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Funding incentives, collaborative dynamics and scientific productivity: Evidence from the EU framework program

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ABSTRACT

In this paper we examine how incentives for collaboration shape collaborative behavior and researcher productivity in the context of EU-funded research networks. EU-funded research networks require researchers to collaborate as a condition for securing research funding. The presence of research funding, therefore, may influence collaborative behavior. Our approach involves isolating the effects of funding, collaboration and previous collaborations (prior to funding) on research output, and examining how the pattern of collaboration affects research productivity over time. Employing a panel of 294 researchers in 39 EU research networks over a 15-year period we find that while the impact of funding on productivity is generally positive the overall impact of collaboration within the funded networks is weak. When we delineate between pre-, during- and post-funding periods, however, we find some important differences. During the period of funding, collaboration did not lead to an increase in research production. In the post-funding period we find that although the number of collaborations decreases within the network, the impact of collaboration on productivity is positive and significant. Our findings suggest that collaborations formed to capitalize on funding opportunities, while not effective in enhancing researcher productivity in the short run, may be an important promoter of effective collaborations in the longer run.

1. Introduction

The idea that collaboration between researchers is a laudable goal is accepted and promoted by many policymakers. EU science policy, which aims to foster the "overall advancement of knowledge" and to create a European Research Area (ERA), is focused on the importance of networks and collaboration as a means to achieve these objectives (Commission of European Communities, 2006). Consequently, EU-funded research networks require researchers to collaborate as a condition for securing research funding. The aim of the funding is to foster both collaboration and to enhance researcher productivity. This policy is based on the assumption that the impact of funding on researcher productivity is expected to derive, at least partially, from the collaboration among partners.

Existing research has focused on the effects of collaboration and funding, but only as independent determinants of research productivity (De Beaver and Rosen, 1979; Durden and Perri, 1995; Landry et al., 1996; Arora and Gambardella, 1996; Hollis, 2001; Godin, 2003). However, the underlying processes linking funding, collaboration and research productivity are highly complex and are yet to be conceptualized in a coherent and widely accepted framework.

Collaboration is viewed as playing an important role in enhancing productivity both through sustaining the process of knowledge creation and as a means to increase the division of tasks and achieve scale economies in research activity (Katz and Martin, 1997; Adams et al., 2005). Existing studies suggest that the effect of collaboration on productivity depends on the characteristics of the relationship, which shape the ability and the motivations to share resources and knowledge among different partners. These studies also highlight that a condition for effective collaboration is balancing the integration of new knowledge with the management of existing relationships (Porac et al., 2004). Therefore, whether the funding opportunity is able to sustain and/or enhance this balance is an important issue for policymakers.

Funding is viewed as having a strong positive effect on productivity because it provides access to research resources rather than because of its impact on collaboration (Lee and Bozeman, 2005).

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It is unclear, however, whether the impact of funding on research collaboration improves researcher productivity.

In order to understand the relationship between collaboration and productivity we need to account for two different effects. First, we need to consider the impact of collaboration on productivity. Second, but contemporaneously, we need to consider the impact of funding on collaboration, which may depend on the characteristics of the collaborative relationship at the moment the partner receives the funding. Consequently, it is not possible to examine how research funding influences the relationship between collaboration and productivity without taking into account how collaborative structures change over time, including the pre-funding and post-funding periods. To date, these issues remain unresolved.

In this paper our contribution is to analyze the effectiveness of collaborative structures in the context of EU research networks by examining the relationship between research collaboration and research productivity when funding is a moderating factor. Our approach addresses the limitations of existing research in two ways. First, we develop a model that isolates the effect of funding as an opportunity to gain resources from its effect on researcher productivity through collaboration. Second, we account for how patterns of collaboration evolve and affect researcher productivity over time.

Our paper is organized as follows. Section 2 outlines the policy context. Section 3 reviews existing research into the determinants of research productivity and the underlying factors that shape the impact of collaboration on productivity. We present our analytical model in Section 4. Section 5 outlines data and methods. Section 6 presents our analysis. Finally we conclude.

2. Policy context

The Framework Programs for Research and Technological Development (Framework Programs) are funding programs created by the EU to support and encourage research in European countries and to create the European Research Area. The detailed objectives and actions vary from one funding period to another depending on different EU Framework Programs. However, the strategy adopted for supporting the development of modern research in a global environment has not changed over time. All EU Framework Programs are rooted in the idea that high level research can be achieved through organizing and strengthening co-operation at different levels, through networking teams and increasing the mobility of individuals and ideas. Collaboration is viewed as being particularly important because high level research is increasingly complex, interdisciplinary, costly and requires (an ever increasing) critical mass to be conducted effectively.

Since the first Framework Program (1984–1987), EU funding criteria explicitly require, as a pre-requisite for accessing the selection procedure, researchers to be self-organized into a collaborative network. However, they are not required to have established prior collaborations. In this respect, each network may include partners who have already worked together prior to gaining funding and those who have not. Therefore, a funded network only defines a formal structure of collaboration, it *does not* imply any pre-funding linkages among the partners. The scope of EU-funded research networks is to combine scientific and technological assets, and to create the conditions for different stocks of specialized knowledge to be transferred across organizations, research groups, and countries (Porac et al., 2004). The purpose of the network is to facilitate the sharing of research resources and, as a formally organized and coordinated structure, to sustain knowledge sharing among partners. The aim of the funding is to enhance the research potential of participants through the benefits of collaboration.

The interaction between partners in a funded network may nevertheless imply different forms of resource and knowledge sharing. Partners in a network may share knowledge through seminars, workshops and conferences and by working together on a research project. As a consequence, their collaboration may include both tangible outputs such as books, patents and articles, and intangible benefits from the interactions. Moreover, the interaction may result in different forms of collaboration that include either strengthening past relationships or creating new ones. Each funded network, therefore, may have different characteristics in terms of the history of the relationships among partners and motivations to collaborate. These characteristics may influence the effectiveness of the collaboration and the potential impact of the funding.

3. Determinants of researcher productivity

Interest in the determinants of researcher productivity dates back to the 1920s and the work of Lotka (1926). Researchers attempting to explain research productivity have focused on a range of factors including: individual researcher characteristics, the academic environment, dynamics of academic careers, the reward system of science and, more recently, on patterns of collaboration. We review these different explanations of researchers' productivity below.

3.1. Traditional approaches to research productivity: individual level and research system reward structure

An early explanation of differences in researcher productivity was that it could simply be a reflection of the substantial predetermined differences among scientists in terms of their natural ability, motivations, and "inner compulsions" to solve the research puzzle even in the absence of external recognition (Cole and Cole, 1973). This hypothesis, known as the "sacred spark" hypothesis, has not provided a compelling explanation for the differences observed in researcher productivity (Allison and Stewart, 1974; Fox, 1983; Stephan, 1996; David, 1994). There is no clear evidence to suggest that abilities are distributed as unequally as publications across scientists. Moreover, even if predetermined differences among individuals could explain some differentials in research performance, they cannot explain increasing differences over the careers of cohorts of scientists (Stephan, 1996).

More recently, scholars have investigated the impact of researcher experience and the characteristics of their working environment on researcher productivity (e.g. the quality of graduate training and the reputation of institutional affiliation). Empirical results based on samples of U.S. researchers and institutions consistently support the positive role played by graduate pre-doctoral training (Reskin, 1977; Long et al., 1979; Chubin et al., 1981) and the prestige of the institution in explaining differences in researcher productivity (Long et al., 1979; Long and McGinnis, 1981). Furthermore, scholars have examined the productivity differences stemming from life-cycles of researchers. These studies typically examine how individuals invest in their human capital over time (Levin and Stephan, 1991; Allison and Stewart, 1974). Following this approach, Levin and Stephan (1991) found that after controlling for individual fixed effects, such as ability and motivations, publishing activity declines with age.

Departing from the analysis of individual differences, sociologists have examined the impact of social structures on research activity, focusing on the role of reward systems in influencing researcher productivity. They argue that the recognition and validation of a researcher's contribution to their field, as accorded by scientific peers, are crucial determinants of research productivity. The "Matthew effect" refers to a problem of misallocation of credit for scientific work, where eminent researchers receive more credit than lesser known researchers, even if their work is similar, due to the nature of the reward system (Merton, 1968). Recognition early in a scientists' career may be reinforced over time as it will facilitate better access to research resources, grants, laboratories, etc., i.e. any advantage will be cumulative. Empirical studies of the effect of cumulative advantage suggest a positive link between past recognition (both in term of quantity and quality of publications), key resources and research productivity (Cole and Cole, 1967; Gaston, 1970; Blume and Sinclair, 1973; Allison and Stewart, 1974; Reskin, 1977).

3.2. Productivity and collaboration

Collaboration and networking have been argued to have a positive impact on researcher productivity (Mellin and Persson, 1996; Katz and Martin, 1997). Collaboration enables researchers to bring together different sets of knowledge and cognitive approaches (Stephan, 1996). The interaction between researchers is expected to lead to the creation of new knowledge (Nahapiet and Ghoshal, 1998), which in turn will enhance researcher productivity. A tension exists, however, between the need for breadth and depth in collaborative relationships (Uzzi, 1997; McFadyen and Cannella, 2004). The greater the number of collaborators in a network, the greater will be the opportunity for a researcher to access a variety of complementary knowledge and skills. Conversely, embedded relationships allow researchers to establish norms and routines that can facilitate collaboration and knowledge transfer throughout the network.

Empirical evidence on the relationship between collaboration and researcher productivity indicates the following. First, there is a positive relationship between the number of collaborations and researcher productivity (Pravdic and Oluic-Vukovic, 1986). However, McFadyen and Cannella (2004) suggest that this relationship is subject to diminishing marginal returns. In addition, Porac et al. (2004) find that the effects of heterogeneity from collaboration are temporal and diminish over time. Second, the duration of collaboration is positively related to researcher productivity (Porac et al., 2004). Focusing on researcher performance in two multi-university research networks funded by the U.S. government, their results show that, in the long run, researcher productivity increased in both networks although the increase was higher for the more heterogeneous network.

3.3. Productivity, funding and collaboration

There is ample evidence across empirical studies that research grants for individual researchers have a positive effect on individual productivity (Lee and Bozeman, 2005; Stephan, 1996); although the intensity of this impact varies depending on the stage of the career (Arora and Gambardella, 1996) and the amount of funding (Godin, 2003). An exception is the analysis of Gaugham and Bozeman (2002), where funding was not significantly related to an increase in publications. Also, many studies indicate that funding oriented towards research teams increases collaboration (Katz and Martin, 1997; Arora et al., 1998; Adams et al., 2005). Conversely, the impact of funded collaboration on research productivity is less clear. One exception is the work of Arora et al. (1998) who found that while funding for research groups decreased team productivity, collaboration would not have occurred without the funding. Their study supports the view that the funding opportunity is a strong motivator for collaboration. Due to the cross-sectional nature of the model, the authors could not directly identify how initial productivity advantages accumulate over time and affect group productivity during the funding and post-funding stages. Two methodological issues need to be addressed if the effects of funding *and* collaboration on researcher productivity are to be disentangled.

First, is the extent to which the impact of collaboration on researcher productivity is related to increasing co-authorship and, consequently, to what extent it depends on other forms of knowledge and resource sharing associated with the funding. In a recent study, Lee and Bozeman (2005) analyzed the relationship between research grants, collaboration, and researcher productivity using a sample of researchers from science and engineering. Modeling the grant as a mediating factor between collaboration and researcher productivity they analyzed the impact of funding on collaboration and the impact of funding on productivity, but omitting to consider the impact of funded collaboration on researcher productivity. Their results indicate that funding is positively related to productivity *and* collaboration. Nevertheless, whether and how the relatively lesser impact of funding on collaboration consequently affects researcher productivity is not clear from their study.

Second, is the impact of pre-funding relationships on researcher productivity. In particular, it is important to identify the extent to which the effect of collaboration on productivity is due to funding *or* merely to the pre-funding trend in collaboration. Although funding may add value, and may allow researchers to continue existing collaborations that otherwise could have been more difficult without funding, it cannot be assumed that the funding necessarily enhances researcher productivity.

The following section develops a framework to analyze the effectiveness of EU-funded research networks that addresses these issues.

4. Analytical model

A central aim of EU research policy involving the funding of research networks is to promote collaboration between researchers across different EU countries.[3] The networks are expected to provide the opportunity for researchers to access and integrate a wide variety of knowledge in order to facilitate the creative process and enhance productivity. For purposes of this study we focus on collaboration within a restricted group of researchers who formally constitute a funded network only after their projects were funded by the EU.[4] All researchers in our sample were awarded the same EU grant, and hence, are similar in terms of reputational status and research excellence. In the absence of a control sample, this creates a potential selection bias problem. Consequently, past performance becomes a relevant variable in our analysis for two reasons. First, past performance may affect current performance due to the "cumulative advantage" hypothesis. Second, past performance defines the level of reputation required to attract public funding. As long as the funding agency bases its selection criteria on researcher reputation, which is a function of past research performance, it follows that past performance is part of the selection bias.

The central aim of our research is to examine the relationships between funding, collaboration and researcher productivity, and how they change over time. We are interested in whether or not collaboration within the funded networks influences the productivity of researchers (in terms of their publication output), after controlling for the effect of the funding. Our approach, as outlined below,

[3] As a condition for accessing the funding, the network should include at least five different institutions from at least three different countries.

[4] For some research projects, funding support includes the reimbursement of the costs of the project including the cost of managing the project, the cost for durable equipment, and all personnel costs for those involved in the project, including their travel and subsistence (for example, projects promoted within the EURATOM program or in the field of Biotechnology). Other forms of support provide the funded partners of the network with a grant up to 100% of the cost for hiring researchers in the early stage of their career, for organizing conferences and meetings that involve the other partners of the network (this is the case for the Research Training Network Program).

involves controlling for fixed effects (skills, country and scientific fields), a range of covariates, including whether there was collaboration within the network before the funding and past performance. Model 1 is our base model, in which we jointly estimate the effects of funding and collaboration on researcher productivity over the 15-year period of our study. Model 2 is our full model, in which we split the collaboration variable into three periods: pre-funding, during- and post-funding.

4.1. Model 1: the base model

In our base model, the relationship between funding, collaboration and research productivity, taking into account fixed effects and past publication performance, is given by Eq. (1):

$$Publ_{it} = \alpha_P(Pub_{i,t-1}) + \alpha_T(Publ_{i,t-2}) + \beta_R Rel_{\_it,1} + \theta_C Country + \theta_F Fund_{it} + \theta_Y Years + \beta_T Trend + \beta_E Expos_{it} + (\eta_i + \varepsilon_{it}) \quad (1)$$

where: $i = 1, \ldots, N$; $t = 1990, \ldots, 2004$; and i denotes the cross-sectional unit and t the time period.

The frequency distribution of the dependent variable ($Publ_{it}$) is left-skewed so we log transformed it to normalize the distribution. Hence, *Publ* is the logarithm of the number of publication per year per researcher ($Publ_{i,t-1}$) is the logarithm of the number of publications produced in the previous year and ($Publ_{i,t-2}$) the publications produced 2 years before. The variable Rel_{it} identifies the collaborative pattern of each researcher in the network during the whole period, from 1990 until 2004. This variable identifies the overall effect of collaboration in the funded network, including the pre- and post-funding period, when the network can be seen only as an informal structure. The variable *Fund* is a dummy specifying the period during which each researcher received funding. *Years* is a dummy variable for each year from 1990 to 2004 and *Trend* captures the effect of the passing of time. *Expos* is a variable for the length of the funding period. *Country dummies* include a range of dummy variables for the major scientific countries and also smaller countries by region. The equation also includes two stochastic disturbance terms: η_i captures all unobserved time constant factors that affect the dependent variable ($Publ_{it}$) and is thus related to the unobserved heterogeneity of the individuals; while ε_{it} is the idiosyncratic error, or time-varying error, and represents the unobserved factors that change over time and affect $Publ_{it}$.

4.2. Model 2: full model

Existing research indicates that funding is a strong motivator of collaboration (Katz and Martin, 1997; Arora et al., 1998). If EU policy is effective in promoting collaboration we would expect to see an increase in researcher productivity, both during- and post-funding. We address this issue in Model 2 and examine whether or not the relationship between collaboration and productivity changes before, during and after the funding period.

As noted above, in our policy context the funding agency did not require network partners to have any existing collaborative relationships, as evidenced by joint publication, in the pre-funding period. Although one of the selection criteria was the "quality of the collaboration", its assessment relates to the clarity with which the funding proposal articulated that "the collaboration will be meaningful, interactive and mutually beneficial for the researchers taking part" and there would be a "convincing explanation of how any less experienced teams will be integrated into the project" (Commission of the European Communities, 1996; European Commission, 2000). Where networks were formed to attract funding, in the absence of pre-funding collaborative relationships (i.e. no joint publication output), it may take longer to achieve effective collaborations when compared to networks with pre-funding collaborative relationships (i.e. joint publication output). Members will need to build trust in order to exchange knowledge effectively (Uzzi, 1997) and new collaborations are difficult to create and manage (Landry and Amara, 1998). Moreover, the requirement in EU projects for partners to be drawn from multiple different countries may exacerbate any potential problems and reduce the effectiveness of the networks in enhancing knowledge creation and sharing (Luukkonen et al., 1992; Katz, 1993). Consequently, the impact of collaboration on researcher productivity may be influenced by the existence of pre-funding collaboration.

We are also interested in during- and post-funding effects of the collaborative activity. The policy objective was to foster collaboration through funding, the aim of which is to enhance researcher productivity. Funding may be a key input into helping build more effective collaborations, which is especially important given the international nature of the collaborations. If funding helps to build more effective relationships between researchers, which may take time to achieve, we might expect to find the effect of collaboration to be strongest in the post-funding period.

In Model 2 (see Eq. (2)) we split the collaboration variable into three elements: collaboration prior to the funding (*Pre_rel*), collaboration during the funding (*Fund_rel*), and collaboration after the funding (*Post_rel*). By doing so we are able to examine the impact of funded collaborations on research output more precisely by controlling for the pre-funding effect of collaboration within the informal network.

$$Publ_{it} = \alpha_P(Pub_{i,t-1}) + \alpha_T(Publ_{i,t-2}) + \beta_A(Pre\_rel_{it}) + \beta_F(Fund\_rel_{it}) + \beta_P(Post\_rel_{it}) + \theta_C Country + \theta_F Fund_{it} + \theta_Y Years + \beta_T Trend + \beta_E Expos_{it} + (\eta_i + \varepsilon_{it}) \quad (2)$$

where: $i = 1, \ldots, N$; $t = 1990, \ldots, 2004$; and i denotes the cross-sectional unit and t the time period.

5. Data and method

In this section we describe the data, method and measures employed for the empirical analysis.

5.1. Data

Our empirical context is the research networks funded under the Research Training Network Program (RTN) of the 4th EU Framework. According to the requirements of the RTN program, a network is composed of at least five institutions (public and/or private) belonging to at least three different EU countries. In order to minimize bias related to field specific behaviors we selected only networks funded in the chemistry sector. We selected this sector for three main reasons. First, after physics, chemistry is the most important field in terms of the number of projects funded in the RTN program. Second, chemistry is a field where bibliometric analysis is applicable since international refereed journals play an important role in communicating results by the research community (Van Raan, 2004). Third, as we were interested in the potential role of industrial partners as collaborators in funded research networks, we chose chemistry because it is a field where there is connectivity between academia and industry.

We recognize, however, that chemistry differs from other fields both in terms of the extent of collaboration and productivity. In relation to the extent of collaboration, the number of co-authors per paper in chemistry is less than in many other fields such as medical science, bioscience, biology and biomedical research (Mellin and Persson, 1996; Glänzel, 2002; Newman, 2001). On the contrary, publishing productivity has been growing at a higher rate in chemistry compared to other fields (Braun et al., 1995; Okubo et al., 1998; Glänzel, 2002). Collaboration is not automatically associated with higher productivity at the level of individual authors. Glänzel (2002) also shows that the increase in productivity with collaboration follows a different pattern in chemistry compared to biomedical science and mathematics. In biomedical science productivity tends to peak with around six co-authors, in mathematics the peak is at one to two co-authors while in chemistry productivity peaks with three or four co-authors. Hence, an additional reason to select chemistry is that the lower incidence of collaboration may provide more scope for effective policy support for research networks. The presence of a high publication output in this discipline underpins our choice of this measure as the most appropriate means of identifying effective collaboration.

The funded projects considered in this analysis, were all classified as projects in the chemistry sector by the EU. This includes research projects in different sub-fields. Analyzing the subject fields of publication of all the partners involved in the network, we found that most publications were concentrated in the sub-fields of multidisciplinary chemistry, physical chemistry, physics (atomic and molecular), inorganic and nuclear chemistry, organic chemistry, biochemistry and polymer science. Moreover, we found that most of the papers published by partners belonging to the same network were concentrated on average within 2–3 sub-fields.

In total there were 39 funded networks in chemistry, involving 296 senior researchers. We included all principal contractors involved in the projects.[5]

The data relating to networks and their partners were drawn from the Cordis database. Cordis includes the list of the projects, the senior researchers in charge of each project funded by EU (other researchers participating in the project but funded by other institutions are excluded) and their affiliation.

The funding period varied in terms of starting date and duration across the networks. In terms of start dates there are three distinct groups, which were approved by different rounds of funding. The first group which includes 14 networks formally started its activities between July 1996 and October 1996. The starting period of the second group, which includes 10 networks, was between November 1997 and December 1997. Finally, a third group includes 15 networks of which 14 began between March and May 1998 and one that began from December 1998. The duration of the projects varied from 48 to 60 months. In total 27 of the 39 networks lasted 48 months, 11 were funded for a 60 months period and 1 for 53 months.

An important consideration in our analysis was the potential impact of a time delay between conducting research and publication of the results. Time delays are a function of both the set-up and coordination of the collaborative research activity, and of the review and publication process. We found that the publication delay in the field of chemistry varied from 8 to 18 months. In order to assess the magnitude of time delays including also the time to set up the project, we contacted a sub-sample of 15 networks.[6] We found for this sub-sample that it was rare for articles to be published within a few months from the starting period. Given this publication delay, we assume that articles published in the same year, or 1 year after the formal start of the project, are likely to be the output of a pre-funding research activity.

We also observed that many publications were in press, just submitted or in preparation at the end of the funding period. This suggests that some articles will still be published in the 2 years following the end of the project. Therefore, we assume a 2 year time delay from the starting year of funding in order to account both for the period for setting-up the networks and the project and the delay in publication. Our funding period, therefore, does not identify the formal start and ending date of the funding but refers to the period in which the output of those funded researchers could be considered to be funded.

Data on publications were collected from the ISI Thompson-Web of Science database. For each senior researcher we collected all articles published (in English) over a period of 15 years (from 1990 until 2004). Finally, we collected the CVs of principal contractors published on their institutional websites. We were unable to collect the same information for all principal contractors but we used the information on age and position for a sub-sample where information was available. This information guided us in making assumptions about publication trends and age effect. The final database contains a total of 23,649 articles published over 15 years by the 294 researchers. Table 1 presents the number of publications relating to the different researchers belonging to the three groups of networks before the funding and during the funding.

5.2. Method

To estimate both models we used the Arellano-Bond estimator for dynamic panel data (Greene, 2003) in its revised version by Blundell and Blond (Baltagi, 2002). The choice of estimator was driven by the opportunity to specifically control for the issues of heterogeneity and endogeneity that could affect scientific production.

The issue of heterogeneity emerges because scientific production is likely to be affected by systematic differences among individuals related to talent, skills, ability, etc. Endogeneity is a more complex issue, given that it can arise from the correlation of various dependent variables and the error terms. In the case of past papers production ($Publ_{i,t-1}$; $Publ_{i,t-2}$), endogeneity may arise from its correlation with the individual specific time-invariant effects (ex.: invariant skills) η_i. Correlation may also exist between collaboration Rel_{it} and the time variant error term ε_{it}. This can occur if the level of collaboration in the network is linked for example to the stage of the career of the researcher. In that case, this (omitted) variable would affect both productivity and also the opportunity to collaborate. Scientists in the late stage of their career could in fact have a higher experience in publishing scientific papers and also a higher level of attractiveness, because of their reputation, as collaborators for the other partners in the network. This specific issue is addressed by the Generalized Method of Moments (GMM) and more in particular by the Blundell–Bond estimator (Blundell and Bond, 1998). This estimation approach, also known as "system GMM", is considered to be more efficient than other GMM estimators because it allows the use of additional instruments which improve the estimation.[7]

Both models are estimated using the same set of instrumental variables (GMM and IVs). These include a set of exogenous and a set of endogenous instruments. The dummy variable for the funding period (*Fund*), the *Trend* variable and *Expos* are considered as exogenous and instrumented in IV-style. To this must be added the variable *Rel* lagged three and four periods. Finally we used the lagged values of the dependent variable as endogenous instruments.

We employ the two-step variant of linear GMM for standard errors estimation. As two-step estimates of the standard errors

[5] Two of these networks include among their partners industry practitioners who have no publications during the 15 years window.

[6] We attempted to obtain this information directly from all network coordinators. This approach was problematic because it was not possible to establish a direct contact with all network coordinators. In addition, even when we could access the official document (the Final Report) reporting the research activity and output of the network, a substantial number of publications were still under submission.

[7] The set of instrumental variables includes the lagged levels and the lagged first differences of predetermined and endogenous variables.

Table 1
Articles published before and during the funding.

	Researchers involved	Pre-funding period[a]			Funding period[b]		
		Total number of publications	Average number of publications per year per net	Average number of publications per year per res.	Total publications	Average number of publications per year per net	Average number of publications per year per res.
Group 1							
48 Months	90				2931	73.27	9.22
60 Months	21	7298	57.92	13.37	1172	58.6	8.15
Total	111				4103	65.93	8.69
Group 2							
48 Months	50	4746	47.46	7.46	1649	52.47	8.19
60 Months	20/19[*]				1230	82.00	13.42
Total	70/69	4746	47.46	7.46	2879	67.23	10.61
Group 3							
48 Months	73	7805	47.18	6.47	2251	56.75	7.78
60 Months	40				1388	69.40	8.85
Total	113	7805	47.18	6.47	3639	63.07	8.31

[*] One of the partners was dropped from the panel in 1999.
[a] Group 1 (1990–1998). Group 2 (1990–1999). Group 3 (1990–2000).
[b] Group 1: 48 months (1999–2002), 60 months (1999–2003). Group 2: 48 months (2000–2003), 60 months (2000–2004). Group 3: 48 months (2001–2004). Group 4: 60 months (2001–2004).

tend to be severely downward biased, we performed the estimation including the finite sample correction to the two-step covariance matrix derived by Windmeijer which make the "two-step robust" variant of the estimation more efficient than the "one-step robust" one.

5.3. Measures

A definition of all variables used in the study, along with comments regarding their economic interpretation is presented in Table 2.

5.3.1. Dependent variable

Research productivity—Researchers widely agree that although it is not the only measure of research output, a count of publications in peer-reviewed journals is the best measure for two main reasons (David, 1994). First, it represents a tangible output of research activity in academia. Second, publications play a central role in the reward system of science where recognition and researchers' material rewards are linked to the disclosure of their findings throughout publications (Van Raan, 2004). Consequently, different studies show that peer assessment of researchers' activity (included the case of applicants for research grants) is strongly related to their publication count (David, 1994). Therefore, as a measurable indicator of the research output, we employed the number of publications per researcher per year. In addition to the normal count of the number of publications per year we also included, as dependent variable, the fractional or adjusted count of publications. The fractional measure accounts for the number of co-authors an individual has on each paper. Thus, if a paper is written by n co-authors, each author would be assigned $1/n$.

The frequency distribution of the cumulated number of publications from 1990 until 1996 is presented in Table 3. Only 3.25% of the sample had not published an article in a peer-review journal before the funding. Table 1 describes the distribution of publications in the pre-funding period and during the funding as defined earlier in Section 5.1. It shows that the average number of publications per researcher per year and per network increased during the funding period for the networks of group 2 and 3 as compared to the pre-funding period. Conversely, for the researchers included in group 1, the number of publications per year per researcher decreased in the funding period, though the publications per network per year increased.

5.3.2. Explanatory variables

5.3.2.1. Collaborative pattern. In order to measure the structure of collaboration we grouped all researchers by their funded network and then constructed an adjacency matrix indicating the existence or inexistence of collaboration between each pair, within each network, for each year from 1990 until 2004. Researchers collaborate in different ways; knowledge sharing and knowledge transfer may occur through formal and informal meetings and may range from simple advice to a commitment to a joint research project. Some collaborations may not produce any tangible outcome while others may involve a publication, as such not all forms of collaboration are easy to measure over time; indeed as noted below, we were unable to obtain data on informal collaboration. Accordingly, we measure collaboration in terms of whether or not two researchers have co-authored a paper. Although collaboration may take a number of forms, a key outcome is a co-authored paper. In order to measure the degree of collaboration of each partner within the network, we then calculated the degree of centrality for each partner in the network for each year. We measured the degree centrality as the number of ties or links each researcher has in the network (Wasserman and Faust, 1994). Degree centrality is here used to measure the individual level of collaboration as proxy for knowledge sharing and for the opportunity to access diverse resources. As our dataset includes networks of different size, we standardized the degree centrality for the size of the network (number of members of the network) less one. The measure of degree centrality, and hence, collaboration and knowledge sharing experience is given by:

$$C_{ij} = \frac{R_{ij}}{n_{j-1}}$$

where R is the number of different co-authors with whom the researcher i has collaborated in the network j, and n is the number of partners of the network j (size of the net). This measure of collaboration as the *number of different interactions in the network* (and *not* as *total number of co-authored publications* of each researcher with his network partners) avoids the problem of potential correlation between the variables measuring collaboration in the network and the number of publications (the dependent variable).

We then used this measure of collaboration (degree centrality) to assess the average impact over time of collaboration, and for determining the impact of collaboration in the three different periods: pre-, during- and post-funding. In summary the variables used to assess the role of collaboration are:

Table 2
Definition of variables included in the estimation.

Symbols	Description of the variable	Economic interpretation
Dependent variable		
Y_{it} = (ln)*Publ*	Number of publications per researcher *i*, at time *t*.	Proxy accounting for the quantity of knowledge produced by each researcher along time.
Independent variables		
Explanatory variables		
$Rel_{\_it}$	Number of different relations of co-authorship within the network for each individual *i*, time *t*.	This variable catches the effect of collaborating in the network. The number of *different* relationship (co-authored publication) is a proxy of the interaction with a “variety of knowledge”.
Pre_rel_{it}	Number of different co-authorship relations in the network in the pre-funding period.	This variable measures the impact of collaboration within the network, through access a “variety of knowledge”, in the pre-funding period.
$Fund\_rel_{it}$	Number of different co-authorship relations during the funding period.	This variable measures the impact of collaboration within the network, through access a “variety of knowledge”, during the funding period.
$Post\_rel_{it}$	Number of different co-authorship relationships after the funding period.	This variable measures the impact of collaboration within the network, through access a “variety of knowledge”, in the post-funding period.
Fund	Dummy variable assuming value 1 if the year of reference for publication falls into the funding period.	This variable identify whether the funding period is particularly relevant in explaining the quantity of publications produced.
Control variables		
(ln)$Publ_{i-1t}$	Lagged values of the dependent variables, i.e. number of publications produced 1 year and 2 years before the year of reference.	This variable controls for the effects on production due to the past, in this sense it incorporate the idea of the Matthew effect and for the level of reputation acquired.
(ln)$Publ_{it-2}$		
Y_90; *Y_91*; ...; *Y_04*	Dummy variables for each year.	It controls for the impact of eventual shocks exogenous (exp. funding period) along time and in particular years.
Expos	Exposure to the program.	It takes into account the number of years the researchers has been “exposed” to the funding.
Trend	Variable that account for the trend in time.	This variable control for the life-cycle performance.
Country dummies: *Great Britain*, *France*, *Germany*, *Central Europe*, *North Europe*, *South Europe* and *Residual*	Dummy variables for the 3 major scientific countries and also country groupings.	These variables control for the geographic location of the researcher.

Table 3
Cumulated number of publications before the funding (1990–1996).

Frequency class	% of the sample
0	3.25
1–50	65.33
51–100	24.19
101–211	7.23

(i) *Rel_*, collaborative pattern for the entire 15 years;
(ii) *Pre_rel*, collaborations in the pre-funding period;
(iii) *Fund_rel* collaborations during the funding period;
(iv) *Post_rel*, collaboration in the post-funding period.

In the second stage of our analysis, Model 2, the pre-funding structure becomes a control variable. Descriptive statistics related to collaboration in the networks are presented in Table 4. In particular, they show that on average collaboration increases during the funding period and then decreases again after the funding. To illustrate the evolution of the publication networks we provide a graphical representation of Networks 5 and 7 in Figs. 1 and 2, respectively. During the pre-funding period Network 5 had two collaborative relationships (Fig. 1a), which increased during the funding period (Fig. 1b) before tailing off again in the post-funding period (Fig. 1c). Post-funding links comprise a co-authorship between original partners and a relationship created during the funding. In contrast, during the pre-funding period Network 7 already involved a network with six interlinkages (Fig. 2a), which increased during the funding period (Fig. 2b). In the post-funding period the linkages became two collaborative relationships involving reconfigured arrangements between the original partners and partners met during the funding (Fig. 2c).

5.3.2.2. Funding dummy. In order to test for the general impact of the program we define a dummy variable which assumes a value of one during the funding period and a value zero before and after the funding. As the relational pattern of collaboration is specified in the model, this variable represents the impact of the funding when the principal contractors of the network share knowledge and resources but are not involved in co-authoring papers.

It is worth noting that, because the starting period of the funding is different for the different groups of networks, the dummy variable does not take the value one at the same time for all the researchers included in the panel. For some of them (researchers in group 1) it takes a value of one from 1999; for the researchers included in group 2, the dummy takes a value of one from 2000 and finally, for researchers in group 3 it takes a value of one from 2001. The length of period for which this dummy variable takes a value of one varies according to the length of time each network was funded. Thus only during the years 2001 and 2002 were all researchers in the panel identified as being funded.

5.3.3. Control variables

5.3.3.1. Path dependency and cumulative advantage ($Publ_{t-1}$ and $Publ_{t-2}$). If the allocation criteria used by funding agencies are based on the reputation of the researchers, the past could have a strong impact on present publication activity. The cumulative advantage effect may affect the actual level of scientific production by researchers, independently from the incentives given by

Table 4
Numbers of relations (co-authoring) within the network by periods.

	Observations	Mean	Standard deviation	Min	Max
Pre-funding	2942	0.361	0.704	0	6
Funding period	1217	0.780	1.103	0	6
Post-funding	251	0.486	0.734	0	3

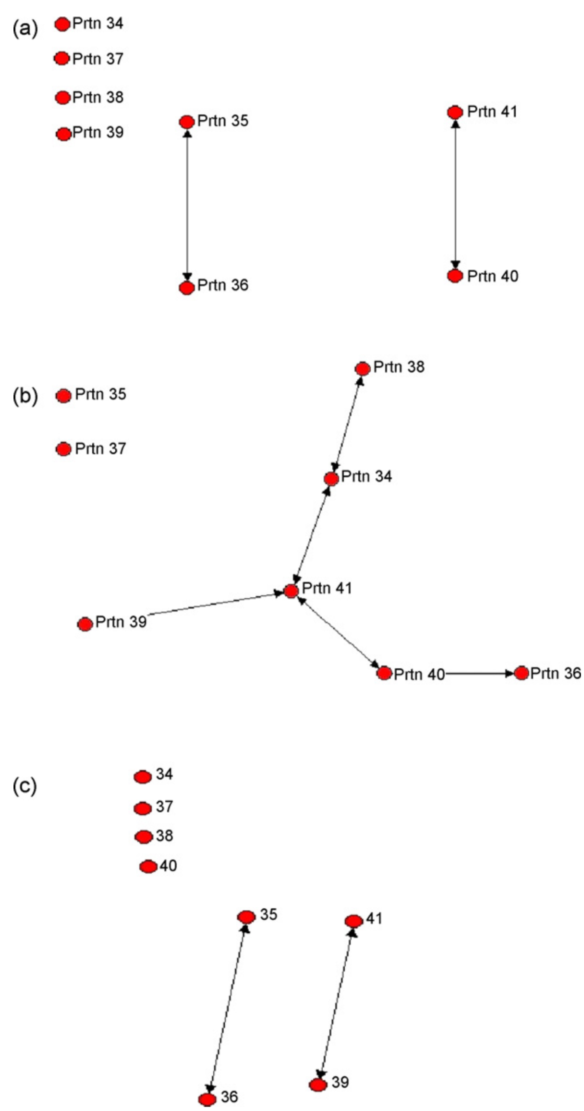

Fig. 1. Network 5 (a) pre-funding (1990–1998) co-authorship links; (b) funding (1999–2002) co-authorships links; (c) post-funding (2003–2004) co-authorship links.

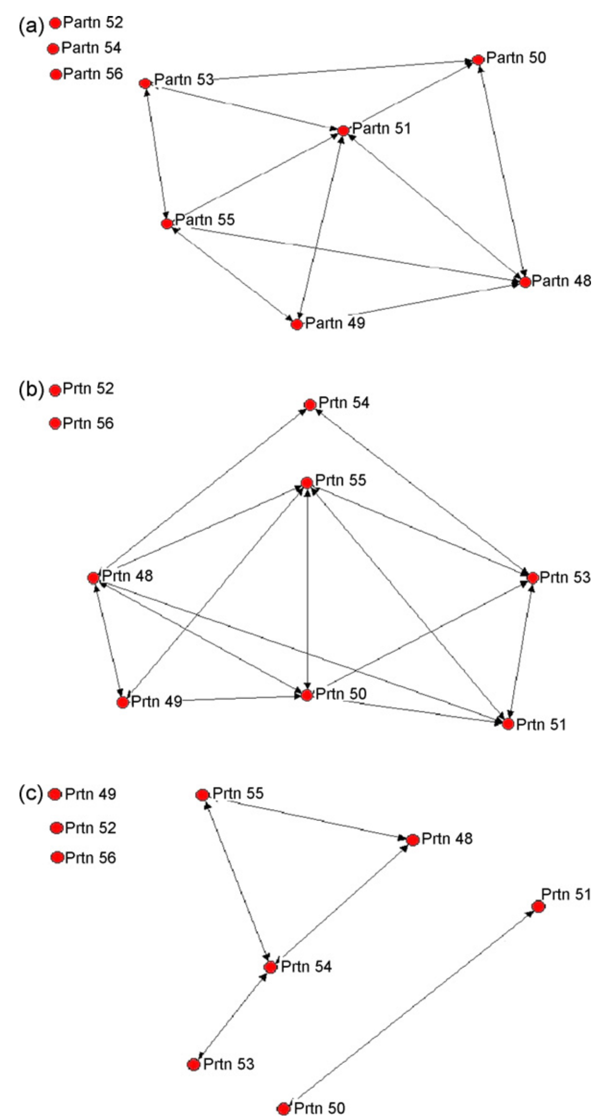

Fig. 2. Network 7 (a) pre-funding (1990–1998) co-authorship links; (b) funding co-authorship links (1999–2002); (c) post-funding (2003–2004) co-authorship links.

the funding (Arora et al., 1998). Therefore, we employ lagged values of the dependent variable, i.e. the number of publications per researcher per year in peer-reviewed journals, to control for any cumulative advantage effect. The past number of publications is, in this framework, a proxy for both past recognition and the stock of past knowledge.

5.3.3.2. Collaborative pattern within the formal network before the funding (Pre_rel). This variable captures the effect of collaboration on researcher productivity in the pre-funding period.

5.3.3.3. Trend. In order to capture the effect of time on publication performance we introduce a trend term. Studies focusing on the relationship between researcher productivity and age indicate that productivity decreases with age as academics move toward the end of their career (Levin and Stephan, 1991).

The trend in scientific publication is used to infer the stage of the career life-cycle of the researchers in the panel as a relevant dimension for interpreting their scientific performance. We can infer the stage of the career life-cycle of the scientists included in the sample from their past publication performance and from their role in the funded network. The researchers considered for the analysis have already published at the moment of receiving the grant (see: Table 3) and each of them is a principal researcher (institutionally representing a node) of the network. Moreover, based on a sub-sample of researchers where information was available we observed that their age ranged from 31 to 57 in 1990 (starting year of the study). As a consequence we expect that the researchers in the sample are mainly senior researchers (40s and early 50s) and so are either at the growing or declining stage of their research career at the moment of the funding and would likely be at the peak or toward the end of their career in the last years of the observation period. Hence, we expect the trend to be not significant or negative. In particular we expect a non-significant trend if the principal investigators are on average at the peak of their careers during the 15-year period.

5.3.3.4. Duration of the funding (Expos). A variable relating to the duration of the funding is introduced in the model to account for any differences in time periods across networks on researcher productivity.

5.3.3.5. Year. A dummy variable was created for each year in order to control for time effects.

Table 5
Model 1: dynamic panel data estimation of researcher productivity.

	Model 1a Dependent: Normal count of (ln)Publ	Model 1b Dependent: Fractional count of (ln)Publ
Control variables		
Past publications		
(ln)$Publ_{i,t-1}$	.243 (.040)***	.197(.036)***
(ln)$Publ_{i,t-2}$	.128 (.035)***	.105(.034)***
Country dummies		
Germany	.407 (.171)**	.515 (.239)**
France	.197 (.158)	.151 (.228)
Great Britain	.388 (.166)**	.487 (.236)**
North Europe	.295 (.162)*	.356 (.229)
Central Europe	.421 (.169)**	.473 (.235)**
South Europe	.214 (.156)	.190 (224)
Trend	.004 (.005)	.001 (.007)
Exposure	−.036 (.017)**	−.032 (.023)
Year dummies	Included (iii)	Included (vi)
Constant	.779 (.166)***	−.136 (.239)
Explanatory variables		
Funding dummy	.146 (.055)***	.169 (.083)**
Structure of collaboration (*Rel*_)	.252 (.126)**	.192 (.136)
Number of instruments	47	47
Wald test	Wald $chi^2(20) = 249.66$	Wald $chi^2(20) = 159.46$
Prob > *F*	0.000	0.000
Hansen test of overid.	$chi^2(25) = 22.49$	$chi^2(25) = 22.83$
Prob > chi^2	0.607	0.587
Arellano-Bond test AR(1) Prob > *z*	0.000	0.000
Arellano-Bond test AR(2) Prob > *z*	0.126	0.143

Robust standard errors in parentheses. Years significant are 1996; 1997; 1998 (positive coeff. and $p < .01$) and 2002 (negative coeff. and $p < .05$). Years significant are 1996; 1997; (positive coeff. and $p < .05$); 1998 (positive coeff. and $p < .1$) and 2002 (negative coeff. and $p < .1$).
* Significance level: $p < .1$.
** Significance level: $p < .05$.
*** Significance level: $p < .01$.

5.3.3.6. Country dummies. In total 21 different countries were represented in our data. In order to simplify the analysis we identified the countries which were best represented in the EU networks by number: *Great Britain* (55 researchers), *France* and *Germany* (45 researchers each). These countries also have the highest level of publications in the chemistry field among the EU countries (Braun et al., 1995). We grouped the remaining countries by region. Group 1 includes *Central European* countries such as Austria, Belgium, Netherlands and Switzerland. Group 2 includes *North European* countries such as Finland, Denmark, Sweden and Ireland. Group 3 includes *Southern European* countries such as Greece, Italy, Spain and Portugal. Group 4 is the *Residual Group* for those countries who only have one or two participants, which includes Hungary, Israel, Canada, USA and the Russian Federation.

6. Results

The results of the estimations for Eqs. (1) and (2) are presented in Tables 5 and 6 respectively, and include both normal and fractional output counts. For ease of interpretation we do not report all the year dummies in the tables.

6.1. Model 1

In Model 1 we jointly estimated the effect of funding and of the structure of collaboration on researcher productivity [normal count (Model 1a) and fractional count (Model 1b)] over the 15-year period, the results are presented in Table 5. We found that past production ($Publ_{i,t-1}$ and $Publ_{i,t-2}$) is positively related to researcher productivity (normal and fractional count). The impact of length of the funding period is significant but, contrary to expectations, negatively related to researcher productivity. *Trend* is positive in this model. The results indicate that funding has a positive and significant impact on researcher productivity, both in terms of the normal and fractional publication counts. Collaboration within the network over the 15-year period has a weakly positive effect on the normal count of research output, but has no significant effect on the fractional count of publications. Finally, in terms of the geographic location of the researcher, Great Britain, Germany and Central Europe were found to be positive and statistically significant at the 5% level for both the normal and fractional count analysis.

The validity (i.e. exogeneity) of the instrument set can be tested using standard GMM Sargan or Hansen tests of over-identifying restrictions. For the robust option, the Hansen test provides more efficient estimate. The null hypothesis of the Hansen test is that the variables used as instruments for the GMM estimation are not exogenous and are therefore not valid as instruments. For this reason we need a *p* value superior to 0.05 to refute the null hypothesis. The Hansen test for over-identifying restrictions indicates that for both estimations the instruments used for the estimation, as a group, are exogenous and thus can be considered as appropriate for the estimations. In addition, the Arellano-Bond test for first order autocorrelation indicates that there is no first order autocorrelation in the residuals. Finally, the Arellano-Bond test for second order autocorrelation does not allow us to refute the null hypothesis that some lags of the dependent variable, which have been be used as instruments, are endogenous. The test indicates that past publication performance, both in terms of normal and fractional count, as expected, is endogenous and the instruments are appropriate.

6.2. Model 2

In Model 2 we examined how funding and collaboration influence researcher productivity [normal count (Model 2a) and fractional count (Model 2b)] over time, see Table 6. We split the collaboration variable into three periods: pre-funding structure, funding structure and post-funding structure. By doing so we were able to capture the effects of collaborations in the pre-funding period and also to examine the productivity effects both during and after the funding period. The results for Model 2 are similar for the normal and fractional count of publications and indicate the following. First, collaboration in the pre-funding and during-funding periods did not significantly enhance researcher productivity. Second, post-funding collaboration is significant and positively related to researcher productivity. It is worth noting that this result is valid both when the dependent variable is the normal count of publications (Model 2a) and in the fractional count (Model 2b). More specifically, after the funding period, and following a decrease in the number of co-authors (see Table 4), collaborations have a positive effect on productivity. Third, the impact of collaboration is stronger than the impact of funding on researcher productivity, though only in the post-funding period. These results suggest that receiving funding increases researcher productivity by approximately 14%, while collaborating with a partner in the network in the post-funding period increases productivity by approximately 70%.

In terms of control variables and diagnostics, the variable for *Trend* is negative and the length of the funding period is not significant for increasing researcher productivity. The Hansen test provides strong confidence that the exogenous instruments are appropriate. The Arellano-Bond test for second order autocorrelation does not allow us to refute the null hypothesis of no second order autocorrelation. The estimation for the *Years* dummies indicates, for both the models and for both the normal and fractional

Table 6
Model 2: dynamic panel data estimation of researcher productivity.

	Model 2a Dependent: Normal count of (ln)Publ	Model 2b Dependent: Fractional count of (ln)Publ
Control variables		
Past publications		
(ln)$Publ_{i,t-1}$	.243 (.040)***	.197(.036)***
(ln)$Publ_{i,t-2}$	.126 (.035)***	.102 (.034)***
Country dummies		
Germany	.410 (.172)**	.523 (.243)**
France	.199 (.159)	.159 (.232)
Great Britain	.389 (.166)**	.490 (.239)**
North Europe	.295 (.163)*	.357 (.240)
Central Europe	.427 (.170)**	.483 (.239)**
South Europe	.215 (.157)	.193 (.228)
Trend	.000 (.006)	−.005 (.008)
Exposure	−.028 (.019)	−.018 (.026)
Year dummies	Included (iii)	Included (vi)
Constant	.801 (.167)***	−.114 (.241)
Explanatory variables		
Funding dummy	.143 (.058)**	.161 (.087)*
Structure of collaboration pre-funding (*Pre_rel*)	.199 (.173)	.130 (.198)
Structure of collaboration during-funding (*Fund_rel*)	.244 (.156)	.170 (.168)
Structure of collaboration in post-funding (*Post_rel*)	.661 (.327)**	.980 (.431)**
Number of instruments	49	47
Wald test	Wald $chi^2(22) = 250.20$	Wald $chi^2(22) = 164.30$
Prob > *F*	0.000	0.000
Hansen test of overid.	$chi^2(25) = 22.53$	$chi^2(25) = 22.29$
Prob > chi^2	0.605	0.619
Arellano-Bond test AR(1) Prob > *z*	0.000	0.000
Arellano-Bond test for AR(2) Prob > *z*	0.133	0.158

Robust standard errors in parentheses. Years significant are 1996; 1997; 1998 (positive coeff. and $p < .01$); 1999; 2000 (positive coeff. and $p < .1$) and 2002 (negative coeff. $p < .05$). Years significant are 1996; 1997; 1998 ($p < .05$).
* Significance level: $p < .1$.
** Significance level: $p < .05$.
*** Significance level: $p < .01$.

count cases, that some of the years of observation are particularly relevant for productivity. Those are just before the funding (1996) and at the beginning of the funding period (1997, 1998). These time effects could presumably be related to the incentive to publish induced by the announcement of the EU call. Finally, and as with the results for Model 1, the only geographic variables that were statistically significant at the 5% level across both the normal and fractional count estimations were Great Britain, Germany and Central Europe.

In order to assess the strength of our results for Model 2 we undertook two robustness checks. First, to assess the robustness of our results in relation to collaboration we re-estimated the models above with the funding dummy taking a value of 1 both during and after the funding period to see whether or not the post-funding collaboration effect persists. Second, we re-estimated the models after removing the funding covariate to see whether or not the effects of the contemporaneous collaboration variable and the post-funding collaboration became more sizable. The robustness checks, not reported here but available from the authors, confirm our previous results where post-funding collaboration is a significant determinant of publication output even when funding is supposed to last after the funding. Moreover when the funding variable is omitted the importance of the collaboration is enhanced as funded collaboration became statistically significant. The robustness checks suggest that there is some overlap between the funding and collaboration variables.

6.3. Extensions to Model 2

In order to better understand our results we performed three extensions of Model 2.

First, we examined the impact of geographic location on researcher productivity. We performed this analysis to examine whether or not researchers from specific countries benefited more than others from the EU networks. To test whether there is a country effect in the post-funding period we interacted the country dummies with a dummy for the post-funding period (the dummy takes value 1 in the post-funding and zero otherwise). Table 7 shows the results of the estimation. We estimated the model with both the normal (Model 3a) and fractional (Model 3b) count of publication as dependent variables. In terms of the normal count estimation we did not find any significant post-funding country effects, however, when we employed the fractional count as the dependent variable the post-funding country effects were positive and statistically significant for the three best represented countries in the program: U.K., France and Germany. These results can be explained by the average pattern of collaboration and of co-authorship across the countries. We found that, especially in 2004, researchers in the U.K., France and Germany had a relatively higher number of publications for a relative lower number of co-authors per paper as compared to the other countries. The average number of co-authors per paper is 3.2 for Germany, 4.2 for France and the U.K., 4.5 in North European countries and an average number of co-authors of 5.3 of Central and South European countries. These results suggest that it is those countries with the best developed science base that benefited most from the program because their researchers tended to work in multiple small groups instead of a fewer larger groups.

Second, we examined the impact of the number of countries involved in a network and its effect on researcher productivity. We conducted this analysis because we were interested in the extent to which the size of the network, in terms of the number of countries,

Table 7
Model 3: dynamic panel data estimation of researcher productivity: country effect in the post-funding period.

	Model 3a Dependent: Normal count of (ln)Publ	Model 3b Dependent: Fractional count of (ln)Publ
Control variables		
Past publications		
$(\ln)Publ_{i,t-1}$	.253 (.039)***	.211(.035)***
$(\ln)Publ_{i,t-2}$	.130 (.035)***	.104 (.033)***
Country dummies		
Germany	.393 (.171)**	.486 (.233)**
France	.183 (.158)	.134 (.224)
Great Britain	.367 (.163)**	.447 (.230)*
North Europe	.278 (.163)*	.309 (.227)
Central Europe	.420 (.168)**	.462 (.230)**
South Europe	.222 (.155)	.176 (.219)
Trend	−.013 (.015)	−.049 (.026)
Exposure	−.000 (.034)	.075 (.066)*
Year dummies	Included (iii)	Included (vi)
Constant	.856 (.185)***	.101 (.258)
Explanatory variables		
Funding dummy	.143 (.059)**	.171 (.086)**
Pre-funding coll. (*Pre_rel*)	.225 (.176)	.199 (.194)
Funding coll. (*Fund_rel*)	.242 (.156)	.166 (.165)
Post-funding coll. (*Post_rel*)	.601 (.340)*	.711 (.401)*
Post-Fund. × Country dummies		
Germany_post	.214 (.189)	.653 (.309)**
France_post	.309 (.215)	.710 (.327)**
Great Britain_post	.307 (.207)	.675 (.332)**
North Europe_post	.278 (.163)	.492 (.331)
Central Europe_post	.420 (.168)	.416 (.343)
South EU Europe_post	.222 (.155)	.376 (.310)
Number of instruments	55	55
Wald test	Wald $chi^2(28) = 264.42$	Wald $chi^2(28) = 185.08$
Prob > *F*	0.000	0.000
Hansen test of overid.	$chi^2(25) = 23.39$	$chi^2(25) = 21.85$
Prob > chi^2	0.555	0.644
Arellano-Bond test AR(1) Prob > *z*	0.000	0.000
Arellano-Bond test AR(2) Prob > *z*	0.140	0.231

Robust standard errors in parentheses. Years significant: 1996; 1997; (positive coeff. and $p < .01$); 1998 (positive coeff. and $p < .05$); 1999 and 2000 (positive coeff. and $p < .1$). Years significant: 1996 ($p < .01$); 1997; 1998 ($p < .05$); 1999 and 2000(positive coeff. and $p < .1$).
* Significance level: $p < .1$.
** Significance level: $p < .05$.
*** Significance level: $p < .01$.

may influence researcher productivity. To conduct this analysis we re-ran Model 2 including a variable for the number of countries in a network, and then again for the number of countries per network standardized by the size of a network. The results, not reported here but available from the authors, indicate that in both cases the variables were not significant and did not add any explanatory power to our model.

Finally, we extended Model 2 by including dummy variables for the different sub-fields in Chemistry. We assigned each researcher to a specific sub-field by observing the subject category of the journal where the majority of their publications were published. We identified 10 main sub-fields (organic chemistry; chemistry multidisciplinary; chemistry analytical; chemistry physics, material science; biotechnology; biochemistry; physics atomic, nuclear; polymer science and others) and introduced sub-field dummies in the estimation. The results, not reported here but available from the authors on request, indicate in the estimation of the full model (also including country effects) that there is no strong field effect on productivity. Only material science in the normal count estimation of the model has a positive effect, suggesting that researchers in that area are, on average, more productive than researchers in other sub-fields. On the contrary, in the fractional count estimation, material science is weakly statistically significant. These results need to be treated with caution, however, due to the small numbers of researchers in each field in the sample.

7. Discussion and conclusion

Our aim in this paper has been to further our understanding of the role of funded collaboration in enhancing researcher productivity. Specifically, our paper sheds light on the effect of funding on the relationship between collaboration and researcher productivity. Our approach enabled us to isolate different impacts of funding and collaboration on researcher productivity, and also to examine how collaboration may be influenced by the funding opportunity over time. The empirical context was EU-funded research networks under the 4th framework. Our analysis of a panel of 296 researchers reveals the following:

First, funding has a more significant direct influence on researcher productivity than collaboration within the network. Second, the effect of collaboration within the network is significant and positively related to researcher productivity only in the post-funding period. Third, although funding has a significant direct impact on researcher productivity, collaborations emerging in the post-funding period, have a stronger impact on researcher productivity. During the funding period there are more links within the network than before or after the funding.

These findings suggest that although the structure of collaboration changes in relation to the funding, it requires time to develop structures of collaboration that are effective in enhancing researcher productivity. Funding, therefore, may have an important role in enabling researchers to establish new collaborations but it does not, on average, create effective collaborations. The positive relation between post-funding collaboration and researcher productivity cannot, therefore, be interpreted as a direct consequence of the funding. Effective collaborations in this period are contingent on a different structure of interaction resulting from the funding period, which are characterized by a smaller number of interactions among the researchers of the network with presumably stronger relationships. Therefore, following Porac et al. (2004), it may be the underlying combination of variety of knowledge and depth of the relationship which is playing a major role in shaping effective collaboration in the post-funding period.

7.1. Limitations

As with all studies, there are limitations associated with our approach. In this study we have only focused on the named researchers involved in the funded networks. We suggest that future research should seek to build on our results to examine wider issues relating to policy intervention in a number of different ways.

First, future research should examine the wider network of relationships, including young researchers involved in the network. The advantage of such an approach is that we would then be able to better understand the impact of the funding on individuals who were starting their career.

Second, future research should include a control group of researchers that applied for the same funding but were not selected. Such an approach would provide a measure of the net impact of the funding in enhancing the effectiveness of collaboration as compared to non-funded networks, while controlling also for the effect due to selection bias.

Third, future research should examine informal aspects of collaboration. We have focused on publications as a tangible indicator of formal collaboration but collaboration may also be informal involving the sharing of knowledge through seminars, workshops, etc. and with intangible benefits. We attempted to collect data on these informal collaborations during the funding period but were unable to obtain this information.

Fourth, the amount of funding may be of interest for future research. We attempted to collect data on the amount of funding of each project but we were also unable to obtain this information. Further research could usefully incorporate such data to gain insights into policy effectiveness and we urge the EU to make such data available in future.

Fifth, to minimize potential bias, our study focused only on one scientific field, chemistry. However, since as noted above the chemistry sector tends to have lower collaboration but higher output than other sectors, further research should examine funding support for other fields to establish the generalizability of our findings.

Finally, our analysis focused on the effects of funding on output as the dependent variable, yet funding may also impact contemporaneous and future collaborations. Further research might usefully examine this outcome of funding by collecting further data on the set of relations of researchers and applying social-network analyses.

7.2. Implications for policymakers

Policymakers need to be able to assess the effectiveness of different support mechanisms, and to design more effective policy instruments. We suggest our research provides the following insights for policy development.

First, our results lead us to suggest that policymakers need to pay close attention to the nature of the pre-funding structures of collaboration since these can be a relevant variable for improving the effectiveness of funding schemes oriented to networks of researchers.

Second, although funding increases collaboration, its impact on researcher productivity is time contingent. Time is required for the collaboration to become effective. Our results suggest that policymakers need to recognize the time required to develop new collaborative relationships. Where there is no collaboration between parties in the pre-funding period, a longer period of support may be required to support the effectiveness of the new collaborative network. This suggest that in monitoring the effectiveness of support measures, policymakers need to consider the longer term effects in the post-funding period as there are substantial lags in establishing working networks and in publishing. Consequently, where policy support is explicitly short-term in nature, the existence of pre-funding collaborative relationships may be an important criterion for allocating funding.

Third, our work resonates with the debate relating to the role of public support for networks. Policymakers need to define structures of public support that are able to combine the individual incentive for research collaboration with the policy objectives of enhancing the research potential of researchers (Glanzel and Schubert, 2004) without creating coordination costs that are greater than the benefits of collaborative research (Landry and Amara, 1998). The choice of research partners in the EU framework may be determined by motivations that are not necessarily related to the benefits of the collaboration. Knowledge markets, both in terms of research collaborators and research commercializers, tend to favour producers that have well-established reputations. Therefore, collaborators with strong reputations may be selected in order to increase the probability of gaining research funding since reputation is generally assumed to be an important aspect of the selection criteria employed by the funding agency (David and Keely, 2003). The alignment of individual and policy objectives will help to improve the effectiveness of the policy intervention.

7.3. Conclusions

To conclude, the evaluation of policy intervention is complex. In our empirical context collaboration and funding are not independent determinants of researcher productivity. Our results demonstrate that the design and assessment of such policy interventions requires an appreciation of how collaborative structures change over time, notably during periods covered by pre-, during- and post-funding of research networks.

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