



Paper to be presented at
DRUID-Asia, Singapore, February 23-25, 2016
Co-organized by DRUID, NUS Business School and SMU - Lee Kong Chian
School of Business.

Exploring New to Self or New to the World: Evidence from Funding and Impact of Academic Scientists Research

Anand Nandkumar
Indian School of Business
Strategy
anand_nandkumar@isb.edu

Reddi Kotha
Singapore Management University
Strategy and Organization
reddikotha@smu.edu.sg

Abstract

When analyzing the performance consequences of exploration explanations do not take into consideration the amount of funding the projects received. We develop predictions that suggest that there may be systematic differences in resource allocation as inventors vary in the type of exploration they conduct. More specifically we suggest when inventors explore new-to-the-world (NW) projects evaluators lacking information to evaluate these projects may rely excessively on the track record of the applicant. Conversely, when inventors explore new-to-self (NS) projects evaluators who are not familiar with the track record of the inventor may excessively discount the track record of the applicant. We test the predictions using matched sample and instrument variable regression on the mismatch between the extent of funding as the type of exploration of the scientist varies and performance of scientists using a sample of 26,253 academic scientists at a large midwestern university from 1970 to 2005.

Exploring New to Self or New to the World: Evidence from Funding and Impact of Academic Scientists Research

Abstract:

When analyzing the performance consequences of exploration explanations do not take into consideration the amount of funding the projects received. We develop predictions that suggest that there may be systematic differences in resource allocation as inventors vary in the type of exploration they conduct. More specifically we suggest when inventors explore new-to-the-world (NW) projects evaluators lacking information to evaluate these projects may rely excessively on the track record of the applicant. Conversely, when inventors explore new-to-self (NS) projects evaluators who are not familiar with the track record of the inventor may excessively discount the track record of the applicant. We test the predictions using matched sample and instrument variable regression on the mismatch between the extent of funding as the type of exploration of the scientist varies and performance of scientists using a sample of 26,253 academic scientists at a large midwestern university from 1970 to 2005.

Keywords: Exploration, Funding, Research-performance, New-to-the-world, New-to-self.

INTRODUCTION

Funding decisions for innovation projects are fraught with difficulty (Bardolet, Fox, and Lovallo, 2011; Lerner and Hall, 2009) due to the information asymmetry (Leland and Pyle, 1977) between the scientists and managers who make decisions about funding innovations, henceforth referred to as *evaluators*. Prior work has highlighted two broad findings that relate to how evaluators make funding decisions and the associated problems that may occur while making such decisions. First, evaluators may look for signals such as the track record of the proposing scientist¹ as a proxy for the future success of the proposed project while making decisions about funding the project (Hsu and Ziedonis, 2013). Second, when inventors explore novel projects, the projects suffer from a negative penalty from evaluators (Boudreau, Guinan, Lakhani, and Riedl, 2012) which implies that such projects may get under-funded – funding for such projects may be lower despite every dollar of funding for such projects yielding as much if not more than innovation projects that conform to existing research paradigms.

To date, to the best of our knowledge, we lack answers on whether the past track record of a researcher substitutes (minimizes) the negative penalty that is associated with projects that have a high degree of exploration content. Moreover, it is also unclear as to whether the extent of substitution varies by the type of exploration undertaken by the scientist. To address these research questions we focus on two of the most common dimensions of exploration by scientists in conjunction with the scientists past track record. The first dimension is when inventors propose projects at the frontiers of science – those new to the world (here on referred to as *NW*), and the second dimension is when they propose projects that are new to themselves (*NS*). We ask if *the exploration (NW or NS) by researchers with*

¹ In this article we use the terms scientists and researchers interchangeably to mean a person that conducts innovation and seeks funding for the same.

varying track record attenuates or exacerbates the mismatch between funding and the performance of the researchers.

To this end, we develop predictions and provide evidence using data collected on academic research projects (conducted by scientists in the realms of biotechnology, engineering, and natural science) that are evaluated for funding by the federal government. Given the difficulty in observing R&D funding decisions at the level of scientists within firms, we make use of a novel dataset where many funding decisions share key qualities with those found R&D-intensive firms.² In our context, evaluators of the funding proposals are academic peers who face competing demands for their scarce time between research, teaching, and service. Etzkowitz (2003: pp110) found that scientists who run laboratories and apply for federal grants describe themselves as “*running a small business.*” Our sample consists of 26,253 academic scientists at a large midwestern university some of whom received federal funding for their innovative technologies between 1970 and 2005. We use a carefully constructed matched sample of similar scientists to test our predictions on funding distortion. To test whether the funding decisions were appropriate, we first estimate how an increase in a type of exploratory context – namely, NS and NW along with the scientist’s track record influences funding. This exercise simply provides us with a rank ordering of how evaluators rank order projects based on the extent of their exploration content and the

² For example, Hounshell, (1998) documents how in Du Pont, projects were evaluated for funding by a committee that were specifically tasked with evaluating the scientific and technical merits of a project while deciding whether to financially support it. Executives at Du Pont based their decisions on whether the project remained interesting and whether it possessed technical merit even if no direct benefits could be demonstrated or measured. This process continued for about three decades and was the back bone of much of the success that Du Pont enjoyed during this period. Similarly Bowen and Purrington, (2008) discuss how at Corning, funding allocation decisions for early stage projects were made by the Corporate Technology Council that was overseen by the CTO. This committee, focused on understanding the technological details of projects instead of standard NPV based analysis while making funding decisions. These two examples illustrate how funding decisions related to R&D are often made based on the technical merits of the project which more or less resembles how federal funding agencies make decisions on projects proposed university scientists in areas related to biomedical, engineering, and natural sciences. Similar examples can also be found about GlaxoSmithKline at <http://hbswk.hbs.edu/item/funding-innovation-is-your-firm-doing-it-wrong>.

scientist's past track record. We then explore mismatches between funding and performance by comparing this order with a similar rank ordering that we estimate for performance conditional on funding. To this end, we estimate how the marginal impact per dollar of funding varies with an increase in a type of exploratory context and the past track record of a scientist.

LITERATURE REVIEW AND PREDICTIONS

"I think that track record counts very heavily. I would rather fund a somewhat average proposal from an outstanding investigator, simply because it's not so difficult to sit down and say, "This is an obvious problem; it should be solved." Everyone can pick out important problems, but not everyone can solve them. This has to be taken into account very heavily" (Cole, Rubin, & Cole, 1977; pp: 144).

Track Record and Screening

Evaluators have to make decisions about whether and how much to fund R&D projects based on two criteria. The first is the *quality* of the project itself, defined as the fit of the proposed project to the funding organization's stated objectives. The second is the *scientist's ability* to implement the project upon receipt of the funding. One may think about evaluators assigning weights to a proposal based on these two parameters. The projects whose sum of the weights exceed a particular threshold value are selected for funding. The funding allocated to a project may increase monotonically with the sum of the weights assigned to the project.

Without information asymmetry, evaluators tend to make appropriate funding decisions by assigning correct weights to both the attractiveness of the proposal and the scientist's implementation ability. The literature, however, suggests that R&D funding decisions are particularly prone to information asymmetry, making it more difficult for evaluators to assess the value of the proposed project (Leland and Pyle, 1977). In the presence of information asymmetry, evaluators rely on other signals such as the scientist's

prior track record. Rindova et al. (2005: pp 1035) suggest that when it is difficult to predict a project's eventual success, evaluators rely on the scientist's track record for two reasons. The first is because they believe that excellent past performance necessarily implies superior implementation ability as also pointed out by Reeder, (1993). Second, evaluators expect that scientists with excellent past performance will continue to propose highly attractive projects (Trope, 1986: pp241), once again assuming that the applicant's past successes offer a reasonable dipstick for future success. We develop arguments on how NW and NS projects affect evaluators' reliance on track records and how such reliance influences the funding outcomes and the ultimate performance of the researchers.

R&D Funding for NW Projects

In a baseline scenario of scientists presenting research based on older, more diffused knowledge in their funding proposals, evaluators are unlikely to experience information asymmetry (since this knowledge is already well understood) and are thus equipped to evaluate the expected success of the project more objectively (Rogers, 1973). In these cases, evaluators will not rely heavily on the applicant's track record when deciding whether or how much to fund the project. On the other hand, when evaluating proposals with less diffused and largely tacit knowledge, evaluators are more likely to encounter greater information asymmetry. Zucker & Darby (1996) found that scientists at the frontiers of science may use tools and techniques that are five to seven years ahead of the rest of the field. In such cases, evaluators may not have sufficient information to judge the proposal on its technical merits and thus rely excessively on the applicant's track record. As argued before, evaluators, are likely to rely on the past track record of scientists on the belief that those with a better track record will likely have superior implementation capability and will also continue to propose high-quality projects, especially as the scientists explore new to the world domains. Therefore, as the extent of NW content in a proposal increases, evaluators are more likely to assign a

higher weight to the both the quality of the proposal and the scientist's ability to implement the project when the scientist's track record is strong. This in turn implies that the amount of funding will increase as well. As such, our hypothesis is as follows:

H1a: When scientists propose NW projects, the track record of the scientist track record becomes more important for funding. Said otherwise, an increase in the track record of a scientist increases funding by more as the NW knowledge in a proposal increases.

R&D Funding for New to Self Projects

When scientists explore NS research topics, two concerns arise: First, evaluators from the new domain are unlikely to be familiar with the past work of the proposing scientist (whose work will be better known in their own area of specialty). Since excellent past performance in a particular domain implies an excellent implementation ability only within the same domain (Reeder, 1993) when proposals contain high levels of NS knowledge, evaluators may then excessively discount the scientist's track record and assign a lower weight for the scientist's implementation ability relative to her "optimal" implementation ability. Second, scientists who explore NS research topics may not know the conventions in the field. The atypical nature of such proposals may dissuade evaluators from being positively disposed to the proposed project at hand. Taken together, these would suggest that as scientists explore NS topics, their track records may be heavily discounted, even though they may be a valid signal of implementation ability. So despite having a significant track record, NS scientists may receive lower funding than similar scientists who conduct research in areas already familiar to peer evaluators.

H1b: When scientists propose NS projects, the track record of the scientist becomes less important for funding. Said otherwise, an increase in the track record of a scientist increases funding by less as the NS knowledge in a proposal increases.

Performance per Dollar Funded: Impact of NW Project Proposals³

Recall that evaluators lacking the relevant knowledge to assess NW projects may rely excessively on the scientist's track record in their scoring. Consequently, NW projects proposed by scientists without a strong track record may be allocated less funding relative to scientists who have similar track records but who propose projects with less NW content. Thus, to receive the same amount of funding, a NW project proposed by a scientist with a relatively modest record must be more credible relative to a project proposed by a scientist with a superior past track record. Therefore per dollar of funding, we would expect NW projects proposed by those with a relatively modest track record to perform better than similar NW projects proposed by scientists with a superior track record.

On the contrary, when allocating resources to scientists who rely on older knowledge for their output, there is no information asymmetry because evaluators are better equipped to screen projects. In such cases, funding allocations are likely scientist's optimal project attractiveness and implementation ability (Li, 2012). Hence, per dollar of funding, we expect the impact of NW projects to be higher when such projects are implemented by scientists with a modest track record relative to those implemented by scientists with a superior track record. Stated otherwise:

H2a: Conditional on the amount of funding received, as the track record of the scientists increases and the extent of the NW content of the project increases the impact of such scientist's output will be lower those with a similar track record but lower NW content project.

Thus, taken together, H1a and H2a suggest that there will be a mismatch between the funding and impact of NW proposals.

Performance per Dollar Funded: Impact of NS Project Proposals

³As we predict the performance outcome of allocations, it is important to note here that we do not build theory on which type of knowledge used to produce output is better or what conditions can improve outputs. There is a substantial body of work that has addressed this question. Here we focus on the challenges of weighing the track records of scientists who explore novel knowledge and the consequences they have on research funding.

Recall again that evaluators are more likely to discount a scientist's track record in proposals containing a high degree of NS. In such cases, although the scientist may have a strong track record, her project will be treated on par with a scientist with a modest track record who proposes a similar project. However, to the extent that prior experience implies superior implementation ability, the impact of these projects may not be similar; in other words, prior experience may imply superior implementation ability. Thus, when prior work is discounted, the weight assigned to the likelihood of the NS proposal's ultimate success may not reflect the scientist's true implementation ability. Moreover, the atypical nature of projects in an NS proposal and their resultant lower weights of their attractiveness also implies that for a scientist with a good past track to receive the same amount of funding when the proposed project is NS, it has to have a higher potential than when a similar scientist proposes a project that is not NS.. On the contrary, the assigned weights of projects that do not contain NS knowledge should more or less reflect the true potential of the project. Thus, NS project implemented by a scientist with a better track record should have a higher impact per dollar of funding than a project that is not NS, proposed by a scientist with a similar track record. Hence, we predict the following:

H2b: Conditional on the amount of funding received, as the track record of the scientists increases and the extent of the NS content of the project increases the impact of such scientist's output will be higher those with a similar track record but lower NS content project.

Thus, taken together, H1b and H2b suggests that there will be a mismatch between funding and impact of NS proposals as well.

METHOD

We study funding of academic researchers from the United States federal agencies as this setting allows us to study the variation in track record, exploration, funding and performance of the academic researchers.

Institutional context

In the United States, two large federal agencies, the National Institute of Health (NIH) and the National Science Foundation (NSF) disseminate a preponderance of research funds to university scientists and account for nearly two-thirds of all federal government research grants for basic research. In 2012, for example, these agencies had budgets of nearly \$30 billion and \$7.8 billion respectively. Whereas NIH is focused on supporting research in biomedical sciences, NSF supports projects more broadly in the sciences including social sciences. The average size of NIH award is nearly \$1.7 million dollars and is spread over 3 to 5 years (Li, 2012). Freeman and Van Reenen (2010) note that in 1980, NIH received 8,515 proposals from first-time applicants and 7,404 from experienced (previously awarded applicants) and that the success rate for first-time applicants was 22% for first-time applicants and 43% for experienced applicants. By 2006 the number of applications from first-time applicants only marginally increased to 9,399 (a 10% increase) whereas those from more experienced applicants stood at 19,822 (a 168% increase) with the success rates being 15% and 24% respectively. Consistent with this insight Azoulay et al., (2011) find that the average tenure of new applicants at NIH almost doubled from 1965 to 2006 from 7.3 years to 12.8 years. Furthermore, in another paper Azoulay et al., (2011) find that NIH grants are more likely to be given to proven and mature areas compared to early and novel areas when compared to grants by the Howard Hughes Institute. Thus, the funding of NIH is predominantly allocated to experienced researchers and for more mature projects.

NSF process is largely similar with a few differences from NIH in evaluating grant proposals. In physical and mathematical sciences, proposals are evaluated by up to 10 ad-hoc mail reviewers. These reviewers are advisory in nature to a program director who then makes a final decision. The panel review is much like the NIH review process and may be supplemented with 4 to 5 mail reviews. The average size of NSF grant in 2006 was \$134,595

(NFS, 2007). These grants are relatively smaller than NIH grants (8% of an NIH grant). Like with NIH, the number of proposals received at NSF has increased over time with more experienced applicants being more successful than new applicants. Between 1997 and 2007, for instance, the number of applications increases from 19,935 to 31, 514. Whereas the success rate for new applicants was 20% in 1997, for experienced applicants (prior successful applicants at NSF) it was 35%. These rates decreased to 15% and 25% respectively in 2006. Experienced researchers constituted 72% of the portfolio of grants awarded in 2006 by NSF. Therefore, a summary view of funding at NSF would also suggest that the past track record of the applicants is correlated with successful grants.

Empirical Setting, Strategy, and Variables

We test the predictions using the-the population of scientists at a large midwestern research university in the U.S. We gathered the grant data from the University dean's office that collects data on all grants received by the employees and students of the University. Also, using the Scopus database for scientific publications, we collected the number of scientific publications that relates to a scientist in a year by matching the first and last names of the scientists. Using this procedure, we acquired all the scientific publications from 1970 through 2010.

Estimation strategy. Our unit of observation is a scientist-year pair and rely on within-scientist variation over time to test our hypotheses. Note that we do not observe data at the level of a proposal. However, several of our measures constructed with a view to using the recent changes in trajectories of scientists. This is based on the assumption that such changes would likely reflect the nature of their proposals as well. This also implies that we cannot observe federal grant applications by academic scientists that were rejected. However, we are mindful of the fact that scientists may systematically differ in both their need for and the ability to raise federal grants. In particular, some scientists could be more research active than

others that as a consequence could drive whether they apply for a federal grant. To ensure that our sample only comprises of research-active scientists, we also restrict our sample only to include ‘active’ scientists, i.e., researchers who have applied and have got funding from any source in the past five-year window. We also restrict our sample to researchers in the domains of science, engineering, and technology areas in which research productivity substantially relies on external funding and dropped researchers who were affiliated with social sciences departments.

Moreover, the funding, as well as performance of scientists, may systematically differ for a variety of reasons. To minimize the possibility that our results are driven by these partly unobserved differences, we construct a matched sample of scientists.⁴ Using the Coarsened Exact Matching (CEM) technique, we match scientists based on their exploration content, department, past track record and their tenure at the university. For every scientist in a specific department with a particular type of exploration content, past track record and tenure, the CEM matching technique finds scientists also within the same department with approximately similar attributes one of whom was funded by a federal grant agency whereas the other was not. Thus, in our context CEM will likely minimize the possibility that our results are driven by selection or even endogeneity which in our case would imply the possibility that scientists choose a particular type of exploration content for reasons associated with federal funding availability. Our resulting sample contains 26,253 unique scientists for the funding estimation.⁵

⁴ We are mindful of the fact that any matching technique is simply based on differences that are observable to the econometrician. However, to the extent that observable and unobservable differences between scientists are correlated with each other, matching enables us to minimize the possibility that our results are driven by unobserved differences.

⁵ In our data we do not observe proposals that were submitted but rejected. Stated otherwise, in our data, we cannot distinguish between scientists who applied for a federal grant but whose proposal was rejected from scientists who did not apply for a federal grant at all in the three year time window. We hence also report regressions that test all our hypotheses on a sample that comprises of all active researchers all of whom received at least a dollar of a federal grant. Using this sample we explore if a particular type of exploration content receives more federal dollars conditional on funding which is an alternative test of our hypotheses H1a and H1b.

Variables: Dependent Variables

Federal funding. The first dependent variable is the total grants made by federal government agencies to a scientist in a three-year forward window. We use a three-year window since federal grants are typically granted for 3 to 5 years. Extending or reducing the grant window does not influence our results. The average grant size per scientist, conditional on getting a federal grant, was \$605,773. To account for varying inflation rates, we convert grants to constant 1985 U.S. dollars.

Performance. Among the three measures of performance of a scientist: citations, publications, and inventions our preferred measure is *forward citations*. This is because citations best capture impact a researcher's work has on the field. One practical hurdle of using citations is the possibility of truncation. Older articles have had more time to be cited, and hence, are more likely to reach the tail of the citation distribution. Moreover, disciplines vary into which they cite prior art. To overcome these issues, we calculate this variable as follows. From the Scopus database, we first acquired the number of forward citations to every article written by a focal scientist for a given year. Given that citations vary by discipline and by publishing year cohort, we calculated a weight that represents the number of citations relative to an average article for that discipline-year cohort. For every scientist's article, we calculated this weight by dividing the number of citations for that focal article by an average that represents the average number of forward citations for the relevant discipline-year pair. We then multiplied the actual number of citations for the focal article by a factor of '1+ weight' to get the number of weighted citations for a particular article. For a scientist year pair, the dependent variable represents the sum of the weighted citations across all articles

This sample neither includes those that did not apply for federal grants nor does it include those who applied for a grant but whose proposal were rejected. We, however, note that our results are qualitatively similar even when we test all our hypotheses on a sample that comprises of all active researchers which lumps both researchers that did not apply for a federal grant in the focal three-year window with those that applied for a federal grant but whose proposals were rejected.

written by the focal scientist until the year of observation. For instance, suppose a scientist had 10 and 5 forward citations for her article published in 2004 and 2005 respectively in the field of cellular biology. Suppose the average number of forward citations for any article published in that area for those respective years were 2 and 4. The weights for years 2004 and 2005 will be $10/2=5$ and $5/4=1.25$ respectively. The weighted citations for this scientist for the year, 2004 will be $10*(1+5)=60$ and for the year 2005 will be $5*(1+1.25)=11.25$. Since we construct cumulative weighted citations, the values for this focal scientist would be 60 for the year 2004 and 71.25 for the year 2005. In the robustness analyzes section, we discuss results of estimations that use a number of publications or inventions as dependent variables.

Independent Variables.

Track record. We proxy the track record of a scientist using the total count of past publications of a scientist calculated until the focal year for that scientist. Since the distribution of this variable is skewed, we use the natural log of this measure in regressions.

We now discuss our measures of NS and NW. Given that we do not observe data at the level of a proposal, we proxy for the NS and NW content of proposals using the NS and NW knowledge of the focal scientist that may have sought a federal grant. Many federal grants are applied well after some proof of concepts have been established, and the recent changes in trajectories of scientists should hence reflect the nature of their proposals as well.

NW knowledge of a Scientist. We follow Azoulay et al., (2011) and use the age of a Scopus keyword as our measure for the newness of knowledge. A keyword is said to be born in the first year it appears in any article indexed in the Scopus database. In is important to note that these keywords are determined by independent experts on behalf of Scopus and hence are not an idiosyncratic interpretation of researchers' work. In essence, this measure captures the extent to which a scientist's research is novel relative to the world's research frontier. For every article published by a scientist, we first calculated the average age of the keywords for

each article. The age of a keyword is calculated as the difference between the year in which the keyword pertaining to the focal scientist's article was born minus the focal year in which the keyword was born. Thus, smaller values imply the relative newness of an article. When there were multiple keywords for an article, we took the average age of all keywords referenced in that article. The variable that we use in our empirical analysis represents the average age of all articles authored by the focal scientist until the focal year. Following Azoulay, et al., (2014) for ease of interpretation, in our regressions, we transform this variable into standard deviations.

NS Knowledge of a Scientist. We measure the NSknowledge by computing the degree of overlap of Scopus keywords found in the focal scientist's articles. The variable that we use in our empirical analysis represents the average overlap of all articles authored by the focal scientist in the immediate three years including the focal year. In essence, an overlap of 1 indicates the perfect specialization of work around a single area, whereas an overlap close to zero reflects an extreme case that highlights the change in the trajectory of a scientist's body of work. Once again, for ease of interpretation, we transform this variable into standard deviations

Control variables.

Tenure. To the extent a scientist learns from her experience and the experience of others, the tenure of a scientist in the academia is an important control variable. We measure this variable in years, starting with the first observed publication, grant application or disclosure made by a scientist until the focal year. Since there may be diminishing returns to tenure, we use tenure and tenure squared as controls.

Supply of federal funding. This variable represents the total grants that the U.S. federal government made to a specific discipline(s) that a scientist is affiliated, in the previous year. Thus, variation in this variable reflects the amount of total federal grants available to

scientists belonging to a discipline across different U.S. universities. We identified the discipline(s) that a focal scientist relates to by using the department, she was affiliated with in a year. Interdisciplinary departments were mapped to multiple disciplines. For example, the department of computer and electrical engineering was mapped to both computer science and electrical engineering.

Grants from other funding organizations. To the extent current evaluators may rely on information that other evaluating institutions have funded a focal scientist, it is important to control for the presence of such funding. We control for grants made by other entities, including three more grant variables that reflect the grants made in the immediately preceding three year window by the university (university funding), for-profit institutions (firm funding), and other non-profit institutions (non-profit grants) that include grants made by a variety of heterogeneous granting institutions that are neither university, federal, nor for profit institutions.

Local resources. Scientists may be located in departments that have discretionary resources. Hence, we also control for the total grants over the immediately preceding three-year period granted to the department to which a focal scientist is affiliated. As with grants made to individual scientists, department grants take four forms: grants made by a federal agency to departments (Department federal funding), grants made the University itself to departments (Department University funding), grants made by for-profit institutions to departments (Department for profit funding), and grants made by other institutions to departments (Department non-profit funding).

Co-author productivity. To ensure that our results are not driven by a focal scientist's affiliation, we control for the quality of the co-authors that a scientist is affiliated using the average number of publications of co-authors of the focal scientist. To construct this measure, we aggregated all the publications of all the co-authors that a scientist was ever affiliated with.

We then divided the resulting number by the total number of co-authors of a focal scientist. As with our other measures, we use the standardized version of this variable in our regressions.

Time dummies. In all our empirical specifications, we control for macroeconomic unobserved time effects using 35-time dummies. The year 1970 is left out in all our specifications as a dummy variable.

Scientist fixed effects: In all our empirical specifications, we control for time-invariant differences between researchers using 26,253 research fixed effects.

RESULTS

Table 1 reports the descriptive statistics of the variables used in our empirical analysis. In Table 2, we report the results of estimations, we use to test the hypotheses. In specification 1-5 we report results of estimations for the amount of funding received from the federal government in a three-year forward window. Specifications 1-3 use a matched sample of ‘active’ researchers. In all specifications, we control for the availability of federal grants in the discipline of the focal scientist, her tenure, the amount of department level grants and grants from other sources. In addition, we also control for the reputation of the co-authors that a scientist is associated with using the cumulative number of productivity of the co-authors that the scientist is associated with. Following the convention in specification 1, we estimate a specification with just the controls. In specification 2 we introduce variables that measure differences in the exploration content NW, NS and their interaction. In specification three we introduce the interaction of NW and NS with the track record of the scientist. We use specification 3 to test the hypotheses 1a and 1b.

Before we discuss results that pertain to the testing of hypotheses related to amount of funding it is important that we point out support for the baseline arguments made by prior literature that we had summarized but not explicitly hypothesized. As predicted by the reputation and attribution literature the coefficient of our proxy for the track record of a

scientist, cumulative publications is positive, and significant predictor of the amount of funding the scientist receives (Table 2, Specification 2, $\beta = 0.232$; $p < 0.01$).

Hypothesis 1a predicted that there would be a greater increase in federal funding when cumulative experience increases by the same amount, for a scientist who pursued NW projects relative to a scientist who pursued older science. Specification 3 of Table 2, suggests that consistent with this prediction the interaction term of NW and cumulative publications is positive and significant ($\beta = 0.10$; $p < 0.01$). For scientists with low new to the world content (mean minus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the funding increases from \$144,567 to \$258,096. In contrast, for scientists with high new to the world content (mean plus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the funding increases from \$526,494 to \$1,052,987.

Hypothesis 1b predicted that there would be a smaller increase in funding when cumulative experience increases by the same amount, for a scientist who does NS research than a scientist who continues to conduct 'old to self' research. Again, consistent with this prediction the interaction of NS and cumulative publications is negative and significant ($\beta = -0.024$; $p < 0.01$). For scientists with low NS content (mean minus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the funding increases from \$425,223 to \$850,445. In contrast to scientists with high NS content (mean plus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the funding increases from \$765,976 to \$944,949. This confirms that funding increases at a slower rate for those who conduct 'new to self' research than for those who conduct 'old to self' research as a track record of the scientist increases.

Impact of Research Estimations

In Table 2 in specifications 6 and 7 we present results of the impact of the research of scientists who received funding. Using the number of citations that the scientists work has received as the dependent variable, we once again estimate within scientist changes in the number of publications as a function of a change in the amount of federal dollars received by the scientist. Given that our hypotheses compare the productivity of a dollar of federal grants on different types of scientists, our regressions compare the effect of a dollar of a federal grant on different types of scientists conditional on receiving at least a dollar of a federal grant. As with specifications on funding, we once again make use of the matched sample of 'active' researchers, to test hypotheses 2a and 2b.

We test the mismatch predictions in hypotheses H2a and H2b. Empirically, this is tested by examining the significance of the track record and exploration: NS or NW. Hypothesis 2a predicted that the joint effect of new science and cumulative publications will not be positively related to the impact of the research since funding was predicted to be positively related, i.e., there is a mismatch (H1a). The joint effect of new science and cumulative publications is negatively related to the impact of the publications of the scientist ($\beta = -0.202$; $p < 0.001$; Table 2, specification 6) This is consistent with a mismatch prediction since those scientists who use novel science and have high track record receive more funding (H1a) but perform no better than others, our results support the prediction. Therefore, hypothesis 2a is supported. For scientists with low new to the world content (mean minus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the citations increase from 12.23 to 24.54. In contrast to scientists with high new to the world content (mean plus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the citations increase from 22.42 to 22.76. This confirms that productivity increases at a faster rate for researchers that pursue for old science than those that pursue NW projects as the track record

of the researcher increases, whereas for funding it was the opposite (H1a) thus confirming the mismatch prediction.

In Hypothesis 2b we predicted that the joint effect of ‘new to self’ and cumulative publications will not be negatively related to impact since we predicted a negative relationship between the interaction in the funding prediction (1b). We find that the interaction term is positive and significant ($\beta = 0.073$ $p < 0.05$; Table 2, specification 6). This supports hypothesis 2b that there is a mismatch between funding and impact of scientists who pursue NS projects as they gain experience. For scientists with low NS content (mean minus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the citations increase from 8.16 to 11.82. In contrast, for scientists with high NS content (mean plus one standard deviation) and when the cumulative publications increase from mean to mean plus one standard deviation the citations increase from 9.87 to 19.74. This confirms that productivity increases at a faster rate for researchers with high NS content than those with low new to self contained as a track record of the researcher increases, whereas for funding it was the opposite (H1b) thus confirming the mismatch prediction. To summarize, the results are consistent with our hypotheses; this can be inferred from the results that confirm that those explore ‘new to self’ who are disfavored in resource allocation perform better than the favored.

ROBUSTNESS ANALYSES

Funding estimations. We test the robustness of the results by excluding all those who did not receive at least a dollar of funding from the federal government in specification 4 and 5 of Table 2. Specification 4 is the sample of active researchers and those who received at least a dollar of funding Specification 5 uses the matched sample of active researchers who have received at least a dollar of funding. We find similar results for hypotheses 1a and 1b

even in these samples. Thus increasing the confidence in our findings for the funding predictions.

Controlling for the endogeneity of funding and performance using instrument variable regression. In specification 7 of Table 2 we report the results of instrument variable regression that uses the change in federal government fund supply as an exogenous instrument for the amount of funding a scientist receives. Freeman and Van Reenen (2009) forcefully argue that the change in the federal supply of funds for a domain be typically not anticipated by the scientists, and it does not vary with the ability of any individual scientist. We find similar results in support of hypothesis 2a ($\beta = -0.162$ $p < 0.05$; Table 4, specification 7) and for hypothesis 2b ($\beta = 0.114$ $p < 0.05$; Table 4, specification 7). Thus increasing the confidence in the results we report.

Alternative performance measures: publications and inventions. We repeat the performance estimation using the number of publications made by the researcher as alternative dependent variables. The results of these estimations are similar to the results we report using citations.

Limitations. Even after the robustness analyzes our results should be interpreted with caution. Our limitation stems from the fact our dataset is at the level of scientists and not a proposal. We hence do not observe the proposals that were rejected. We lump the scientists that have not applied for a federal grant with those who applied for a federal grant but got rejected. We have however, matched scientists based on observable characteristics and also attempted to construct a sample of research active scientists. In addition, we have also focused on a sample of scientists from engineering and sciences departments that heavily rely on federal grants for their research productivity. Thus, to the extent that these characteristics predict whether a scientist would likely apply for a grant the extent of bias if any should be minimal.

CONCLUSION

The prior literature suggests that asymmetric information is a significant impediment to firms making decisions about how much to fund R&D projects and which R&D projects to fund. When confronted with information asymmetry, evaluators tend to favor often scientists with a better track record. Another strand of the literature further suggests that innovation projects that do not conform to the existing research paradigms and penalized by a panel of experts. To the best of our knowledge, the literature has not yet explored whether the past track record of a researcher substitutes (minimizes) for the negative penalty that are associated with projects that have a high degree of exploration content whether the extent of substitution varies by the type of exploration undertaken by the scientist. In this paper, we explore how the two of the most common dimensions of exploration by scientists in conjunction with the scientists past track record distorted R&D funding decisions, especially in scenarios when the organization tasked with making R&D funding decisions are at arm's length to the scientists that conduct research.

We find support for the prediction made by the prior literature that asymmetric information leads to reliance on easily available pertinent information: past track record. We also find that reliance on past track record may systematically distort R&D funding decisions, especially when the exploration content of an R&D project is either NW or NS. We find that experts may overly rely on the proposing scientist's prior track record when a project has a high level of NW exploration content. However, they may excessively discount the proposing scientist's prior track record when a has a high level of NS exploration content. Both of these may distort R&D funding decisions and may result in suboptimal R&D performance per dollar of R&D funding. The findings have implications wherever invention and evaluation of resource allocation are separated such as in the case of technology startups and venture capital industry, divisions seeking to fund from corporate headquarters, or academic scientists seeking research funding as we find.

REFERENCES

- Azoulay, P., Stuart, T., & Wang, Y. 2014. Matthew: Effect or Fable? *Management Science*, 60(1): 92–109.
- Boudreau, K., Guinan, E. C., Lakhani, K. R., & Riedl, C. 2012. *The Novelty Paradox & Bias for Normal Science: Evidence from Randomized Medical Grant Proposal Evaluations*. Harvard Business School Working Paper No. 13-053.
- Cole, S., Cole, J. R., & Rubin, L. 1977. Peer review and the support of science. *Scientific American*, 237: 34–41.
- Etzkowitz, H. 2003. Research groups as “quasi-firms”: the invention of the entrepreneurial university. *Research Policy*, 32(1): 109–121.
- Freeman, R., & Van Reenen, J. 2009. What if Congress doubled R&D spending on the physical sciences? In J. Lerner & S. Stern (Eds.), *Innovation Policy and the Economy*: 1–38. Chicago: University of Chicago Press.
- Hitt, M. A., & Ireland, R. D. (1985). Corporate distinctive competence, strategy, industry and performance. *Strategic Management Journal*, 6(3), 273-293.
- Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal*, 34(7), 761-781
- Jacob, B. A., & Lefgren, L. 2011. The impact of research grant funding on scientific productivity. *Journal of Public Economics*, 95(9–10): 1168–1177.
- Li, D. 2012. *Information, Bias, and Efficiency in Expert Evaluation: Evidence from the NIH*. MIT Working Paper: 1–57.
- Reeder, G. D. 1993. Trait-Behavior Relations and Dispositional Inference. *Personality and Social Psychology Bulletin*, 19(5): 586–593.
- Rindova, V. P., Williamson, I. O., Petkova, A. P., & Sever, J. M. 2005. Being Good or Being Known: An Empirical Examination of the Dimensions, Antecedents, and Consequences of Organizational Reputation. *Academy of Management Journal*, 48(6): 1033–1049.
- Roberts, P. W., & Dowling, G. R. 2002. Corporate reputation and sustained superior financial performance. *Strategic Management Journal*, 23(12): 1077–1093.
- Rogers, E. M. 1973. *Communication strategies for family planning*. New York: Free Press.
- Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22(4): 287–306.
- Sakakibara, M. (1997). Heterogeneity of firm capabilities and cooperative research and development: an empirical examination of motives. *Strategic Management Journal*, 18(S1), 143-164.
- Trope, Y. 1986. Identification and inferential processes in dispositional attribution. *Psychological Review*, 93(3): 239–257.
- Uotila, J., Maula, M., Keil, T., & Zahra, S. A. (2009). Exploration, exploitation, and financial performance: analysis of S&P 500 corporations. *Strategic Management Journal*, 30(2), 221-231.
- Zucker, L. G., & Darby, M. R. 1996. Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. *Proceedings of the National Academy of Sciences*, 93(23), 12709-12716.

Table 1 Variable description and summary statistics

Variable	Description	Mean	Std. dev.
Federal funding for a researcher 3 year forward	Amount of federal funding a scientist receives in the following 3 years in millions of USD	0.214	1.782
Impact	Weighted cumulative citations, in standard deviations	0.343	1.115
Total federal fund supply 3 year forward	The total federal funds available for a domain of research in the following 3 years in millions of USD	3,633.761	6,032.60
Cumulative publications	The total number of publications by a scientists until the previous year	13.344	25.396
NS	Overlap in key words of publications of a scientists averaged over the past 3 years	0.853	0.262
NW	Average age of the keywords of publications made by a scientist over the past 3 years	-30.680	19.035
Total cumulative grants	Total grants raised by a scientist from all sources until the previous year in millions of USD	0.980	5.835
Tenure	The number of years from when the scientists enters the dataset	8.045	7.658
Fed 3 year	Average federal grants received by in the past 3 years in millions of USD	0.214	1.782
TTO 3 year	Total grants received from the TTO over the past 3 years in millions of USD	0.009	0.051
Profit 3 year	Total grants received from for profit firms over the past 3 years in millions of USD	0.014	0.142
Other 3 year	Total grants received from other not for profit agencies over the past 3 years in millions of USD	0.029	0.218
Co-author productivity	Average number of publications made by all coauthors of a scientist until the previous year	9.121	18.762
Department TTO 3 year	Total grants received from the TTO by the department that the scientists is affiliated to over the past 3 years in millions of USD	0.015	0.123
Department profit 3 year	Total grants received from for profit firms by the department that the scientists is affiliated to over the past 3 years in millions of USD	0.002	0.105
Department TTO 3 year	Total grants received from other non-profit agencies by the department that the scientists is affiliated to over the past 3 years in millions of USD	0.014	0.122
Department other 3 year	Total grants received from agencies by the department that the scientists is affiliated to over the past 3 years in millions of USD	0.323	1.331
Department fed 3 year	Total grants received from federal agencies by the department that the scientists is affiliated to over the past 3 years in millions of USD	0.0003	0.001
Year dummies	34 year dummies one each for years 1971-2005		
Scientists fixed effects	26253 fixed effects one for each scientist		

Table 2: Fixed Effects Funding and Impact Regressions

	Federal Funding (1-5)					Impact Regressions (6 & 7)	
	Matched sample of active researchers			Conditional on funding sample	Conditional on funding matched sample	Conditional on funding sample	IV Conditional on funding matched sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cumulative publications		0.232*** (0.016)	0.272*** (0.020)	0.091** (0.042)	0.158*** (0.057)	0.224** (0.119)	0.333** (0.151)
NS		-0.022* (0.012)	0.012 (0.013)	0.048* (0.029)	0.105*** (0.038)	-0.023 (0.046)	0.027 (0.057)
Cuml pubs.X NS (H1b, H2b)			-0.024*** (0.007)	-0.044*** (0.014)	-0.067*** (0.020)	0.073** (0.035)	0.114** (0.046)
NW		0.051** (0.024)	-0.009 (0.024)	-0.065 (0.060)	-0.098 (0.079)	0.201*** (0.067)	0.181** (0.086)
Cuml. pubs X NW (H1a, H1b)			0.100*** (0.010)	0.080*** (0.019)	0.104*** (0.029)	-0.202*** (0.060)	-0.162** (0.073)
NS X NW		-0.024** (0.010)	0.005 (0.011)	0.034 (0.025)	0.024 (0.032)	-0.029 (0.040)	-0.017 (0.055)
Total cuml grants	-0.425*** (0.007)	-0.442*** (0.007)	-0.443*** (0.007)	-0.281*** (0.012)	-0.351*** (0.015)	0.570*** (0.111)	2.210*** (0.338)
Tenure	0.005 (0.005)	0.001 (0.005)	-0.012** (0.005)	0.023* (0.014)	0.025 (0.019)	0.242 (0.175)	0.598*** (0.118)
Tenure square	-0.000** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	0.369*** (0.066)	0.198** (0.078)
TTO 3 year	2.201*** (0.123)	2.220*** (0.124)	2.203*** (0.123)	0.205** (0.088)	1.663*** (0.237)	0.312*** (0.067)	0.342*** (0.107)
Profit 3 year	0.963*** (0.045)	0.941*** (0.045)	0.930*** (0.045)	0.850*** (0.077)	0.999*** (0.095)	0.031*** (0.011)	0.041** (0.016)
Other 3 year	-0.161*** (0.031)	-0.151*** (0.031)	-0.155*** (0.031)	-0.038 (0.053)	-0.101 (0.064)	0.000 (0.000)	0.000 (0.001)
Co-author productivity	0.192*** (0.012)	0.062*** (0.015)	0.066*** (0.015)	0.168*** (0.037)	0.198*** (0.047)	-0.000 (0.021)	0.005 (0.025)
Dep TTO 3 year	-0.056 (0.047)	-0.045 (0.047)	-0.035 (0.047)	-0.049 (0.105)	-0.108 (0.128)	0.058 (0.131)	0.032 (0.164)
Dep profit 3 year	0.030 (0.052)	0.034 (0.052)	0.030 (0.052)	0.094 (0.105)	0.008 (0.127)	-0.252* (0.126)	-0.258* (0.151)
Dep other 3 year	-0.007 (0.006)	-0.008 (0.006)	-0.007 (0.006)	-0.004 (0.017)	-0.013 (0.021)	-28.238 (45.397)	-27.371 (51.976)
Dep fed 3 year	-1.940 (6.320)	-1.115 (6.324)	-1.480 (6.318)	-17.874 (36.925)	-18.033 (40.968)	-0.938** (0.414)	-1.338** (0.583)
Fed Fund Supply	0.123*** (0.015)	0.138*** (0.016)	0.158*** (0.016)	0.245*** (0.040)	0.270*** (0.051)		
Fed 3 year [†]						0.766** (0.326)	0.973** (0.417)
Constant	-0.136** (0.063)	-0.070 (0.067)	0.035 (0.068)	0.387* (0.231)	0.443 (0.306)	0.583** (0.278)	0.846** (0.370)
N	73,773	73,773	73,773	16,463	12,689	18,512	18,512
Within R-squared	0.089	0.094	0.096	0.084	0.094	0.062	0.055
Number of scientists	26,253	26,253	26,253	2,099	1,921	2,099	2,099

[†] Instrumented with federal supply in specification 7. Year and scientist fixed effects included but not reported for the sake of brevity. Standard errors in parentheses; *** p<0.01, ** p<0.05, *p<.10

Figures 1-4: Funding and Performance of Scientists by Track Record and Type of Exploration

