The potential benefits of costly applications in grant contests

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Abstract

When funding public goods, resources are often allocated via mechanisms that resemble contests, especially in the case of scientific grants. A common critique of these contests is that they induce "too much" effort from participants working on applications. However, this paper emphasizes the importance of understanding the externalities associated with participation in these contests before drawing conclusions about the optimal mechanism design. Survey-based estimates suggest that the social costs of time spent on scientific grant applications may not be a first-order concern in non-emergencies. Still, further research is required to better understand how scientists compete in grant contests.

Keywords: contests; public goods; grants; scientific funding

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1 Introduction

In the case of scientific grants, there is no shortage of critiques claiming that funding contests incentivize scientists to spend "too much" time and effort on the application process. Furthermore, critics suggest this problem should be addressed by introducing randomized lotteries or reducing application requirements (Vaesen and Katzav 2017; Gross and Bergstrom 2019; Else 2021; Dresler et al. 2022; Thompson 2022). More generally, it has long been appreciated that competitions structured as contests can induce overinvestment relative to the social optimum when participants' effort is unproductive or duplicative (Loury 1979).

However, these conclusions do not always hold in the case of public goods where the presence of positive externalities can lead contests to have desirable social properties (e.g., Morgan 2000). Fast and easy contests are not always the most efficient. Similarly, this paper illustrates the (social) benefit of inducing (privately) costly effort in contests for funding public goods, so long as that work is directed towards the public good, here, "science."

2 Theoretical models

2.1 Baseline

There is a single funder who will award a grant valued v to one of n scientists. Once awarded, the grant generates social benefits of mv, where $m > 1$ determines the degree to which the grant generates positive externalities.[1] Scientists are equal in all regards (an assumption relaxed below) and can compete for the grant by submitting an application. Let x_i be the effort scientist i invests in their application with cx_i denoting the disutility from this effort ($c > 0$). I focus on the symmetric equilibrium where all scientists choose the same effort, x^*.

The funder's optimization problem is to choose a funding regime that maximizes the difference between the value generated by the grant and the total disutility of scientists' effort, $mv - ncx^*$.

One option is to use a "contest" regime where the probability that a scientist wins the grant is given by $\frac{x^*}{nx^*}$. It is straightforward to show the symmetric equilibrium gives $x^* = v\frac{(n-1)}{cn^2}$, which implies that the social value created is $(m - \frac{(n-1)}{n})v \equiv s_{\text{contest}}$.

Alternatively, the social planner could use a "lottery" regime by randomly allocating the grant to one scientist. Assuming this randomization is costless, the social value created is simply $mv \equiv s_{\text{lottery}}$. This will always generate more social value than in the first case ($s_{\text{lottery}} > s_{\text{contest}}$). This sort of argument either explicitly or implicitly underlies many of the proposals for lottery-based funding mechanisms: the introduction of randomness reduces the effort scientists invest in the grant competition.

However, this argument ignores the reality that the effort put forward in grant competitions generates

[1] The private return to winning the grant is v and the size of the positive externalities is $mv - v$.

spillovers – scientists can generate, refine, and share their ideas, regardless of whether or not they ultimately receive the funding. In other words, the effort exerted in these contest can involve positive (or negative) externalities.

2.2 Incorporating application effort with externalities

Two observations suggest there may be positive externalities from participation in funding contests. First, applications almost always require some degree of "science" to be performed. As evidence to this, researchers participating in federal grant competitions report that approximately 38% of their time spent on proposal preparation contributes directly to their scholarship (Schneider 2018).[2]

Second, studies of science funding agencies typically find that (1) researchers who compete for these grants publish much more than those who do not apply, (2) applicants tend to publish ideas related to their applications whether they are funded or not, and (3) the estimated treatment effect of receiving these grants based on comparisons of the publication output of funded and un-funded applicants appears relatively small or even negative (Jacob and Lefgren 2011; Li 2017; Wang et al. 2019; Ayoubi et al. 2019; Myers 2020). These patterns could be described by selection effects dominating the returns to the grant funding, but they are also consistent with these competitions incentivizing significant amount of productive research effort.

However, there may also be negative externalities associated with application effort. Most notably, the social opportunity costs of this effort may be non-trivial because effort spent towards applications reduces the amount of effort that could be spent directly on other scientific activities.[3]

To see how these externalities change the optimal regime choice, let w determine the degree of these externalities so that wx^* is the social benefit (or cost if $w < 0$) each scientist's effort generates. This leads to a new problem for the funder: maximize $mv - n(c - w)x^*$. Scientists' strategies remain unchanged since, by definition, they do not take externalities into account when making their decisions.

The social value generated by the contest regime in this setting is $(m - (c - w)\frac{(n-1)}{cn}))v \equiv s'_{\text{contest}}$, while the value of the lottery regime is unchanged. The contest is more efficient if the social value of the effort externalities is greater than the private cost of that effort ($s'_{\text{contest}} > s_{\text{lottery}}$ if $w > c$). Furthermore, the social return to increasing competition (n) is increasing in the size of these externalities ($\partial s'_{\text{contest}} / \partial n \partial w > 0$). Similarly, larger competitions have more to gain from increasing the size of the effort externalities.

[2] It seems reasonable to treat this self-reported estimate as a lower bound since it would be in scientists' self-interest to report a low estimate on a survey focused on the (private) costs of grant applications.

[3] There also may be social costs of effort insofar as the delay in time necessary to accommodate the effort induced by the contest leads the social value of the grant to be reduced (e.g., in an emergency). I return to this important caveat in the discussion.

2.3 Model extension

Appendix A provides an extended and more realistic model of a grant competition. It is based closely on Gross and Bergstrom's (2019) model of a scientific funding contest, which draws on earlier work on auction and matching theories by Moldovanu and Sela (2001) and Hoppe et al. (2009). Compared to the simple model, it incorporates multiple grants, heterogeneity in scientists' abilities, and noise in the contest success function.

Without any positive externalities in the application process, the Gross and Bergstrom (2019) model arrives at the same two results as above: (1) contests become less efficient as they become more competitive (where "efficiency" is the social value generated per grant awarded); and (2) contests can be made more efficient when they involve a lottery.

However, just as in the simple model, both of these results can be reversed by positive externalities in the application process. The realistic complications introduced do not alter the role of these externalities.

3 Current estimates of relevant parameters

The theory above emphasizes the importance of understanding the social benefits and costs of scientists' application effort. Appendix B decomposes the problem into a few more parameters and suggests the answer will depend largely on the sign and magnitude of w.[4]

Two important determinants of w are: (a) the amount of effort redirected from science towards applications, and (b) the relative social value of application effort versus scientific effort. How do scientists reallocate their time when they spend less time on fundraising for their research? Appendix B reports regression estimates using survey data from Myers et al. (2020) that suggest the elasticity of research time with respect to reduced fundraising time is small ($a \approx 0.05$), especially when compared to the elasticity of research time with respect to reduced teaching or other time, which are four to five times larger. To the second question, the results of Schneider (2018) suggest that at least one third of the effort spent on applications is scientifically useful ($b \approx 0.38$).

Together, these estimates suggest that a 10% decrease in total application effort would eliminate 3.8% of (application-based) scientific effort but generate only 0.5% of (non-application-based) scientific effort. The social costs of marginal time spent on grant applications appear smaller than the social benefits. Still, these estimates are based on self-reported data and non-experimental analyses. More rigorous measurement and research designs are needed.

[4] As long as w is not very close to zero (or negative), it is likely greater than c because the externalities of science are so large (Lakdawalla et al. 2010). See Appendix B for more.

4 Discussion

This paper demonstrates the potential benefits of inducing effort in scientific grant contests. In general, this result is not new – it is a well-known result in economic theory that the social value of effort in contests depends on whether that effort generates positive or negative externalities. But it is a result that is worth re-emphasizing as the rigidities exposed during the COVID-19 pandemic have sparked many calls for faster and easier grant mechanisms. Such mechanisms may certainly be warranted in emergencies when the social value of awarding grants decays quickly, and there are some remarkable examples of how impactful fast grants to scientists can be (Else 2021; Thompson 2022). However, this paper is concerned with non-emergencies and the funding of normal science.[5]

Estimates of some relevant parameters suggest that current science funding systems are likely not wildly distorting incentives on the margin. But this paper *does not* take a stance on whether the application processes of these systems are socially optimal. Unnecessary requirements or overly burdensome standards may be pervasive. Rather, this paper emphasizes that there can be large returns to designing grant applications that incentivize scientists to conduct science before the funding is awarded.

Intuitively, application-centric work should probably not require substantial funding since this could handicap scientists in resource-intensive fields and those yet to acquire much funding. This suggests the type of effort that applications should incentivize should be towards theoretical and conceptual tasks: formalizing research questions, describing research designs and plans of work, etc.

Still, continued theoretical and empirical research is necessary to better understand the parameters highlighted here, as well as many of the complicated and dynamic factors not addressed. For example, the models in this paper effectively assume a perfect correlation between scientists' productivity as researchers and their ability to compete in the grant contests – it assumes the best researcher is also the best grant-writer. The pervasiveness of discussions surrounding "granstmanship" amongst researchers suggests this is very likely not the case (e.g., Sauer and Gabbi 2018; Botham et al. 2020).

More generally, the results imply that program evaluations comparing the outcomes of marginally funded and non-funded scientists (e.g., Jacob and Lefgren 2011; Myers 2020) may be limited in their policy relevance. While these research designs can provide strong internal validity with respect to scientist-level effects, they cannot identify the possibly large effects a contest has on all who participate.

[5] For an excellent overview of grants as funding mechanisms in science more generally, see Azoulay and Li (2022).

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A Detailed model

A.1 Baseline

The following closely matches Gross and Bergstrom's (2019) model. Some minor changes are also made to more closely align the model with traditional economic definitions of private versus social costs and benefits.

There is a single funding contest run by the social planner, whose budget is such that they can fund a proportion of researchers given by p. Each researcher i has a single idea they need funding to pursue and the quality of that idea is given by the scalar $v_i \geq 0$, which is private information known only to i, but it is drawn from a publicly known distribution F.

The sequence of events and nature of the contest is as follows:

1. Researchers draw v_i from F.
2. Researchers choose how much effort to exert to develop an application of quality x_i, where the private costs of applying are given by $c(v_i, x_i)$.
3. Applications are reviewed in a "noisy" process that imperfectly ranks applications per their quality (x_i) and applications are funded subject to the budget constraint given by p.
4. Researchers with funded applications receive a payoff of v_i. All researchers (funded or not) recoup some share of the private costs of applying, given by the parameter $k \in [0, 1]$. The planner receives a payoff of mv_i if v_i is funded.[6]

Each researcher's optimal choice of application quality (x_i^*) is given by the bid function

$$b(v_i) = \arg\max_{x_i} \; v_i\eta(x_i) - c(v_i, x_i)(1 - k) \equiv x_i^* \; , \tag{A.1}$$

where η is the contest success function and describes the equilibrium funding probability for an application of quality x_i. This function depends on the payline (p), the distribution of realized applications, and the amount of noise in the review process.

The expected value of the contest for each applicant (if participating) is

$$v_i\eta\big(b(v_i)\big) - c\big(v_i, b(v_i)\big)(1 - k) \tag{A.2}$$

and zero otherwise. By assumption, only applicants with positive expected values will enter the

[6] Gross and Bergstrom (2019) also include a private payoff for funded applications (the v_0 parameter in their model) that does not enter into the planner's objective function. Since I am adopting the traditional economic definition of a social planner which incorporates the utility of all parties (scientists included), this term should also enter the planners' payoff. Instead, I am using the m parameter to clearly generate a wedge between the private and social payoffs of the grant. This effectively sets v_0 to zero in terms of Gross and Bergstrom's (2019) model. Whether or not v_0 is included in my model turns out to be irrelevant since it is an additive term and unrelated to the degree of effort-based externalities, and the addition of the m parameter only shifts the levels of the costs and benefits in the model which is not the focus.

contest. Also, unfunded applications generate no value beyond the private returns accrued to those applicants per the parameter k.

In the case without any positive externalities from application effort, the expected value per award (the measure of the contests' efficiency) for the social planner is

$$\frac{1}{p}\left(\underbrace{\int mv\eta\big(b(v)\big)dF(v)}_{\text{benefit}} - \underbrace{\int c\big(v,b(v)\big)(1-k)dF(v)}_{\text{cost}}\right) . \tag{A.3}$$

Gross and Bergstrom (2019) show that the efficiency of the contest is decreasing in the payline, p (where the top p applications are funded) as well as the value of instituting a lottery. is the same as the efficiency of a contest with a lottery line of p, even if the share that can be funded is less than p.

Formally, let f be the share of applications that can be funded given the budget. In a standard contest, a payline p is set to equal f such that the top $p = f$ applications are funded. In the lottery mechanism, a lottery line l is set greater than or equal to f such that the top l applications are entered into a randomized lottery where f are funded. Gross and Bergstrom (2019) show that the efficiency of a payline of $p = f$ is the same as the efficiency of a lottery line of $l \geq f$. For example, the efficiency of a contest with a lottery line of 30% is the same as the efficiency of a non-lottery contest with a payline of 30%, even if less than 30% of the applications can be funded. Loosely speaking, the presence of a lottery lowers the optimal choice of effort for each scientist by reducing the effective level of competition they will face.

A.2 Adding effort externalities

I incorporate effort externalities into this model by assuming that the planner's benefit now includes a "bid-effort externality" function $w(v,x)$, which can be thought of as the opposite of the private cost function, $c(v,x)$.[7] Now, the per-award benefit to the planner (omitting the cost component, which remains unchanged) is

$$\frac{1}{p}\int w\big(v,b(v)\big) + mv\eta\big(b(v)\big)dF(v) . \tag{A.4}$$

The researcher's problem has not changed, so their bid function remains the same as in Equation A.1.

Participants who work harder on their bid likely generate more externalities, but it is reasonable to assume there are decreasing returns (i.e., the initial conception of an idea may lead to many future

[7] Very similar results (reported below) are obtained if one incorporates this externality by assuming that a portion of the idea's quality is realized and value by the social planner regardless of whether or not the idea is funded, with that portion realized being determined by the scientists' bid.

ideas, but the 100th hour of work on a proposal is assumed to be spent on more wasteful activities). Thus, I choose a concave function for w defined below.

A.3 Assumptions

The following distributions and functional forms are exactly as in Gross and Bergstrom (2019):

- Distribution of idea quality: $F(v) = 1 - (16/9)(1 - v)^2)$, $v \in [0.25, 1]$
- $c(v, x) = x^2/v$
- $k = 1/3$
- Joint distribution of actual and evaluated quality: Clayton copula, $\theta = 10$

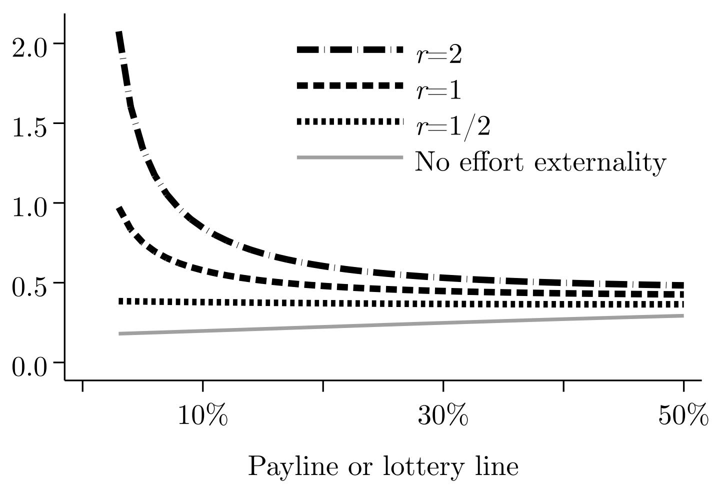
I set $m = 1$, which eliminates the positive externalities generated by science in my model, but allows me to match Gross and Bergstrom's (2019) results exactly in the baseline case.

To parameterize the bid effort externalities, I choose a function form for w that mirrors c as a sort of inverse cost function:

$$w(v, x) = kv(x)^{1/r} , \tag{A.5}$$

where r influences the shape of the function. w also includes the k parameter that governs how much of their disutility from effort scientists recoup because that effort is spent on valuable research activities (per $kc(v, x)$).

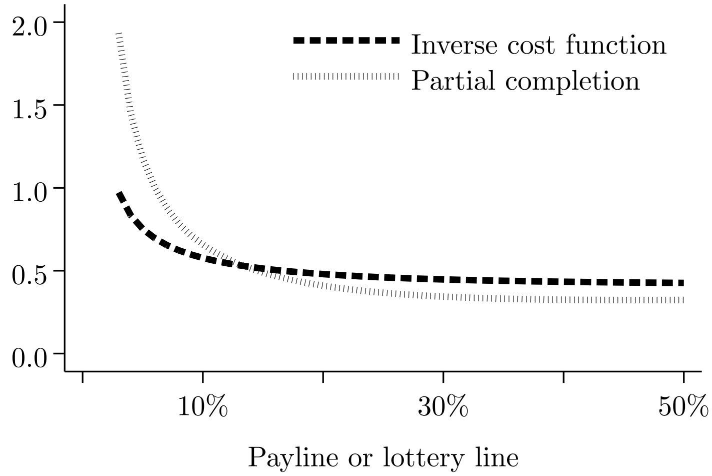
Figure A.1: Contest efficiency



Notes: Plots the efficiency (social value per grant awarded) of the detailed model without and with application effort externalities, varying the r parameter in Eq. A.5, as a function of the payline (the share of applications awarded) or lottery line (the share of applications eligible for a randomized lottery) of the contest.

Figure A.1 illustrates the contest's efficiency under the baseline case of no effort externalities (exactly replicating Gross and Bergstrom (2019); see their Figure 3) as well as with externalities under a range of values for r. Because the support of the bid values lies below one, values of $r < 1$,

Figure A.2: Contest efficiency, alternative externality forms



Notes: Plots the efficiency (social value per grant awarded) of the detailed model with application effort externalities, assuming the externalities arise either per the "Inverse cost function" or the "Partial completion" assumption (described in this sub-section).

which dramatically reduce the size of the effort externalities, are necessary to eliminate the pattern whereby more competition increases the efficiency of the contest. At $r = 1/2$, the private costs and externalities perfectly offset, leading the efficiency of the contest to be equal under all levels of competition.

A.4 Alternative externality formulation

Another way one could incorporate bid effort externalities into this model would be to assume that a fraction of the idea's quality is produced as a function of each applicant's bid, regardless of funding status, with the remainder only being realized if the grant is awarded. For simplicity, let's also assume that the scientists' utility function is unchanged, which implies that they receive the full private value of the idea (v_i) only if funded whereas the social planner receives some portion of this value in the application process and (for those funded) the remainder.

Formally, the the per-award benefit to the planner (omitting the cost component, which remains unchanged) is now

$$\frac{1}{p}\int w(b(v))v + \Big(1 - w(b(v))\Big)v\eta(b(v))dF(v) \ , \tag{A.6}$$

where $w(b(v))v$ is the partial realization of all ideas due to application effort, and $\Big(1 - w(b(v))\Big)v$ is the realization of the remainder of each idea's value for the subset funded.

Assuming the functional form of w is again similar in nature to the other parts of the model, $w(b(v)) = b(v_i)^{(1/2)}/3$, yields very similar results to the original formulation of externalities – see Figure A.2.

B Relevant parameters and estimates

B.1 Quantifying w and c

It is helpful to decompose $w - c$ (the size of application effort externalities compared to their private costs) into a few more parameters with empirical analogues. $w - c$ should be proportional to

$$(b - a)(v - d_{\text{science}}) - (1 - b)d_{\text{redtape}} \tag{B.1}$$

where b is the percent of application effort that involves science (i.e., as opposed to "red tape"), a is the percent of scientific effort lost due to (total) application effort, v is the social benefit of scientific effort, and the d parameters are the private costs of scientific and red tape effort, respectively.[8]

As a starting point, it is well-known that scientific effort is characterized by extremely large externalities, with researchers capturing as little as 5% of the value they generate (Lakdawalla et al. 2010). This implies $v - d_{\text{science}}$ is likely to be on the order of 20-fold. This in turn suggests that, unless the red tape effort of applications is an order of magnitude more costly than scientific effort, the magnitude of $w - c$ will be driven mostly by the opportunity costs of applications as captured by $b - a$. Certainly, one would expect $d_{\text{science}} < d_{\text{redtape}}$, but not to the degree it would offset the positive externalities of scientific effort.

The next subsection and the main text describe some estimates for b and a. However, empirical analyses focusing on these and related parameters are few and far between. There is much to be learned about the specific nature and heterogeneity of these forces.

B.2 Opportunity cost and time use

In order to quantify the social opportunity costs of scientists spending time on grant applications, it is important to know how scientists allocate their time across activities (the a parameter in the subsection above). Myers et al. (2020) conducted a survey of U.S. and European academic scientists that asked about their time allocations prior to the onset of the COVID-19 pandemic.[9] Table 1 reports the summary statistics for all research faculty that responded to the survey and reported their time use. The Table reports statistics for both the full sample as well as those who report a non-trivial amount of time spent "fundraising" for their own research (e.g., grantwriting).

To investigate how scientists reallocate their time, Table 2 reports the results from a series of regressions that regress scientists' research time on their fundraising time and (possibly) their time spent on teaching, other duties (e.g., administration), as well as a large vector of covariates

[8] This model implicitly assumes that the social benefit of scientific effort done within the context of a grant application is equal to the scientific effort done elsewhere, which may or may not be true. There do not appear to be any obvious theoretical reasons, nor any empirical estimates, suggesting the value of "science" done as a part of an application may be less valuable than the "science" done elsewhere.

[9] See Myers et al. (2020) for further details on the sampling methodology and instrument.

Table 1: Summary statistics of scientists' time use, hours-per-week

	Full sample		Fundraisers	
	mean	s.d.	mean	s.d.
Research time	23.6	11.0	23.8	10.3
Fundraising time	8.6	5.5	10.6	5.2
Teaching time	16.3	9.3	15.9	8.4
Other time	12.8	8.3	12.3	7.3
N obs.	4,712		3,370	

Notes: The "Fundraisers" sample restricts to scientists who report more than the lowest non-zero amount of time spent on fundraising (3.5 hours per week on average). The "Other" category includes administration and other responsibilities related to one's position.

also collected in the Myers et al. (2020) data.[10] The Table also reports the implied elasticities at the sample means, which suggest that scientists are relatively unlikely to reallocate time from fundraising to research – the elasticity of research time with respect to reduced fundraising time is consistently less than 0.07. This is likely an underestimate, since there are likely unobservable features of scientists (e.g., their productivity as fundraisers or researchers) that leads them to sort into positions with different (unobservable) constraints on their time.

[10]The additional covariates includes location and field-of-study indicators, age, gender, tenure status, marital status, and indicators for the number and age of dependents at home. When the covariates are included in the model, they are selected via Lasso. All models are estimated using Stata and either the `regress` or `poregress` command, the latter for the Lasso-based models.

Table 2: Changes in scientists' time use

	D.V. = Research time					
	Full sample				Fundraisers	
	(1)	(2)	(3)	(4)	(5)	(6)
Fundraising time	0.0160	–0.0183	–0.105***	–0.119***	–0.140***	–0.153***
	(0.0274)	(0.0287)	(0.0270)	(0.0283)	(0.0294)	(0.0301)
Teaching time			–0.455***	–0.433***	–0.457***	–0.439***
			(0.0165)	(0.0165)	(0.0179)	(0.0178)
Other time			–0.433***	–0.438***	–0.478***	–0.491***
			(0.0170)	(0.0172)	(0.0206)	(0.0204)
Elasticity						
Fundraising	0.01	–0.01	–0.04	–0.04	–0.06	–0.07
Teaching			–0.31	–0.30	–0.30	–0.29
Other			–0.23	–0.24	–0.25	–0.26
N obs.	4,712	4,712	4,712	4,712	3,370	3,370
$L(X)$		Y		Y		Y

Notes: Robust standard errors in parentheses; * $p < 0.1$, *** $p < 0.01$. Scientist-level observations. Independent and dependent variables are measured in hours-per-week. $L(X)$ indicates that Lasso is used to select from demographic and professional covariates which are interacted with field and location indicators interacted. Elasticities are reported at sample means.