Uncertainty and Individual Discretion in Allocating Research Funds

By

Michael Kearney
S.M Technology and Policy
MIT, 2011

B.A. Mathematics and Political Science
Williams College, 2009

SUBMITTED TO THE SLOAN SCHOOL OF MANAGEMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN MANAGEMENT RESEARCH

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

February 2019

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Signature of Author: 

Michael Kearney
Department of Management
1/18/2019

Certified by: 

Pierre Azoulay
International Programs Professor of Management
Thesis Supervisor

Accepted by: 

Ezra Zuckerman Sivan
Alvin J. Siteman (1948) Professor of Entrepreneurship and Strategy
Deputy Dean
Professor, Technological Innovation, Entrepreneurship, and Strategic Management and Work and Organization Studies
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Submitted to the Sloan School of Management on January 18, 2019 in partial fulfilment of the Requirements for the degree of Masters of Science in Management Research

Abstract

There is a long-standing tradition in public research funding agencies of distributing funds via peer review, which aggregates evaluations of proposed research ideas from a group of external experts. Despite complaints that this process is biased against novel ideas, there is poor understanding of an alternative system that may overcome this bias: the use of individual discretion. Here, we conduct the first quantitative study of how individual discretion affects a research funding portfolio. Using internal project selection data from the Advanced Research Projects Agency-Energy (ARPA-E), we describe how a portfolio of projects selected by individual discretion differs from a portfolio of projects selected by traditional peer review. We show that ARPA-E program directors prefer to fund proposals with greater disagreement among experts, especially if at least one reviewer thinks highly of the proposal. This preference leads ARPA-E to fund more uncertain and creative research ideas, which supports the agency’s mission of pursuing novel ideas for transformational energy technology.

Thesis Supervisor: Pierre Azoulay
Title: International Programs Professor of Management

1 This work is co-authored with Anna Goldstein, PhD.
1. Introduction

There exists broad scholarly agreement on the importance of public research funding for promoting innovation and economic growth, due to the underinvestment of the private sector and the cumulative nature of knowledge (Arrow, 1962; Dasgupta and David, 1994). Despite the strong justification for public research funding organizations, there has been insufficient empirical review of how such programs are managed and, in particular, how they decide to allocate their funding across proposed research projects. The key challenge to project selection is dealing with the inherent uncertainty of innovation. There is significant uncertainty both in the research itself and in the “realm of human activity,” i.e. markets for technology (Rosenberg, 1996, 1990). Together, these uncertainties make it extremely difficult to forecast the value of any research activity ex ante.

In public research funding agencies, the dominant project selection method is peer review, wherein projects are selected by aggregating the opinions of a group of external experts. The drawbacks of peer review have been frequently articulated in the literature. Among these are complaints that reviewers discount novel ideas (Boudreau et al., 2016) and that consensus decisions result in a failure to fund “high-risk/high-return research” (Linton, 2016).

Meanwhile, empirical assessment of alternative designs for research funding allocation has been elusive. In particular, there is a gap in the literature concerning the method of project selection that empowers program staff to use individual discretion. The Defense Advanced Research Projects Agency (DARPA) is the canonical example of an agency that gives program managers freedom to distribute funds without soliciting external peer review. Research on DARPA has focused primarily on active program management, wherein autonomy in project selection is but one element of a larger programmatic strategy (Bonvillian and van Atta, 2011; Fuchs, 2010), and has been mostly limited to qualitative studies.

In this paper, we add to this literature with a quantitative assessment of project selection practices at an agency that, like DARPA, claims to rely on the discretion of its program staff for funding decisions: the Advanced Research Projects Agency-Energy (ARPA-E). ARPA-E provides a unique opportunity for this assessment because, while they give program directors discretion in selecting proposals to fund, they also solicit peer reviews of all submitted proposals. This allows us to compare ARPA-E’s research portfolio with counterfactual alternative portfolios and address the following questions: Does a portfolio of projects selected by individual discretion differ from a portfolio of projects selected by traditional peer review? If so, how do the program director’s decisions relate to the opinions of external peer reviewers? And finally, what is the impact of this project selection practice on the research outputs of the portfolio?
We answer these questions using data on all ARPA-E proposals from 2009-2015 and interviews with multiple program directors. Our findings are five-fold: (1) approximately half of ARPA-E projects are “promoted”, i.e. selected despite low review scores; (2) proposals are more likely to be selected if reviewers disagree on the quality of the proposal, particularly if the proposal has at least one champion; (3) reviewer comments likely play a role in project selection, as certain words, e.g. *creative*, are highly correlated with selection; (4) idiosyncratic differences between program directors and the need to construct a diversified research portfolio may also influence project selection; and (5) “promoted” projects perform equally well on average compared to non-“promoted” projects on short-term metrics.

2. Background

2.1. Decision-making for research funding

For decades, the conventional approach to allocating funds from a public research funding program has been to use a peer review process of some kind. For nearly as long, there have been debates within the scientific community about whether and how to use peer review to determine which research ideas are worth funding. Many have criticized peer review for its inefficiency and its conservative bias, while others defend peer review for its resistance to corruption and political influence. In this section, we review some of the broad discussion around peer review, in order to make a clear comparison with the use of individual discretion.

The origin of modern peer review for funding proposals in the US has been traced to the 1940’s in the Office of Naval Research, with “an informal ‘seeking of a second opinion’ by the grants manager, who mailed a copy of a proposal on the periphery of his competence to a colleague and followed up with a phone call” (Roy, 1985). This method of gathering outside opinions as decision-making inputs gained popularity, and a variety of different peer review systems have since proliferated, perhaps due to the appeal of a “system of institutionalized vigilance” that could produce an impartial appraisal of an idea’s merit (Merton, 1973). Over time, political pressure on US federal agencies has put more decision-making power in the hands of reviewers rather than program staff (Baldwin, 2017).

The most common implementation of peer review for grant-making, labeled “traditional peer review” by Guthrie and co-authors (2013), is as follows: a set of proposed projects are evaluated by a group of experts, either as an in-person panel or individually in writing. Panelists may be asked to reach consensus on which proposals should be funded, or they may simply be asked to submit their individual opinions after discussion. In either case, proposals are typically ranked in order of funding priority and some portion of proposals is funded, depending on the budget of the program. This generic description applies
to the peer review process at many grant-making organizations—most notably the National Institutes of Health (NIH), which collectively entail the largest public research investment in the US with a budget of $32 billion in 2016 (National Institutes of Health, 2017).

A vast literature outlines the many potential shortcomings of peer review for research proposals. Generally, complaints relate to the equity, efficiency, or effectiveness of the process (Guthrie et al., 2013; Ismail et al., 2009; Wessely, 1998). Regarding equity, Lee et al. (2013) reviews commonly cited sources of bias in peer review including, but not limited to, nationality, language, gender, and prestige. Others have highlighted the perception that insular “old boy” networks contaminate peer review systems (Gillespie et al., 1985). There are also concerns regarding the efficiency of peer review, i.e. whether the process can be administered at a reasonable cost (Gordon and Poulin, 2009). As a smaller proportion of proposals receive funding, the time burden on individual researchers is greater. Researchers must prepare and submit more proposals, while also spending more time reviewing others’ proposals (NIH, 2008).

As for effectiveness, there is a stream of literature investigating the ability of peer review to identify the best projects *ex ante*.\(^2\) Li and Agha (2015) found value in peer review for nearly 30 years of NIH R01 grants, in that a proposal’s scoring percentile explained some of the variation in the quantity of publications and citations it yielded. Yet follow up work by Fang and co-authors (2016) on the same dataset found that scores were only able to predict performance at the top percentiles and not for the majority of grants. Lauer and co-workers (2015) found no associations between percentile score and R01 grant productivity at one of the institutes at NIH, when accounting for grant amount. Kaplan et al. (2008) called for a greater number of reviewers to provide greater “statistical precision” in determining a proposal’s value.

Most importantly in the context of our study, a number of scholars have put forth the critique that peer review is biased against riskier, more novel research (Braben, 2004; Chubin and Hackett, 1990; Linton, 2016; Luukkonen, 2012; Travis and Collins, 1991; Wessely, 1998). Boudreau et al. (2016) found that reviewers are systematically biased against more novel research proposals. Because high-impact ideas tend to also have high novelty (Foster et al., 2015; Uzzi et al., 2013; Wang et al., 2017), peer review also seems be poorly suited to selecting projects with the greatest impact.

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\(^2\) Much of the quantitative research on peer review focuses on US biomedical research support, specifically at the NIH, perhaps due to its size, longevity or willingness to make data accessible to researchers.
Naturally, alternatives and modifications to peer review have been proposed to reduce bias against more innovative efforts. A wide variety of modified peer review systems have been proposed by scholars across a range of disciplines; suggestions range from adjustments in how scores are ranked to radically different systems of evaluation (Bollen et al., 2014; Casadevall and Fang, 2014; Cook et al., 2005; Johnson, 2008; Kaplan et al., 2008; Marsh et al., 2008; Roy, 1985). Linton (2016) argues that the range of peer review scores for a given project should be taken into consideration in order to counteract bias against novelty.

Despite abundant criticism and suggested alternatives, many people support retaining the general framework of peer review as it exists today. As the American Academy of Sciences put it in their report *Restoring the Foundation*, “no better system has been devised” (2014). In order make a strong argument for adopting any particular method of project selection, or even for preserving the status quo, a better understanding is needed of how each method impacts a research portfolio and its outcomes. The empirical evidence for or against any given system is scant; programs are reluctant to experiment with their procedures, and so reforms have been adopted based on intuition rather than controlled study (Azoulay, 2012; Lauer and Nakamura, 2015).

Reliance on an individual expert opinion to select proposals, as opposed to a more “democratic” system based on a set of review scores, has not been the subject of any empirical studies, to our knowledge. The canonical example of this practice is at DARPA, where scientists and engineers are hired as short-term staff members and empowered to select which proposals to fund. These program managers may seek external opinions but are not bound to act on them. Individual discretion is endorsed by those who note its use at DARPA to support novel ideas that would have been rejected by a peer review panel (Cook-Deegan, 1996; “In Defence of DARPA,” 2003). However, this model is not always popular; programs that do not fund the highest-scoring projects may experience pushback and concerns over transparency and fairness (Van Noorden, 2015).

Our study of ARPA-E adds quantitative evidence to the discussion of empowering program staff to make research funding decisions. ARPA-E solicits multiple external reviews for each proposal, but they ultimately rely on the individual discretion of program director (PD) to choose which projects to fund within a technical program. This practice allows us to compare the decisions made by these staff members to the alternative decisions that could have been made based solely on the external peer reviews.

2.2. ARPA-E

In its 2007 report *Rising Above the Gathering Storm*, a committee of the National Academies called for the creation of a DARPA-like agency within the Department of Energy (DOE) to pursue transformational
innovation in energy technology (The National Academies, 2007). The Advanced Research Projects Agency - Energy (ARPA-E) was tasked with “identifying and promoting revolutionary advances in fundamental science; translating scientific discoveries and cutting-edge inventions into technological innovations; and accelerating transformational technological advances in areas that industry itself is not likely to undertake because of technical and financial uncertainty” (110th Congress, 2007). To accomplish this, ARPA-E internalized the practices of active program management similar to those utilized at DARPA.

ARPA-E was established by the America COMPETES Act and first funded through the American Recovery and Reinvestment Act in 2009. Its statutory goal is to advance energy technology that reduces greenhouse gas emissions, reduces energy imports and improves energy efficiency of the US economy. ARPA-E is expected to “overcome the long-term and high-risk technological barriers in the development of energy technologies” (110th Congress 2007, sec. 5012). The first solicitation from ARPA-E stated its intention to fund “high-risk concepts with potentially high-payoff” (ARPA-E, 2009).³

As DARPA does for the US military, ARPA-E designs technical programs around specific technical challenges that could result in a transformational impact on the US energy system. ARPA-E states that their goal is to support research that “creates fundamentally new learning curves” (ARPA-E, 2015). There is no clear path or roadmap to successfully creating or enabling new technology. Uncertainty is therefore a desirable feature for ARPA-E’s operations, due to the uncertain nature of transformational innovation compared to research that pursues incremental advances to existing technology.

One of the defining features of ARPA-E, like DARPA before it, is the autonomy granted to the PDs. A recent assessment of ARPA-E by the National Academies found that the independence of PDs is essential to the success of ARPA-E, and our interviews with PDs support this point. PDs are allotted significant discretion in selecting projects for funding, in addition to defining their own program within which to solicit projects and managing the projects after selection. It is not difficult to imagine that this autonomy in selection could have dramatic effects on the portfolio of projects that receive funding.

Upon hiring, ARPA-E PDs design a program with specific technical targets, and the agency solicits research proposals through a Funding Opportunity Announcement (FOA), such as Batteries for Electrical

³ “High-risk” here should be distinguished from scientifically unsound or unfeasible. ARPA-E solicitations state consistently that, “The proposed work may be high risk, but must be feasible.”
Energy Storage in Transportation (BEEST) issued in 2010.\textsuperscript{4} The PD then oversees the merit review process,\textsuperscript{5} which begins with the submission of concept papers, brief summaries of proposed research ideas. ARPA-E solicits reviews of concept papers from a variety of external experts, including university-, industry-, and government-affiliated researchers. A subset of applicants is then encouraged to submit a full proposal. Full proposals include a detailed account of the research effort, milestones, timeline and budget for the proposed project.

Each full proposal is reviewed by another set of external reviewers, who provide numerical scores and comments. Applicants are then given the chance to briefly reply to these review comments. At the end of the review process, the PD submits a recommendation to the Director of ARPA-E of which proposals to select, based on their own review of the application, the content of the external reviews, and the replies received from the applicant.\textsuperscript{6} Proposals are then formally selected by the Director for negotiation to become a funded project, though our interviews with ARPA-E staff indicate that the vast majority of selection decisions follow the recommendation of the PD.

The implementation of individual discretion at ARPA-E is made possible by its unique organizational structure within DOE. Like DARPA’s program managers, ARPA-E PDs are technical experts hired for 3-year rotations.\textsuperscript{7} The agency’s mission to accelerate transformational change in energy technology, and PDs are empowered to make bold choices in pursuit of this mission. ARPA-E PDs are just as likely to be considered “peers” as any external reviewer; it is their position inside the agency and their empowerment to make decisions without consensus that sets the ARPA-E selection process apart from traditional peer review.

\textsuperscript{4} The BEEST program aimed to develop “advanced battery chemistries, architectures, and manufacturing processes with the potential to provide EV [electric vehicle] battery system level energy densities exceeding 200 Wh/kg (mass density) and 300 Wh/liter (volumetric density) at system level costs of $250/kWh or below” (ARPA-E, 2010). According to the FOA, the typical cost of a lithium-ion battery system at the time was $800-$1200/kWh. Lowering the upfront cost of battery systems would open up a larger market for EVs and lead to cost savings, reduced oil imports, and reduced carbon emissions from an increasingly clean electricity supply. The BEEST program was allocated $35 million, and it funded 10 research teams from around the US including companies, universities, and national labs.

\textsuperscript{5} Each FOA at ARPA-E is accompanied by a Merit Review Plan, which is executed by a Merit Review Board chaired by the program director that crafted the program. Our summary of the proposal and selection process is based on an example Merit Review Plan provided by ARPA-E, as well as interviews with ARPA-E staff.

\textsuperscript{6} Exceptions to this practice are made when the PD has a conflict of interest for a particular proposal. In this case, an alternate PD coordinates the proposal’s review and manages the project if the proposal is selected.

\textsuperscript{7} The original authorizing act for ARPA-E specifies a 3-year renewable term and the authority of the Director to hire personnel “without regard to the civil service laws” (110th Congress, 2007).
3. Hypotheses

It is clear that ARPA-E’s PDs are nominally empowered to use their judgment and discretion to allocate funding, yet the existence of this policy does not guarantee any particular difference between ARPA-E’s research portfolio and one that strictly adheres to peer review. Perhaps PDs choose to fund only those projects that are well-liked by reviewers, despite having the ability to make choices independent of review scores. Furthermore, if PDs’ decisions do not rely on reviewer opinions, how are they made instead? Because individual discretion as a method of allocating research funding is poorly studied, this question remains open. Here we list several hypotheses for how PDs at ARPA-E decide which projects to fund, each of which will be explored in this study.

Hypothesis 1. Selection is based on a combination of scoring attributes

Given a set of proposals, each with a distribution of scores from external review, there are a number of possible heuristics that could contribute to a PD’s decision-making. Selections could correlate with the center of mass of the distribution, the width, the location of one of the two tails, or some combination of these elements.

The width of the score distribution is of particular interest, as it measures the extent of disagreement among reviewers. Following Knight’s (1921) treatment of uncertainty as an unknown probability distribution of success, we consider uncertainty as the extent to which the world’s top experts disagree on the merits of a proposed project. Assuming that reviewers are at the forefront of the research topic at hand, we take their lack of consensus to indicate a state of uncertainty. Similarly, standard deviation of scores has been used elsewhere as a measure of risk or volatility for a proposed project (Linton, 2016).

The extremes (minimum and maximum) of the score distribution are also of interest, as they provide a more specific description of the type of disagreement among reviewers. We take these metrics to indicate the extent to which the proposal had any reviewers as either detractors or champions.

Hypothesis 2. Selection is based on weighting of reviewer scores

The ranking of scores or a linear combination of scoring elements implies an equal weight given to each reviewer’s opinion. It is possible that PDs instead consider some reviewers’ opinions more valuable than others. A bias toward or against the scores of certain reviewers would lead PDs to make decisions that diverge from the average review scores.

Hypothesis 3. Selection is based on reviewer comments
In addition to providing numeric scores, reviewers of ARPA-E proposals also include written comments about the proposal’s strengths and weaknesses. PD’s decisions could be informed significantly by these comments, which give context for the scores and provide richer information on each reviewer’s opinion.

Hypothesis 4. Selection is based on the need for a diverse portfolio of technical approaches

Within each FOA for a program at ARPA-E, there are often several possible approaches outlined to reaching the technical targets. The PDs may choose to fund a portfolio that includes multiple approaches, making direct comparisons only within smaller groups of similar proposals.

Hypothesis 5. Selection is based on idiosyncratic PD preferences

Because of the autonomy given to each PD, their decisions may be dominated by their own individual preferences, rather than any discernible trends over the entire agency. For example, there may be variation between individual PDs in their tolerance for risk, leading to variation in how low scores are taken into consideration.

4. Data

In order to establish how individual discretion is implemented in practice at ARPA-E, we compiled datasets of all proposals and funded projects in ARPA-E’s funding history during two on-site visits to ARPA-E. We supplemented these datasets with intellectual property and market engagement outcomes (collected by ARPA-E), publication outcomes (collected by the authors from Web of Science), and founding year for companies (collected by the authors from public information). These data were completely scrubbed of identifying information in order to protect the confidentiality of the applicants.

4.1. Proposals

Our dataset of proposals contains all review scores for proposals submitted to ARPA-E through Dec. 31, 2015. For most FOAs, reviewers rated an application on each of the following four criteria using a five-point scale, with 5 being the highest possible score:8

1. Impact on ARPA-E Mission Area
2. Overall Scientific and Technical Merit

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8 Review questions for OPEN 2012, CHARGES and IDEAS did not fit this format, and so we exclude review data from those programs. We also exclude proposals for the CONNECT program, because these are for outreach projects rather than research and development.
We use the weights stated in the FOA for each component (Impact, Merit, Qualifications, and Management) to calculate an overall score for each proposal-reviewer pair.\textsuperscript{10} One obvious shortcoming of our proposal review data is that ARPA-E’s funding decisions may take into account the additional information provided in the applicant’s replies to reviewer comments.

For the purpose of understanding decision-making by an individual PD, we exclude projects from “open” (non-targeted) programs, for which decision-making around project selection involved multiple PDs. Proposals in “open” programs span a wide range of technology types and are not directly compared to each other. The resulting dataset contains 1,216 proposals. Of these, 43 proposals have scores from only one external reviewer, so these are excluded from any analysis of standard deviation around mean score. 90\% of proposals received 2, 3, or 4 reviews, with an average of 3 reviews. 31\% of proposals in our dataset were selected for negotiation.

### Table 1: Descriptive Statistics for Dataset of ARPA-E Proposals

| Variable                            | N   | Mean | S.D. | Min. | Max. |
|-------------------------------------|-----|------|------|------|------|
| Selected                            | 1216| 0.3  | 0.46 | 0    | 1    |
| Budget requested (million USD)      | 1216| 2.81 | 1.86 | 0.14 | 10.00|
| Number of reviews                   | 1216| 3    | 0.92 | 1    | 7    |
| Mean categorical scores             |     |      |      |      |      |
| Impact                              | 1216| 3.2  | 0.74 | 1    | 5    |
| Merit                               | 1216| 3.1  | 0.75 | 1    | 5    |
| Qualifications                      | 1216| 3.6  | 0.76 | 1    | 5    |
| Management                          | 1216| 3.8  | 1.0  | 1    | 5    |
| Weighted overall scores             |     |      |      |      |      |
| Mean                                | 1216| 3.4  | 0.69 | 1.0  | 4.9  |
| Standard deviation                  | 1173| 0.74 | 0.46 | 0.0  | 2.6  |
| Median                              | 1216| 3.5  | 0.76 | 1.0  | 4.9  |
| Minimum                             | 1216| 2.7  | 0.92 | 1.0  | 4.9  |
| Maximum                             | 1216| 4.0  | 0.71 | 1.0  | 5.0  |

Note: Sample is the set of ARPA-E proposals submitted 2009-2015 to targeted research programs with overall weighted review scores in the format listed in Section 4.1.

\textsuperscript{9} Before 2014, the ratings for “Sound Management Plan” were either “Yes” or “No”. We coded these as 5 and 1 respectively.

\textsuperscript{10} The most common and most recent weighting scheme was 30\% each for Impact, Merit, and Qualifications, and 10\% for Management. FOAs for Electrofuels, BEEST, and IMPACCT made no statements on category weighting. Later programs in 2010 stated that the categories are of “equal weight,” so we assigned 25\% weight to each category in those four FOAs.
We also look in detail at the words used by reviewers in their comments on the proposals. We choose a set of adjectives that indicate novelty or uncertainty, including words with positive and negative connotations that appear in the reviews of more than 1% of ARPA-E proposals. We count the instances of each word in any of the comments within each review of a given proposal, and we subtract the instances of “not [word]” (e.g. “not novel”), leaving a simplified count of affirmative descriptions. At the proposal level, we then create two variables: a binary variable for whether any reviewer used a given word to describe the proposal (W), and a continuous variable for percent of reviewers that used that word (X).

Table 2 shows the means of these two variables for each word.

Table 2: Word Occurrence in External Reviews of ARPA-E Proposals

| Word (N = 1209) | Percent of applications described with word (mean of W) | Average percent of reviews using word (mean of X) | T-test for mean overall score (S) [S|W=1 – S|W=0] |
|----------------|--------------------------------------------------------|-------------------------------------------------|-----------------------------------------------|
| Positive       |                                                        |                                                 |                                               |
| innovative     | 52%                                                    | 24%                                             | 6.10                                          |
| unique         | 39%                                                    | 15%                                             | 5.60                                          |
| risky          | 11%                                                    | 4%                                              | 4.02                                          |
| ambitious      | 12%                                                    | -8%                                             | 3.15                                          |
| new            | 59%                                                    | 28%                                             | 2.74                                          |
| novel          | 47%                                                    | 21%                                             | 1.98                                          |
| creative       | 5%                                                     | 2%                                              | 1.91                                          |
| uncertain      | 12%                                                    | 4%                                              | 1.82                                          |
| Neutral        |                                                        |                                                 |                                               |
| difficult      | 43%                                                    | 18%                                             | 0.86                                          |
| untested       | 1%                                                     | -2%                                             | 0.04                                          |
| unknown        | 8%                                                     | 3%                                              | -0.01                                         |
| original       | 5%                                                     | 2%                                              | -0.59                                         |
| premature      | 3%                                                     | 1%                                              | -0.66                                         |
| Negative       |                                                        |                                                 |                                               |
| unproven       | 3%                                                     | 1%                                              | -1.65                                         |
| unrealistic    | 7%                                                     | 2%                                              | -1.82                                         |
| impossible     | 5%                                                     | 2%                                              | -4.25                                         |

Note: Two-tailed t-test with unequal variance. “Positive” defined as p<0.10 and t>0; “negative” defined as p<0.10 and t<0.

Also in Table 2, we group the proposals that were described by at least one reviewer with a given word, and compare their overall scores against those that were not described by that word. The sign and significance of these differences let us identify a few words as being significantly positive for reviewers on average, such as innovative, unique, risky, or ambitious, and some that are significantly negative, such as impossible.

4.2. Projects
After the applicant and ARPA-E complete negotiations on milestones, objectives, and budget, selected proposals become projects. Many ARPA-E projects are executed as partnerships between multiple organizations; for simplicity, we categorize projects by the organization type of the lead recipient. We separate private company awardees into two categories: startups (founded no more than 5 years prior to the project start date) and established firms.

We create an indicator variable for whether a project was selected based on individual discretion, compared to a counterfactual set of ranking methods. We call these projects “promoted,” in the sense that they were selected despite a relatively low score. Our general method for identifying “promoted” projects is to create a hypothetical score cutoff for each program; this is the cutoff that would be used if projects were selected for funding based on ranking review scores.

We create the cutoff for each program based on the number of projects selected. We take the number of proposals selected under a given FOA to be $N$, and then place the cutoff at the $N$th highest mean overall score. Proposals selected from scores below this cutoff are considered “promoted.” This process is then repeated for rankings based on minimum overall score and maximum overall score. Because the size of a given program is limited by its budget rather than by an arbitrary number of projects, we also test alternative versions of the score cutoff based on the budget for a program rather than the number of projects selected.

In order to address the impact of project selection practices, we need quantitative indicators of research progress. We use publications, patents and market engagement metrics as the outcomes of interest for ARPA-E projects, while acknowledging that these are highly imperfect indicators of value for a research project. Furthermore, given the time lag on these metrics and the fact that our study period is only 5 years long, we are only able to capture an early glimpse at the productivity of ARPA-E projects.

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11 The primary mechanism for ARPA-E funding is a cooperative agreement. When a national lab participates in a project, whether or not it is the lead recipient, it is funded separately through a contract mechanism. Additionally, some non-lead members of a project team may have a separate award issued to their organization during the course of the project. In these cases, we combine the data for multiple awards into a single project. As a result, our unit of analysis is a cohesive technical effort by a team of researchers.

12 In the budget-based method, we tally the cumulative proposed budgets of the proposals to a given FOA, starting from the highest mean overall score, until this cumulative budget reaches the total budget listed in the FOA. For nearly every program, this method produced a higher score cutoff than the one based on number of projects; we focus our analysis on the projects-based metric to obtain a conservative estimate of the number of “promoted” projects.
Publication data were collected for each award through Dec. 31, 2015. We collected these data by searching Web of Science for all award or work authorization numbers for ARPA-E projects. Some publications are flagged as “highly cited” if they exceed the top percentile of citations for papers published in the same year and journal subject category.

Awardees are required as part of their cooperative agreement to acknowledge ARPA-E support in any patents and also to report intellectual property to DOE. ARPA-E has, in collaboration with the DOE General Counsel’s office, collected data on invention disclosures, patent applications, and patents issued as a result of each project. We obtained these data from ARPA-E on inventive outcomes for each award through Dec. 31, 2015.

ARPA-E also tracks the progress of awardees in market engagement. Each spring, to coincide with their annual summit, ARPA-E publishes a list of projects that have received (i) follow-on private funding, (ii) those that have additional government partnerships and (iii) those that have formed companies. We separately obtained from ARPA-E a list of awards that have led to (iv) initial public offerings (IPOs), (v) acquisitions, or (vi) commercial products. All of these outputs are those that the awardee reports as being directly attributable to ARPA-E support. We also obtained the dollar amounts of private funding deals, when these were reported to ARPA-E. Our market engagement data are through February 2016.

We created two aggregated metrics which combine the three categories of external outputs that we measure: publications, inventions and market engagement. First, we measure whether a project produced at least one external sign of progress: a publication, a patent application, or some form of market engagement (among the six types of market engagement measured). Second, we measure whether a project received all three of the key metrics: a publication, a patent application, and some form of market engagement.

We exclude projects that were still in progress in 2016 by limiting our dataset to those that ended on or before Dec. 31, 2015. As such, the latest start date for a project included in our dataset is June 2014. We also limit our dataset to only the proposals with scoring data in targeted programs, rather than “open” programs that span all areas of energy technology. The final dataset contains 165 funded projects, totaling $393 million of funding from ARPA-E.

13 “Company formation” for our purposes includes startup company awardees for which the ARPA-E award was their first funding.
Table 3: Descriptive Statistics for Dataset of ARPA-E Projects

| Variable                              | Mean | S.D. | Min. | Max. |
|---------------------------------------|------|------|------|------|
| Initial project length (years)        | 2.22 | 0.76 | 0.42 | 3.04 |
| Final project length (years)          | 2.72 | 1.02 | 0.38 | 5.00 |
| Initial award amount (million USD)    | 2.14 | 1.41 | 0.20 | 6.00 |
| Final award amount (million USD)      | 2.38 | 1.53 | 0.20 | 6.67 |
| “Promoted”                            |      |      |      |      |
| Low mean score                        | 0.55 | 0.50 | 0    | 1    |
| Low min. score                        | 0.52 | 0.50 | 0    | 1    |
| Low max. score                        | 0.47 | 0.50 | 0    | 1    |
| All around (3/3)                      | 0.28 | 0.45 | 0    | 1    |
| Not at all (0/3)                      | 0.27 | 0.45 | 0    | 1    |
| External outputs                      |      |      |      |      |
| At least 1 publication                | 0.45 | 0.50 | 0    | 1    |
| At Least 1 patent application         | 0.42 | 0.50 | 0    | 1    |
| Market engagement                     | 0.32 | 0.47 | 0    | 1    |
| Any external outputs (>0 of 3)        | 0.75 | 0.44 | 0    | 1    |
| All external outputs (3 of 3)         | 0.08 | 0.28 | 0    | 1    |

Note: Sample is the set of ARPA-E projects completed 2009-2015 (N = 165) within targeted research programs with overall weighted review scores in the format listed in Section 4.1. The “promoted” variable marks whether a proposal was selected despite a score below a hypothetical cutoff, calculated based on the number of projects funded in a given technical program. Project outputs are measured through Dec. 31, 2015.

In addition to collecting the extensive data described above, we interviewed nine current and former ARPA-E technical staff members. The information provided in those interviews informs our analyses below.

5. Results

In this section, we apply our data and interviews with ARPA-E staff to address the questions around which we have formed hypotheses in Section 3: How does a portfolio of projects selected under individual discretion compare to one selected by peer review? What application-level characteristics correlate with project selection? How do descriptions within reviewer comments influence selection decisions? Is selection also driven by other factors, such as idiosyncratic differences between PDs and the need to fill a diversified research portfolio? Finally, we conclude this section with an early effort to evaluate how individual discretion influences research outputs across the portfolio.

5.1. Does a portfolio of projects selected by a single expert with individual discretion differ from a portfolio of projects selected by a group of experts in peer review?

Before turning to our hypotheses on what informational inputs ARPA-E PDs use to select projects, we first establish that their decisions are different from a counterfactual peer-reviewed program. As a stylized construct to represent traditional peer review, we consider three scoring elements that could be ranked for selection purposes:
1. *Mean score:* weigh every score equally in determining a proposal’s quality
2. *Minimum score:* select for proposals with no detractors, by only weighing the lowest score received by each
3. *Maximum score:* select for proposals with champions, by only weighing the highest score received by each

Importantly, these three score ranking methods have different implications for the extent of uncertainty in the funded portfolio. The extent of possible disagreement decreases as the mean score approaches its upper limit of 5.0; this concept is illustrated in Figure 1. Selecting proposals with the highest mean score mechanically limits the amount of disagreement that will be tolerated; the same is true for minimum score. Selecting the highest maximum scores, on the other hand, places no restrictions on the extent of disagreement. A proposal may receive a maximum score of 5.0, regardless of whether other reviewers scored it as a 1.0.

**Figure 1: Scoring Statistics for ARPA-E Proposals**

![Scoring Statistics for ARPA-E Proposals](image)

Note: Each plot depicts an element of the score distribution for proposals submitted to ARPA-E vs. the standard deviation of those scores.

Do ARPA-E’s selection decisions resemble any of these three score ranking methods? Comparing the overall scores for funded and unfunded proposals, it is clear that neither mean, minimum nor maximum score is the sole deciding factor for PDs when selecting proposals (Figure 2). All three measures of the score distribution (min., mean and max.) are higher for funded proposals, and yet there is significant overlap of scores between funded and unfunded proposals. Some projects were selected despite very low scores, and some were not selected despite very high scores.
Figure 2: Box Plots of Scoring Statistics for Unfunded and Funded ARPA-E Proposals

Note: Modified box plot depicts percentiles of score distributions for funded and unfunded ARPA-E proposals. Outside values ($< 25^{th}$ percentile – 1.5 · interquartile range) are plotted as points.

The data depicted in Figure 2 represent proposals aggregated across 33 different technical programs. The conditions for program directors' decision-making varied significantly between programs—for example, in the funding available, or the number of proposals submitted. In order to analyze the extent of program director discretion used to select ARPA-E projects, we consider selection at the level of the technical program.

Comparing the scores of funded and unfunded proposals in a single technical program at ARPA-E (Figure 3), we see that project selection was clearly not based on ranking scores. The fact that the set of selected projects cannot be inferred based solely on their scores is the hallmark of individual discretion. In fact, nearly half of selected projects across the entire set of ARPA-E proposals are “promoted” from a low score: 55% “promoted” by mean score, 52% “promoted” by minimum score, and 47% “promoted” by maximum score (Table 3).
Figure 3: Proposals to the BEEST Program

![Graph showing the variation in scoring elements across the entire set of ARPA-E proposals. The mean score varies across the full scoring scale from 1 to 5, and the standard deviation of scores around the mean is as high as 2.6 for some proposals (Table 1).](image)

Note: Scores for proposals to the ARPA-E Batteries for Electrical Energy Storage in Transportation (BEEST) program, shown in order of three ranking criteria. Of 74 proposals, 9 were selected for funding. “Promoted” proposals were selected despite a score below a hypothetical cutoff, which was the score of the 9th highest scoring proposal.

Despite the clear evidence of individual discretion for project selection at ARPA-E, one would expect selection decisions to correlate with the external review scores in some way. After all, ARPA-E program directors are technical experts and members of the same research community from which external reviewers are sourced. Indeed, if scores were unrelated to selection, i.e. if there were a uniform probability of selection across scores, then we would observe a higher percentage of projects labeled as “promoted”—closer to the overall rejection rate for full proposals, which is 69%.

5.2. What review score characteristics correlate with project selection?

Having shown that a portfolio of projects selected via individual discretion differs substantially from one selected by simple score ranking, we now address Hypothesis 1: that PDs use some combination of scoring elements to select projects. Our interviews with ARPA-E staff indicate that there is a culture of risk-taking at the agency, which pushes PDs to select some proposals that are not uniformly liked by external reviewers. This risk-taking could manifest in our dataset in several ways, such as a preference for a wide range of scores, or even a preference for low scores.

Figure 4 illustrates the variation in scoring elements across the entire set of ARPA-E proposals. The mean score varies across the full scoring scale from 1 to 5, and the standard deviation of scores around the mean is as high as 2.6 for some proposals (Table 1).
Figure 4: Scores of ARPA-E Proposals Ranked by Mean Score

Note: Proposals to ARPA-E ranked in order of mean score, with minimum and maximum scores also plotted.

Are ARPA-E selection decisions predictable based on the scoring characteristics of the proposals? We estimate the relevant correlations in Table 4 using a linear probability model:

\[ Y_i = \alpha_0 + \alpha_1 Score_i + \varphi_i + \epsilon_i \]

\( Y_i \) is the binary outcome variable for whether proposal \( i \) was selected; \( Score_i \) is the scoring element of interest for proposal \( i \), e.g. mean overall review score; \( \varphi \) is a fixed effect for the technical program. Our choice of a linear probability model is based on the ease of interpretation for these results. Similar results using a logit model are shown in the Appendix (Table A1).

Our three simple score heuristics (mean, minimum, and maximum score) are all individually predictive of selection at ARPA-E. Of the three, mean score has the strongest correlation; there is a 19% greater probability of selection for each additional point in the mean overall score. Yet the \( R^2 \) value is relatively low (0.13), indicating that only a small portion of variation in selection is explained by the mean score. Minimum score has both the weakest correlation (8% increased probability of selection per additional point) and the least explanatory value (\( R^2 = 0.08 \)).
Table 4: Predicting Selection by Review Score Distribution

|                | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       |
|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Mean Overall Score | 0.194***  |           |           |           | 0.251***  |           |           |
|                 | (0.043)   |           |           |           | (0.029)   |           |           |
| Min. Overall Score |           | 0.078*   |           |           |           | 0.026     | -0.033    |
|                 |           | (0.044)   |           |           | (0.040)   | (0.042)   |           |
| Max. Overall Score |           |           | 0.174***  |           |           | 0.161***  | 0.056*    |
|                 |           |           | (0.029)   |           |           | (0.021)   | (0.031)   |
| SD Overall Score |           |           |           | 0.060     |           | 0.137**   |           |
|                 |           |           |           | (0.069)   |           | (0.066)   |           |
| Med. Overall Score |           |           |           |           |           |           | 0.164***  |
|                 |           |           |           |           |           |           | (0.033)   |
| Program F.E.    | Y         | Y         | Y         | Y         | Y         | Y         | Y         |
| N               | 1216      | 1216      | 1216      | 1173      | 1173      | 1216      | 1216      |
| R²              | 0.131     | 0.080     | 0.123     | 0.064     | 0.164     | 0.125     | 0.143     |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.  
* p < 0.10, ** p < 0.05, *** p < 0.01

Several additional relationships between score and selection are explored in the Appendix. The overall score is broken down into its components, showing that scores for Merit and Impact are predictive of selection, while scores for Qualifications and Management have little to no statistical relationship to selection (Table A2). In Table A3 and Table A4, we reproduce the analyses from Table 4 for Merit and Impact scores separately, with nearly identical results to the trends on overall score.

In order qualify the strength of the correlations between score and selection, we compare them to the relationship between score and hypothetical selection under each of three systematic selection methods (Table A5). We find that the linear coefficients predicting selection for both mean score and maximum score (0.194 and 0.174, respectively) are less than half what they would be if ARPA-E selected projects by ranking those scores (0.468 and 0.415). For minimum score, the association is even weaker: the coefficient predicting actual selection is five times smaller than the coefficient predicting a high minimum score.

We also estimate the predictive power of reviewer disagreement on selection at ARPA-E. The standard deviation of overall scores for a proposal does not significantly correlate on its own with selection for a given program (Model 4), but it has a positive and significant coefficient when controlling for the mean overall score (Model 5). In other words, ARPA-E PDs tend to fund proposals on which reviewers disagree, given the same mean overall score.
The tendency of ARPA-E PDs to select projects with a wide spread of scores is not necessarily symmetric around the mean score. In fact, when minimum and maximum score are both accounted for, the coefficient on minimum score disappears. This suggests that ARPA-E PDs are more likely to select proposals that were highly-rated by at least one reviewer, but they are not deterred by the presence of a low rating. This trend persists when median score is included (Model 7 in Table 4). ARPA-E PDs tend to agree with the bulk of reviewers, and they also tend to agree with scores in the upper tail of the distribution. They use their discretion to surface proposals that have at least one champion, regardless of whether there are any detractors.

The number of external review scores recorded for proposals in our primary dataset ranges from 1 to 7. Standard deviation is of course a less reliable measure of reviewer disagreement for a very small set of reviews, so in the Appendix, we exclude the proposals with less than 3 reviews and repeat the analyses above. The findings above are robust, except that the coefficient on standard deviation in Model 5 loses significance (Table A6). Yet the coefficient on maximum score in Model 7 gains in both size and significance, confirming that ARPA-E PDs tend to select projects specifically with upside potential, indicated by the presence of a high rating by at least one reviewer.

Another way to measure the uncertainty associated with “promoted” proposals is to compare them to those that were rejected, despite high scores—we call this category of proposals “demoted.” Compared to a counterfactual program that select projects based solely on scores, the effect of individual discretion is to replace “demoted” projects with “promoted” projects. In the Appendix, we show that the spread of scores for “promoted” proposals is greater than for “demoted” proposals on the basis of mean score (Table A7), even beyond the mechanical association of mean score and standard deviation. These results support our finding that the use of individual discretion serves to allow uncertainty in the ARPA-E portfolio.

The regressions above implicitly give equal weight to each reviewer’s opinion, by giving equal consideration to each score in the score distribution for a proposal. In order to quantitatively address Hypothesis 2—that PDs give different weights to individual reviewers’ scores—we would need to measure the difference in how each reviewer’s scoring scale relates to the probability of selection. Unfortunately, we are not able to calculate reliable differences in score weighting, because each reviewer typically only reviews a small sample of proposals; the median number of reviews is 6 among the set of 553 reviewers in our dataset, and 79% of reviewers only review proposals within a single technical program.
However, interviews with ARPA-E staff indicate that the PD's knowledge of the reviewer can at times impact the weight he or she gives that review. Examples of this weighting include discounting a reviewer's opinion when the topic of the proposal is far from their area of expertise, or observing a reviewer's tendency to give especially low scores and considering the score in that relative context.

5.3. Can descriptors in review comments explain project selection?

Next, we look beyond the numeric scores and consider Hypothesis 3: that the information contained in the review comments offers some explanation of ARPA-E PDs selection decisions. Indeed, in our interviews, multiple ARPA-E PDs described ignoring the review scores and instead considering the written content of the reviews. In an attempt to capture this phenomenon, we measure the correlation of selection with certain descriptive words in the review comments.

Table 5: Predicting Selection by Word Occurrence

| Word         | T-test for mean overall score (S) [S|W=1 - S|W=0] | Coefficient on X predicting project selection |
|--------------|-----------------------------------------------|-----------------------------------------------|
|              |                                               | Alone                                         | With mean overall score |
| Positive     |                                               |                                               |                             |
| innovative   | 6.10                                          | 0.155**                                       | 0.083                       |
|              |                                               | (0.065)                                       | (0.060)                     |
| unique       | 5.60                                          | 0.104                                         | 0.013                       |
|              |                                               | (0.070)                                       | (0.073)                     |
| risky        | 4.02                                          | 0.195                                         | 0.077                       |
|              |                                               | (0.117)                                       | (0.123)                     |
| ambitious    | 3.15                                          | 0.175                                         | 0.142                       |
|              |                                               | (0.132)                                       | (0.131)                     |
| new          | 2.74                                          | 0.010                                         | -0.003                      |
|              |                                               | (0.045)                                       | (0.043)                     |
| novel        | 1.98                                          | 0.033                                         | 0.031                       |
|              |                                               | (0.051)                                       | (0.050)                     |
| creative     | 1.91                                          | 0.444***                                      | 0.382***                    |
|              |                                               | (0.156)                                       | (0.136)                     |
| uncertain    | 1.82                                          | -0.123                                        | -0.135                      |
|              |                                               | (0.091)                                       | (0.094)                     |
| Neutral      |                                               |                                               |                             |
| difficult    | 0.86                                          | -0.110*                                       | -0.088                      |
|              |                                               | (0.062)                                       | (0.059)                     |
| untested     | 0.04                                          | 0.006                                         | 0.214                       |
|              |                                               | (0.312)                                       | (0.260)                     |
| unknown      | -0.01                                         | -0.091                                        | -0.045                      |
|              |                                               | (0.112)                                       | (0.113)                     |
| original     | -0.59                                         | -0.109                                        | -0.079                      |
|              |                                               | (0.123)                                       | (0.134)                     |
| premature    | -0.66                                         | 0.195                                         | 0.227                       |
|              |                                               | (0.190)                                       | (0.186)                     |
| Negative     |                                               |                                               |                             |
unproven   -1.65      -0.173    -0.107
          (0.113) (0.120)
unrealistic -1.82      0.062     0.162
           (0.176) (0.173)
impossible  -4.25     -0.311*   -0.045
            (0.181) (0.170)

Note: Column 2 is duplicated for reference from Table 2. Two-tailed t-test with unequal variance. “Positive” defined as p<0.10 and t>0; “negative” defined as p<0.10 and t<0. Columns 3 and 4 are regression coefficients for OLS models of project selection (with program fixed effects) based on the percent of reviews featuring that word as a description, either alone (Column 3) or controlling for the mean overall score of that proposal (Column 4).

Relatively few of these descriptive words predicted selection: reviewers’ use of innovative and creative increases with the probability of selection, and use of difficult and impossible decreases with probability of selection. Controlling for mean score, however, eliminates three out of four of these trends, such that ARPA-E PDs do not appear to take any additional information from those descriptions beyond the score.

Use of the word creative, however, stands out as having predictive power beyond the overall review score. When a reviewer describes some element of the proposal as creative, ARPA-E PDs are on average significantly more likely to fund that proposal, even over other proposals in the same program with the same average score.

5.4. Additional explanations for project selection

Two final hypotheses relate to the inputs for project selection, and yet we are not able to test them quantitatively using the data in this study. Instead we look for supporting evidence in the qualitative data collected through interviews with ARPA-E staff.

First, we consider Hypothesis 4: that projects are selected in order to fill out a diverse portfolio of technical approaches to the program’s technical challenge. Our interviews with PDs and ARPA-E leadership indicate that this is an important consideration. PDs are encouraged to construct a portfolio of different types of technology, in order to maximize the chance that one or more projects will be able to achieve the targets set out in the FOA. The BEEST program, for example, funded projects aimed at new anode materials, new manufacturing processes, and non-lithium battery designs. The value of each project to a diverse portfolio may not be obvious to external reviewers, who only see a small sample of proposals, but it can be taken into account by a PD with a holistic view of the program and the goals of the agency in mind.

Second, Hypothesis 5 is that PDs have idiosyncratic preferences and strategies for project selection. Although we cannot quantify this effect without larger samples of decisions made by each PD across multiple technical programs, we find evidence in our interviews that ARPA-E PDs differ somewhat in
their attitudes regarding project selection. Elements of a proposal may be more or less appealing to different PDs based on their own personal risk tolerance and their professional experience. For example, some PDs report constructing a portfolio that is diverse along the dimension of risk, so that each program has a mix of safe and risky projects. Other PDs report a more uniform preference for high-risk projects.

5.5. Short-term impact of selection method

So far in this section, we have investigated how ARPA-E PDs make selection decisions. Next, we look for the effect of these choices on the performance of ARPA-E’s research portfolio. In particular, we are interested in the performance of “promoted” projects, which would have been rejected if not for individual discretion. Unfortunately, this analysis is limited, because we cannot observe outputs from projects that would have been accepted if not for individual discretion. Additionally, it is important to note that even the longest-running projects in our dataset began only six years before the end of our study period; it is too early to observe the full extent of research outputs from the ARPA-E portfolio. Nonetheless, we endeavor to see how the additional uncertainty baked into the portfolio through “promoted” projects affects their research outputs, compared to those projects that were uncontroversial.

Modeling the probability of research outputs requires that we test the inclusion of several control variables, as there are inherent features of a project that can impact the rate of publishing, patenting and/or market activity. Outputs may be associated with both the organization type (university, established firm, startup, non-profit or National Lab) and project funding amount. Here we control for the initially negotiated project budget, in order to compare projects that were prospectively similar at the outset. The final funding amount is endogenous, as many of the award budgets were adjusted mid-project, and these adjustments likely related to project performance.

We ask whether the projects that were “promoted” by individual discretion of ARPA-E PDs were more or less productive, in terms of publications, patent applications, or market engagement metrics, compared to the projects with high review scores. We address this question with regressions of the form:

\[ Y_i = \alpha_0 + \alpha_1 Promoted_i + \alpha_2 \ln(\text{initial funding amount}_i) + \varphi_i + \delta_i + \epsilon_i \]

\(Y_i\) in this case is the binary outcome variable for whether project \(i\) resulted in a given output measure; "Promoted\(_i\)" is a binary indicator for whether the proposal for project \(i\) scored below a hypothetical score cutoff; \(\varphi_i\) is a fixed effect for the technical program; \(\delta_i\) is the fixed effect for the type of organization leading the project. In Table 6, we test several models for the relationship between “promoted” (on the basis of mean scores) and one particular output: whether or not a project produced a publication. No association is found, regardless of the control variable structure.
Table 6: Control Variables for Publication Output

|                        | (1)     | (2)     | (3)     | (4)     | (5)     |
|------------------------|---------|---------|---------|---------|---------|
| "Promoted"             | 0.051   | 0.067   | -0.074  | -0.056  | -0.055  |
| (low mean score)       | (0.089) | (0.094) | (0.074) | (0.079) | (0.076) |
| Program F.E.           | Y       | Y       | Y       | Y       | Y       |
| Org. Type F.E.         |         |         |         |         |         |
| Initial Award Amount   |         | Y       |         |         |         |
| Log of Initial Award Amount |       |         |         |         | Y       |
| N                      | 165     | 165     | 165     | 165     | 165     |
| R²                     | 0.003   | 0.162   | 0.362   | 0.367   | 0.367   |

Note: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.

* p < 0.10, ** p < 0.05, *** p < 0.01

Next, we test all three “promoted” variables for an association with multiple project outputs. The estimations in Table 7 do not show a significant difference in external measures of short-term performance between low-scoring and high-scoring projects. Projects that are “promoted” from a low review score are indistinguishable in terms of output from those that would have been selected even without individual discretion, within the error of our measurement. Of the 15 regressions shown in Table 7, there are two exceptions: decreased probability of a patent application and of achieving any single measure of progress from those projects that received a low minimum score. In the Appendix, we show the same 15 regressions using alternative independent variables: (i) mean, min. and max. review scores (Table A8) and (ii) an alternative calculation of the “promoted” variable based on the program budget (Table A9). Again, we find no consistent trends.
Table 7: Outputs of “Promoted” Projects

| Dependent Variable: | (1) At Least 1 Publication | (2) At Least 1 Patent Application | (3) Market Engagement | (4) Any External Output | (5) All External Outputs |
|---------------------|--------------------------|----------------------------------|----------------------|------------------------|-------------------------|
| “Promoted” (low mean score) | -0.055 (0.076) | 0.026 (0.116) | 0.031 (0.085) | 0.042 (0.071) | -0.016 (0.076) |
| N                   | 165                      | 165                              | 165                  | 165                    | 165                     |
| $R^2$               | 0.367                    | 0.327                            | 0.284                | 0.362                  | 0.163                   |
| “Promoted” (low min. score) | -0.023 (0.086) | -0.140** (0.066) | 0.008 (0.075) | -0.109* (0.062) | -0.039 (0.053) |
| N                   | 165                      | 165                              | 165                  | 165                    | 165                     |
| $R^2$               | 0.366                    | 0.339                            | 0.284                | 0.370                  | 0.165                   |
| “Promoted” (low max. score) | 0.074 (0.073) | -0.047 (0.081) | 0.073 (0.091) | 0.047 (0.064) | 0.052 (0.061) |
| N                   | 165                      | 165                              | 165                  | 165                    | 165                     |
| $R^2$               | 0.370                    | 0.328                            | 0.288                | 0.363                  | 0.169                   |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program. The models include controls for the log of initial award amount, as well as a fixed effect for technical program and a fixed effect for the organization type (same as Model 5 in Table 6).

* p < 0.10, ** p < 0.05, *** p < 0.01

As a further check for differences in project performance among proposals with different scores, we create two additional variables: one for being “promoted” by all three score rankings (mean, min., and max.) and one for not being “promoted” at all—for the group of projects that would have been selected by all three ranking methods. The regressions in Table 8 further demonstrate that the projects selected via PD discretion have roughly equivalent performance to those that were uncontroversial (i.e. scored highly in external review).
Table 8: Outputs of “Promoted” All Around vs. Not at All “Promoted” Projects

|                        | (1) At Least 1 Publication | (2) At Least 1 Patent Application | (3) Market Engagement | (4) Any External Output | (5) All External Outputs |
|------------------------|---------------------------|----------------------------------|-----------------------|-------------------------|-------------------------|
| “Promoted” all around (low mean, min., and max. score) | 0.066 (0.092)             | -0.220 (0.144)                  | 0.040 (0.106)         | -0.032 (0.075)          | 0.010 (0.070)           |
| Not “promoted” by any measure | 0.014 (0.082)             | -0.086 (0.083)                  | -0.086 (0.056)        | -0.012 (0.085)          | -0.037 (0.056)          |
| N                      | 165                       | 165                              | 165                   | 165                     | 165                     |
| $R^2$                  | 0.368                     | 0.351                            | 0.291                 | 0.361                   | 0.165                   |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program. The models include controls for the log of initial award amount, as well as a fixed effect for technical program and a fixed effect for the organization type. The base category is projects that were “promoted” by one or two measures, but not all three.

* p < 0.10, ** p < 0.05, *** p < 0.01

Beyond the five metrics above, we also consider several other short-term research output metrics: volume of publications, publications that receive relatively high numbers of citations, patents issued rather than simply applied for, and the amount of private funding obtained. Regressions of these outputs vs. a project’s “promoted” status (shown in Table A10 in the Appendix) also point to an equivalence between projects that were well-liked by external reviewers and those that were not.

6. Discussion

Our results show that: (1) the portfolio of ARPA-E projects selected under individual discretion differs significantly from the portfolio that would be selected by ranking of peer review scores; (2) proposals are more likely to be selected if reviewers disagree on the quality of the proposal, particularly if the proposal has at least one champion; (3) reviewer comments likely play a role in project selection, as certain words, e.g. creative, are highly correlated with selection; (4) idiosyncratic differences between PDs and the need to construct a diversified research portfolio may also influence project selection; and finally, (5) “promoted” projects perform equally well on average to non-“promoted” projects on short-term metrics.

Regarding the first result, approximately half of the selection decisions made by ARPA-E PDs diverge from the aggregated opinions of external reviewers, whether that opinion is measured by the mean score or by either extreme of the distribution. Selection decisions do correlate with scores, but these correlations are much lower than they would be for a program that implements peer review by selecting proposals with top review scores. This confirms that ARPA-E PDs use their autonomy and that the content of the agency’s portfolio is different as a result.
Having shown that ARPA-E PDs do not rely solely on review scores for decision-making, our second, third and fourth results describe potential alternative inputs to their decisions. Here, we note an important caveat: our findings describe correlations, rather than a causal effect of any particular feature of a proposal on its chances of being selected. Program directors may be influenced causally by scores or comments in external reviews, or they may base their decisions entirely on unobserved variables that happen to correlate with external reviews. Rather than attempting to describe the mindset of each program director when making selections, we describe the *ex ante* qualities of selected proposals and, by extension, ARPA-E’s research portfolio as a whole.

We find that the research portfolio constructed by individual discretion of PDs carries more collective uncertainty than one based on ranking of peer review scores. For two proposals in a given ARPA-E program receiving the same median score, the proposal with the higher maximum score is more likely to be selected, regardless of its minimum score. The tendency to prefer proposals with champions, whether or not there are detractors, indicates an openness to uncertainty on the part of ARPA-E PDs. There is evidence of champion-based funding allocation in other settings, such as the Gates Foundation’s Grand Challenges Exploration programs (Grand Challenges, 2016) and some angel financing groups (Kerr et al., 2014).

Our focus thus far has been on the use of a proposal’s overall score, and yet it is important to recall that this score is a composite of a reviewers’ assessment of the four review criteria (Impact, Merit, Qualifications, and Management). The trends in selection related to overall score appear to be driven equally by the scores for Merit and Impact. Interestingly, these two scoring categories are analogous to two sources of uncertainty related to research activities: (i) technical uncertainty, i.e. the inability to predict whether a project will achieve its technical goals, and (ii) market uncertainty, i.e. the inability to predict whether, conditional on technical success, the targeted technology will penetrate the market in any meaningful way. In this context, it seems that ARPA-E PDs’ use of discretion exposes the agency to both technical and market uncertainty in equal parts.

Our analyses of reviewer word usage add color to our understanding of how PDs select projects, beyond whether or how they use numeric scores. ARPA-E PDs especially favor proposals with features that reviewers consider “innovative” and “creative”, while disliking projects with the descriptions “difficult” or “impossible.” The word *creative*, in particular, has a strong correlation with selection beyond the effect of the proposal’s mean score, pointing to a preference among PDs for new ideas. The fact that ARPA-E PDs use their autonomy to select creative projects provides an interesting contrast to an alternative
method of stimulating creativity documented by Azoulay et al. (2011): giving researchers themselves the freedom to explore different research directions.

The obvious next question is whether ARPA-E’s openness to uncertainty has translated into a measurable difference in the impact of its portfolio. We find no significant difference in short-term research outputs for those projects “promoted” from low scores by individual discretion, and yet we are cautious in interpreting these results. Because our study design does not capture outputs from unfunded proposals, we cannot directly compare the set of funded ARPA-E projects to the project ideas that were rejected. It could be that ARPA-E projects as a whole perform better, worse, or the same as the projects that would have been funded using alternative selection methods—although we note that research published elsewhere shows high performance of ARPA-E projects on both patenting and publication outcomes compared to other funding sources within DOE (The National Academies 2017).

We recognize that publications, patent applications and market engagement are not measures of success in themselves. Rather, they are early signs of progress toward the ultimate goal of ARPA-E, which is to have a transformational impact on the US energy system. This impact will take decades to materialize as the technologies created with ARPA-E support are developed and deployed. Projects selected using individual discretion at ARPA-E may ultimately have more divergent long-term outcomes, due to a higher level of uncertainty ex ante. Even if many ARPA-E projects result in technical failure, the costs of those projects could be dwarfed by the returns on just a few hugely impactful projects. Indeed, DARPA’s support of research in the 1950’s and 1960’s that led to the development of the internet and the Global Positioning System (GPS) (Alexandrow, 2008; Waldrop, 2008) is often invoked to justify the public investment in DARPA over the years. Time will tell what kind of technological change ARPA-E’s funding brings about in the long-term.

In designing a research program, administrators must choose strategies that best fit their organization’s goals. In this paper, we show that managing project selection through individual discretion can result in a broadly different portfolio than managing through peer review. The potential for introducing uncertainty is useful for an agency like ARPA-E, which targets high-risk, high-reward research; it may be inappropriate for an agency that is not similarly mission-oriented. It is also important to note that the selection decision is only one of many elements of program design. There is likely an interplay between the mode of project selection and other program features, such as organizational structure and project management strategy. These complementarities would be a productive avenue for future research.

7. Conclusion
Like DARPA before it, ARPA-E uses individual discretion to select which research projects to fund. By also collecting external reviews of the proposed projects, ARPA-E has provided a unique opportunity to study the impact of this approach. In this paper, we provide the first quantitative study of individual discretion as a method of project selection for a research funding agency.

We show that ARPA-E program staff use their significant autonomy to construct a research portfolio that diverges from the consensus of external peer reviewers. As a result of this practice, the ARPA-E portfolio encompasses more prospective uncertainty and creativity than a program that simply funds proposals with the highest review scores. To the extent that uncertainty and creativity in a research proposal correspond to novelty of the research activities, we find that individual discretion allows ARPA-E to avoid the bias against novelty associated with traditional peer review.

The fact that program directors are nominally empowered at ARPA-E does not guarantee this outcome for the agency. Empowered program directors could have chosen instead to fund projects that overlap exactly with the opinions of external reviewers, rather than choosing more uncertain projects. Our findings here point to an intentional choice on the part of the agency to encourage its staff to make bold choices. This approach is a good fit for ARPA-E, given its mission to pursue transformational energy research.

Acknowledgements

Our analysis originated as a consulting engagement with the National Academies of Science, Engineering and Medicine for a study on ARPA-E (The National Academies 2017). One author was supported by a fellowship from the Belfer Center for Science and International Affairs. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. We are thankful for helpful discussions with Laura Diaz Anadon, Pierre Azoulay, Paul Beaton, Iain Cockburn, Gail Cohen, Jeff Furman, Daniel Kim, Josh Krieger, Gilbert Metcalf, Ramana Nanda, Venky Narayanamurti, Scott Stern, and participants in the NBER Productivity and Innovation seminar. We also thank current and former ARPA-E staff, in particular Dave Dixon, Ron Faibish, Andy Kim and Ashley Leasure, for their assistance in data collection. All errors or omissions are our own.

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Table A1: Predicting Selection by Review Score Distribution – Logit Model

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Mean Overall Score** | 3.415*** | 6.480*** | | | | | |
| | (1.130) | (1.743) | | | | | |
| **Min. Overall Score** | 1.507* | 1.155 | 0.853 | | | | |
| | (0.351) | (0.240) | (0.170) | | | | |
| **Max. Overall Score** | 3.410*** | 3.196*** | 1.750** | | | | |
| | (0.880) | (0.697) | (0.414) | | | | |
| **SD Overall Score** | 1.358 | 3.077*** | | | | | |
| | (0.474) | (1.263) | | | | | |
| **Med. Overall Score** | | | | | | | 2.620*** |
| | | | | | | | (0.532) |
| **Program F.E.** | Y | Y | Y | Y | Y | Y | Y |
| **N** | 1216 | 1216 | 1216 | 1173 | 1173 | 1216 | 1216 |
| **Pseudo R²** | 0.120 | 0.067 | 0.117 | 0.052 | 0.163 | 0.118 | 0.137 |

Notes: Standard errors in parentheses. All regressions are logit with robust standard error, clustered by technical program. Coefficients are exponentiated, i.e. odds ratio of outcome for two groups with a difference of 1 score unit in the independent variable.

* p < 0.10, ** p < 0.05, *** p < 0.01
Table A2: Predicting Selection by Component Scores

Dependent Variable:
ARPA-E Selected Proposal
for Funding

|                          | (1)              | (2)                       | (3)                       |
|--------------------------|------------------|---------------------------|---------------------------|
| Min. Impact Score        | 0.054*           | (0.030)                   |                           |
| Min. Merit Score         | 0.075**          | (0.034)                   |                           |
| Min. Qualifications Score| -0.049           | (0.030)                   |                           |
| Min. Management Score    | 0.012            | (0.012)                   |                           |
| Mean Impact Score        | 0.103***         | (0.030)                   |                           |
| Mean Merit Score         | 0.147***         | (0.045)                   |                           |
| Mean Qualifications Score| -0.025           | (0.040)                   |                           |
| Mean Management Score    | -0.021           | (0.021)                   |                           |
| Max. Impact Score        | 0.068***         | (0.023)                   |                           |
| Max. Merit Score         | 0.104***         | (0.032)                   |                           |
| Max. Qualifications Score| 0.026            | (0.022)                   |                           |
| Max. Management Score    | -0.023           | (0.027)                   |                           |
| Program F.E.             | Y                | Y                         | Y                         |
| N                        | 1216             | 1216                      | 1216                      |
| R²                       | 0.096            | 0.156                     | 0.141                     |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.

* p < 0.10, ** p < 0.05, *** p < 0.01
### Table A3: Predicting Selection by Review Score Distribution (Impact)

|                      | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       |
|----------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Mean Impact Score    | 0.200***  | 0.233***  |           |           |           |           |           |
|                      | (0.029)   | (0.022)   |           |           |           |           |           |
| Min. Impact Score    | 0.087**   |           | 0.043     | -0.012    |           |           |           |
|                      | (0.037)   |           | (0.037)   | (0.040)   |           |           |           |
| Max. Impact Score    |           | 0.158***  | 0.141***  | 0.048**   |           |           |           |
|                      |           | (0.016)   | (0.016)   | (0.021)   |           |           |           |
| SD Impact Score      |           | 0.046     | 0.074     |           |           |           |           |
|                      |           | (0.061)   | (0.056)   |           |           |           |           |
| Med. Impact Score    |           |           |           |           |           |           | 0.152***  |
|                      |           |           |           |           |           |           | (0.030)   |

**Program F.E.**

|                      | Y         | Y         | Y         | Y         | Y         | Y         | Y         |
|----------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| **N**                | 1216      | 1216      | 1216      | 1173      | 1173      | 1216      | 1216      |
| **R²**               | 0.145     | 0.086     | 0.128     | 0.063     | 0.169     | 0.134     | 0.155     |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.

* p < 0.10, ** p < 0.05, *** p < 0.01

### Table A4: Predicting Selection by Review Score Distribution (Merit)

|                      | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       |
|----------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Mean Merit Score     | 0.201***  |           |           |           |           |           |           |
|                      | (0.030)   |           |           |           |           |           |           |
| Min. Merit Score     | 0.090**   |           |           |           | 0.039     | -0.026    |           |
|                      | (0.036)   |           |           |           | (0.035)   | (0.043)   |           |
| Max. Merit Score     |           | 0.165***  |           |           | 0.148***  | 0.055*    |           |
|                      |           | (0.021)   |           |           | (0.018)   | (0.027)   |           |
| SD Merit Score       |           | 0.064     | 0.095*    |           |           |           |           |
|                      |           | (0.059)   | (0.056)   |           |           |           |           |
| Med. Merit Score     |           |           |           |           | 0.162***  |           |           |
|                      |           |           |           |           | (0.038)   |           |           |

**Program F.E.**

|                      | Y         | Y         | Y         | Y         | Y         | Y         | Y         |
|----------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| **N**                | 1216      | 1216      | 1216      | 1173      | 1173      | 1216      | 1216      |
| **R²**               | 0.149     | 0.088     | 0.135     | 0.065     | 0.174     | 0.140     | 0.161     |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.

* p < 0.10, ** p < 0.05, *** p < 0.01
Table A5: Predicting Counterfactual Selection by Scores

| Dependent Variable: | High Mean Score | High Mean Score | High Minimum Score | High Minimum Score | High Maximum Score | High Maximum Score |
|---------------------|----------------|----------------|--------------------|--------------------|--------------------|--------------------|
|                     | (1)            | (2)            | (3)                | (4)                | (5)                | (6)                |
| Mean Overall Score  | 0.468***       | 0.470***       | 0.388***           | 0.413***           | 0.415***           | 0.468***           |
|                     | (0.033)        | (0.040)        | (0.025)            | (0.029)            | (0.037)            | (0.044)            |
| Min. Overall Score  | 0.468***       | 0.470***       | 0.388***           | 0.413***           | 0.415***           | 0.468***           |
|                     | (0.033)        | (0.040)        | (0.025)            | (0.029)            | (0.037)            | (0.044)            |
| Max. Overall Score  | -0.142***      | 0.059          | 0.034              | 0.105              | 0.195***           | 0.091**            |
|                     | (0.029)        | (0.038)        | (0.030)            | (0.074)            | (0.032)            | (0.039)            |
| SD Overall Score    | -0.142***      | 0.059          | 0.034              | 0.105              | 0.195***           | 0.091**            |
|                     | (0.029)        | (0.038)        | (0.030)            | (0.074)            | (0.032)            | (0.039)            |

| Program F.E. | Y | Y | Y | Y | Y | Y |
|--------------|---|---|---|---|---|---|
| N            | 1216 | 1173 | 1216 | 1173 | 1216 | 1173 |
| R²           | 0.461 | 0.485 | 0.579 | 0.577 | 0.406 | 0.434 |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program. The models include a fixed effect for technical program.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A6: Predicting Selection by Review Score Distribution – Proposals with >2 External Reviews

| Dependent Variable: | ARPA-E Selected Proposal for Funding |
|---------------------|-------------------------------------|
|                     | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       |
| Mean Overall Score  | 0.251***  | 0.263***  |          |          |          |          |          |
|                     | (0.039)   | (0.036)   |          |          |          |          |          |
| Min. Overall Score  | 0.101**   | 0.044     | -0.011   |          |          |          |          |
|                     | (0.048)   | (0.049)   | (0.050)  |          |          |          |          |
| Max. Overall Score  | 0.216***  | 0.195***  | 0.091**  |          |          |          |          |
|                     | (0.030)   | (0.032)   | (0.039)  |          |          |          |          |
| SD Overall Score    | 0.034     | 0.105     |          |          |          |          |          |
|                     | (0.084)   | (0.074)   |          |          |          |          |          |
| Med. Overall Score  | 0.161***  |          |          |          |          |          |          |
|                     | (0.034)   |          |          |          |          |          |          |

| Program F.E. | Y | Y | Y | Y | Y | Y |
|--------------|---|---|---|---|---|---|
| N            | 943 | 943 | 943 | 943 | 943 | 943 |
| R²           | 0.168 | 0.106 | 0.150 | 0.082 | 0.174 | 0.154 | 0.175 |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A7: Reviewer Disagreement Over “Promoted” and “Demoted” Proposals
Dependent Variable: Standard Deviation of Overall Scores

|                          | (1)            | (2)            | (3)            |
|--------------------------|----------------|----------------|----------------|
| "Promoted" (low min. score) | -0.049 (0.060) |                |                |
| Min. Overall Score       | -0.535*** (0.050) |                |                |
| "Promoted" (low mean score) | 0.227** (0.106) |                |                |
| Mean Overall Score       | -0.303** (0.148) |                |                |
| "Promoted" (low max. score) |                | 0.031 (0.098)  |                |
| Max. Overall Score       | 0.375*** (0.073) |                |                |

| Program F.E. | Y    | Y    | Y    |
|--------------|------|------|------|
| N            | 376  | 340  | 353  |
| R²           | 0.799| 0.440| 0.388|

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program.

* p < 0.10, ** p < 0.05, *** p < 0.01

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Table A8: Project Outputs vs. Scoring Element

| Dependent Variable: | At Least 1 Publication | At Least 1 Patent Application | Market Engagement | Any External Output | All External Outputs |
|---------------------|------------------------|-------------------------------|-------------------|---------------------|----------------------|
|                     | (1)                    | (2)                          | (3)               | (4)                 | (5)                  |
| Min. Overall Score  |                        |                               |                   |                     |                      |
|                     | 0.047 (0.041)          | 0.019 (0.027)                | -0.038 (0.029)    | 0.040 (0.026)       | 0.011 (0.031)        |
| N                   | 165                    | 165                           | 165               | 165                 | 165                  |
| R²                  | 0.371                  | 0.327                         | 0.288             | 0.366               | 0.163                |
| Mean Overall Score  |                        |                               |                   |                     |                      |
|                     | 0.076 (0.059)          | 0.075 (0.057)                | -0.049 (0.048)    | 0.059* (0.033)      | 0.031 (0.036)        |
| N                   | 165                    | 165                           | 165               | 165                 | 165                  |
| R²                  | 0.372                  | 0.333                         | 0.287             | 0.366               | 0.166                |
| Max. Overall Score  |                        |                               |                   |                     |                      |
|                     | 0.017 (0.037)          | 0.102** (0.041)              | -0.008 (0.047)    | 0.022 (0.037)       | 0.022 (0.015)        |
| N                   | 165                    | 165                           | 165               | 165                 | 165                  |
| R²                  | 0.366                  | 0.344                         | 0.284             | 0.361               | 0.165                |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program. The models include controls for the initial award amount, as well as a fixed effect for technical program and a fixed effect for the organization type.

* p < 0.10, ** p < 0.05, *** p < 0.01
### Table A9: Outputs of “Promoted” Projects by Budget Criteria

| Dependent Variable: | At Least 1 Publication | At Least 1 Patent Application | Market Engagement | Any External Output | All External Outputs |
|---------------------|------------------------|-------------------------------|-------------------|---------------------|----------------------|
|                     | (1)                    | (2)                           | (3)               | (4)                 | (5)                  |
| “Promoted” by budget (low min. overall score) | -0.015 | (0.090) | -0.081 | (0.095) | 0.074 | (0.066) | -0.087 | (0.087) | 0.035 | (0.048) |
| N                   | 165                   | 165                           | 165               | 165                 | 165                  |
| R²                  | 0.366                 | 0.331                         | 0.288             | 0.367               | 0.165                |
| “Promoted” by budget (low mean overall score) | -0.123 | (0.072) | 0.002 | (0.101) | 0.001 | (0.081) | -0.025 | (0.097) | -0.018 | (0.060) |
| N                   | 165                   | 165                           | 165               | 165                 | 165                  |
| R²                  | 0.375                 | 0.326                         | 0.284             | 0.361               | 0.163                |
| “Promoted” by budget (low max. overall score) | 0.040 | (0.062) | -0.123 | (0.077) | 0.019 | (0.078) | -0.035 | (0.081) | 0.055 | (0.047) |
| N                   | 165                   | 165                           | 165               | 165                 | 165                  |
| R²                  | 0.367                 | 0.338                         | 0.284             | 0.362               | 0.169                |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program. The models include controls for the log of initial award amount, as well as a fixed effect for technical program and a fixed effect for the organization type.

### Table A10: Additional Outputs of “Promoted” All Around vs. Not at All “Promoted” Projects

| Dependent Variable: | Number of Publications | At Least 1 Highly Cited Publication | At Least 1 Patent Issued | Private Funding Amount (Million USD) |
|---------------------|------------------------|-------------------------------------|--------------------------|--------------------------------------|
|                     | (1)                    | (2)                                | (3)                      | (4)                                  |
| “Promoted” all around (low mean, min., and max. overall score) | 0.912 | (1.131) | 0.121* | (0.062) | 0.063 | (0.109) | -4.114 | (2.998) |
| N                   | 165                   | 165                                | 165                      | 165                                  |
| R²                  | 0.564                 | 0.117                             | -0.043                   | -1.586                               |
| Not “promoted” by any measure | 0.564 | (0.867) | 0.117 | (0.086) | -0.043 | (0.071) | -1.586 | (3.958) |
| N                   | 165                   | 165                                | 165                      | 165                                  |
| R²                  | 0.337                 | 0.208                             | 0.284                    | 0.332                                |

Notes: Standard errors in parentheses. All regressions are OLS with robust standard error, clustered by technical program. The models include controls for the initial award amount, as well as a fixed effect for technical program and a fixed effect for the organization type. The base category is projects that were “promoted” by one or two measures, but not all three.

* p < 0.10, ** p < 0.05, *** p < 0.01