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Do collaborations enhance the high-quality output of scientific institutions?
Evidence from the Italian Research Assessment Exercise (2001-2003)

Maria Rosaria Carillo*, Erasmo Papagni**, and Alessandro Sapio***

Abstract

In this paper, we analyse the effects of research collaborations on the scientific output of academic institutions, drawing on data from the first official Italian research assessment exercise. We measure the scientific performance of a research unit as the number of publications that received an excellent grade in the evaluation process. Different aspects of scientific collaboration are taken into account, such as the degree of openness of a research team towards other institutions and/or other countries, the frequency of co-authorships, and the average size of a collaborating team. Using econometric models for count data, we find that collaborations are more effective when they imply knowledge exchange resulting from collaboration with external or foreign colleagues, are very frequent, and the collaborating teams have a small size.

Keywords: Academic departments; Productivity; Knowledge externalities

JEL codes: I21, D2

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1. Introduction

In recent years, scientific productivity has become one of the most important issues for economic policy, as witnessed by the growing number of studies on the part of economists and other social scientists. Central to this issue is the increasing trend in scientific collaborations both between individuals and organizations since the 1980s in all fields of research (Durden and Perri, 1995; Laband and Tollison, 2000; Beaver, 2001; Rosenblat and Möbius, 2004; Goyal et al., 2006). Much of this phenomenon has taken the form of co-authorship, which has increased sharply in recent years (Slaughter and Leslie, 1997; Laband and Tollison, 2000; Ziman, 2000; Gibbons et al., 1994; Adams et al., 2005; Wagner and Leyesdoff, 2005; Bammer, 2008), but there has also been a huge rise in other forms of co-operation which are less formal than co-authorship, such as visiting periods, conferences, and international scientific organizations, which have the same effect of massively boosting knowledge exchange and social interaction among researchers. Such increasing trend in cooperation not only takes the form of a huge rise in the several forms of collaborations, but it also extends to different levels: between researchers, whether they belong to the same department or to different departments, and between institutions, whether in the same country or across borders (Katz and Martin, 1997; Kalaizidakis et al. 2004; Adams et al. 2005).

This increasing trend in collaboration is favourably viewed by policy makers. Indeed, most governments have launched initiatives, such as bringing researchers together in large new centres of excellence and financing research projects carried out by universities of different countries, with the aim of developing collaborations among individual researchers, departments and universities[1]. Implicit in these policies is the belief that a higher level of collaboration will boost research productivity both at the individual and institutional level. Nevertheless, there is no clear consensus in the literature as to whether or how an increase in collaboration raises productivity in the scientific sector: some of the reasons adduced to account for collaboration, such as the mentor motive and preference motive[2], do not aim to raise the productivity of *all* researchers who collaborate, and may even be detrimental for the productivity of some. Furthermore, even accepting that collaborations enhance the efficiency

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1 See on this point Katz and Martin (1997) and Bonaccorsi and Daraio (2005).

2 Several explanations have been advanced for the growing incidence of academic collaboration: the explosion of knowledge which has increased the gains from specialization (McDowell and Melvin, 1983); the reduction in communication costs brought about by technical change (Rosenblat and Möbius, 2004); the "mentor" motive and changed preferences for collaboration (Laband and Piette, 1995; Bozeman and Corley, 2004). While the first two motives aim to increase efficiency, collaborations could also be take place for other motives that increase utility but not necessarily the efficiency of the sector.

of science, it is not yet clear how and through which channels this may occur.

An initial problem that emerges in this regard is whether collaborations affect the quality or quantity of scientific production. In the literature both aspects have been considered: evidence has been obtained to support the hypothesis that both dimensions are positively affected by collaboration (Durden and Perri, 1995), while others have found evidence that collaborations enhance only the quality of scientific product, not the quantity (Hollis, 2001; Adams et al., 2005). However, recently the balance has tipped in favour of the hypothesis that collaborations affect mainly the quality of scientific production (Hollis, 2001; Laband and Tollison, 2000 and 2003; Rosenblat and Möbius, 2004).

Besides the question of the quantity-quality trade-off, another important aspect that should be better analyzed, in order to implement a sound policy to increase the efficiency of the science sector, is what forms of collaboration are more effective at raising scientific productivity. In this regard, it is important to ascertain whether formal collaboration, such as co-authorship, is more effective than informal collaboration, such as exchanges of ideas during discussions, conferences and visiting periods, and refereeing. Again, it also needs to be established whether interaction among researchers within the same institution is more effective than that among researchers belonging to different institutions and/or to different countries (He et al., 2009).

Different findings could lead to rather different policy instruments. For example, if external collaborations are more effective, researcher mobility and exchanges among different institutions should be favoured, while if internal collaborations within the same department or institution are more effective, policy makers should encourage the establishment of large agglomerations of research units so as to raise the probability of developing better matching.

Finally, there is the question of what level of analysis is best able to capture the effect of collaborations. In other words, is it better to consider the single researcher as the unit of analysis, or a more aggregate unit, such as the department or the university? To date, the literature has privileged the individual level: relatively few papers have focused on departments or universities (Mowery, 1992; Powell, 1996; Kalaizidakis et al., 2004; Adams et al., 2005; Ramos et al., 2006). However, since interactions among researchers have important spillover effects, that are external to the single researcher, but internal to a unit of research defined at a more aggregate level, we think that the department level should be preferred.

In this paper we contribute to the literature on research collaboration by focusing on high-quality research and adopting a more aggregate level of analysis. Our unit of analysis is a department defined on the basis of the institution and on the field of research in which it operates. Moreover, we also consider whether different characteristics of collaborations, such as the degree of openness of a research team towards other institutions and/or other countries, the frequency of co-authorship and average size of each collaborating team, may have different effects on the production of high-quality research.

We estimate a model of scientific production by using mainly data drawn from the Italian research assessment exercise the period 2001-2003, which was the first official evaluation of academic research performance in Italy. In our paper high-quality research is measured as the number of excellent articles, as defined by panels of experts which classified all scientific output from Italian universities according to several degrees of quality, ranging from excellent to limited[3].

In the literature, use is often made of other measures of research quality, such as citation counts, indexes based on the number of pages and the quality of the journal in which articles are published (Laband and Piette, 1995; Hollis, 2001). Nevertheless, we preferred peer review of publications since this measure has the advantage of using all the available information (citations, impact factor, number of pages etc.) from competent referees who can make a more comprehensive assessment than metric-based indicators (Clerides et al., 2011).

In our model of scientific production, the dependent variable is the number of excellent articles produced by a single department and the set of explanatory variables includes some indicators of intellectual collaborations, which can give a comprehensive description of scientific collaborations within a scientific institution and among different institutions, whether national or foreign. Our aim is to analyse whether collaboration may boost the quality of scientific production of a unit of research[4] and, if so, which form of collaboration is the most effective. To estimate our equation we use both a negative binomial model, to allow for data overdispersion, and an exponential Poisson model estimated with instrumental variables (GMM methodology), to take into account endogeneity problems.

The results are particularly interesting. First of all, we find that more collaborations of a formal kind, that take the form of co-authorship, positively affect the production of high-quality science if they give rise to small co-authoring teams, each working on different research projects. By contrast, if co-authorships are concentrated on few research projects, they lose

3 Reale et al. (2007) also analyzed the Italian research assessment exercise (RAE), focusing on the reliability of peer review.

4 We use alternatively the two terms *research units* and *department* to indicate the same thing: a group of researchers who, in a given institution (often a university), work in a given scientific field.

their effectiveness at raising the quality of research. Hence we can conclude that co-authorship may have a positive and significant effect on the production of high-quality research only if it is sufficiently frequent, where we measure the degree of frequency with the proportion of research projects carried out by collaborating teams.

Besides the frequency of co-authorship, the characteristic of collaborations that really enhances the high-quality productivity of scientists is their openness, i.e. the degree of knowledge exchange resulting from collaboration with scholars who do not work in the same department and/or institute. According to regression results, such positive effects of external co-authorships are statistically significant and rather strong when we consider publications that received higher-quality grades, while they may prove negative when publications of lower grades are considered. This effect is even greater in the case of interactions among researchers from different countries, even if they occur less formally, such as through discussions, conferences or visiting periods. Indeed, we find a strong positive association between international exchanges of researchers and the probability of producing excellent publications.

We have also estimated the model for two subsamples: the science fields and the social science fields, to allow for the differences between the two macro-areas of research. These results lend support to the view that, in order to improve the quality of its publications, a scientific organization has to encourage interactions with scientists from other institutions and countries.

The paper is structured as follows. Section 2 reviews the main empirical and theoretical findings on scientific collaboration. Section 3 presents an empirical model of scientific production and describes the data and the empirical strategy. The results are discussed in Section 4, while Section 5 concludes.

2. Intellectual collaboration and scientific output: a literature review

As we have already noted, the empirical literature on the effects of collaboration on scientific production has not yielded clear-cut conclusions. The latter often depend on the manner in which academic performance is measured, on the variable used to capture intellectual collaboration and, finally, on the level at which the analysis is carried out, i.e. if the research unit is an individual or an institution. As regards the measure of academic performance, the main difference consists in the quantity or quality aspect of scientific production. The whole picture is further complicated by the fact that each of these dimensions of research output can be measured differently. On measuring academic performance of 592 scientists of different fields by their total number of publications, De Solla Price and Beaver (1966) found a positive correlation between productivity and the amount of collaboration of the authors (p. 1014).

Zuckerman's study (1967) of 41 Nobel laureates, using a similar measure of academic performance, showed that Nobel prize winners published more and were more apt to collaborate than a matched sample of scientists. Durden and Perri (1995) used both total articles and per capita articles to measure academic performance, finding that co-authorship enhances the productivity of a single researcher in economics. Further, from cross-sectional data of individual researchers in different fields Landry et al. (1998) found that higher rates of co-authorship are correlated with higher numbers of articles published. However, McDowell and Smith (1992), who analyzed individual scientists active in several fields, found no evidence that co-authorship increased the number of articles per scholar, when total articles were divided by the number of co-authors. Similar results were obtained by Hollis (2001) on a panel of individual researchers in Economics, finding that when scientific production (articles or citations) is divided by the number of authors, co-authorship is negatively correlated to scientific productivity. To explain this result, Hollis suggests that the contribution of co-authorship is mainly in terms of quality, while it may have detrimental effects on quantity, since "easy papers", which are also more likely to be published, are produced by single researchers.

The idea that the rise in the quality of research can be obtained at the cost of incurring a reduction in its quantity is also advanced by Rosenblat and Möbius (2004), albeit proposing a rather different explanation. The authors in question argue that the reduction in communication costs has enhanced collaboration between distant agents, but at the same time has reduced collaboration between individuals with different characteristics, since it enables researchers to be more selective in choosing their partners. The expected effect could be an increase in the quality of matching and in the collaboration of highly talented researchers, but at the same time a reduction in the quality of collaboration and in the productivity of less talented individuals. As a consequence, there can be a "polarization" effect among researchers, raising the production of high-quality articles, whilst reducing the low- and medium-quality articles. Hence the net effect on total production could be negative. The polarization effect is also clear in the results found by Pravdic and Oliuic-Vukovic (1986), who analyzed collaborative patterns in chemistry at both individual and group level. The authors found that the effect of collaboration on scientific output depends upon the type of links, since collaboration with high-productivity scientists tends to increase productivity, while collaboration with low-productivity scientists generally decreases it. Hence co-authorship may increase the quality of research only if it gives rise to better matching; otherwise it can be detrimental also in terms of quality.

Finally, Laband and Tollison (2000), drawing on information from the Journal of Political Economy (JPE) submission and acceptance lists for the period 1982-1986, provide empirical evidence that co-authored scientific papers are more likely to be accepted for publication on JPE than sole-authored papers. They interpreted this result as confirmation that the gains from co-authorship occur, at least partially, in the form of higher-quality manuscripts. Besides the question of the quality-quantity trade-off, the whole picture is further complicated by the fact that it is not clear which types of collaborations are really effective at enhancing research productivity. So far, collaboration has been simply equated with co-authorship, but there are different forms of collaboration, informal and formal, such as visiting periods, institutional participation in the same research projects, or even only comments informally provided by colleagues, that occur very often among scientists. The effects of these different types of collaboration deserve attention since they could be very important in the process of science production. Moreover, even within the co-authorship form of collaboration there are other differences that are important to detect, since the most suitable policy instruments change according to the case. For example, co-authorship could take place among researchers belonging to different institutions and/or to different countries, or among researchers who belong to the same institution. Now if the policy makers want to sustain the first type of collaboration, they have to incentivize researcher mobility, while to support the second type it is better to establish large institutions and/or large research centres of excellence[5].

As regards the importance of informal collaboration, mention should be made of the interesting, comprehensive paper by Laband and Tollison (2000), who estimated the value of collegial commentary and informal collaboration on published papers in economics by using detailed data on the 251 feature articles published in *REStat* during the years 1976–80. They found that informal collaborations are very valuable, since they increase dramatically the quality of published articles, particularly when they occur during the period of the researcher's training.

All the papers discussed so far analyse the effects of scientific collaboration at the level of the individual researcher. However, in order to analyse the effects of collaboration, given the

[5] On this particular aspect it is worth to mention the paper of He et al. (2009) who, by using a longitudinal data set of biomedical scientists at New Zealand university, analyse both the productivity effects of within university collaborations and of international collaborations. They find that both are positively related to the article's quality.

presence of spillovers due to interactions among scientists (Carillo and Papagni, 2007 and Carillo et al. 2008), the department or research institution could be the most suitable unit of analysis. Indeed, most policies set up by governments aiming to foster collaboration are at the institutional, rather than individual level. On this aspect the empirical literature is less extensive and overlaps, at least partially, with the question of "the departmental effect" (Allison and Long, 1990, and Carayol and Matt, 2006).

Adams et al. (2005) is one of the few papers that analyzes the effects of collaboration on the scientific productivity of an institution. Using panel data on scientific papers written in 110 top U.S. research universities in the period 1981-1999, the authors analyse the determinants as well as the effects on productivity of institutional collaboration. They found that collaboration among institutions, especially international collaboration, increases an institution's quality of research, but reduces its quantity. They conclude, that "a trade off of fewer papers in return for larger overall scientific influence may be taking place" (p.261). Sutter and Kocher (2004) analyze the determinants of co-authorship at institutional level of U.S. universities and found evidence that a majority of U.S. universities produce more co-authored than sole-authored papers in top journals. However, they do not analyze the effects of such patterns of collaboration upon scientific productivity.

Kalaitzidakis et al. (2004) analyze the effects on the productivity of European economics departments only of a particular type of collaboration, that with North American universities. They found that collaborations with American universities have a positive and significant effect on the publication performance of European universities. This paper is of great interest for our purposes since they use an indicator of international collaboration very close to the one we adopted: visiting periods and training undertaken by European economists in North America. However, they analyze only international collaborations, but not collaborations developed within the same institutions, as in our case. Further, Ramos et al. (2006), upon analyzing the performance of Spanish universities in economics and business, found that co-authorships have no significant effect on scientific production, but international collaborations always have a positive and significant effect. This latter result is again very interesting, since it is similar to that obtained by Kalaitzidakis et al. (2004) and, as we will see later on, by our paper. Finally, other empirical papers examining institutional collaborations in science and technology are those by Mowery (1992), Powell (1996), Adams and Griliches (2000) and Adams (2002). However, these papers analyse the factors that enhance inter-institutional collaborations, but not their productivity effects.

3. An empirical model of scientific production

What chiefly emerges from the above literature review is that collaboration results in a better quality of publications, but not necessarily in more publications. From a policy maker's point of view, it is important to understand whether and what types of collaborations are more effective at spurring academic productivity. Building upon the research agenda suggested by the literature review, we seek to perform an econometric analysis of the relationship between research quality, measured at the level of research units, and the extent and types of collaborations between researchers. The conceptual framework for this analysis is provided by an empirical model of scientific production, presented herein.

Let $y^{q}_{i,k}$ be the number of publications of quality q by a department i=1,...,I(k) that operates in field k=1,..., 20, where I(k) is the number of departments active in field k. Each research unit or department is identified by a pair (i, k). We assume that publications are the outcome of a production process in which researchers' effort, $R_{i,k}$, and knowledge, $A_{i,k}$, are translated into research outputs through a production function $F^{q}(.)$:

$$y^{q}_{i,k} = F^{q}(A_{i,k}\ R_{i,k})$$

The labour-augmenting knowledge factor $A_{i,k}$ is in turn a function of intellectual collaborations ($c_{i,k}$), department-specific characteristics ($x_{i,k}$), characteristics (z_i) which are specific to the institution or university to which the research unit belongs, and field-specific effects (w_k), i.e. features that characterize the technology or organization of the specific research field within which the research unit is active:

$$A_{i,k} = A(c_{i,k}\,,\ x_{i,k}\,,\ z_i\,,\ w_k)$$

Our empirical analysis aims to estimate the marginal effect of c on y^{q}, controlling for sources of heterogeneity across research units, research institutions and academic fields. In the following subsections, with reference to our sample we illustrate our empirical definitions of research units (Section 3.1), scientific output measures (Section 3.2), indicators of scientific collaboration (Section 3.3) and control variables (Section 3.4).

3.1 Defining research units

In defining research units and in measuring research input and output, we rely on data from the 2001-2003 Italian RAE[6], which is the first government evaluation of research output from Italian universities and research organizations – and so far the only one.[7] Assessment was performed between February and December 2005 under the responsibility of a Steering Committee for Research Assessment (CIVR). In a nutshell, the assessment process worked as follows. Each research institution was invited by the CIVR to submit a number of research products, among those published during the 2001-2003 period, to panels of experts nominated by the CIVR for each field. As a rule, each participating institution had to submit a number of research products equal to half the number of full-time equivalent (FTE) researchers.[8] This rule means that, if $R_{i,k}$ is measured as the number of tenured researchers affiliated to institution i in field k, the number of publications to be submitted by i in k was $0.5R_{i,k}$. Hence only a subset of the overall scientific production of academic units was evaluated, namely the works chosen by academic institutes. In turn, each panel appointed two referees for each publication, and the referees were asked to rate the products according to four grades: excellent, good, acceptable, limited.[9] The referees were invited to express a motivated evaluation of each publication also taking account of metric-based indicators, such as citation statistics and the impact factor of scientific journals.

The CIVR dataset provides information on 932 research units in Italy, hosted by 102 research institutions (mainly universities and research centres) and working in 20 research fields. The fields covered by the dataset include 14 main fields and 6 special fields. Units defined according to the CIVR dataset include all researchers affiliated to the same university or research institute, who belong to scientific sectors as defined by the Ministry of Education, University and Research[10].

3.2 Quality of scientific output

Our dependent variable y^q is the number of high-quality publications of research units,

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6 More information and data can be found at https://civr.cineca.it/

7 A new research assessment exercise, focusing on the 2004-2010 period, is under way.

8 Researchers are measured by the CIVR in FTE units under the assumption that each university researcher spends half of her/his working time teaching and the other half doing research.

9 Hence, $\sum_q y^q_{i,k} = 0.5R_{i,k}$, with q = { excellent, good, acceptable, limited}. The empirical distribution of products across grades in the CIVR dataset was the following: 30% excellent, 46% good, 19% acceptable, 5% limited.

10 This definition is useful in that scientists who belong to the same university and to the same field are exposed to the same set of organization-specific opportunities and constraints. It allows the role of the “institutional distance” between units to be appraised as a determinant of the cross-unit variance in academic performance.

measured by the number of publications awarded the grade “excellent” in the research assessment exercise. This is a measure of research output coming from a process of referee evaluation, while most works in the economics of science make use of metric-based indicators, such as citation counts, the impact factor and the h-index. The advantages of our choice can be easily argued by referring to the extensive literature on the subject. Indeed, the shortcomings of citations as a measure of research quality and innovativeness are well documented (Medoff 2003; Weingart, 2005; Oswald 2007; Clerides et al. 2011; Coupe et al. 2011). Referee-based evaluation of scientific productivity, which also lies at the core of the British RAE, can overcome most of those shortcomings because, although referees usually take account of citation counts and journals' impact factor, at the same time they use further qualitative information to build their evaluation. Furthermore, referee-based indicators fare better than metric-based indicators in assessing quality in those fields, such as Literature, Law or History, where monographs are an important outlet for research dissemination.

One problem with the Italian RAE is that the mechanism adopted to select the publications that each academic organization submitted to the evaluation does not guarantee randomness of the sample. However, excellent publications can be considered representative of the whole production of high-quality articles and books. Indeed, unit managers would logically only submit the best scientific products which, in their view, were more likely to be awarded excellent grades. In this respect, it is worth noting that one of the declared aims of the CIVR assessment exercise was to provide the Ministry of Education, University and Research with merit-based criteria for the allocation of a share of the budgets of public research organizations. This would create incentives for the research units to take the assessment seriously. Accordingly, excellent publications are unlikely to be affected by censoring problems, since the publications not submitted to CIVR are unlikely to be excellent.[11] In any case, in order to avoid censoring problems we use in our estimates only the data of those organizations that in a given field have a number other than zero of publications classified in at least one of the grades lower than excellent[12].

11 Instead, censoring can be a problem if we use good, acceptable or limited publications. To see this, consider that if research units submit their best outputs, then the publications not submitted to CIVR may be quite similar to the CIVR-submitted products of lower quality. Hence, while the number of excellent products in the CIVR sample is a good approximation of the number of excellent products in the whole population of research products, there could be a non-negligible number of publications of lower quality that are not included in the CIVR sample.

12 The number of excluded cases is very small: 28, and refers to academic institutions with just a few researchers active in a given field. The same cut of observations on data of publications classified in grades lower than excellent would reduce significantly the representativeness of the dataset.

3.3 Scientific collaboration indicators

In studying the impact of collaboration on research quality, we seek to capture four essential dimensions of scientific collaboration: the number and average size of co-authorships formed within a research unit, and the extent of formal and informal inter-institution collaborations. Consistent with these aims, we selected four proxies of intellectual collaboration, measured at the research unit level (2001-2003 averages): (the share of co-authored scientific products (i.e. products featuring at least two authors); the average number of authors per submitted publication; the ratio between non-affiliated authors and affiliated authors; and the turnover of international visiting scholars. In the empirical model previously described, such indicators are included in vector $c_{i,k}$. Let us describe these variables in greater detail.

The first indicator is equal to the percentage of products that feature at least two authors, submitted by a research unit. By means of this variable, since we seek to measure the number of collaborating research teams upon the total number of research teams, we capture the extent of co-authorship over the research activity of a department. A similar indicator was used by Sutter and Kocher (2004), while Laband and Piette (1995), Mixon (1997) and Medoff (2003) used simple dummies to capture whether publications were co-authored by more than two or three scholars.

The second indicator is given by the number of authors per publication submitted by a unit. In this way we capture the average size of each collaborating team. A large average size of research teams means that collaborations are concentrated upon few research projects. While we do not have strong expectations on the effect of this variable on scientific excellence, the existing literature underlines the existence of diminishing returns with respect to the size of the collaboration team, and shows that the relationship between team size and scientific excellence varies across fields.

The intensity of external co-authorships is measured by the ratio between the number of authors that are not affiliated to the unit, and the number of affiliated authors of all the publications submitted by the unit. Formally, let $n_{i,k}$ be the number of authors of the publications submitted to the CIVR by unit (i, k). Since such publications can be co-authored with researchers who are not affiliated to unit (i, k), one can write $n_{i,k} = n_{i,k}^{in} + n_{i,k}^{out}$ where the addenda indicate, respectively, the number of affiliated and non-affiliated authors per unit (i, k). Our indicator of formal external collaborations therefore reads $n_{i,k}^{in} / n_{i,k}^{out}$. This variable sheds light on quite an important aspect of academic collaboration. Indeed, the effectiveness of social interactions in science may depend on whether co-authorships involve systematic face-to-face contacts or long-distance communication. In particular, external co-authorships entail high communication and coordination costs; yet the best matching is more likely found by outward-oriented researchers.

The fourth and last indicator of inter-institution collaborations is given by the turnover of international visiting scholars (incoming and outgoing) per FTE researcher. The numerator includes affiliated researchers who have visited foreign research units, as well as foreign researchers hosted by Italian institutions, for at least three months during the period covered by the research assessment (2001-2003). This is a measure of openness to the international exchange of knowledge, motivated by collaborations that may also be informal, and that are characterized by face-to-face interaction. As such, this variable is able to capture the effects of international spillovers on scientific knowledge.

3.4 Control variables

Our control variables include the characteristics of the research unit (or department), characteristics specific to the university to which the research unit belongs, and field-specific effects.

a. Department-specific controls

Department-specific characteristics (vector $x_{i,k}$) include the number of PhD students and post-doctoral fellows per FTE researcher, and proxies of the average ability of unit members. PhD and post-docs can alternatively enhance the marginal product of researchers by offering research assistance, or diminish it if they increase the teaching load upon researchers.

To capture the average ability of the research unit members, we use two proxies: the amount of research funds granted by the Italian Ministry of Education, University and Research (MIUR) in the years 2001-2003; and the average age of the unit members. We thus consider both the ability for research due to innate time-invariant talent and the skills that scientists acquire through learning on the job. The former is captured by research funds, since in awarding funds, MIUR takes account of the quality of the proposals, the proponents' CVs and their past publication records. In particular, since the amount of funds received in a period is mostly affected by past academic performance, the amount of research funds collected in 2001-2003 should capture the long-term qualitative features of the research environment, not directly observable in our dataset, and hence can be considered exogenous with respect to the quality of works published in 2001-2003.

The other proxy for skills we use, the average age of a unit's researchers,[13] accounts for variations in the marginal productivity of researchers and in their involvement in administrative and organizational responsibilities linked to their age and experience. At the research unit level, the researchers' average age depends on the relative weight of different generations of scientists, and the age distribution of a research unit can significantly affect the organization of its research activity. Experienced researchers might compensate their declining scientific contributions by training youngsters and collecting funds, so that productivity at the research unit level is not reduced (see Bonaccorsi and Daraio 2003 on this point).[14]

b. Institution- and field-specific controls

The institution-specific characteristics that affect the quality of a unit's publications (z_i in the empirical model) are approximated by dummy variables, as well as by the "age" of an academic institution, i.e. the years elapsed from its establishment up to 2004, and the number of administrative staff members per FTE researcher. The age variable captures the degree of reputation and prestige of academic institutions, presumably higher among universities and research institutes with a longer tradition. Reputation and prestige can also exert a positive influence on the likelihood of publishing in top journals, as well as on the attitude of editors towards the publications submitted for peer review. While the availability of more staff members may boost the productivity of researchers by providing skilled bureaucratic and technical assistance (e.g. in the maintenance of experimental laboratories, in drafting research project proposals), it could also be correlated with heavier teaching loads that may push down the average productivity of department members. Dummy variables are used to account for cross-field differences in academic production processes (w_k).

The input and output variables described above are organized in a cross-section of research units. Summary statistics for the selected variables are reported in Table 1 for the whole sample and for two macro-fields: Science and Social Science. Science includes 11 fields: Mathematics, Physics, Chemistry, Geology, Biology, Medicine, Agriculture, Engineering, Electronics, Computing, Nano technologies, Aerospace. Social Science includes 5 fields: Literature and Arts, History, Philosophy and Psychology, Law, Economics and Statistics, Political and Social Sciences.

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13 Source: Ministry of Education, University and Research.

14 When a single scientist is considered, in many fields the evidence shows that productivity has an inverse U shape in the life cycle (Levin and Stephan, 1991), since the level of investment in research skills declines when scientists approach their retirement date.

4 Econometric methods and results

4.1 The econometric approach

In the econometric analysis of scientific productivity, the Poisson regression model is the reference tool whenever the output of research is measured by counts, as in our case and in previous papers (e.g. Zucker et al. 2006, Bauwens et al. 2008). However, the Poisson model assumes that mean and variance of the dependent variable are equal, an assumption that does not find support in our dataset: the standard deviation of the publication counts is larger than its mean (see Table 1). Such overdispersion can be handled by means of a negative binomial regression model. We therefore model the conditional expected value of $y_{i,k}^q$ (previously defined) as follows:

$$\mu_{i,k} = E(y_{i,k}^q \mid X_{i,k}) = \exp(X'_{i,k}\,\beta_q)$$

and its variance as $\mu_{i,k} + \alpha\,\mu_{i,k}^2$. In this formulation, $X_{i,k}$ is a vector of explanatory variables and β_q is the vector of parameters. The negative binomial regression model holds when $\alpha \neq 0$; the Poisson model is a special case when $\alpha = 0$. The model is estimated by maximum likelihood and the hypothesis of no overdispersion ($\alpha = 0$) is subject to testing (see Cameron and Trivedi, 2005; Winkelmann, 2008). This method provides estimates of parameters' standard errors robust to heteroskedasticity.

In the cross-section data that we use, the causal interpretation of the estimated parameters can be questioned by endogeneity issues, for at least two reasons. First, both scientific productivity and collaborations are influenced by scientists' ability. This can be seen as an omitted variable or joint causation problem. Indeed, researchers endowed with higher talent have a stronger incentive to collaborate with similar colleagues, and often they find these co-authors in other institutions or abroad. Hence the omission of ability would bring about a correlation between collaboration indicators and the error term, leading to inconsistent estimates if not corrected by the use of an appropriate estimator. We tackle such endogeneity problems by including in the negative binomial model: dummy variables to control for unobserved heterogeneity due to the features of ability specific of institutions or scientific fields; proxies for the average scientific ability of unit members. As mentioned in Section 3, ability can be suitably approximated by the amount of national research grants and the average age of researchers in a unit.

Second, the number of visiting scholars per FTE researcher is likely to be affected by endogeneity problems. In particular, endogeneity might be due to measurement errors and simultaneity. The latter issue arises because scientific productivity and visiting scholars in our database are simultaneous: both refer to the 2001-2003 period. This simultaneity problem is partly mitigated by the fact that visiting periods enjoyed in 2001-2003 are rooted in past relationships with foreign institutions. Concerning measurement errors, the *visiting scholars* variable is a composite indicator providing information both on stays abroad based on consolidated long-term relationships between universities, and on visits based on short-lived or recently established relationships. We believe that stays abroad can fully deliver their benefits on the academic productivity of a unit only if they are based on consolidated, long-term contacts. Recently-established relationships may still be unable to effectively stimulate productivity; short-lived visits are probably unable to exert any positive impact. We therefore see visiting periods based on one-off or recent relationships as noise disturbing what we consider the truly interesting signal – visiting periods based on durable international relationships. If such measurement errors are not controlled for, the estimated marginal effect of visiting scholars on high-quality publications is likely to reflect a mix between highly effective informal intellectual exchanges (based on long-term contacts) and weaker informal collaborations (recent relationships, short-lived visits).

In order to avoid this bias, we look for instrumental variables that satisfy two requirements: they should be lagged with respect to the period of interest (2001-2003), so as to avoid simultaneity, and they should be sources of exogenous variation only for visiting periods based on consolidated long-term relationships. We identified two instrumental variables: the number of students in international mobility, and the amount of funds for students' international mobility (both measured in 1999; source: MIUR). We believe that agreements for student exchanges are more likely to be proposed or engineered by scholars who entertain long-term international collaborations. Indeed, researchers with weak CVs and low language skills are unlikely to bear the bargaining costs of striking such agreements, and are more prone to free-ride on efforts made by their more internationally visible colleagues. At the same time, there is no reason to expect correlation with the error term, since the fact that more students were involved in international exchange programmes yesterday need not lead to better scientific performance of the research units today. These two instrumental variables should capture that part of the variation in current international mobility due to a correlation with its past values, hence exogenous with respect to current scientific productivity.

It must be noted that the two instrumental variables vary across academic institutions, but not across units. Hence, IV estimation cannot be carried out when dummy variables for institutions are included in the econometric model. We estimate an exponential Poisson model with an additive error term via GMM[15] with instruments for the international mobility of researchers, and replace the institution-specific dummy variables with other variables, such as age of the university and administrative staff, that vary across institutions, but not across fields.[16]

In summary, we estimate two models for the number of excellent publications. In the first we assume that the dependent variable is explained by a negative binomial model in which we include dummy variables for fields and academic organizations and two proxies of average department talent to control for unobserved heterogeneity. The second model is an exponential Poisson estimated with instrumental variables (GMM methodology) to account for the likely endogeneity of the variable that approximates for international visiting periods of researchers. The two-step GMM estimator allows for likely over-dispersion by providing a robust estimate of the covariance matrix of the estimated parameters.

We also perform estimates on two sub-samples: Science fields and Social Science fields, in order to analyze the possible differences between these two macro-areas of research. It is worth noting that if our empirical model captures the essential features of the scientific production process, then the variables that explain the number of excellent products should be significantly correlated with the lowest-quality products, but with opposite signs. Hence, for the sake of robustness we also present estimates which use the number of acceptable publications as the dependent variable

4.2 Results

We analyze the results of the model for the total number of articles of excellent grade produced by a department. Table [2] reports the coefficients of the negative binomial model, whereas the results from GMM estimations are given in Table [3]. To save space, the coefficients of dummies for fields and institutions are omitted. Before giving the detailed results, a couple of remarks are in order.

15 See Mullahy (1997), Cameron and Trivedi (2005) and Winkelmann (2008).

16 In countries where academic jobs are allocated through markets, the number of researchers and the number of PhD and post-docs may be endogenous to scientific productivity, too. Yet the number of researchers in our Italian database is a stock variable that is the outcome of national competitions held before 2001-2003, and with incentives to scientific productivity lacking, the mobility of researchers between academic institutions was driven by factors that are exogenous to the scientific production process. PhDs and post-doc scholarships tend to be awarded to former students of unit members.

Several indicators of the performance of the models show that the whole econometric exercise is able to capture the main features of the productivity of Italian research organizations. Negative binomial regressions display values of the pseudo-R^2 statistic between 0.26 and 0.31, that is, moderately high values for a cross-sectional study. Most of the estimated parameters display high *t* statistics. The likelihood-ratio test suggests rejection of the null of $\alpha=0$ (i.e. equality of mean and variance of the distribution of the dependent variable) in any specification, providing confirmation of the significant presence of excessive dispersion in the data of the dependent variable.

The main choices we made in our modelling strategy seem confirmed in estimation results. Indeed, the inclusion of dummy variables for academic organizations improves the fit and with the variable *national research grants* helps to account for relevant unobserved factors. Moving on to the results of the GMM estimates, we find some confirmation and further results on the model for excellent publications. The values of the Hansen J test statistic provide support for the null of valid orthogonal instrumental variables in GMM estimates. Comparing the GMM with the GMM-IV estimates (see table 3), we see that the endogenous variable *visiting periods* becomes statistically significant and shows a higher coefficient.Finally, the different econometric models (negative binomial and GMM) give similar results, in particular with respect to the variables approximating for collaborations among researchers, and jointly provide a set of complementary econometric results which look robust.

4.2.1 The basic specification

Let us now look at the individual variables. Since we take natural logarithms of the explanatory variables (with the exclusion of visiting periods), the estimated parameters can be directly interpreted as elasticities. The regression results confirm the importance of human capital inputs. Indeed, the parameters of the number of researchers are always significant and positive, with values very close to one especially in GMM regressions. The same parameter equals one in estimates on two subsamples: Science and Social Science (see Table 4). Since this variable coincides with department size, we can maintain that the efficiency of the production of excellent papers does not depend on the size of departments. In the context of the present econometric model, this result confirms the importance of the variables accounting for the effects of collaborations. Indeed, the size of a department would affect the work of researchers by enhancing the opportunities for collaborations with internal colleagues and by inducing a lower or a stronger search for external collaborators. Since we account for these effects with proxy variables of collaborations, the size of a department does not add anything to the estimation of these effects.

One of the most important issues in the econometric model is how we deal with unobserved ability of department members. In section 3 we emphasized the difference between innate talent and skills connected to the age and experience of researchers. Regression results confirm this intuition, since the two components of ability display a very different behaviour. The proxy for the average talent of department researchers, the value of national research grants, shows a positive and statistically significant coefficient in the case of excellent products (see tables 2 and 3). Also when we divide the whole sample into two macro research fields, we find that higher ability increases the product of excellent publications in both research fields. As a robustness check, we note that this variable presents a negative and non-significant coefficient in regressions of "acceptable" publications whose results are listed in table (3). We can then conclude that the average ability of the researchers of a department strongly affects the distribution of scientific products because it increases the excellent products and reduces those of lower quality grades.

The component of ability linked to experience instead has a weak effect: the coefficient associated to the researchers' average age displays statistical significance only when we break down the whole sample into the Science and Social Science fields (see table 4). In Social Science, units with younger researchers have greater productivity than those with older members, and the estimated parameter is significant and shows quite a high elasticity while in Science, researchers' average age shows a positive parameter, albeit not significant. The fact that, conversely, the best Social Science units are relatively young may signal that in some disciplines, such as Economics and Statistics, methodological and technical innovations appear quite frequently: because younger fellows move swifter down the learning curve, units with a lower average age are better able to implement such innovations.

As concerns the context variables, in general we obtain different results in different specifications of the econometric model. For example, the variable age of the research institution, which captures its reputation, has a coefficient positive and not significant in estimates of the total count of excellent publications (see table 3)[17]. However, when we break down the whole sample into Social Science and Science (see table 4), this variable affects researchers' productivity positively and significantly in the Social Science sample, but not in

17 We do not have this variable in the negative binomial model since the model contains dummy variables for institutions.

Science. These results suggest that older institutions are able to exploit their larger stock of organizational experience or to attract talented researchers only in Social Science, while in Science older universities are unable to fully exploit their reputation. The PHD students variable, which can alternatively capture teaching loads or research assistance, shows a coefficient with a positive sign, but not statistically significant, as well as the variable *administrative staff*.

4.2.2 The effects of scientific collaboration and interaction

A first glance at the results reported in tables (2) and (3) shows that the share of co-authorships positively affects the number of publications of high-quality grade. The elasticity is around 60% in the negative binomial model with dummy variables for institutions and fields (see table 2), and is even greater (up to 76.4%) after having controlled for endogeneity (table 3). The variable measuring the number of authors per publication is not significant in any econometric specification. The two results seen together can give a comprehensive picture of the effects of collaboration: if co-authorships are spread over a large number of projects, they are very effective at raising the quality of research, but if they involve only a few projects, even if these include many collaborating researchers, they lose their positive effects. This can be explained by the presence of decreasing returns to scale, that arise at very low scales, which offset the positive effects of collaboration.

The variable that captures the intensity of external co-authorships has a positive and a significant effect in all the models estimated with excellent products. In the negative binomial model, this variable is always positive and significant, as well as in the GMM regressions, whether before or after controlling for the endogeneity of visiting periods. More precisely, the reported coefficients imply that units with twice the share of external co-authors show an increase in the probability of producing excellent publications by 45.52% (GMM estimate with instrumental variables). Hence, high-quality research greatly benefits from interactions with colleagues affiliated to other academic organizations. Interestingly, the *external authors* variable shows a negative and significant coefficient estimate in the case of acceptable products (see table 3). Thus the picture that emerges is that formal collaborations between authors from different institutions do greatly alter the distribution of quality of scientific products, because they increase the number of excellent products and, at the same time, reduce that of products of inferior quality. The main advantages of cooperative research may well be connected to the openness to different scientific environments and greater freedom in the choice of collaborators.

The importance of knowledge exchange with colleagues in other research organizations is confirmed by the estimated effect of the turnover of international scholars on the number of excellent publications. In this case, we applied GMM-IV to overcome the problem raised by the probable endogeneity of the variable: when we use the GMM-IV methodology its coefficient becomes statistically significant. The correction for endogeneity takes the parameter from 0.008 to 0.08 (see Table 3) which corresponds to an elasticity of 0.154. This result is confirmed by the estimated coefficient in the case of acceptable publications, which is negative and not significant. Once again, we find that the collaborations between authors from different institutions increase the quality of scientific research, even when these interactions and contacts are informal, as occurs during visiting periods.

In this respect, estimates of field-group data provide further interesting insights. Indeed, Table (4) shows that external collaboration is important for the quality of publications in the fields of science and in those of social science, albeit with a much higher effect for the latter macro-field of research. On the contrary, visiting periods to and from foreign universities significantly improve the productivity of researchers in science but do not change that of social scientists. The different behaviour with respect to the external co-authorship can be explained by the fact that the practice of co-authorship is already widespread among Italian researchers in the sciences, while it is quite new and gaining strength in social science research, with huge positive effects on productivity, while the result of no effectiveness of international interactions on social science productivity seems to signal both the peculiarity of some fields as Literature, Arts and Law, where Italian is the main language, and the enduring backwardness of some parts of the Italian system of research in social sciences in terms of closure to the world community.

4.3 An alternative definition of the dependent variable: scientific publications "fractioned" by the number of authors

So far in this paper we have attempted to explain the effects of collaboration on total scientific output of high quality, measuring this with the total number of articles rated excellent by CIVR referees. However, a different strategy to measuring the quality of co-authored research output ascribes only a share of total output to a single author or an institution. For example, Adams et al. (2005) estimate a model of scientific publications in which the output is measured by the sum of fractions of citations to papers by a university in a given field. Another notable quantitative study is that of Hollis (2001) where the quality of the publications of a single economist is measured as the ratio of the value of a quality index to the number of authors of the publications.

This approach is based on the idea that the output of a research team can be divided into several parts, and that each part can be attributed to an individual researcher. However, while this may hold when a scientific product is measured only in terms of quantity, it may not hold when it is measured also in terms of quality: if scientific output is measured in terms of quality, dividing the output by the number of authors, it is likely to underestimate the contribution of collaboration to scientific production. In the research team a large part of the work also consists in monitoring the work of others, or in training younger researchers. Moreover, the research activities of a team can contain some duplication of functions which, whilst not ensuring an increase in the amount of scientific publications, guarantee an increase in their quality. If we divide publications by the number of authors, we eliminate by definition the team work that can give rise only to an increase in quality.

Of course, some authors may well adopt a free rider behaviour or there can be such high transaction and coordinating costs as to reduce the productivity of a team also in terms of quality. In this case, if we do not divide by the number of co-authors, we may overestimate the effect of team collaboration. For this reason, although our preferred measure of the quality of publications is the absolute number of excellent articles, we provide a robustness check of our results by using as a dependent variable the total number of excellent articles multiplied by $n_{i,k}^{in}$ / $n_{i,k}$, where $n_{i,k}^{in}$ is the number of authors of excellent publications affiliated to one department and $n_{i,k}$ is the total number of authors of the same publications submitted to the CIVR for evaluation, given that in this case the collaboration effects are underestimated.

The independent variables are the same as in the previous regression models, except for the variable *external authors* which does not enter the estimated equations because it is negatively correlated with the dependent variable by definition. The dependent variable is the logarithm of the excellent publications ascribed to a department. We estimate a linear model with OLS and apply the GMM to account for the endogeneity of the variable international visiting scholars, in which case we use the same instrumental variables as in the non-linear case. Furthermore, we estimate an exponential model of the fractional number of excellent publications similar to that we used for the count number in the previous sub-sections. In this case too, we apply GMM instrumental variables with the same set of regressors and instruments as in table (3).

Regression results are shown in table (5). The estimated parameters of the extent of co-authorship in all the estimated models are positive but not statistically significant, while the size of a team shows a negative and significant coefficient. So as expected, with this definition of the dependent variable there is an underestimation of the effects of formal collaboration, which lose significance although still showing a positive sign. However, the variable that captures the international mobility of researchers maintains its significance and has a positive effect on high-quality research. Hence, this feature of social interactions in the scientific community seems to approximate the essence of knowledge exchange and its importance for science. Estimates also confirm the relevance of the time-invariant ability in the production of high-quality research with a positive and significant coefficient, while the component of ability captured by the average age of researchers is, as in the previous case, not statistically significant. The other context variables, such as PhD students, administrative staff and the age of the institution are not significant.

5 Conclusion

In this paper we investigated the effects of co-authorship and other forms of social interaction on the productivity of scientists. This issue has become crucial in any debate on policies to foster science in advanced countries, since there is currently extensive collaboration in the community of researchers. We approached the issue empirically by estimating econometric models for count data from the first assessment of the research output of 102 Italian universities and research organizations, whether public or private. The data refer to 20 disciplines, and have several positive features, the chief one being that research products are assigned to four different quality categories through a process of peer evaluation, which is more reliable than the common use of metric-based indicators.

The picture that emerges from the results of this econometric exercise on the determinants of high-quality scientific productivity shows the importance of co-authorship if this involves more than one research project and the collaborating teams are small. Moreover, we find that what really matters for enhancing the quality of research are the flows of knowledge that arise from collaborations among researchers from different institutions and/or countries. These are among the most robust determinants of the production of excellent publications. Among the control variables, the proxy for time-invariant ability of the department members is the most effective at increasing the production of excellent publications.

The overall set of regression results has strong implications for science policy. It emphasises that knowledge exchange with researchers in the global scientific community is vital for those who aim to achieve the highest quality of research, and has limited or even negative effects on those who do not compete for international prestige in academic research.

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Table 1. Summary statistics.

	Obs.	Mean	Std.Dev.	Min	Max
Excellent publications	931	6.19	16.55	0	367
Researchers	931	39.37	75.19	0.3	1319.3
PhD & post-docs	931	1.21	1.75	0	24.3
Age of institution	928	264.19	298.3	4	916
Admin. staff per res.	931	41.35	84.15	0	1125.75
National res. grants	931	1348.38	12169.77	0	366700
Avg. age unit members	758	44.59	3.33	29.5	55
% co-authored publ.	931	0.68	0.38	0	1
Authors per publ.	931	5.43	16.69	1	325.75
External authors ratio	931	0.62	1.41	0	32.33
Visiting periods	931	2.21	6.25	0	107.1
Science					
Excellent publications	641	6.71	19.3	0	367
Researchers	641	41.73	87.53	0.5	1319.3
PhD & post-docs	641	1.15	1.7	0	23.9
Age of institution	641	267.13	298.99	5	916
Admin. staff per res.	641	44.64	98.2	0	1125.75
National res. grants	641	1793.59	14644.45	0	366700
Avg. age unit members	513	43.97	3.22	29.5	55
% co-authored publ.	641	0.89	0.21	0	1
Authors per publ.	641	7.21	19.85	1	325.75
External authors ratio	641	0.83	1.65	0	32.33
Visiting periods	641	2.54	7.35	0	107.1
Social science					
Excellent publications	290	5.03	7.39	0	58
Researchers	290	34.16	34.48	0.3	198.2
PhD & post-docs	290	1.35	1.85	0	24.3
Age of institution	287	257.61	297.15	4	916
Admin. staff per res.	290	34.08	36.8	0.34	223.97
National res. grants	290	364.32	505.9	0	3652
Avg. age unit members	245	45.88	3.2	34.5	54
% co-authored publ.	290	0.23	0.27	0	1
Authors per publ.	290	1.48	0.64	1	4.14

External authors ratio	290	0.15	0.29	0	3
Visiting periods	290	1.47	2.31	0	13.4

Table 2. Determinants of the number of excellent scientific publications in Italy (2001-2003). ML estimates of Negative Binomial models.

Publications	(1) excellent	(2) excellent	(3) excellent
Researchers	0.987*** (40.69)	0.903*** (25.77)	0.792*** (16.08)
PhD & post-docs	0.204** (3.13)	0.079 (0.95)	-0.006 (-0.07)
% co-authored public.	0.532* (1.99)	0.586* (2.22)	0.607* (2.11)
Authors per publication	0.041 (0.74)	0.012 (0.22)	0.043 (0.76)
External authors ratio	0.310** (3.05)	0.355*** (3.48)	0.298** (2.76)
Visiting periods	0.012** (2.89)	0.005 (0.91)	0.003 (0.39)
National res. grants			0.115*** (5.32)
Avg. age of unit members			-0.054 (-0.08)
Ln α (over-dispersion)	-2.257*** (-14.91)	-3.005*** (-13.29)	-3.245*** (-11.85)
Pseudo R-squared	0.2695	0.3056	0.3074
N. observations	904	904	759
Field dummies	yes	yes	yes
Institution dummies	no	yes	yes

Notes: The dependent variable is the absolute number of excellent publications. All the regressors, except for the variable *visiting periods*, are taken as logarithms. The variable *average age of unit members* refers only to university faculties. Heteroskedasticity robust *t*-statistics are in parentheses. Symbols *, **, *** refer to 10%, 5% and 1% levels of significance.

Table 3. Determinants of the number of excellent scientific publications in Italy (2001-2003). GMM estimates of Poisson models.

Publications	(1) excellent	(2) excellent	(3) acceptable
Researchers	0.997*** (13.96)	1.012*** (10.33)	0.695*** (8.56)
PhD & post-docs	0.083 (0.98)	-0.096 (-0.58)	-0.051 (-0.64)
National res. grants	0.131*** (4.97)	0.099*** (2.89)	-0.046 (-1.13)
Avg.age of unit members	-0.713 (-1.30)	-0.184 (-0.27)	0.938 (1.50)
Age of institution	0.021 (1.15)	0.017 (0.74)	-0.006 (-0.31)
Admin. staff per res.	-0.211 (-1.34)	0.020 (0.10)	0.517** (2.46)
% co-authored public.	0.563* (1.98)	0.764** (2.16)	0.564* (1.68)
Authors per public.	0.029 (0.65)	-0.124 (-0.97)	-0.211* (-1.88)
External authors ratio	0.369*** (3.61)	0.455*** (2.99)	-0.518*** (-3.31)
Visiting periods	0.008 (1.96)	0.085** (2.55)	-0.078 (-0.86)
N. obs.	757	726	725
Hansen's J		.036 (p = 0.849)	3.392 (p = 0.065)
Instrumental variables	no	yes	yes
Field dummies	yes	yes	yes

Notes: The dependent variable is the absolute number of excellent publications. All the regressors, except for the variable *visiting periods*, are taken as logarithms. The variable *average age of unit members* refers only to university faculties. In specifications (2) and (3) the variable *visiting periods* is endogenous and the instruments are the number of students visiting foreign universities in 1999 and the value of funds for students visiting foreign universities in 1999. Heteroskedasticity robust *z*-statistics are in parentheses. Symbols *, **, *** refer to 10%, 5% and 1% levels of significance.

Table 4. Determinants of the number of excellent scientific publications in Italy (2001-2003). GMM estimates of Poisson models. Science fields and Social Science fields.

Fields	**(1) Science**	**(2) Social Science**
Researchers	1.025*** (7.54)	1.222*** (4.30)
PhD & post-docs	-0.149 (-0.66)	-0.041 (-0.33)
National res. grants	0.088** (2.35)	0.178** (2.22)
Av. age of unit members	0.764 (0.85)	-2.748** (-2.18)
Age of institution	0.001 (0.03)	0.057* (1.73)
Admin. staff per res.	-0.011 (-0.05)	-0.424 (-0.62)
% co-authored public.	-0131 (-0.21)	0.589 (0.94)
Authors per public.	-0.080 (-0.52)	-0.42 (-0.61)
External authors ratio	0.413** (2.44)	1.320* (1.88)
Visiting periods	0.089** (2.53)	-0.005 (-0.05)
N. obs.	492	234
Hansen's J	0.048 (p=0.825)	0.031 (p = 0.861)
Instrumental variables	yes	yes
Field dummies	yes	yes

Notes: The dependent variable is the absolute number of excellent publications. All the regressors, except for the variable *visiting periods*, are taken as logarithms. The variable *average age of unit members* refers only to university faculties. In specifications (2) and (3) the variable *visiting periods* is endogenous and the instruments are the number of students visiting foreign universities in 1999 and the value of funds for students visiting foreign universities in 1999. Heteroskedasticity robust *z*-statistics are in parentheses. Symbols *, **, *** refer to 10%, 5% and 1% levels of significance.

Table 5. Determinants of the number of excellent scientific publications ascribed to each academic organization in Italy (2001-2003).

	OLS	GMM	Exponential GMM
Researchers	0.362*** (10.80)	0.239*** (2.87)	1.012*** (9.43)
PhD & post-docs	0.037 (0.75)	-0.270 (-1.34)	-0.036 (-0.20)
National res. grants	0.057*** (4.29)	-0.170 (-0.37)	0.098** (2.57)
Av. age of unit members	0.107 (0.42)	0.266 (0.51)	-0.115 (-0.16)
Age of institution	0.050*** (4.08)	0.031 (0.85)	0.020 (0.83)
Admin. staff per res.	0.734*** (5.05)	1.743*** (3.36)	0.088 (0.37)
% co-authored public.	0.063 (0.37)	0.186 (0.48)	0.381 (0.96)
Authors per public.	-0.080** (-2.28)	-0.174 (-1.15)	-0.282** (-1.99)
Visiting periods	0.015*** (3.51)	0.290** (2.05)	0.086** (2.18)
R-squared	0.740		
Hansen's J (overid.)		0.799 (p = 0.371)	0.666 (p = 0.414)
N. obs.	757	726	726
Field dummies	yes	yes	yes
Instrumental variables	no	yes	yes

Notes: The dependent variable in OLS and GMM estimates is the log of the total number of excellent articles multiplied by n_i/n , where n_i is the number of authors affiliated to a department and n is the total number of authors, while in exponential GMM the dependent variable is the same but untransformed in log. All the regressors, but the variable *visiting periods*, are taken as logarithms. The variable *average age of unit members* refers only to university faculties. In specifications GMM and exponential GMM the variable *visiting periods* is endogenous and the instruments are the number of students visiting foreign universities in 1999 and the value of funds for students visiting foreign universities in 1999. Heteroskedasticity robust *t* and *z*-statistics are in parentheses. Symbols *, **, *** refer to 10%, 5% and 1% levels of significance.