What kinds of R&D consortia enhance SMEs productivity?

A hierarchical Bayesian approach for the analysis of a small-business innovation policy

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Abstract

We investigate the benefits in terms of labor productivity arising for small and medium sized firms from R&D collaboration with larger companies, universities and other agents. We focus on policy-supported R&D consortia, so as to understand what types of consortia are more effective and therefore should be promoted by policies. We put forward a set of theoretically and empirically grounded arguments based on the costs and benefits of collaborations, and we develop a consistent empirical analysis on data related to an innovation policy implemented in Italy at the regional level. A characteristic of the program is that firms could participate in multiple consortia both simultaneously and over time, which results in a hierarchical data structure with imperfectly disjoint classes. We adopt a hierarchical Bayesian approach for inference, which allows us to properly account for the complex structure of the data. We find that potential competition among small firms reduces the benefits of collaboration. Conversely, benefits increase in consortia that include firms with some R&D history or, most important, large firms. Both the presence of academic partners and that of intermediaries is beneficial only under certain conditions.

Keywords: R&D consortia; innovation policy; small and medium-sized enterprises; hierarchical Bayesian models; imperfectly disjoint groups

JEL codes: C11, C39, L53, O32, O25

1. Introduction

Since the late ‘80s different strands of economic and management literature have shown that research and development (henceforth: R&D) collaborations can be beneficial both at the firm and at the societal level, via the promotion and the internalization of knowledge spillovers (Spence, 1984; Katz, 1986; d’Aspremont and Jacquemin, 1988; Kogut 1988; Hagedoorn 1993; Das and Teng 2000). Aware of this widespread academic consensus, a large number of countries and regions have developed their own R&D-collaboration policies. The EU, for example, has widely used this tool to support various forms of partnership both in large-scale programs such as FP7, and in smaller scale innovation programs. Individual EU regions have also launched small-scale R&D collaboration programs to support upgrading and innovation in small and medium-sized firms (SMEs, in what follows).

This latter context of policy-making is characterized by strong peculiarities, regarding both the goals pursued by the programs and the types of agents involved. However, these aspects have not been extensively investigated in the literature to date, except for a handful of studies (Bougrain and Haudeville, 2002; Bizan, 2003), while most of the analyses on policy-elicited R&D collaborations have been concerned with large-scale consortia: whether the conclusions reached by such literature are immediately applicable to the growing number of policies that intend to upgrade the knowledge and skills of small firms is a question open to debate. Most important, very little is known about what types of consortia are more effective at improving the performance of this type of firms. Some studies have investigated the benefits arising from pairwise alliances (e.g. the collaboration between a firm and a university or between an SMEs and a large firm) but, only in some cases, they have focused on consortia as a whole (Branstetter and Sakakibara, 2002; Bizan, 2003; Schwartz et al., 2010).

Focusing on one example of small-business R&D policy, our paper contributes to fill this gap by carrying out an analysis on the relative effectiveness of alternative configurations of R&D consortia involving SMEs.,Our analysis adds novelty to the existing literature with respect to two aspects. First, we analyze in great detail and contrast the benefits that may arise for SMEs in the presence of alternative and complex consortium configurations encompassing several kinds of partners. Second, we adopt an original approach to analyze the relative effectiveness of consortia. This approach accounts for the fact that firms could participate in multiple consortia both simultaneously and over time, which results in a hierarchical data structure with imperfectly disjoint classes. The characteristics of the program and the related complex structure of the data make inference on the benefits ascribable to each consortium challenging. In order to address these inferential issues, we adopt a Bayesian approach with hierarchical priors for the consortium membership parameters depending on consortium's characteristics. This is a major methodological innovation in the literature. Markov Chain Monte Carlo (MCMC) methods are used to derive the posterior distributions of the model parameters and the quantities of primary interest.

A limitation of our approach is that – like all previous studies on this topic – it does not explicitly model the process of consortium formation, which may be the result of the agents' strategic behavior and which does constitute a serious prerequisite in order to claim any causality. The issue of network formation has been explored in theory (Jackson and Wolinsky 1996), but solutions for its empirical treatment are still in a pioneering phase (Toivonen et al. 2010; Christakis et al. 2010; Goldsmith-Pinkham and Imbens, 2013). Instead, we focus on the consortium after its inception, basically assuming exogenous consortia. Despite this, we believe that the proposed analysis is still interesting, since the decision on which types of consortia policies should promote can realistically be viewed as a choice between alternative static configurations.

The remainder of the paper proceeds as follows. Section two defines some theoretical and empirically-grounded hypotheses on the characteristics of well-performing consortia involving SMEs. Sections three and four are respectively devoted to the illustration of data and of the Bayesian approach to estimation, with technical details relegated to the Appendix. Section five presents and discusses the main results of the analysis and section six concludes.

2. Are all partnerships good for SMEs?

In recent years, many countries and regions around the world have launched programs promoting R&D collaborations, which are regarded as being beneficial both at the firm and at the societal levels (Katz 1986; d'Aspremont and Jacquemin 1988). The rationale of these policies is provided mainly by the economic and innovation management literatures and can be summarized as follows.

Firm investments in R&D produce positive externalities (knowledge spillovers) that benefit not only the investing firm, but also other non-investing agents. Under these circumstances, the agents' incentives to undertake R&D is likely to diminish (Spence, 1984). Individual incentives to undertake R&D can be restored when agents group in a consortium, because this allows agents to internalize the return of their investment, (Katz, 1986). Moreover, as stressed in the innovation management literature, R&D collaboration can help firms explore and exploit possible knowledge complementarities, share risks and pool their resources and competencies so as to reach a critical mass and increase efficiency (see Hagedoorn et al., 2000 for a review).

These aspects are particularly important for SMEs, which usually may rely on a limited array of internal human and financial resources to be deployed in the innovation process. Through the collaboration, the firms, especially the smaller ones, may more easily provide the resources necessary to innovate and therefore to become more productive (Girliches, 1995; Hall et al., 2009). This is why many policymakers, particularly those operating at regional level, have launched R&D collaboration policies targeting SMEs (Asheim et al., 2003; OECD 2010, 2011).

However, despite the theoretical consensus on the benefits of R&D consortia and the diffusion of related policies, little is known about what types of consortia are more effective at improving firms' performance.

The most significant findings of the theoretical and empirical literatures on R&D collaborations point to three main aspects of the R&D collaborations that are likely to affect participating firms and their performance: i) outgoing spillovers and competition-collaboration dynamics; ii) incoming spillovers and absorptive capacity; iii) organizational issues. In what follows we will try to adapt some of the findings of the literature to the specific case of SMEs.

The first aspect refers to the fact that the presence of market competition among firms (even potential) can lead the firms to reduce their effort in the partnership, for fear of leakage of relevant information. This type of behavior, particularly if generalized, can reduce the amount of spillovers that can be internalized by the partnership and, therefore, the consortium performance (Cassiman and Veugelers 2002). One might imagine that this dynamic is characteristic of large firms that compete with non-negligible market shares. Empirical evidence shows instead that also SMEs with small market shares, are afraid to unintentionally transmit relevant information to their potential competitors (Hoffman and Schlosser, 2001). Moreover, we argue that in the case of SMEs, this fear can be aggravated by a peculiarity of the SMEs themselves. In fact, as shown by Kitching and Blackburn (1999) and MacDonald (2004), SMEs make limited use of formal mechanisms such as intellectual property rights to appropriate returns from their innovative effort. Instead, they rely more on informal mechanisms, which, however, are less able than formal ones to protect an enterprise, especially one involved in R&D collaborations (Nieto and Santamaria 2010). Therefore, we may formulate our first hypothesis as follows:

H1: Competition or potential competition among SMEs has a negative effect on consortium performances.

The second aspect refers to the fact that the most successful collaborations are those that include the presence of knowledgeable agents (such as universities or large firms), because in these cases the partnership will produce a high level of incoming spillovers (Branstetter and Sakakibara, 2002, 2003; Schwartz et al., 2010). However, the mere availability of spillovers within the partnership does not guarantee *per se* that knowledge is effectively absorbed by the recipient firm, unless the latter has a certain degree of absorptive capacity or, in other words, a sufficient amount of prior knowledge, competencies and experience helping it to understand how to take advantage of the knowledge spillover (Cohen and Levinthal 1989).

Both the incoming spillover and the absorptive capacity arguments are crucial for smaller firms. On the one hand, knowledge spillovers are particularly important for small firms, because the latter need to complement their limited internal knowledge and competencies with the insertion of external ones (Acs et al. 1994; Audretsch and Vivarelli, 1996). On the other hand, the same limited presence of internal resources and competencies for innovation may limit the ability of small firms to absorb knowledge from outside their boundaries. This happens because SMEs tend to carry out mostly informal R&D activities, if any (Kleinknecht and Reijnen 1991), often relying on non-permanent departments, or entrusting this task to unspecialized personnel that is also allocated to other activities in the enterprise. In addition, smaller firms often lack the knowledge and expertise in areas that are complementary to R&D, such as, for example, management, marketing and others (Trajtenberg 2001).

The collaboration with a large firm or a university might be useful for the purpose of increasing the performance of SMEs (Rothwell and Dogdson 1991; Nooteboom 1999; Sadowski et al. 2003), at least in principle. In practice, we find a mixed evidence. While the relationships between SMEs and large firms generally have a positive impact on a large number of firm outcomes, the relationship with the university is more controversial (Bougrain and Haudeville, 2002; Okamuro, 2007). On the one hand, some studies show that this relationship may be difficult, because of a huge difference of the two parties in terms of knowledge and language, or because of a potential lack of incentives from the side of the university in the collaboration, or also because of the presence of relevant set-up costs of the relations (Todtling and Kauffman 2001). On the other hand, the literature also describes cases in which small firms and universities have a direct and fruitful relationship (Ortega-Argilés et al., 2009). This is particularly true for highly innovative SMEs, operating in high-tech sectors. However, even in non-high-tech sectors the partnership with an university can bring some benefit. Therefore, we formulate the hypothesis 2a and 2b as follows:

H2a: Consortia that work better are those in which SMEs having absorptive capacity combine with one or more universities.

H2b: Consortia that work better are those in which SMEs having absorptive capacity combine with one or more large firms.

To support SMEs (and other types of firms) in building their relations with universities many policy-makers have funded the creation of specialized intermediaries, such as technology transfer centers or innovation centers (Izushi, 2003; Howells 2006). These intermediaries can also be found in the private sector, where they operate as innovation service providers. The presence of intermediaries may be useful in order to facilitate the exchange of knowledge and competencies among agents who differ in languages, decision-making horizons, systems of incentives and objectives, and so on (Howells, 2006). Therefore, they are able to add some value to the collaboration particularly when partners belong to different institutional spheres. Besides this role of "matchmakers", intermediaries also offer a range of innovation and technological services that can be interesting and beneficial for small firms, provided they have some degree of familiarity with R&D and innovation activities (Howells, 2006). Drawing on the above, we may formulate our hypotheses H3a and H3b as follows:

H3a: Consortia that work better are those in which SMEs having absorptive capacity combine with one or more intermediaries.

H3b: Complex consortia, including a range of heterogeneous agents work better when one or more intermediaries are called to act as matchmakers.

The third aspect refers to all the organizational features that may enhance or diminish the performance of the collaboration, starting from the consortium size. Obviously, larger consortia can mobilize a more substantial amount of resources and competencies. However, they can also lead to an increase in transaction costs generated by the presence of many partners who have to reach common decisions, and whose effort has to be monitored. With respect to this issue, evidence is still controversial. For instance, the findings of Bizan (2003), and Schwarz et al. (2010) suggest that larger projects bring benefits that are greater than the transaction costs that may arise. On the contrary, Okamuro (2007) finds evidence that firm performance may suffer from relevant transaction costs associated with the management of large-scale collaborative projects. In the case of consortia composed of SMEs, we argue that the benefits of reaching a critical mass of resources and competencies to be invested in R&D can overwhelm the higher transaction costs generated by the increased number of partners. Therefore, we formulate the following hypothesis:

H4: Large-scale consortia perform relatively better than small-scale consortia.

Another organizational issue considered here refers to the governance model of the consortium, which may be more or less decentralized. Horizontal models are likely to imply that the partners are all actively involved in the project. Instead, more hierarchical models imply the presence of one or a few partners acting as leaders. In the case of SME consortia, the presence of a leader could be on the one hand a positive element, as it might help reduce coordination costs borne by each partner, and might provide guidance to the innovative activity of the consortium. Of course, this happens only if those who exercise the role of leader are able to do so. On the other hand, if centralization is too high, peripheral partners could have low incentives to be fully involved in the project, as their interests might be insufficiently taken into account by the leaders. This latter situation could reduce peripheral partners' effort, and thus raise a moral hazard problem. In this case, it is difficult to formulate a univocal hypothesis.

3. Data from a regional policy in support of R&D consortia

The empirical analysis focuses on a set of policies supporting R&D consortia that have been implemented by the regional government of Tuscany (Italy). We have examined a set of four programmes implemented in different waves by the public agency in the time span from 2002 to 2008[1]. The programs were aimed at supporting innovative projects implemented by consortia of heterogeneous agents[2]. These interventions were intended to raise the innovative capacity of micro enterprises and SMEs, which constitute the large majority of enterprises in the region. In particular, the policy has encouraged the formation of R&D consortia (mostly) focused on process innovation. The outcomes of the projects were expected to be primarily adopted by the partner SMEs themselves.

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[1] The empirical research was carried out over an extended time span, since the authors have participated in the monitoring of the programs. Monitoring reports are available, upon request to Tuscany's regional government, industry and innovation department.

[2] Here, consortium and (funded) innovative project are synonym. Agents (firms, universities and all the other types of agents that will be presented below) group together to elaborate an innovative project and to participate to a competitive bid. If the project is selected for funding, they form a consortium that will carry out the project. Therefore, the life of the consortium starts with the beginning of the project and ends with the end of the project.

The policy has been initially developed through two programs (lines 1.7.1 and 1.7.2 of the Regional Single Programming Document) - co-funded by the European regional development funds (ERDF) – encouraging the inception of relatively small R&D projects, and also the dissemination/diffusion of existing technologies. Another strand of the policy has consisted of two additional programs drawing upon the resources offered by the EU Regional Programme of Innovative Actions (RPIA). In all cases, great emphasis has been placed on process innovation. The whole set of programmes has been assigned almost 37 million euros, representing around 40% of the total funds spent on innovation policies by the regional government in that period. Half of these funds have been assigned to programs (or waves) in which projects were funded at 100%, while the rest has been administered in co-funding (with shares ranging from 75% to 85% of admittable costs). Through the four programs, the public agency has funded 168 projects.

The various programs have addressed a set of technological targets, such as ICT and multimedia, opto-electronics, mechanics, biotechnologies, and others. The identification of the sector(s) of application of R&D outcomes was left to the consortium members.

Both the size and the composition of individual consortia have only partly been influenced by the rules set by the public agency, and specified within each tender. Depending on the technology target, the consortia were required to include at least one university or one intermediary (innovation center, technology transfer center), or none at all. The same holds true for the number of participating SMEs. In some technology areas, the minimum was set at five, while in others there was no specific requirement. Some programs admitted multiple participations at the same time, and multiparticipation over time was always allowed. Projects could last no longer than 18 months. On average, they have lasted one year, with a very limited variability.

Once formal eligibility criteria were fulfilled, incentives were not granted automatically, but by means of a selection procedure based on the evaluation of submitted projects by a committee of experts. In case of a positive response, consortia were able to decide how to allocate the funds among their members. Large companies could be part of the consortium, but were not allowed to receive funds. Instead, universities and intermediaries were eligible for funding.

Our dataset is based primarily on the administrative records held by the governmental body that has implemented the program. It includes some data on the beneficiaries and also characteristics of the consortia and of the related projects. The public agency has also provided us with additional information and reports collected during process evaluation, allowing us to reconstruct some qualitative aspects of the projects that would not otherwise have been available on the basis of mere ex ante records concerning application and admission to the incentive. Finally, for each of the companies participating in funded consortia, we have collected balance sheet data from the AIDA-Bureau Van Dijk dataset. On the one hand, this has allowed us to control some of the information that the companies had provided to the public agency at the time of application. For example, if the firm had stated in the application that it had an internal R&D department, we checked for the presence of non-episodic R&D expenditures in the years immediately preceding the inception of the consortium. On the other hand, balance sheets have enabled us to enrich the dataset of administrative records with important information on the performance of firms one year before the consortium was started, and then during the project and after its completion. The use of balance sheet data poses some limitations in the Italian context, arising from the fact that not all companies are obliged by law to keep and publish their financial statements (such is the case of sole proprietorships and companies with unlimited liability). In addition, very small firms are permitted to draw up a balance statement in a simplified form. These two circumstances obviously raise a problem of missing data or, at best, the problem that only the data required in simplified statements are available for all firms. In order to minimize the impact and, where possible, overcome this problem, we have focused on a limited set of balance-sheet variables that were available for the vast majority of businesses. Where these were not available, we could directly (via phone) collect missing information from companies thanks to a formal request made by the public agency inviting them to provide – ex post – additional information.

Table 1 reports some key descriptive statistics on SMEs that have participated in the consortia funded by the programs. These statistics are limited to those cases – 143 consortia – in which there is more than a single SME taking part in the project. It is evident that single-SME consortia are alien to the rationale underlying incentives to inter-firm R&D cooperation, and that they are more likely to fall under a general technology transfer policy rationale. It should also be noted that the table reports participations, and in our case, participations do not simply coincide with participants because of the possibility of each SME taking part in more than one consortium[3].

[3] Repeated participation has been a widely diffused practice. In fact, only 448 SMEs have joined only one consortium.

Table 1 – Some descriptive statistics on enterprises that have participated in the R&D consortia

variable	*description*	*Mean*	*SD.*	*Min*	*Max*
	Continuous variables				
Y= productivity of labor 1 year after the completion of the project (t+2) (produ3)		53959.23	36919.49	−35573.00	256416
produ1	productivity of labor 1 year prior to the start of the project (t-1)	45751.59	28551.66	−45589.00	196081
p_dif12	Pct variation between the productivity of labor in the year of the start of the project (t) and produ1	0.34	2.08	−1.24	35.15
grant	amount in Euros of the grant(s) obtained for participation to the project(s) in a given year	16482.07	29466.20	0.00	281347.50
	Categorical variables	*Proportion*			
empl1	n. of employees 1 year prior to the start of the project (t-1)				
	<10	0.410			
	10-49	0.438			
	>49 (reference group)	0.152			
e_dif21	Difference between n. of employees in the year of the start of the project (t) and empl1.				
	<0 (reference group)	0.198			
	=0	0.474			
	>0	0.328			
Igrant	Dummy that takes a value of 1 if the firm has received a grant	0.816			
prev_part	Dummy that takes a value of 1 in case of participations that were started and completed in past years	0.192			
multi_part	Dummy that takes a value of 1 if the firm is taking part in (same-time) overlapping projects, but these projects have started in different (adjoining) years	0.197			
rd_dept	Dummy that takes a value of 1 if the firm had a permanent R&D dept prior to the start of the project, and 0 otherwise	0.144			
patents	Dummy that takes a value of 1 if the n. of patent applications filed during 10 years prior to the start of the project up to (t-1) is greater than zero	0.224			
sector1	Low-tech or medium-low manufacturing	0.390			
sector2	Medium-high or high- tech manufacturing	0.220			
sector3	Knowledge-intensive business services	0.257			
sector4	other services	0.133			
year1	year of participation in the program: 2002	0.206			
year2	year of participation: 2004-2005	0.410			
year3	year of participation: 2006-2007	0.226			
year4	year of participation: 2008	0.158			

Note to table 1: The number of observations is 646. All monetary values have been deflated (base year = 2000).

4. The empirical strategy

If we look more closely at the dataset described in the previous section, we may observe that data are laid in a hierarchical structure, with firms on the lower level, and projects/consortia on the upper level. The hierarchical structure of the data is remarkably complex, because firms may participate in multiple consortia/projects both in a specific time point/spell and over time. In other words, firms are clustered in non-disjoint groups with simultaneous and over time multiple-membership. In order to gather information on consortium characteristics associated with better performances, it is crucial to account for the complex data structure.

We face this issue using a hierarchical Bayesian approach, where we model the conditional distribution of the outcome variable (a measure of firm's labor productivity) given firm's characteristics and consortium membership and we specify hierarchical priors for the consortium membership parameters that depend on consortium characteristics.

In order to formally specify our model we first introduce some notation, discussing the information we have and how it can be used to answer the research question of interest. We construct a dataset where each firm participating in the study is repeated as many times as the years in which it joints a consortium, and we consider the observed data as a random sample of firms. Let n be the total number of observations, firm-years. For simplicity of exposition we will omit to specify that each record in the dataset represents a firm in a given year in the sequel; we will refer to observation units as firms.

In our study we consider labor productivity measured one year after the completion of the project as outcome variable. We are of course aware of the vast literature on the expected benefits of cooperation. Contributions have stressed both the importance of considering: i) the immediate effects of cooperation on innovation inputs, due to incoming spillovers, knowledge acquisition or research acceleration (Hagedoorn et al. 2000; Caloghirou et al. 2003) or to cost reduction (Beath et al. 1998); ii) the effects in terms of technological success (e.g. novelty of innovations, as in Amara and Landry 2005) or productivity of research (e.g. patent applications, Branstetter and Sakakibara 2002); iii) the effects in terms of economic success: innovative sales, productivity (Belderbos et al. 2004) or other performance indicators. These latter approaches, similarly to the one we adopt in this study, investigate the benefits of R&D cooperation in an indirect fashion, i.e. without looking at (and modeling) how cooperation affects innovation inputs, and how these inputs later result into outputs. We will use here only labor productivity as outcome measure for the following reasons. Firstly, as stated in section 4, the programs analyzed here wanted to promote the upgrading of SMEs by means of process innovations that were expected to be primarily adopted by the partner SMEs themselves. As a consequence, most of the projects we observe have focused on process innovations, and this makes any measure related to product innovation (such as the sales of innovative products) rather inconsistent with what was actually promoted by the policy. Secondly, we have verified that some of the alternative measures used in the literature, such as patent applications, relate to events that are very rare for SMEs in our case of small-scale projects, both prior to and after the consortium inception. This is not surprising given that propensity to patent varies a lot across sectors and technological fields, and our consortia are very diverse with respect to this point. In addition, it is well known that SMEs usually have a relatively low propensity to patent (Acs and Audretsch 1988).

Let Y_i denote labor productivity one year after the completion of the project for firm i. We specify the following regression model:

$$Y_i = \beta_0 + \sum_{j=1}^{J} \beta_j x_{ij} + \sum_{k=1}^{K} \gamma_k P_{ik} + \varepsilon_i \tag{1}$$

i=1, …, n; where ε_i are independent, random variables, normally-distributed with mean equal to zero and variance σ_ε^2, P_{ik}, k = 1,..., K, are binary variables equal to 1 if firm i participates in consortium k in a given year and 0 otherwise, K is the number of consortia/projects (in our study K=143), and x_{ij}, j = 1, …, J are explanatory variables, including information on firms' performances preceding project inception and firms' background characteristics, such as NACE two-digit sector and year of the call for tender (see Table 1 for a detailed description of these background covariates). Firms' performances preceding project inception are described using lagged values for labor productivity and number of employees (measured one year before the inception of the project), and the percent variation of labor productivity and number of employees between the year the current project starts and the year before. Adjusting for these covariates allows us to control for firms' attributes that remain unobserved, which could endogenously determine labor productivity both before and after a firm joins a consortium. The vector of explanatory variables (x_{i1}, …, x_{iJ}) also includes binary variables to account for previous participations in projects that have been completed before the inception of the current project, and multiple participations in projects that are initiated in different years but are still ongoing at the moment the current project starts.

The consortium/project dummies, P_{ik}, k = 1,..., K, allow us to account for multiple participations occurring in a given year (simultaneous participations) and their coefficients, the parameters γ_1, …, γ_K are the quantities of primary interest: They provide information on the contribution of each consortium to the productivity of the participating SMEs.

We assume that ε_i are mutually independent, have a Normal distribution with variance σ_ε^2, and are independent of both the explanatory variables (x_{i1}, …, x_{iJ}) and the binary variables P_{ik}. Therefore the likelihood function based on the regress Equation (1) is

$$\mathcal{L}(\boldsymbol{\beta},\gamma,\sigma_\varepsilon^2)=\prod_{i=1}^{n}\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left\{-\frac{1}{2\sigma_\varepsilon^2}\left(Y_i-\beta_0-\sum_{j=1}^{J}\beta_j x_{ij}-\sum_{k=1}^{K}P_{ik}\gamma_k\right)^2\right\}$$

To implement the Bayesian approach, we need to specify prior distributions for the parameters. Let $\boldsymbol{\beta} = (\beta_0, \beta_{1,\dots,}\beta_J)$ and $\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_K)$.We use a multivariate Normal prior distribution for $\boldsymbol{\beta}$ and an Inverse-χ^2 distribution for the variance parameter σ_ε^2: $\boldsymbol{\beta} \sim N(\underline{\boldsymbol{\mu}}_\beta, \underline{\sigma}^2{}_\beta I_{J+1})$, where I_{J+1} is the J+1 x J+1 identity matrix, and $\sigma_\varepsilon^2 \sim \text{Inv-}\chi^2(\underline{\nu}_\varepsilon, \underline{s}_\varepsilon^2)$. For the $\boldsymbol{\gamma}$ parameters we specify a Normal prior with mean depending on consortium's characteristics selected on the basis of suggestions coming from the economic literature (Section 2). Let $(z_{k1}, \dots, z_{kH})$ denote the vector of covariates describing consortium's characteristics. We assume that

$$\gamma_k \sim N(\mu_k,\sigma_\gamma^2) \qquad \text{with} \qquad \mu_k=\alpha_0+\sum_{h=1}^{H}\alpha_h z_{kh} \tag{2}$$

The hierarchical structure of the prior arises because we consider $\boldsymbol{\alpha} = (\alpha_0, \dots, \alpha_K)$ and σ_γ^2 as unknown parameters with their own prior: $\boldsymbol{\alpha} = (\alpha_0, \dots, \alpha_K) \sim N(\underline{\boldsymbol{\mu}}_\alpha, \underline{\sigma}^2{}_\alpha)$ and $\sigma_\gamma^2 \sim \text{Inv-}\chi^2(\underline{\nu}_\gamma, \underline{s}^2{}_\gamma)$. All the parameter are assumed to be independent in the prior. Therefore the posterior distribution is

$$p(\boldsymbol{\alpha},\boldsymbol{\beta},\gamma,\sigma_\varepsilon^2,\sigma_\gamma^2|\boldsymbol{Y},\boldsymbol{X},\boldsymbol{P},\boldsymbol{Z})=$$
$$p(\boldsymbol{\alpha})\times p(\boldsymbol{\beta})\times p(\sigma_\varepsilon^2)\times p(\sigma_\gamma^2)\times\prod_{k=1}^{K}\left[\frac{1}{\sqrt{2\pi}}\frac{1}{\sqrt{\sigma_\eta^2}}\exp\left\{-\frac{1}{2\sigma_\eta^2}\left(\gamma_k-\alpha_0-\sum_{h=1}^{H}\alpha_h z_{kh}\right)^2\right\}\right]\times$$
$$\prod_{i=1}^{N}\left[\frac{1}{\sqrt{2\pi}}\frac{1}{\sqrt{\sigma_\varepsilon^2}}\exp\left\{-\frac{1}{2\sigma_\varepsilon^2}\left(Y_i-\beta_0-\sum_{j=1}^{J}\beta_j x_{ij}-\sum_{k=1}^{K}\gamma_k P_{ik}\right)^2\right\}\right]$$

where **Y**, **X**, **P** are matrix stacking observations for all the *n* firms.

We specified relatively flat prior distributions and simulated the posterior distributions using an MCMC algorithm based on two chains, which were run for 100 000 iterations after a burn-in stage of 25 000 iterations saving every 25th iteration. Convergence of the algorithm was assessed using the potential scale-reduction statistic (Gelman and Rubin, 1992), which suggested good mixing of the chains for each estimand, providing no evidence against convergence (details of calculations are available upon request to the authors). We conclude this section with some discussion on the variables we use to describe consortium's characteristics in Equation (2).

We first consider three sets of variables, which provide information on level of competition, absorptive capacity, and organizational issues according to the discussion in Section 2.

As a proxy for competition among consortium members, we use the Gini index of concentration calculated on SMEs' NACE three-digit sectors (variable: *competition*).

As for absorptive capacity and opportunities to absorb incoming spillovers we have considered the following variables. Consortium's absorptive capacity is measured using a binary variable equal to 1 if a consortium includes SMEs that had a permanent R&D department prior to the consortium inception and 0 otherwise (*RD*). The presence of large enterprises and universities is measured by the following variables: a binary variable taking on value 1 if at least one large company is part of the project, and 0 otherwise (*large_ent*); and a binary variable taking on value 1 if at least one university (or research center) is part of the project, and 0 otherwise (*universities*). The presence of intermediaries in the consortium is captured by a homonymous binary variable (*intermediaries*). In order to investigate hypothesis 3, we also consider the interaction between RD and *large_ent* (*potential_interfirm_absorption*) and the interaction between *RD* and *universities* (*potential_research_absorption*).

Finally, two variables are used as proxy for the organizational features of the consortia: *avg_budg_ph,* a measure of consortium size, derived by averaging the total consortium budget over the number of all participants, not only SMEs, and *budget_dispersion*, a variable measuring how horizontal the governance model is, defined as the reciprocal of the Gini index calculated on the budget shares of all participants.

Additional variables we use to describe consortia include binary variables for the program that has funded the consortium, information on the project, such as the technological area and the target sector of application, and a binary variable (*near_to_application*) equal to 1 if a consortium focuses on a project that is in the initial R&D stage and 0 if a consortium focuses on a project that is relatively close to engineering and testing stages. We expect that projects that are relatively close to engineering and testing stages more likely lead to measurable results one year after the completion of the project.

Finally we consider a measure of the mean and the coefficient of variation of firms' labor productivity preceding project injection calculated using information on all the participating SMEs (*mean_p* and *vc_p*). These variables may provide valued information on inter-consortia differences and within-group heterogeneity. In fact, although we control for firms' labor productivity preceding project injection in Equation (1), using information at consortium level may at least partially account for unobserved self-selection mechanisms underlying firms' decision about joining one consortium rather than another.

Table 2 - Some descriptive statistics on consortium-level explanatory variables

Variable	*definition*	*expected sign*	*Mean*	*SD*	*Min*	*Max*
Continuous variables						
competition	Gini index estimated on SMEs at three-digit sectors within the project	-	0.495	0.275	0.000	0.910
budget_dispersion	Reciprocal of the Gini index estimated on the budget shares of all partners.	+/-	0.658	0.145	0.190	1.000

partners	Number of partners	+	12.573	8.057	3.000	37.000
mean_p	Avg group productivity, estimated on SMEs, one year prior to the start of the project	c	45331.550	16551.711	17523.779	95697.867
vc_p	Group-level variation coefficient of productivity, estimated on SMEs, one year prior to the start of the project	c	0.592	0.409	0.000	2.713
Categorical variables			*Proportion*			
RD	Dummy that takes a value of 1 if the SMEs had a permanent R&D dept prior to consortium inception, and 0 otherwise	+	0.545			
large_ent (LE)	Dummy that takes the value of 1 if at least one large company is part of the project, and 0 otherwise.	0	0.105			
potential_interfirm_ absorption (PIFA)	Interaction btw rd and large_ent.	+	0.070			
universities (A)	Dummy that takes the value of 1 if at least one university is part of the project, and 0 otherwise	0	0.755			
potential_research _absorption (PRA)	Interaction btw rd and universities.	+	0.469			
intermediaries (I)	Dummy that takes a value of 1 if at least one intermediary is part of the project, and 0 otherwise.	0	0.545			
potential_intermediary _absorption (PINA)	Interaction btw rd and intermediaries	+	0.357			
near to application	Dummy that takes a value of 1 if project focuses on near-to-application R&D, and 0 otherwise	c	0.594			
program 1.7.1	Identifies a specific program	c	0.776			
program 1.7.2	Identifies a specific program	c	0.049			
program prai/itt (888)	Identifies a specific program	c	0.091			
program prai/vinci (999)	Identifies a specific program	c	0.084			
target industry 1	R&D outcomes are intended to be applied in: Made in Italy industries (textiles, clothing, footwear, furniture, jewellery, agro-industry, cultural goods)	c	0.350			
target industry 2	Energy & environment	c	0.203			
target industry 3	Mechanics	c	0.056			
target industry 4	More than one specific industry	c	0.168			
target industry 5	Biomedical	c	0.070			
target industry 6	Logistics/transportation, shipbuilding	c	0.126			
target industry 7	Other industries	c	0.028			

Note to table 2: "+", "–" or "+/-" in the third column means that the expected signs of the coefficients of the variables are, respectively, positive, negative or ambiguous; c stands for control variable. The number of consortia is 143.

5. Results

Let us now present the main results of the application. Table 3 shows means, standard deviations and relevant percentiles of the posterior distributions of model parameters β_1, …,

β_J and σ^2_ε. Our results suggest that there exist a quite strong positive association between labor productivity one year after the completion of the project and firm's productivity levels and trends preceding consortium inception: the posterior mean for the coefficients on these variables is positive and their 95% posterior credibility intervals do not cover zero. Also we find that firms' labour productivity is higher for firms that have previous non-transitory R&D experiences (witnessed by the presence of an R&D department) and firms being active in sectors other than low- or medium-low technology manufacturing. In fact the posterior distributions for the coefficients on the presence of an R&D department and the dummy variables for the activity sector are centred on positive values and imply that those coefficients take on positive values with probabilities greater than 88%.

Conversely, post-consortium productivity levels seems to be negatively associated with previous attitude to patents and past employment growth (this latter result is not surprising, as our outcome variable is productivity per capita).

Table 3 – Means, standard deviations and relevant percentiles of the posterior distribution of the first-level model parameters

First-level coefficient	Coeff	Mean	SD	50%	2.50%	97.50%	Prob coeff	
							<=0	>0
Constant	β_1	16202.58	7689.95	16183.4	1372.66	31522.78	0.02	0.98
produ1	β_2	0.68	0.05	0.68	0.59	0.77	0	1
p_dif21	β_3	3043.98	624.86	3045.63	1820.28	4255.55	0	1
grant	β_4	0.06	0.05	0.06	−0.04	0.16	0.12	0.88
empl1<10	β_5	−711.00	4392.49	−731.28	−9338.18	7976.57	0.56	0.44
empl12 [10, 50)	β_6	−2716.30	3891.89	−2808.97	−10241.38	5020.91	0.75	0.25
e_dif21=0	β_7	−2345.59	3634.63	−2347.85	−9494.77	4772.11	0.74	0.26
e_dif21>0	β_8	−7538.21	3655.08	−7536.73	−14647.24	−543.37	0.98	0.02
grant>0	β_9	1287.02	3504.54	1278.92	−5528.95	8225.33	0.36	0.64
prev_part	β_{10}	−2836.43	3734.25	−2840.56	−10014.59	4532.55	0.77	0.23
multi_part	β_{11}	5903.32	3695.48	5959.81	−1384.30	13173.38	0.06	0.94
rd_dept	β_{12}	8618.26	3906.45	8600.71	918.20	16311.86	0.01	0.99
patents	β_{13}	−4171.40	3711.90	−4154.25	−11411.57	3130.99	0.87	0.13

Sector2	β_{14}	6932.84	3606.98	6976.99	−43.94	13783.56	0.03	0.97
Sector3	β_{15}	5215.32	4422.81	5201.34	−3421.79	13781.75	0.12	0.88
Sector4	β_{16}	17052.84	4181.36	17047.78	8800.86	25250.94	0	1
Year=2004/05	β_{17}	2991.08	4404.9	2972.04	−5632.21	11894.87	0.25	0.75
Year=2006/07	β_{18}	5203.79	5030.43	5191.27	−4617.19	14932.76	0.15	0.85
Year=2008	β_{19}	−2378.76	6254.21	−2427.17	−14663.25	9911.56	0.65	0.35
consortium (143)	γ_1 - γ_{143}	see Appendix						
Variance	σ_ε^2	938428918.08	55520035.82	936769932.19	834936729.39	1049822188.04		

Rather than dwell on the role played by these control variables, it is much more informative and interesting to focus on consortium-level parameters (table A in the Appendix). Here, we can observe that 68 out of 169 parameters - which corresponds to 40% of all consortia - have a positive posterior mean. Out of the 68 consortium parameters with positive posterior mean, 40 consortium parameters have a posterior probability to be positive greater than 70%, 21 have a posterior probability to be positive greater than 80% and 10 have a posterior probability to be positive greater than 90%. These results suggest that there exist consortia stimulating firms' labor productivity. From the viewpoint of a public decision maker, called to improve policy or to design new interventions, it is crucial to know the characteristics of consortia that may contribute to increase SMEs' labor productivity. Therefore, from an innovation policy perspective, it is highly useful to open these black boxes and glance at their inside, assessing the importance of a number of consortium characteristics.

To this end, we can look at the posterior distribution of the parameters of the prior distributions for the consortium parameters. Table 4 shows the means, standard deviations and relevant percentiles of the posterior distribution of those parameters. In order to get some insight on "optimal consortium's characteristics", we also derive the posterior distributions of a number of meaningful consortium profiles, which provide information on the possible benefits arising for small firms in the presence of alternative configurations.

Table 4 – Means, standard deviations and relevant percentiles of the posterior distribution of the second-level model parameters

Second-level coefficient	Coeff	Mean	SD	50%	2.50%	97.50%	Prob coeff	
							<=0	>0
Constant	α_1	5871.87	13777.15	5732.04	−20546.12	32707.26	0.34	0.66
Competition	α_2	−13995.60	5972.72	−13918.06	−25653.94	−2409.25	0.99	0.01
budget_dispersion	α_3	−978.47	9956.04	−965.15	−20498.59	18383.87	0.54	0.46
Partners	α_4	87.35	262.28	86.52	−422.67	615.37	0.37	0.63
mean_p	α_5	−0.06	0.08	−0.06	−0.22	0.11	0.76	0.24
vc_p	α_6	−2602.66	3410.34	−2572.73	−9365.16	3983.7	0.78	0.22
RD	α_7	7083.39	7440.51	7120.02	−7528.19	21459.19	0.17	0.83
large_ent (LE)	α_8	7108.05	8192.61	7048.8	−8993.10	23393.57	0.19	0.81
university (A)	α_9	5088.13	4258.52	5029.84	−3001.78	13618.13	0.12	0.88
PIFA	α_{10}	2790.39	9957.49	2742.04	−16566.45	22086.12	0.39	0.61
PRA	α_{11}	−13114.85	7504.51	−13060.28	−27778.86	1468.16	0.96	0.04
intermediaries (I)	α_{12}	−3853.53	4656.66	−3877.27	−13129.65	5391.36	0.8	0.2
PINA	α_{13}	2668.21	6304.19	2604.48	−9892.24	15149.57	0.33	0.67
near to application	α_{14}	341.8	3114.94	310.35	−5737.69	6519.83	0.46	0.54
program=1.7.1	α_{15}	5733.83	6099.76	5753.71	−6117.37	17725.12	0.17	0.83
program=888	α_{16}	3585.62	7476.53	3651.19	−11117.41	18192.54	0.31	0.69
program=999	α_{17}	5414.87	9834.89	5392.3	−13499.37	25080.7	0.29	0.71
industry1	α_{18}	−4476.70	7924.44	−4342.23	−20355.69	10592.74	0.71	0.29
industry2	α_{19}	−1218.19	8086.56	−1161.39	−17081.83	14184.07	0.55	0.45
industry3	α_{20}	11747.76	9416.21	11920.95	−6727.35	29998.65	0.11	0.89
industry4	α_{21}	1470.68	8232.63	1600.36	−14796.32	17389.62	0.42	0.58
industry5	α_{22}	−4088.91	9923.99	−4131.68	−23803.74	15196.15	0.66	0.34
industry6	α_{23}	−1041.83	8960.19	−915.38	−18842.60	16213.38	0.54	0.46
Variance	σ_η^2	22305939.78	17829489.15	17944907.86	1733222.10	69651482.31		

As can be seen in Table 4, competition is a key characteristic. The posterior mean of the coefficient for competition is -13995.60, with a standard deviation of 5972.72 and the posterior probability that the coefficient is negative is approximately 99%. Therefore there is a strong evidence that consortia with high competition levels may reduce post-project firms' labor productivity. This result suggests that competition has a negative impact on labor productivity confirming theoretical predictions (H1). If we believe in economic theory, this might occur because firms deploy a limited effort when carrying out R&D activities jointly with potential competitors. An alternative interpretation relies on the managerial argument according to which, even if competition among similar firms was kept down by their superior interest in completing the R&D project, too much similarity is unlikely to bring about new and useful knowledge (Nooteboom et al., 2007). Although the other coefficients have a high posterior variability, they do play a role in framing a more comprehensive and interesting picture.

Table 5 – Means, standard deviations and relevant percentiles of the posterior distribution of meaningful consortium profiles

Variable	Coeff	Mean	SD	50%	2.50%	97.50%	Prob coeff	
							<=0	>0
RD	α_7	7083.39	7440.51	7120.02	−7528.19	21459.19	0.17	0.83
RD +LE	$\alpha_7+\alpha_8+\alpha_{10}$	16981.83	10268.63	17098.79	−3197.38	36750.65	0.05	0.95
RD +A	$\alpha_7+\alpha_9+\alpha_{11}$	−943.32	5630.42	−933.19	−11991.21	10071.18	0.57	0.43
RD +I	$\alpha_7+\alpha_{12}+\alpha_{13}$	5898.07	6735.29	5855.95	−7455.15	19000.77	0.19	0.81
RD +LE+A	$\alpha_7+\alpha_8+\alpha_9+\alpha_{10}+\alpha_{11}$	8955.12	8360.22	8943.94	−7228.96	25267.79	0.15	0.85
RD +LE+I	$\alpha_7+\alpha_8+\alpha_{10}+\alpha_{12}+\alpha_{13}$	15796.51	8878.17	15724.99	−1574.96	32693.81	0.04	0.96
RD +A+I	$\alpha_7+\alpha_9+\alpha_{11}+\alpha_{12}+\alpha_{13}$	−2128.64	5518.77	−2092.14	−12943.07	8574.88	0.65	0.35
RD +LE+A+I	$\alpha_7+\alpha_8+\alpha_9+\alpha_{10}+\alpha_{11}+\alpha_{12}+\alpha_{13}$	7769.79	7212.66	7737.73	−6401.13	21965.75	0.14	0.86
LE	α_8	7108.05	8192.61	7048.80	−8993.10	23393.57	0.19	0.81
A	α_9	5088.13	4258.52	5029.84	−3001.78	13618.13	0.12	0.88
I	α_{12}	−3853.53	4656.66	−3877.27	−13129.65	5391.36	0.80	0.20
LE+A	$\alpha_8+\alpha_9$	12196.18	9237.88	12085.40	−5665.90	30497.02	0.09	0.91
LE+I	$\alpha_8+\alpha_{12}$	3254.52	9626.13	3134.48	−15470.23	21763.39	0.36	0.64
A+I	$\alpha_9+\alpha_{12}$	1234.60	5717.66	1254.68	−9953.21	12394.53	0.42	0.58
LE+A+I	$\alpha_8+\alpha_9+\alpha_{12}$	8342.65	10185.98	8315.03	−11842.37	28404.88	0.20	0.80

Table 5 shows some summary statistics of the posterior distributions for linear combinations of the coefficients on consortium's characteristics, which the prior means for the consortium's parameters depend on. These linear combinations define a number of meaningful consortium profiles.

Here we focus on two basic types of consortium profiles: those in which firms have absorptive capacity and those in which they do not have it. This distinction is important because outcomes for firms obviously depend on the ability of the firms themselves to absorb information and knowledge produced by the different types of agents with whom they collaborate in the consortium.

Consortia including firms with earlier R&D experience and thus endowed with some absorptive capacity increase labor productivity (the posterior probability that the coefficient for earlier R&D experience is positive is more than 80%). The performance of this kind of consortia seems to be considerably enhanced if at least a large firm is involved in the partnership. In fact the posterior distribution of the linear combination $\alpha_7+\alpha_8+\alpha_{10}$, which characterizes consortia including firms with earlier R&D experience and at least a large firm, is shifted to the right with respect to the posterior distribution of the parameter α_7, which characterizes consortia including only firms with earlier R&D experience: the posterior mean of $\alpha_7+\alpha_8+\alpha_{10}$ is more than doubles than that of α_7 and the probability that the sum $\alpha_7+\alpha_8+\alpha_{10}$ is positive is approximately 95%. This result confirms H2b, i.e. the idea that smaller partners can take advantage of the leadership abilities and of the business knowledge of larger partners. Not surprisingly, if the consortium comprises small firms that have no absorptive capacity, the presence of large firms may still increase labor productivity as shown by the posterior mean of the coefficient α_8 which, however, has a quite large posterior variability.

As for H2a we find no evidence that universities add something to consortia involving firms with some absorptive capacity, and this evidence contradicts our hypothesis and the literature on which it was formulated. Surprisingly, slightly better results are achieved by grouping universities with small firms having no absorptive capacity: the posterior distribution of the coefficient for universities (α_9) is centred on positive values and provides a probability of

88% that the coefficient is positive. Considering the nature of the consortia observed here, this contradiction can be only apparent. In general, universities are interested in working on large projects involving basic research, where the constraints of time, budget and application sectors are not particularly narrow (Hall et al. 2000). This is not the kind of environment offered by the projects and consortia analysed here, which focused on narrow, applied research objectives to be achieved in a relatively short time. Given the small scale of our projects, monetary incentives provided to universities have been relatively modest. Therefore, we can reasonably expect that projects that worked better were those in which universities have simply transferred a ready-to-use technology to the non-R&D performing firms, without being engaged in a closer collaboration that could be possibly required by R&D performers. The motivation of universities may substantially rise if at least a large firm is involved in the project. In fact, the posterior probability that consortia including both large firms and universities may increase SMEs' performance – irrespective of SMEs' absorptive capacity – is greater than 85% (see the posterior distributions of $\alpha_8+\alpha_9$ and $\alpha_7+\alpha_8+ \alpha_9+\alpha_{10}$ in Table 5).

Another relevant consortium's characteristic is the presence of an intermediary acting as a mediator between SMEs and large firms and/or universities. Our results suggest that the presence of an intermediary is beneficial only if the consortium includes small firms which, based on their previous R&D experience, are able to fruitfully take advantage of the mediation skills of the intermediary. Therefore hypothesis H3a is confirmed. Specifically in consortia including firms with some absorptive capacity and large firms, the presence of an intermediary does no harm, but neither it provides substantial additional benefits (as we can see comparing the posterior distributions of $\alpha_8+\alpha_9+\alpha_{11}$ and $\alpha_8+\alpha_9+\alpha_{13}+\alpha_{11}+\alpha_{14}$ in Table 5). The same applies to the more complex type of consortia where an intermediary is called to assist the many-to-many relationships between SMEs having some absorptive capacity, large firms and universities. Even in this case, we find some evidence this type of consortia may increase firms' labor productivity (the probability that the linear combination $\alpha_7+\alpha_8+\alpha_9+\alpha_{10}+\alpha_{11}+\alpha_{12}+\alpha_{13}$ is positive is 86%), but the presence of an intermediary does not seem to be crucial.

As far as consortia with no absorptive capacity are concerned, projects involving SMEs, large enterprises and universities seems to be the best-performing. The presence of an intermediary in this type of consortia does not bring any benefit. These results suggest that our hypothesis H3b is not confirmed.

In conclusion, the general impression we draw from this detailed analysis of alternative consortium configurations is that the success of cooperation strongly relies on the relation between the small firms and a large industrial partners, while the addition of other members to the party should be pursued with caution, as it is not unlikely to bring ambiguous, if not inferior, results.

Finally, with regard to the organizational characteristics of the consortia, we find no clear evidence to support our hypothesis H4, namely that the larger consortia add more to the performance of the small firms involved. The same applies to the governance model of the consortium.

To further investigate our theoretical hypotheses, we look at the posterior predictive distributions of labor productivity for a hypothetical firm participating in different types of consortia. All error terms are fixed at their mean values of zero. The hypothetical firm is average with respect to the continuous characteristics and modal with respect to the categorical variables: it corresponds to an average productive small firm, active in relatively low technology manufacturing, with no R&D history or relevant innovation experience.

Also the hypothetical consortia are average with respect to the continuous characteristics and modal with respect to the categorical variables but may involve different type of firms. Figure

1 shows the posterior predictive distributions of labor productivity for a hypothetical firm participating in three types of consortium: (1) a consortium involving only firms with some absorptive capacity; (2) a consortium involving firms with some absorptive capacity and large enterprises; and (3) a consortium involving firms with some absorptive capacity and universities. As we can see in Figure 1, hypothesis 2a does not seem to be supported by the data: the presence of universities in a consortium involving firms with some absorptive capacity does not seem to be effective in increasing labor productivity of our hypothetical firm. Conversely, the presence of a large enterprise may lead to an increase in labor productivity (H2b is confirmed). Of course, as the hypothetical firm under analysis used to be a relatively weak innovator, the results on labor productivity are not overall outstanding.

Figure 1. Posterior predictive distributions of labor productivity for a hypothetical firm participating in three types of consortium: (1) a consortium involving only firms with some absorptive capacity (solid line); (2) a consortium involving firms with some absorptive capacity and large enterprises (dashed line); and (3) a consortium involving firms with some absorptive capacity and universities (dotted line)

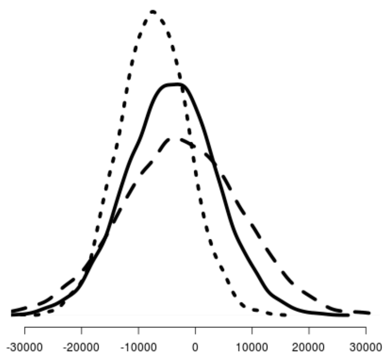
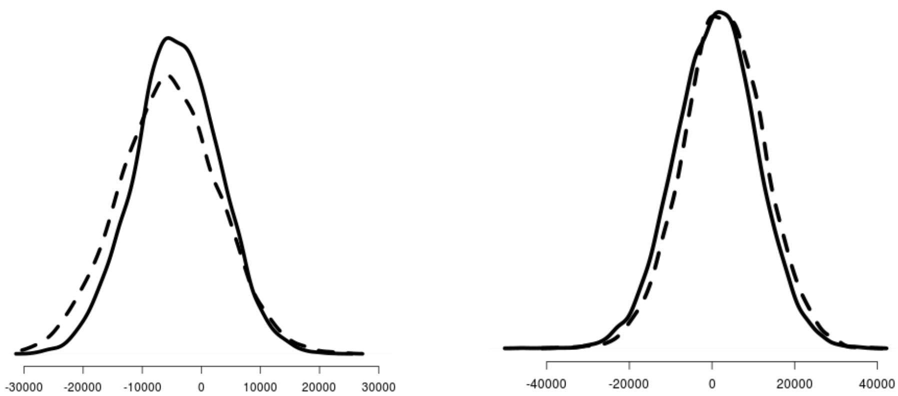


Figure 2 focuses on the role of intermediaries, and confirms that our data does not seem to support Hypothesis 3. In fact, the presence of intermediaries in a consortium involving both large enterprises and universities does not seem to affect labor productivity of our hypothetical firm irrespective of the presence in the consortium of firms having absorptive capacity.

Figure 2. Posterior predictive distributions of labor productivity for the hypothetical firm participating in (a) a consortium involving firms with some absorptive capacity, large enterprises and universities with (solid line) and without (dashed line) the presence of intermediaries; (b) a consortium involving firms with no absorptive capacity, large enterprises and university with (solid line) and without (dashed line) the presence of intermediaries



(a) (b)

6. Concluding remarks

In this paper, we have analyzed policy-elicited consortia involving SMEs. Taking a Bayesian approach for inference, we have examined what kinds of consortia contribute more to the enhancement of the productivity of SMEs. The results of our analysis show that consortia work better when participating small firms are not potential or effective competitors and when large firms are involved. On the contrary, the presence of a university does not always bring substantial benefits, and this also applies in the case where one or more intermediaries are involved in the consortium. This last result, only partially obtained in previous studies, seems to contradict the optimistic attitude with which university-industry technology transfer is sometimes pursued by decision makers in the area of innovation policy, where it is regarded not only as a way to promote high-technology firms, but also as a mean to trigger the technological upgrading of weaker innovators, such as those involved in the program analyzed here. Caution is required also with intermediaries, whose role can be positive and effective only under certain conditions, namely the fact that the small firm has some degree of absorptive capacity. Perhaps the contribution of intermediaries might have been more evident had we taken into account the learning and behavioral dimensions of SMEs, without expecting these dimensions to raise productivity or performance in the short run.

We also find that more complex forms of consortia, where SMEs are matched with an array of different types of agents, do not exhibit a higher performance than the simplest forms of consortia, in which SMEs cooperate with larger companies. These results should be interpreted bearing in mind that small firms are heterogeneous. Perhaps, simpler configurations of the consortia are better suited to the subsidized innovation projects observed here, which are not aimed at the development of complex or radical innovations and are mainly carried out by firms that are not on the innovation frontier.

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Appendix γ

Table A. Means and standard deviations of the posterior distribution of consortia

Coeff	Mean	SD	P(Coeff <=0)	P(Coeff >0)
γ_{1}	−8988.13	8092.05	0.87	0.13
γ_{2}	−1722.40	9437.07	0.57	0.43
γ_{3}	8068.59	10636.67	0.23	0.77
γ_{4}	−4875.20	8170.47	0.73	0.27
γ_{5}	8864.69	7441.20	0.11	0.89
γ_{6}	14074.06	8668.79	0.05	0.95
γ_{7}	5693.28	8762.15	0.25	0.75
γ_{8}	−3763.86	7517.00	0.69	0.31
γ_{9}	−10524.57	8629.91	0.89	0.11
γ_{10}	−1537.48	8344.44	0.58	0.42
γ_{11}	−3603.39	8050.01	0.68	0.32
γ_{12}	−2717.50	8824.20	0.63	0.37
γ_{13}	−4863.99	7934.76	0.72	0.28
γ_{14}	6906.05	8636.15	0.21	0.79
γ_{15}	−7852.93	9412.15	0.80	0.20
γ_{16}	8409.99	8616.97	0.16	0.84
γ_{17}	−5077.09	7298.19	0.76	0.24
γ_{18}	4124.23	7710.29	0.30	0.70
γ_{19}	456.55	9339.53	0.48	0.52
γ_{20}	−803.89	8387.67	0.54	0.46
γ_{21}	−60.28	8136.52	0.50	0.50
γ_{22}	−2337.66	9513.55	0.60	0.40
γ_{23}	3612.49	7996.53	0.32	0.68
γ_{24}	−1374.06	9191.40	0.56	0.44
γ_{25}	8944.43	10505.27	0.19	0.81
γ_{26}	−2620.99	9841.21	0.61	0.39
γ_{27}	−1033.83	8677.75	0.55	0.45
γ_{28}	144.50	8887.70	0.49	0.51
γ_{29}	−7227.75	7855.69	0.83	0.17
γ_{30}	−9633.91	8987.43	0.86	0.14
γ_{31}	−1208.52	8592.94	0.55	0.45
γ_{32}	554.41	9661.01	0.47	0.53
γ_{33}	839.12	9403.67	0.47	0.53
γ_{34}	9966.63	11704.18	0.19	0.81
γ_{35}	−8273.06	8578.81	0.83	0.17
γ_{36}	13295.41	9114.86	0.07	0.93
γ_{37}	5918.47	10224.35	0.28	0.72
γ_{38}	−1726.29	8357.59	0.59	0.41
γ_{39}	−182.51	8037.56	0.51	0.49
γ_{40}	2617.16	10261.05	0.40	0.60
γ_{41}	−2225.26	7530.81	0.62	0.38
γ_{42}	3232.90	7776.74	0.33	0.67
γ_{43}	5165.50	9919.07	0.30	0.70
γ_{44}	−2094.60	8077.89	0.60	0.40
γ_{45}	4435.17	8810.18	0.31	0.69
γ_{46}	3466.08	9472.76	0.36	0.64

γ_{47}	6318.92	8384.87	0.22	0.78
γ_{48}	−6239.72	8863.64	0.76	0.24

Table A. Means and standard deviations of the posterior distribution of consortia (cont.)

Coeff	Mean	SD	P(Coeff <=0)	P(Coeff >0)
γ_{49}	−9166.22	7917.32	0.88	0.12
γ_{50}	−7005.71	9381.44	0.78	0.22
γ_{51}	−435.20	8107.79	0.52	0.48
γ_{52}	2730.51	8833.65	0.37	0.63
γ_{53}	−2972.96	8000.08	0.65	0.35
γ_{54}	8736.25	7376.92	0.11	0.89
γ_{55}	−2609.51	10009.5	0.60	0.40
γ_{56}	−11029.94	7587.79	0.93	0.07
γ_{57}	4415.62	7302.22	0.27	0.73
γ_{58}	−7012.88	7536.65	0.82	0.18
γ_{59}	−1641.02	8065.85	0.58	0.42
γ_{60}	−375.29	8588.05	0.52	0.48
γ_{61}	−11828.34	9515.19	0.89	0.11
γ_{62}	−2199.43	9082.45	0.60	0.40
γ_{63}	−8597.81	8209.9	0.85	0.15
γ_{64}	−2990.64	8949.69	0.63	0.37
γ_{65}	−8790.45	8924.27	0.84	0.16
γ_{66}	−2899.25	9810.26	0.62	0.38
γ_{67}	−5693.78	8628.44	0.74	0.26
γ_{68}	4114.71	8801.24	0.32	0.68
γ_{69}	5846.8	8127.28	0.23	0.77
γ_{70}	5107.02	7655.7	0.25	0.75
γ_{71}	9673	9393.62	0.15	0.85
γ_{72}	5221.29	7237.59	0.23	0.77
γ_{73}	5189.95	7242.81	0.23	0.77
γ_{74}	−10253.63	8132.91	0.90	0.10
γ_{75}	1429.66	8200.26	0.43	0.57
γ_{76}	1505.65	8118.1	0.44	0.56
γ_{77}	13434.54	8458.7	0.06	0.94
γ_{78}	5733.82	8528.39	0.25	0.75
γ_{79}	−8048.07	7970.76	0.85	0.15
γ_{80}	14792.37	8503.75	0.04	0.96
γ_{81}	12316.33	8480.62	0.07	0.93
γ_{82}	733.01	7908.8	0.46	0.54
γ_{83}	−3904.21	9126.65	0.67	0.33
γ_{84}	14515.44	8609.11	0.04	0.96
γ_{85}	−7375.23	8321.88	0.81	0.19
γ_{86}	5330	10036.81	0.30	0.70
γ_{87}	10643.97	8416.91	0.10	0.90
γ_{88}	10305.87	10530.18	0.17	0.83
γ_{89}	8204.31	10450.99	0.22	0.78
γ_{90}	−3092.48	8994.58	0.64	0.36
γ_{91}	4130.4	10975.07	0.35	0.65
γ_{92}	−904.36	9000.25	0.54	0.46
γ_{93}	−5722.53	8078.37	0.76	0.24
γ_{94}	2575.25	9451.02	0.40	0.60
γ_{95}	−961.13	7938.07	0.55	0.45
γ_{96}	−4332.13	8354.27	0.70	0.30

Table A. Means and standard deviations of the posterior distribution of consortia (cont.)

Coeff	Mean	SD	P(Coeff <=0)	P(Coeff >0)
γ_{97}	−4182.02	8710.34	0.70	0.30
γ_{98}	2745.99	9022.40	0.39	0.61
γ_{99}	−12982.08	9864.73	0.91	0.09
γ_{100}	−2292.86	7562.03	0.62	0.38
γ_{101}	−2567.16	8466.20	0.62	0.38
γ_{102}	8730.88	9383.97	0.17	0.83
γ_{103}	−276.71	10857.70	0.52	0.48
γ_{104}	3865.21	9837.59	0.34	0.66
γ_{105}	−1840.36	8734.05	0.58	0.42
γ_{106}	−2293.35	8895.72	0.61	0.39
γ_{107}	3627.82	9434.15	0.35	0.65
γ_{108}	345.59	8290.01	0.48	0.52
γ_{109}	−1447.36	7822.43	0.57	0.43
γ_{110}	11640.23	9280.05	0.10	0.90
γ_{111}	12640.81	9534.93	0.09	0.91
γ_{112}	1045.58	8842.62	0.45	0.55
γ_{113}	4352.31	9697.35	0.33	0.67
γ_{114}	1288.11	8885.12	0.44	0.56
γ_{115}	−558.20	8083.85	0.52	0.48
γ_{116}	−2370.21	8295.80	0.62	0.38
γ_{117}	−3463.39	9273.09	0.65	0.35
γ_{118}	7755.42	9585.65	0.21	0.79
γ_{119}	590.06	8696.41	0.48	0.52
γ_{120}	−5602.82	8933.76	0.73	0.27
γ_{121}	10805.35	8715.42	0.10	0.90
γ_{122}	7050.44	10957.81	0.26	0.74
γ_{123}	−9084.27	8134.38	0.87	0.13
γ_{124}	−2207.59	8712.29	0.60	0.40
γ_{125}	13264.11	10949.92	0.11	0.89
γ_{126}	−559.39	10642.22	0.52	0.48
γ_{127}	−8112.95	10138.62	0.78	0.22
γ_{128}	6237.15	10532.91	0.28	0.72
γ_{129}	−5806.59	9703.88	0.72	0.28
γ_{130}	6102.13	9871.79	0.27	0.73
γ_{131}	3573.21	9693.96	0.35	0.65
γ_{132}	−6914.07	9035.42	0.78	0.22
γ_{133}	5847.32	11292.33	0.29	0.71
γ_{134}	−13130.89	8755.21	0.93	0.07
γ_{135}	14566.37	13636.21	0.14	0.86
γ_{136}	−5139.08	9147.02	0.71	0.29
γ_{137}	1755.36	10280.71	0.43	0.57
γ_{138}	−3918.75	8661.92	0.67	0.33
γ_{139}	−456.47	8208.14	0.53	0.47
γ_{140}	−6516.74	8771.84	0.78	0.22
γ_{141}	2241.72	7553.68	0.38	0.62
γ_{142}	−5025.86	8092.29	0.73	0.27
γ_{143}	12332.88	9857.00	0.10	0.90