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THE LOCUS OF KNOWLEDGE EXTERNALITIES AND THE COST OF KNOWLEDGE[1]

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ABSTRACT. This paper provides an extended CDM approach to analyse jointly the simultaneous effects of knowledge spillovers in the knowledge generation function and in the technology production function. It introduces the distinction between imitation and knowledge externalities and articulates the hypothesis that spillovers yield their effects via three well distinct mechanisms: i) knowledge externalities that exert positive and direct effects on the knowledge production function, and ii) indirect effects on the technology production function via their effects on the cost

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of knowledge; iii) imitation externalities exert direct and positive effects on productivity in the technology production function. We test our hypotheses on a large panel of Italian companies distributed in the NUTS2 regions for the period 2005 – 2009. The econometric analysis consists in a model comprising a system of equations that test the simultaneous role of spillovers in the knowledge generation function and the technology production function with the inclusion of endogenous knowledge costs. The results confirm that the access to external knowledge – as an input in the knowledge generation function – plays a key role in increasing the knowledge output and – as an input in the technology production function – has positive indirect and direct effects on the productivity of firms.

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KEY WORDS: SPILLOVERS; KNOWLEDGE EXTERNALITIES; IMITATION EXTERNALITIES; TECHNOLOGY PRODUCTION FUNCTION; KNOWLEDGE GENERATION FUCNTION; KNOWLEDGE COSTS; CDM.

1. INTRODUCTION

A sequence of overlapping investigations has characterized the fast development of the economics of knowledge. The economics of knowledge rests on two pillars: the investigation on the role of knowledge in the production of all the other goods implemented with the technology production function[2], and analysis of activities that enable the generation of new technological knowledge implemented by means of the knowledge generation function[3]. These two strands of literature have grown quite

[2] Following Zvi Griliches (1979: 95) we call technology production function the standard production function augmented by the inclusion among the inputs of "a measure of the current state of technical knowledge, determined in part by current and past research and development expenditures". In the CDM literature this equation is called "productivity equation".

[3] Following Zvi Griliches (1979: 95) we call "knowledge generation function" the activity that enables to generate new technological knowledge: "An alternative approach would complicate this

apart in a sequence. The focus of the empirical analysis has been first concentrated on the technology production function and subsequently shifted towards the analysis of the knowledge production function. The path breaking CDM approach articulated by Crepon, Duguet and Mairesse (1998) has made possible to reconcile in a single framework these two strands of literature by means of a systemic approach where both the technology production function and the knowledge production function are part of a single system of equation.

Quite surprisingly the CDM approach has not – yet – been used to investigate the role of spillovers. Yet both strands of literature had confirmed the important role of spillovers.

After the great success of the notion of spillovers in the framework of the technology production function, in fact, the role of spillovers has been again highlighted in terms of knowledge externalities in the context of the knowledge production function (Rigby, 2015; Boschma, Balland, Kogle, 2014).

The empirical evidence confirms that spillovers play a significant role both in the technology production function and in the knowledge production function. Yet, in a systemic and simultaneous approach, knowledge, generated in the knowledge generation function with the benefit of knowledge externalities that enable to access and use external knowledge

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model further by adding an annual knowledge production function of the form K = H(R, K) and defining K accordingly". In the CDM literature this equation is called "innovation equation".

at costs below equilibrium, becomes an endogenous input in the technology production function, where knowledge is an input next to capital and labor in the production of all the other goods. The question whether knowledge spillovers matter in both equations seems legitimate. As a matter of fact spillovers yield knowledge externalities upstream and imitation externalities downstream. The former consist in the access to knowledge inputs that enable the generation of further knowledge. The latter yield additional knowledge ready-to-be-used-again, which augments the amount of knowledge that can be used to produce all the other goods. The positive effects of spillover in terms of imitation externalities in the downstream technology production function might simply reflect the effects already exerted by spillovers in terms of knowledge externalities in the upstream generation of new knowledge. The missing identification of the distinct effects of knowledge externalities and imitation externalities and the consequent overlapping of these two fields of investigation raises the question whether these results are actually consistent or are the consequence of the sequential use of different methodologies that have not, yet, been applied simultaneously (Antonelli, 2009; Antonelli and David, 2016).

The aim of this paper is to elaborate an extended CDM methodology that enables to analyze the actual locus of spillovers and to test whether they apply both and simultaneously in the technology production function and in the knowledge generation function or just in the generation of knowledge. In our approach knowledge externalities exert their effects both and simultaneously in the upstream knowledge generation function and in the downstream technology production function. The attempt to account for the endogeneity of knowledge externalities is further reinforced by the enrichment of the CDM approach with the introduction of endogenous knowledge costs.

The rest of the paper is structured as it follows. Section 2 recalls the foundations of the knowledge generation process and applies them to studying the role of knowledge and its cost in the technology production function. Section 3 outlines the analytical framework, while Section 4 presents the dataset, the methodology and the variables. The results of the empirical investigation are discussed in Section 5. Section 6 concludes by summarizing the results and the avenues for further research.

2. FROM THE TECHNOLOGY PRODUCTION FUNCTION TO THE KNOWLEDGE GENERATION FUNCTION AND BACK. THE ROLE OF KNOWLEDGE COSTS

2.1 THE ROLE OF SPILLOVERS IN THE TECHNOLOGY PRODUCTION FUNCTION AND IN THE KNOWLEDGE PRODUCTION FUNCTION

Large evidence confirms the merit of the intuition of Zvi Griliches (1979). The Arrovian properties of knowledge and especially limited appropriability yield not only negative consequences in terms of missing incentives to generate knowledge, but also positive ones. Proprietary knowledge cannot be – fully – appropriated by inventors. It spills and –

because of its substantial non-exhaustibility - can be used again by other firms. The repeated use of knowledge yields externalities that account for total factor productivity. The specification of the technology production function - the standard production function augmented with the inclusion, next to capital and labor, of knowledge as a relevant input- enabled to appreciate the effects of R&D activities and more generally technological knowledge to the production of all the other goods. In a second step the technology production function became the platform into which the role of knowledge spilling from third parties could be appreciated. The framework enabled to confirm the strong and positive effects on the levels of output and total factor productivity not only of internal knowledge but also of the external knowledge – ready to be used again - spilling from other firms that could not fully appropriate it (Adams, 1990; Griliches, 1992). As the systematic and inclusive reviews of Hall and Mairesse, (2006) and Hall, Mairesse and Mohnen, (2010) show, the positive effects of both internal knowledge and spillovers became one of the cornerstones of the economics of knowledge. Knowledge spilling from third parties can be used again and helps firms to better exploit their own internal stock of knowledge.

The successful results of the enquiry about the properties of technological knowledge as an economic good in the production of all the other goods have pushed the economics of knowledge to make a further step with the identification and exploration of the characteristics of the processes that enable the generation of knowledge as an economic activity. The analysis of knowledge conceived as the output of an intentional process lead

Griliches (1979) to specify the knowledge generation function (Pakes and Griliches 1984; Jaffe, 1986).

In this context, both the internal stocks of knowledge generated by each firm in the past and the stock of external knowledge generated by third parties, but not fully appropriated, are now recognized as indispensable inputs that enter necessarily into the recombinant generation of knowledge as an output (Weitzman, 1996). In the knowledge generation function, external knowledge is an essential input in the recombinant generation of new knowledge: internal and external knowledge are complementary inputs that can be substituted only to a limited extent. As a consequence the access conditions to external knowledge become crucial: firms that have no access at all to external knowledge cannot actually produce any new knowledge even if they are able to mobilize large amounts of internal knowledge by means of R&D activities. Firms that have limited and expensive access to external knowledge can produce, with a given budget, a smaller amount of technological knowledge with higher costs (Cohen and Levinthal, 1989 and 1990). Antonelli and Colombelli (2015a) review the large empirical evidence that has confirmed the strong and positive role of knowledge externalities in the recombinant generation of new technological knowledge.

According to the results of the two abovementioned waves of investigations, spillovers matter both: i) in the technology production function, which enables to study the role of external knowledge as an input – ready to be used again - next to capital and labor and internal knowledge, and ii) in the generation of knowledge where external knowledge enters as a indispensable input, next to internal knowledge, in the recombinant knowledge generation process. These two waves of investigations have been conducted separately and sequentially.

The literature provides only a few attempts to integrate the analysis of knowledge externalities in the CDM approach. Ben Hassine, Boudier, and Mathieu (2017) do use a CDM approach, but include the analysis of spillovers only in the “productivity equation” and make no effort to account for its endogeneity. Along similar lines Goya, Vayá and Suriñach (2013) do not include the analysis of spillover in the “innovation equation” as they claim that “investment intensity depends much more on internal factors (such as availability of funding) than what other firms do” (p.6). Lhuillery (2011) instead includes the stock of knowledge of rivals in the R&D equation but does not take into account the role of spillovers in the productivity equation. In sum, it seems possible to claim that no effort has been made, so far, to take into account the role of knowledge spillovers both in the innovation and the productivity equations of the CDM system.

This paper tests the hypothesis that the results of the two separated waves of investigations are consistent and apply jointly: spillovers do affect both the technology production function and the knowledge production function. Spillovers exert a positive role in the technology production function as they enable the imitation of technological knowledge introduced by third parties and ready to be used again. The access to external knowledge is important to exploit the internal stock of knowledge.

Spillovers also exert a positive role in the knowledge generation function as they provide knowledge inputs that feed the recombinant generation of new technological knowledge. In the first case spillovers are the vectors of imitation externalities that enable to use again knowledge generated by third parties and ready to be used again. In the second case, they are the carriers of knowledge externalities that enable to use external knowledge as a complementary input in the recombinant knowledge generation process (Aghion, Akcigit, Howitt, 2015).

The joint and simultaneous analysis of the role of spillovers in both a technology production function and a knowledge production function leads to an extended CDM approach that allows testing whether spillovers: i) matter directly in both the equations, as they yield respectively imitation and knowledge externalities or, instead; ii) exert their positive role only and directly in the generation of technological knowledge, as carriers of knowledge externalities, but do not affect directly the production of the other goods represented by the technology production function; iii) exert indirect effects that take place via the cost of knowledge as an input in the technology production function.

The simultaneous analysis of the role of spillovers in both the technology production function and the knowledge generation function enables to identify, highlight and test the role of two important and quite different notions of imitation externalities and knowledge externalities. Let us explore these two couples of concepts.

Knowledge spilling from third parties -that can be used again as such- yields imitation externalities that exert a direct and positive role in the downstream production function. Knowledge spilling from third parties that can be used as an intermediary input in the recombinant generation of new knowledge yields knowledge externalities. Knowledge externalities exert direct positive effects in the upstream knowledge generation function, and indirect positive effects in the downstream technology production function via the reduction of knowledge costs.

Knowledge and imitation externalities engender two distinct types of complementarity: generation complementarity in the knowledge generation function and exploitation complementarity in the technology production function.

Generation complementarity consists in the complementarity between external and internal knowledge in the generation of new knowledge. When generation complementarity applies external knowledge is an indispensable input in the generation of new knowledge conducted together with internal research and learning efforts. A firm that does not fund and perform any R&D activity cannot benefit of knowledge externalities and is unable to produce any new knowledge, as much as an isolated firm localized in a context that does not provide any knowledge externality cannot produce any new knowledge. This analysis lead to the hypothesis that the amount of knowledge output that a firm is able to generate is strictly contingent upon the interactive relationship between the research effort of each firm and the levels of current efforts of all the other co-localized firms (Antonelli and Colombelli, 2015a and b).

Exploitation complementarity consists in the complementarity between internal and external knowledge in the exploitation of knowledge. The access and use to external knowledge-ready-to be used-again is strictly necessary to exploit the internal stock of knowledge. Firms that do not have access to external knowledge are unable to exploit their own internal stock.

2.2. KNOWLEDGE COST

The focus on knowledge cost enables to identify the consequences of knowledge externalities on the upstream generation of new knowledge as an output and to assess its effects on the downstream technology production function where knowledge enters as an input (Antonelli and Colombelli, 2015b). The stock of knowledge external to each firm contributes the recombinant generation of new technological knowledge. Because of its limited appropriability, in fact, proprietary knowledge generated at each point in time, spills out of the command of the 'inventors' and benefits all potential users. Inventors can retain the command of their proprietary knowledge only for a limited time window. Eventually, because of its limited exhaustibility and substantial cumulability, all the flows of knowledge produced at each point in time add to the stock of public knowledge, with the time lag due to the limited appropriation windows, so that it keeps increasing.

Knowledge spillovers help reducing the costs of external knowledge and engender pecuniary knowledge externalities. For given levels of absorption costs, the lower are the levels of knowledge appropriability and the lower are the costs of accessing and using external knowledge, hence the lower the costs of external knowledge as a necessary and strictly complementary input in the recombinant generation of new knowledge. Consequently, the lower are the costs of knowledge, as an output, generated upstream with the benefit of knowledge externalities, and the lower the costs of the goods that are produced downstream using knowledge as an input.

The focus on knowledge costs enables to grasp the overlapping role of knowledge spillovers. Knowledge spillovers and pecuniary knowledge externalities, in fact, exert their powerful and positive effects with the reduction of the costs of knowledge as an input into the technology production function. In the downstream production of all the other goods, spillovers exert a twin effect: a) directly via the imitation externalities that enable to access external knowledge ready-to-be used again, and b) indirectly via the reduction of the costs of the knowledge generated upstream by means of the access to the complementary external knowledge inputs. The final effect is the reduction of the costs of the goods produced using knowledge as an input and hence the increase of productivity.

3. THE ANALYTICAL FRAMEWORK AND THE HYPOTHESES

The CDM systemic framework implemented by Crépon, Duguet, Mairesse, (1998) provides the starting point. The CDM model consists in a system of three equations, the R&D equation, the innovation equation and the productivity equation that are estimated simultaneously[4]. The CDM model is a major methodological innovation itself as it is the first attempt to appreciate the interdependencies between the three levels of analysis that have been analyzed separately. Yet the CDM model does not take into account the pervasive and ambiguous role of spillovers in the technology production function and the knowledge generation function. For this reason it seems necessary to implement the CDM approach so as to analyze and identify in an integrated context the actual role of spillovers as carriers of: i) imitation externalities in the productivity equation and ii) knowledge externalities in the innovation equation. The inclusion of knowledge costs seems the most appropriate way to extend the CDM approach so as to include the twin role of spillovers as carriers of both knowledge and imitation externalities. Let us present our implementation of the three equations of the CDM model by means of the introduction knowledge costs.

Firms' decision to engage in R&D activities and the determinants of the amount of R&D activities:

(1) R&D = (X)

[4] For the sake of consistency when applying the CDM model we follow the CDM literature and call "innovation equation" the "knowledge generation function" and "productivity equation" the "technology production fucntion".

where X is a vector of independent variables including firms' size and intangible assets.

The generation of new technological knowledge (TK) is influenced by the stock of internal knowledge (IT) and the stock of external knowledge available in the region (ET):

(2) TK = (IT, ET)

The inclusion of knowledge externalities in equation (2) is the first innovation to the standard specification of the CDM approach that does not take into account the role of spillovers in terms of knowledge externalities in the recombinant generation of knowledge. This inclusion rests upon our basic hypothesis supported by the consistent results of a large empirical literature that confirm their strong and positive role in the recombinant generation of new knowledge. Generation complementarities between internal research efforts and external knowledge spilling in the system are at work here.

Finally the productivity equation, where labour productivity Y/L is determined by the capital intensity (K/L), the endogenous cost of knowledge (T*) that is the result of the estimated levels of R&D expenditures and knowledge output and an interaction variable that accounts for the exploitation complementarities between external and internal knowledge. This specification of the productivity equation enables to account for the twin effects of knowledge spillovers: i) the upstream knowledge externalities via the reduced costs of knowledge generated internally and ii) the downstream imitation externalities with the direct and multiplicative effects. Spillovers exert their effects in equation (2) and helps producing more knowledge. The larger are the levels of pecuniary knowledge externalities and the larger, with a given budget, is the expected output in terms of new knowledge and consequently the lower the costs of knowledge. The costs of knowledge - reduced by the positive effects of knowledge externalities in the upstream generation of knowledge - are expected to play a positive role in accounting for the levels of labor productivity in downstream activities. External knowledge accessed by means of the imitation of ready-to-be-used-knowledge empowers the amount of knowledge generated upstream internally. Hence, the productivity equation (eq. 3) now includes - next to a vector (X) of characteristics of the firms such as size- the intensity of capital, the stock of internal and external knowledge in a multiplicative relationship that accounts for their exploitation complementarities and the cost of knowledge:

(3) $Y/L = (K/L, T^*, ET\&TK, X)$

Equation (3) applies the standard specification of the technology production function of the CDM approach with two innovative inclusions According to our discussion of the literature and our hypotheses in fact we include T* to account for the indirect and upstream effects of knowledge externalities: external knowledge in fact has already exerted its effects in equation (2) in terms of knowledge externalities reducing the endogenous costs of knowledge (T*). Next, we expect that the stock of internal knowledge generated upstream (TK) exert a positive and significant role in a multiplicative relationship with the stock of external knowledge (ET) to account for the role of imitation externalities in terms of exploitation complementarities. The econometric analysis is expected to test the hypothesis and provide reliable evidence whether the inclusion is effective.

The large literature on the positive role of spillovers in the technology production function tested independently suggests that spillovers would add their direct effects to their indirect ones that are already taken into account via the – reduced – levels of knowledge costs. According to the alternative hypothesis, instead, spillovers would not exert any effect on productivity levels, because their effects do take already place indirectly via the reduction of the costs of knowledge. The simultaneous test of the model that already takes into account the role of knowledge externalities in the upstream knowledge generation function enables to test whether spillovers are the carriers of both imitation and knowledge externalities, or just knowledge externalities.

Our system of three equations can be summarized as it follows. First, firms choose whether to perform R&D and, if so, by how much. Then, depending on the extent of their own R&D, knowledge externalities with their generation complementarities, and other factors, they achieve a certain knowledge output. Knowledge cost can be easily calculated as the ratio of estimated value of the R&D stock and the estimated value of knowledge output. Hence our knowledge stock is fully endogenous and takes into account the effects of knowledge externalities. Finally, the productivity equation enables to test the effects on labor productivity of the upstream knowledge externalities by means of the effects of the reduced levels of knowledge costs on the efficiency of firms. The farther are the costs of knowledge, below equilibrium levels, and the larger the productivity levels (Antonelli, 2013; Antonelli and Gehringer, 2016). We expect that knowledge externalities already accounted for by equation (2) exert an indirect influence on productivity via the reduction of knowledge costs. Spillovers should, moreover, exert direct positive effects as they enable firms to imitate technological knowledge introduced by other firms and ready to be used again with a multiplicative effect on the stock of internal knowledge that account for their exploitation commplementarity.

4. DATA, METHODOLOGY AND VARIABLES

4.1 DATASET

The paper focuses on a sample of Italian companies in the period 2005-2009. Our source of data is AIDA by Bureau Van Dijk, which contains financial information on Italian companies. We also use data from the OECD REGPAT database, which provides regional information on the addresses of patent applicants and inventors as well as on technological classes cited in patents granted by the European Patent Office (EPO) and the World Intellectual Property Organization (WIPO), under the Patent Co-operation Treaty (PCT).

In order to match the firm level data with data on patents, we draw on the work by Lotti and Marin (2013), which develops an improved (compared to recent efforts to match applicants in PATSTAT with firms in the Bureau van Dijk databases) cleaning routine to maximize exact matches, followed by an approximate matching based on multiple combination of similarity scores. This matching covers 68% of EPO applications by Italian firms for the entire period and 89% for the years 2000-2009[5].

As the focus of the paper is on knowledge spillovers and their multiple effects in terms of knowledge and imitation externalities and the cost of knowledge, we concentrate the empirical analysis of a sample of firms for which technological knowledge plays an important role and restricted our sample to firms operating in High-Tech and Medium-High-Tech sectors. These firms are indeed the main local actors in the generation of new technological knowledge process.

We finally obtained an unbalanced panel of 134,554 observations on 32,218 firms. Table 1 shows the sectoral distribution of our sample. Around 18% of firms operate in High-Tech sectors, while about 82% of firms belongs to Medium-High-Tech sectors.

The following section describes the econometric methodologies and the specifications used for the estimations of the model's four equations.

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[5] As it is well known the attempts to identify the value of patents are exposed significant errors (Van Zeebroeck, van Pottelsberghe, 2011). We follow the empirical literature on the matter and we rely on the simple measure of the quantity of patents.

4.2 THE ECONOMETRIC STRATEGY: METHODOLOGY AND VARIABLES

The econometric strategy implemented in this paper allows taking into account the methodological problems discussed in what it follows. First, only a minority of firms formally invests and reports R&D expenditures. Studies restricted to this sub-sample of firms are affected by a selection-bias problem. Also only relatively few firms do patent their innovation activities, and thus analyses limited to them may be similarly biased. Finally, it must be acknowledged that R&D is endogenous in the innovation equation while the cost of knowledge is endogenous in the productivity equation. The empirical methodology also needs to cope with the simultaneity problem.

All these estimation problems are treated by relying on a model that consists of a system of equations. We deal with simultaneity by using a two-stage estimation procedure. We also take care of selection problems by using a Heckman procedure (Heckman, 1979) in the research equation. In particular, we adopt the estimation method proposed by Wooldridge (1995), which can be used in a panel setting in order to estimate R&D expenditures for non-reporting firms. The innovation and the productivity equations are estimated using a recursive system.

R&D EQUATIONS

To describe the firm research behaviour, it is necessary to take into account the latent amount of R&D expenditures. We follow the model developed by Crépon, Duguet and Mairesse in 1998. The econometric specification of equation (1) leads to the two equations (4) and (5), where the first equation accounts for the fact that the firm is engaged in research activities, and the second one for the intensity of these activities.

Let $D\_R\&D_i$* be the latent dependent variable whether to invest in R&D or not, and $LnR\&D_i$* be the latent or true intensity of R&D investment of firm i. $D\_R\&D_i$ and $LnR\&D_i$ are the corresponding observed variables.

The two-equation R&D investment model is written as follows:

4) $D\_R\&D_i^* = \beta_1 x_i^1 + u_i^1$

with $D\_R\&D_i=1$ if $D\_R\&D^*_i>0$, $D\_R\&D_i=0$ otherwise.

5) $LnR\&D_i^*/(D\_R\&D_i = 1) = \beta_2 x_i^2 + u_i^2$

with $LnR\&D_i= LnR\&D^*_i$ if $LnR\&D_i>0$, $LnR\&D_i=0$ otherwise.

The x^1_i and x^2_i are the explanatory variables, β_1 and β_2 the respective coefficients u^1_i and u^2_i follow a bivariate normal distribution with correlation coefficient ρ.

The independent variable explaining, first, the probability to engage in R&D activities and, second, the levels of these activities, is intangible assets. Investment in intangible assets can be considered a reliable proxy for predicting R&D activities. Indeed, the broad array of activities that are necessary to explore and recombine the existing stock of knowledge, both internal and external to each firm, and exploit it can be predicted using this measure. The selection equation (4) also includes a measure of firm size. Finally, both equations include a set of industry and time dummies to capture market and cycle conditions (see the following section for all variables' detailed specification).

We estimate equations (4) and (5) following the methodology proposed by Wooldridge (1995) and applying bootstrapping to both equations. This method can be used in a panel setting to take into accounts that there may be some unobserved time-variant factors that can affect selection and influence R&D levels through the error term. In this approach, the time-invariant effects are assumed to be linked with x^1_{it} through a linear function of k^1_i on the time averages of x^1_{it} (denoted with x^1_i_bar) and an orthogonal error term a_i that exhibits no variation over time and is independent of x^1_{it} and u^1_{it}:

$k^1_i = x^1_i\_bar + a_i$

Equation (4) can be rewritten as follows:

$$4a)\ D\_R\&D^*_{it} = \beta_1 x^1_{it} + \gamma_1 \bar{x}^1_i + v^1_{it}$$

with the composite error term $v^1_{it} = u^1_{it} + a_i$ being independent from x^1_{it} and normally distributed with zero mean and variance σ2. In this approach, to obtain estimates for the Inverse Mill's Ratio, a standard probit on the selection equation (4a) is estimated for each t relying on bootstrapped standard errors (200 repetitions).

In this approach, equation (5) can be rewritten as follows:

$$5a)\ LnR\&D_{it}^{*}/(D\_R\&D_{it} = 1) = \beta_1 x_{it}^2 + \gamma_2 \bar{x}_i^2 + \zeta\lambda_{it}^2 + v_{it}^2$$

where λ_{it} is the Invers Mill's Ratio and v^2_{it} is an orthogonal residual.

According to Wooldridge (1995), equation (5) can be estimated by including the t IMRs obtained from the selection equation for each time period along with the regressors. This method allows the error term to be correlated with the IMRs, Equation (5a) can thus be consistently estimated by pooled OLS. Following Wooldridge (2010), we calculate panel bootstrapped standard errors (200 repetitions) clustered by firm in order to obtain standard errors corrected for first stage probit estimates and robust to heteroskedasticity and serial correlation.

By applying this approach, we are able to predict the potential R&D for non-reporting firms (*lnR&D_hat*). Our model indeed is based on the assumption that all firms perform innovative activities, although some of them do not report the related R&D investments.

THE INNOVATION EQUATION

The econometric specification of the innovation equation (See equation (2)) is equation (6), where the knowledge output is measured in terms of number of patents while all terms on the right hand side enter in logarithmic form. Equation 6 is formalised as follows:

6) $NPAT_{it}^{*} = \beta_l lnR\&D_{it}^{*} + \beta_3 x_{it}^{3} + u_{it}^{3}$

Where $lnR\&D^{*}_{it}$ is our latent research variable, x^3_{it} is a vector of other explanatory variables, β_l and β_4 are the respective coefficients and u^3_{it} is the error term.

Here, the output measure is explained by a set of independent time varying variables that aim at capturing the specific relevant characteristics of the size of the internal knowledge base and its interaction with the amount of external knowledge. Also specific firms' characteristics are taken into account (see the following section for their detailed specification).

As the dependent variable, i.e. *NPAT*, measuring the number of firm patent applications, is a count variable, equation (6) is estimated using count models that prove more appropriate in dealing with non-negative integers.

More precisely, equations (6) can be estimated by means of either a Poisson or a negative binomial model. Since our dependent variable is over-dispersed, as showed in Table 3 by the fact that its variance is far larger than the mean for the sampled firms, the negative binomial estimator seems to be more appropriate. However, since firms included in our sample belong to different industrial sectors, they show a different patenting behaviour. For this reason a zero-inflated regression model seems appropriate to test equation (6). Zero-inflated models attempt to account for excess zeros by means of the estimation of two equations simultaneously, one for the count model and one for the excess zeros. In other words, zero-inflated models deal with two sources of over-dispersion: a qualitative part, which explains the presence or absence of patent count, and a quantitative part, which explains the positive patent count for firms having at least one patent in a given year time. Zero-inflated regression models might be a good option if there are more zeros than would be expected by either a Poisson or negative binomial model. We thus finally use a zero-inflated negative binomial regression estimator. To account for the panel nature of our dataset, we cluster on firms identifiers to correct the standard errors for within cluster similar values.

THE PRODUCTIVITY EQUATION WITH ENDOGENOUS KNOWLEDGE COSTS AND IMITATION EXTERNALITIES

The econometric specification of equation (3), the productivity equation, leads to equations (7) and (8). In equation (7) the cost of knowledge is the endogenous variable. For each firm, the endogenous cost of knowledge is measured as the ratio of R&D expenditures (predicted from equations (4) and (5)) to the number of patent applications (predicted from equation (6)):

7) KCOST = R&D* / NPAT**

Knowledge costs are endogenous and specific to each observation as both the R&D (R&D*) and the patent (NPAT*) measures are the predicted values of the econometric estimates of the respective equations (4) and (5).

The econometric specification of the productivity equation (equation 3) is formalized by equation (8) as it follows:

8) $Y/L_{it} = \beta_l KCOST^*_{it} + \beta_4 x^4_{it} + u^4_{it}$

Here, the dependent variable is labor productivity measured as deflated value added per employee (in logarithm). x^4_{it} is a vector of explanatory variables other than the estimated including physical capital per employee, firms' size, R&D per employee and the interaction between the internal knowledge base and the amount of external knowledge. β_l is the elasticity of total factor productivity with respect to the cost of knowledge, β_4 is the vector of coefficients for the explanatory variables and u^4_{it} is the error term.

The use of predicted innovation costs in the productivity equation instead of the predicted innovation success is a major departure from the standard CDM model. The classical CDM model tests the impact of innovation output 'given' the inputs. This is a limit of the CDM model that can be overcome with the account of the endogenous determinants of the costs of knowledge. The absolute amount of R&D expenditures of the firms considered is quite low and it represents an average of less than 2% of sales. Consequently, although it is true that from an 'accounting' point of view, the inclusion of both innovation output and R&D may lead to multiple counting of labour and capital used for research (in K/L, in R&D expenditure and in the innovative output), the risks to generate potentially biased estimates are negligible. In order to minimize them and to take into account the effects of the limited appropriability of knowledge and its uncontrolled leakage we include the flow of R&D expenditures instead of the stock. Knowledge spillovers limit the cumulability and reduce the time window into which the flows of R&D expenditures exert their effect internally, within the boundaries of the firm. The stock of external knowledge instead is augmented by the flows of R&D expenditures performed by each firm. What matters for productivity is not only the innovation output but also and primarily its cost (once they are accounted for in labour and capital input and in the innovation equation). The difference between equilibrium and actual innovation costs stemming from knowledge externalities is the single plausible explanation for productivity growth. If knowledge were a standard economic good with high appropriability and non-exhaustibility, its marginal output would match its costs: there would be no relationship between innovation and productivity growth. Productivity growth stems not only from the multiplicative relationship between the internal and the external stock of knowledge but also from the internal generation of knowledge at costs that are below equilibrium levels. This is due to the full range of effects of the Arrovian limited appropriability of knowledge as an economic good of which Zvi Griliches saw the positive effects in terms of spillover, rather than just the negative ones in terms of missing incentives (Antonelli, 2013; Antonelli and Gehringer, 2016).

Following the CDM approach, we could simply estimate equation (8) by ordinary least squares (OLS), with a robust covariance matrix. However, to take into account the panel nature of our data, we opted for a fixed effect estimator with a robust covariance matrix.[6]

4.3 VARIABLES MEASUREMENT METHODS

In this section we describe all variables measurement method.

We first compute a set of variables at the firm level. *D_R&D* is a dummy taking value 1 if firm's R&D expenditures are positive. *LnR&D* is measured as the logarithm of R&D expenditures reported in the firm's balance sheets and is expressed in real values. *LnIA* is the logarithm of deflated intangible assets for firm i at time t-1 and is used in equation (4) and (5) to predict R&D expenditures[7]. *NPat* is the flow of patent applications for firm i at time t. *ln(R&D/Empl)* is the logarithm of R&D expenditures divided by the number of employees.

KCOST is the cost of knowledge output. To compute the *KCOST* variable we use estimated values of both R&D, as obtained from equations (4) and (5), and *NPAT*, as obtained from equations (6). Finally, the variable *Size* is

[6] Equations (6) and (8) have also been estimated simultaneously by applying the 3-stages least square estimator. We obtained similar results. This confirms the robustness of our analysis.

[7] It is worth stressing an important limitation in this respect. According to accounting rules, firms can choose to 'capitalize' R&D expenditure voluntarily. Moreover, small firms in Italy are required to submit to the Chamber of Commerce a 'synthetic version' of the balance sheet while the submission of a 'full version' (in which R&D is separated from total intangible assets) is only voluntary.

measured as the log of total assets for firm i at time t-1 and is expressed in real values.

We further compute other variables to proxy for the knowledge that is external to each firm. *lnRegPStock* is the intensity of a regional knowledge stock and is measured as the log of patents stock over population for the region (NUTS2) of firm i at time t-1. To better approximate the locus of knowledge generation, patents are assigned to regions according to the inventors' address. This variable is computed by applying the permanent inventory method (PIM) to regional patent applications. In so doing we use a rate of obsolescence of 15% per annum. Patents seem to be a reliable proxy of the stock of external knowledge as they measure the amount of codified knowledge that has been generated within the region.

The stock of internal knowledge instead is better proxied by the levels of R&D expenditures (*LnR&D*) that –especially after the implementation of the procedures elaborated in the Oslo Manual (OECD, 2005)- are expected to account for the full range of efforts of each firm to generate new technological knowledge. The levels of R&D expenditures reflect, in fact, a wide range of activities including the absorption of external knowledge and the valorization of the internal stock of tacit knowledge accumulated by means of learning processes.

Moreover, to catch the multiplicative complementarity between internal and external knowledge in equations (5), (6) and (8), we develop the interaction term *lnR&D_hat *lnRegPStock*. Specifically, in this interaction term the levels of estimated R&D activities at the firm level multiply the levels of external knowledge in terms of estimated patents in the innovation equation. The multiplicative relationship stresses the strict complementarity between external and internal knowledge in the generation of knowledge (Antonelli and Colombelli, 2015a and b). This specification enables to test the hypothesis that the amount of knowledge output that a firm is able to generate is strictly contingent upon the interactive relationship between its research efforts and the levels of current efforts of all the other co-localized firms.

The interaction term enters also equations (6) and (8). Here the multiplicative relationship stresses the strict complementarity between external and internal knowledge in the exploitation of knowledge. This specification enables to test the hypothesis that the amount of knowledge output that a firm is able to exploit is strictly contingent upon the interactive relationship between its research efforts and the levels of current efforts of all the other co-localized firms.

Finally, our estimating equations include time and sectoral dummies in order to control for time and industry effects.

For each variable the measurement method is defined in Table 1. Descriptive statistics and the correlation matrix for the baseline cost function can be found in Table 2 and 3, respectively.

Table 1, 2 and 3 about here

As shown in Table 2 – panel A), the *lnCost* variable is skewed right (Skewness is about 0.5). Not surprisingly, the size class breakdown of the variable in Table 2 – panel B) shows that the cost of knowledge decreases with firm size: micro companies face much higher costs than SMEs and large companies. Looking at the sectorial breakdown, it appears that companies in High-Tech sectors are associated with higher knowledge costs.

4.4 RESULTS

Table 4 shows the results for the R&D equations estimated using the Wooldridge procedures. More precisely, the *t* estimates of equation (4a) are reported in Panel A while the estimates of equation (5a) are reported in Panel B. The two sets of equations allow predicting the potential R&D for not reporting firms.

Table 4 about here

Table 5 shows the estimation results of the zero-inflated negative binomial regressions for equation (6). The Vuong test, comparing the zero-inflated models with the negative binomial regression models, indicates that the zero-inflated negative binomial is a better fit than the standard negative binomial in all of the regressions.

Our results confirm the hypothesis that the generation of new technological knowledge is determined by: i) the estimated levels of R&D activities, ii) the amount of external knowledge that firms can access, and iii) the size of a firm. First, R&D activities contribute with a significant effect the generation of new knowledge, as confirmed by the positive and significant coefficient of *lnR&D_hat*. Second, the positive and significant role of external knowledge is confirmed by the results of the *lnRegPStock* variable. These results confirm with strong and significant evidence the positive role of knowledge externalities. Generation complementarities are not significant: this result seems to suggest that knowledge externalities help to generate knowledge but that external knowledge is not indispensable. Finally, also *lnSize* is found to be positively and significantly related to a firm probability to patent. These results confirm the Schumpeterian hypothesis about the advantages of large corporations in the introduction of technological innovations: the sheer size of a firm increases the probability to generate new technological knowledge (Acs and Audretsch, 1990; Cohen and Klepper, 1996).

Table 5 about here

The estimation of equation (6) enables to measure, for each firm, the endogenous cost of knowledge to be included in the productivity equation. This variable is computed as the ratio between predicted R&D expenditures and the predicted number of patent applications. It is worth noting that the correlation between the predicted and the real costs of knowledge (being the latter measured as the ratio of R&D expenditures to the number of patent applications for the innovating firms) is equal to 0.8084.

Table 6 exhibits the estimation results of equation (8). The econometric evidence fully confirms our hypothesis. The cost of knowledge has a strong and significant negative effect on labor productivity: the lower is the cost of knowledge and the larger is the labor productivity. The indirect effect of upstream knowledge externalities on the downstream production of all the other goods is strong. The size of firms is again significant and positive suggesting that the size of firms matters both in the generation and in the exploitation of knowledge. The control of the capital intensity exhibits the expected positive role while the *ln(R&D/Empl)* variable is not significant. The significant results of the multiplicative variable between internal and external knowledge confirm the role of the exploitation complementarity between internal and external knowledge.

Table 6 about here

The Italian evidence investigated by means of an augmented CDM model that includes knowledge costs as an endogenous variable, suggests that spillovers exert strong and positive direct effects upstream, in the generation of knowledge, with significant and positive consequences on the cost of knowledge that, in turn, affect indirectly the downstream production of all the other goods. The expected direct effects of spillovers in the productivity equation, in terms of imitation effects, are moreover confirmed in their multiplicative relationship with the stock of internal knowledge. The effects of spillovers are threefold. According to the empirical evidence of our extended systemic approach, they are, simulateneously:

i) strong and direct upstream as carriers of knowledge externalities;

ii) indirect downstream via the reduction of the costs of knowledge as an input in the downstream production of all the other goods; and

iii) effective directly in the downstream production of all the other goods via the multiplicative relationship between the internal and the external stock of knowledge that captures the effects of imitation externalities in the access external knowledge ready-to-be-used-again.

We further check the robustness of our results. First, as SMEs and big firms are likely to depend and exploit external knowledge differently, we divided sampled firms in different size classes: micro (less than 10 employees), SMEs (employees in the range 10-250) and large companies (more than 250 employees). Table 7 shows the estimation results of equation (8) for the different size classes. These results confirm the robustness of our analysis. The cost of knowledge has a strong and significant negative effect on labour productivity for micro and SMEs while is not significant for large companies. The result of the interaction variable elaborated to account for the role of imitation externalities and of the exploitation complementarity between internal and external knowledge is positive and significant for micro and SMEs while is not significant for large companies. The size of firms is significant and positive only for large firms while is negative and significant for micro-firms. Finally, the control of the capital intensity shows a positive impact on productivity, as expected, while the *ln(R&D/Empl)* variable is never significant.

To further check the robustness of our results, we also divided sampled firms according to their technological intensity: medium-high-tech (MHT) vs high-tech (HT) firms. Table 8 presents the estimation results of equation (8) for the different sectoral categories. Results of both categories are consistent with the results for the full sample. In particular, the cost of knowledge has a strong and significant negative effect on labour productivity for both HT and MHT firms. The effects of the multiplicative complementarity between internal and external knowledge used to account for the role of imitation externalities and their exploitation complementarity with internal research and learning efforts are instead positive and significant only for the group of MHT firms. Also the size of firms is significant and positive only for MHT firms. Also in these estimations, the control of the capital intensity exhibits the expected positive role while the *ln(R&D/Empl)* variable is not significant in any of the estimations.

Table 7 and 8 about here

These results are quite important as they provide a set of coherent and consistent clues that confirm that imitation externalities are most important for small and medium size firms, especially in medium-high-tech sectors. Exploitation complementarity is confirmed for these firms. Large corporations in all sectors, together with smaller firms active in high tech sectors, rely less on the multiple mechanisms of knowledge and imitation externalities. The internal generation of knowledge plays a stronger role and, consistently, the indirect effects of upstream knowledge externalities in terms of reduced knowledge costs, exert a stronger role than imitation externalities.

These results might suggest the hypothesis that large corporations and smaller firms in high tech sectors enjoy the indirect effects of the advantages of knowledge externalities made available in the system by scientific institutions. Small and medium size firms active in medium-high-tech sectors rely much more on imitation externalities than on knowledge externalities. The access to knowledge ready-to-be-used-again plays a much stronger role. Hence the horizontal dissemination of knowledge among smaller medium high-tech firms, including competitors, is more important than the vertical flows of knowledge that support the knowledge generation activity of corporations and high tech smaller firms.

6. CONCLUSIONS AND IMPLICATIONS FOR FURTHER RESEARCH

The analysis of effects of knowledge spillovers in the knowledge generation function and in the technology production function has been implemented by two quite separated fields of investigation. The simultaneous analysis of the role of external knowledge in both the upstream generation of knowledge and in the downstream production of all the other goods yields important results paving to way to a fertile and integrated field investigation.

This approach has enabled to identify, highlight and test some important specifications. Spillovers yield knowledge externalities when they provide knowledge inputs –at costs below equilibrium- that enter as inputs in the upstream generation of knowledge and imitation externalities when they enable to access knowledge-ready-to-be-used-again –at costs below equilibrium- in the downstream technology production function. External knowledge is qualified by generation complementarity when it is an indispensable input strictly necessary for the generation of new knowledge. External knowledge is qualified by exploitation complementarity when it is an indispensable input in the technology production function, strictly necessary to exploit the internal stocks of knowledge.

This approach has enabled to elaborate an augmented version of the CDM approach that takes advantage of it systemic frame and operationalize the analysis of the multiple effects of the access to knowledge spilling in the system testing the hypotheses that external knowledge i) supports the upstream recombinant generation of new technological knowledge with the provision of cheap knowledge inputs and ii) consequently helps reducing the cost of knowledge used downstream to produce all the other goods; and iii) enables the imitation of technological knowledge introduced by other firms, but ready to be used again. The extension of the CDM approach with the introduction of the analysis of knowledge costs has enabled to explore simultaneously the role of the stock of knowledge internal and external to each firm both in the technology production function and in the knowledge production function.

The empirical analysis, based upon a panel of Italian companies in the period 2005 – 2009, has been articulated in a system of equations. After the prediction of R&D expenditure for non-reporting firms, the innovation equation has enabled to assess the positive effects of firms' size, internal and external knowledge stocks on the firm probability of patenting. The econometric model with the productivity on the right hand side, and on the left hand side the unit costs of patent and the stock of external knowledge fully confirmed our hypotheses.

In the Italian case spillovers engender knowledge externalities that do play a significant and direct role in the knowledge production function. The consequent reduction of knowledge costs affects in turn the downstream production of all the other goods with a positive and strong effect on labor productivity. The expected direct effects of spillovers in the technology production function, in terms of imitation externalities, moreover, are also confirmed. The effects of knowledge externalities are direct in the former and indirect in the latter via the reduction of the costs of knowledge.

The results of the simultaneous test of the role of spillovers in a system of equations that includes a knowledge production function and a technology production function suggest that the role of spillovers should be reconsidered in an integrated framework that enables to study their effects both direct and indirect in the upstream production of knowledge and the downstream production of all the other goods. The extended CDM model, augmented by the inclusion of knowledge costs to analyze the triple role of spillovers, seems to be a useful methodological contribution that enriches its analytical capability.

The focus on the analysis knowledge costs, their determinants and their effects seems useful to implement the CDM approach, and more generally to identify the twin role of spillovers as carriers of a) knowledge inputs that can be used to generate new knowledge and b) knowledge ready to be used again and to take into account jointly the effects of knowledge and imitation externalities and the mechanisms and channels by means of which they exert their effects on productivity levels.

The results of the analysis carried out in this paper confirm and actually augment the understanding of the important role of the twin positive externalities stemming from the limited appropriability of knowledge. The appreciation of the relevance of both knowledge and imitation externalities is important both to implement strategic decision making at the firm level, and policy-making. At the firm level it seems most important to take into account the effects of a wide array of conducts, in terms of access to knowledge and imitation externalities, including not only the choice of the location of plants and offices, but also the opportunities provided by user-producer interactions both downstream with customers and upstream with the providers of inputs, and by the mobility of skilled personnel. At the policy level, more attention should be paid to interventions aimed at increasing the access and use of external knowledge spilling in the system.

Further research is clearly needed on this issue. In particular, extending the research to other countries would allow for more heterogeneity in both firms and regional characteristics and further check the robustness of our results. A cross-country comparison would allow generalizing our findings.

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