Funding Academic Research: Grant Application, Partnership, Award, and Output

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Abstract

Funding agencies tend to allocate (scarce) resources using a bottom-up competitive process. This paper analyzes the determinants and the consequences of the choices made in each of the stages of the funding process. We build on previous research (Banal-Estañol, Macho-Stadler, and Pérez-Castrillo 2013, 2018, and 2019) using, and present new results based on, one of the major public organizations funding academic research worldwide: the UK's Engineering and Physical Sciences Research Council.

1 Introduction

Most academic research worldwide is financed with public funds, distributed through funding agencies for scientific research such as the National Science Foundation (NSF) or the UK Research Councils. Funding agencies tend to allocate (scarce) resources using a bottom-up competitive process. As depicted in Figure 1, the process often runs as follows. Given a funding program (or a call), eligible academics decide whether to submit an application. In some cases, academics can decide whether to incorporate project partners (e.g., firms) to the application. Funding agencies decide then which of the applications should receive funding and which should not. Funded teams develop the project and obtain outputs in the form of, for instance, academic publications.

[Insert Figure 1 here]

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The Economics of Science literature has been analyzing parts of this process. Some papers analyze the award decisions of the agencies, and the potential biases in the award decision-making process (Boudreau et al., 2016, and Li, 2017). Others study the effects of the (different types of the) grant programs on project outputs (e.g., Azoulay et al., 2011, and Jacob and Lefgren, 2011). Finally, some papers analyze which academics collaborate with private firms and which university-industry partnerships are formed to develop research projects (Banal-Estañol et al., 2018; Mindruta, 2013). But we are not aware of any unified analysis of the entire process, from one end to the other.

This paper analyzes the determinants and the consequences of the choices made in each of the stages of the same funding process. We build on previous research (Banal-Estañol, Macho-Stadler, and Pérez-Castrillo, 2013, 2018, and 2019) using, and present new results based on, one of the major public organizations funding academic research worldwide: the UK's Engineering and Physical Sciences Research Council (EPSRC). The EPSRC research grants represent more than half of the overall research funding of the engineering departments in the UK, around 20% of the total UK science budget.

The first question we ask is: *which academics choose to apply and which choose not to?* As it is well known, applying for grants tends to be incredibly time-consuming. Research on the National Health and Medical Research Council (NHMRC) of Australia (Herbert et al., 2013), for instance, estimated that the 3727 grant proposals submitted in 2012 (out of which just 21% were successful) took 34 working days on average, for an estimated 550 working years of researchers' time spent. Applying for funds also has a great impact on personal workloads, stress and family relationships (Herbert et al., 2014). But, on the other hand, it is key for society that original and prolific researchers do apply for funds, as the objective of most calls is to fund the best research projects, i.e., those that can generate high-quality, high-impact output (Tijssen et al., 2002).

Our second question is: *which academics choose to apply in collaboration with firms, and with which firms, and which academics select to apply on their own*? Collaboration has benefits and costs. In surveys, academics claim that industry collaboration provides them with additional funds and insights (Lee, 2000; Mansfield, 1995), but it might also bias their selection of research topics and methodology (Florida and Cohen, 1999). Collaboration has recently been linked to a higher number of academic publications (Fabrizio and DiMinin, 2008; Azoulay et al., 2009). But Agrawal and Henderson (2002) do not find significant effects. Goldfarb (2008) even reports a negative effect for researchers who maintain funding relationships with an applied sponsor. Banal-Estañol et al. (2015) suggest that the relationship between industry collaboration and academic output may resemble an inverted U-shaped curve.

Our third question is: *which grant proposals do get funded and which do not?* We shall analyze which characteristics make it more (or less) likely that an application will be successful and obtain funding. Public funding agencies profess to allocate funds on the basis of scientific merit. For instance, the EPSRC states that "Research Quality (excellence) will always be preeminent and no proposal can be funded without clearly demonstrating this aspect."[1] Funding agencies should thus use the information available in the application to construct output estimates and award funding to the applications with the highest expected output. If this is the case, or if there are biases or departures from this objective, is an open and controversial question.

Out last question is: *what is the output, in terms of academic publications, of the funded research projects*? We should compare which proposals are funded against those that are successful in terms of academic output to detect biases in the award-decision process. We shall argue that, if a certain attribute increases (decreases) the likelihood of success, then the agency should be more lenient (strict) toward proposals with this attribute. For instance, if applicants from top institutions are, ceteris paribus, likely to perform better than those based at lower-ranked institutions then the evaluation process should, ceteris paribus, positively discriminate in favor of researchers at top institutions. We will analyze, in addition, the characteristics of the project partners.

The organization of the paper is the following. In Section 2 we present the data base. Section 3 considers the characteristics of the academics that apply to the research grant and the ones who do not apply. Section 4 addresses the collaboration issue, and studies which academics submit proposal in collaboration with firms and which ones submit non-collaborative projects. This section also studies the characteristics of the partners in the collaborative projects. Section 5 studies the funding decision. Section 6 is dedicated to the analysis of the publication results. Section 7 concludes by pointing to several interesting questions overlooked in this paper.

2 Data and variables

The data we use come from a sample of research grants that were submitted by engineers in UK institutions to the EPSRC for eventual financing over the period 1991-2007. The EPSRC records contain, for each application, information on the principal investigator (PI) and the other team members (or coinvestigators). This information allows us to construct the variable size of the team, defined as the sum of the number of coinvestigators and the PI (*Num team members*). The files also include, for each application, the start and end dates (from which we compute the project *duration*), the amount of funding requested (from which we construct *funds per capita*, which is the ratio between total funding and size of the team), and the holding organization (a UK university). Moreover, we have information whether the application was funded or not (and we construct the dummy variable *award*, which is equal to one if the project was funded).

In the EPSRC program, PIs must be academic employees of an eligible UK organization. In fact, in almost all the applications of our data base, the PI and the team members are employees of the holding organization. We obtain the information on the academics at the UK universities from 1991 to 2007 from the academic calendar census of all the engineering departments of 40 major

[1] See https://www.epsrc.ac.uk/newsevents/pubs/standard-calls-reviewer-helptext.

universities in the UK, available at the British Library (see Banal-Estañol et al., 2015, for details). We match the EPSRC grant applications with the academics in the calendar census. Our dataset is formed by the applications that include, as a PI or as a team member, at least one of the academic engineers in the calendar database. We discard the projects of large teams (more than 10 academics), so that individual characteristics matter.[2] Our initial sample has $17,251$ projects over 12 years (1996-2007) on which we have information on at least one member. The number of projects whose PI is in our database is $13,389$.

We use the EPSRC files on the projects from the period 1991-1995 to construct variables that reflect the researchers' application experience with the EPSRC. We identify, for each applicant, the number of his/her EPSRC applications in the previous five years, both as a PI and as a coinvestigator. We associate to each applicant variables that count the number of grant applications in the previous five years (*appl experience*), and the number of grants awarded in the last five years (*succ appl experience*). We also construct variables that count the number of projects submitted and awarded in the previous year (*appl experience last year* and *succ appl experience last year*). We aggregate the information of all the team members to define variables on the team's average application experience.

For each researcher in our dataset, we construct several measures that proxy for scientific ability and type of research, using his/her publications in the Web of Science (WoS) for the five years prior to the start of the project. For example, if the initial year of a project is 2005, then we take into consideration the publications during the period 2000 to 2004. We construct annual measures using the years in which the researcher is in our calendar database. For each of these proxies, we aggregate the information of all the team members to define average team variables. But, in some of the regressions (as clearly stated in the heading) we use the information about the PI only.

As a measure of *scientific ability*, we use the normal count (*count of papers*), the average impact-factor per publication (*impact per paper*), and an adjusted number of citations (*norm citations*). The impact factors come from the Science Citation Index's (SCI) Journal Impact Factors (JIF), attributed to the publishing journal in the year of publication. We use the citations to each paper taking the information in 2007. Since this is not a homogeneous measure (because the number of citations depends on the publication year of the paper), our citation measure is based on the number of citations in 2007 divided by the average number of citations received by the papers published in the same year.

We use the Patent Board classification (Narin et al., 1976) to build proxies for the *type of research* pursued. The Patent Board classification, updated by Hamilton (2003) for the National Science Foundation, comprises all journals in the Science Citation Index from 1973 to 2003 and, based on the cross-citation matrices, it classifies journals into four categories: (1) applied technology, (2) engineering and technological science, (3) applied and targeted basic research, and (4) basic scientific research. The first two categories are considered to be

[2] This implies discarding a 1.5% of the projects.

technology-oriented and the last two science-oriented (see Godin, 1996, and van Looy et al., 2006). As a result, some authors aggregate the first two categories into an applied research category and the last two into a "basic research" category (Breschi et al., 2008). But other authors consider the first and the third categories applied research and the second and the fourth basic (van Looy et al., 2006). We take into account both approaches and define two measures of "appliedness": the fraction of publications in the first and in the first and second categories, relative to the count of publications in all four categories (*research type*, and *research type (b),* respectively). Consequently, appliedness is measured in the most basic, most applied axis, and takes values in the interval $[0, 1]$.

We assemble *demographic* characteristics of each researcher through several sources. *Academic rank* information on a scale of 1 to 4 (corresponding to lecturer, senior lecturer, reader, and professor) is available from the academic calendar census. We compute the ratio of females in the research team (*ratio female*). We obtain information on Ph.D. year and granting institution from specialized websites (ethos.bl.uk/Home.do and www.theses.com) and from departmental or personal web pages. This allows us to compute *academic age*, defined as the difference between the year of the project and the date of his/her Ph.D.[3]

We compute the fraction of team members who have (or whether the PI has) a Ph.D. form a university different from the holding university of the project (*PhD outside*). We also disaggregate this information into variables that identify whether the Ph.D. was obtained in the US or in any other country outside the UK (*PhD US* and *PhD foreign non-US,* respectively), or whether it is from a UK university in the elite Russel Group or not in the Russell group (*PhD outside RG* and *PhD outside non-RG*, respectively). Moreover, we follow the different jobs of the academics and, among the insiders, we identify the *silver-corded* faculty, those who have worked in another organization since graduation.

We also identify whether there are any external institution collaborating with the academics in the application. We construct dummy variables that take value of 1 for projects with firms as partners (*Dum firms*), or with government institutions or associations as partners (*Dum govern institutions* and *Dum associations*, respectively).

Finally, we identify whether the holding organization is in the *Russell group.* To obtain a different variable about the quality of the holding organization, we extract additional information from the 2008 Research Assessment Exercise (RAE). The RAE evaluates the quality of research undertaken by UK institutions. We define an aggregate measure (at the level of the university) of the number of papers that are at the top category of their discipline, the so-called "four" star papers, as opposed to the one, two, or three star papers (*uni top publications*).

To construct average team variables we aggregate the individual variables. Table 1 presents the variables used in the analysis.

[3] If a researcher does not hold a Ph.D. we equate the Ph.D. year and the year of the first publication of the researcher plus two. This convention is the best aproximation for the academics for whom we do have the Ph.D. year.

[Insert Table 1 here]

3 Who chooses to apply and who chooses not to?

In most of the paper, the unit of observation is a grant application to the EPSRC funding program. However, in this section, the unit of observation is an academic, that is, an engineering working in one of the 40 UK universities. We want to understand the characteristics of the academics who apply for funding.

Table 2 offers some preliminary information on the average publication record and educational background of the applicants and the non-applicants in the period 1996-2007. The raws of table 2 refer to different groups of academics defined as a function of the number of applications they have submitted to the EPSRC. We classify the applicants in four categories, by their quartile on the frequency of applications. An academic belongs to quartile 1 if the number of his/her applications is in the top 25% of all the academics, and academics in quartile 4 are those with relatively less applications. The last row corresponds to the group of researchers that have not applied to an EPSRC grant in this period. The first column shows that the researchers in the first application quartile have published significantly more papers that those in the other quartiles, and that the researchers who have never applied to an EPSRC grant have significantly less publications than the ones who applied. This is also true when we consider the average count of the researchers' publication per year, or the average impact per paper. The table also shows the percentage of researchers in each quartile having obtained their Ph.D. in a foreign institution. This percentage is larger in the groups that apply more often for EPSRC grants, and it is the lowest in the group of researchers that have never applied. The opposite happens for the percentage of insiders in each group.

[Insert Table 2 here]

Table 2 suggests that the most prolific and active researchers are those that participate more often in the EPSRC calls. To better understand the drivers of the academics' decision, Table 3 reports the coefficients of the OLS estimation for the number of applications of an engineer in a year, either as a member of a team (columns 1 to 5) or as PI (columns 6 and 7), as a function of his/her characteristics.

[Insert Table 3 here]

The coefficient for count and impact per paper of publications if positive and very significant in all the regressions. Therefore, the more prolific a researcher and the higher the impact of the journal where he/she publishes, the larger the number of applications he/she submits. However, the number of citations of the papers is not significant, once we control for the previous variables. More applied researchers tend to apply less often, although the effect is not significant in terms of applications as a PI. Researchers with higher academic rank, holding a Ph.D. from a university other than the holding institution (independently on whether they graduated from a foreign or domestic, prestigious or no-prestigious university), and working in a university from the Russell group tend to apply more often to the EPSRC grants. Also, silver-corded researchers tend to apply more often than insiders who have never leaved their alma mater. In contrast, academics with higher academic age tend to apply less often.

The coefficient for application experience in the past four years (number of applications as well as number of successful applications) is positive and significant. However, when we consider the applications submitted the previous year, while the number of applications still has a positive coefficient, the number of successful applications last year has a negative and significant coefficient (columns 5 and 7), suggesting that an academic will apply less often one year as a team member or as a PI if he/she has some project/s funded the previous year.

4 Who collaborates with firms and characteristics of the collaborative projects

University-industry collaboration has been in the policy agenda in recent years and the issue has influenced the design of funding programs. They often include a concern about promoting knowledge transfer to society. Moreover, even in the cases where the granting program does not aim at inducing this behavior, the evaluation panels may be inclined at fostering university-industry collaboration. In this section, we study the characteristics of the academics who choose to collaborate with firms in the grant application, and the joint characteristics of the matched formed by academics and firms to explain who collaborates with whom.

Given that from this section on the unit of analysis is a project, we first present in Table 4 some descriptive statistics of the $17,251$ projects in our dataset.

[Insert Table 4 here]

The percentage of projects in our dataset that were awarded is 34.1%. The average academic in our database publishes 3.16 papers (with an average impact per paper of 1.024) per year. The mean of the count of papers is higher than the median (2.2), suggesting that the distribution is negatively skewed. The average type is 0.252. Since the type in defined in interval $[0, 1]$, 0 being the type of the less applied papers, the type of research tends to be basic research. This is reinforced by the fact that the median of the type is much lower than the mean (0.1 versus 0.252). The average academic in our project has submitted 1.278 projects per year in the previous years. In our projects, the average researcher has an academic rank of 2.79 in the scale 1 to 4, and an average academic age of 17.65. In average, the ratio of researchers with a Ph.D. outside the holding institution of the projects is 69.5%, and around 78.6% of the projects have a university from the Russell group as the holding institution, although these universities represent 57.5% of the pool of universities in our dataset (23 out of 40). In the projects in our database, the average ratio of females in the teams is very small (6.6%). The average size of the teams is 2.54 academics, and 43.5% of the applications are in collaboration with a firm. Finally, the applications have an average duration of 2.77 years and the amount requested per capita for the whole duration of the project is $\pounds 128,000$.

In this section, the variables measuring ability and type of research are again central. But here we will emphasize that while ability (e.g., the capacity to produce high-quality scientific output) is a "vertical" characteristic, the type of research is a "horizontal" characteristic. That is, all participants tend to agree that more able academics (or firms) are better partners than less able academics (or firms). However, being a more applied or a more basic academic is not necessarily good or bad. In relation to type of research, participants can be more concerned about their affinity (e.g., preferences for a type of scientific research) than to the absolute level of the characteristic. We explore whether collaboration decisions are affected both by ability-based and affinity-based characteristics of the potential collaborators. We also consider whether individual or institutional characteristics are more important.[4]

4.1 Collaborative vs. non-collaborative projects

Some academics prefer to collaborate with firm whereas others prefer not to. Several authors have discussed the costs and benefits of collaboration for participants on both sides of the market. Academics claim that industry collaboration provides them with additional funds and insights (Lee, 2000; Mansfield, 1995), but it might also bias their selection of research topics and methodology (Florida and Cohen, 1999). Collaboration may also affect the publication record of academics, although the evidence is not clear.[5] Firms report collaborating with academics to get access to new university research and discoveries (Lee, 2000). Some of these outcomes, however, have no or little commercial value (Jensen et al., 2003). Firms are also concerned with the differences in terms of organizational and institutional structure, and with the existence of the open science culture in academia (Dasgupta and David, 1994). But the evidence also points the fact that collaboration allows firms to obtain better patents, more products and increased sales (Cockburn and Henderson, 1998; Cassiman and Veugelers, 2006; Zucker et al., 2002).[6]

[4] This section is related to Banal-Estañol et al. (2018). However, the tables that we show here introduce new variables and provide insights on new aspects of the collaboration decision.

[5] For example, Agrawal and Henderson (2002) find no effect of the number of patents on the number of publications. In contrast, Azoulay et al. (2009) link collaboration to a higher number of academic research publications. Banal-Estañol et al. (2015) find an inverted U-shaped relationship between industry collaboration and academic research output.

[6] Academic researchers' individual characteristics and attitudes, as well as local group norms play a role in the collaboration decision (Louis et al., 1989). Firms' size, absorptive capacity

First, we test for the characteristics of the academics that submitted collaborative instead of non-collaborative projects. We cannot test which firms would be more likely to conduct non-collaborative projects because in those cases they cannot apply for EPSRC funding and they are, therefore, not in our dataset.

Table 5 reports the results of the probit regressions on the academics' likelihood to collaborate. The dependent variable is a dummy variable which takes a value of 1 if the academics choose to submit a collaborative project and a value of 0 if they submit a non-collaborative one. We control for year fixed effects, and report robust standard errors.

[Insert Table 5 here]

The two first columns of Table 5 report the results when we consider variables reflecting team characteristics. Concerning ability and type, the literature on the costs and benefits from collaboration allows us to make predictions on who among the academics collaborate and who stays independent. As for the ability, if the costs due to collaboration are not too large, the most able researchers (and the most able firms) engage in collaboration whereas the least able stay independent. Concerning the horizontal attribute, if the types of academics are generally more basic than those of firms, we should expect that the most applied researchers collaborate, whereas the most basic researchers develop projects on their own. Column 1 shows that when we measure ability in terms of number of papers published in journals with impact, it is indeed the case that the most able academics as well as the most applied ones are significantly more likely to collaborate. However, those teams whose previously-published papers have a higher average impact are more likely to stay independent. Therefore, while one of our characteristics that proxy for ability is associated to collaborative projects, the other is associated to non-collaborative projects.[7]

Column 1 also suggests that teams based in a university in the Russell group, as well as teams with a higher ratio of members holding a Ph.D. from an institution different from the holding university tend to collaborate less with firms. The coefficient of the size of the team is positive and significant while the coefficient of the square of the size is negative and significant. They indicate that larger teams tend to collaborate more with firms but the effect decreases with size.

Column 2 runs a similar regression, disaggregating the information about the university of origin of the outsiders and considering the silver-corded academics. The coefficient for all the categories of outsiders is negative (although the one corresponding to universities of the Russell group is not significant). It also

and the adoption of open search strategies are also important factors in the firms' willingness to collaborate (Veugelers and Cassiman, 2005; Mohnen and Hoareau, 2003; Bercovitz and Feldman, 2007). Geographical proximity between the researchers' university and the firms has also been shown to be important, particularly for researchers in universities with modestly rated faculties (Audretsch and Stephan, 1996).

[7] In Banal-Estañol et al. (2018) we show that teams with higher impact-factor-weighted sum of publications per year (a measure that takes into account the count, the impact per paper, and the size of the team) are more likely to submit collaborative projects.

shows that silver-corded researchers are those who are more likely to collaborate, even more than "inbreed" academics (those who have never left the university where they did their Ph.D.).

Column 3 shows that the results are similar if we use variables that refer to the PI instead of the team of academics, although the PI's academic rank has a positive and significant coefficient while his/her academic age has the opposite effect. For the PI, the count of publications appears not to be significant.

4.2 Who collaborates with whom

We also address the question who collaborates with whom in the collaborative projects. Previous literature has discussed the characteristics that make a potential partner more appealing. For instance, Cockburn and Henderson (1998) find that all academics, but especially those that are more research-oriented, might prefer firms that encourage their employees to publish scientific articles. Similarly, all firms might prefer to collaborate with "star" academics, as their input increases firm performance (Zucker et al., 2002). Research-oriented firms and star academics, however, might not be willing or able to collaborate with all participants on the other side of the market. Based on 46 case-study interviews, Carayol (2003) proposes a typology of business-science collaborations and argues that firms involved in high (low) risk projects are matched with academic teams of a high (low) excellence. Agarwal and Ohyama (2013) study, both theoretically and empirically, the labor market for scientists. The academic and private sectors choose among scientists who differ in their ability and preferences, and scientists choose between academia and industry.

To understand the joint characteristics of the collaborative pairs, Banal-Estañol et al. (2018) consider the collaboration decisions as the outcomes of a two-sided matching market collaboration process and use the conclusions of the literature on assignment games to interpret the results of our estimations.[8] The most useful property of this literature to obtain predictions on the attributes of the matched pairs in a stable (i.e., competitive) outcome is that stable matchings are necessarily efficient. Therefore,[9] if the cross-partial derivative of the value function with respect to an attribute of the academic and the same attribute of the firm is positive, then we should expect the matching to be positive assortative (see, e.g., Legros and Newman, 2002). Consider, for example, that the attribute is the partners' ability. The cross-partial derivative is positive if partner abilities are complementary, in which case the most able academics will be matched to the most able firms in a stable outcome. On the contrary, if the cross-partial derivative of the value function with respect to an attribute of the academics and firms is negative, that is, if partner attributes are substitute, we expect the matching to be negative assortative.

The previous framework suggests three predictions. First, given that it is reasonable to think of ability as a complementary attribute, the matching should

[8] This framework follows the approach of Shapley and Shubik (1972) and Becker (1973).

[9] Assuming the value function is twice-continuously differentiable.

be positive assortative in terms of scientific ability, i.e., top academics collaborate with top firms and less able academics collaborate with less able firms. Second, the matching should also be positive assortative in terms of affinity, i.e., academics with more applied bias collaborate with firms with more applied bias. The reason for this prediction, however, is different. Assuming that academics and firms would like to work on projects closed to their most preferred type, a positive assortative matching in terms of affinity minimizes the total inefficiencies due to the distance between the ideal types of the matched partners. Appropriate (pecuniary or non-pecuniary) transfers ensure that the equilibrium matching maximizes the sum of values of all partnerships, and not necessarily the value of any particular one. Finally, we expect the matching to be negative assortative in terms of ability-affinity pairs, i.e., the higher the ability of the academics, the closer they are to their partners in terms of ideal type.

To test the previous hypotheses, we need data about the characteristics of the firms. Given that we have only data of their publications (also from the WoS) from 2001 to 2007, our initial sample only includes the EPSRC proposals with the starting year 2005, 2006 or 2007. We have $1,735$ firms, which are involved in $2,057$ projects; that is, 35% of the projects are "collaborative" projects. The average number of researchers in each project is 2.86, and the average number of firms in each collaborative project is 2.43. We use similar variables for academics and firms concerning ability and type to those described in the previous section.

While the main empirical strategy in Banal-Estañol et al. (2018) is based in the Fox's (2008) maximum score estimation method, here we follow Agrawal et al. (2008) and Gompers et al. (2016). Their method rely on the analysis of the characteristics of matched and non-matched counterfactual pairs. We construct the set of counterfactual collaborations, i.e., collaborations that were possible but were not formed, in the following way. We take the teams of academics and the teams of firms that have a collaborative project. A pair formed by any of these teams of academics and any of these teams of firms is a potential counterfactual if they do not form an actual collaboration but have a collaborative project in the same year and in the same sector with other partners. For each actual collaborative project, we select four of these counterfactual pairs. We add the resulting $8,195$ counterfactual pairs to the $2,057$ actual pairs in the matching regressions. The set of plausible counterfactual collaborations, when contrasted with the set of actual collaborations, enables us to assess the significance of various pair-wise characteristics in determining the likelihood of forming a partnership.

We run probit regressions on the likelihood to form a partnership, using a dependent variable which has a value of 1 if the partnership is an actual pair and a value of 0 if it is a counterfactual pair. To see whether there is positive (or negative) assortative matching in one characteristic, say ability, we regress the likelihood of being an actual match over the product of the abilities of the two partners. This product represents the cross-partial derivative of the probability of being matched over the ability of the academic and that of the firm. The matching is, on average, positive assortative if the associated coefficient is positive. If the coefficient of the cross-partial derivative is negative then we say that the matching is negative assortative.

By construction of the counterfactual pairs, the individual characteristics have no impact on the likelihood of forming a partnership, as each academic and firm in an actual pair are also included in four counterfactual pairs. In all the regressions, we include year and sector fixed effects, and report robust standard errors clustered at the academic researcher level. Given that the previous literature has highlighted the role of geographical proximity in the decision to collaborate or not, we also include in all the regressions the variable that measures the geographical distance between academics and firms.[10] However, this variable turns out to be non-significant in all the regressions.

Table 6 shows the probit regressions over the joint variables that measure (i) the ability of the academics and the firms, (ii) the type of the academics and the firms and (iii) the ability of one partner and the distance in terms of type between the two partners.

[Insert Table 6 here]

Columns 1 and 2 provide estimates of the cross-partial derivatives for the two measures of scientific ability, the impact and count of publications, as well as for the type. All the coefficients are positive and significant, thus providing support for the prediction of positive assortative matching in terms of ability and type. Therefore, the partnerships that have higher ability and more applied academics together with higher ability and more applied firms (and lower ability and less applied academics together with lower ability and less applied firms) are more likely to be an actual formed partnership, as opposed to a counterfactual non-formed partnership. As shown in column 3, we obtain similar results if we use the measures of the principal investigator instead of the ones for the entire team of academics in the project.

Column 4 presents the results of a more indirect test of assortativeness in types, which consists of estimating the effect of the distance between types. Our theoretical model suggests that the distance between the types of the academics and the firms should lower the probability of being matched. The result in column 4 confirms this intuition: there is a strong negative effect of the distance in types on the probability of matching.

Column 5 takes into account the joint variables on the ability of one partner and the distance in terms of type between the two partners. The coefficients of the two variables are negative and significant, thus providing support for a negative assortative matching. That is, a better academic (or firm) is less likely to be matched with a very different firm (academic) in terms of type probably because better academics (firms) suffer relatively more than worse ones from collaborating with distant firms (academics). As in column 4, the coefficient of the joint variable for impact is positive and significant and that of the type distance is negative and significant. Column 6 presents the results of the cross-effects between the impact of one partner and the type of the other.

[10] See Banal-Estañol et al. (2018) for details about the construction of this variable.

The coefficients for both variables are negative and significant, suggesting that a better academic (or firm) is less likely to be matched with a more applied firm (academic).

Summarizing, Table 6 provides support for the predictions of positive matching in terms of ability and affinity, respectively. It also supports the idea of negative assortative matching in terms of ability-affinity pairs.

5 Who gets financed

Let us turn now to the decision on the allocation of funds among the grant applicants. According to its 2006 strategic plan, the aim of EPSRC is to provide financial support for qualified academics and ideas. Its four priorities are to stimulate creative, adventurous research, to attract, nurture, and support talented scientists and engineers, to build better knowledge transfer between research base and industry via increased collaboration, and to encourage multidisciplinary research.

We know surprisingly little on the role that personal, institutional, and discipline factors play in obtaining funding in academia. Most funding organizations claim to apply competitive, merit-based selection procedures, and therefore the probability of success should depend on the applicants' productivity. Although there is evidence that this is indeed the case, some researchers have questioned the organizations administering the granting process, the peer review cadre, and the process itself (Viner et al., 2004). Critiques often refer to peer review as a process vulnerable to cronyism (Travis and Collins, 1991), favouring the mediocre and orthodox (Horrobin, 1996) and subject to opportunistic behavior by peers (McCutcheon, 1997). Some even suggest that the outcome distribution is not wholly meritocratic (Wenneras and Wold, 1997; Hedge and Mowery, 2008). Grimpe (2012) indeed shows that obtaining government grants is not influenced by a scientist productivity, measured in terms of publication or patent stock, but by other personal characteristics, such as whether he/she heads a research group, and by institutional and discipline characteristics. Academic rank and departmental status have also been shown to correlate with application results (Cole et al., 1981; Viner et al., 2004).

We have addressed this question in Banal-Estañol et al. (2019), where we emphasize the influence of the diversity of the research teams. Here we focus on the influence on the funding decision of the same characteristics (and variables) that we have used in the previous sections: the ability, type, application experience, university of graduation, and demographic attributes of the academics, as well the size of the team, the prestige of the university, and the presence of partners.

Other papers have considered the granting decision. Boudreau et al. (2016) links novelty with the outcome of a grant evaluation process. They were involved in the design of a call for a seed grant, addressed to individual scientists rather than to teams, for a research-intensive US medical school. They constructed a measure of novelty based on the project's MeSH keywords, which capture key aspects of the research proposal. They compare the pairs of MeSH terms in each proposal with pairs that had already appeared in the literature. Boudreau et al. (2016) show that evaluation scores are negatively related to the fraction of pairs that are new to the literature. Our paper Banal-Estañol et al. (2019) reinforces their results, indicating that radicalness/novelty may not be supported, using a different approach, based on the characteristics of the applicant individuals and teams rather than on the characteristics of the proposal. The results by Li (2017) suggest that the likelihood of obtaining a grant is higher if the reviewers' research is related to the applicant's work, so the identity of the panel members matters in the grant application process.

Table 7 states the results of the probit regression where the dependent variable is a dummy variable equal to 1 if the project was awarded and 0 otherwise.

[Insert Table 7 here]

Table 7 shows that the most able (measured in terms of count of publications) as well as the less applied researchers (measured in terms of the fraction of publications in the first category of the Patent Board classification) are significantly more likely to be successful. Although the average impact of the publications is not significant in column 1 (where we include the variable reporting the normalized citations, which is never significant), it is always positive and significant when we drop the variable normalized citations. Therefore, academics publishing in high-impact journals are more likely to obtain the grant.

Previous experience (measured in terms of number of past EPSRC applications) does not help in the process. But both academic rank and academic age are significant: the first one has a positive coefficient while the effect of the second one is negative. Thus, academics with higher prestige are more likely to be successful in the application process but, once the prestige is taken into account, younger researchers are more successful than older researchers. The prestige of the holding university also matters: being affiliated with a university of the Russell group makes the project more likely to be funded. On the other hand, column 1 shows that researchers having obtained their Ph.D. in an institution outside the holding organization are less likely to see their application granted. Columns 3 to 7 show that the negative effect is particularly strong for those academics with a Ph.D. in either a foreign country outside the US or a UK university in the Russell group.

The coefficient for the ratio of female researchers in the team is negative but is never significant. As for the size of the team, the coefficients show that larger teams have lower chances to get financing but the effect is concave.

Column 2 introduces the variables related to the effect of partners. It clearly shows that the only relevant information is whether firms are involved in the application. Collaborative projects have *ceteris paribus* a higher likelihood of success than non-collaborative projects.

For robustness, column 4 runs a similar regression than the one presented in column 3 but using the alternative measure of type, which considers as applied not only the papers in the first category (technology) but also those in the second category (engineering and technological science). Also using this measure, the regression uncovers a negative and significant effect of applied research on the likelihood of success in the application process.

Column 5 shows that although experience, defined as having participated in previous applications, does not have any significant influence, having a high rate of past successes positively influences the likelihood of obtaining a grant. Thus, our result supports the existence of a Matthew effect on the application process (Defazio et al., 2009).[11] Column 6 reports the results when we use a different measure for the quality of the holding university: the number of papers in top (four star) journals. They reinforce the idea that the academic quality of the holding institution (or its prestige) matters.

Finally, column 7 shows the coefficients when we use the variables associated to the PI, instead of those corresponding the whole team. Results are very similar to those reported previously. Note however that they suggest that insider PIs who are silver-corded may be the academics with higher chances of getting funded.

6 Output

A grant program like the EPSRC's aims at stimulating academic research that is published in academic journals. In this section we offer some evidence of the characteristics of the teams that (having obtained the grant) are more likely to publish the results in journals with impact.

In addition to the variables that we have described previously, we require a measure of output for the (funded) EPSRC projects. Since 2008, the WoS database has been systematically collecting information on funding sources from the acknowledgments. We use this limited information which, for our projects, can only reflect some of the publications derived from projects with starting year 2005, 2006, or 2007. In this period, there are $1,428$ awarded projects out the $5,188$ applications present in our dataset. We have identified 963 publications in the years 2008-2010 that acknowledge one of these EPSRC projects as a funding source. Then, as proxy for the project's research output, we use a dummy variable that takes a value of 1 if the project has at least one publication (and a value of 0 if it has no publication)

To account for a potential differential selection, we use the two-stage Heckman probit selection model, which provides consistent, asymptotically efficient estimates for all the parameters. As an instrument for the exclusion restriction, we construct a variable that provides the stringency of the evaluation process in a given quarter: the fraction of overall EPSRC grants awarded in a given quarter. This variable affects the likelihood of funding but there is no reason to

[11] In their evaluation of NIH career development awards, Carter et al. (1987) compare successful versus unsuccessful applicants and also find that success increases future grant funding but not publication-based measures of research productivity. Similarly, Laudel (2006) finds that the track record of the researcher's previous grant success, in addition to his/her qualifications and experience, are the best predictors of grant approval.

think that it will affect the likelihood of publishing a paper.

Table 8 reports the coefficients of the Heckman probit model. The number of observations for the second stage is $1,428$.

[Insert Table 8 here]

Column 1 shows, as expected, that projects awarded to more prolific researchers are more likely to end up in publications. Projects of more basic researchers and of academics working in universities in the Russell group (which are characteristics that helped in the award process) are also more likely to end up with at least one publication. On the other hand, although academic rank helps in the selection process, the coefficient associated with this measure in the output regression is negative. It is not significant in the regressions where we consider team characteristics but it is strongly significant in column 4, where we take into account the characteristics of the PI.

More interesting, outside researchers, who find more difficult to obtain financing, are more likely to publish at least one paper out of the project. Column 2 shows that the positive coefficients for the variables associated to outsiders are significant for all the groups except for those researchers having obtained the Ph.D. in a university not in the Russell group. Larger teams are also more likely to publish the results of their project (although they were less likely to obtain financing).

Finally, the effect of collaboration with industry partners does not have a significant effect on the likelihood that projects lead to publications, although the effect is negative and significant when we consider the characteristics of the PI only.[12]

7 Conclusion

In this paper, we have empirically analyzed all the stages of the EPSRC funding process, from the academics' decision whether to apply (and whether to do it in a collaborative project or not), through the agency's choice of the projects to finance, to the final output of the successful projects in terms of publications. We now briefly discuss the effect of some of the characteristics of the researchers in those stages.

As one would expect, prolific academics (those with a high count of publications) not only apply more often to the EPSRC than researchers with less publications, but they are also more likely to obtain grants, and to publish the results of their grants. We could argue that this is the "natural" way: since prolific academics are expected to be more successful in obtaining new, publishable results, the agency is more likely to award them projects, hence these academics

[12] Banal-Estañol et al. (2015) make a deeper analysis of the effect of collaboration on the output of the projects. They show that the research projects in collaboration with firms produce more scientific output than those without them if and only if the firms in the project are research-intensive. Their results also indicate that the appliedness of the output is increasing in the appliedness of both the university and firm partners.

have more incentives to enter the process in the first place. A similar history holds for theoretical researchers (that is, those doing less applied work) and academics in prestigious Russell group university: they are more likely to apply, and to be successful in both the award and the output stage. The only difference between these groups is that prolific academics are more likely to apply in collaboration with firms, whereas projects submitted by theoretical researchers and projects under the umbrella of universities of the Russell group are more likely to be non-collaborative.

Both, being prestigious in terms of academic rank and having obtained the Ph.D. from an institution outside his/her current affiliation, makes an academic more active in terms of applications to the EPSRC. However, the influence of these characteristics on the success in the concession and the publication processes is very different. On the one hand, a higher rank makes being awarded the grant more likely although the likelihood of publishing at least a paper out of the project is lower. On the other hand, outsiders find it more difficult to see their application awarded although their successful grants are more likely to generate papers than those obtained by insiders. Therefore, our results hint at the existence of a, voluntary or involuntary, bias in favor of high-ranked academics and against researchers whose affiliation is different from their institution of graduation. Some bias may also exist with respect to the size of the teams because larger teams are penalized in the award process although they do generally better in the publication process.[13]

Finally, it is worth mentioning that while collaborative projects are more likely to be financed, they are not more likely to see their results published. In this case, one may argue that collaborative projects may be more likely to lead to other outputs, such as patents, which we have not taken into account and that may compensate for the lower publication rate.

The analysis from the application decision to the output of the projects, which we have developed in this paper, gives us a broad view of the processes that fund academic research. Still, there are additional aspects of these processes that deserve study and that are in our research agenda. First, we shall study, both theoretically and empirically, the causes and the consequences of academic collaboration among researchers. Many programs foster collaboration between academic scientists, bringing them in larger centres or in interdisciplinary research groups (Katz and Martin, 1997). But, it is an open question as to whether and, more importantly, which collaborations should be promoted or subsidized. For example, should we encourage the formation of teams including various numbers of different types of academic researchers, such as seniors and juniors, specialists and generalists or applied and basic researchers? Second, the influence of the characteristics of the members of the evaluation panel on the type of teams and projects that are awarded is still a question that deserves further analysis.

[13] The results in Banal-Estañol et al. (2019) suggest the existence of a bias also with respect to diverse teams, as the effect of diversity in the output regression is generally positive whereas that obtained in the grant award decision regression is negative.

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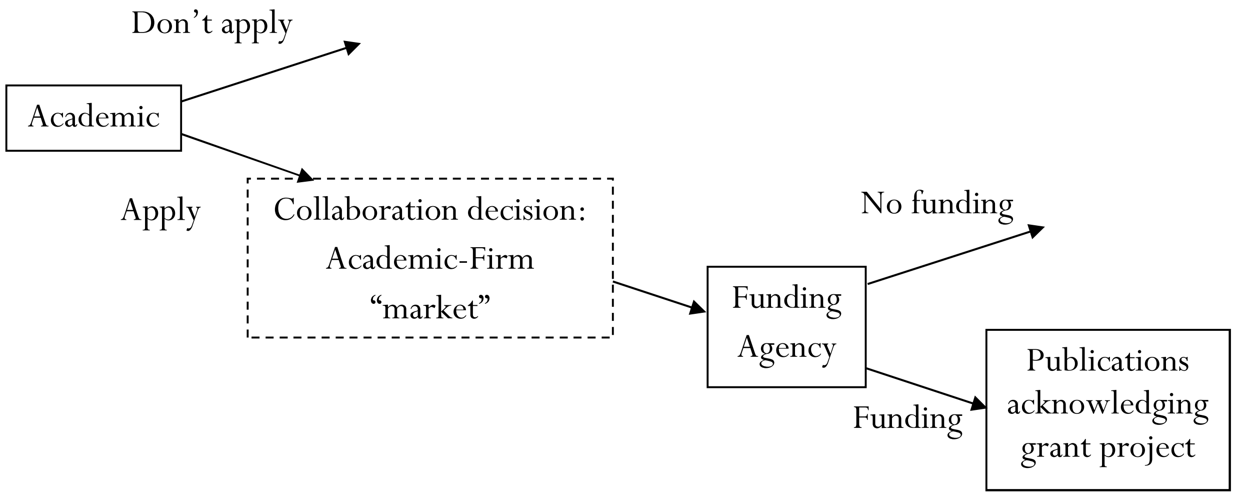

Figure 1. The process of grant application, partnership, award and output of academic research

Table 1. List of variables

In this table we report the variables we use in the regressions and their definition.

Name of variable	Definition of variable
Award	dummy equal to 1 if the application is awarded
Success	dummy equal to 1 if the project is in the top quartile in normalized citations
Count of papers	# of papers per year and per academic
Impact per paper	Total impact of the papers / # of papers
Citations	annual per-capita normalized citations of papers
Research type	ratio # of papers category 1 / # of papers all categories
Research type (b)	ratio # of papers category 1 or 2 / # of papers all categories
Appl experience	# of applications in previous 4 years per year
Succ appl experience	# of applications awarded in previous 4 years per year
Appl experience last year	# of applications in last year
Succ appl experience last year	# of applications awarded in last year
Ratio PhD outside	fraction of PhD degrees from different than the current uni
Ratio PhD US	fraction of PhD degrees in the US
Ratio PhD foreign non-US	fraction of PhD degrees in a foreign country different from the US
Ratio PhD outside RG	fraction of PhD degrees in a UK Russell group uni different from holding uni
Ratio PhD outside non-RG	fraction of PhD degrees in a UK non-Russell group uni different from holding uni
Ratio silver-corded	fraction of PhD degrees in holding uni with past jobs outside holding uni
Academic rank	academic rank on a scale 1 to 4
Ratio female	fraction of females in the team
Russell group	dummy variable equal to 1 if uni in the Russell group
Uni top publications	# of papers in three-start journals by engineers at the holding uni
Duration	duration of the project (in years)
Funds per cap	ratio of requested funding / # of members of the team (in millions)
Fraction awarded	fraction of money awarded within a given quarter
Dum firms	dummy equal to 1 if at least one firm collaborates
Dum govern institutions	dummy equal to 1 if at least one gov institution collaborates
Dum associations	dummy equal to 1 if at least one professional association collaborates
Dum univ abroad	dummy equal to 1 if at least one foreign university collaborates
Num team members	sum of the # of coinvestigators and the PI

Table 2. Characteristics of the applicants

We report some characteristics of the applicant researchers as a function on the average number of applications

	Avg count of total publications	Avg count of publications per year	Avg impact-weighted sum of publications per year	Percentage of researchers with PhD US	Percentage of researchers with PhD foreign non-US	Percentage of researchers insiders	Count researchers
Quartile 1	40,353	3,741	5,159	0,036	0,075	0,307	851
Quartile 2	20,938	1,984	2,190	0,029	0,094	0,351	837
Quartile 3	13,419	1,330	1,301	0,020	0,061	0,387	866
Quartile 4	8,378	0,877	0,838	0,015	0,060	0,420	826
Never applied	3,837	0,440	0,419	0,013	0,033	0,406	722

Table 3. Number of applications

This table reports the coefficients of the OLS model for the number of applications in a year either as a team member (columns (1) to (5)) or as a PI (columns (6) and (7)) against measures of academic and personal caracteristics of the researcher. Year fixed effects are also included in all regressions. We report robust standard errors.

	Number of applications as team member					Number of applications as PI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Count of papers	0.061***	0.061***	0.060***	0.060***	0.085***	0.031***	0.047***
	[0.008]	[0.005]	[0.005]	[0.005]	[0.009]	[0.005]	[0.004]
Impact per paper	0.104***	0.101***	0.082***	0.101***	0.077***	0.050***	0.036***
	[0.019]	[0.017]	[0.017]	[0.017]	[0.021]	[0.012]	[0.011]
Research type	-0.069***	-0.067***		-0.064***	-0.076***	-0.022	-0.025
	[0.023]	[0.023]		[0.023]	[0.023]	[0.016]	[0.016]
Appl experience	0.157***	0.157***	0.158***	0.149***		0.008**	
	[0.004]	[0.004]	[0.004]	[0.005]		[0.004]	
Dum PhD outside	0.116***						
	[0.017]						
Academic rank	0.096***	0.096***	0.097***	0.094***	0.142***	0.058***	0.095***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.006]	[0.006]
Academic age	-0.021***	-0.021***	-0.021***	-0.020***	-0.020***	-0.013***	-0.014***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Dum female	-0.037	-0.035	-0.035	-0.033	-0.047	-0.004	-0.006
	[0.033]	[0.033]	[0.033]	[0.033]	[0.033]	[0.023]	[0.023]
Russell group	0.126***	0.122***	0.124***	0.119***	0.118***	0.052***	0.051***
	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.013]	[0.013]
Norm citations	-0.000					-0.001	
	[0.004]					[0.003]	
Dum PhD US		0.174***	0.169***	0.175***	0.189***	0.132***	0.138***
		[0.059]	[0.059]	[0.059]	[0.060]	[0.041]	[0.041]
Dum PhD foreign non-US		0.212***	0.209***	0.219***	0.145***	0.172***	0.147***
		[0.039]	[0.039]	[0.039]	[0.039]	[0.028]	[0.028]
Dum PhD outside RG		0.114***	0.113***	0.116***	0.114***	0.095***	0.103***
		[0.018]	[0.018]	[0.018]	[0.019]	[0.013]	[0.013]
Dum PhD outside non-RG		0.090***	0.092***	0.092***	0.076***	0.074***	0.070***
		[0.026]	[0.026]	[0.026]	[0.027]	[0.018]	[0.019]
Dum silver-corded		0.122*	0.120*	0.121*	0.111	0.124**	0.149***
		[0.070]	[0.070]	[0.070]	[0.070]	[0.050]	[0.052]
Research type (b)			-0.139***				
			[0.030]				
Succ appl experience				0.025**			
				[0.011]			
Appl experience last year					0.403***		
					[0.011]		
Succ appl experience last year					-0.074***		
					[0.021]		
Appl experience as PI						0.142***	
						[0.006]	
Appl experience as PI last year							0.366***
							[0.012]
Succ appl experience as PI last year							-0.117***
							[0.021]
Observations	24,388	24,388	24,388	24,388	24,360	24,388	24,360

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Descriptive statistics
We report the descriptive statistics for the main variables.

Variables	Observations	Mean	St dev	Median
Awarded	17.251	0,341	0,474	0
Count of papers (x10)	17.251	0,316	0,301	0,220
Impact per paper	17.251	1,024	0,950	0,819
Research type	17.251	0,252	0,320	0,100
Application experience	17.251	1,278	1,174	1
Academic rank	17.251	2,789	1,009	3
Academic age	17.251	17,646	7,755	17
Ratio PhD outside	17.251	0,695	0,405	1
Ratio female	17.251	0,066	0,209	0
Russell group	17.251	0,786	0,410	1
Num team members	17.251	2,541	1,639	2
Dum firms	17.251	0,435	0,496	0
Duration (in years)	17.251	2,766	1,020	3
Funds per cap (in Million £)	17.251	0,128	0,277	0,082

Table 5. Collaboration decision

This table reports the coefficients of the probit model for the decision whether to collaborate with firms against variables measuring academic and personal characteristics of the team members (columns (1) and (2)) or the PI (column (3)) and control variables. Year fixed effects are also included in all regressions. We report robust standard errors.

	Team characteristics		PI characteristics
	(1)	(2)	(3)
Count of papers	0.101**	0.095**	0.023
	[0.041]	[0.041]	[0.041]
Impact per paper	-0.079***	-0.076***	-0.070***
	[0.020]	[0.019]	[0.020]
Research type	0.442***	0.437***	0.401***
	[0.041]	[0.041]	[0.042]
Appl experience	0.010	0.007	0.010
	[0.011]	[0.011]	[0.011]
Academic rank	-0.008	-0.007	0.027**
	[0.012]	[0.013]	[0.012]
Academic age	0.000	-0.001	-0.005***
	[0.002]	[0.002]	[0.002]
Ratio PhD outside	-0.053**		
	[0.024]		
Ratio female	0.075	0.069	0.039
	[0.048]	[0.048]	[0.047]
Russell group	-0.043*	-0.039	-0.049*
	[0.024]	[0.024]	[0.028]
Num team members	0.244***	0.243***	0.266***
	[0.019]	[0.019]	[0.023]
Num team members square	-0.028***	-0.028***	-0.028***
	[0.002]	[0.002]	[0.003]
Ratio PhD US		-0.374***	-0.242***
		[0.072]	[0.067]
Ratio PhD foreign non-US		-0.248***	-0.122***
		[0.049]	[0.047]
Ratio PhD outside RG		-0.006	0.032
		[0.027]	[0.027]
Ratio PhD outside non-RG		-0.115***	-0.031
		[0.039]	[0.036]
Ratio silver-corded		0.179**	0.218***
		[0.079]	[0.077]
Constant	-0.550***	-0.539***	-0.629***
	[0.076]	[0.076]	[0.081]
Observations	17,251	17,251	13,389

*** p<0.01, ** p<0.05, * p<0.1

Table 6. Matching between teams academics and firms

This table reports the results of the probit regressions for the likelihood of matching as a function of the joint characteristics of academics and firms. Year and sector fixed effects are included in all the regressions. We report robust standard errors clustered at the academic researcher level.

	(1)	(2)	(3)	(4)	(5)	(6)
Academics' impact*Firms' impact	0.027***			0.024***	0.044***	0.046***
	[0.006]			[0.005]	[0.008]	[0.009]
Academics' type*Firms' type	0.163***	0.161***				0.160***
	[0.052]	[0.052]				[0.052]
Academics' count*Firms' count		0.136***				
		[0.026]				
PI' impact*Firms' impact			0.074***			
			[0.027]			
PI' type*Firms' type			0.147***			
			[0.053]			
Type distance				-0.600***	-0.463***	
				[0.068]	[0.071]	
Academics' impact*Type distance					-0.782***	
					[0.145]	
Firms' impact*Type distance					-0.033***	
					[0.009]	
Academics' impact*Firms' type						-0.420***
						[0.084]
Firms' impact*Academics' type						-0.021***
						[0.005]
Geographical distance	-0.000	-0.000	-0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-0.127***	-0.125***	-0.117***	0.174***	0.136***	-0.110**
	[0.044]	[0.044]	[0.045]	[0.033]	[0.034]	[0.045]
Observations	7323	7323	6426	7323	7323	7323

*** p<0.01, ** p<0.05, * p<0.1

Table 7. Concession of a grant

This table reports the coefficients of the probit model for the award decision against variables measuring academic and personal characteristics of the team members (columns (1) to (6)) or the PI (column (7)) and control variables. Year fixed effects are also included in all regressions. We report robust standard errors.

	Team characteristics						PI characteristics
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Count of papers	0.098*	0.140***	0.140***	0.146***	0.013	0.111***	0.161***
	[0.059]	[0.041]	[0.041]	[0.041]	[0.041]	[0.041]	[0.041]
Impact per paper	0.018	0.027**	0.029**	0.026**	0.029***	0.030***	0.031***
	[0.012]	[0.011]	[0.011]	[0.012]	[0.011]	[0.011]	[0.012]
Research type	-0.097***	-0.109***	-0.104***		-0.098***	-0.094***	-0.114***
	[0.035]	[0.035]	[0.035]		[0.035]	[0.035]	[0.036]
Appl experience	-0.002	-0.003	-0.005	-0.005		-0.002	-0.013
	[0.011]	[0.011]	[0.011]	[0.011]		[0.011]	[0.011]
Academic rank	0.095***	0.094***	0.093***	0.093***	0.075***	0.096***	0.093***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Academic age	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***	-0.006***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Ratio PhD outside	-0.104***	-0.101***					
	[0.025]	[0.025]					
Ratio female	-0.031	-0.035	-0.038	-0.039	-0.050	-0.056	-0.015
	[0.049]	[0.049]	[0.049]	[0.049]	[0.049]	[0.049]	[0.048]
Russell group	0.137***	0.141***	0.140***	0.137***	0.127***		0.137***
	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]		[0.029]
Num team members	-0.108***	-0.119***	-0.122***	-0.123***	-0.129***	-0.115***	-0.110***
	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.023]
Num team members squared	0.012***	0.013***	0.014***	0.014***	0.014***	0.013***	0.011***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]
Duration	-0.098***	-0.106***	-0.106***	-0.104***	-0.104***	-0.106***	-0.135***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.014]
Funds per cap	-0.131	-0.122	-0.122	-0.123	-0.136*	-0.123	-0.065
	[0.084]	[0.083]	[0.083]	[0.083]	[0.082]	[0.085]	[0.070]
Norm citations	0.003						
	[0.003]						
Dum firms		0.121***	0.124***	0.125***	0.123***	0.119***	0.129***
		[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.024]
Dum govern institutions		0.041					
		[0.042]					
Dum associations		0.040					
		[0.054]					
Dum univ abroad		0.029					
		[0.048]					
Ratio PhD US			-0.026	-0.025	-0.025	-0.071	0.007
			[0.069]	[0.069]	[0.069]	[0.069]	[0.067]
Ratio PhD foreign non-US			-0.224***	-0.221***	-0.194***	-0.203***	-0.175***
			[0.050]	[0.050]	[0.050]	[0.050]	[0.049]
Ratio PhD outside RG			-0.078***	-0.077***	-0.080***	-0.058**	-0.070***
			[0.028]	[0.028]	[0.028]	[0.028]	[0.027]
Ratio PhD outside non-RG			-0.036	-0.033	-0.024	0.005	-0.076**
			[0.040]	[0.039]	[0.040]	[0.040]	[0.037]
Ratio silver-corded			0.126	0.127	0.095	0.106	0.197***
			[0.078]	[0.078]	[0.079]	[0.079]	[0.075]
Research type (b)				-0.086**			
				[0.037]			
Succ appl experience					0.179***		
					[0.024]		
Uni top publications						0.000***	
						[0.000]	
Constant	-0.040	-0.082	-0.091	-0.056	-0.010	-0.084	-0.038
	[0.071]	[0.071]	[0.071]	[0.077]	[0.071]	[0.070]	[0.077]
Observations	17,251	17,251	17,251	17,251	17,251	17,251	13,389

*** p<0.01, ** p<0.05, * p<0.1

Table 8. Project success
This table reports the coefficients of the Heckmann probit model for the likelihood that the project leads to at least one publications against variables measuring academic and personal characteristics of the team members (columns (1) to (3)) or the PI (column (4)), whether the project was collaborative (columns (3) and (4)) and control variables. Year fixed effects are also included in all regressions. We report robust standard errors.

	Team characteristics			IP caracteristics
	(1)	(2)	(3)	(4)
Count of papers	0.435***	0.425***	0.425***	0.137**
	[0.142]	[0.142]	[0.143]	[0.054]
Impact per paper	-0.027	-0.034	-0.034	-0.045***
	[0.039]	[0.039]	[0.039]	[0.017]
Research type	-0.477***	-0.452***	-0.453***	-0.081
	[0.146]	[0.147]	[0.147]	[0.077]
Appl experience	-0.040	-0.033	-0.034	-0.025
	[0.034]	[0.034]	[0.034]	[0.018]
Academic rank	-0.048	-0.050	-0.051	-0.137***
	[0.057]	[0.059]	[0.059]	[0.027]
Academic age	-0.015**	-0.011*	-0.011*	0.006*
	[0.006]	[0.006]	[0.006]	[0.003]
Ratio PhD outside	0.288***			
	[0.101]			
Ratio female	-0.168	-0.186	-0.187	-0.114
	[0.169]	[0.170]	[0.170]	[0.083]
Russell group	0.436***	0.431***	0.431***	0.382***
	[0.115]	[0.116]	[0.117]	[0.062]
Num team members	0.176**	0.192**	0.193**	0.140***
	[0.076]	[0.078]	[0.078]	[0.043]
Num team members squared	-0.015*	-0.016*	-0.016*	-0.011**
	[0.009]	[0.009]	[0.009]	[0.005]
Duration	0.195***	0.197***	0.197***	0.172***
	[0.048]	[0.048]	[0.048]	[0.028]
Funds per cap	0.693**	0.719**	0.722**	0.672***
	[0.318]	[0.329]	[0.327]	[0.182]
Ratio PhD US		0.512**	0.514**	0.199
		[0.242]	[0.242]	[0.127]
Ratio PhD foreign non-US		0.595***	0.596***	0.221**
		[0.164]	[0.163]	[0.086]
Ratio PhD outside RG		0.230**	0.231**	0.096*
		[0.114]	[0.114]	[0.058]
Ratio PhD outside non-RG		0.093	0.093	0.022
		[0.152]	[0.152]	[0.075]
Ratio silver-corded		-0.389	-0.390	-0.187
		[0.277]	[0.277]	[0.128]
Dum firms			0.001	-0.083*
			[0.081]	[0.049]
Constant	-1.966***	-1.994***	-1.986***	0.382***
	[0.384]	[0.411]	[0.415]	[0.135]
Observations	5,188	5,188	5,188	4,159

*** p<0.01, ** p<0.05, * p<0.1