American Economic Journal: Applied Economics 2026, 18(4): 348–379
https://doi.org/10.1257/app.20240477

Money, Time, and Grant Design†

By Kyle Myers and Wei Yang Tham*

We conduct survey experiments to test how the design of scientific grants—the money and time awarded—can be used to manage researchers. On average, researchers are relatively unwilling to trade off money for time when choosing among grants. However, there is significant heterogeneity in researchers' preferences. Conditional on receiving a grant, different designs cause only minor changes in researchers' plans for how they would use the funding. Marginal changes in grant design are more relevant for selection effects (funders' ability to attract certain researchers) than treatment effects (funders' ability to change researchers' strategies). (*JEL* C83, I23, O31)

Businesses, governments, and philanthropies that fund research and development (R&D) must decide not only how much to invest in researchers but how to structure the investments. Often, these investments are in the form of grants: "upfront payments for the delivery of incompletely specified and non-contractable R&D output" (Azoulay and Li 2021, 120). There is growing evidence that R&D grants, as currently designed, can have large private and social returns—more grants lead to more innovation (Howell 2017; Azoulay, Zivin, Li, and Sampat 2019; Myers and Lanahan 2022; Santoleri, Mina, Di Minin, and Martelli 2024). However, it is still unclear how alternative grant designs might be able to influence the rate or direction of innovation.

There are many considerations in grant design, from the application process to the final reporting requirements. In this paper, we focus on the effect of arguably the two most salient features of grant design: the amount of funding awarded (money) and the duration of time the funding is available (time). Incentive-based theories of innovation (e.g., Holmstrom 1989; Manso 2011) suggest that changing these two features could cause researchers to pursue different types of projects. That is, grant design could have a treatment effect on the types of strategies that researchers pursue. However, grants are typically self-selected by researchers who have heterogeneous

* Myers: Harvard Business School and NBER (email: kmyers@hbs.edu); Tham: University of Toronto (email: weiyang.tham@utoronto.ca). Author order is alphabetical. Xavier Jaravel was coeditor for this article. This project received financial support from the Alfred P. Sloan Foundation (#G-2020-13934) and the Harvard Business School. This project would not have been possible without the excellent work of Rachel Mural, Nina Cohodes, and Yilun Xu as well as input from Marie Thursby, Jerry Thursby, and Karim Lakhani. We have received helpful comments from Amitabh Chandra, Matt Clancy, Ryan Hill, Jeffrey Furman, Fabian Gaessler, Joshua Graff Zivin, Benjamin Jones, Megan MacGarvie, Gustavo Manso, Ramana Nanda, Sam Ransbotham, Henry Sauermann, Jesse Shapiro, Carolyn Stein, Michael Tushman, John Walsh, and seminar participants at the BSE Summer Forum, DRUID, JOMT, NBER Productivity Seminar, NBER Summer Institute, Ohio State University, Northwestern University, WEFI, and REER. IRB approval was obtained from Harvard University (IRB22-0578).

† Go to https://doi.org/10.1257/app.20240477 to visit the article page for additional materials and author disclosure statement(s).

preferences, payoffs, and production functions. Thus, grant design could also influence the composition of researchers through selection effects.[1]

Research organizations frequently emphasize the treatment effects of their grant designs.[2] But it is rarely noted that any correlation between grant design and outcomes observed in practice might instead be due to different designs attracting different types of researchers. The best evidence to date that grant design may be instrumental is due to Azoulay, Graff Zivin, and Manso (2011). They evaluate the publication output of biomedical researchers who receive larger, longer, and more flexible grants using matching methods and find patterns that are directionally consistent with theoretical predictions. However, experimental tests that randomize real-world grants are exceptionally rare and may continue to be prohibitively costly.

Separating selection and treatment effects is important here because managers and policymakers are typically working with a scarce supply of researchers (Goolsbee 1998). If a new grant program influences outcomes mainly through selection (i.e., attracting certain types of researchers), the program's effects may not persist; outcomes will change as new types of researchers enter the program. With a better understanding of the effects of grant design, managers and policymakers can choose the correct lever to pull—whether to focus on recruitment and selection effects or on incentives and treatment effects.

To make progress on this topic, we use a new survey to estimate researchers' preferences and beliefs about the effect of grant designs. Our sample is a nationally representative collection of research-active professors spanning all major fields of science across all major academic research institutions in the United States (Myers et al. 2023). We use hypothetical experiments embedded in the survey in order to answer the following empirical questions: (i) How willing are researchers to trade off the money and time included in a grant, and (ii) conditional on receiving a grant, how do the money and time components of the grant affect researchers' strategies? The first question informs selection effects; the second informs treatment effects.

First, we investigate selection effects by estimating researchers' preferences over grant design. There is evidence that researchers respond to funding amounts when considering which grants to pursue (Myers 2020) and the timing of funding is important (Tham 2023; Tham, Staudt, Perlman, and Cheng 2024), but there is no empirical work on researchers' demand for grants with different designs. Science funders have attempted to solicit this sort of preference before using informal or qualitative approaches,[3] but not in a quantitative way tied to an economic model as we do here. Researchers surely want more money and more time, but what is the relative importance of those two features? And while there is likely to be heterogeneity in preferences across researchers, what predicts researchers' preferences, and how large is this heterogeneity?

[1] See Azoulay and Li (2021) and Carnehl, Ottaviani, and Preusser (2024) for relevant literature reviews.

[2] When the prestigious Howard Hughes Medical Institute (HHMI) extended their grants from five to seven years, they stated that the extra "years of stable support allows [researchers] to take more risk and achieve more transformative advances" (HHMI 2017). When the US National Institutes of Health (NIH) announced the Maximizing Investigators' Research Award, which offered a new grant design with smaller amounts but longer durations, they stated that "with more sustained support, investigators will have more freedom to innovate and explore new lines of inquiry" (Rockey and Collins 2014).

[3] For example, see National Science Foundation (2002); Knox (2004); Wessner and Munari (2017).

We answer these questions by estimating researchers' willingness to trade off money and time. We start by assuming that each researcher i's indirect utility from a grant of dollar amount A and duration D is of the form $v_i(A,D) = \alpha_i A^{\gamma} D^{1-\gamma}$, where the key parameter is $\gamma \in [0,1]$. A smaller γ would indicate a higher willingness to trade off money for time. We directly solicit researchers' indifference points in a thought experiment using hypothetical grants with randomized attributes. On average, a researcher is only willing to trade off approximately \$50,000 from a grant to extend it by one year ($\gamma \approx 0.8$). We consistently estimate magnitudes on this scale under alternative assumptions (e.g., explorations of CES utility functions with different assumptions for the elasticity of substitution). This result implies that a 10 percent increase in grant size is valued roughly the same as a 45 percent increase in grant duration—relatively speaking, money is much more important to researchers than time.[4]

We also test the extent to which researchers have heterogeneous preferences for money and time. We motivate these tests with simple models that predict the strongest preference for money, relative to time, among researchers who are more capital intensive, can more easily access funding through other sources, are less risk averse, have higher discount rates, and receive more direct utility from research grant funding (e.g., in the form of salary buyouts). When we split the sample along each of these dimensions, we find results consistent with our predictions. Importantly, these results show that manipulating grant design to change strategies will also induce selection effects that will generate changes in the composition of researchers being funded.

Our second empirical exercise studies how effective grant design could be in influencing researchers' strategies. We ask researchers what strategic changes they would undertake if they received a hypothetical grant, the amount and duration of which is randomized. This hypothetical grant is posed as a sudden influx of funding, and we provide specific details to eliminate idiosyncratic features of grants that might contaminate researchers' responses.[5] This sort of unanticipated grant receipt is rare in practice; however, it allows us to isolate researchers' responses to grant designs without any selection effects.

In the experiment, researchers respond to the randomized hypothetical grant by choosing from a menu of five subjective options, which are described in discipline-agnostic language, as to how the grant would lead them to change some strategic aspects of their work.[6] Two options are based on the "risk-versus-speed" trade-off at the core of principal-agent models that seek to balance risk-taking

[4] Of course, this doesn't imply that researchers' preferences are perfectly aligned with the social optimum.

[5] For example, we emphasize that the funding may be used for any research project and the funding amount and duration are fixed and non-negotiable in order to rule out no-cost extensions (https://www.ninds.nih.gov/funding/manage-your-award/during-award/no-cost-extension).

[6] Specifically, the five options are "Pursue riskier projects," "Increase speed," "Pursue projects less related to your current work," "Increase the size of ongoing projects," and "Increase accuracy or reliability." We do not take a stance on the relative social value of any strategy. Instead, our goal is to inform a policymaker or manager who already has preferences over these strategies. "Strategy" is a nebulous concept in the context of basic science, and our formulations are not clearly mutually exclusive. But they are informed by extensive interviews with researchers across all major fields in the sample. Furthermore, the summary statistics and results of the experiment are consistent with researchers treating these options as relatively exclusive.

against shirking with the use of long-term incentives (e.g., Holmstrom 1989; Manso 2011; Lerner and Wulf 2007; Aghion, Van Reenen, and Zingales 2013; Tian and Wang 2014; Barrot 2017; Nanda and Rhodes-Kropf 2017). Two options are based on the decision to start new research projects or expand ongoing work, which helps us investigate the degree to which grants may constrain researchers' directions (e.g., Jia, Wang, and Szymanski 2017; Arts and Fleming 2018; Myers 2020; Hill et al. 2025). Last, one option focuses on researchers' willingness to engage in activities that improve the accuracy or reliability of their work, which is motivated by the growing attention placed on so-called replication crises that may be arising because of constraints on researchers' time horizons or budgets (e.g., Pashler and Harris 2012; Smaldino and McElreath 2016; Kasy 2021).[7]

Our focus is not on the rate of researchers' output but rather on the direction and nature of that output. Thus, we assume that the level of strategy that any researcher employs is fixed (i.e., their choices are perfect substitutes) and focus on how the different designs incentivize substitution across the menu of strategies.

Through a combination of standard regressions and machine-learning methods that search for heterogeneous treatment effects, we find some statistically significant effects. Larger grants increase researchers' willingness to pursue riskier projects. Longer grants also increase researchers' willingness to pursue riskier projects, but only among tenured professors. All researchers are more likely to decrease the speed of their work when receiving longer grants. We also find results consistent with researchers exhibiting decreasing returns to the scale of their projects.

Overall, however, we estimate small treatment effects of grant designs. Realistic changes to designs (e.g., in the range of 15–30 percent) correspond to only 1–2 percentage point changes in the probability of researchers choosing certain strategies. Notably, our investigations into the potential for heterogeneous treatment effects rarely yield any statistically significant evidence of heterogeneity. Together, this suggests that the practical influence of marginal changes to any one grant that a researcher receives may be quite limited.

Before detailing the experiments, we pay considerable attention to the respondents' attention and the potential for nonresponse bias. As a test of attention, we compare researchers' self-reported annual salaries to those we observe on publicly available websites (only for researchers at institutions where such data are made public). We find strong agreement between the two, which suggests mostly truthful reporting along this dimension. While our survey experiments involve hypothetical scenarios, we are able to explore grant designs that are plausible but rarely seen in practice. While some of our measures are subjective, they provide a unique, ex ante observation of researchers' beliefs in contrast to the typical approach in this literature, which relies on censored, ex post observations (e.g., transformations of publication output).[8]

[7] We also ask researchers how they would spend the grant funds across a menu of input categories to investigate how certain inputs are connected to certain strategies.

[8] We follow a long line of prior work that has used surveys of researchers to uncover their otherwise unobservable features, choices, preferences, or beliefs (e.g., Levin and Stephan 1991; Fox and Stephan 2001; Stern 2004; Sauermann and Cohen 2010; Curty et al. 2017; Levecque et al. 2017; Shortlidge and Eddy 2018; Cohen, Sauermann, and Stephan 2020; Philipps 2022). See Stantcheva (2022) for a full discussion of the trade-offs of survey-based empirical analyses.

We address the potential for nonresponse biases in two ways. First, we use data obtained for both respondents and nonrespondents on the amount of research funding flowing to their institutions (sourced from the National Science Foundation) and, for a subset of the population, their publication and grant flows. We estimate some statistically significant differences; however, these differences are all very small, economically speaking—typically close to 5 percent in magnitude. Our second approach to potential nonresponse bias makes use of the randomized participation incentives and reminders in the survey. Both the incentives and reminders had a significant influence on researchers' willingness to complete the survey, which provides us with the variation necessary to implement the sample selection correction method of Heckman (1979).

The paper proceeds as follows: Section I provides motivating summary statistics about the current distribution of research grants and some key institutional and financial details; Section II details the survey, including the population, the sampling process, the survey instrument, and our approaches to testing for—and mitigating the potential of—nonresponse bias; Section III describes the first survey experiment, which solicits researchers' preferences over grant attributes; Section IV describes the second survey experiment, which tests how grant designs influence researchers' strategies; last, Section V discusses our results in the context of related work and motivates future studies on tools for managing the rate and direction of innovation.

I. Grants in Practice

A. *Distribution of Observed Grant Designs*

Historically, the distribution of grants flowing to universities has been difficult to observe. Collecting and connecting data from the dozens of large government agencies and hundreds of smaller organizations is no small task, and surveying researchers about their full history of grants is not reasonable. Thankfully, the "Dimensions" dataset provides a new look at what types of grants researchers are receiving by aggregating across a large number of funders who publicly report data (Digital Science 2018).[9] Because it relies on publicly reported grants, the Dimensions data are limited in their coverage of research investments at universities by businesses, so here we can focus only on nonbusiness grants.[10]

Figure 1 provides a new look at the distribution of grant designs across US academic research institutions. It shows the joint distribution of the size and duration of research grants. For consistency, we restrict our attention to grants awarded to the institutions from which we sourced our survey population, which we detail in the next section. In short, this includes the 150 largest institutions of higher education in the United States per the annual amount of R&D funding flowing to the institutions. We start with all 311,477 grants in the Dimensions data from 2000 to 2012 awarded

[9] As of this paper, Dimensions sources grant data from 233 different US-based funders.

[10] Recent federal survey evidence suggests that business-originated research funding accounts for roughly 5 percent of all annual research funding at institutions of higher education (US National Center for Science and Engineering Statistics 2021).

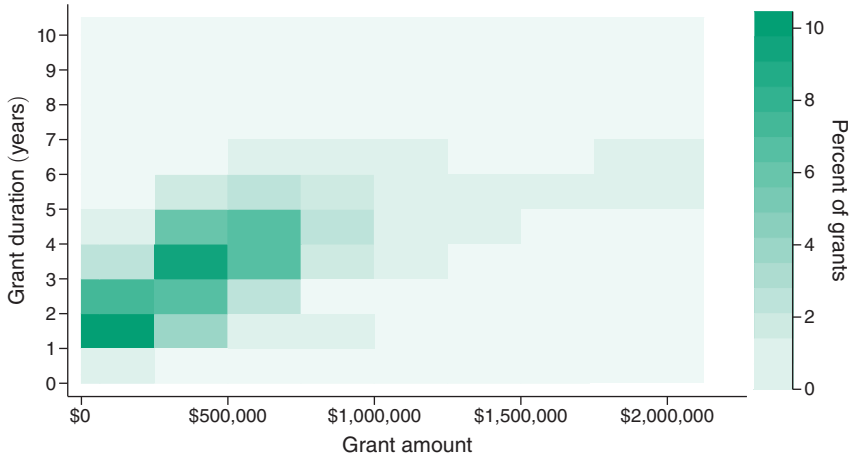


FIGURE 1. DISTRIBUTION OF OBSERVED GRANT DESIGNS

Notes: Displays the share of grant designs as a two-dimensional histogram, where the intensity of the color reflects the percentage of all grants in the cell and cells span one year and $250,000 in amount. Based on 222,041 grants at the focal institutions from 2000–2012. Data sourced from the Dimensions database (Digital Science 2018).

to any researcher at all institutions in our population. We then restrict our attention to grants from US-based funders (295,004) with funding amount data (259,358). Of these, 222,041 are within the support of our thought experiments: ten years long or less, and $2 million or less. [11]

A few patterns emerge. Grants longer than six years are exceptionally rare. Even small, long grants that might resemble some form of insurance are rare; less than 1.5 percent of grants are longer than six years and smaller than $1 million. Another clear pattern is the positive correlation between the size and duration of research grants. On average, a grant that is one year longer will award about $500,000 more in total.[12]

Overall, it is clear that the full space of reasonable grant designs has not yet been explored much. The patterns illustrated here may reflect some optimal staging of investments by funders looking to learn information about risky projects (Dixit and Pindyck 1994). However, it may also reflect a missing market for certain grants, possibly driven by the fiscal costs of long-term outlays or rules and regulations that restrict the duration of financial arrangements between funders and grantees.[13]

[11] We focus on 2000–2012 to avoid censoring since duration is measured ex post in these data. Funding is converted to 2022 dollars per the Consumer Price Index (US Bureau of Labor Statistics 2025).

[12] This also holds on a per-year basis; an additional year is associated with $40,000 more per year.

[13] For example, see https://grants.nih.gov/grants/policy/nihgps/html5/section_5/5.3_funding.htm for the NIH's policy that limits grant "segments" to a maximum of five years.

Below, we use our survey experiments to understand what might happen to the type of science and composition of researchers if funders start to change this distribution. Also, we use these observed data to make some novel inferences about funders' preferences over grant designs and compare those to our estimates of researchers' preferences.

B. *Institutional Details*

Azoulay and Li (2021) and Carnehl, Ottaviani, and Preusser (2024) provide excellent reviews of scientific grants more broadly. Here, we outline a few important details relevant to our experiments. Loosely speaking, there are four sets of parameters that govern the use of research grants as resources: (i) the total amount of money awarded, (ii) the duration over which that money can be used, (iii) the rate at which the money is awarded (i.e., dollars awarded per year), and (iv) the rules about who is in control of the money and what it can or cannot be used to purchase. In our experiments, we focus on the first two elements—total amount of money and time—since these both are the most universally applicable and are relatively straightforward to quantify and manipulate. We attempt to shut down variation in the third element by posing all experiments as questions about the receipt of a grant where *all* of the money is awarded and available to the researcher immediately.[14] We attempt to shut down variation in the fourth element by always specifying that the grants are "unrestricted." Of course, each respondent will interpret this phrasing differently, but pilot tests with researchers indicated that it was a relatively efficient and clear way of communicating that the money would not be tied to any particular project or input.

An important institutional detail is that explicit borrowing and saving research funding appear to be very rare. We are unaware of any instances where a researcher has an explicit contract with their institution where they could, for example, borrow funding from the institution and, upon the receipt of a grant in the future, pay the institution back. None of our conversations with researchers have indicated that the institutions in our sample have the financial vehicles to substitute money across time in this way. Likewise, the reason why the duration element of grant design is important is because there is no "saving" of funds beyond the date of the grant.

Of course, implicit or relational contracts between researchers and their institutions may exist. For example, most modern research grants include "indirect costs" that flow to the institution directly. Thus, one can certainly imagine an equilibrium where researchers who are more productive at obtaining grants can more easily lobby for some funding directly from their institution as an implicit loan. These dimensions are interesting, but conversations with researchers suggested to us that they were of second order relative to the (simpler) issues of how much money and

[14] We also make it clear that the duration of the grant is fixed and nonnegotiable since it is common in practice to observe "no-cost extensions," where funders make unused money available after the original duration of the grant. Unfortunately, we are unaware of any data that explicitly would allow us to report summary statistics on these dimensions. Discussions with researchers indicate that even when grants are observed to flow to researchers in subdivided amounts on some regular basis (e.g., annually), it is frequently feasible to access the full amount of money granted at any point during the duration specified.

time each grant provides. Still, these (and many other) institutional features loom in the background of all of our respondents' answers, and so we interpret all of our results through the lens of the prevailing institutional environment, which we elaborate on further in our discussion.

II. Survey, Population, and Sample Statistics

A. *Population and Sampling*

We make use of the National Survey of Academic Researchers, which is detailed in Myers et al. (2023). We provide a brief overview of the survey methodology here. The target population is US professors who conduct research at major institutions of higher education. This was formalized by selecting approximately 150 of the largest institutions in the United States per their total R&D funding reported in the National Science Foundation's 2019 Higher Education R&D survey (US National Center for Science and Engineering Statistics 2021) and manually collecting professors' information from public websites. Recruitment emails were sent to a random 50 percent of the population from October 2022 to March 2023.

The population consisted of 264,036 unique emails. We emailed a total of 131,672 individuals, and 4,388 (3.33 percent) completed the survey.[15] We then restrict the sample to the 4,175 individuals (95.1 percent of respondents) who reported being a professor and spending a nonzero amount of time on research. Our final sample consists of professors from engineering, math, and related fields (703); humanities and related fields (786; e.g., history, linguistics); medical sciences (1,165; e.g., schools of medicine or public health); natural sciences (655; e.g., biology, chemistry, physics); and social sciences (866; e.g., economics, psychology, sociology). We use these five aggregate groupings of fields throughout our discussion and empirical analyses given the small sample sizes within narrower field definitions. Table 1 reports some key summary statistics for our sample. The summary statistics related to the survey experiments are reported in the sections below, and Supplemental Appendix A.1 contains a larger table with all covariates in the survey used in any of our analyses.

It is important to demonstrate that survey participants have some demand for funding for their research since the experiments are irrelevant to any researcher with no demand for funding (e.g., their only input is their own effort). To illustrate this, Supplemental Appendix Figure A1 plots the distribution of expected research funding over the five years from the time of survey forward for each of the five broad scientific fields. This is the sum of guaranteed funding the researcher has from either prior awards or guaranteed future funding flows plus their expected fundraising over the same period. The vast majority ($>$ 75 percent) of researchers in each field have nonzero funding expectations. Furthermore, each distribution shows significant support over the range studied in the experiments below; research grants are important across all of science.

[15] This response rate is more than twice what has been obtained from sourcing academic researcher contacts from the corresponding author data contained within the publication record (e.g., Myers et al. 2020).

Table 1—Summary Statistics: Survey Sample

	Count	Mean	SD
Broad field {0,1}			
Engineering, math, and related	4,175	0.17	0.37
Humanities and related	4,175	0.19	0.39
Medical and health sciences	4,175	0.28	0.45
Natural sciences	4,175	0.16	0.36
Social sciences	4,175	0.21	0.41
Research			
Guaranteed funding	4,175	430,699.40	1,085,486.21
Fundraising expectations	4,175	549,238.32	1,055,926.36
Professional			
Has tenure {0,1}	4,175	0.59	0.49
Total salary	4,175	156,820.36	93,741.46
Soft-money salary	4,175	25,336.53	45,407.18
Total work hrs./week	4,175	49.88	13.06
Share of time spent on research [0,1]	4,175	0.39	0.20
Share of time spent on fundraising [0,1]	4,175	0.09	0.11
Sociodemographic			
Age	4,084	49.31	12.52
Female {0,1}	3,992	0.41	0.49
Non-White race/ethnicity {0,1}	4,110	0.24	0.43
Num. dependents in household	4,104	0.98	1.13
US immigrant {0,1}	4,088	0.27	0.44

Notes: "Guaranteed" research funding includes funds from prior awards and any other guaranteed sources over the next five years; "Fundraising expectations" are researchers' beliefs about how much funds they will obtain from nonguaranteed sources over the next five years. All variables are continuous and bounded below at zero unless otherwise specified. Responses to sociodemographic questions were not mandatory, hence the differences in the count of observations.

One key institutional detail to note that is not reflected in these statistics is the rarity of any mechanisms for saving or borrowing grant funds. On the saving side, most grants are only fungible for a fixed period—this is the parameter we focus on when we vary the "duration" of grants in the experiments. In reality, anecdotes suggest that duration can be negotiated on the scale of one to two additional years through so-called "no-cost extensions." In our experiment, we do our best to shut down this channel by explicitly stating that the duration is nonnegotiable. On the borrowing side, we have never heard of any financial mechanism whereby a researcher could receive funds, for example, directly from their institution under the expectation that they pay those funds back via future grant fundraising.[16]

[16] Of course, institutions will vary in their willingness to grant researchers funding, and implicit or relational contracts between researchers and administrators may exist. But the net effect of this all will shape the responsiveness of researchers to our experimental levers, and this net effect is what is relevant to managers or policymakers seeking to influence researchers amidst the current institutional environment.

B. *Addressing Potential Survey Biases*

Attention and Representativeness.—Ideally, our respondents would report all answers truthfully, and these responses would reflect the full population in terms of their preferences over and responses to different grant designs. We can never formally test this, but we can take some steps to investigate the possibility of inattention and nonresponse bias and, in the case of nonresponse bias, possibly account for it.

As a test of respondents' attention and their willingness to report truthfully, Myers et al. (2023) compare respondents' self-reported salaries to their publicly reported salaries for the subset of researchers at institutions that make such data public. The two show a close degree of alignment with a correlation of about 0.75, and the difference between the self-reported and publicly reported salary is less than 30 percent for roughly three-quarters of observations.[17] This suggests the vast majority of respondents are responding truthfully along this dimension.

Myers et al. (2023) also report two comparisons of the population and sample professors using observable data on institutional funding levels and professor-level grant funding and publication output. In both cases, the respondent sample is quite similar to the population. The average difference in funding amounts between the institutions of respondents and nonrespondents is generally in the range of 4–6 percent, and there are no statistically significant differences in the grant funding or publication output metrics between the two groups. Some of these exercises are replicated in Supplemental Appendix A.2. Overall, our respondent sample appears very similar to the population along many observable dimensions.

Sample Selection Correction.—Despite the overlap in observable data, our respondents may still differ on other unobservable dimensions. If these unobservable differences are related to our focal parameters of interest (e.g., researchers' preferences over grant designs), this may generate a nonresponse bias. To account for this possibility, we implement the sample selection correction approach first developed by Heckman (1979). This approach makes use of excluded variables that cause entry into the sample (i.e., completion of our survey) but are plausibly orthogonal to the parameters of interest.

We generated the variation necessary for this approach with randomized recruitment strategies. During the recruitment process, we randomly allocated each email to one of four different incentive arms and one of three different reminder arms. The four incentive arms were (i) no incentive, (ii) entry into a lottery to win a gift card, (iii) the ability to vote for a set of charities to receive a donation, and (iv) both the second and third incentives. The three reminder arms involved no, one, or two reminders, respectively.

Supplemental Appendix A.3 reports the effect of the incentives and reminders. We find that stronger incentives lead to a small increase in completion rates, while the reminders are much more powerful. Both induce a significant increase in completion rates; the completion rate for researchers that receive no incentives and no

[17] Discrepancies between self-reported and publicly reported salaries can be due to a combination of recall error, inattention, or the time lag between the publicly reported salary and when the survey was taken.

reminders is roughly 1.9 percent, whereas the completion rate for those who receive both incentives and both reminders is roughly 4.5 percent.

Using the randomized variation from these incentives, combined with the information on each professor's rank, institution, and inferred field of study, we then estimated individuals' propensity to complete the survey conditional on being sampled. From these predicted probabilities, we constructed the inverse Mills ratio and include this variable in all regressions. Assuming that researchers' responsiveness to either participation instrument is orthogonal to our focal parameters, this will control for any unobservable differences (in a focal parameter) between our sample and the population (Heckman 1979).[18]

III. Researchers' Preferences

A. *Empirical Model*

Here, our focus is on researchers' preferences over grant designs and how, when given freedom to choose which grants to pursue, these preferences may lead to selection effects that influence the composition of researchers who pursue particular grants.[19]

We assume that each grant g is defined by a pair of parameters (A_g, D_g), which describe the total dollar amount A of the grant and the duration D of the grant in terms of how many years the researcher has access to the funds. Researcher i's indirect utility from a grant is

$$v_i(A_g, D_g) = \alpha_i A_g^{\gamma} D_g^{1-\gamma}, \tag{1}$$

where α_i is a researcher-specific taste shifter and γ is a common parameter that describes scientists' relative preference for funding amount versus duration.

To motivate the analyses and arrive at our main regression equation, consider a survey experiment where each researcher i observes a pair of grants $g = (1,2)$ where (A_{i1}, D_{i1}) and (D_{i2}) are randomly specified by the experimenter. The respondent is asked to report the value A_{i2} that makes them indifferent between the two grants such that $v(A_{i1}, D_{i1}) = v(A_{i2}, D_{i2})$. We assume that researchers' responses $(\tilde{A}_{i2})$ are the truth plus i.i.d. noise, such that $\tilde{A}_{i2} = A_{i2} + \epsilon_i$. This allows us to write

$$\gamma \log(A_{i1}) + (1-\gamma)\log(D_{i1}) = \gamma \log(\tilde{A}_{i2} - \epsilon_i) + (1-\gamma)\log(D_{i2}). \tag{2}$$

We obtain our main estimating equation by solving equation (2) for $\tilde{A}_{i2}$:

$$\tilde{A}_{i2} = \frac{A_{i1}}{\exp\left(\frac{1-\gamma}{\gamma}\log\left(\frac{D_{i2}}{D_{i1}}\right)\right)} + \epsilon_i, \tag{3}$$

[18] Obviously, this approach does sacrifice some potential sample size. But using the full set of reminders and incentives in all recruitments would have eliminated our ability to implement any correction for potential nonresponse bias.

[19] The next analyses (in Section IV) focus on identifying the treatment effect(s) of grant design conditional on receiving the grant.

which we estimate via non-linear least squares.[20]

Our Cobb-Douglas formulation is a special case of the more flexible constant elasticity of substitution (CES) form, where the Cobb-Douglas form assumes that the elasticity of substitution between the two factors is equal to one. However, besides its simplicity, we don't have good a priori evidence as to why we should assume a unit elasticity here. To explore this assumption, we also report results where we estimate the γ parameter from a CES model given a range of alternative assumptions about the elasticity of substitution. To preview, we find similar results across a range of assumed elasticities spanning 0.5 to 2. Furthermore, we find the Cobb-Douglas unit elasticity assumption to perform well in terms of model fit.

Equation (1) is a reduced-form representation of a more complex model of researchers' production and consumption decisions detailed in Supplemental Appendix B.1. Comparative statics derived from stylized simplifications of that model illustrate how the γ parameter should be related to five key features: (i) the capital intensity of a researcher's work (i.e., their returns to scale with respect to funding), where more capital-intensive researchers should have a larger γ; (ii) the ease with which the researcher can acquire additional funding through other means (i.e., their fundraising productivity, which determines their expected intertemporal budget constraint), where researchers more capable at obtaining funding should have a larger γ; (iii) researchers' risk aversion, where more risk-averse researchers should have a smaller γ; (iv) the discount rate, where researchers that discount future periods more should have a larger γ; and (v) researchers' direct utility from grant funding (e.g., in the form of salary buyout), which should be associated with an increase in γ. These are the dimensions along which we may see heterogeneity across researchers that would signal the importance of selection effects induced by grant designs.

Below, we use empirical proxies to test how much γ varies with these features. We do so by estimating alternative specifications of equation (3) where we assume that γ is a linear function of a constant term and these features. That is, we assume $\gamma_i = \textit{Constant} + \beta X_i$, and we estimate the *Constant* and the linear parameter(s) β. In these cases, we standardize the features to have a mean of zero and a standard deviation of one so that the *Constant* term can be interpreted as the estimate of the average γ_i in the sample (and so that our estimate of γ in the homogeneous parameter model should be approximately equal to our estimate for the *Constant*). Furthermore, this allows for an easier comparison of the estimates of the β parameter for each feature since each β will estimate the change in a researchers' γ_i given a one standard deviation increase in the feature.

B. *Survey Experiment*

To generate the data necessary to estimate equation (3), we present respondents with a hypothetical scenario where an anonymous donor would like to award

[20] Note that the design of this grant is designed to be uncorrelated with the design of the hypothetical grant in the first survey experiment. Among the pairwise correlations of the two grant attributes in the first survey experiment and the three attributes in this survey experiment, the absolute value of any correlation is never larger than 0.03.

Table 2—Summary Statistics: Grant Indifference Experiment

	Count	Mean	SD	Min	Max
Randomized elements					
Grant #1: Duration (years)	4,175	3.5	1.1	2	5
Grant #1: Amount ($)	4,175	781,904.2	690,313.1	100,000	2,000,000
Grant #2: Duration (years)	4,175	8.0	1.4	6	10
Researcher's response at indifference					
Grant #2: Amount ($)	4,175	607,129.1	584,626.5	10,000	2,000,000

Note: Summary statistics of the randomized elements and response for the grant preferences survey experiment.

the researcher with a single research grant.[21] The donor presents the researcher two options: Grant #1 and Grant #2, where the first is set to be shorter than the second. The amount of Grant #1 is shown, but the amount of Grant #2 is not. The respondent is then asked to state the funding amount of Grant #2 that would make them indifferent between both grants.

Supplemental Appendix A.4 contains a screenshot of how the question was posed to respondents. The framing and verbiage of the question were developed based on pilot tests with researchers from a range of fields and career stages. These pilot tests indicated that any confusion about the question was most likely to arise around the timing of funding flows (e.g., could they spend more money upfront instead of the same amount each year?) and the possibility of "renewals" or "extensions." This motivated our choices (i) to simplify the funding flow to be a lump sum awarded immediately, which proved to be easy for researchers to understand,[22] and (ii) to eliminate the possibility of renewals or extensions where the funds could be used beyond the stated duration.[23] Relatedly, the pilot tests surfaced no potential concern for experimenter demand effects, and we have no hypothesis as to why such demand effects would occur in this experiment.

The amount of Grant #1 is a uniform random draw from {$100,000, $250,000, $500,000, $1,000,000, $2,000,000}. The duration of Grants #1 and #2 are uniform random draws from {2, 3, 4, 5} and {6, 7, 8, 9, 10} years, respectively (and independently from the Grant #1 draw). Table 2 reports the summary statistics for the four key variables related to this survey experiment. The randomized elements have the expected statistics (e.g., the mean of the variables are approximately equal the mean of the distributions from which they're drawn).

Table 2 also starts to illustrate the degree to which researchers are willing to trade off funding amount and duration. With Grant #2 being 4.5 years longer than Grant #1 on average, researchers report that they would be indifferent between both grants if Grant #2 is roughly $165,000 smaller. This suggests that researchers would be willing to trade approximately $35,000 per year gained on a grant. Below, we report the marginal rates of substitution based on our estimation of the formal model of researchers' utility.

[21] The framing of an anonymous donor was chosen because some researchers may have (heterogeneous) preferences over funders' identity for reasons related to prestige.

[22] Researchers typically request a total budget in grant applications.

[23] Specifically, the text reads, "Note: All funding awarded in the first year. After expiration, unused funds are forfeited, and no extensions are permitted."

Table 3—Researchers' Willingness to Trade Off Grant Funding Amount and Duration

		$\gamma_i = Constant + \beta X_i$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ	0.767 (0.0070)						
Constant		0.767 (0.0039)	0.767 (0.0039)	0.768 (0.0039)	0.767 (0.0039)	0.767 (0.0039)	0.768 (0.0070)
Age		0.0155 (0.0039)					0.0150 (0.0072)
Funding intensity			0.0196 (0.0041)				0.0166 (0.0063)
Risk appetite				0.0181 (0.0038)			0.0150 (0.0073)
Soft money salary share					0.0124 (0.0039)		0.00581 (0.0072)
Fundraising productivity						0.0127 (0.0037)	0.00798 (0.0058)
Marginal rate of substitution	\$68,000/year						
Observations	4,175	4,175	4,175	4,175	4,175	4,175	4,175

Note: Reports results from estimating equation (3) to identify a single γ parameter (column 1) or allowing γ to depend on a constant term and some standardized observables (columns 2–7); robust standard errors in parentheses.

C. *Average Willingness to Substitute Money and Time*

Table 3 reports our estimates of γ obtained by estimating equation (3) via nonlinear least squares. When we estimate a single parameter that represents researchers' average preferences (column 1), we estimate γ to be 0.77. This magnitude implies a marginal rate of substitution of approximately \$68,000 per year at the means of the Grant #1 distribution. This implies that researchers value a 10 percent increase in funding the same that they value a 33 percent increase in duration. Relatively speaking, dollars appear to be more than three times as important as duration in the context of grant design.

Supplemental Appendix B.2 reports results where we use the more general CES functional form and a range of assumptions about that elasticity. With elasticities spanning 0.5 to 2.0, we consistently estimate marginal rates of substitution on the scale of \$40,000–\$70,000 per year. Furthermore, our Cobb-Douglas specification appears to be near the local optimum of model fit that we identify when examining the RMSE of the models. These findings give us confidence that our results are not heavily influenced by our assumption on the elasticity of substitution.[24]

Supplemental Appendix B.3 includes alternative versions of our main specification (Table 3, column 1). We explore specifications that drop outlier observations

[24] In a further exploration of our functional form assumptions, Supplemental Appendix B.4 reports results from an alternative specification of the researchers' utility function that does not assume constant returns to scale. This is done by leveraging another component of the survey, which we detail further in the Supplemental Appendix. Still, we find that the relative value researchers place on funding amount versus duration is very similar to the estimates obtained using our main specification.

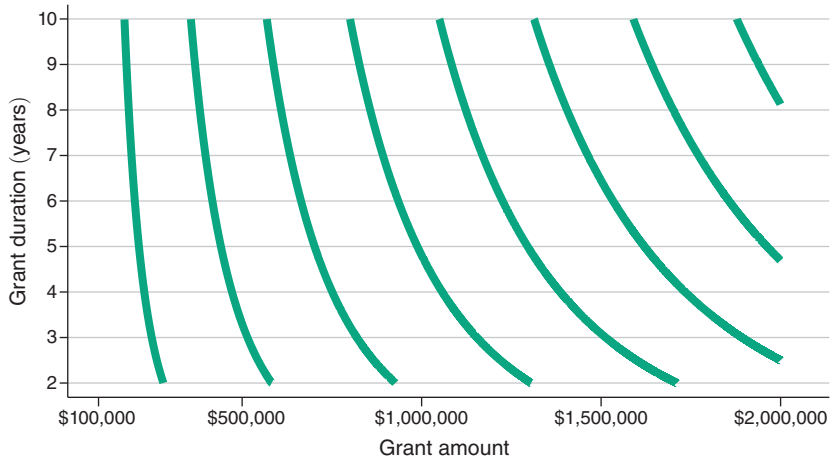


FIGURE 2. GRANT DESIGN INDIFFERENCE CURVES

Notes: Plots indifference curves over the support of the variation in the duration and size of the hypothetical research grants considered by respondents, based on the preferred γ estimate (Table 3, column 1).

and include the sample selection correction control (i.e., the standardized inverse Mills ratio). Overall, the results are unchanged. The sample selection control is not statistically significant at conventional levels and the magnitude is small. This suggests that our sample is not comprised of individuals with especially high or low γ values compared to the population.

To visualize the magnitudes implied by our estimates, Figure 2 plots the indifference curves implied by our estimate of γ over the support of the experimental variation. The plot illustrates how, for grants less than roughly $500,000, researchers are relatively unwilling to sacrifice any of those funds to extend the duration of the grant. Once grant sizes extend beyond $1,000,000, this trade-off becomes more meaningful.

D. *Heterogeneous Preferences*

As outlined above, researchers may have heterogeneous preferences over money and time. Understanding this heterogeneity can shed light on the different types of researchers that funders can attract using different grant designs (i.e., the selection effects). The model of researchers' production and consumption in Supplemental Appendix B.1 motivates five specific features of researchers that should be predictive of their preferences over money and time. To summarize the predictions, we expect the strongest preferences for funding amount (relative to duration) to be among researchers who (i) discount the future at a higher rate, (ii) are more funding intensive in their production functions, (iii) are less risk averse, (iv) receive more direct utility from grant funding, and (v) are more productive at fundraising for their research.

To test these predictions, we estimate from versions of equation (3) where we assume each researchers' γ_i parameter is a linear function of proxies for these

five features. To proxy for discount rates, we use researchers' age. To proxy for funding intensity, we divide researchers' total expected funding amount by their time spent on research to generate a ratio of dollars (of total funding) per hour (of researchers' time spent on research) that plausibly reflects how important funding is to the researchers' work. To proxy for risk aversion, we use a survey question that asked researchers to report (on Likert scale spanning 0–10) how much risk they believe they take in their work. To proxy for researchers' direct utility from funding, we use the share of their salary that is sourced via "soft money" (i.e., paid for directly by grant funding). Last, to proxy for fundraising productivity, we divide researchers' expected funding in the next five years (excluding any guarantees) by the number of hours they expect to spend on fundraising in that same period to arrive at another ratio of dollars (of expected funds raised) per hour (of researchers' time spent fundraising).

In columns 2–6 of Table 3, we report estimates allowing γ_i to vary along each of these dimensions independently. All proxies are standardized so that the *Constant* term estimated is roughly equivalent to the average γ estimate for the full sample and all coefficients can be interpreted as the marginal change in γ_i from the mean associated with a one standard deviation increase in the proxy. In all cases, we confirm the predictions of the theory. Across the five proxies, a one standard deviation increase in the proxy is associated with a 0.012–0.020 increase in γ_i. Column 7 of Table 3 includes all five proxies simultaneously in order to estimate conditional associations. The proxies are clearly positively correlated, but the same qualitative conclusions remain.

In order to provide an illustration of the heterogeneity in researchers' preferences, we use the estimates from the specification reported in column 7 of Table 3 to predict each researchers' γ_i parameter.[25] Figure 3 plots the distribution of researcher-specific marginal rates of substitution implied by our predictions for their γ_i. Although the absolute value of these marginal rates of substitution are all relatively low, the figure illustrates important heterogeneity. Some researchers are willing to substitute funding for time nearly twice as much as others, and our stylized theory of scientific production provides some guidance as to who these researchers are.

In Supplemental Appendix B.6 we report some additional explorations of heterogeneity in researchers' preferences across major fields of study, their tenure status, and their gender. We find statistically significant differences across fields, but the magnitudes of the average differences across fields are relatively small when compared to the variation illustrated in, for example, Figure 3. We cannot reject a null hypothesis that tenure status and gender are predictive of researchers' preferences over money and time.

How well are funders' preferences for grant designs aligned with researchers' preferences? Having funders undertake a survey experiment such as the one described above was not feasible. However, in Supplemental Appendix C we undertake two exploratory exercises to provide a preliminary view of funders' preferences. In both cases, we use publicly reported data on grant designs and make a strong assumption

[25] We construct our estimate as the linear prediction: $\widehat{\gamma_i} = \widehat{Constant} + \sum_X \widehat{\beta_X} X$.

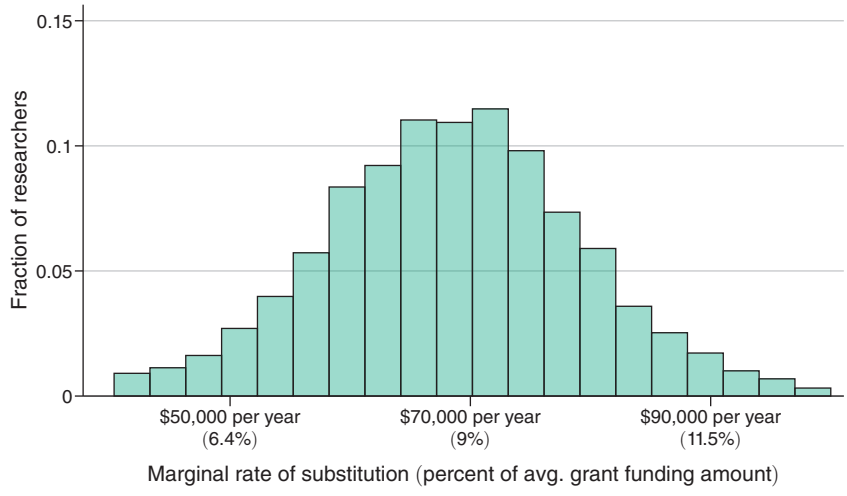


FIGURE 3. HETEROGENEOUS PREFERENCE ESTIMATES

Note: Plots the distribution of researcher-specific marginal rates of substitution based on the predictions for $\gamma_i = Constant + \sum_X \beta_X X$ using the coefficient estimates reported in Table 3, column 7.

that the realized distribution of grant designs reflects only the funders' preferences (i.e., funders are monopsonists). First, we study the NIH's MIRA program (referenced in the introduction) and compare it to the more traditional grant design at the NIH. Second, we analyze the broader distribution of grant designs across all of science (i.e., the data shown in Figure 1). The results from these exercises should be interpreted with caution, but they suggest that funders' substitution parameter (γ^{funder}) is on the scale of 0.4. Intuitively, funders should be more willing to trade off grant amount for duration since there are plausibly tighter constraints on their annual budgets than on their time horizons. When compared to researchers' preferences, funders appear to be providing researchers with a set of grant opportunities that are longer and smaller than researchers would prefer. Such a disconnect could be due to funders' desire to attract certain types of researchers along the dimensions we explored here. However, it may also be due to a belief among funders that they can directly affect the type of science that researchers pursue with their grant designs. We test this hypothesis in the next section.

IV. Grant Design and Research Strategy

A. *Survey Experiment*

How might grant design affect researchers' strategies? To begin, it is useful to map the two focal grant design parameters—money and time—to the two levers on which much of the literature on managing innovation has focused: financial slack and long-term incentives. In many contexts, financial slack is often operationalized as free cash flow. Here, in the setting of academic research grants, the clear analogue

is the amount of funding. Larger grants can enable the acquisition of more scientific inputs because funding for one's research is quite costly to obtain. Academic researchers spend an average of about 15 percent of their time fundraising for their work (Myers et al. 2020), and success rates at major funding agencies are on the scale of 10–20 percent (De Vrieze 2017). Long-term incentives are often operationalized as the duration of employment contracts, the time-horizon of stock options, or the use of "golden parachutes." Here, the analogue is the duration that grant funds are made available. Longer grants can change researchers' expectations and uncertainty about their future funding, which may have important consequences. For example, Tham (2023) and Tham, Staudt, Perlman, and Cheng (2024) show how interruptions to researchers' funding expectations can disrupt their spending flows and their ability to retain skilled labor in their laboratories.

The structure of this experiment is as follows: First, we present the respondent with a hypothetical scenario where they have just been awarded an (unexpected) grant, the size and duration of which is randomized; then we ask the respondent what the most important changes to their research strategies would be after they received this grant. For these hypothetical grants, the dollar amount and duration are independent random draws from {$100,000, $250,000, $500,000, $1,000,000, $2,000,000} and {2, 3, 4, 5, 6, 7, 8, 9, 10} years, respectively, which aligns with the distribution of grant designs explored in the preference experiment.

Supplemental Appendix A.4 contains a screenshot of how the scenario was posed to researchers. As with the experiment where we solicited researchers' preferences, the framing and verbiage shown to researchers was informed by pilot interviews with a variety of researchers and is again structured as an unexpected award from an anonymous donor. We again frame the grant as one where the funding amount is provided immediately as a lump-sum award, and no extensions are not permitted (i.e., any unused funding is forfeited after the stated duration).[26]

Notably, this sort of unexpected windfall of funding is rather rare in practice. While there are instances where researchers receive unexpected prizes that include research funding, most funding is obtained by researchers self-selecting into funding competitions. However, our goal with this exercise is to estimate the treatment effect of grant design on researchers' strategies without conditioning on the selection process. That way, if grant design is an instrumental determinant of researchers' strategies, this experiment (in combination with the previous experiment soliciting researchers' preferences) can help us understand the degree to which the effect of grant designs might be through channels of selection versus treatment.

If grant design can affect researchers' strategies, we should see researchers systematically making different choices about their strategic response to grants with different designs. To capture this, we present researchers with five possibilities of how they might change their strategies: (i) pursue riskier projects, (ii) increase

[26] The exclusion of renewals or extensions does eliminate a potential incentive whereby the researchers' performance during the period of the grant may influence their ability to obtain another grant from the funder. However, pilot tests indicated a wide range of understandings about grant extensions and made us concerned about introducing heterogeneity in researchers' responses due to their erroneous assumptions about the nature of any extension process. Furthermore, the general incentive, whereby a researchers' performance influences both their short-term output and longer-term ability to obtain inputs, is still present in this experiment.

speed, (iii) pursue projects less related to your current work, (iv) increase the size of ongoing projects, or (v) increase accuracy or reliability.

These five options were motivated by prevailing theories and were worded based on pilot interviews with researchers in order to arrive at simple, discipline-agnostic language. We don't take a stance on the social value of any of these strategies. Rather, our goal is to understand the extent to which policymakers or managers might incentivize particular strategies with particular grant designs. And, as in the case of the preference experiment, there is no clear a priori reason that researchers would view any of these strategies as more or less socially valuable. So we are relatively unconcerned with the possibility of experimenter demand effects.

When presented with the hypothetical grant and these five options, respondents must choose the two "most important" changes that they would make to their science if they received such a grant. Underlying our approach is an assumption that these strategies are perfect substitutes—researchers always have some fixed "quantity of strategy," and the only question is how their strategic focus is allocated across the five categories we offer.

We structured the question in this way based off of our pilot interviews. These pilots suggested that any quantification of strategic choices beyond binary indicators would be difficult to interpret and generate significant survey burden and that, furthermore, unless respondents were constrained to select a subset of the responses, inferring the relative priority of their choices would be difficult. In what follows, we summarize the hypothesized effects of funding amounts and duration on researchers' choice among the five strategic options.

Risk and Speed.—Regarding the effect of duration on risk-taking and speed, principal-agent and multitasking models predict that long-term reward structures can induce risk taking at the potential cost of shirking or other forms of negative selection (Holmstrom 1989; Manso 2011; Hellmann and Thiele 2011; Nanda and Rhodes-Kropf 2017). This suggests that longer grants should increase researchers' risk taking and decrease their speed. In the same vein, models of investment with financing frictions tend to predict that positive shocks to net worth (e.g., cash flows) lower producers' risk aversion (Froot and Stein 1998; Krieger, Li, and Papanikolaou 2022). This suggests that larger grants should increase researchers' risk taking. To the extent that it is risky for researchers to slow their pace of work, these theories would also predict a reduced focus on speed in response to larger grants. The results of Azoulay, Fons-Rosen, and Graff Zivin (2011) are consistent with these predictions focused on risk taking, where HHMI-funded scientists (who have longer and larger guaranteed funding arrangements) exhibit a higher variance in their publication outcomes compared to matched controls.

New and Ongoing Projects.—Conditional on changes in risk tolerance, researchers' decisions about how they invest grants in new and ongoing projects will reveal details about the net expected returns to grant funding over a project's life cycle. These net returns will be determined by researchers' input costs, output production, and risk-adjusted payoff expectations as more grant resources are invested in a project. On the cost side, studies of R&D at firms tend to suggest that there

are large adjustment costs (Hall 2002), with academic researchers behaving as if they face large adjustment costs as well (Myers 2020). This suggests the possibilities of convex returns to investment in new projects. On the production side, the complexities of modern science suggest that there are many opportunities for scale economies and positive externalities that could give rise to unconventional relationships between inputs and outputs. Still, many inputs to science are scarce, which suggests that many projects will face decreasing returns to scale. In Supplemental Appendix D.5, we use a simple model to predict how the relative magnitude of our coefficients related to these two strategies will imply different functional forms of the within-project returns to grant resources. In short, our results will allow us to infer whether the within-project returns to scale are one of three forms: (i) constant or increasing, (ii) decreasing, or (iii) nonmonotonic.

Accuracy.—Models of racing in science suggest that the priority reward structure has the potential to incentivize low-quality pursuits of high-value research questions (Bryan and Lemus 2017). This sort of competitive pressure appears to be relevant in practice, especially when researchers are financially or time constrained, leading to replication concerns, biased statistical reporting, and low-quality experimental designs (Pashler and Harris 2012; Smaldino and McElreath 2016; Andrews and Kasy 2019; Hill and Stein 2021; Bryan, Lemus, and Marshall 2022). There continue to be numerous calls for new institutions and incentives to address these issues,[27] but whether grants with certain designs may be able to counteract this pressure remains unclear, and this motivates the "increase accuracy or reliability" option.

Validated, ex ante measures of strategy in the context of science do not yet exist, but each of these options is clearly motivated by prior studies of researchers. An obvious limitation here is that these are subjective descriptions of a subset of all possible strategies that researchers could undertake. Furthermore, while formal models can draw sharp distinctions between these concepts, they clearly have some potential overlap and, as subjective concepts, are not necessarily exhaustive or mutually exclusive.[28] Still, the traditional approach of making inferences from researchers' output (e.g., publications) has its own set of drawbacks,[29] and so we view this approach as a new, complementary one.

Table 4 reports the summary statistics for the randomized and response variables in this survey experiment.

[27] For example, see https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(15)60696-1/fulltext, https://www.newscientist.com/article/2314703-the-replication-crisis-has-spread-through-science-can-it-be-fixed/, or https://www.vox.com/future-perfect/23489211/replication-crisis-project-meta-science-psychology for commentary and coverage.

[28] To this point of mutual exclusivity, we explored some alternative specifications where we grouped the questions and, in general, found no evidence suggesting that researchers treated answers as being highly similar.

[29] Those measures are ex post realizations and may suffer from a truncation bias when failed projects do not produce observable output. For example, see Franzoni and Stephan (2023) for a discussion of the difficulties of quantifying risk taking in science.

Table 4—Summary Statistics: Strategy Survey Experiment

	Count	Mean	SD	Min	Max
Randomized elements					
Grant duration (years)	4,175	6.06	2.56	2	10
Grant amount ($)	4,175	778,239.52	684,075.23	100,000	2,000,000
Strategic changes {0,1}					
Increase speed	4,175	0.36	0.48	0	1
Pursue riskier projects	4,175	0.53	0.50	0	1
Pursue new directions	4,175	0.33	0.47	0	1
Increase size of ongoing projects	4,175	0.61	0.49	0	1
Increase accuracy	4,175	0.17	0.38	0	1

Note: Summary statistics of the two randomized elements of the research strategy survey experiment and the respondent's answers to the question of "What are the two most important changes this grant would enable you to make in your research?"

B. *Empirical Approach*

To explore the effect of grant design on researchers' probability of choosing a particular strategy, we estimate five regressions of the form

$$Y_i^k = h^k\left(A_i, D_i, \mathbf{X}_i\right), \tag{4}$$

where the Y is an indicator that equals one if strategy k is chosen by the researcher in response to the randomized grant, the funding amount and duration are A and D, and $\mathbf{X}$ is a vector of covariates solicited elsewhere in the survey (see Supplemental Appendix A for a full listing of these covariates and their summary statistics). We explore a range of functional forms of h. In the simplest scenario, we test only the main effects of the randomized grant amount and duration, and estimate five separate OLS regressions using each of the five indicators as the dependent variable. In the Supplemental Appendix, we also report results from OLS regressions after using Lasso to select controls from the rest of the survey data to possibly improve our precision, as well as estimates from a single discrete choice model that jointly estimates how researchers' propensity to choose a particular strategy depends on grant attributes.[30]

For clarity, consider our OLS regression specification:

$$Y_i^k = \alpha^k + \beta_A^k A_i + \beta_D^k D_i + \epsilon_i^k, \tag{5}$$

which we estimate for each of the five strategies indexed by k. Written this way, our coefficient estimates (β_A^k, β_D^k) will sum to zero across the five models (i.e., $\sum_k \beta_A^k = 0$); again, we are only estimating how grant design leads to substitution across these options. Positive values of our coefficients indicate that as grants get larger or longer, researchers increasingly prioritize some strategy because, with

[30] Due to software limitations and the format of the question, we could not randomize the order in which the strategy options were presented to respondents, and so we make no causal inferences from the estimated values of the intercepts in the regressions.

Table 5—Effect of Grant Designs on Researchers' Strategies

	Faster (1)	More risk (2)	New directions (3)	Larger ongoing projects (4)	More accurate (5)
log(Duration)	−0.056	0.012	0.008	0.018	0.018
	(0.015)	(0.016)	(0.015)	(0.015)	(0.011)
log(Amount)	−0.025	0.017	−0.016	0.026	−0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Family-wise p-values					
Duration	< 0.01	0.83	0.85	0.61	0.49
Amount	< 0.01	0.12	0.12	< 0.01	0.85
Dep. var. mean	0.36	0.53	0.33	0.61	0.17
Observations	4,175	4,175	4,175	4,175	4,175

Notes: Shows results from OLS regressions where the dependent variables are indicators that equal one if the strategy listed at the top of the column was chosen as one of the "two most important changes" that researchers would make in response to receiving a grant of a given (randomized) size and duration. Robust standard errors shown in parentheses. The family-wise *p*-values adjust for the ten hypotheses tested and are based on 10,000 bootstraps of the free step-down procedure of Westfall and Young (1993).

those additional resources, that strategy has become marginally more useful to the researcher. Conversely, negative values indicate which strategies researchers substitute away from as grants get larger or longer. Our statistical tests of the null are therefore tests of whether or not researchers systematically substitute to or away from particular strategies.

We are particularly interested in the possibility of heterogeneous responses, given the idiosyncrasies of each researcher's situation. To do this, we use the causal forests algorithm developed by Wager and Athey (2018) to estimate conditional average partial effects (CAPEs) of the grant attributes. This approach yields informative distributions of effects but does not directly reveal the features of researchers associated with larger or smaller CAPEs. To understand the heterogeneity in a more low-dimensional manner, we then use the best-linear-projection methodology to test how the CAPEs vary with a select number of covariates (Chernozhukov, Demirer, Duflo, and Fernandez-Val 2018).[31]

C. *Results*

Table 5 reports our simplest version of the analyses, where we conduct five separate OLS regressions of strategic choice indicators on the grant attributes.[32] We report conventional robust standard errors as well as the family-wise *p*-values, which adjust for the fact that we are testing ten hypotheses (five outcome variables and two

[31] All of these analyses are performed in R using the grf package (Tibshirani, Athey, Sverdrup, and Wager 2022).

[32] Since the independent variables are identical in each regression, estimating each OLS regression separately is identical to joint estimation via, for example, the seemingly-unrelated-regression approach.

independent variables).[33] Supplemental Appendix D reports the results from a logit choice model that jointly estimates researchers' propensities to choose each strategy. It more closely reflects the structure of the choice facing the respondent, but it yields very similar results. Likewise, the post-Lasso OLS regressions reported there, where covariates are included to potentially improve precision, also show very similar results. Supplemental Appendix Figure D1 reports the results from using causal forests to estimate the CAPE distributions.[34]

Three patterns emerge, which we investigate and discuss further in the subsections below. First, we find that larger and longer grants lead researchers to prioritize speed less, but that such grants can also increase researchers' willingness to take risks. Second, as grant size increases, researchers shift their strategic focus *toward* increasing the size of ongoing projects and *away* from starting new projects. Third, grant designs appear to have no effect on researchers' focus on the accuracy of their science.

One might also hypothesize the existence of an interaction effect whereby money and time influence researchers in a nonseparable way (e.g., the effect of duration is increasing in the amount of money). Notably, our exploration of heterogeneous treatment effects of each parameter includes the other parameter as a potential determinant of heterogeneity—we let the causal forests tell us whether there is a significant interaction term. We find no evidence for this sort of interaction effect.

Risk and Speed.—The first column of Table 5 clearly shows that larger and longer grants lead to a decreased emphasis on speed (equivalently, smaller and shorter grants lead to an increased emphasis on speed). This result is intuitive but by no means guaranteed given the wide array of time horizons over which researchers are likely optimizing (e.g., due to the heterogeneity in tenure status, contract lengths, ages, etc.). The socially optimal pace of science is far from clear given that there are good reasons that science moves both "too fast" (e.g., as in the racing models of Loury 1979, which has some empirical support from Bryan, Lemus, and Marshall 2022) and "too slow" (e.g., as is emphasized by Nanda and Rhodes-Kropf 2017, who study how the provision of long-term incentives affects the extensive margin of innovation). Still, it does suggest that grant design is a tool for manipulating researchers' speed.

The large body of work showing how long-term incentives can induce risk taking in firms (Lerner and Wulf 2007; Aghion, Van Reenen, and Zingales 2013; Tian and Wang 2014) and the analogous results of Azoulay, Graff Zivin, and Manso (2011) suggest that we should find some increased willingness to take risks when receiving longer grants. But we do not see an average effect of this sort (see column 2 of Table 5). This result aligns with recent work by Carson et al. (2022), who study business managers' hypothetical choices over innovation projects and find that, on average, explicit incentives for risk taking are relatively ineffective and most people are simply too risk averse for the incentives to have an effect.

[33] We make use of Jones, Molitor, and Reif's (2019) implementation of the free step-down procedure of Westfall and Young (1993) as codified in their Stata package wyoung.

[34] The means of each CAPE reported in Supplemental Appendix Figure D1 are approximately equal to the mean effects reported in Supplemental Appendix Table D.

However, the CAPE distribution in Supplemental Appendix Figure D1, panel B clearly shows a large degree of heterogeneity in researchers' responsiveness to grant duration with respect to risk taking. This particular relationship is one of only two CAPE distributions that represent statistically significant degrees of heterogeneity. To better understand this heterogeneity, Supplemental Appendix D.3 reports the best linear predictors of the CAPEs. The best predictor of researchers' responsiveness to grant duration with respect to risk taking is their tenure status—the effect of a log-point increase in grant duration on researchers' willingness to take risks is roughly 10 percentage points larger for tenured professors compared to nontenured professors (compared to the statistically insignificant mean effect of 0.01). This suggests that grant duration may be a useful incentive for risk taking as the aforementioned theories would suggest, but only among researchers who have the complementary job security, reputation, or resources associated with tenure. Conversely, nontenured researchers may be facing performance evaluations on time scales that render marginal changes in grant duration irrelevant.

This result is consistent with Azoulay, Graff Zivin, and Manso (2011), in that their sample consists entirely of elite researchers who may already have—or are clearly on a path to—a tenured or de facto tenured position but are still on the younger end of the age spectrum. Our findings help guide the generalizability of those results and identify the conditions under which researchers might be incentivized to take risks with longer grants.

New and Ongoing Projects.—The third and fourth columns of Table 5 indicate the grant duration has no effect on researchers' decision to start new projects or expand the size of ongoing projects. However, we do find that larger grants lead researchers to shift their focus away from starting new projects and toward the expansion of ongoing projects. Equivalently, as grants get smaller, researchers are more likely to use those smaller amounts of funds to start new projects. The motivating model described in Supplemental Appendix D.5 suggests that this result is indicative of researchers exhibiting decreasing returns to scale within projects.

Taken together with our results on risk, we find that scientists are willing to take more risks when they have more funding, but those risks are still based on their ongoing work rather than risks from venturing into wholly new territory. This is consistent with the idea that it is relatively difficult to induce scientists to change the direction of their research (Myers 2020), while also suggesting that scientists' reluctance may not primarily be about risk.[35] It also points to the importance of distinguishing between risk and other aspects of innovation such as novelty that intuitively appear to be related to risk but are conceptually distinct and in practice may operate differently (Azoulay and Greenblatt 2025).

Our search for heterogeneous responses did find significant differences in researchers' willingness to start new projects as a function of grant amount (see Supplemental Appendix Figure D1, panel C). This suggests that there is significant heterogeneity in the costs and/or benefits of researchers' initial work on a project.

[35] However, other notions of uncertainty such as Knightian uncertainty may still be at play here.

Loosely speaking, it appears that there are meaningful differences in how easily researchers can learn about the quality of their new ideas—some researchers exhibit much high returns to initial investments in a project than others. Still, researchers are indicating that overall they perceive there to be decreasing returns to scale within their projects. This finding is relevant for policies that seek to limit the amount of grant funding that researchers can obtain, and suggests future work to more directly estimate the degree of these decreasing returns to scale would be worthwhile.[36]

Accuracy.—The least popular strategic choice overall is the *increase accuracy or reliability* option, and there are no average or heterogeneous effects to suggest that grant design can shift researchers' choices along this dimension. The importance of preventing and detecting false positives and negatives in science has come to be appreciated (e.g., Pashler and Harris 2012; Andrews and Kasy 2019). Our results suggest that the reason that researchers may be underinvesting in efforts related to accuracy or reliability is *not* because they lack the resources to do so but is because those efforts are underincentivized in the market for science.

D. *Grants and Input Allocations*

In the preceding analyses, we find that grant design can affect researchers' strategies (i.e., grant size influencing the choice of new directions versus larger ongoing projects). How much of this responsiveness is due to the grants allowing researchers to obtain new inputs for their work? Or, more generally, how much might grant design influence researchers' input choices?

A full investigation into such questions is beyond the scope of this paper, but we did solicit a second set of outcomes in this survey experiment, which allows us to estimate how grants with different designs are used. In the survey, after respondents were asked to report how their strategies would change in response to receiving the hypothetical grant, we asked them to report how they would spend those funds across five different input categories: (i) their own salary; (ii) their own training; (iii) travel; (iv) equipment, data, or supplies; and (v) salaries or wages for other new or current researchers, students, or staff.

Pilot testing with researchers indicated that soliciting precise allocations across these categories (e.g., percentage of dollars spent) was an excessive burden and would likely involve a tremendous amount of uncertainty since most researchers do not have specific knowledge about input costs. As a lower-burden alternative, we simply asked respondents to indicate if they would spend "None," "Some," or "A lot" of the hypothetical grant funds on each category; researchers were much more comfortable with this format.

To conduct empirical analyses of the responses, we code the three possible responses to values of 0, 1, and 2. Then we convert these values into shares by dividing each response by the sum of the responses across all categories (e.g., if a researcher reports "Some" for all categories, then all categories will receive a 0.2

[36] We cannot speak to researcher-level returns to scale, so we cannot speak to policies that limit the total amount of funding that a researcher obtains.

Table 6—Summary Statistics: Input Allocations

	Count	Mean	SD
Randomized elements			
Grant duration (years)	4,175	6.06	2.56
Grant amount ($)	4,175	778,239.52	684,075.23
Input allocation share [0,1]			
Own salary	4,175	0.18	0.13
Own training	4,175	0.08	0.10
Travel	4,175	0.18	0.10
Equipment or supplies	4,175	0.21	0.13
Others' salaries	4,175	0.34	0.14

Notes: Summary statistics of the two randomized elements of the research strategy survey experiment (duplicating the first two rows of Table 4) and respondents' allocation of funding amounts across input categories. Input allocation responses are standardized such that input shares sum to one.

share of the funding from the hypothetical grant). As with our analyses of researchers' strategic responses, we are less concerned with the precise magnitudes of the effects, and instead our focus is on testing whether we can reject the null in particular directions.

Table 6 shows the summary statistics for the share of funding that researchers allocate to each of the five inputs. For simplicity, we report the results from five separate OLS regressions using the input shares for each category as the dependent variables in Table 7.[37] Overall, grant duration has no significant effect on input allocations. But we do find grant size to have some clear effects.

First, we see that larger grants lead researchers to allocate a greater share of funding toward both their own salary and their own training. By construction, this increase must come with a decrease elsewhere, and it appears that almost all of the decrease is occurring in the "Others' salaries" category. To be clear, this does not mean that researchers are claiming to reduce their total spending on this category. Instead, they are indicating that as grants get larger in size, a smaller share of the additional funding will be spent on others' salaries or wages.

We cannot test whether this shift in allocations is due to supply constraints (e.g., researchers cannot attract additional labor to work with them) or due to researchers' demand for labor shrinking as grant size increases (e.g., their own time is the main constraint that the increased funding allows them to address).

The fact that we find larger grants increase researchers' spending shares on themselves (i.e., salary and training) and decrease spending shares on others (e.g., students, staff scientists) while simultaneously decreasing their likelihood of pursuing new research directions suggests a connection between strategies and inputs. This relationship is consistent with researchers' teams—their students and staff—being a key part of helping them explore new research directions.

We lack the variation or data to dig further into this question to disentangle how much these results are driven by the supply or demand side, and we cannot formally

[37] Unreported results from joint estimation of all choices via a fractional response regressions with a logit model for the conditional mean yield very similar results.

Table 7—Effect of Grant Designs on Researchers' Input Allocations

	Own salary (1)	Own training (2)	Travel (3)	Equipment or supplies (4)	Others' salaries (5)
log(Duration)	−0.007	0.000	0.002	−0.001	0.005
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
log(Amount)	0.008	0.008	−0.001	−0.003	−0.012
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Family-wise p-values					
Duration	0.37	0.97	0.93	0.97	0.68
Amount	< 0.01	< 0.01	0.97	0.51	< 0.01
Dep. var. mean	0.18	0.08	0.18	0.21	0.34
Observations	4,175	4,175	4,175	4,175	4,175

Notes: Shows results from OLS regressions where the dependent variables are the share of the (randomized) grant that would be allocated to each input category. Robust standard errors shown in parentheses. The family-wise *p*-values adjust for the ten hypotheses tested and are based on 10,000 bootstraps of the free step-down procedure of Westfall and Young (1993).

connect specific inputs to specific strategies given the variation in our data.[38] Still, recent work has begun to highlight how the wages and employment outcomes of researchers' teams can be influenced by funding shocks (Tham, Staudt, Perlman, and Cheng 2024), and continued work on how inputs and strategies are connected within the scientific production function seems especially promising.

V. Discussion

Understanding how grant design can be used to manage science requires understanding the incentives and institutions that transform inputs and outputs into objects that researchers value (e.g., job security, salary, prestige). Practical examples of such factors include researchers' taste for science (Stern 2004; Roach and Sauermann 2010), the tenure process and output measurement schemes (MacLeod and Urquiola 2020), intellectual property regimes (Hvide and Jones 2018), the nature of competition within fields (Hill and Stein 2019), gatekeeping (Azoulay, Fons-Rosen, and Graff Zivin 2019), and other social factors more generally (Shapin 1995). Our analyses provide new insights about grant designs given the incentives and institutions surrounding researchers. We investigate both the selection and treatment effects that can be induced by grants with different designs.

Since the vast majority of grants require researchers to self-select their grant pursuits, the usefulness of grant designs depends both on these treatment effects and on the presence of any selection effects—grant designs may change the number and composition of researchers who pursue them. To this point, our first survey experiment

[38] It is tempting to devise a two-stage analyses where we test how grant design influences input choices and, in turn, how these input choices effect strategic choices. However, our randomized grant designs are not valid instrumental variables, because grant design may influence other features of the researchers' production functions besides these specific input choices (i.e., we cannot guarantee that the exclusion restriction holds).

sheds new light on researchers' preferences over grant design. Our results indicate that while there is some willingness by researchers to trade off grant size (total grant dollars) for duration (years that grant dollars are available), they value relative changes in size nearly four times as much as changes in duration. The γ parameter that we estimate subsumes several structural parameters, and our heterogeneity analyses indicate that there is some significant variation in preferences across researchers. Disentangling this heterogeneity further to better understand selection effects would require a much richer model and more complicated experiments. For example, we use age as a proxy for researchers discount rates, but it would be important to disentangle researchers' actual discount rates versus the dynamic incentives that they face (e.g., due to career concerns) over their life cycle.

Our results do support the existence of treatment effects; grants appear to affect researchers' strategies. As predicted by prior theories, longer grants increase researchers' plans to take risks in their work, but only if the researcher has the job security of tenure. This finding aligns with the work of Azoulay, Graff Zivin, and Manso (2011) but provides new evidence as to some important boundary conditions. Furthermore, these longer grants reduce *all* researchers' focus on speed. More work remains to be done on the connection between these two strategies and its implications for optimal grant design.[39]

When scaled to reflect the degree of grant design variation that we see in practice, these treatment effects are small. In the example of the NIH's use of MIRA grants versus traditional R01 grants (where the MIRA grant is roughly 15 percent smaller and 30 percent longer than the R01 grant), our estimates imply that receiving one or the other would only change researchers' probabilities of choosing certain strategies by about 1 percentage point. Overall, our results from our two experiments indicate that the selection effects of grant design and how they might influence the composition of researchers in an area are likely more important than the treatment effect of how those grant designs might influence *how* researchers conduct their science.

More generally, our results are informative for ongoing debates about the optimal distribution of science. It is frequently claimed that researchers do not take enough risks, do not explore enough new ideas, and are not careful enough in their work, and that a key source of these distortions is the suboptimal design of R&D grants (Thompson 2022; Ford 2024). But our results suggest that, to the extent that the direction of science is distorted, it may be that the key frictions are located in other parts of the market for science, such as the herding incentives that arise in the context of cumulative innovation (Bryan and Lemus 2017; Hopenhayn and Squintani 2021) or the misaligned incentives that arise due to our limited ability to measure output (Wang, Veugelers, and Stephan 2017; Bhattacharya and Packalen 2020; Hager, Schwarz, and Waldinger 2024). Of course, we cannot speak to how broader, general equilibrium changes in the funding landscape (e.g., where all grants in a field have more or less money or time) might influence the direction of science.

[39] See Nanda and Rhodes-Kropf (2017) for a discussion of how alternative innovation policies can influence the types of projects that funders are willing to support, and of the importance of understanding how this selection process influences the extensive margin.

A key limitation of this paper is that we rely on non-incentivized stated preferences from a small sample of researchers. As noted by Stantcheva (2022), this allows us to "create our own variation" and measure variables that are difficult or impossible to observe in existing datasets (e.g., bibliometric data). Nonetheless, this comes at the cost of having to assume that these stated preferences are informative about actual behavior and that our sample is representative of the population. Our investigations into respondents' attention and accuracy (using salary comparisons) and their representativeness (using data comparisons and sample selection correction techniques) suggest that these issues may not loom large in this specific survey. However, our survey experiments ask researchers to consider consequential decisions on a much faster time scale (e.g., seconds, minutes) than they do in practice (e.g., days, weeks). Thus, to the extent that it is costly to mentally engage with the longer-term implications of choices, our results may be biased and reflect larger discount rates than researchers exhibit in practice (e.g., Deck and Jahedi 2015).

Still, our results indicate that grants can be instrumental and that the large costs of field experiments with stronger guarantees of representativeness may be worth the investment to better understand how grant design can be used to manage science. We also hope that our focus on measuring researchers' ex ante strategies motivates future work to better understand how researchers choose their pursuits and allocate their resources. The vast majority of empirical studies of science make ex post inferences about researchers' strategies (e.g., using publication outcomes), but our approach illustrates an alternative. Clearly, obtaining data on researchers' ex ante strategies is challenging, but it may prove essential for understanding the ways in which researchers' intentions ultimately lead to the outcomes of interest.

The findings also motivate some potentially interesting questions related to the plausibility and usefulness of allowing researchers to borrow or save grant funding, in the financial sense of those terms. To our knowledge, such practices are extremely rare. However, the heterogeneity that we identify in preferences for money versus time suggests that there may be individuals willing to use such a mechanism that would allow them to, for example, borrow against future grant funding. Of course, this is highly hypothetical, and one immediately encounters a number of challenges given the structure of grants in practice. In that vein, our results on researchers having strong preferences for money over time may be connected to the broader phenomenon whereby people seem to save less (e.g., via annuities) than standard discounting models would suggest (Benartzi, Previtero, and Thaler 2011). More inquiry into researchers' time horizons and new financial vehicles for science funding is surely warranted.

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