Key success drivers in public research grants: Funding the seeds of radical innovation in academia?[*]

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Abstract

We study what makes a research grant application successful in terms of ability, type of research, experience, and demographics of the applicants. But our main objective is to investigate whether public funding organizations support the teams that are most likely to undertake transformative or "radical" research. Making use of the literature on recombinant innovation, we characterize such "radical teams" as those formed by eclectic and non-usual collaborators, and those that are heterogeneous and scientifically diverse. Our results, using data from the UK's Engineering and Physical Sciences Research Council (EPSRC), show that the more able, more basic, and more senior researchers, working in a top university, are more likely to be successful. But, radical teams are less likely to be funded by funding bodies. Our analysis of the research output of the awarded projects suggests that, voluntarily or involuntarily, the evaluation process in these organizations is biased against radical teams.

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1 Introduction

Radical innovations are widely understood to be the main engines of technological progress and economic growth. R&D firms and the government institutions that support them are constantly searching for radical or breakthrough technologies that can fundamentally change existing markets. Similarly, public funding agencies for scientific research, such as the National Science Foundation (NSF) or the UK Research Councils, often encourage and provide support for "transformative" research—research that holds the potential to radically change our knowledge or understanding of current science or engineering concepts.[1] The NSF, for example, has recently included an emphasis on "potentially transformative research" in its merit review criteria.

This paper analyzes the award decisions of one of the major public funding organizations for scientific research worldwide, the UK's Engineering and Physical Sciences Research Council (EPSRC). We study first what makes a project grant application successful in terms of ability, type of research, experience, and demographics of the applicant(s). But our main objective is to investigate the attitude of funding organizations toward radicalness. We study whether a funding body such as the EPSRC fosters, or on the contrary represses, the *seeds of radical innovation in academia*. That is, if, among the pool of applicants, those that are more likely to produce transformative or radical research are also more likely to be successful in the application process.[2] Subsequently, we explore the different explanations for the results of the grant decision-making process using the research output of the awarded projects.

We use the extant innovation literature to first identify the characteristics of individuals and teams associated with radical research. Innovation scholars argue that radical innovations tend to be those that have combined knowledge across technological boundaries (Fleming, 2001; Sorenson and Fleming, 2004; Gruber et al., 2012; Verhoeven et al., 2015). Knowledge tends to evolve as a cumulative process, resulting in well-circumscribed domains (Nerkar, 2003; Carnabuci and Bruggeman, 2009). Combining knowledge across boundaries is thus necessary to break away from existing trajectories and generate path-breaking inventions (Fleming, 2001). Similarly, in science, research within physical and scientific boundaries is believed to be an improbable source

[1] The term "transformative research" has been used by the NSF. At the National Institutes of Health (NIH) the phrase is sometimes rendered as "translational research." Within the European Research Council (ERC), the term often used is "frontier research."

[2] The focus of our paper is on the award decisions themselves rather than on the effects of the grant program. Azoulay et al. (2011) showed that researchers supported by funding bodies that tolerate early failure, reward long-term success, and do not limit freedom, such as the Howard Hughes Medical Institute (HHMI), are more likely to produce breakthroughs than comparable grantees from the National Institutes of Health (NIH), which has short review cycles, pre-defined deliverables, and renewal policies that are unforgiving of failure.

of the most fruitful ideas (Uzzi et al., 2013). Instead, research that spans knowledge domains, effectively combining diversity of knowledge, is more likely to prompt breakthroughs. Models of creativity also emphasize that innovation is spurred through original combinations that spark new insights (Guimerà et al., 2005; Jones et al., 2008; Jones, 2009).

Building on this literature, we associate radicalness with the degree of knowledge diversity and recombination potential embedded in academic research teams. We argue, in turn, that "eclectic" researchers (e.g., interdisciplinary or mobile) should bring in greater diversity of knowledge, and are thus more likely to generate path-breaking outcomes. Second, teams rather than lone researchers, and especially teams of researchers that do not tend to work together, shall also offer greater recombinant potential. Finally, teams that are heterogeneous, demographically and/or scientifically, are even more likely to be diverse and thus to produce radical research.

We make use of a novel dataset that overlaps all the EPSRC applications, funded or not funded, with the calendar census of all the engineering departments of 40 major UK universities between 1991 and 2007 (Banal-Estanol et al., 2015).[3] We use the publication and grant application record of each applicant to build individual proxies of ability, type of research, and application experience. We aggregate these proxies, alongside other demographics, to construct average team variables (our "basic" drivers) as well as variables that reflect individual and team knowledge diversity and recombination potential (our "radical" variables).

Our results provide, initially, some reassurance regarding the award process in funding bodies. We show that the most able researchers (measured in terms of quantity and quality of past publications) are significantly more likely to be successful. More applied researchers (in terms of type of past publications) are less likely to be funded. Past experience (in terms of number of past EPSRC applications) does not affect the likelihood of award. But, both the academic rank and affiliation with an elite university significantly increase statistically and quantitatively, the probability of success, even if we control for the publication record of the applicants.

Our results also indicate that "radical teams" are less likely to be selected by funding organizations. Interdisciplinary researchers are not more nor less likely to be successful. But, teams formed by (or including) "outsiders," i.e., researchers who obtained their Ph.D. degree in another institution, are significantly less likely to obtain funding. Teams of researchers are also less likely to be funded than lone researchers, and new teams have even lower chances than usual collaborators. Heterogeneous teams, in terms of application experience or academic rank,

[3]Banal-Estanol et al. (2013a; 2013b) used part of this dataset and other information to analyze endogeneous collaboration patterns between academics and firms and the consequences, in terms of publication activity, of these collaborations.

have a similar likelihood of success than homogeneous teams. But, scientifically diverse teams, in the sense that they combine basic and applied researchers, are significantly less likely to be financed.

Radical teams may be less likely to be funded because the expected research output of their projects is lower or because, voluntarily or involuntarily, the evaluation process is biased against radical teams. We investigate if there is a bias by comparing the results of the award decision regression against those of a research output regression. We take into account that there is sample selection as the output regressions can only be run on the subsample of projects that were awarded. Our results hint at a bias, as the effect of radicalness in the output regression is generally positive whereas that obtained in the grant award decision regression is negative.

We discuss four possible explanations of this bias in the selection process of funding organizations. First, projects offering greater recombinant opportunity may be more complex to evaluate (Nightingale, 1998). Second, evaluators of radical projects, often from different disciplines, may have different evaluation criteria and views on the merits of a proposal. Li (2014) finds evidence that evaluators are biased in favor of projects in their own area. Third, the process may favor "safe" rather than "risky" proposals. Projects tend to be scored on the basis of "doability" and "grant renewals," be they formal or de facto, have a much higher chance of being positively reviewed (Stephan, 2014). Fourth, committees may be especially likely to reject radical projects, as they may have more dispersed evaluations (Sah and Stiglitz, 1986; 1988).

We know surprisingly little on the role that personal, institutional, and discipline factors play in obtaining funding in academia. Funding organizations often claim to apply competitive, merit-based selection procedures, and therefore the probability of success should be dependent on the applicants' productivity. Although there is some 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 scientist productivity, measured in terms of publication or patent stock, but by other personal characteristics, such as whether s/he 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).

Boudreau et al. (2016) is, to our knowledge, the only previous work that links novelty (or radicalness) 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 compared 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. Thus, our paper 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.

2 Measuring radical innovation in academia

We base our empirical strategy on the idea that the public funding organization or "agency" maximizes an objective function $f(Q, R, X)$, where Q and R represent the ability and radicalness of the research team, and X contains other factors (such as the type of research or the characteristics of the holding university). The agency shall fund a project if and only if $f(\cdot)$ is above a certain threshold. This threshold may arise because the agency has a limited budget or because it imposes minimum requirements. In our econometric model, we shall view the objective of the agency as an (unobserved) latent variable that depends linearly on our variables of interest,

$$f(Q, R, X) = aQ + bR + cX + \varepsilon,$$

where ε is a normally distributed error term. Thus, the likelihood of funding increases in the ability and radicalness of the team if and only if $a > 0$ and $b > 0$, respectively.

Most papers use the same variables to proxy for the ability of the research team: the quantity and/or the quality of past publications and the number and/or value of previous grants (Grimpe, 2012; Banal-Estanol et al., 2013b). And there is some evidence that the probability of success in the funding process depends positively on the scientific productivity of the team of applicants, i.e., $a > 0$ (Viner et al., 2004). But, it is far less obvious, and there is far less agreement on how to measure the degree of radicalness of a research team, let alone assess its effect on the likelihood of funding success, i.e., whether b is positive or negative.

This section proposes three measures of the degree of radicalness of academic research teams, i.e., the level of R. We make use of the literature in recombinant innovation (Weitzman, 1998; Fleming, 2001; Singh and Fleming, 2010), which argues that bringing together ideas from different sources is the key driver of radical innovation. Although recombinant innovation among unrelated knowledge domains may be more likely to fail, such innovations, when successful, are also more likely to have an impact as recombination across unrelated domains can lead to completely new principles and applications (Fleming, 2001). Greater diversity of knowledge enables not only greater recombinant opportunity but also a more rigorous assessment of that opportunity (Singh and Fleming, 2010).[4]

2.1 Eclectic researchers

Eclectic researchers, e.g. those that combine different disciplines or institutional experiences, are more likely to draw ideas from different sources, and are therefore more likely to produce radical innovation. Indeed, interdisciplinary researchers are often thought of as being better suited to identifying ways of solving complex problems, generating new research avenues, and challenging established beliefs (Barry et al., 2008). Hollingsworth (2007), for example, compares the laboratories where 291 major discoveries in biomedical sciences occurred, with other laboratories, also headed by highly visible scientists, but who never made major discoveries. The laboratories that made discoveries were all headed by directors who had the capacity to integrate diversity and to address problems relevant to numerous fields of science.

Mobile researchers should also be more likely to bring different knowledge and capabilities. Previous research has documented a natural organizational tendency toward the exploitation of familiar knowledge (March, 1991). Recruiting individuals from outside the organization instead has been shown to enhance a firm's access to external ideas, thus enabling it to complement the exploitation of native ideas with the exploration of foreign ideas (Singh and Agrawal, 2011).

Instead, academic inbreeding, defined as the recruitment practice in which universities hire their own doctoral students after graduation, has been closely associated with the concept of immobility (Berelson, 1960). Horta et al. (2009) confirm that inbred faculty collaborate and exchange less information with those outside their institutions and, as a result, are less integrated into national and international networks. This lack of connectivity with the exterior of the university lends support to the view that inbred faculty contribute to the organizational stagnation of knowledge. "Silver-corded faculty," that is, academics working at the same university where they were awarded their doctoral degree but having previously worked at another university after concluding the doctorate (Berelson, 1960), also tend to favor internal over external information exchanges, but are more productive (Caplow and McGee, 1958; Horta, 2013).

[4] Conti et al. (2014) show that "better" inventors, in the sense that they have larger patent records, generate a higher rate of inventions but each of their inventions has a lower probability of being a breakthrough. The net effect is positive: more established inventors display a higher rate of breakthroughs than brand-new inventors. Our measures of radicalness take the quality of the researchers as given.

2.2 (New) teams

Teams are more likely to span knowledge domains than lone researchers, and are thus more likely to produce transformative research (Uzzi et al., 2013). Working in teams increases the likelihood of scientists integrating multiple and divergent perspectives (Falk-Krzesinski et al., 2011). Singh and Fleming (2010) show, indeed, that the patents generated by inventors working in a team are more likely to represent breakthroughs than the patents generated by lone inventors.[5]

Comparing new teams with past collaborators, past collaboration not only improves the ability of team members to cooperate with each other but also provides information about the other. In addition, repeated interaction creates trust both in terms of motives and in terms of competencies (Cowan et al., 2004). That is why firms that have engaged in partnerships in the past are more likely to collaborate in the future (Gulati, 1995; Chung et al., 2000). But partnership inertia has drawbacks, especially in terms of incorporating different knowledge bases and creating original knowledge combinations. Consistent with this argument, Singh and Fleming (2010) show that the patents of teams of inventors with a higher number of past patents are more likely to end up as breakthroughs, but the probability of breakthrough decreases if those past patents are from the same team.

2.3 Heterogeneous teams

Heterogeneous teams have greater opportunity to leverage the expertise of each team member and use a wider range of information. Diversity can be for example in terms of application experience or academic rank. In other contexts, team diversity has already been linked to greater and broader knowledge bases and better innovative outcomes. For example, using an experiment with MBA students, Dahlin et al. (2005) find that heterogeneity allows groups to benefit from informational diversity.

Scientifically diverse teams—those that are multidisciplinary—are often postulated to be the most successful in accelerating innovation (Post et al., 2009), even if they are more difficult to manage (O'Connor at al., 2003). Intellectually diverse teams, not dominated by a single view, are also argued to be more successful than an individual is ever likely to be (Disis and Slattery, 2010).[6] In his study, Hollingsworth (2007) shows that almost all of the major discoveries were

[5] Patents from teams were 28% more likely to be in the 95th percentile of cited patents than those from lone investigators. Overall, patents from teams were twice as likely to be cited and 22% less likely to have no citations as compared with patents associated with a single inventor.

[6] Singh and Fleming (2010) also show that the positive effects of teams on patents are mediated by the diversity of the technical experience of team members, defined as the distinct technology classes the inventor or inventors have patented in before.

made in laboratories with significant scientific diversity. Significantly, none of the 291 discoveries occurred in laboratories that were narrow in scope and more oriented to the issues involving a single discipline.

3 Data and variables

We analyze the award decisions of the EPSRC, the main UK government agency for funding research in engineering and the physical sciences. The aim of EPSRC is to provide financial support for qualified academics and ideas. According to its 2006 strategic plan, its four priorities are to (1) stimulate creative, adventurous research, (2) attract, nurture, and support talented scientists and engineers, (3) build better knowledge transfer between research base and industry via increased collaboration, and (4) encourage multidisciplinary research.

Our unit of observation is a grant application to conduct a particular research project. The EPSRC records contain, for each application, information on the principal investigator (PI) and the coinvestigators, the start and end dates (which allow us to compute duration), the holding organization, as well as the amount of funding requested.[7] We also know whether the application was funded or not. PIs must be academic employees of an eligible UK organization. In almost all the applications, the PI and the coinvestigators are employees of the holding organization. Standard grants do not have constraints on the length or on the funding requested. Funding is awarded on the basis of a peer-reviewed, competitive procedure.

We match all the EPSRC grant applications from 1991 to 2007 with the academic calendar census of all the engineering departments of 40 major universities in the UK, available at the British Library (see Banal-Estanol et al., 2015, for details). We use the applications that include, as a PI or as a coinvestigator, at least one of the academic engineers in the calendar database. We discard the projects of teams of more than 10 academics, so that individual characteristics matter, but the results are very similar when we include all the projects (only 1.5% of the projects involve more than 10 academics).[8]

Our initial sample has $18,576$ projects over 12 years (1996-2007) whose team includes at least one researcher with full information. In some of our regressions, we use data of the whole team of academic researchers while in others we use information of the PI only. The number of projects whose PI is in our database is $15,308$. We also use information from $8,090$ projects from the period 1991-1995 to construct some of our variables.

[7] We observe no difference between funds requested and funds awarded.

[8] For robustness, we have also run all the regressions for applications proposed by teams of at most six academics. All results are similar.

We now describe the variables used in the analysis. We first introduce the "basic" drivers, which shall be the main determinants of grant approval, as well as of the "radical" variables, which proxy for a team's knowledge diversity and recombination potential. Table 1 provides a summary of all the variables.

[Insert Table 1 here]

3.1 Basic variables

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 of the PI only.

As a measure of *scientific ability*, we use the normal count ("count"), the weighted-impact-factor sum of publications ("impact"), the average impact-factor per publication ("average impact"), an adjusted number of citations ("citations"), and the number of top-cited papers ("count of top 5%"). 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 depend 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. The variable that counts the papers in the top 5% is based on the number of citations received by all papers in the year of publication.

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 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 ("type research", and "type 1+2"). Consequently, appliedness is measured in the most basic, most applied axis, and takes values in the interval $[0, 1]$.

We use the EPSRC files to construct variables that reflect the EPSRC *application experience*. We identify, for each applicant, his/her EPSRC applications in the previous four years, both as a PI and as a coinvestigator. We associate to each applicant variables that count the number of past grant applications ("past appl"), and the number of past grants awarded ("past appl aw"). We also define the success rate as the number of projects awarded divided by the number of applications ("past succ rate"). As before, we aggregate the information of all the team members to define variables on the team's average application experience.

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 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.[9]

Finally, we also identify whether the *holding organization* is in the elite "Russell group". 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 of the fraction 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 papers").

3.2 Radical variables

Using the characteristics described in section 2, we construct several variables that measure the degree of radicalness of academic research teams. We divide the variables in the same three categories of section 2.

Eclectic researchers To construct measures of interdisciplinarity, we assign each publication of our academics to a research field using the Thomson-ISI Essential Science Indicator (ESI) database that assigns to each journal in the SCI one (and only one) field (as e.g., Lee et al.,

[9]Some researchers do not hold a Ph.D. For some others, we have not been able to identify the year. In those cases, we equate the Ph.D. year and the year of the first publication of the researcher plus two. We use this convention because it is the best aproximation for the academics for whom we do have the Ph.D. year.

2015). The classification includes 22 ESI fields in science and social sciences. We build two individual measures of interdisciplinarity. The first one is the number of distinct fields in which the researcher has published ("fields").[10] We also define the share of publications (in the five previous years) of an individual in each of the 22 categories by dividing the number of publications in each category by the total number of publications. Then, we measure interdisciplinarity as the dispersion over fields using the equivalent to the Herfindahl index (also known as the Simpson diversity index). The index I is computed as the sum of the squares of the shares of a researcher's fields of publication. Since this index may be counterintuitive as a measure of interdisciplinarity, we use $(1 - I)$ and denote it by "H-interdisciplinarity"; but similar results are obtained if we use $1/I$.

We build mobility measures using the Ph.D. granting institution and the calendar census. We compute first the fraction of team members who have (or whether the PI has) a Ph.D. in the US or in any other country outside the UK ("US phd" and "foreign non-US phd"). Second, we follow the researchers and define them as "outsiders" if, at the time of the project application, they were working at a different institution than the one from which they graduated. Among the insiders, we distinguish between "inbreed" and "silver-corded" faculty, by identifying whether they have worked in another organization since graduation. We compute the fraction of outsiders as well as the fraction of silver-corded faculty in the team. Finally, we create a variable that computes the average number of job moves in the five previous years among the members of the project ("job moves").

(New) teams We first create a variable measuring the "team size" defined as the sum of the number of coinvestigators and the PI. We also construct several variables that reflect prior collaborations in grant applications. We compute the number of pairs in the team that have submitted together at least one grant application in the last four years ("prior pairs"). We also use a measure that takes into account the number of times that these pairs have collaborated, relative to the size of the team ("past links per cap"). For the latter, we construct a similar variable using the awarded projects only ("past links per cap aw").

Heterogeneous teams As measures of heterogeneity in terms of type of research and application experience, we compute normalized standard deviations across team members ("st dev type," "st dev past appl," and "st dev past appl aw"). The normalized standard deviation of

[10] One of the ESI fields is multidisciplinary. However, we neither discard it or use it as a measure of multidisciplinarity because Thomson-ISI ESI includes very few journals in this category—only 36 out of 11,155—and very few of our researchers have publications in those journals.

a variable is the ratio between the standard deviation and the mean of the variable. In terms of academic rank, we define a "diversity in academic rank" variable that represents the balance between the group of junior (academic rank levels 1 and 2) and the group of senior (academic rank levels 3 and 4) researchers in the team. This variable takes a value of 0 if all have identical academic rank and reaches a value of 1/2 if the number of juniors and seniors are the same. Finally, we build measures of interdisciplinarity of the team, by using the number of distinct fields where the researchers in the team have published and the Herfindahl index of the fields at the team level ("fields team" and "H-interdisciplinarity team").

3.3 Descriptive statistics

As shown in Table 2*a*, applications have an average duration of 2.75 years and the amount requested per capita for the whole duration of the project is $\pounds 128,000$. The percentage of projects awarded is 33.8%. The average academic in our projects publishes 3.79 impact-factor weighted articles per year; the mean is higher than the median (1.77) suggesting that the distribution is negatively skewed. The average type is 0.25, and it is negatively correlated with impact, suggesting that the more applied researchers publish less in high-impact journals. The average academic in our project has applied, in previous years, for 1.7 projects per year.

[Insert Table 2 here]

As previous literature suggests, the publication record of silver-corded academics is similar to that of the outsiders. In particular, the correlation of the silver-corded dummy with the impact is positive and that with the type of research is negative. This is the same for academics holding a Ph.D. from the US and other foreign countries (although the latter is not significant). On the contrary, the dummy variable for inbreed academics is negatively correlated with impact and positively correlated with type of research.

Around 77% 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). The projects from these universities have academics which have higher impact, are more basic, and have more experience in the application process. Table 2*b* provides a list of the aggregate number of projects submitted by each university, as well as the fraction awarded. Although the universities of Oxford and Cambridge do not have more applications, they do have a higher percentage of projects awarded.

4 Empirical results on the award decision

We run probit regressions on the likelihood that an application is funded over the basic and the radical variables. As explained earlier, we shall view the objective of the agency, denoted by $f(Q, R, X)$, as an (unobserved) latent variable that depends linearly on our variables of interest. The agency shall fund a project if and only if $f(\cdot)$ is above a certain threshold. As a result, the dependent variable takes a value of 1 if the project is awarded and a value of 0 if it is not. In all the regressions, we control for year fixed effects and report robust standard errors. We also control for the duration of the project and for the per-capita amount of funding requested.[11]

4.1 Basic drivers

Table 3 reports the marginal effects of the basic drivers. Column 1 shows that the most able (measured in terms of impact-factor-weighted sum 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. In terms of magnitudes, the effect of the ability, although very significant, is small: 10 extra papers in a journal of impact factor equal to one per year of each team member increases the likelihood of success by 2.4%. The effects of the type of research are also small: a change from all publications being basic to all being applied decreases the likelihood of success by 2.3%. Past experience (measured in terms of number of past EPSRC applications) is not significant. But, both seniority and affiliation with a university of the Russell group are positive and significant, both statistically and quantitatively. A step up the career ladder increases the chances by 2.7% whereas being part of the Russell group increases them by 5.3%.

Columns 2 to 4 use alternative measures of ability. They show that the count and the impact per paper are both important determinants of success (column 2). The number of citations (column 3) and having published top-cited papers (column 4) also have a positive influence on the likelihood of success. For instance, an extra paper per year in the top 5% in terms of number of citations of each team member increases the likelihood of funding by 2.2%.

The regression in column 5 uses an alternative measure of type, by considering as applied not only the papers in the first category (technology) but also those in the second category (engineering and technological science). The effect is negative but no longer significant, suggesting that the rate of applied papers decreases the likelihood of funding only if they are very applied.

[11] In all the regressions, the duration of the project has a negative effect on the likelihood that the project is awarded whereas the per-capita amount of funding requested does not have any significant effect. We do not display the coefficients associated with these control variables but they are available upon request.

Columns 6 and 7 show that although experience, defined as participating in previous applications, does not have any significant influence, having participated in awarded projects (column 6) and having a high rate of past success (column 7) positively influence the likelihood of success. Thus, our results support the existence of a Matthew effect on the application process (Defazio et al., 2009). 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. Laudel (2006) also 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. Column 8 includes academic age and it indicates that, taking into account the academic rank, it has a negative effect on the probability of success.

Column 9 reports the results of using a different measure for the quality of the holding university: the number of papers in top (four star) journals. The effect using this variable is also very significant, suggesting that the academic quality of the holding institution matters.

Finally, column 10 shows the coefficients of the variables referring to the PI's, instead of those of the whole team. The results are very similar, although the PI's experience in the application process is weakly negative. But, it is worth noticing that the marginal effect of an additional PI's publication is substantially larger than that of the average team member.[12]

[Insert Table 3 here]

In sum, the empirical results in Table 3 show that the academics' ability, seniority, and success in previous applications, as well as the university's eminence, are important determinants of success in the EPSRC application process. Our results also suggest that the very applied academics find it more difficult to obtain financing.

4.2 Eclectic researchers

Table 4 presents the results of regressions that use several measures of academics' interdisciplinarity and mobility. Since this is an individual characteristic, we focus on the results of the variables related to the PI, but we also display the results of the variables related to the average team member. Conditional on the basic drivers, interdisciplinarity of the PI does not have a significant influence on the likelihood of success in the grant application process (column 1). Also,

[12] Table 3 reports the results for the team and the PI using the most representative variables. But the results using other proxies are very similar. We have also run regressions using the number of top 1% papers in terms of citations, total financing requested in past applications, and number of active researchers in engineering at the university, among others.

whether the PI did the Ph.D. in the US does not have a significant influence on the likelihood of success in the grant application process (column 2). However, the effect is significant and negative for the variable that represents whether the PI obtained a Ph.D. from a foreign country other than the US. This result suggests that some "external" scholars may face difficulties in the EPSRC application process.

[Insert Table 4 here]

The next regressions analyze the effect of the PI being an outsider, that is, not having obtained the Ph.D. at the same university where the PI currently works. As column 3 reveals, an outsider PI is less likely to get the project funded than an insider PI: an outsider PI has a 3.1% lower probability of seeing his/her project funded than an insider PI. In column 4 we include the insiders who are silver-corded academics. Although the descriptive statistics showed that silver-corded and outsider researchers are similar in terms of impact, type, application experience, and academic rank, both types of PI have very different effect on the likelihood of success: in contrast to an outsider PI, a silver-corded PI is significantly more likely to see his/her project financed than an inbreed PI. Column 5 suggests that mobility per se, that is, changing jobs, does not have a significant influence on the likelihood of obtaining financing for the project.

Columns 6 to 8 of Table 4 show that the sign of the coefficients for Ph.D. origin and mobility are similar when we consider the variables associated with the whole team instead of those associated with the PI although the variable silver-corded is not significant for the team.[13]

In sum, the results in Table 4 suggest that the decision-making process may hamper the success of eclectic researchers. We show that academics who did their Ph.D. at a different university are significantly less likely to see their application awarded than academics of similar characteristics who have never left the university where they obtained their Ph.D., or who left for a time period but then returned. Interdisciplinary researchers are not treated more positively than non-interdisciplinary ones.

4.3 (New) teams

As shown in all the regressions in Table 5, teams of a larger size are less likely to be funded, although the effect is not significant in all the regressions. Teams of academics with previous experience working together are more likely to succeed. This is true for all our measures of "old teams", using the number of pairs of academics in the team that have jointly participated in at

[13] The results are similar when we consider only those teams composed entirely by academics with a Ph.D. in the UK.

least one prior application (column 2), or the number of times that these pairs have collaborated, relative to the size of the team, independently if we take into account all projects (column 3) or those that are awarded only (column 4). All the coefficients associated with these variables are positive and significant.[14] Finally, columns 5 and 6 show that the results are the same if we consider the past collaborations of the PI instead of those of the whole team.

[Insert Table 5 here]

In sum, Table 5 suggests that teams have lower chances of obtaining financing for their project than lone inventors, and teams of researchers that have not collaborated together in previous EPSRC applications have even lower chances than those that have collaborated together.

4.4 Heterogeneous teams

Table 6 reports the effects of the variables that measure team heterogeneity with respect to type of research, application experience, and academic rank (columns 1 to 4), using projects with at least two members only. Teams of academics with diverse levels of application experience or academic rank (columns 2 and 4) do not seem to have a lower likelihood of success than homogeneous teams. But, scientifically diverse teams, in the sense that they combine basic and applied academics, as well as teams whose academics have diverse experience in terms of awarded grants, are less likely to be financed (columns 1 and 3). Finally, diversity in terms of fields or interdisciplinarity (column 5) has no significant influence on the likelihood of obtaining funding for the application.

[Insert Table 6 here]

In sum, our results regarding the effect of team's heterogeneity suggest that the decision-making process does not help (and it may hamper the success of) diverse teams. It does not encourage multidisciplinary research either.

5 Is there a bias against radical teams?

Overall, the empirical results of section 4 suggest that the likelihood of success in the grant application process increases with the ability, and decreases with the radicalness, of the research

[14] The coefficients are also positive and significant if we measure the past collaborations through the absolute number of collaborations, or relative to the size of the team, or the absolute number of pairs that have collaborated in awarded projects.

team. Radical teams may be less likely to be financed for at least two reasons. First, despite having more chances of generating path-breaking outcomes, the projects of radical teams may have lower expected research output than those of non-radical teams. Second, voluntarily or involuntarily, the evaluation process may be biased against radical teams. Agencies, for example, may evaluate radical projects with the same expected output more negatively because they are riskier or because their quality is more difficult to assess.

In this section, we investigate if there is a bias against radical teams by comparing the results of the "award decision" regression of the previous section against those of a "research output" regression. Let us also express project research output as a linear function of our variables of interest,

$$g(Q, R, X) = a'Q + b'R + c'X + \varepsilon',$$

where Q and R again represent the ability and radicalness of the research team, Y contains other factors, and ε' is a normally distributed error term. We shall view project research output as another (unobserved) latent variable. We expect the results of the project to be published in a scientific journal if and only if $g(\cdot)$ is above some threshold. According to our framework, in which output the agency uses as objective function $f(Q, R, X) = aQ + bR + cX + \varepsilon$, we shall say that the agency is biased against radical research if $b < b'$. As we show below, our empirical results hint at a bias, as the effect of radicalness in the output regression is generally positive ($b' > 0$) whereas that obtained in the grant award decision regression is negative ($b < 0$).

Our regressions on the research output take into account that there is sample selection (Heckman, 1979; Van de Ven and Van Pragg, 1981). Indeed, we can only run the output regression on the subsample of projects that were awarded. When the error terms ε and ε' are correlated, standard probit techniques applied to the output regression would yield biased results. We therefore rely on the Heckman probit selection model, which provides consistent, asymptotically efficient estimates for all the parameters of the award decision ("selection") regression and the output ("probit") regression. For the model to be well identified, we drop project duration and per-capita amount of funding requested from the output regression.

5.1 Additional data and variables

In addition to the variables that we have described in section 3, we require measures of output for the (funded) EPSRC projects. We again make use of the WoS database, which has been systematically collecting information on funding sources from the acknowledgments of the publications since 2008. As a result of this coverage period, we restrict the set of projects to those in the period 2005-2007.[15]

In the period 2005-2007, there are $1,493$ awarded projects in our dataset. We have identified 963 publications in the years 2008-2010 that acknowledge one of these EPSRC projects as a funding source. Of the $1,493$ projects, 383 (that is, 25.65%) have at least one publication. The average number of publications in those projects is 2.51. Also, there are 199 projects with at least two publications in the dataset.

As proxies of the project's research output, we use two dummy variables: the first one takes a value of 1 if the project has at least one publication (and a value of 0 if it has no publication) whereas the second dummy variable takes a value of 1 only if we can associate at least two publications to the project.

5.2 Empirical results of the output regression

We first run a Heckman probit regression on the likelihood that an awarded application has at least one paper published in our database. Table 7 reports the marginal effects of the basic drivers and some of the radical variables. With respect to the basic drivers, column 1 shows, as expected, that projects awarded to more able researchers are more likely to end up in publications. Also, projects of more basic researchers and of academics working in universities in the Russell group (which helped in the grant application 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 not significant.

[Insert Table 7 here]

Our radical variables have either a positive or a non-significant effect on the output. As column 2 shows, interdisciplinarity does not influence the probability of publishing. However, as shown by columns 3 to 6, PIs or teams composed of academics with a foreign Ph.D., and those who are outsiders of the university, are more likely to generate publications out of a project. But, remember that our results in the previous section showed that they are, at the same time, less likely to get their applications funded. Columns 7 and 8 show that larger teams and teams with past experience of working together are more likely to get one publication out of the project. Larger teams, instead, were shown to be less likely to get funded. New teams, i.e., teams with lower number of past links, is the only variable related to radicalness that is both negatively related to the probability of success in the application process and in the generation of academic

[15] We have replicated tables 3 to 6 using projects from 2005 to 2007 only. The results are similar to those of the full sample although the significance of the coefficient is lower. These tables are available upon request.

output. The variables associated with heterogeneous and diverse teams have a non-significant effect on the likelihood of publication (columns 9 to 11).

Table 8 replicates Table 7 with a dummy that takes the value of 1 only if the project has produced at least two publications. The results are qualitatively similar for the basic variables and for the variables related to Ph.D. origin (more significant for the team and less significant for the PI). Interestingly, diversity in academic rank has now a positive impact on the likelihood that the project will lead to at least two publications.

[Insert Table 8 here]

Taken together, the results of tables 7 and 8 suggest that projects awarded to radical teams are more likely to generate scientific publications than projects awarded to non-radical teams.

6 Discussion and conclusion

Our analysis first shows that academics with a strong record of publications are, not surprisingly, more likely to obtain financing from public funding organizations such as the EPSRC. This result is indeed reassuring and it is robust to several measures of research productivity. The magnitude of the effect, however, is rather small. Applied researchers are slightly less likely to see their projects funded than basic researchers of the same ability. Although pure application experience does not affect the chances of success, we identify a Matthew effect in the sense that past success in the application process helps to explain current success. But, other characteristics seem to be quantitatively more important. Senior researchers and those working at a prestigious university are substantially more likely to be successful in the search for funding.

This may be because the prestige of the academics or the university in which they work induces a bias in the decision-making process. But it could also be that senior researchers prepare better applications and elite universities give researchers more support. We distinguish between these explanations using the output of the subsample of projects that were awarded. We find that projects submitted by more able researchers, or those in elite universities, are not only more likely to be awarded but are also more likely to end up in publications. But academic rank helps in the grant selection process while it is not a significant determinant of research output.

We also show that individuals and teams that are more prone to producing radical or transformative research are less likely to succeed in the application process than others of the same ability, type, academic rank, experience, and university. For instance, academics who did their Ph.D. at a different university are significantly less likely to see their application awarded than academics of similar characteristics who have never left the university where they obtained their Ph.D., or who left for some time but then returned. Our results also show that teams—in particular those formed by academics with no or few prior links among them—are less likely to be funded than lone researchers or teams composed of researchers with prior collaborations. Our regressions also suggest that team diversity is not rewarded by the evaluation committees. Teams that combine academics with different levels of application experience, or those that gather senior and junior members, and those that unite researchers from several disciplines, have similar chances of success to homogeneous teams. But, scientifically diverse teams, in the sense that they combine basic and applied academics, are less likely to succeed in the grant award process.

Insiders may have a narrower view of their field of research and conduct research within the context of the discipline, and may thus be less likely to produce radical research. But they may also be more likely to generate some publishable result out of the project. Teams, especially new ones, may also be more likely to challenge the orthodoxy in the field and to explore innovative avenues and ideas, but they may also find it more difficult to work together and generate output. Similarly, difficulties for team work may emerge in diverse and heterogeneous teams, even though they have the potential to produce more innovative outcomes. If funding organizations focus on research output, radical teams may be at a disadvantage. To assess whether the decision to penalize radicalness is due to a bias of the evaluation process against radical teams, we analyze again the determinants of research output. The comparison of the signs of the coefficients associated with the radical variables in the concession and output regressions hints at the existence of a bias against radical teams. Our radical variables generally have either a positive or a non-significant effect on the likelihood of obtaining output but they have a negative one on the likelihood of obtaining funding.

Radical innovation in academia may not receive as much support from funding organizations as non-radical innovation for several reasons. First, the evaluation of radical projects may be more complex. As in firms (Nightingale, 1998; Nooteboom, 2000), decision-makers in academia have limited cognitive capabilities. They may find it more difficult to identify potentially fruitful combinations of pieces of knowledge that are unrelated to their existing knowledge bases and/or to each other. Boudreau et al. (2016), for example, argue that reviewers may find it difficult to evaluate novel ideas and may tend to discount them.

Second, evaluators often have expertise in (or preferences for) one topic or approach (Li, 2014), and therefore proposals from radical teams may require experts from several disciplines. But then these applications may fail to reach the standard of each of these disciplines and excel in all of them. The fact that an interdisciplinary project, for instance, combines knowledge from (and produces results useful for) different disciplines and thus has the potential to produce more innovative results may not be taken into account.

Third, “safe” (“doable”) proposals may have a better chance of approval than “risky” proposals. Academics on both sides of the Atlantic have voiced concerns about this proclivity for risk aversion and conservatism in the funding allocation process (Luukkonen, 2012; Stephan, 2014). Mueller et al. (2012) provide experimental evidence that individuals indeed experience a negative bias toward creativity (relative to practicality) when they face uncertainty.

Fourth, committees, which tend to be an essential part of this (noisy) selection process (Sah and Stiglitz, 1986; 1988), may find it more difficult to endorse radical applications than individual decision-makers. Given that the expected outcomes of radical projects are less well-defined and more uncertain, they tend to have more disperse evaluations. Committee members may also attribute different weights to the left and right tails of the outcome distributions, resulting in different evaluations. That may make radical projects less successful, as it may be relatively more difficult to reach consensus among committee members (if evaluation is more subjective) or more difficult to reach minimum threshold levels (if evaluation is more quantitative).

Overall, our results suggest that some of the objectives of public funding organizations may be easier to achieve than others. For example, talented academics typically have a better record of publications than regular ones. Thus, if one of the priorities of the agency is the support of talented academics, then committees can base their decisions on the record of publications. The support of creative, adventurous research, and the encouragement of transformative research may be more complex to achieve. Our analysis is a caution of the unintended consequences of the process and calls for paying special attention to radical teams.

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Table 1. List of variables

We report in this table the variables we use in the regressions and their definition. The last column indicates the category of each variable (and the regression in which they are introduced): B = Basic drivers, E = Eclectic researchers, T = (New) teams and H = Heterogeneous teams.

Name of variable	Definition of variable	
Duration	duration of the project (in years)	B
Funds per cap	ratio of requested funding / # of members of the team (in millions)	B
Count	annual per-capita # of ISI papers in previous 5 years (in 10s)	B
Impact	annual per-capita impact of the papers in previous 5 years (in 10s)	B
Average impact	ratio Impact / Count	B
Citations	annual per-capita normalized citations of papers (in 10s)	B
Count of top 5%	annual per-capita # of papers among the top 5% in citations	B
Type research	ratio # of papers category 1 / # of papers all categories	B
Type 1+2	ratio # of papers categories 1-2 / # of papers all categories	B
Past appl	total # of applications in previous 4 years per year	B
Past appl aw	total # of awarded applications in previous 4 years per year	B
Past succ rate	ratio Past appl aw / Past appl	B
Academic rank	academic rank on a scale 1 to 4	B
Academic age	difference between the year of the project and the date of the PhD	B
Russell group	dummy variable equal to 1 if Univ in the Russell group	B
Uni top papers	# of papers at top category in Univ Engineering depts (in 1000s)	B
Fields	# of fields in the publications	E
H Interdisciplinarity	H index of fields in the publications	E
US phd	fraction of PhD degrees in the US	E
Foreign non-US phd	fraction of PhD degrees in a foreign country but no the US	E
Outsider	fraction of PhD degrees from different than the current university	E
Inbreed	fraction of PhD degrees in the same university and never moved	E
Silver corded	fraction of PhD degrees in the same university but moved in between	E
Job moves	# of job moves in last 5 years	E
Team size	sum of the # of coinvestigators and the PI	T
Prior pairs	# of pairs of researchers submitted together in past 4 years	T
Past links per cap	ratio # of times pairs submitted together past 4 years / Team size	T
Past links per cap aw	ratio # of times pairs awarded together past 4 years / Team size	T
St dev type	normalized std deviation of type of team members	H
St dev past appl	normalized std deviation of past applications of team members	H
St dev past appl aw	normalized std deviation awarded past applications team members	H
Diversity academic rank	minimum {ratio of # of academic rank levels 1 and 2 / total, 1 minus this ratio}	H
Fields team	# of fields in the publications of all the members of the team	H
H Interdisciplinarity team	H index of fields in the publications of all the members of the team	H

Table 2a. Descriptive statistics

We report the descriptive statistics for the dependent variable (awarded), the basic independent variables (impact, type of research, past applications, academic rank and Russell group), as well as for the duration (in years) and the amount requested per capita (in Million £) of the team of academics. We also report variables related to the academics' mobility and Ph.D. origin. ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

Variables	Observations	Mean	St dev	Median	Corr. Awarded	Corr. Impact	Corr. Type	Corr. Past appl	Corr. Acad. rank
Duration (in years)	18,576	2.753	1.014	3					
Funds per cap (in M£)	18,576	.128	.275	0.082					
Awarded	18,576	.338	.473	0					
Impact (in 10s)	18,576	.379	.567	.177	.032***				
Type research	18,576	.254	.326	.1	-.024***	-.327***			
Past appl	18,576	1.705	1.233	1.4	.033***	.421***	-.149***		
Academic rank	18,576	2.786	1.033	3	.057***	.249***	-.056***	.338***	
Russell group	18,576	.774	.41	1	.042***	.116***	-.021***	.087***	.005
Outsider	17,759	.697	.408	1	-.032***	.023***	-.064***	.037***	.047***
Inbreed	17,759	.281	.398	0	.028***	-.034***	.070***	-.049***	-.054***
Silver corded	17,759	.021	.129	0	.017	.031***	-.015**	.035***	.018**
US phd	17,784	.030	.148	0	.004	.023***	-.054***	.001	-.002
Foreign non-US phd	17,784	.070	.225	0	-.047***	.007	-.020***	-.028***	-.089***

Table 2b. List of universities

This table presents the total number of projects and the fraction of awarded projects in each university, as well as the total number of projects and the average fraction of projects awarded in Russell and non-Russell group universities. * The University of Manchester was formed in 2004 by the merger of the University of Manchester Institute of Science and Technology (UMIST) and Victoria University. We include all of their projects prior to 2004.

Russell Group	Number of projects	Fraction awarded	Non-Russell Group	Number of projects	Fraction awarded
University of Birmingham	809	0.35	University of Aberdeen	132	0.28
University of Bristol	410	0.36	Aston University	187	0.33
University of Cambridge	1,089	0.44	Brunel University	290	0.17
Cardiff University	346	0.22	City University	189	0.31
Durham University	194	0.29	University of Dundee	183	0.32
University of Edinburgh	463	0.32	University of Essex	141	0.33
University of Exeter	153	0.29	University of Hull	138	0.28
University of Glasgow	508	0.34	Heriot-Watt University	410	0.27
Imperial College London	1,560	0.38	Lancaster University	59	0.36
King's College London	192	0.28	University of Leicester	199	0.28
University of Leeds	965	0.35	Loughborough University	996	0.31
University of Liverpool	511	0.34	University of Reading	55	0.24
The University of Manchester*	1,528	0.33	University of Salford	172	0.38
Newcastle University	654	0.32	University of Strathclyde	550	0.29
University of Nottingham	862	0.33	Swansea University	376	0.39
University of Oxford	681	0.40	University of Wales, Bangor	123	0.29
Queen Mary, University of London	381	0.35			
Queen's University of Belfast	406	0.30	Total	4,200	0.30
University of Sheffield	1,085	0.36			
University of Southampton	670	0.34			
University College London	519	0.35			
University of Warwick	264	0.34			
University of York	126	0.32			
Total	14,376	0.35			

Table 3. Basic Drivers

This table reports the marginal effects of the probit regressions for the probability that an application is awarded based on a set of observable characteristics. The dependent variable is a dummy variable equal to one if the application is awarded, and zero otherwise. Independent variables are characteristics of the academic team. Column 1 is the base regression. It uses the impact, the type of research, the number of past applications, and the academic rank of the team, and a dummy variable equal to one if the university is in the Russell group, and zero otherwise. Columns 2 to 4 use as measures of ability, instead of the impact, the count and the impact per paper; the number of citations; and the number of top 5% cited papers, respectively. Column 5 uses the papers in the cathegories 1 and 2 of the Patent Board Classification, instead of only those in cathegory 1, to measure the type. Columns 6 and 7 use the number of per-capita awarded proyects and the rate of past successful applications, instead of the number of applications, as measures of experience. Column 8 includes the average academic age of the team. Column 9 considers the number of top (four star) papers as a measure of the university scientific level. Column 10 uses measures for the PI instead of the whole team. We report robust standard errors. Year fixed effects are included in all regressions, and we control for duration (which has a significant negative effect) and per-capita requested funding (which has no significant effect). ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

	(1) Base	(2) Ability 2	(3) Ability 3	(4) Ability 4	(5) Type 2	(6) Experience 2	(7) Experience 3	(8) Academic age	(9) University 2	(10) PI
Impact	0.024***				0.024***	0.003	0.024***	0.025***	0.018**	0.035***
	[0.007]				[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Type research	-0.023**	-0.014	-0.025**	-0.026**		-0.019*	-0.022*	-0.026**	-0.020*	-0.023**
	[0.011]	[0.012]	[0.011]	[0.011]		[0.011]	[0.011]	[0.011]	[0.011]	[0.012]
Past appl	0.004	0.002	0.004	0.005	0.004			0.003	0.005*	-0.005*
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]			[0.003]	[0.003]	[0.003]
Academic rank	0.027***	0.025***	0.026***	0.027***	0.027***	0.018***	0.029***	0.037***	0.027***	0.028***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]
Russell group	0.053***	0.051***	0.052***	0.052***	0.052***	0.043***	0.043***	0.052***		0.053***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]		[0.009]
Count		0.056***								
		[0.014]								
Average impact		0.008**								
		[0.004]								
Citations			0.003***							
			[0.001]							
Count of top 5%				0.022***						
				[0.006]						
Type 1+2					-0.015					
					[0.012]					
Past appl aw						0.072***				
						[0.006]				
Past succ rate							0.212***			
							[0.014]			
Academic age								-0.002***		
								[0.001]		
Uni top papers									0.011***	
									[0.001]	
Observations	18,576	18,576	18,576	18,576	18,576	18,576	17,978	18,192	18,575	15,308

Table 4. Eclectic researchers

This table reports the marginal effects of the probit regressions for the probability that an application is awarded based on a set of observable characteristics. The dependent variable is a dummy variable equal to one if the application is awarded, and zero otherwise. Independent variables are characteristics of the academic team. All columns use the impact, the type of research, the number of past applications, and the academic rank either of the PI or of the team, and a dummy variable equal to one if the university is in the Russell group, and zero otherwise. In addition, column 1 uses the sum of the number of fields of the journals where the PI has published and the Herfindahl index of the fields. Column 2 uses whether the PI has a Ph.D. in the US or in a foreign country other than the US. Column 3 uses whether the PI is an outsider, while column 4 adds whether the PI is silver-corded. Column 5 uses the average number of affiliations of the PI in the last five years. Columns 6, 7, and 8 use similar variables as columns 2, 4, and 5 but they use the averages for the whole team instead of the PI. We report robust standard errors. Year fixed effects are included in all regressions, and we control for duration (which has a significant negative effect) and per-capita requested funding (which has no significant effect). ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

	(1) PI Interdis	(2) PI PhD origin	(3) PI outsider 1	(4) PI outsider 2	(5) PI moves	(6) PhD origin	(7) Outsider	(8) Moves
Impact	0.036***	0.007***	0.007***	0.007***	0.007***	0.024***	0.024***	0.025***
	[0.008]	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.007]	[0.007]
Type research	-0.025**	-0.037***	-0.040***	-0.039***	-0.025**	-0.032***	-0.033***	-0.023**
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.011]
Past appl	-0.006**	-0.005	-0.005	-0.005	-0.005*	0.003	0.004	0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Academic rank	0.029***	0.026***	0.027***	0.027***	0.027***	0.026***	0.027***	0.027***
	[0.003]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]	[0.004]
Russell group	0.052***	0.053***	0.053***	0.051***	0.053***	0.052***	0.051***	0.052***
	[0.009]	[0.010]	[0.010]	[0.010]	[0.009]	[0.009]	[0.009]	[0.008]
Fields	-0.002							
	[0.006]							
H interdisciplinarity	0.011							
	[0.027]							
US phd		0.022				0.003		
		[0.022]				[0.023]		
Foreign non-US phd		-0.033**				-0.059***		
		[0.015]				[0.016]		
Outsider			-0.031***	-0.026***			-0.032***	
			[0.009]	[0.009]			[0.009]	
Silver corded				0.070***			0.039	
				[0.026]			[0.027]	
Job moves					0.014			0.014
					[0.012]			[0.013]
Observations	15,047	14,249	14,249	14,249	15,308	17,784	17,759	18,576

Table 5. New Teams

This table reports the marginal effects of the probit regressions for the probability that an application is awarded based on a set of observable characteristics. The dependent variable is a dummy variable equal to one if the application is awarded, and zero otherwise. Independent variables are characteristics of the academic team. All columns use the impact, the type of research, the number of past applications, and the academic rank of the team, and a dummy variable equal to one if the university is in the Russell group, and zero otherwise. In addition, columns 1 to 4 use the size of the team, the number of pairs of academics in the team that have applied together in the past, the number of times that pairs have applied together divided by the team size, and a similar measure that only considers awarded projects, respectively, as measures of previous joint work by the team members. Columns 5 and 6 use similar variables as columns 1 and 2 but considering only those pairs that include the PI. We report robust standard errors. Year fixed effects are included in all regressions, and we control for duration (which has a significant negative effect) and per-capita requested funding (which has no significant effect). ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

	(1) Teams	(2) Old teams 1	(3) Old teams 2	(4) Old teams 3	(5) PI 1	(6) PI 2
Impact	0.024***	0.024***	0.024***	0.023***	0.035***	0.034***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Type research	-0.023**	-0.023**	-0.024**	-0.024**	-0.023**	-0.024**
	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]	[0.012]
Past appl	0.004	0.003	0.002	0.001	-0.007**	-0.007**
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Academic rank	0.027***	0.027***	0.027***	0.027***	0.028***	0.029***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]
Russell group	0.053***	0.053***	0.053***	0.053***	0.054***	0.055***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]
Team size	-0.002	-0.006**	-0.004	-0.006**	-0.016***	-0.012***
	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]	[0.003]
Prior pairs		0.008***			0.025***	
		[0.003]			[0.006]	
Past links per cap			0.003*			0.006***
			[0.002]			[0.002]
Past links per cap aw				0.021***		
				[0.004]		
Observations	18,576	18,576	18,576	18,576	15,308	15,308

Table 6. Heterogeneous teams

This table reports the marginal effects of the probit regressions for the probability that an application is awarded based on a set of observable characteristics. The dependent variable is a dummy variable equal to one if the application is awarded, and zero otherwise. Independent variables are characteristics of the academic team. All columns use the impact, the type of research, the number of past applications, and the academic rank of the team, and a dummy variable equal to one if the university is in the Russell group, and zero otherwise. In addition, columns 1 to 3 use the normalized standard deviations of the type, the number of past aplications, and the number of past applications awarded (together with the average number), respectively. Column 4 measures diversity in academic rank with the minimum between the number of team members with academic rank levels 1 and 2 and one minus this number. Column 5 uses the sum of the number of fields of the journals where the researchers of the team have published and the Herfindahl index of the fields. We report robust standard errors. Year fixed effects are included in all regressions, and we control for duration (which has a significant negative effect) and per-capita requested funding (which has no significant effect). ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

	(1) Type	(2) Experience 1	(3) Experience 2	(4) Rank div	(5) Multidisciplinary
Impact	0.039**	0.045***	0.005	0.042***	0.041***
	[0.019]	[0.013]	[0.013]	[0.011]	[0.012]
Type research	-0.063**	0.009	0.010	0.002	0.008
	[0.031]	[0.018]	[0.018]	[0.017]	[0.017]
Past appl	-0.000	0.000		0.001	0.001
	[0.007]	[0.006]		[0.005]	[0.005]
Academic rank	0.038***	0.045***	0.027***	0.040***	0.039***
	[0.009]	[0.007]	[0.007]	[0.007]	[0.007]
Russell group	0.029*	0.045***	0.031**	0.043***	0.042***
	[0.016]	[0.012]	[0.013]	[0.012]	[0.012]
St dev type	-0.030**				
	[0.015]				
St dev past appl		-0.012			
		[0.013]			
Past appl aw			0.089***		
			[0.013]		
St dev past appl aw			-0.029***		
			[0.011]		
Diversity academic rank				0.010	
				[0.022]	
Fields team					0.000
					[0.005]
H interdisciplinarity team					0.028
					[0.032]
Observations	5,290	8,319	7,905	9,049	9,018

Table 7. Output (at least one publication)

This table reports the marginal effects of the Heckman probit selection model for the output of the awarded projects on a set of observable characteristics. In the selection equation we include, in addition to the variables that we will use in the output regression, the duration and the total grant value of the project. The dependent variable is a dummy variable equal to one if the awarded project has had at least one publication, and zero otherwise. Independent variables are characteristics of the academic team. All columns use the impact, the type of research, the number of past applications, and the academic rank of the team, and a dummy variable equal to one if the university is in the Russell group, and zero otherwise. In addition, column 2 includes the number of fields and the Herfindahl index of the fields the PI has published in. Column 3 includes a variable that indicates if the PI holds a foreign Phd, while column 4 includes one that indicates if the PI is an outsider. Similarly, columns 5 and 6 use the fraction of team members that hold a foreign Phd and the fraction that are outsiders, respectively. Columns 7 and 8 use team size and the number of pairs that have collaborated in the past. Columns 9 to 11 use the normalized standard deviations of the type, the number of past applications awarded (together with the average number), and the diversity in academic rank. We report robust standard errors. Year fixed effects are included in all regressions. ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

	(1) Base	(2) PI eclectic 1	(3) PI eclectic 2	(4) PI eclectic 3	(5) Eclectic 4	(6) Eclectic 5	(7) New teams 1	(8) New teams 2	(9) Heterog. 1	(10) Heterog. 2	(11) Heterog. 3
Impact	0.013**	0.025**	0.021*	0.024*	0.012**	0.023**	0.013**	0.012**	0.023*	0.024***	0.034***
	[0.005]	[0.013]	[0.013]	[0.013]	[0.005]	[0.011]	[0.005]	[0.005]	[0.014]	[0.008]	[0.009]
Type research	-0.037***	-0.087**	-0.069*	-0.074*	-0.031**	-0.056**	-0.038***	-0.037***	-0.048	-0.029	-0.024
	[0.013]	[0.043]	[0.038]	[0.039]	[0.013]	[0.028]	[0.013]	[0.013]	[0.034]	[0.020]	[0.020]
Past appl	0.001	-0.000	0.001	-0.001	0.001	-0.001	0.001	0.001	-0.002		-0.010**
	[0.003]	[0.006]	[0.007]	[0.007]	[0.003]	[0.005]	[0.003]	[0.003]	[0.007]		[0.005]
Academic rank	0.002	-0.010	-0.011	-0.016	0.003	-0.005	0.001	0.002	0.004	0.008	0.018*
	[0.004]	[0.012]	[0.012]	[0.013]	[0.004]	[0.008]	[0.004]	[0.004]	[0.009]	[0.008]	[0.010]
Russell group	0.047***	0.096***	0.110***	0.115***	0.052***	0.084***	0.047***	0.047***	0.047**	0.050***	0.036**
	[0.011]	[0.037]	[0.040]	[0.040]	[0.011]	[0.028]	[0.011]	[0.011]	[0.022]	[0.017]	[0.015]
Fields		0.001									
		[0.011]									
H interdisciplinarity		-0.026									
		[0.062]									
US phd			0.024		0.025						
			[0.054]		[0.019]						
Foreign non-US phd			0.089**		0.030**						
			[0.044]		[0.012]						
Outsider				0.064**		0.036*					
				[0.031]		[0.021]					
Team size							0.005***	0.002			
							[0.002]	[0.002]			
Prior pairs								0.006***			
								[0.002]			
St dev type									0.001		
									[0.014]		
Past appl aw										0.007	
										[0.011]	
St dev past appl aw										-0.004	
										[0.011]	
Diversity academic rank											0.013
											[0.023]
Observations	5,436	4,499	4,287	4,287	5,266	5,261	5,436	5,436	1,669	2,365	2,606

Table 8. Output (at least two publications)

This table reports the marginal effects of the Heckman probit selection model for the output of the awarded projects on a set of observable characteristics. In the selection equation we include, in addition to the variables that we will use in the output regression, the duration and the total grant value of the project. The dependent variable is a dummy variable equal to one if the awarded project has had at least two publications, and zero otherwise. Independent variables are characteristics of the academic team. All columns use the impact, the type of research, the number of past applications, and the academic rank of the team, and a dummy variable equal to one if the university is in the Russell group, and zero otherwise. In addition, column 2 includes the number of fields and the Herfindahl index of the fields the PI has published in. Column 3 includes a variable that indicates if the PI holds a foreign Phd, while column 4 includes one that indicates if the PI is an outsider. Similarly, columns 5 and 6 use the fraction of team members that hold a foreign Phd and the fraction that are outsiders, respectively. Columns 7 and 8 use team size and the number of pairs that have collaborated in the past. Columns 9 to 11 use the normalized standard deviations of the type, the number of past applications awarded (together with the average number), and the diversity in academic rank. We report robust standard errors. Year fixed effects are included in all regressions. ***, ** and * indicate that coefficients are significant at the 1%, 5%, and 10% levels, respectively.

	(1) Base	(2) PI eclectic 1	(3) PI eclectic 2	(4) PI eclectic 3	(5) Eclectic 4	(6) Eclectic 5	(7) New teams 1	(8) New teams 2	(9) Heterog. 1	(10) Heterog. 2	(11) Heterog. 3
Impact	0.008**	0.006	0.006	0.007	0.007*	0.012**	0.008**	0.008**	0.020**	0.019***	0.021***
	[0.003]	[0.006]	[0.007]	[0.007]	[0.004]	[0.006]	[0.003]	[0.003]	[0.008]	[0.006]	[0.006]
Type research	-0.029***	-0.051*	-0.050*	-0.053*	-0.026**	-0.037**	-0.030***	-0.029***	-0.011	-0.015	-0.026
	[0.010]	[0.027]	[0.028]	[0.028]	[0.010]	[0.018]	[0.010]	[0.010]	[0.026]	[0.016]	[0.016]
Past appl	-0.000	-0.003	-0.003	-0.004	0.000	-0.002	-0.000	-0.001	0.002		-0.005*
	[0.002]	[0.003]	[0.004]	[0.004]	[0.002]	[0.003]	[0.002]	[0.002]	[0.005]		[0.003]
Academic rank	0.001	-0.003	-0.001	-0.004	0.002	-0.001	0.000	0.001	0.011*	0.015***	0.029***
	[0.002]	[0.006]	[0.006]	[0.006]	[0.003]	[0.004]	[0.003]	[0.003]	[0.007]	[0.005]	[0.008]
Russell group	0.034***	0.054**	0.068**	0.071**	0.036***	0.050***	0.034***	0.033***	0.016	0.025**	0.026**
	[0.009]	[0.024]	[0.030]	[0.030]	[0.009]	[0.017]	[0.009]	[0.009]	[0.016]	[0.013]	[0.012]
Fields		0.007									
		[0.006]									
H interdisciplinarity		-0.039									
		[0.038]									
US phd			0.021		0.038***						
			[0.030]		[0.012]						
Foreign non-US phd			0.056*		0.030***						
			[0.029]		[0.008]						
Outsider				0.030		0.022*					
				[0.019]		[0.012]					
Team size							0.004***	0.002			
							[0.001]	[0.001]			
Prior pairs								0.004***			
								[0.001]			
St dev type									0.004		
									[0.011]		
Past appl aw										-0.002	
										[0.007]	
St dev past appl aw										-0.005	
										[0.008]	
Diversity academic rank											0.037**
											[0.018]
Observations	5,436	4,499	4,287	4,287	5,261	5,266	5,436	5,436	1,669	2,365	2,606