Knowledge Flows and Innovative Performance: Evidence from Italian firms

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Abstract

This paper looks at the relationship between innovative inputs and outputs (i.e the Knowledge Production Function) using data from the 2012 Italian Community Innovation Survey. We focus on interrelated economic and econometric issues and, in particular, we mainly consider (i) the choice of innovative inputs and (ii) the barriers to innovation, while accounting for (iii) sample selection issues on the inputs-side and (iv) the endogeneity in the inputs-outputs relationship.

Jel Classification: O30; D22

Keywords: R&D; Innovation; Productivity; CDM; Firm growth.

I. Introduction

An active area of research in the economics of growth focuses on the role of innovation as a determinant of productivity growth at the firm-level. Traditionally, this literature has concentrated on the innovative inputs, e.g. research and development (R&D), neglecting that innovation can be itself the outcome of a "production" process (e.g. Hall and Mairesse, 1995). The first attempt to explicitly model the innovative input-output relationship is due to Griliches (1979, 1990), who introduced a three-equation model representing the transformation process from innovative inputs to innovative outputs (the so-called Knowledge Production Function, KPF). One of the main issues in such approach lies in the choice of innovative inputs and outputs. Due to the lack of data, Griliches restricts the analysis to R&D expenditure and patents as innovative inputs and outputs, respectively. However, innovation clearly results from a complex production process that entails both many inputs (e.g. internal and external sources of knowledge) and outputs (e.g. many kinds of innovations with differing degrees of novelty). In order to capture such complexity, innovation surveys have started to be conducted both at the national and at the European level from the nineties.
These surveys provide rich datasets that allow better understanding and empirical estimation of the KPF. As a consequence, an extended version of the KPF was proposed by Crépon et al. (1998) who exploit the

Community Innovation Survey datasets[1]. Specifically, Crépon et al. (1998) introduced a four-equations model, now known as CDM model, that links innovation inputs and outputs to productivity, which shows that: R&D activity is positive related to firm size and market share; the innovation output measured, alternatively, by the number of patents or innovative sales depends positively on the amount invested in R&D; and, finally, that innovation output positively affect firm productivity.

This seminal contribution has generated a number of extensions. For instance, for the Italian case, Parisi et al. (2006) use data from the 6th and 7th survey on manufacturing firms by Mediocredito Centrale (MCC) - to investigate the role of R&D, "embodied knowledge", and their interaction (i.e the absorptive capacity) as determinants of product and process innovations. Hall et al. (2013) use data from the 7th to the 10th waves of the Survey on Manufacturing Firms conducted by Unicredit, to explore R&D and ICT investment as innovative inputs. Other studies, instead, extend the analysis of the relationship between innovation and productivity to compare results across a range of European economies at different stages of development (see, for example, Mate-Sanchez-Vala and Harris, 2014; Crowley and McCann, 2018). These studies often focus on the impact of regional factors on innovation performance (see for example Lòpez-Bazo and Montellòn, 2017) and on the role of innovation barriers in shaping the innovation-productivity relationship (see, among the others, D'Este et al., 2012; Hölzl and Janger, 2014; Coad et al., 2015).

Building on this background, this paper analyses the relationship between innovative inputs and outputs, as described by the KPF, while dealing with some econometric issues which generally affect investigations based on innovation surveys and, speficically, the sample selection problem on the inputs-side and the endogeneity problem due to the potential reverse causality in the inputs-outputs relationship. Using the 2012 Italian Community Innovation Survey, we empirically investigate the KPF by concentrating on: (i) the choice of innovative inputs and (ii) the effect of the barriers to innovation. We estimate the KPF in a multi-output framework. Specifically, we consider in-house R&D, as innovative input,and four different innovation outputs (product, process, organizational and marketing innovations).

The next section presents the data and the empirical strategy. Section 3 presents a set of results. Section 4 sets the conclusions.

II. Data and Empirical Strategy

In our analysis, we exploit data from the 2012 Italian Community Innovation Survey (CIS) containing information for the period 2010-2012 on the innovative inputs and outputs of 18,697 firms with at least 10 employees operating in the manufacturing and service sectors. Following Crépon et al (1998), in the first stage we treat the decision to invest in intramural R&D (RD) and the amount of resources invested (the R&D intensity, RD_int_i) using an Heckman sample selection model:

$$1^{st}\text{ stage}\begin{cases} RD_i = \delta_1 z_i + \varepsilon_{1i} \\ RD\_int_i = \gamma_1 x_i + \mu_{1i} \end{cases} \tag{1}$$

here z_i,and x_i are two vectors of explanatory variables which include, for example, firm size and funding at regional, national or European level. In addition, we include as exclusion restrictions (only for $z_{i,}$), some variables which represent factors that influence the decision to innovate as, for example, the presence of market and cost barriers and the human capital (see table A in the appendix for the list of variables). Finally, ε and μ are random terms which are assumed to be Normal but not uncorrelated.

In the second stage (see eq. 2) we estimate a standard knowledge production function including, as a determinant, the predicted value of the R&D intensity (with respect to sales) obtained from the first stage

[1]Since, these surveys have become a crucial source for scholars and policy analysts (see Mairesse and Mohnen 2010; Mohnen and Hall, 2013).

($RD\_\hat{int}_i$). The inclusion of the predicted value of the R&D intensity allows taking into account those cases of non-reporting R&D firms and to control for the endogeneity in the relation between the innovation effort (R&D intensity) and the innovation outputs (knowledge production function).

$$2^{nd} \text{ stage } \Big\{ inn\_output_i = \beta_0 + \beta_1 RD\_\hat{int}_i + \beta_4 w_i + u_i \tag{2}$$

Moreover, we also include a set of control variables w_i which includes firm size, sector and information on whether the firm is part of a group.

III. Results

This section reports the results of our baseline specification where only intramural R&D is considered as innovative input. In table 1, the first two columns present the results of the Heckman selection model for the decision to invest in intramural R&D and columns 3 to 6 focus on the Knowledge Production Function (KPF). From column 1, we observe how national funding, high and medium levels of human capital, selling to international markets, cooperation in innovative activity, the decision to invest in intramural R&D extert a positive and statistically significant impact on investment in R&D. Column 2 reports the estimation results on the magnitude of investment in intramural R&D. We note that European funding and being part of a group positively affects the size of this type of investment. Larger firms, however, invest significantly less in intramural R&D compared to smaller firms. This result, potentially counterintuitive, is in line with other studies (see for example Hall et al, 2009; Santi and Santoleri, 2017). A potential interpretation for this result could come by further investigation of the comparative advantage of alternative forms of R&D investment. Estimates of the Knowledge Production Function (columns 3-6) show that, as expected, intramural R&D significantly and positively affects the probability to be an innovator for all types of innovation (product, process, organizational and marketing), as well as being of medium and large size. On the contrary, being part of a group reduces the probability of introducing product, process and marketing innovation, while it is not significant for organizational innovation.

Table 1: **Empirical results**

	Heckman model		Knowledge Production Function (MvProbit)			
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**RD**	**RD_int**	**Product**	**Process**	**Organizational**	**Marketing**
RD_int_hat			21.32***	7.30**	16.10***	12.45***
			(5.40)	(2.18)	(4.42)	(3.72)
firm size (medium)	0.147***	-0.017***	0.417***	0.149**	0.471***	0.255***
	(3.29)	(4.54)	(5.23)	(2.15)	(6.30)	(3.66)
firm size (large)	0.484***	-0.025***	0.746***	0.308***	0.932***	0.537***
	(8.72)	(5.15)	(6.92)	(3.34)	(9.28)	(5.83)
national funding	0.351***	0.004				
	(8.50)	(1.29)				
european funding	0.396***	0.018***				
	(4.69)	(3.49)				
group	0.112***	0.006*	-0.093**	-0.133***	-0.015	-0.113***
	(2.66)	(1.68)	(2.06)	(3.18)	(0.34)	(2.70)
human capital (medium)	0.227***					
	(5.37)					
human capital (high)	0.182***					
	(3.03)					
international markets	0.423***					
	(10.21)					
cooperation	0.542***					
	(11.87)					
market barriers	0.047					
	(0.68)					
cost barriers	0.047					
	(1.11)					
Mill's ratio	-0.015**					
	(2.21)					
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,719	6,719	6,733	6,733	6,733	6,733

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
Source: Author's estimation

IV. Conclusions

This paper aims at investigating the link between the inputs and outputs of the innovation process, comparing innovators with different profiles. We have reported here some preliminary results that are part of a more extensive analysis. First, we rely on the standard CDM framework and estimate the Knowledge Production Function considering only intramural R&D as innovative input. Results show that the decision to invest in R&D is positively influenced by national funding, human capital, international sales and cooperation in innovative activity. The investment in intramural R&D positively depends on European funding and being part of a group, and negatively on firm size. Finally, the KPF estimates show a positive influence of intramural R&D and firm size for all types of innovation, while the effect of being part of a large group is negative.

In future research we aim to include more than one innovative input within the analysis, relaxing the hypothesis of independence among inputs in the investment decision process. To this end, a multivariate Heckman model would be a possible, but nontrivial, solution. Moreover, we aim to test the absorptive capacity hypothesis due to Cohen and Levinthal (1990) within the Knowledge Production Function.

APPENDIX - Table A List of variables

Code	***Label***
Inn_output	**Process** innovation during 2010-2012 (1: yes; 0: no)
	Product innovation during 2010-2012 (1: yes; 0: no)
	Organisational innovation during 2010-2012 (1: yes; 0: no)
	Marketing innovation during 2010-2012 (1: yes; 0: no)
RD_int	R&D intensity: Expenditure in intramural R&D in 2012 / turnover in 2010 in log
RD	Intramural R&D during 2010-2012 (1: yes; 0: no)
Sector	Sector dummy variables at 2-digit NACE classification
Firm size	Number of employees in 2012 (0: 1-49 employees; 1: more than 49 employees)
Group	Enterprise part of a group during 2010-2012 (1: yes; 0: no)
Funding	Funding at national and European level.
Exclusion restrictions	
Human capital	High if the share of graduate employees is larger than 75% and medium if the share is in the range 25-74%
International market	Enterprise selling goods and services in European or international markets during 2010-2012 (1: yes; 0: no)
Cooperation	Cooperation in innovative activity
Market barriers	Dummy equal to 1 if the firm attributes to market barriers high-medium importance, and 0 otherwise.
Cost barriers	Dummy equal to 1 if the firm attributes to cost barriers high-medium importance, and 0 otherwise.

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