

Money, Time, and Grant Design

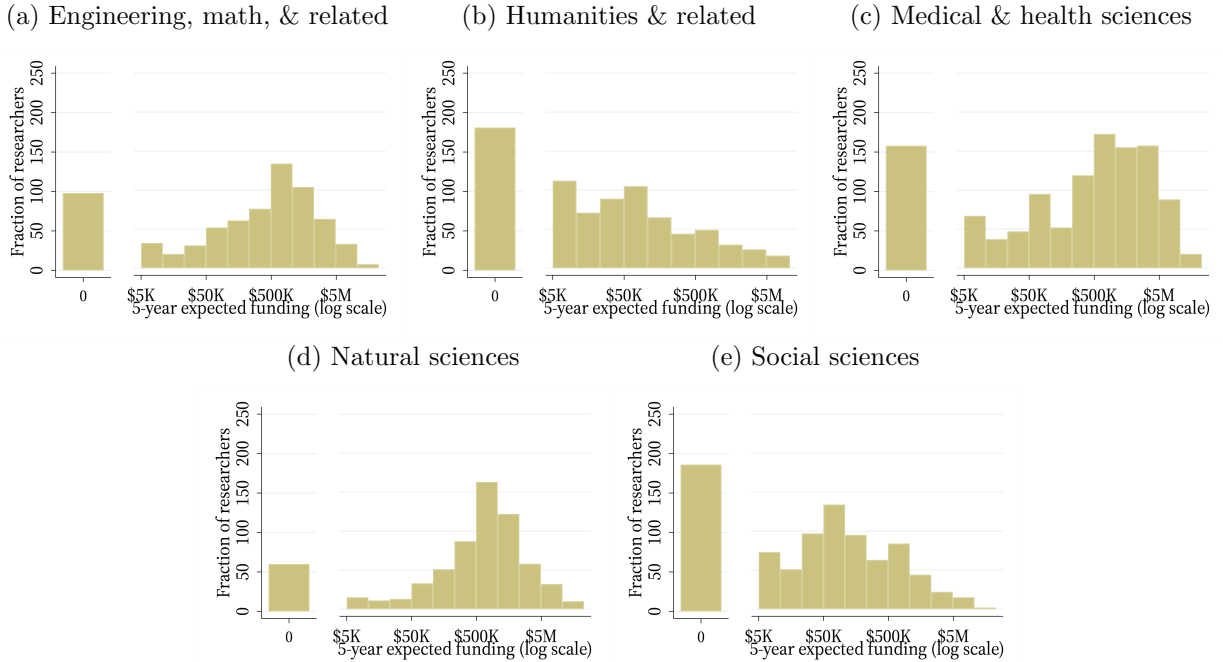
Kyle R. Myers & Wei Yang Tham

A Additional summary statistics

A.1 Full summary statistics for covariates

Tables [A1-A2](#) report the mean and standard deviation for all variables ever used in the analyses. If the count of observations is less than the full sample (4,175), it is because respondents were not required to answer the question and some chose not to — this only is relevant for the socio-demographic questions. Figure [A1](#) plots the distribution of expected research funding across the five broad fields to illustrate the pervasiveness of demand for research grants.

Figure A1: Expected research funding by broad field



Note: Shows the within-field distributions of researchers' total expected research funding over the next five years, which is the sum of existing funding and expected fundraising amounts over the same period.

A.2 Population and sample comparisons

Here we replicate the two tests of representativeness for the survey as also done in [Myers et al. \(2023\)](#). First, [A2](#) shows this comparison based on data from the National Science Foundation’s HERD survey ([US National Center for Science and Engineering Statistics 2021](#)), which reports institutional-level data on the total amount of funding flows into all of the institutions in our population (recall, our population was constructed using the HERD, which is why this data is available for the full population).

Figure [A2](#) reports the distributions and regression tests for mean differences in six metrics of institution-level research funding that compare respondents to the full set of researchers invited to participate (“Sample e-mailed”). The distributions overlap to a large degree (see Panel a). We do estimate statistically significant differences in means (see Panel b), but the magnitudes of these differences are all in the range of approximately 4–6%.

Figure [A3](#) reports the results of a similar exercise, instead using individual-level data on researchers’ publication output and grant receipts. This data was obtained by performing a fuzzy match of our population (i.e., using names and institution data) to the Dimensions database ([Digital Science 2018](#)), which includes disambiguated researcher-level records. We focus on researchers’ publications and grants during the twenty years prior (2003–2022) and see very little differences between our respondents and the full set of individuals invited to the survey. The distributions have strong overlap over the full support (see Panel a), and the mean differences are all insignificant and/or smaller than 7.5%.

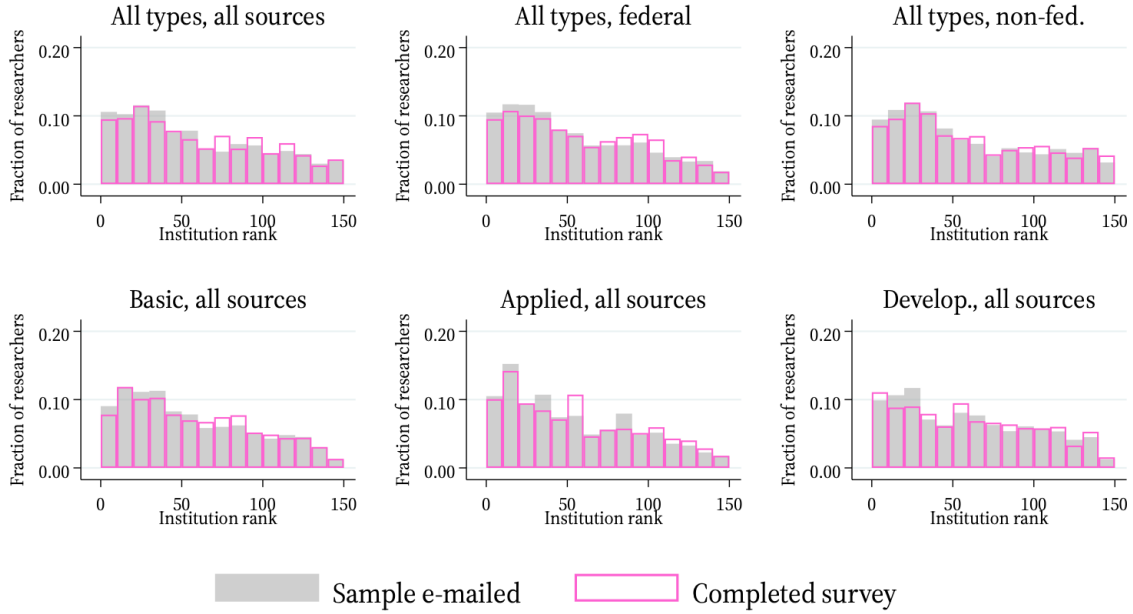
A.3 Randomized incentives

In order to implement the sample selection correction methods of [Heckman \(1979\)](#), we must have a source of variation in survey participation that is uncorrelated with any of the focal parameters. With such variation in hand, a control function can be constructed and included in the focal regressions to condition on any variation in respondents’ answers that otherwise would have been unobservable, endogenous, and led to biased estimates. Furthermore, the statistical significance of this control function can shed light on the degree to which selection into the survey on (relevant endogenous) unobservables may have occurred.

To generate the necessary variation in participation, we implemented randomized incentives and reminders in our e-mail strategy. Each e-mail was randomly assigned to (1) one of four incentive arms comprising a gift card lottery or a donation on the respondents’ behalf to a charity of their choice, and (2) one of three reminder schedules including zero, one, or two reminders. Figure [A4a](#) shows the raw data and statistical tests of the effects of these arms

Figure A2: Recruitment versus completion sample comparison per HERD metrics

(a) Distributions per HERD R&D measures



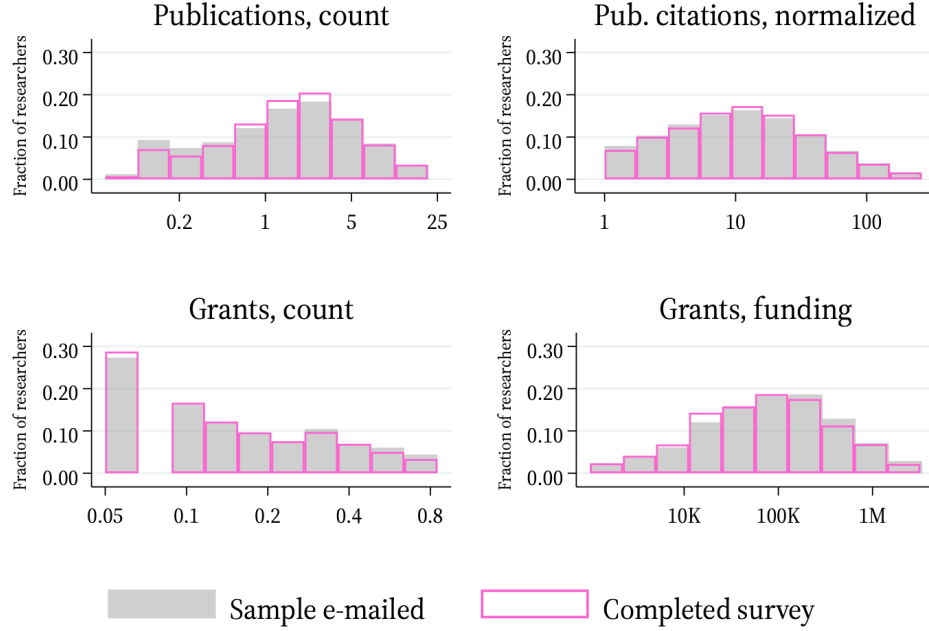
(b) Regression estimates of mean differences

	All sources, by type			All types, by source		
	All (1)	Federal (2)	Non-fed. (3)	Basic (4)	Applied (5)	Develop. (6)
Completed survey	-35.01*** (6.953)	-21.30*** (4.511)	-13.71*** (3.062)	-24.31*** (4.867)	-7.170*** (2.492)	-3.812*** (1.328)
Constant	649.1*** (1.308)	351.7*** (0.863)	297.4*** (0.578)	413.2*** (0.917)	176.7*** (0.459)	60.46*** (0.254)
% diff.	-5.4%	-6.1%	-4.6%	-5.9%	-4.1%	-6.3%
<i>N</i> obs.	130,785	130,785	130,785	130,785	130,735	128,169

Note: Panel (a) compares the distributions of e-mailed professors and respondents per the rank of their institution along each dimension of R&D funding. Panel (b) reports estimates from a regression of each sampled professor’s institutional R&D funding (in 2019 \$-M) on a dummy for whether the sampled individual completed the survey; the “% diff.” row reports the mean difference in the measure as a percentage of the non-respondent average (i.e., it is the ratio of the two coefficients); robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All institutional data is from the 2019 NSF HERD ([US National Center for Science and Engineering Statistics 2021](#)).

Figure A3: Recruitment versus completion sample comparison per Dimensions metrics

(a) Distributions per Dimensions publications and grants



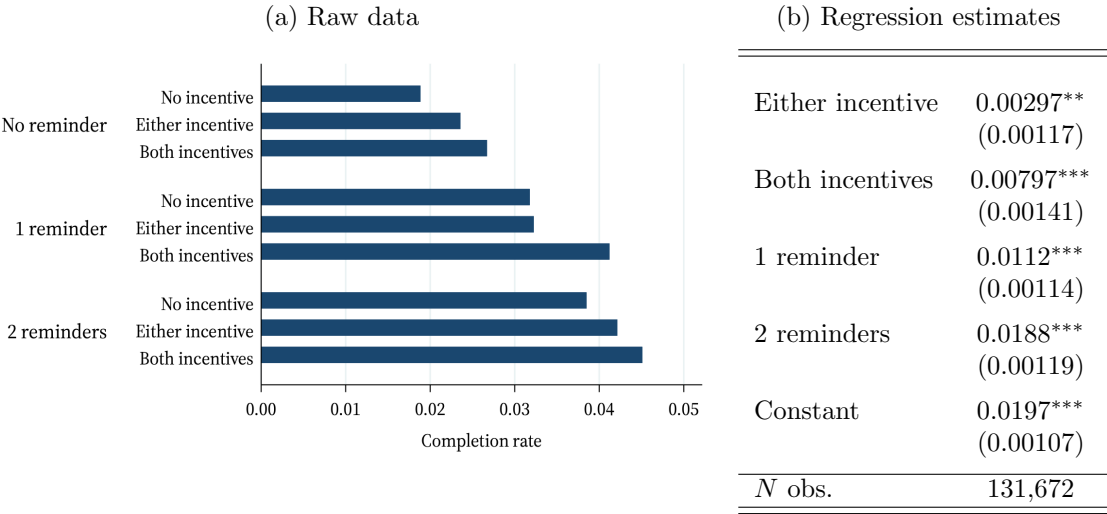
(b) Regression estimates of mean differences

	Pub., count (1)	Pub. cites, normalized (2)	Grant, count (3)	Grant, total \$ (4)
Completed survey	-0.111 (0.0688)	-0.575 (0.807)	0.00878** (0.00343)	-5568.8 (8519.4)
Constant	2.906*** (0.0158)	20.59*** (0.185)	0.117*** (0.000715)	121272.4*** (2093.0)
% diff.	-3.8%	-2.8%	7.5%	-4.6%
<i>N</i> obs.	87,000	87,000	87,000	87,000

Note: Panel (a) compares the distributions of e-mailed professors and respondents per each dimension of individual-level publication output and grant funding per year (2003–2022). Panel (b) reports estimates from a regression of each sampled professor’s publication or grant metric on a dummy for whether the sampled individual completed the survey; the “% diff.” row reports the mean difference in the measure as a percentage of the non-respondent average (i.e., it is the ratio of the two coefficients); robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All publication and grant data is from the Dimensions database ([Digital Science 2018](#)).

(aggregating the incentive arms in Panel a, and assuming linear separability of the treatments in the regressions shown in Panel b). There are clear effects, with the “most treated” invites (i.e., both incentives and two reminders) increasing the probability of survey participation by roughly 2.7 percentage points to roughly 4.5%, yielding an average response rate roughly more than twice as large as the “least treated” invites (i.e., no reminders and no incentives) whose response rate was 1.9%.

Figure A4: Completion rate by incentive and reminder arms



Note: Panel (a) shows the average completion rate by each combination of incentive and reminder arm; Panel (b) shows estimates from a linear probability model of completion as a function of incentives and reminders; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A1: Full summary statistics for covariates

	count	mean	sd
Professional			
<u>Rank {0,1}</u>			
Adjunct, clinical, teaching, other	4,175	0.06	0.23
Assistant	4,175	0.25	0.44
Associate	4,175	0.25	0.43
Emeritus or retired	4,175	0.03	0.17
Full	4,175	0.41	0.49
<u>Tenure {0,1}</u>			
Not on tenure track, not applicable	4,175	0.20	0.40
On tenure track, pre-tenure	4,175	0.22	0.41
Tenured	4,175	0.59	0.49
<u>Salary</u>			
Base	4,175	120,649.10	79,692.66
Grant-sponsored or	4,175	25,336.53	45,407.18
Supplementary	4,175	5,142.51	16,566.07
Clinical	4,175	5,692.22	37,375.73
Outside activities	4,175	7,798.80	29,703.94
Guaranteed research funding	4,175	430,699.40	1,085,486.21
Research fundraising expectations	4,175	549,238.32	1,055,926.36
Total work hrs./week	4,175	49.88	13.06
<u>Share of work time [0,1]</u>			
Research	4,175	0.39	0.20
Fundraising	4,175	0.09	0.11
Teaching	4,175	0.27	0.17
Administration	4,175	0.15	0.14
Clinical	4,175	0.04	0.14
Other	4,175	0.06	0.09
<u>Aggregate field [0,1]</u>			
Humanities	4,175	0.17	0.37
Medical & health	4,175	0.19	0.39
Natural	4,175	0.28	0.45
Social & mathematical	4,175	0.16	0.36
Social sciences	4,175	0.21	0.41

Table A2: Full summary statistics for covariates, continued

	count	mean	sd
Socio-demographic			
Age	4,084	49.31	12.52
Female {0,1}	3,992	0.41	0.49
Married or in partnership {0,1}	4,044	0.84	0.36
U.S. immigrant {0,1}	4,088	0.27	0.44
3rd generation in U.S. or less {0,1}	2,848	0.44	0.50
Household annual income	4,045	260,819.53	215,128.41
Num. household dependents	4,104	0.98	1.13
<u>Race/ethnicity {0,1}</u>			
Asian	4,175	0.12	0.33
Black	4,175	0.03	0.17
Hispanic	4,175	0.06	0.23
White	4,175	0.78	0.42
Other	4,175	0.05	0.22
Risk-taking			
Research, own belief	4,175	4.63	2.35
Research, others' belief	4,175	4.56	2.40
Personal life	4,175	5.25	2.12
Research			
Objective: ask or answer questions [0,10]	4,175	4.85	2.57
<u>Output {0,1,2}</u>			
Journal articles	4,175	1.87	0.37
Books	4,175	0.52	0.69
Materials, methods, or tools	4,175	0.70	0.68
Products	4,175	0.47	0.64
<u>Audience {0,1,2}</u>			
Academics	4,175	1.88	0.36
Policymakers	4,175	0.84	0.69
Businesses and orgs.	4,175	0.54	0.62
General public	4,175	0.83	0.62
Other			
Inverse Mills Ratio	4,175	2.40	0.10

A.4 Additional survey experiment details

Figure A5 shows the thought experiment shown to respondents when soliciting their preferences over grant designs. The framing and text were informed by pilot interviews with researchers across a range of disciplines and were designed to leave as little uncertainty about the grant design as possible. The respondent is asked to report the smallest amount of funding in “Grant B”, which is always set to a (randomly) longer duration than that of the (randomized) duration in “Grant A”, that would make them prefer it over “Grant A”. We do not solicit the exact indifference point because pilot testing indicated that the concept of indifference was costly for many researchers to engage with. However, they were much more comfortable engaging with the question as worded here. Thus, we must assume that the value of “Grant B” that achieves indifference for the respondent is infinitesimally smaller (e.g., \$1) than what they report to the question in the survey.

Figure A5: Respondent view of selection experiment

NSAR

Thought experiment:
Grant size versus duration

An anonymous donor has decided to give you research funding and is allowing you to choose between two options, Grant A or Grant B. You may only choose one. The features of these grants are described below:

Note: All funding awarded in the first year. After expiration, unused funds are forfeited, and no extensions are permitted.

	Funds expire after	Total funding amount
Grant A:	4 years	\$1,000,000
Grant B: more time less funding	6 years	\$_____?

Q. What is the smallest amount of funding that Grant B could contain to make you prefer it over Grant A?

Note: Complete the following sentence by typing numbers in the box. Your answer must be less than or equal to the size of Grant A, \$1,000,000

You would prefer Grant B as long it included at least \$ in total, but if it included any less than that, you would prefer Grant A.

Next

Note: Shows a respondent’s view of an example thought experiment soliciting the respondent’s approximate indifference point between two grants.

Figure A6 shows the thought experiment shown to respondents when soliciting their strategic responses to a hypothetical grant. First, they are shown a screen that only describes the

48

details of the thought experiment (left side of Figure A6). The red, bold text highlights the randomized components of the amount and duration of the grant. As in the previous thought experiment, we communicate the fact that all of the funding is awarded immediately, any unused funds cannot be retained after the duration of the grant, and there are no “renewals” or “extensions” of the grant possible.

After viewing the setup of this thought experiment, the respondents are shown the right side of Figure A6, which solicits respondents’ plans for how they’d use the grant regarding their top two strategic changes as well as their qualitative allocation of the grant across the five input categories. The strategic choice options are designed such that the same strategy cannot be chosen from both drop-down menus. The phrasing of the strategic options and the input categories was also informed by pilot interviews. Only a 3-point Likert scale is used in the input allocation exercise because pilot tests indicated a significant time cost and uncertainty on behalf of the respondent if we attempted to solicit anything more detailed.

Figure A6: Respondent view of treatment experiment

Thought experiment:
How would you use a hypothetical grant?

Consider the following:
An anonymous donor has decided to give you an unrestricted **research grant of \$2,000,000**, all of which would be available to you immediately in the first year, but after **7 years** you would lose any unused funds and no grant renewals or extensions could occur.

On the next page, we'll ask how you would use this hypothetical grant.

Next

Q. If you received this \$2,000,000 grant (which is the total amount you could spend over 7 years), what are the two most important changes it would enable you to make in your research?

Most important change: Pursue projects less related to your current work

Second most important change: Pursue riskier projects

Q. If you received this \$2,000,000 grant (which is the total amount you could spend over 7 years), approximately, how much of the funding would you spend on the following categories?

	None	Some	A lot
Salary or wages for other researchers, students, or staff (i.e., new hires or current employees)	☐	☐	☒
Your own salary (e.g., teaching or clinical buyouts)	☐	☒	☐
Travel	☐	☒	☐
Your own training or education	☒	☐	☐
Equipment, instruments, data, or any materials	☐	☒	☐

Next

Note: Shows a respondent’s view of an example thought experiment about their use of a hypothetical research grant, including the preface (left side) and the response fields (right side).

B Additional results on researchers' preferences

B.1 A model of researchers' production and consumption

The main empirical model of researchers' preferences over grant amount and duration (Eq. 1: $\alpha A^\gamma D^{1-\gamma}$) is, effectively, a reduced form representation of a more complex model of researchers' production and consumption patterns. The following subsections motivate tests of heterogeneity across researchers in terms of their preferences (i.e., γ).

First, we specify a more expansive model of researchers' utility from the receipt of a grant that has some amount A and duration D :

$$\begin{aligned}
 V(\vec{a}_i; \theta_i, A, D) = \max_{\vec{a}_i} & \sum_t^T \delta_i^t u_i(f_i(\beta_i + a_{it}), a_{it}) \\
 s.t. & \\
 & \sum_t a_{it} \leq A \\
 & a_{it} = 0 \text{ if } t > D,
 \end{aligned} \tag{B1}$$

where the key choice for the researcher is how to allocate the grant over periods $t = (1, 2, \dots, T)$. The notation of the model is as follows: $\vec{a} = (a_1, a_2, \dots, a_T)$ represents the vector of choices about how to allocate the funding over time; θ is the set of parameters that govern the researcher's discount rate δ , their utility function u , their production function f , and their guaranteed funding β , which is available every year; u and f are assumed to be concave; and all parameters and variables are implicitly unique to each researcher. The two constraints dictate how much grant funding is at the researcher's disposal and how long they have access to those funds. In the context of this model, the focal empirical parameter of γ represents the marginal utility of an increase in grant amount ($\partial V / \partial A$) relative to the marginal utility of an increase in grant duration ($\partial V / \partial D$) after the researcher has re-optimized their allocations over time.

Researchers value grants with more funding (larger A) because they enable more production within a given year, and they value grants with a longer duration (larger D) because they enable more years of production on the steeper portion of the production function.⁴⁰

⁴⁰Anecdotal conversations with researchers indicate that they also value longer grants because of the reduced variance in their future funding streams, which is not formalized in our motivating model. Practically, this enables researchers to better plan their work over longer horizons. For example, a common remark by researchers when considering a longer grant is that it would allow them to offer their staff and students longer (formal or informal) contracts. Another (un-modeled) potential benefit of longer grants is that it provides

In this model, researchers derive positive utility not just from the outputs of their work, but also from their inputs directly. This reflects two realities; first, grant funds can often be used for researchers’ salaries; second, as sociological studies and popular critiques of science have long pointed out, researchers are not immune to “empire-building” tendencies, where funding levels can play a prominent role in delineating social one’s status (Merton 1968; Shapin 1995; Madsen and Aagaard 2020).⁴¹

The model abstracts away from any of the researchers’ choices about their effort or their research strategies, with the production function f summarizing each researchers’ ability to convert funding into output they value.

Overall, the value derived from outputs and inputs depends on the incentives and institutions that transform these things into objects that researchers value (e.g., job security, salary, prestige) and their preferences for those objects. All of these forces and preferences are summarized by u . Practical examples of factors shaping u 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), gate-keeping (Azoulay et al. 2019a), and social factors more generally (Shapin 1995).

In the Appendix Section B.5 below, we used highly simplified versions of this model to make some predictions about heterogeneity.

B.2 Alternative CES functional forms

Our preferred specification of a Cobb-Douglas utility function is a special case of the Constant Elasticity of Substitution (CES) function with an assumed unit elasticity. In our case, the more general CES function can be written as:

$$v(A_i, D_i) = \alpha_i (\gamma A_i^\rho + (1 - \gamma) D_i^\rho)^{1/\rho}, \quad (\text{B2})$$

insurance for future supply or demand shocks — e.g., if a researcher believes there is a new technology on the horizon that would increase their own productivity, they could reserve funding for future periods.

⁴¹Since most grants are obtained through competitive evaluations, they also serve as signals about researchers’ abilities. There is logic to this given the unobservability of researchers’ effort and the fact that most grants are awarded via peer review processes — they are signals that peers value a researchers’ ideas. Thus, they can have more direct and indirect value to each researcher depending on their position. Furthermore, grants often include overhead funding that flows to the researchers’ institution, with these “indirect costs” accounting for a significant fraction of a grants total value (Johnston et al. 2015). However, our thought experiment abstracts away from both of these points since they are non-competitive and devoid of indirect costs.

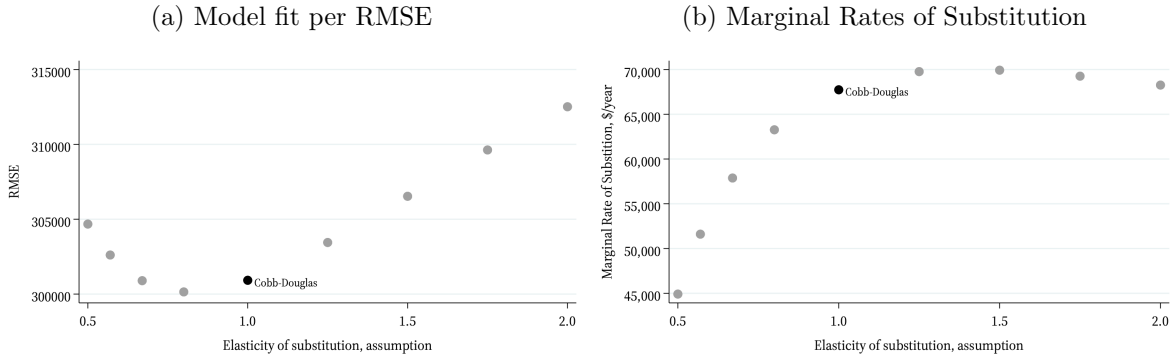
where the elasticity of substitution is $\sigma = 1/(1 - \rho)$. With a CES function, our focal estimating equation based on the thought experiment data is generalized from Equation 3 to:

$$\tilde{A}_{i2} = \left(A_{i1}^\rho + ((1 - \gamma)/\gamma)(D_{i1}^\rho - D_{i2}^\rho) \right)^{1/\rho} + \epsilon_i, \quad (\text{B3})$$

where ρ is determined by the elasticity of substitution (σ) that we assume. This still leaves the single focal parameter, γ to be estimated. To explore the sensitivity of our results to our assumption about σ , we estimate a series of models with an assumed elasticity of substitution spanning from 0.5 to 2.0.

First, we explore which assumed value of σ fits the data best by plotting the model's RMSE across our range of assumptions in Figure B1 Panel (a). Our preferred assumption of the Cobb-Douglas unit elasticity appears quite close to the (local) minimum in model errors that we explore. This gives us some confidence that unit elasticity is a reasonable assumption. Figure B1 Panel (b) plots the marginal rates of substitution (in funding dollars per year). Unsurprisingly, larger assumed elasticities yield larger marginal rates of substitution. But across the full range of assumptions, we consistently estimate magnitudes between \$45,000 and \$70,000 dollars per year. Overall, we find that researchers are only willing to sacrifice 5–8% of their grant funding to extend their access to that funding.

Figure B1: Preference estimates under alternative elasticity of substitution assumptions



Note: Panel (a) plots the RMSE when estimating the γ parameter under alternative assumptions for the elasticity of substitution in the CES utility function. Panel (b) plots the marginal rate of substitution implied by the γ estimate at the sample means under the same range of assumptions. In both panels, the Cobb-Douglas case (unit elasticity) is highlighted, as it is the basis of all other results on preferences.

B.3 Main results on preferences, reporting sample selection correction estimates

Table B1 reports results from estimating Eq. 3 with the Inverse Mills Ratio (IMR) included as a control variable to account for the possibility of sample selection. The IMR variable is

constructed following Heckman (1979) using the randomized survey participation incentives and reminders as instrumental variables.

Table B1: Researchers’ willingness to trade off grant funding amount and duration, reporting sample selection coefficient

	(1)	(2)	(3)	(4)
γ	0.767*** (0.00698)	0.779*** (0.00676)	0.817*** (0.00591)	0.848*** (0.00533)
IMR	-9645.0* (5286.4)	-6260.8 (4472.4)	-5905.1* (3391.8)	-5089.1* (3035.3)
Marginal rate of substitution	67,708 [8.7%]	63,430 [8.1%]	50,091 [6.4%]	40,004 [5.1%]
Excl. above ptile. N obs.	4,175	99 th 4,134	95 th 3,978	90 th 3,777

Note: Reports results from estimating Eq. 3 using alternative samples; larger γ values reflect a stronger taste for funding amount compared to duration; marginal rate of substitution (\$ per year) is reported at the means and is shown in brackets as a percentage of average funding amount; the “Excl. above ptile.” samples drop responses where $(A_{i1} - \tilde{A}_{i2})/A_{i1}$ is at or above the reported percentile; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The IMR row reports the coefficients on the standardized Inverse Mills Ratios included in the regressions.

B.4 Alternative estimation of grant preferences

The empirical model of grant preferences in the main paper assumes constant returns to scale (CRS; $\gamma + (1 - \gamma) = 1$). We can relax this assumption by making use of a third thought experiment in the data. Although this third experiment was designed for another research question, it provides the variation necessary to estimate a more flexible model that has a separate utility parameter for both grant size and duration.

In this other experiment, we asked respondents to report their willingness to trade off their annual salary in exchange for increases in their guaranteed research budget, effectively, a grant. This was done twice, by asking respondents how low of a salary they would be willing to take in exchange for having access to an additional \$250,000 or \$1,000,000 for 5 years.

To begin, first consider a new indirect utility function that depends on researchers’ annual salary S , their current guaranteed research budget over the coming 5 years B , and a new

grant of amount A and duration D :

$$v(S_{ig}, B_i, A_{ig}, D_{ig}) = \alpha S_{ig}^\sigma (B_i + A_{ig})^\rho D_{ig}^\delta . \quad (\text{B4})$$

In order to use the variation from the thought experiments, we assume we can decompose Equation B4 into two separate functions that describe researchers' preferences over the new grant (evaluating just A and D) and their preferences over an increase in their 5-year guaranteed budget and a corresponding change in their salary:

$$\begin{aligned} v_1(A_{ig}, D_{ig}) &= \alpha_{i1} A_{ig}^\rho D_{ig}^\delta \\ v_2(S_{ig}, B_i, A_{ig}) &= \alpha_{i2} S_{ig}^\sigma (B_i + A_{ig})^\rho . \end{aligned} \quad (\text{B5})$$

To summarize, we have researchers' responses to three different scenarios: (1) being indifferent between two grants that vary in their size and duration, call these grants $g = \{1, 2\}$; (2) being indifferent between some decrease in their salary and an increase in their research budget by \$250,000, call this increase grant $g = 3$; and (3) being indifferent between some decrease in their salary and an increase in their research budget by \$1,000,000, call this increase grant $g = 4$. Thus, we have three equations:

$$\begin{aligned} v_1(A_{i1}, D_{i1}) &= v_1(A_{i2}, D_{i2}) \\ v_2(S_{i0}, B_i) &= v_2(S_{i3}, B_i, A_{i3}) \\ v_2(S_{i0}, B_i) &= v_2(S_{i4}, B_i, A_{i4}) , \end{aligned} \quad (\text{B6})$$

where S_{i0} indicates their current salary and B_i is their current 5-year research budget guarantee. The thought experiments involve providing $(A_{i1}, D_{i1}, D_{i2}, A_{i3}, A_{i4})$ to the respondents, who in turn report the values (A_{i2}, S_{i3}, S_{i4}) such that indifference holds. We use these three equations to generate the three moment conditions necessary to identify the key parameters σ , ρ , and δ .

Table B2 reports the results from GMM estimation of the key parameters. The ratio of these alternative estimates of the elasticities of grant size (σ) and duration (δ), $\frac{0.75}{0.22}=3.41$, are very close to our estimate of this same ratio under the CRS assumption we use in the main results, $\frac{0.77}{(1-0.77)}=3.26$. We take this as evidence that the CRS assumption is not distorting our results on the relative preferences researchers have for grant designs.

Table B2: Non-CRS based grant preference estimates

	(1)
σ (salary)	1.016*** (0.001)
ρ (grant amount)	0.075*** (0.004)
δ (grant duration)	0.022*** (0.001)
N obs.	4,003

Note: GMM estimates of parameters in Eq. B5 based on the three moments generated by the indifference points shown in Eq. B6; bootstrapped standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Predicting heterogeneity in grant design preferences

Deriving comparative statics from Equation B1 without making further assumptions is particularly challenging. But, our goal is only to motivate tests of heterogeneity in researchers' relative preferences for grant funding amount versus duration (γ). So below, we take a much simpler approach of eliminating all but one of the four sources of heterogeneity in the model (δ, u, f, β) and then testing whether, in each stylized model, researchers' relative preferences for amount versus design is increasing or decreasing in a given parameter.⁴²

Throughout, we define $V_{A,D} \equiv V(a; \theta, A, D)$, $a^*(V_{A,D}) \equiv \arg \max_a V_{A,D}(a)$, and $\tilde{\gamma} \equiv \frac{\frac{\partial V_{A,D}}{\partial A}}{\frac{\partial V_{A,D}}{\partial D}}$, noting that $\tilde{\gamma}$ is proportional to γ as defined in the main empirical model shown in Equation 1.

In all cases below, we focus only on the scenarios where $A = \{1, 2\}$ and $D = \{1, 2\}$ and evaluate preferences based on changes from initial values of $A = 1$ and $D = 1$. This simplifies the construction of the partial derivatives that define researchers' preferences. The relative value of an increase amount is: $\frac{\partial V_{1,1}}{\partial A} = V_{2,1} - V_{1,1}$, and the relative value of an increase in duration is: $\frac{\partial V_{1,1}}{\partial D} = V_{1,2} - V_{1,1}$.

Discount rate

To study the effect of researchers' discount rates on their grant preferences, we assume that the production and consumption functions, where grant funding a is the input, can

⁴²Each stylized model retains concavity in the production (or consumption) function since linear formulations eliminate any concerns for the temporal dimension and in turn eliminate the value of grant duration by construction.

be jointly given by $a_t^{1/2}$. In this case, there is no heterogeneity in researchers' production or consumption functions, nor in their guaranteed funding flows ($\beta = 0$). Focusing first on changes in grant amount for a $D = 1$ grant, researchers' utility, optimal input allocations, and marginal valuations are given by:

$$\begin{aligned} V_{1,1} &= \max_a a^{1/2} \\ a^*(V_{1,1}) &= a^*(V_{2,1}) = 1 \\ \frac{\partial V_{1,1}}{\partial A} &= 2^{1/2} - 1. \end{aligned}$$

There are no costs to spending the grant funding, so all funds are used (as will be the case in all 1-year grant scenarios). Next, focusing on changes in grant duration for a $A = 1$ grant, researchers' utility, optimal input allocations, and marginal valuations are given by:

$$\begin{aligned} V_{1,2} &= \max_a a^{1/2} + \delta(1 - a)^{1/2} \\ a^*(V_{1,2}) &= \frac{1}{\delta^2 + 1} \\ \frac{\partial V_{1,1}}{\partial D} &= \left(\frac{1}{\delta^2 + 1}\right)^{1/2} + \delta\left(1 - \left(\frac{1}{\delta^2 + 1}\right)\right)^{1/2} - 1. \end{aligned}$$

Thus, the ratio of researchers' marginal value from increases in grant amount versus duration is given by:

$$\tilde{\gamma}(\delta) = \frac{(2^{1/2} - 1^{1/2})}{\left(\left(\frac{1}{\delta^2 + 1}\right)^{1/2} + \delta\left(1 - \left(\frac{1}{\delta^2 + 1}\right)\right)^{1/2} - 1^{1/2}\right)},$$

where $\partial\tilde{\gamma}/\partial\delta < 0$. Thus, we should expect researchers that discount future periods at a larger rate (smaller δ) to have a stronger preference for grant amount (larger γ).

Capital-intensity, risk-aversion, and direct utility

Here, we focus on the role of capital-intensity (i.e., convexity of f w.r.t. a), risk-aversion (i.e., convexity of u w.r.t. $f(a)$), and direct utility of grant funding (i.e., convexity of u w.r.t. a). We assume that the production and consumption functions, where grant funding a is the input, can be jointly given by a_t^κ . All three of these features are captured by κ : a larger value indicates a more convex production function w.r.t. funding, larger risk tolerance, and larger direct utility of grant funding. In this case, there is no discounting of the second period ($\delta = 0$) and no heterogeneity in researchers' guaranteed funding flow ($\beta = 0$). Focusing first on changes in grant amount for a $D = 1$ grant, researchers' utility, optimal input allocations,

and marginal valuations are given by:

$$\begin{aligned} V_{1,1} &= \max_a a^\kappa \\ a^*(V_{1,1}) &= a^*(V_{2,1}) = 1 \\ \frac{\partial V_{1,1}}{\partial A} &= 2^\kappa - 1 \end{aligned}$$

There are no costs to spending the grant funding, so all funds are used. Next, focusing on changes in grant duration for a $A = 1$ grant, researchers' utility, optimal input allocations, and marginal valuations are given by:

$$\begin{aligned} V_{1,2} &= \max_a a^\kappa + (1-a)^\kappa \\ a^*(V_{1,2}) &= \frac{1}{2} \\ \frac{\partial V_{1,1}}{\partial D} &= \left(\frac{1}{2}\right)^\kappa + \left(\frac{1}{2}\right)^\kappa - 1. \end{aligned}$$

Thus, the ratio of researchers' marginal value from increases in grant amount versus duration is given by:

$$\tilde{\gamma}(\kappa) = \frac{2^\kappa - 1}{\left(\frac{1}{2}\right)^\kappa + \left(\frac{1}{2}\right)^\kappa - 1},$$

where $\partial \tilde{\gamma} / \partial \kappa > 0$. Thus, we should expect researchers that are more capital-intensive, more risk-loving, and receive more direct utility from funding to have a stronger preference for grant amount (larger γ).

Fundraising productivity

Here, we focus on the role of researchers' ability to obtain research funding (beyond the focal grant), which we capture with β . We assume that the production and consumption functions, where grant funding a is the input, can be jointly given by $(\beta + a_t)^{1/2}$. In this case, there is no discounting of the second period ($\delta = 0$) and no heterogeneity in researchers' production or consumption functions. Focusing first on changes in grant amount for a $D = 1$ grant, researchers' utility, optimal input allocations, and marginal valuations are given by:

$$\begin{aligned} V_{1,1} &= \max_a (\beta + a)^{1/2} \\ a^*(V_{1,1}) &= a^*(V_{2,1}) = 1 \\ \frac{\partial V_{1,1}}{\partial A} &= (\beta + 2)^{1/2} - (\beta + 1)^{1/2} \end{aligned}$$

There are no costs to spending the grant funding, so all funds are used. Next, focusing on changes in grant duration for a $A = 1$ grant, researchers' utility, optimal input allocations, and marginal valuations are given by:

$$\begin{aligned} V_{1,2} &= \max_a (\beta + a)^{1/2} + (1 - (\beta + a))^{1/2} \\ a^*(V_{1,2}) &= \frac{1}{2} - \beta \\ \frac{\partial V_{1,1}}{\partial D} &= (\beta + (\frac{1}{2} - \beta))^{1/2} + (1 - (\beta + (\frac{1}{2} - \beta)))^{1/2} - (\beta + 1)^{1/2}. \end{aligned}$$

Thus, the ratio of researchers' marginal value from increases in grant amount versus duration is given by:

$$\tilde{\gamma}(\beta) = \frac{(\beta + 2)^{1/2} - (\beta + 1)^{1/2}}{(\beta + (\frac{1}{2} - \beta))^{1/2} + (1 - (\beta + (\frac{1}{2} - \beta)))^{1/2} - (\beta + 1)^{1/2}},$$

where $\partial \tilde{\gamma} / \partial \beta > 0$. Thus, we should expect researchers who are more productive at securing funding for their research every period to have a stronger preferences for grant amount (larger γ). Intuitively, researchers who are good at fundraising have a larger inter-temporal budget constraint, which moves them “further up” their production function in the future and increases the relative value of being further up their production function in the present.

B.6 Additional heterogeneity in grant design preferences

Table B3 reports group-specific estimates of γ based on a researchers' major field of study (Col. 1), tenure status (Col. 2), and self-reported gender (Col. 3). The bottom of the table reports p -values from tests of equality in the estimates within each model. We find statistically significant differences in γ estimates across major fields; however, the magnitude of the differences is smaller than what we observe when we estimate γ to be a function of theory-motivated features. We estimate smaller and statistically insignificant differences between researchers split based on their tenure status or gender.

Table B3: Heterogeneity in the amount-duration tradeoff, per other features

	(1)	(2)	(3)
Engineering and math	0.760*** (0.0089)		
Humanities	0.740*** (0.0090)		
Medicine	0.779*** (0.0073)		
Natural sciences	0.782*** (0.0097)		
Social sciences	0.769*** (0.0089)		
Not tenured		0.759*** (0.0060)	
Tenured		0.773*** (0.0051)	
Male			0.769*** (0.0050)
Female			0.764*** (0.0062)
<i>p</i> -val of diff.	0.01	0.07	0.46
<i>N</i> obs.	4,175	4,175	4,175

Note: Reports results from estimating Eq. 3 allowing γ to be group-specific; robust standard errors in parentheses (below the parameter estimates) and *p*-values from tests of the null hypothesis that group-specific estimates are equal (at the bottom of the table); * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Funders' revealed preferences over grant designs

C.1 Funders' preferences

For simplicity, assume the grant market is served by a single supplier, one “aggregate funder” that reflects the aggregated behavior of all individual funders. Researchers are the consumers. The aggregate funder's budget is exogenously determined and the aggregate demand for grants of all types is inelastic. No matter which set of grants the funder chooses to offer, researchers will pursue, and be awarded, all of them. This assumption seems relatively plausible given the fact that published success rates across funders are on the scale of 10-20% (see [here](#) for more). This implies that the funder is ignoring researchers' preferences, which will lead us to over-estimate their preferences (i.e., our estimate of γ_{fund} will be larger than the true value to the extent funders are in fact incorporating researchers' preferences into their portfolio decisions).

We assume the funder's maximization problem is given by:

$$\max_{\mathbf{N}} \sum_{a=\underline{A}}^{\bar{A}} \sum_{d=\underline{D}}^{\bar{D}} \pi(N_{ad}, a^{\gamma_{\text{fund}}} d^{1-\gamma_{\text{fund}}}), \quad (\text{C1})$$

where $\mathbf{N} = (N_{\underline{A}, \underline{D}}, \dots, N_{\bar{A}, \bar{D}})$ and π is a value function that describes the funder's net costs and benefits of awarding N_{ad} grants of amount a and duration d . Furthermore, assume that π is well-behaved and increasing and concave in its arguments: $\pi' > 0, \pi'' < 0$. π would be concave if funders prefer strategies that involve diversification across different grant designs, for example, to learn about the value of projects with small investments before making larger investments. Implicitly, π incorporates the funder's budget constraint.

Since the funder's valuation of their grant portfolio is separable in the groupings of amount and duration per a and d , then, in equilibrium, they will choose an allocation, $\mathbf{N}^*$, that equalizes the marginal returns across all groups (i.e., $\frac{\partial \pi}{\partial N_{ad}}$ is equal for all ad groups).

Here, just as changes in prices set by a monopolist firm are informative about changes in the firm's marginal costs, the observed distribution of grant types ($\mathbf{N}^*$; as shown in Figure 1) will be informative about the funder's preferences. Ideally, we would have some theory or data to be more specific about the shape of π in order to estimate $\frac{\partial \pi}{\partial a}$ and $\frac{\partial \pi}{\partial d}$, but we do not. We can still speak to the *relative* value the funder appears to place on grant size and duration per γ_{fund} .

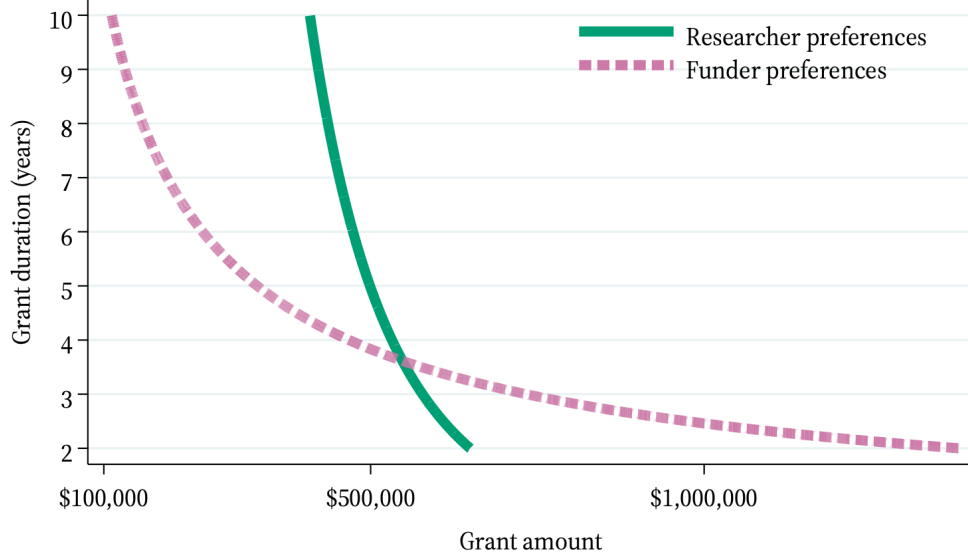
Note that the funder's choice of N_{ad}^* can be written as $\phi(a^{\gamma_{\text{fund}}} d^{1-\gamma_{\text{fund}}})$, where the shape of ϕ

is governed by π . Then, the relationship between N_{ad}^* and (a, d) will be informative of γ_{fund} since:

$$\frac{\partial N_{ad}^*/\partial a}{\partial N_{ad}^*/\partial d} = \frac{\partial \phi(a^{\gamma_{\text{fund}}} d^{1-\gamma_{\text{fund}}})/\partial a}{\partial \phi(a^{\gamma_{\text{fund}}} d^{1-\gamma_{\text{fund}}})/\partial d} = \frac{\gamma_{\text{fund}} d}{(1 - \gamma_{\text{fund}}) a}. \quad (\text{C2})$$

Thus, by regressing N_{ad}^* on a and d , the ratio of those coefficients (and the sample means) can be used to infer γ_{fund} .

Figure C1: Grant design preferences, researchers versus funders



Note: Shows the preferences of researchers per the survey-based thought experiment (γ), and of funders per observed distribution of research grants in the Dimensions data (γ^{fund}); the intersection of the curves is chosen to be the average grant size and duration.

Using \$100,000 bins for a and 1-year bins for d , a regression of the number of grants in each bin on the grant size and duration indicates that there are -150.3 (s.e.=34.7) fewer grants for every \$100,000 increase and -355.8 (s.e.=72.4) fewer grants for every 1-year increase. These coefficients imply a γ_{fund} of 0.39. Figure C1 plots the indifference curve implied by this estimate, contrasted with researchers' preferences.

This approach is likely identifying an upper bound of γ^{fund} because of our assumption that funders do not respond to researchers' demand. Thus, if they are in fact responding to demand already, and we know from the prior analyses researchers' γ is approaching 0.8, then our estimate of funders' preferences is biased upward. Still, funders are clearly much more willing to trade off size for duration. Intuitively, the time constraints facing funders must be less important than their cash constraints. But, it is notable how different funders' and researchers' preferences appear to be. In a sense, it appears funders are already pulling researchers towards a "longer-smaller" portfolio of grants than they would prefer.

D Additional results on strategic responses

D.1 Main results on strategic responses, reporting sample selection correction estimates

Table D1 replicates the results from the same analyses as reported in Table 5, but here also reporting the coefficient estimates associated with the Inverse Mills Ratio (IMR) covariate and the constant term. In all cases, we do not reject the null hypothesis of no sample selection effects with none of the IMR coefficients being significantly different from zero (Heckman 1979). The strong effects of the participation incentives and reminders reported in Section A.3 suggests that the IMR control is valid in the sense that there is non-trivial variation in the IMR driven by those randomized incentives and reminders. We still cannot rule out that there are no other unobservable dimensions of heterogeneity that are both correlated with researchers’ responsiveness to either the incentives or the reminders as well as our focal parameters (i.e., researchers’ strategic responsiveness to grant designs). However, we have no qualitative, theoretical, or other empirical reason to suggest any specific sources of such lingering selection that we could investigate further.

Table D1: Effect of grant designs on researchers’ strategies, reporting sample selection coefficient

	Faster (1)	More risk (2)	New directions (3)	Larger ongoing projects (4)	More accurate (5)
log(Duration)	-0.056*** (0.015)	0.012 (0.016)	0.008 (0.015)	0.018 (0.015)	0.018 (0.011)
log(Amount)	-0.025*** (0.007)	0.017** (0.007)	-0.016** (0.007)	0.026*** (0.007)	-0.003 (0.006)
IMR	-0.008 (0.007)	0.003 (0.008)	0.010 (0.007)	-0.005 (0.008)	0.000 (0.006)
Constant	0.776*** (0.097)	0.285*** (0.101)	0.533*** (0.095)	0.228** (0.099)	0.178** (0.077)
dep. var. mean	0.36	0.53	0.33	0.61	0.17
N obs.	4,175	4,175	4,175	4,175	4,175

Note: 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. The IMR row reports the coefficient on the standardized Inverse Mills Ratio. Robust standard errors shown in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Joint estimation of strategic responses

In the main text, we estimate five separate OLS models where we regress an indicator variable for whether the researcher chose each strategy on the (randomized) grant attributes they were provided with. This approach abstracts away from the fact that the researcher is effectively making a single, discrete choice decision about which pair of strategies to select.⁴³ To more closely model the structure of this problem, we can convert our data into researcher (i) by strategy (j) level observations and estimate a logit model of the form:

$$\Pr(\text{Strategy change}_{ij} = 1 \mid D_i, A_i, X_i) = \frac{\exp(\log(D_i)\beta_j^D + \log(A_i)\beta_j^A + \mathbf{X}\boldsymbol{\delta})}{1 + \exp(\log(D_i)\beta_j^D + \log(A_i)\beta_j^A + \mathbf{X}\boldsymbol{\delta})}, \quad (\text{D1})$$

which allows the effect of the grant attributes to depend on the strategy being considered. Now, instead of five OLS regressions, we have a single logit regression. Table D2 reports the results of estimating Equation D1 either without any covariates (Col. 1) or by using cross-fit partialing-out Lasso to select and include some covariates (Col. 2) per Chernozhukov et al. (2018a). In both cases, the results mirror those of our simpler, OLS-based approach shown in the main text.

D.3 Heterogeneous effects

Figure D1 plots the individual-level Conditional Average Partial Effects (CAPEs) based on the high-dimensional vector of covariates included in the causal forests (see Tables A1-A2 for the full list of those covariates).

To better understand the sources of that heterogeneity in a more low-dimensional way, Figure D2 reports some of the Best Linear Predictors of the CAPEs (Semenova and Chernozhukov 2021). Loosely speaking, the Best Linear Predictor approach regresses an individual’s CAPE on some covariate in order to test how the CAPE covaries with that observable, effectively testing whether that covariate mediates the focal causal effect. To do this, we make use of the `best_linear_projection` function within the `grf` package (Tibshirani et al. (2022)).

There is no systematic way for choosing which observables to test here, so Figure D2 reports only any observable which yields a p -value in a univariate regression of less than 0.01. The “Univariate coefficient” reported is in standard deviation units and relative to the mean CAPE (i.e., the mean treatment effect). Thus, a univariate coefficient of 0.1 for Humanities would indicate that the effect of the grant attribute on the focal strategy is 0.1 larger for

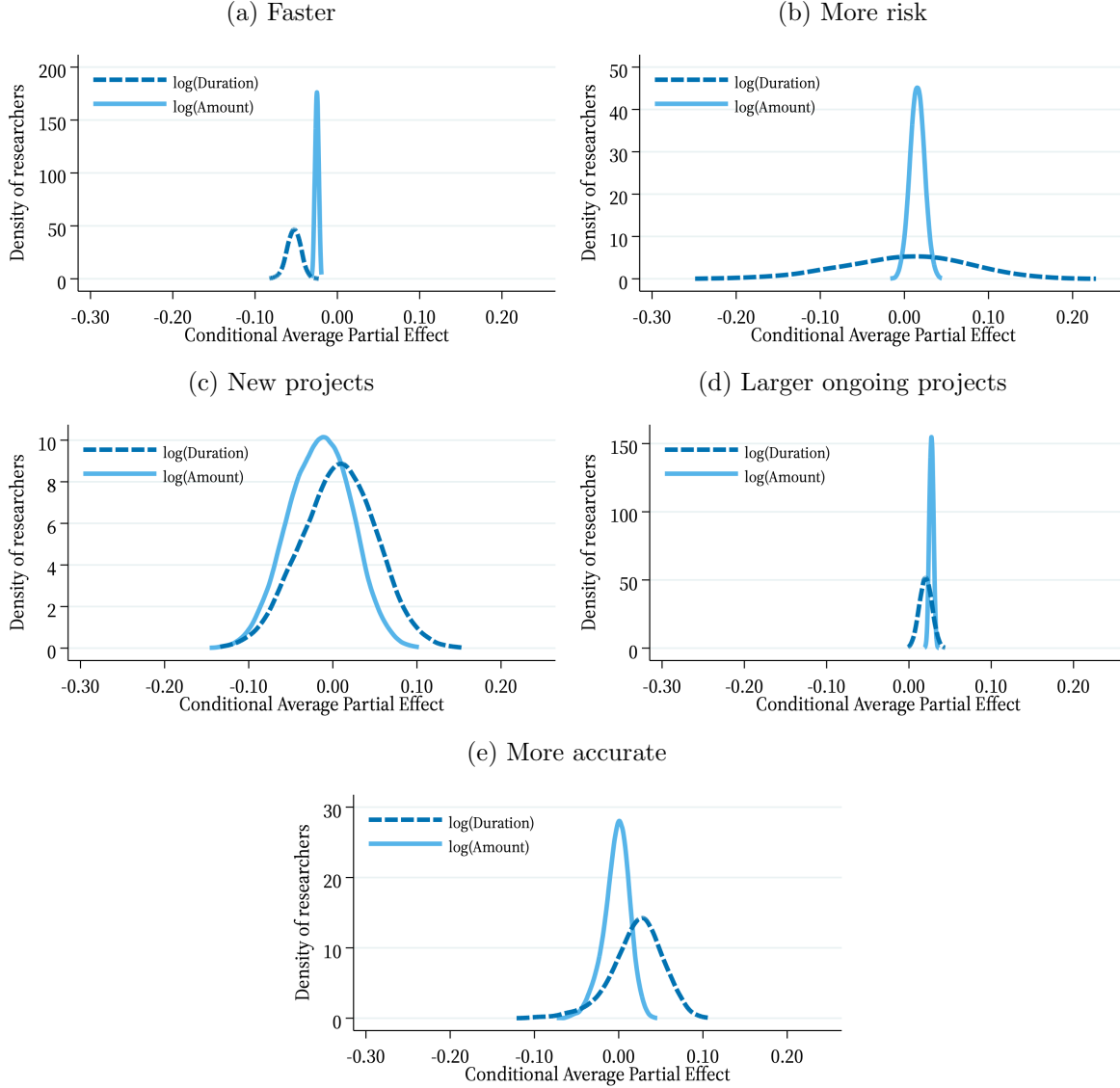
⁴³Recall, the researcher is told they have received some grant and are asked to choose the “top 2” most important changes to their research the grant would enable.

Table D2: Logit model of strategy changes in response to grant design

	(1)	(2)
More risk		
× log(Duration)	0.048 (0.062)	0.050 (0.063)
× log(Amount)	0.069** (0.030)	0.069** (0.030)
Faster		
× log(Duration)	-0.239*** (0.065)	-0.243*** (0.065)
× log(Amount)	-0.107*** (0.031)	-0.104*** (0.031)
New direction		
× log(Duration)	0.034 (0.066)	0.043 (0.067)
× log(Amount)	-0.073** (0.031)	-0.079** (0.032)
Ongoing bigger		
× log(Duration)	0.078 (0.063)	0.083 (0.064)
× log(Amount)	0.111*** (0.030)	0.117*** (0.031)
More accurate		
× log(Duration)	0.125 (0.082)	0.122 (0.083)
× log(Amount)	-0.019 (0.040)	-0.019 (0.040)
$L(\mathbf{X})$		Y
Ni obs.	4,175	4,175
Nij obs.	20,875	20,875

Note: Reports the estimates of β_j^D and β_j^S for each of the strategic options (indexed by j) per Eq. D1. Col. 1 includes no covariates and Col. 2 includes any Lasso selected covariates. Robust standard errors shown in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure D1: Heterogeneous effects of grant designs on researchers' strategies



Note: Each panel shows the distribution of the Conditional Average Partial Effects (CAPEs), which are estimated separately for the two randomized grant attributes using the causal forest method of [Wager and Athey \(2018\)](#); the CAPE is defined as $E[cov[W, Y|X]/var[W|X]]$, where $W = \{\log(duration), \log(size)\}$, Y is the dependent variable, and X are the covariates. The only two distributions that show statistically significant heterogeneity are (1) the effect of grant duration on risk-taking ($p < 0.001$) in Panel (b), and (2) the effect of grant funding amount on undertaking new projects ($p < 0.001$) in Panel (c).

researchers in that field compared to the rest of the sample.

Figure D2: Univariate Best Linear Predictors of heterogeneous treatment effects

(a) Faster		(b) More risk	
	Univar. coef.		Univar. coef.
<u>Size</u>		<u>Size</u>	
Outputs: Books	-0.021***	<i>n/a</i>	
<u>Duration</u>		<u>Duration</u>	
<i>n/a</i>		Tenured	0.084***
		Not on tenure-track	-0.097***
(c) New projects		(d) Larger ongoing projects	(e) More accurate
	Univar. coef.		Univar. coef.
<u>Size</u>		<u>Size</u>	
Outputs: Books	0.021***	<i>n/a</i>	
<u>Duration</u>		<u>Duration</u>	
<i>n/a</i>		Outputs: Products	0.039***

Note: Reports the results from univariate Best Linear Predictors (BLP) regressions of the Conditional Average Partial Effects (CAPEs) on aggregate field indicators as well as other select covariates; only variables with univariate coefficient p -values of 0.01 or less are shown; “n/a” indicates that no covariates had p -values less than 0.01 in the BLP regressions. The mean effects are reported in Table 5. Robust standard errors, which account for the fact that the CAPEs are estimated objects, shown in parentheses; *** $p < 0.01$

D.4 Alternative estimation of heterogeneity

In the main analyses, we estimate researchers’ heterogeneous strategic responses to grant design using the causal forest method of [Wager and Athey \(2018\)](#). That approach is appealing because it allows for the estimation of unit-specific partial effects. However, in order to obtain a lower-dimensional understanding of what covariates are influencing the heterogeneity captured by the random forest, we must ex-post select variables of interest.

An alternative approach is to directly focus on identifying treatment-covariate interaction terms that are “important” with the use of machine learning tools such as the lasso. Here, we follow an algorithm inspired by the approaches of [Imai and Ratkovic \(2013\)](#) and [Blackwell and Olson \(2022\)](#) that uses two stages of lassos. The algorithm is as follows:

1. Generate interaction terms between each randomized grant attributes (amount A and

duration D) and all covariates $\mathbf{X}$

2. Perform a lasso regression of a given dependent variable on $(A, D, A \times \mathbf{X}, D \times \mathbf{X}, \mathbf{X})$; let $L_{A,D,\mathbf{X}}^1$ denote the subset of attribute-covariate interaction terms selected in this step, i.e., from the possible set $(A \times \mathbf{X}, D \times \mathbf{X})$
3. Perform a cross-fit partialing-out lasso linear regression of a given dependent variable on $(A, D, L_{A,D,\mathbf{X}}^1)$ using $\mathbf{X}$ as the set of high-dimensional controls (Chernozhukov et al. 2015)

This approach relies on a separate penalty parameter to be used in the selection of interaction terms (Step 2.) and in the selection of covariates (Step 3.) as suggested by Imai and Ratkovic (2013). And by using a post-selection inference method (Chernozhukov et al. 2015), we are attempting to avoid regularization biases as noted by Blackwell and Olson (2022).

Table D3 reports the results from this alternative approach. Overall, the results are consistent with the random forests approach. Notably, tenure status is again observed to be a clear moderator of the effect of grant duration on risk-taking. The main effect estimates also align with our other estimation approach.

D.5 Returns to scale and new versus old projects

Here, we provide a stylized model of a producer’s decision to allocate a windfall of inputs into “new” or “ongoing” projects and how this decision depends on the returns to scale of the producers’ production function. The purpose of this model is to provide guidance on how to interpret the effect of grant designs on researchers’ decisions to invest grant resources in new or ongoing projects (as reflected by the β^{new} and β^{ongoing} coefficients that we estimate in Section 5.1 (see Eq. 5).

The producer has a production function $f()$ that is common to all projects.⁴⁴ The production function converts inputs X into some output with a constant marginal payoff normalized to 1. For now, assume only that output is increasing in inputs and non-negative: $f' > 0$ and $f(0) = 0$. The producer has two projects that they can invest in: an ongoing project where $\bar{X}_{\text{ongoing}}$ has already been invested, and a new project where $\bar{X}_{\text{new}}$ has already been invested. As suggested by the names, more inputs have been invested in the ongoing project: $\bar{X}_{\text{ongoing}} > \bar{X}_{\text{new}}$.⁴⁵

⁴⁴Our goal here is to provide a rationalization of results that does not rely on uncertainty, since we capture that dimension separately in the survey. Hence, we abstract away from the reality that new projects may be more uncertain than ongoing projects.

⁴⁵We do not formally model the source of this differential investment, but it could be due to the unmodeled

Table D3: Heterogeneous strategic responses to grant attributes

	Faster	More risk	New directions	Larger ongoing projects	More accurate
log(Duration)	-0.030 (0.023)	-0.052** (0.023)	0.015 (0.017)	0.019 (0.015)	0.019* (0.011)
× Male	-0.044 (0.030)				
× Tenured		0.094*** (0.030)			
× On t.t., not tenured			-0.045 (0.035)		
× Audience: Policymakers					0.015 (0.011)
log(Amount)	-0.018 (0.013)	0.012 (0.010)	-0.016** (0.007)	0.026*** (0.008)	-0.003 (0.006)
× Age	0.002 (0.008)				
× Assistant professor	0.027 (0.028)				
× Full professor	-0.014 (0.017)	0.011 (0.016)			
× On t.t., not tenured	-0.015 (0.029)				
× Engineering & related	-0.036** (0.018)				
× Total salary		0.001 (0.008)			
× Fundraising expect.		0.005 (0.006)			
× Research risk, own belief			-0.012 (0.007)		
× Humanities & related				0.009 (0.018)	
Incl. main effect	Y	Y	Y	Y	Y
Lasso method	plug-in	plug-in	plug-in	plug-in	plug-in
NX var. sel.	11/62	19/62	7/62	4/62	7/62
dep. var. mean	0.36	0.53	0.33	0.61	0.17
N obs.	4,175	4,175	4,175	4,175	4,175

Note: Robust standard errors shown in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To connect this model to our experiment, consider a scenario where the producer randomly receives a windfall of additional inputs; let the size of this windfall be given by Δ . Now, they must choose some fraction s of Δ to allocate to the ongoing project, with the remainder $(1-s)$ being allocated to the new project. Thus, their optimization problem is as follows:

$$\max_{s \in [0,1]} f(\bar{X}_{\text{ongoing}} + s \times \Delta) + f(\bar{X}_{\text{new}} + (1-s) \times \Delta) . \quad (\text{D2})$$

The optimal allocation choice (s^*) is either a corner solution (i.e., $s^* = \{0, 1\}$) or an interior solution (i.e., $s^* \in (0, 1)$). If an interior solution exists, it equates the marginal product across the two projects:

$$f'(\bar{X}_{\text{ongoing}} + s^* \times \Delta) = f'(\bar{X}_{\text{new}} + (1-s^*) \times \Delta) . \quad (\text{D3})$$

The producer's choice of how to allocate this windfall of inputs is analogous to researchers' choice of how to respond to the hypothetical grant in our experiments by either starting new projects or scaling up ongoing projects. Here in this model, the key comparative static is $\partial s^* / \partial \Delta$, which describes how the producer's allocation choice depends on the size of the input windfall. In our regressions using the experimental data (per Eq. 5), the coefficients β^{new} and β^{ongoing} capture the same relationship: how researchers' decisions to focus on new or ongoing projects depends on the amount of grant resources they've (randomly) received.

In the model, the sign of $\partial s^* / \partial \Delta$ will depend on the shape of f , which yields three possible outcomes when we map this to our empirical setting. If there are constant returns to scale ($f'' = 0$), then there is no relationship between s and Δ , since marginal returns are equal at all initial investment levels. If this is true among the researchers in our experiment, then we should find $\beta^{\text{new}} = \beta^{\text{ongoing}}$, since the amount or duration of a grant will have no bearing on researchers' decision to focus on either project type. Similarly, if f is convex ($f'' > 0$), then the optimal choice in the model is the corner solution of always investing all of Δ into the ongoing project, regardless of the size of Δ . Analogously, if researchers' within-project returns to scale are convex, then their choice to focus on new versus ongoing projects would be independent of the amount or duration of a grant and we'd estimate $\beta^{\text{new}} = \beta^{\text{ongoing}}$.

If the returns to scale are concave ($f'' < 0$), then, in the model, the producer will allocate a larger portion of larger windfalls to the ongoing project ($\partial s^* / \partial \Delta > 0$).⁴⁶ If this is true

differences in risk or differences in input costs (e.g., it is initially harder to raise money for new directions).

⁴⁶To see this, note that global concavity in f would imply that the interior solution to Eq. D3 simplifies to $\bar{X}_{\text{ongoing}} + s^* \times \Delta = \bar{X}_{\text{new}} + (1-s^*) \times \Delta$, which yields: $s^* = \frac{\bar{X}_{\text{new}} + \Delta - \bar{X}_{\text{ongoing}}}{2\Delta}$. Thus, $\frac{\partial s^*}{\partial \Delta} = \frac{\bar{X}_{\text{ongoing}} - \bar{X}_{\text{new}}}{2\Delta^2}$, which is greater than zero because $\bar{X}_{\text{ongoing}} > \bar{X}_{\text{new}}$.

among the researchers in our experiment, then we should find $\beta^{\text{new}} < \beta^{\text{ongoing}}$, since larger (or longer) grants would increasingly lead researchers to allocate resources towards ongoing projects.

The final scenario possible in the model is $\partial s^*/\partial \Delta < 0$, which is only possible if there are both increasing and decreasing returns to scale (i.e., f'' is non-monotonic). This could be possible if there were both convex and concave portions of the production function (e.g., sigmoid-shaped functions with convexity at low input levels and concavity at high input levels). Practically, this could correspond to fixed costs unique to new projects. If this scenario holds among the researchers in our experiment, then we should find $\beta^{\text{new}} > \beta^{\text{ongoing}}$, since larger (or longer) grants would increasingly lead researchers to allocate resources towards new projects to take advantages of the increasing returns to scale at lower levels of investments.

To summarize, the model delivers three scenarios that we can separately identify in our data based on the relative magnitudes of the regression coefficients as follows:

$$\partial s^*/\partial \Delta \begin{cases} = 0, \text{ if } f'' \geq 0 \text{ (convex or linear)} & \implies \beta^{\text{new}} = \beta^{\text{ongoing}} \\ > 0, \text{ if } f'' < 0 \text{ (concave)} & \implies \beta^{\text{new}} < \beta^{\text{ongoing}} \\ < 0, \text{ if } f'' \text{ is non-monotonic} & \implies \beta^{\text{new}} > \beta^{\text{ongoing}} \end{cases} .$$

D.6 Effects at the limits of grant design

To get a sense of the limits grant designs, Figure D3 plots the predicted choice probabilities for each strategy given designs at the limits of the dollar amount and duration explored in the thought experiment. These predicted probabilities are based on the point estimates from the logistic regression model. Thus, they are “generous” in that we do not force any point estimates that do not reject the null (per their standard errors) to zero.

We find that a “MIRA-sized change in grant design” (i.e., an additional 30% in duration and a 15% decline in amount) leads to no more than a 1 p.p. change in the probability of any strategy being chosen. Using the full support of grant designs from the thought experiment, the point estimates and confidence intervals indicate that it takes a tremendous amount of difference in grant design (i.e., plus or minus approximately \$2 million and/or 8 years) to change choice probabilities by an amount that could reasonably be considered meaningful (i.e, approximately 10 p.p.). For comparison, \$2 million is an order of magnitude larger than the median funding expectations of professors in the sample, and 8 years is roughly 3 times the average duration of non-tenure-track professors contracts (approximately 2.5 years) and the average amount of time before a pre-tenure professor’s tenure evaluation (approximately

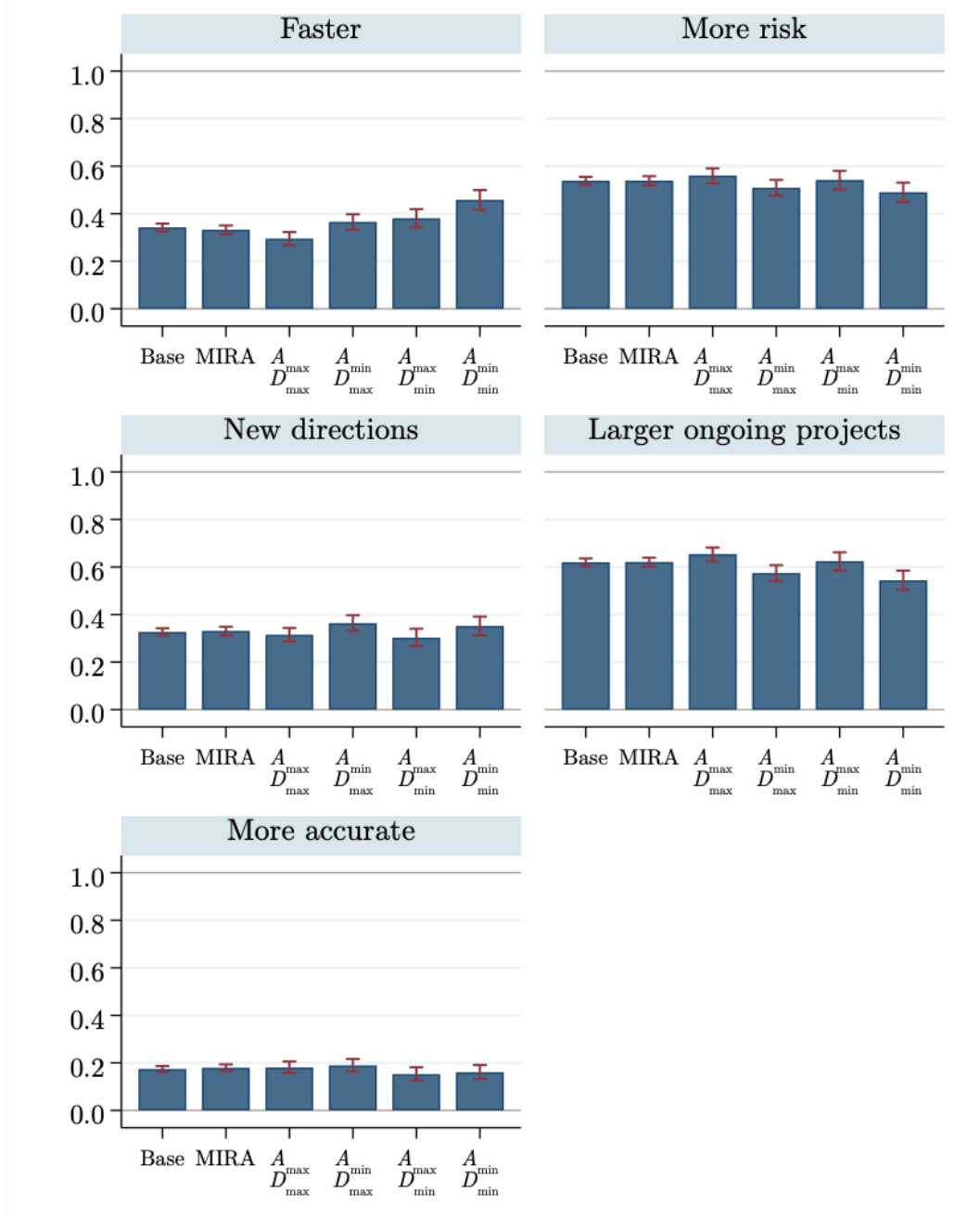
2.5 years). Table D4 summarizes these ranges based on estimates from the full sample, as well as estimates from just the non-tenured and tenured subsamples.

Table D4: Span of probabilities at observed and limits of grant designs

	mean	MIRA	Point Estimate		95% C.I.	
			min	max	min	max
<u>Panel (a): Full sample</u>						
Faster	0.34	0.33	0.29	0.46	0.27	0.50
More risk	0.54	0.54	0.49	0.56	0.45	0.59
New directions	0.33	0.33	0.30	0.36	0.27	0.40
Larger ongoing projects	0.62	0.62	0.54	0.65	0.50	0.68
More accurate	0.17	0.18	0.15	0.19	0.13	0.22
<u>Panel (b): Non-tenured</u>						
Faster	0.40	0.39	0.36	0.48	0.32	0.54
More risk	0.47	0.45	0.42	0.52	0.37	0.58
New directions	0.31	0.32	0.27	0.35	0.22	0.41
Larger ongoing projects	0.63	0.63	0.55	0.66	0.48	0.70
More accurate	0.20	0.21	0.17	0.22	0.13	0.27
<u>Panel (c): Tenured</u>						
Faster	0.30	0.29	0.25	0.44	0.22	0.50
More risk	0.59	0.60	0.50	0.63	0.44	0.67
New directions	0.34	0.34	0.32	0.37	0.28	0.43
Larger ongoing projects	0.62	0.61	0.54	0.65	0.49	0.69
More accurate	0.16	0.16	0.14	0.17	0.11	0.20

Note: Reports the predicted probabilities of choosing a strategy when receiving (Column 1) an average grant in the thought experiment (“Base”); (Column 2) a grant that is 30% longer and 15% smaller than average, reflecting the same relative change as the MIRA grants compared to traditional R01 grants at the NIH (“MIRA”); (Columns 3-6) report the minimum and maximum choice probabilities obtained under any grant design in the thought experiment using either the point estimates or the 95% confidence intervals.

Figure D3: Choice probabilities at observed and limits of grant designs



Note: Reports the predicted probabilities of choosing a strategy when receiving (1) an average grant in the thought experiment (“Base”), (2) a grant that is 30% longer and 15% smaller than average, reflecting the same relative change as the MIRA grants compared to traditional R01 grants at the NIH (“MIRA”); (3-6) grants with the largest or smallest dollar amount in the thought experiment ($A_{max} = \$2,000,000$; $A_{min} = \$100,000$) and the longest or shortest duration in the thought experiment ($D_{max} = 2$ years; $D_{min} = 10$ years). All predicted probabilities are based on the logit models.