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Carillo, Maria Rosaria, Papagni, Erasmo and Capitanio, Fabian

Università degli Studi di Napoli, Parthenope, Seconda Università di Napoli, Università di Napoli Federico II

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Maria Rosaria Carillo,* Erasmo Papagni** and Fabian Capitanio***

* Università degli Studi di Napoli, Parthenope,

Istituto Studi Economici,

Via Medina 40, 80133, Napoli, Italy.

tel:081/8284044,

e-mail:carillo@unina.it, carillo@uninav.it.

** Seconda Università di Napoli,

Corso Gran Priorato di Malta, 81043, Capua, Italy.

e-mail: erasmo.papagni@unina2.it

*** Università di Napoli Federico II and University of York

Dipartimento di Economia Agraria,

Via Università, Portici, Italy,

e-mail : capitani@unina.it

Abstract

Recent economic research has focused on the economic effects of the social environment. In the economic literature, important phenomena are considered, at least in part, as results of the individual's social environment. There is a similar revival of interest among economists who analyse the world of science and basic research. In this case as well, the environment plays a key role in the agent's behaviour. This paper makes an empirical analysis of the influence of social interactions on scientists' productivity. In the econometric analysis we investigate the aggregate importance of this phenomenon through the analysis of data on publications in four scientific fields of seven advanced countries. We find that social interactions among researchers have positive effects on a scientist's productivity and that there is a U-shaped relation between the size of a scientific network and individual productivity. We interpret this result as providing evidence for threshold externalities and increasing returns to scale.

Keywords: scientists' productivity, increasing returns in science, social interactions.

1. Introduction

Recent economic research has focused on the economic effects of the social environment (see, e.g., Ackerlof, 1997; Durlauf and Young, 2001; Durlauf, 2004). In the economic literature, important phenomena such as educational choice, labour market participation and crime behaviour are considered, at least in part, as results of the individual's social environment.

Indeed, in such a framework, individual decisions depend on those of others who are in its neighbourhood or in the same social group due to the influence of social interactions among agents[1].

This paper aims to analyze the influence of social interactions on scientists' productivity. In this respect, we investigate the aggregate importance of this phenomenon by analysing data on publications in four scientific fields of seven advanced countries.

The hypothesis of social interactions in science finds support in economic and sociological literature which stresses the importance of both collective norms and network structure in basic research. Actually, the rules of full disclosure of new finds and their evaluation by peers make basic research a collective enterprise which often is referred to as Invisible College (David, 1998). Linkages among scientists have been investigated by several scholars (e.g., Laband and Tollison, 2000; Newman, 2001; Rosenblat and Mobius, 2004; Goyal et al., 2006) who find the important evidence of the emergence of a small world in science characterized by one large component, within which social distance among researchers is very small, and other small components, that are quite isolated. Within the giant component formal and informal connections among scientists are very important.

To specify the econometric model, we also refer to some theoretical propositions from Carillo and Papagni (2007) where a model of growth with social interactions in basic research is put forward. In this model a large group of researchers endowed with heterogeneous talent are engaged in a contest: the first to publish a new result in the field wins a prize. This event occurs with a probability that depends on individual effort and on the effort and ability of the other researchers.

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[1] Social interactions or non-market interactions are defined as interactions among agents which are direct and not mediated by prices (see Manski, 2000 and Glaeser and Scheinkman, 2000). A clearer definition has been provided by Brock and Durlauf (2001), as follows: "social interactions we refer to the idea that the utility or pay-off an individual receives from a given action depends on the choices of others in that individual's reference group" (Ibidem, p. 235). A similar revival of interest is growing among economists who analyze the world of science and basic research (Stephan, 1996). In this case as well, the environment plays a key role in the agent's behavior. In common parlance their world is often referred to as the "scientific community", stressing both its segregation and the importance of the group.

Social interactions among scientists are embedded in a CES index of effort and talent of the community of researchers. The equilibrium solution of the model tells us that a scientist's productivity depends on the social environment in terms of community size and quality of colleagues. Moreover, the model shows the relation between the size of a scientific network and the scientist's productivity can be non-monotone, with a section of the curve in which increasing returns emerge.

Econometric investigation of data on articles for the fields of engineering, medicine, natural sciences and social sciences in seven advanced countries during the period 1988-2001 shows that scientists productivity depends on research in the same field performed in other countries and on research done in other fields by scientists in the same country. Hence, regressions show significant externality effects of basic research. Scale effects and increasing returns also find support in the regressions of publications per scientist as a quadratic function of the size of the scientific community by country which highlight a U-shaped relation, first decreasing and then increasing.

We believe that our results add to the scant literature on environmental effects on the productivity of scientists. Some other interesting contributions come from sociology. Allison and Long (1990) investigate the effect of university departments on publication productivity with individual data and find that causality runs from department to scientist productivity.

Long and McGinnis (1981) find similar results with reference to larger organisations such as universities. A recent interesting contribution to the issue from the world of economics comes from Carayol and Matt (2006) who study the determinants of publication productivity of faculty members of Louis Pasteur University. They find evidence that the quality of colleagues in laboratories positively affects individual performance. Carayol and Matt also deal with the issue of the size of the research organization but find evidence for decreasing returns to scale in the science sector.

All the above papers provide important evidence for the influence of the environment, narrowly defined as the department, universities, etc., upon research, but do not deal with the wider context of the scientific community as exemplified by the notion of Invisible Colleges (David, 1998). Our paper seems closer to Adams and Griliches (2000) who estimate a production function of articles and citations on data from USA universities broken down by field. They estimate returns to scale and find a value lower than one, but admit that their model does not consider the effect of research externalities between fields and across countries.

The paper is organized as follows. In section 2 we deal with the literature that emphasizes several forms of social interactions in science and their consequences for its productivity. Section 3 contains the econometric analysis, followed by our conclusions in section 4.

2. Norms of open science and social interactions among scientists

Social interactions among researchers are a key factor for scientific knowledge production due not only to unintentional externality effects, which often arise in knowledge production, but also the norms[2] which regulate the institution of open science (David, 1988). These render scientific production not so much the result of a single researcher's effort, but rather the outcome of a cognitive process which involves the whole scientific community.

The first norm is communalism, by which a researcher identifies with the community of scientists. Communalism allows science to run as a collective enterprise where everyone is expected to share knowledge with others. The second norm is universalism, by which the scientific community is open to all persons of competence regardless of their personal and ascriptive attributes. Two further norms are disinterest and originality: the former reinforces communalism, while the latter establishes that only the first discoverer of new knowledge obtains a reward. This method of assignation of the reward, labelled by the sociological literature as the priority rule, makes scientific production a winner takes all contest and gives scientists powerful incentives to innovate because rewards, both in terms of recognition and resources, invariably accrue to those who discover things first (Merton, 1957; Dasgupta and David, 1994). The last norm is scepticism, by which all contributors are subject to critical analysis and a new discovery is accepted as a new scientific proposition only when this process of revision has occurred.

All the above norms stress the importance of social interactions among scientists which occur within the scientific network. Communalism, for example, emphasises the co-operative nature of inquiry, stressing that the accumulation of reliable knowledge is a social process. Another consequence of communalism is the full disclosure of findings and methods (Dasgupta and David, 1994), which forms a key aspect of the social and communal program of inquiry. Indeed, full disclosure makes disseminating and publishing the results of research particularly intense.

Thus the social nature of scientific production becomes more effective since it makes new ideas available to the whole scientific community.

Moreover, full disclosure legitimates what Merton called organized scepticism, which supports the expectation that all claims will be subjected to trials of replications and verifications. The norm of scepticism affects the capacity of the entire scientific community to attain scientific closure (David, 2004) which is the emergence of a preponderant consensus concerning the validity or invalidity of particular scientific propositions.

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[2] These were mainly analysed by Merton (1957) and labelled with the acronym CUDOS.

Summing up, social interactions which occur within the scientific community make scientific production possible, since they promote the circulation and creation of new ideas and the attainment of scientific closure upon a new scientific proposition.

2.1 Effects of the size and features of scientific networks on scientists' productivity

As we have seen, social interactions are a prerequisite for scientific production. It is thus important to understand what features of scientific networks favour the occurrence of social interactions among researchers.

One factor is the size of the scientific network: the larger the number of scientists, the more likely they are to interact by participating in conferences, seminars, research groups, etc. Moreover collaboration between researchers, which is a particular form of social interaction, is favoured by a large scientific community because of a sort of a thick market externality by which, in a thick scientific market, it is easier to find a scientist to collaborate with. The implication is that the size of the scientific network may have a positive effect on the average productivity of the science sector.

However, norms which regulate academia entail not only collaborative relations among peers, but also competitive ones. Indeed, as we have stressed, another fundamental norm is originality which ensures that only the first discoverer obtains the reward for innovation.

This method of assigning rewards engenders particularly intense competition among scientists, given that the higher the number of other researchers, the lower the probability of a researcher being the first to arrive at an innovation and then to obtain the reward for it. This effect may reduce the effort of a single researcher and consequently his/her productivity.

The above considerations imply that the size of the scientific network may have ambiguous effects on the average productivity of the sector, since on the one hand larger scientific networks imply greater social exchange among researchers with positive effects on their productivity. On the other, a large number of researchers increases competition, with negative effects on the productivity of the single researcher. If the positive effect of social interactions prevails, there could be increasing returns to scale, in the sense that there will be a positive relation between the size of the sector and its average productivity. Otherwise, if the competition effect prevails, there could be decreasing returns to scale by which the productivity of the individual researcher decreases as the size of the sector grows.

The empirical literature on scientific research seems to confirm the prevalence of increasing returns to scale. Cole and Phelan (1999), for example, find a positive relation between number of scientists and the average number of highly cited articles per scientist[3]. Aizman and Noy (2007) investigate the extent to which scale effects account for countries' share of major prizes (such as Nobel, Fields and Kyoto). They find that the relation between the lagged GDP of a country, which is positively linked to investment in research, and its share of prizes can be explained by a quadratic function with positive parameters: above a certain threshold there is a ”take off” range, where the share of prizes increases at an accelerating rate with the relative GDP share of the country. This finding would confirm the hypothesis of the existence of a threshold effect and positive returns to scale linked to network externalities.

Besides the size of scientific networks, it might reasonably be expected that also the manner in which researchers interact with one another affects the amount of social exchange due to social interactions and, hence, their productivity. For example, frequency and distribution of social interactions among agents change the intensity of social exchanges within networks of the same size: several and more equally distributed interactions increase the social exchange among scientists. In addition, homogeneity or heterogeneity is an important factor, as high homogeneity makes scientific closure easier to attain, although it may have perverse effects on creativity[4]. Recently, several papers have appeared which analyze the evolution of scientific networks for different scientific disciplines in terms of size and structure[5].

Many authors (Albert and Barabasi, 2002; Goyal et al., 2006 and Rosenblat and Mobius, 2004) have found an apparent trend toward a marked increase in the size of scientific networks and a reduction in the social distance between researchers. Goyal et al. (2006), for example, by running an empirical analysis on economists, found that the size of this network grew substantially over the period 1970-2000, while the number of non-collaborating economists declined sharply. They interpret these findings as evidence that the scientific network of economists is expanding and at the same time the social distance between them is diminishing, with a consequent increase in social exchange. This trend is generally explained by the sharp reduction in communication costs made possible by new information technologies (Kim, Morse and Zingales, 2006 and Rosenblat and Mobius, 2004).

[3] More interestingly, the correlation index between the two variables was 0.86 for 24 industrialized countries and 0.55 for a whole sample which also included less developed countries.

[4] Heterogeneity may favor creativity since more different ideas can be combined to obtain new ones (on this point see Weitzman, 1998).

[5] See Albert and Barabasi (2002), Ravasz and Barabasi (2003), Newman (2001) and Watts and Strogaz (1988) for medicine, physics and computer science, Grossman, (2002) for mathematics, Goyal et al. (2006) and Rosenblat and Mobius (2002) for economics.

Although this literature provides interesting insights - both applied and theoretical - into the phenomenon of social interactions in scientific production, a general theory is still missing. In the next section we summarise the main arguments of a recent paper by Carillo and Papagni (2007) which aims at the theoretical analysis of social interactions in science in a general equilibrium model. This model provides some guidelines on the questions of the presence of increasing returns and externality effects in basic research that will be useful for defining of the econometric analysis which follows in section 3.

2.2 A model of scientific production

In several respects, the model of scientific production presented here follows the paper by Carillo and Papagni (2007), which analyses the effects on scientific production and growth rate of the economy produced by social interactions arising between scientists who belong to the same scientific community. Following Carillo and Papagni (2007), we assume that the scientific production consists in a contest where each scientist participates with other researchers to be the first to attain a new result. The winner of this race is awarded a state funded monetary prize. The state funds scientific research since knowledge is a pure public good which improves productivity in the rest of the economy. Another major assumption is that the research environment has an important influence on scientists' productivity due to collective norms in the science sector.

More particularly, we assume that the science sector is made up by a continuum of agents, indexed by $i \in [0,1]$, who are endowed with skills denoted by $\delta_i \in [\delta_l, 1]$. Talent is distributed in the population according to a distribution function $F(\delta)$. In each period the number of potential discoveries is limited and assumed equal to one. This assumption implies that the innovative race is such that a number of researchers greater than one seek the same innovation, even if only one of them will be the first to do so and obtain the reward[6].

This type of contest successfully captures what happens in the scientific world, where innovations or advances in a scientific discipline are limited, and scientific communities are often engaged with problems on which there is consensus as to their importance for advancing scientific knowledge.

As we have already highlighted one important norm in science is the priority rule which only the first who arrives at an innovation gains the reward for it. Hence, we assume that each researcher participates in a collective contest where only the first to obtain the innovation has the reward *m*.

[6] A race of this kind arises only when the number of innovations is limited: otherwise, each researcher would seek to produce a different innovation in order to maximize his/her chances of obtaining the reward (Zeira, 2003).

The arrival of a new idea in the whole scientific sector is uncertain and has probability *S*, while the probability that, if an innovation occurs, individual *i* is the first discoverer is denoted by q_i. Hence, the probability of success of an individual researcher is given by the probability that an innovation arrives in the sector multiplied by the conditional probability that the first innovator is the i_{th} individual

$$p_i = q_i S \qquad (1)$$

The conditional probability that the i_{th} individual arrives at an innovation q_i depends directly on the resources that the individual researcher devotes to his/her research, denoted by $h_i = e_i\delta_i$ where e_i is effort, and it is an inverse function of the resources, denoted by *H*, that all other researchers devote to that same research activity: $q_i = \frac{h_i}{H}$. This implies that probability q_i can be expressed as:

$$q_i = \frac{e_i\delta_i}{\int_{\delta_l}^{1} h(\delta)dF(\delta)} \qquad (2)$$

Hence, in this model, the greater the amount of resources that other researchers invest in the job, the lower is the conditional probability that scientist *i* is the first to discover the innovation. This negative relation captures the intensity of competition in scientific races and is defined as the *competition effect*.

Another crucial assumption concerns the probability of the event "one innovation occurs in the science sector", which is assumed to depend on social interactions in terms of the exchange of knowledge among researchers. This probability may depend on two aggregate dimensions of basic research which should affect social interactions: one is the size of the scientific network, because the larger the number of agents, the more likely are interactions and collaborations that reduce the social distance among them. The other dimension is the quality of social interactions, because more frequent and more equally distributed interactions increase the social exchange among scientists within a given network. Such externality effects which arise in the context of basic research can be summarized in a CES index function of scientists effort and talent:

$$S = s\left[\int_{\delta_l}^{1} h(\delta)^{\frac{\chi-1}{\chi}} dF(\delta)\right]^{\frac{\chi}{\chi-1}} \qquad (3)$$

This indicator[7] captures both the effect of network size, and also the effects of changes in the intensity of social exchange within a given network. In fact, when $\frac{1}{\chi} > 0$, individual resources invested in research are complements and the network structure experiences low social exchange since the high *h* individuals cannot easily transfer their knowledge to less talented scientists, thereby reducing the average level of *h*. When $\frac{1}{\chi} < 0$, individuals are substitutes and the social exchange is high since the most talented scientists may more easily transfer their knowledge to the low *h* types, thereby pulling the average level of *h* upward.

In every time period scientists participate in the contest for a new find by choosing the value of effort. This decision relies on maximizing the expected utility that is made up by the utility from consumption and disutility from effort on the job as follows:

$$u_i = mp(e_i, \delta_i, R, \bar{e}) - de_i, \qquad (4)$$

where $R = 1 - \delta_l$ is the size of the research sector, $\bar{e}$ is the effort of the other researchers and *m* is the monetary reward from an innovation. From the utility function it is easy to derive that the optimal value of e_i depends positively on the reward from an innovation and on the probability of success of an individual researcher. In turn the latter p_i depends positively on the resources invested in research by the individual scientist. In conclusion, all variables that influence p_i, also affect the productivity of a single researcher, either due to their direct effects, or because they induce an increase in the effort employed in this activity by the individual researcher. From equations (1), (2), (3) p_i is given by

$$p_i = \frac{e_i \delta_i}{\int_{\delta_l}^{1} h(\delta) dF(\delta)} s \left[\int_{\delta_l}^{1} h(\delta)^{\frac{\chi-1}{\chi}} dF(\delta) \right]^{\frac{\chi}{\chi-1}} \qquad (5)$$

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[7] This indicator was used by Benabou (1996a and 1996b) to capture the influence of social interactions on the formation of local human capital, while in the case analyzed here, the influence of the environment on the probability of achieving an innovation represents a social capital typical of the research sector that can benefit all those who belong to it.

From this equation, it is easy to see that the probability of a success of an individual researcher, which captures the basic research productivity, is affected by two main effects of opposite sign: the competition effect, which reduces the probability p_i and hence also the incentive to effort, and the social interactions effect, which may increase it. The latter effect may be strong in environment made up by agents with substitute characteristics, while it is more likely to be low in communities where researcher interactions are made difficult by cultural or communication factors. These two effects are also influenced by the size of the research sector; in the two integrals in the above equation are both affected by the size of the research sector given by $1-\delta_t$. This implies that the probability of a success of a single researcher, hence the average productivity of the science sector can be a non-monotone function of the number of researchers entering the race because, on one side, it not only reinforces competition among researchers, but it also increases the opportunities for social exchange in the scientific community. If competition effect prevails, there will be decreasing returns to scale, in the sense that average productivity declines as the number of scientists increases, if social interactions effect prevails there will be increasing returns to scale with an increasing average productivity as the number of researchers increases.

Hence, this paper underlines the channels through which social interactions can cause increasing returns to scale in science sector but leaves to empirical analysis the task of identifying and quantifying such relationships. Actually, these results seem consistent with the evidence found by Aizenman and Noy (2007) and by Cole and Phelan (1999), by which increasing returns to scale in the science sector mainly occur in more developed countries, which have also more developed science sectors.

In the following section we will investigate the relation between size, average productivity of the science sector and the quality of social interactions relying on international data on publications and expenditure on research by field. We summarize the main lines of the previous discussion in the following three hypotheses:

Hypothesis 1: Average productivity of basic research is an increasing function of scientists' remuneration;

Hypothesis 2: Social interactions in scientific networks are significant determinants of scientists' productivity;

Hypothesis 3: There could be a nonlinear relationship between average productivity of the science sector and its size, with increasing returns to scale if social interactions are strong enough.

3. Econometric analysis of scientific publications

In this section we present an econometric study of scientific production in four fields of some of the most industrialized countries. As is very common in the literature, the output of basic research is proxied by the number of articles (source: ISI-Thompson). Scientific production depends on the resources invested in the sector, while some indicators will be considered as proxies of the intensity of social exchange.

3.1 Econometric model

In order to test the main predictions of the model of scientific production we specify a nonlinear single-equation econometric model of the number of articles per researcher, *AP*, in which we include the following explanatory variables:

ARE: the ratio of basic research expenditure to the number of researchers;

RE: expenditure on basic research;

RE^2 : squared value of *RE*;

N: number of researchers in basic research;

N^2 : squared value of *N*;

SI: expenditure on basic research made by other countries.

Variables derive from data on: Higher Education Researchers, source OECD; Academic R&D Expenditure in USA $ at constant 1995 prices, source OECD[8].

We specify the basic equation to test the hypotheses 1-3. The first step is to estimate the relation between size and output in the science sector. We are thus able to evaluate the presence of nonlinearities and identify the sections of the curve where returns are increasing or decreasing. The quadratic term in this equation allows us to verify the existence of a threshold effect in the size

[8] The number of higher education researchers by field is unavailable. Hence, we calculated this variable by the product of the aggregate number of researchers by the share of R&D expenditure of each field.

variable. If the function of average productivity is U shaped, then we know that there is a minimum size above which increasing returns emerge.

In regression equations we alternate the variables *N* and *RE* as proxies of the size of the sector. The variable *ARE* approximates the average amount of resources that each researcher can count on in his/her job. It is meant to proxy for salaries that should provide incentives for the participants in scientific contests. The choice of this indicator depends on the lack of international data on wages in basic research.

In the second step we concentrate on estimating the contribution to scientific production of externalities deriving from social interactions. We use in regressions the following indicators: *SI* research expenditure in the same field made by other countries; *RE* research expenditure in other fields in the same country. The first variable is a proxy of scientific interactions which occur among scientists within the same field but across countries. The other variable is a classic proxy of knowledge spillovers, used in any econometric study of industrial R&D (e.g. Nadiri and Shankerman, 1989). It could also account for social interactions among researchers of affine fields.

As common in analyses of scientific production (e.g. Adams and Griliches, 2000), we assume a dynamic model to account for the complexity of the process of basic research. A general ADL version of the basic equation used in estimates looks like:

$$AP_{i,t} = \sum_{l=1}^{m} \alpha_l AP_{i,t-l} + \sum_{l=0}^{n} \beta_l ARE_{i,t-l} + \sum_{l=0}^{p} \gamma_l N_{i,t-l} + \sum_{l=0}^{q} \delta_l N^2{}_{i,t-l} +$$

$$+ \sum_{l=0}^{r} \lambda_l SI_{i,t-l} + \eta_i + u_{i,t}, \qquad (6)$$

$$i = 1,2,....7; \qquad t = 1,2,........T.$$

where η_i denotes country dummies and $u_{i,t}$ is a random i.i.d. perturbation. However, we are interested in the long-run determinants of basic research output whose importance can be appreciated by the long-run multipliers:

$$\Theta_R = \phi \sum_{l=0}^{n} \beta_l; \qquad \Theta_N = \phi \sum_{l=0}^{p} \gamma_l; \qquad \Theta_{N^2} = \phi \sum_{l=0}^{q} \delta_l; \qquad \Theta_{SI} = \phi \sum_{l=0}^{r} \lambda_l;$$

where $\phi = \left(1 - \sum_{l=0}^{m} \alpha_l \right)^{-1}$.

Direct estimation of eq. (8) is hindered by problems of collinearity among regressors and does not provide multipliers. Hence, we follow Wickens and Breusch (1988) who suggest several reformulations of the ADL equation that allow direct estimation of long-run effects. In particular, we chose the following reformulation:

$$AP_{i,t} = -\phi\sum_{l=1}^{m}\alpha_l(AP_{i,t} - AP_{i,t-l}) + \Theta_R ARE_{i,t} - \phi\sum_{l=0}^{n}\beta_l(ARE_{i,t} - ARE_{i,t-l}) +$$

$$+\Theta_N N_{i,t} - \phi\sum_{l=0}^{p}\gamma_l(N_{i,t} - N_{i,t-l}) + \Theta_{N^2} N^2{}_{i,t} - \phi\sum_{l=0}^{q}\delta_l(N^2{}_{i,t} - N^2{}_{i,t-l}) + \qquad (7)$$

$$+\Theta_{SI} SI_{i,t} - \phi\sum_{l=0}^{r}\lambda_l(SI_{i,t} - SI_{i,t-l}) + \phi\eta_i + \phi u_{i,t},$$
$$i = 1,2,....7; \quad t = 1,2,........T.$$

which can be obtained by subtracting $AP_{i,t}\sum_{l=1}^{m}\alpha_l$ from each side of eq. (6).

3.2 Empirical results

Estimation of eq. (7) provides the same long-run multipliers as those obtainable from the ADL eq. (6) when the estimation method is Instrumental Variables with the set of instruments given by all the explanatory variables in the original equation (Wickens and Breusch, 1988). We adopted this strategy for several specifications of eq. (6).
A first-order autoregression of residuals provides a test of the null hypothesis of absence of autocorrelation that is invariant to the transformation of the perturbation $u_{i,t}$. After some preliminary regressions we chose a one-year lag for all equation specifications except one which required a lag of two years. The results presented in tables 1-3 show a very good fit of the estimated equations and the absence of error autocorrelation. Table 1 presents the parameters of the basic equation (7) estimated on data for the sum of five scientific fields: engineering, medicine; agriculture; natural sciences; social sciences. The first column refers to the relation between average number of articles and size of the sector. Parameters of the number of researchers are both significant and lend support to the existence of a U relation with *AP*. Hence, the results confirm our hypothesis concerning the presence of a threshold above which larger scientific sectors imply greater productivity of researchers. The variable *ARE* which is a proxy for wages, enters this equation with a parameter that is not significant. The aggregate value of this variable may well not approximate for scientists' salaries, while other kinds of effects could be captured by the size variable.

The third column in table 1 presents parameters of the same equation augmented with *SI* the amount of research expenditure made by other countries. This variable enters the equation with a significant positive parameter, meaning that there is a positive social interactions effect in scientist productivity. Hence, research carried out by individuals in different countries flows to the international community through several channels. Of interest is also the analysis of country fixed effects which can be interpreted with reference to the influence of factors specific to the national organisation of science. Indeed, both regressions in table 1 show a clear hierarchy among the seven advanced countries considered. USA and Japan present the highest value of fixed effects followed by Germany and the UK, while Italy and Canada occupy the lowest position in the ranking.

Hence, although our model captures significant features of scientific production in these countries, it shows that there are other important phenomena such as the traditional involvement in research, the production of human capital, etc. captured by country-dummies.

Table 2 presents the regression results for engineering and medicine where the proxy variable of the size is the amount of research expenditure *RE*. We also investigated the effects of research carried out in other fields in the same country. Both these regressions show many significant parameters, high goodness of fit and the lack of residual autocorrelation. The relation between size and scientist productivity found for all fields is confirmed in these two cases. Also, there is confirmation of the strong statistical significance of the research efforts by other countries, even at the field level. The novelty with respect to the aggregate estimates is made by the investigation of relations with other fields. In this respect, we found a negative and significant effect of research performed in natural sciences on productivity both in engineering and in medicine, revealing that in these cases the competition effect prevails, which is probably due to the overlapping of issues investigated.

Country-fixed effects tell us that in these two fields the USA has a much more productive research system than others. The high value of the parameter for France in medicine confirms what is well known: the established tradition of this country in the field.

In table 3 the estimated parameters of article production in social sciences and natural sciences are shown. Even though the equation of the first field presents a high goodness of fit, it shows worse results than those found in previous regressions. Variables that approximate for social exchange do not enter the equation with significant parameters. This result comes as no great surprise since this field contains distinct disciplines as literature and law that are naturally rooted in the culture of each country.

However, the non-linear relation between size *RE* and output is confirmed by significant coefficients, meaning that other causes of increasing returns may be relevant in the field.

The third column in table 3 shows the results of the regression on data of natural sciences. In this case, the best specification is that without country dummy variables. Most of the variables enter the equation with significant parameters. Size and productivity show the same relation as before. Quite interestingly, there is a negative effect of the research in the field done by researchers in other countries, meaning that the competition effect prevails over those of social interactions. Also of interest is the positive linkage between research output in natural sciences and research expenditure in medicine. In this case, it seems that medicine provides the field of natural sciences with knowledge which is more basic and positively affects its scientific production.

It can be noted that in regressions by field the variable *ARE* always assumes significant and positive estimated parameters. Hence, it seems that the average amount of resources per researcher at field level provides a good approximation of the monetary incentives for scientists' productivity.

4. Conclusions

In this paper, we addressed the question of the presence of increasing returns in scientific production due to the effect of social interactions. Econometric analysis of data on publications of scientists in seven advanced countries in the fields of engineering, medicine, natural sciences and social sciences in the period 1988-2001 shows a nonlinear model that describes a U-shaped relation between articles per scientist and size of the basic research. Scientists' productivity is positively affected by the research carried out in other countries in the same field. Interactions among fields also arise from the regression results, hinting at the importance of knowledge exchanges due to social interactions also among researchers working in different fields.

These results provide quantitative information on the effects of social interactions in academic research and on the conditions for increasing returns. The reason for the emergence of increasing returns only in an aggregate level should be investigated by further research on the specific ways in which scientists interact in the community. Existing research on Invisible Colleges may provide several insights into the issue that could be tested with more appropriate data. Moreover, this phenomenon still requires theoretical analysis in greater depth that could benefit from the applied research.

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Table 1- Regressions of the number of articles per researcher. Four fields of science

Dependent var. AP	*Parameter*	*Student's t*	*Parameter*	*Student's t*
	*(1)**		*(2)***	
$AP_t - AP_{t-1}$	-7.075	-3.32	-5.334	-3.57
$ARE_t - ARE_{t-1}$	0.148	2.21	0.110	3.30
ARE_t	-0.018	-0.87	-0.037	-1.93
$N_t - N_{t-1}$	-1.091	-2.90	-0.824	-2.91
N_t	-0.350	-3.75	-0.434	-4.88
$N^2_t - N^2_{t-1}$	0.026	2.96	0.019	2.96
N^2_t	0.007	3.22	0.009	4.36
$SI_t - SI_{t-1}$			0.001	0.47
SI_t			0.001	2.01
USA	5.242	4.33	5.834	5.67
JAP	4.512	3.98	4.758	5.25
GER	2.908	3.99	2.905	5.17
CAN	1.884	4.09	1.744	4.93
ITA	2.004	3.66	1.832	4.42
FRA	2.507	3.87	2.443	4.93
UK	2.655	4.51	2.615	5.79
R^2	0.79		0.87	
ρ	-0.136	-1.29	-0.133	-1.24
Observations	91		91	

* The estimation method is Instrumental Variables with instruments given by the dummy variables and the variables *ARE, N,* N^2 taken at the time *t* and *t-1*; three time-dummy variables have been included; ρ is the parameter of a first-order autoregression of residuals.

** The estimation method is Instrumental Variables with instruments given by the dummy variables and the variables *ARE, N,* N^2, *SI* taken at the time *t* and *t-1*; three time-dummy variables have been included; ρ is the parameter of a first-order autoregression of residuals.

Table 2- Regressions of the number of articles per researcher. Engineering and Medicine.

Dependent var. AP	*Parameter*	*Student's t*	*Parameter*	*Student's t*
	*Engineering**		*Medicine***	
$AP_t - AP_{t-1}$	-3.811	-2.88	-6.087	-3.24
$ARE_t - ARE_{t-1}$	0.255	2.87	0.563	3.19
ARE_t	0.089	7.23	0.118	6.31
$RE_t - RE_{t-1}$	-0.557	-2.68	-0.354	-2.45
RE_t	-0.183	-4.01	-0.131	-3.14
$RE^2_t - RE^2_{t-1}$	0.007	2.43	0.002	1.83
RE^2_t	0.002	3.45	0.002	3.66
$SI_t - SI_{t-1}$	-0.006	-0.55	0.016	0.98
SI_t	0.007	2.40	0.008	2.37
$REnat._t - REnat._{t-1}$	0.054	1.64	0.098	1.32
$REnat._t$	-0.041	-3.13	-0.190	-2.79
USA	6.557	5.15	15.535	4.27
JAP	3.022	4.04	3.272	3.55
GER	1.979	3.99	3.823	3.50
CAN	0.418	1.36	0.346	0.73
ITA	0.629	1.75	1.742	2.29
FRA	1.704	3.57	5.102	3.04
UK	1.398	3.63	3.965	3.88
R2	0.89		0.87	
ρ	-0.105	-0.93	0.019	0.17
Observations	91		91	

* The estimation method is Instrumental Variables with instruments given by the country dummy variables and the variables *ARE, RE,* RE^2, *SI*, *REnat.* taken at the time *t* and *t-1*; ρ is the parameter of a first-order autoregression of residuals.

** The estimation method is Instrumental Variables with instruments given by the dummy variables and the variables *ARE, RE,* RE^2, *SI*, *REnat* taken at the time *t* and *t-1*; six time-dummy variables have been included; ρ is the parameter of a first-order autoregression of residuals.

Table 3- Regressions of the number of articles per researcher. Social Science and Natural Science.

Dependent var. AP	*Parameter*	*Student's t*	*Parameter*	*Student's t*
	*Social Science**		*Natural Science***	
$AP_t - AP_{t-1}$	-4.115	-3.75	-20.107	-5.06
$AP_t - AP_{t-2}$	1.441	3.20		
$ARE_t - ARE_{t-1}$	0.015	0.42	0.397	3.26
$ARE_t - ARE_{t-2}$	-0.007	-0.27		
ARE_t	-0.009	-0.92	0.056	4.87
$N_t - N_{t-1}$	-1.411	-1.54	-5.263	-3.73
$N_t - N_{t-2}$	0.317	0.55		
N_t	-0.740	-3.60	0.491	4.07
$N^2_t - N^2_{t-1}$	0.001	1.62	0.004	2.96
$N^2_t - N^2_{t-2}$	-0.0002	-0.55		
N^2_t	0.0005	3.42	-0.0008	-3.05
$SI_t - SI_{t-1}$			-0.036	-0.71
SI_t			-0.016	-2.00
$REmed._t - Remed._{t-1}$			-0.0001	-0.53
$REmed._t$			0.00004	2.02
USA	250.961	7.84		
JAP	262.387	3.44		
GER	114.111	3.40		
CAN	91.854	3.82		
ITA	62.649	2.57		
FRA	62.679	3.22		
UK	107.99	4.26		
R2	0.97		0.28	
ρ	-0.182	-0.017	-0.137	-1.27
Observations	84		91	

* The estimation method is Instrumental Variables with instruments given by the country dummy variables and the variables *ARE, N,* N^2, taken at the time *t, t-1* and *t-2*; ρ is the parameter of a first-order autoregression of residuals.
** The estimation method is Instrumental Variables with instruments given by the dummy variables and the variables *ARE, N,* N^2, *SI*, *REmed* taken at the time *t* and *t-1*; ρ is the parameter of a first-order autoregression of residuals.