995) based on false discovery rates (FDR).

A FDR is the maximum proportion that one is willing to accept of apparently significant results (discoveries) being false positives.

- The statistical significance of all our estimated treatment effects is preserved by setting the FDR at 15%, which entails that, in general, it is very unlikely that our discoveries are false positives

- A FDR of 15% is required l=I and m=C

- In all the other cases, a FDR that is smaller than 15% is sufficient to confirm the statistical significance of our findings

Discussion

	Collaboration subsidy	Individual subsidy
Program is attractive for	Less R&D experienced SMEs; can be more open to collaborations	More R&D experienced SMEs; not very open to collaborations
Program works in	+ networking with Univ. + R&D	+ R&D effort
Program should try to attract		
- to improve networking	+ More R&D experienced SMEs, not very open to collaborations	
- to improve R&D effort	+ Less R&D experienced SMEs; more open to collaborations; + More R&D experienced SMEs	Continue to attract more R&D experienced SMEs

Conclusion (methodology)

- Multiple-treatment framework first applied to enterprise policy area
- Application of recently proposed covariate-balancing propensity score
- Management of issues related to survey non-response
- Multiple testing