Expected Productivity and Efficiency in Science

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December 2025

Many contend the allocation of resources across scientists is inefficient. But the extent of this inefficiency remains unclear because outputs and prices are challenging to measure. We develop a method to overcome these challenges and evaluate the market for science. Our model of researchers' labor supply shows how their willingness to pay for inputs reveals their expected productivity. We estimate the model's parameters using data from a nationally representative survey and find the distribution of productivity to be very skewed. The counterfactuals indicate that a more efficient allocation of the current budget would be worth billions of dollars annually.

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This project received financial support from The Alfred P. Sloan Foundation and the Harvard Business School. There are no financial relationships or other potential conflicts of interest that apply to the authors. This project would not have been possible without the excellent work of Rachel Mural, Nina Cohodes, and Yilun Xu and input from Marie Thursby, Jerry Thursby, and Karim Lakhani. We received helpful comments from Stefano Baruffaldi, Nick Bloom, Judy Chevalier, Matt Clancy, Zoë Cullen, Shane Greenstein, Matt Grennan, Daniel Gross, Bronwyn Hall, Sabrina Howell, Bruce Kogut, Petra Moser, David Rivers, Jesse Shapiro, Tim Simcoe, Chad Syverson, Joel Waldfogel, as well as seminar participants at Columbia, JOMT, MIT, the Workshop on the Organisation Economics and Policy of Scientific Research, the Banff Productivity Innovation and Economic Growth Conference, the NBER Productivity Lunch, Boston University TPRI, IIOC, Washington University in St. Louis, the Conference on the Economics of Innovation in Memory of Zvi Griliches, and Catholic University of Milan.

1. Introduction

Science has continuously proven to be the engine of economic growth.[1] Academic science, in particular, is now a $100 billion engine for the United States (e.g., Azoulay et al. 2019; Fleming et al. 2019; Gibbons and NCSES 2024). However, there is growing evidence that science is getting harder (Jones 2009; Bloom et al. 2020a), and there are a growing number of debates about the functioning of scientific institutions.[2] Understanding productivity and efficiency in science has become increasingly important.

A long line of work, which we review below, has documented allocative inefficiencies in science; researchers are denied resources for reasons unrelated to their productivity. While it is clear we can do better at allocating resources, it is unclear *how much* better we can do. How much more knowledge could be produced if we improved the allocation of resources to best support the most talented scientists? Answering this question first requires answering another question: what is the distribution of marginal returns across researchers? In this paper, we formalize and answer both of these questions.

Progress on these questions has been slow because estimating productivity in science poses some major challenges. First, the output of science is difficult to observe; how does one quantify a unit of knowledge? Bibliometric data is popular; however, as noted by Adams and Griliches (1998), "*what constitutes a scientific paper makes for an elastic yardstick of scientific achievement*." Second, scientific inputs are rarely allocated via price mechanisms and researchers face large adjustment costs (Myers 2020; Baruffaldi and Gaessler 2025). These facts violate key assumptions at the core of most conventional methods for productivity estimation.

To overcome these challenges, we develop a method for estimating productivity without data on output quantities or input prices. As in conventional methods, we leverage the fact that producers' input choices reveal information about their productivity. However, our approach involves a new step: the direct solicitation of producers' willingness to pay (WTP) for inputs.

We assume that each individual producer (i.e., a scientist) derives indirect utility from their output and other sources of consumption, and we allow their total factor productivities, technologies (i.e., factor mix), and preferences to be idiosyncratic. Producers also have idiosyncratic budgets (i.e., salaries), which they can use for consumption or use to

[1]For motivating theory, see: Jones (2005). For a recent review, see: Bryan and Williams (2021).

[2]For coverage in popular press, see: Rohn (2017); Ioannidis (2018); Piper (2019); Mills (2021).

purchase inputs from us, the experimenters. The key is that, conditional on individuals' budgets, technologies, and preferences, one producer will only have a higher WTP compared to another if they believe they are more productive. Thus, the variation in WTP for inputs can then be used to recover the distribution of individual-level productivity and, through counterfactuals, quantify the value from more efficiently allocating inputs.

In order to apply this method to the market for science, we first present a new model of researchers' labor supply and consumption decisions. Researchers have heterogeneous preferences and derive utility from three sources: their salary, their scientific output (i.e., the quantity of knowledge they produce), and their leisure time. An (exogenous) contract specifies their salary, administrative duties, and guaranteed funding. Given their contract, researchers choose how to allocate their time across fundraising (e.g., writing grants)[3], research, and leisure given their beliefs, budgets, and constraints. Each researcher has a unique production function with constant returns to scale, defined by two researcher-specific parameters: (*i*) a funding-intensity parameter that determines the relative weight of the two key inputs, funding and time, and (*ii*) a total factor productivity (TFP) parameter that describes the efficiency with which researchers produce scientific output using their inputs.

To identify researchers' WTP for inputs, we use the logic of compensating variation to solve for the salary change that would leave the researcher indifferent to alternative contracts, where these alternatives specify counterfactual amounts of guaranteed research funding or administrative duties. This variation in salary — our measure of researchers' WTP for inputs — depends on productivity because the expected change in scientific output, given the counterfactual funding or duties, depends on the researcher's productivity beliefs.[4]

In order to generate the data necessary to estimate the model, we make use of a nationally representative survey of research-active professors across all major fields of science at roughly 150 major institutions of higher education in the US; for details, see Myers et al. (2023).[5] The survey solicits researchers' salaries, time allocations, and access to

[3]We allow for heterogeneity in researchers' ability to fundraise.

[4]Notably, this approach allows us to solicit researchers' WTP without asking directly for their literal willingness to give us, the experimenters, money out of their own pockets in exchange for inputs. This is important because, in practice, the lack of explicit price mechanisms in scientific input markets leads researchers to often reject the premise of a question that asks for their own, direct out-of-pocket WTP for inputs.

[5]Evidence is provided in Myers et al. (2023) suggesting the presence of non-response bias in the sample is very low on observable dimensions such as institutional rank, grant funding, and publication rates; some

inputs. Importantly, the survey also includes a series of hypothetical experiments that solicit researchers' willingness to trade off their salary for more research funding or fewer administrative duties.

Researchers' willingness to pay for inputs are of plausible magnitudes and behavior. The median researcher is willing to pay 10 cents for $1 of research funding and $68 for one less hour of administrative duties. The components of the model explain a large fraction of the variation in researchers' responses (82–96%) and, for the most part, responses do not appear to reflect sample selection or systematic noise in respondents' willingness to pay for any hypothetical good. Furthermore, researchers' willingness to pay for free time is strongly correlated with their implied hourly wages as expected.

Our estimates of productivity beliefs vary widely across researchers, even after accounting for outliers. Within major fields of study, the ratio of the 90^{th} and 10^{th} percentile of TFP is approximately 52. When we look in narrower fields of study and attempt to control for other sources of heterogeneity, we estimate 90–10 TFP ratios to be approximately 29. This represents a high degree of dispersion compared to what is observed in commercial markets at the firm-level (e.g., Syverson 2011); however, this scale of dispersion in productivity across individual workers has been observed in some high-skilled settings (e.g., Sackman, Erikson, and Grant 1968). Motivated by Gabaix (2009), we investigate the upper tail of the TFP distribution and find it to exhibit power laws.

As a sign of face validity, our productivity estimates are positively correlated with common metrics of knowledge production (e.g., publications, citations, grant funding) and exhibits a similar degree of dispersion as those metrics. Notably, our estimates indicate that approximately half of the variance in scientific output across individual researchers is due to variance in their productivity.[6] The high degree of dispersion suggests that it may be hard for the market to facilitate positive selection on productivity.

To evaluate allocative efficiency, we compare inputs and outputs under actual allocations, to those under alternative allocations. Specifically, we consider two alternative objectives: (*i*) maximize total scientific output, or (*ii*) maximize researchers' private utility. Using the model, we can solve for the allocation of inputs that achieves an objective while allowing for researchers' behavioral responses as they re-optimize their choices.

of this is reprinted in the Appendix.

[6]We are unable to distinguish the degree to which our productivity estimates reflects an individual's fixed capabilities as a researcher versus any cumulative advantage they have acquired (c.f., Hall and Mairesse 2024).

Overall, we find evidence of a moderate degree of efficiency given our proposed objectives. The correlations between researchers' actual input levels and the optima implied by our model generally span 0.4–0.8; more productive researchers acquire more inputs on average. However, there are significant gains from alternative allocations. Our counterfactuals suggest that total annual scientific output could be increased by approximately 160%. The private value to researchers of this additional output is on the scale of 5%. Estimating the social value of this growth requires assumptions about externalities, which we explore.

To provide another way of characterizing the gains from reallocation, we ask the following: how much would funding levels need to increase under actual allocations to produce the same growth in output as our alternative allocations that hold input levels fixed? We find that aggregate funding levels would need to increase roughly 40% to achieve the same growth in output our alternative allocations can achieve. That we can obtain a 160% growth in aggregate output from a 40% increase in aggregate funding is due to the combination of a mechanical composition effect and a endogenous behavioral response, which we detail further. Conservative approaches to scaling these estimates to the size of the population imply gains from reallocation that are equivalent to multi-billion dollar increases in annual funding.

We also evaluate the degree to which differences in aggregate output across major fields of study are due to differences in the number of researchers, their productivities, their input levels, or the fields' allocative efficiency. Overall, differences in allocative efficiency are the largest determinant of differences in aggregate output. At efficient allocations, the gaps in output between fields shrink by 20–50%.

Lastly, we unpack the counterfactuals to explore the following questions: Is the efficient allocation of inputs implied by the model more or less concentrated than the actual allocation? How does the reallocation of each input (i.e., funding and time) independently change the results? How much does the efficient allocation change under different objectives? What is the distribution of input wedges (i.e., the difference between their optimal and actual input levels) across researchers? Are researchers' input wedges predictable given their observable features?

Our estimates come with some important caveats. First, we face a set of challenges common to all existing productivity estimation techniques.[7] Second, we face some unique limitations: (*i*) our method provides only ex-ante productivity beliefs and has no way of identifying ex-post differences in production; and (*ii*) the identifying variation in our data is based on stated preferences from hypothetical experiments. Throughout the paper we engage with these limitations by providing robustness tests of our assumptions and face validity tests of the data. Overall, the results from these tests give us confidence in our conclusions. Still, we interpret our results as plausible upper bounds on the productivity dispersion and gains from reallocation in science. Given the dearth of quantitative evidence in this area, we view our estimates and methodology as valuable inputs for future theoretical and empirical studies in the economics of science and innovation.

After a brief review of our connection to the literature, the rest of the paper proceeds as follows: Section 2 provides the general framework of and key assumptions underpinning our methodology; Section 3 details the survey data; Section **??** describes our model of researchers' production and consumption; Section 4 describes and reports the results of the survey experiments; Section 5 provides the model estimates; Section 6 contains our counterfactual allocation exercises; and Section 7 concludes with a discussion of our results and the usefulness of our methodology more generally.

Related Literature

Our paper sits primarily at the intersection of two bodies of literature: empirical studies of science and markets for innovation (i.e., Merton 1973; Stephan 1996; Bryan and Williams 2021); and economic studies of producers' productivity and factor misallocation (i.e., Syverson 2011; Restuccia and Rogerson 2017; De Loecker and Syverson 2021). More generally, we are focused on a classic challenge in labor economics of estimating worker-level productivity metrics (i.e., Hoffman and Stanton 2024).

The meta-science literature has long been interested in misallocation. Following a long line of sociological work (Merton 1973; Zuckerman 1988; Shapin 1995) economists have quantified some status-based frictions (Azoulay, Fons-Rosen, and Graff Zivin 2019) and have also studied potential frictions such as: political lobbying (Hegde and Sampat 2015), information asymmetries regarding researchers' output (Hager, Schwarz, and Waldinger 2024), and competitive pressures from priority-based credit mechanisms (Hill and Stein 2025). However, the scientific production function is rarely formalized in a way that

[7]Namely, (*i*) noise due to mismeasurement or misspecification; and (*ii*) the presence of unmodeled heterogeneity in output prices (or preferences over payoffs).

yields the structural parameters necessary for quantifying productivity dispersion or allocative efficiency. Rosenbloom et al. (2015) finds the marginal returns to scientific funding (per bibliometrics) are relatively similar across US universities, which is suggestive of allocative efficiency. Taking a more dynamic view, Qiu (2023) estimates the discount rate that rationalizes funding allocations at the US National Institutes of Health and finds a relatively high discount rate, which suggests young scientists may be under-funded.

Looking towards the productivity literature, our methodology is centered on understanding producers' factor demand, which follows the logic of identification based on input cost shares (e.g., Hsieh and Klenow 2009) or the inversion of input demand into control functions (e.g., Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). Much work has been done to extend these methods to account for features such as unobservable prices (De Loecker et al. 2016), adjustment costs (Petrin and Sivadasan 2013; Asker, Collard-Wexler, and De Loecker 2014), as well as measurement error and heterogeneity (Kim, Petrin, and Song 2016; Gollin and Udry 2021). To our knowledge, we are the first to formalize an approach for estimating production functions without data on output quantities and input prices.

We also follow a growing body of work using surveys to study the determinants of productivity in settings with inputs and outputs that are subjective or difficult to measure (e.g., Bloom, Sadun, and Van Reenen 2012; Atkin, Khandelwal, and Osman 2019). We are not the first to solicit producers' WTP for inputs (c.f., Cole et al. 2013; Wossen et al. 2024); however, those studies tend to have an inherent interest in producers' demand for a specific input. Our work also runs parallel to the development of methods that use (quasi-)experimental variation to estimate misallocation (e.g., Sraer and Thesmar 2023; Carrillo et al. 2023).

2. Methodological Framework and Model of Science

In this section, we show how a scientist's expectations about their productivity can be estimated by using information about their WTP for a fixed amount of inputs. We discuss the method in general terms in Section 2.1 and then describe our specific model of researchers' labor supply, including functional form assumptions, in Section 2.2. Additional details regarding the model and estimation are contained in Appendix C.

To illustrate our approach to estimating productivity, the following simple example shows how soliciting scientists' WTP for an input can be used to estimate their productivity:

Utility maximizing scientists are indexed by i and are endowed with expected income, M (e.g., a guaranteed salary). Scientists produce research output, Q, using a single variable input, X (e.g., research funding). Scientists obtain the input by incurring heterogeneous, convex costs given by: $X_i^{c_i}$, where $c_i > 1$. Scientists produce research output according to a linear research production function: $Q_i = \alpha_i \times X_i$, where α_i is the focal productivity parameter. Scientists' utility function is linear in income and research output less costs. They maximize utility by choosing X_i:

$$\max_{X_i \geq 0} \; M_i + bQ_i - X_i^{c_i} \quad \text{s.t.} \quad Q_i = \alpha_i X_i,$$

where b is the marginal utility of research output relative to income, the numeraire. We cannot observe the productivity or cost parameters (α_i, c_i), and we cannot observe output (Q_i). Our goal is to estimate productivity (α_i).[8]

Our solution is to solicit scientists' willingness to pay (WTP_i) for a fixed quantity of input using their income (M_i). Consider an experiment where scientists are asked to report their WTP to obtain 1 unit of X without incurring the convex costs. By definition, they will choose WTP_i that makes them indifferent between purchasing and not purchasing the additional unit of X. Formally, WTP_i solves:

$$\max_{X_i} \left[M_i + b \times \alpha_i \times X_i - X_i^{c_i} \right] = \max_{\widetilde{X}_i} \left[(M_i - WTP_i) + b \times \alpha_i \times (\widetilde{X} + 1) - X_i^{c_i} \right].$$

This yields a simple expression for identifying scientists' productivity expectations that does not require output quantities or input costs: $\alpha_i = WTP_i / b$. Clearly, this requires observing or making assumptions about b, a point we highlight below.

2.1. Framework, Assumptions, and Estimation

2.1.1. General Framework

Our goal is to estimate individual producers' rational expectations about their productivity in a single future period of production. Despite revolving around forecasts, we present

[8] Note that, even if we could also observe or estimate producers' expected input choice, X_i^*, then the first order condition, $X_i^* = (b \times \alpha_i / c_i)^{1/(c_i - 1)}$, still does not separately identify the productivity and cost parameters (α_i, c_i).

the framework as static; there is no dynamic optimization.[9]

There are N individuals indexed by i. For simplicity, we focus on the case where individuals use a single, variable input X to produce some quantity Q of output; extensions to multiple inputs and stocks are possible. Individuals have heterogeneous production functions with a Hicks-neutral total factor productivity (TFP) term: $Q_i = \alpha_i \times f_i(X_i)$, which is monotonically increasing in X.[10] Estimating the TFP parameter α_i is our primary goal.

Individuals' benefits are governed by idiosyncratic functions $b_i(M_i, Q_i)$, which depend on output levels (Q_i) and an endowment of money that is guaranteed regardless of output (M_i). For individual scientists, M_i would reflect their guaranteed salary, and the benefit function would describe their utility from their salary as well as any additional benefits that they expect to receive from producing more research output (e.g., prestige, expectations of a promotion).[11] Total costs depend on an input cost function $c(X_i, \mu_i)$ and there may also be constraints on input levels denoted by $g(X_i, \mu_i) = 0$.

Thus, individuals choose input levels that maximize their payoff per:

$$\begin{aligned} \max_{X_i} \quad & b_i\big(M_i, \alpha_i \times f_i(X_i)\big) - c(X_i) \\ \text{subject to} \quad & g_i(X_i) = 0 \, , \end{aligned} \tag{1}$$

where we define X_i^* as the argument that maximizes Equation (1). Solving the first order conditions of the producer's problem (Eq. 1), ignoring constraints in what follows for simplicity, yields:

$$\alpha_i \times \frac{\partial}{\partial X_i} b_i\big(M_i, \alpha_i \times f_i(X_i)\big) \times \frac{\partial}{\partial X_i} f_i(X_i) - \frac{\partial}{\partial X_i} c_i(X_i) = 0 \, , \tag{2}$$

which shows that productivity (α_i) is an implicit function of observables and the unknown parameters that govern the functions $b_i(\cdot)$,$f_i(\cdot)$, and $c_i(\cdot)$. At this point, productivity is not separately identified from these unknown parameters.

In order to identify the parameters in Eq. 2, we experimentally solicit individuals' WTP for some amount of the input using their own money M_i (e.g., directly from us, the experimenters). For example, we offer the producer an opportunity to purchase Δ units

[9] In so doing, we implicitly load dynamic considerations related to career progression onto other parameters in the model. We also omit the expectation operator despite variables being forecasts.
[10] Thus, α_i is a TFP-Quantity (TFPQ) parameter.
[11] For simplicity, we do not allow for financial markets, but they could be incorporated.

of X and solicit their WTP (e.g., via stated preferences or incentive-compatible revealed preferences), which would be deducted from their M_i.

To see the value of this experiment, first consider the individual's optimization problem in the scenario where they choose to pay their WTP to purchase Δ inputs from us:

$$\max_{\widetilde{X}_i} \quad b_i\big(M_i - WTP_i\,, \alpha_i \times f_i(\widetilde{X}_i + \Delta)\big) - c_i(\widetilde{X}_i)\ , \tag{3}$$

where we define $\widetilde{X}_i^*$ as the argument that maximizes Equation (3). In this scenario, the individual's WTP_i is subtracted from their M_i since they are both in monetary units and treated as perfect substitutes in the benefit function. The inputs purchased, Δ, are added to the production function, but the producer's cost function, $c_i(\cdot)$, still only depends on the quantity of inputs they choose to obtain after the experiment.

Therefore, the producer's WTP for Δ units of the input equates the following:

$$\underbrace{b_i\big(M_i, \alpha_i \times f_i(X_i^*)\big) - c_i(X_i^*)}_{\substack{\text{expected utility in} \\ \text{no-purchase scenario}}} = \underbrace{b_i\big(M_i - WTP_i, \alpha_i \times f_i(\widetilde{X}_i^*)\big) - c_i(\widetilde{X}_i^*)}_{\substack{\text{expected utility in} \\ \text{scenario paying } WTP \text{ for } \Delta}}\ , \tag{4}$$

That is, their WTP make them indfferent between (i) the scenario where they don't purchase the inputs from us (left-hand side of Eq. 4) and (ii) the scenario where they do purchase from us (right-hand side of Eq. 4). Next, we walk through the key assumptions that facilitate identification of α_i through the inversion of Equation (4).

2.1.2. Key Assumptions

Assumption 1 — Convex Input Costs. *The direct costs of inputs are convex:* $\partial c_i(\cdot)/\partial X_i > 0$ *and* $\partial^2 c_i(\cdot)/\partial X_i^2 > 0$. These convexities can be due to any sort of friction or adjustment cost. If this assumption does not hold, then the producer's WTP in the experiment may not depend on their productivity, as we illustrate below.[12]

Assumption 2 — Monotonic Benefits. *The benefit function* $b_i(\cdot)$ *is strictly monotonically increasing in* Q_i *and* M_i. This implies that more money or more output always increases the

[12]This is perhaps the least intuitive of our assumptions. Formally, this assumption ensures the necessary rank condition for estimation. Intuitively, the WTP experiment operates via an implicit linear cost schedule, so if the individual already faces a linear cost schedule when obtaining inputs, our WTP experiment may simply reflect those linear costs as a corner solution (i.e., the producer would never pay us, the experimenters, more for an input than what they pay in their own input market).

individuals' payoff and, importantly, that $b_i(\cdot)$ is invertible. In the language of traditional producers, this assumption implies that scientists are price-takers.

Assumption 3 — Homogeneous or Observable Output Benefits. *The benefits due to output, given by $\partial b_i/\partial Q_i$, are either homogeneous or depend on observable covariates.*

Unobservable heterogeneity in the returns to producing more output would not allow us to separately identify individual-specific returns to output from their productivity. Thus, these returns must either be observable (and assumed to capture all quality differences), a function of other observables (in which case they can be estimates), or unobservable and homogeneous (in which case individual productivity beliefs are identified up to a common level shifter). In the language of traditional producers, this assumption implies that, conditional on observables, the output is a commodity and all producers face common output prices.[13]

Assumption 4 — Observable Money and Plans. *Individuals' monetary constraints, per M_i, and optimal input plans X_i^* are observable.* There are some knife-edge cases where these variables need not be observed and productivity is identified by the experiment alone, such as the example above. However, those cases are likely rare in practice.

2.1.3. Estimation

Let Δ be the amount of input offered to the scientist in the experiment and WTP_i^{obs} be scientists' reported willingness to pay for those Δ units. Furthermore, let $\boldsymbol{\mu}_i$ be the vector of parameters that govern the production, benefit, and cost functions. Under Assumption 2 — the benefit function (b) is invertible — we can write a producer's WTP_i as a function:

$$WTP_i = \Pi(\Delta, M_i, X_i^*; \boldsymbol{\mu}_i) \equiv \widehat{WTP}(\Delta, M_i, X_i^*; \boldsymbol{\mu}_i) \,, \tag{5}$$

which leaves only the unknown parameters $\boldsymbol{\mu}_i$ to be estimated. This approach makes use of the fact that productivity (α_i) and optimal allocations in the purchase scenario of the WTP experiment ($\widetilde{X}_i^*$) are implicit functions of observables and unknown parameters.[14] Now, we have a theoretical prediction of a producer's WTP_i for Δ.

[13]Recall our simple, illustrative example at the beginning of this section — we showed that $\alpha_i = WTP_i/b$; however, if in fact the benefits of output are given by b_i, which is unobservable, then we cannot separately identify α_i from b_i.

[14]Specifically, Assumptions 1 and 2 generally guarantees that WTP_i is a direct function of α_i, which, by Equation (C13) in the Appendix, depends on $\boldsymbol{\mu}$.

In general, the GMM estimator for μ_i solves the minimization problem:

$$\min_{\mu_i} \quad \sum_{i=1}^{N} \Big(\widehat{WTP}(\Delta, M_i, X_i^* \,; \mu_i) - WTP_i^{\text{obs}} \Big)^2 , \tag{6}$$

which identifies μ_i given standard GMM identification conditions being met. Particularly relevant for identification is the rank condition, which requires that the matrix of derivatives of the stacked moment conditions with respect to the vector of parameters has full rank.[15] It can be shown that Assumption 1 (Convex Input Costs) is a sufficient condition for the rank condition being met.

Note that instead of soliciting individuals' WTP directly, the experimenter could solicit individuals' current income, M_i, as well as their income that would make them indifferent to receiving δ, and this income-at-indifference could be used for identification. Also, if there are constraints on individuals' input levels, they could be offered to pay to relax those constraints. Furthermore, depending on the variation in the data, it may not be possible to be allow for full heterogeneity in the parameters that govern the production, benefit, and cost functions. In this case, the experimenter could assume μ_i is given by a vector of common unobservables, say μ, and idiosyncratic observable variables, say Z_i, and estimate μ via the GMM estimator above.

2.2. Researchers' Labor Supply and Functional Forms

Researchers supply their labor to maximize their utility conditional on a contract from their primary institution, which is a triplet of state variables $\mathbf{S}_i = (M_i, G_i, D_i)$: salary M_i (\$), guaranteed funding G_i (\$), and administrative and teaching duties D_i (hours).[16] Given their contract, researchers choose how much time to spend on research (R_i), fundraising (F_i), which together with duties (D_i) sum up to yield their total work hours (H_i).

The quantity of knowledge Q_i that researchers produce is a Cobb-Douglas function of total funding B_i and research time R_i, which includes researcher-specific productivities (α_i) and output elasticities (per γ_i). Additionally, we assume a minimum funding amount $B_{\min}$, and that all work hours are non-negative and have an upper bound $H_{\max}$.

[15]This condition fails, for example, if the WTP does not directly depend on a specific parameter, or if a parameter is redundant.

[16]We use the term "*contract*" loosely, since, for example, a researcher's guaranteed funding may come in part from future flows of funding from grants obtained outside the institution. In the context of the methodological framework presented in Section 2, the function $b_{1i}(\cdot) + b_{2i}(\cdot)$ serves the role of the "benefit" function, while labor disutility $c_i(\cdot)$ represents the cost function, which is parameterized to be convex.

Researchers' indirect utility is given by:

$$\mathcal{V}(\mathbf{S}_i, \theta_i, \mu_i) = \max_{R_i, F_i, H_i} b_{1i}(M_i) + b_{2i}(Q_i) - c_i(R_i, F_i, D_i) \tag{7a}$$

subject to

$$B_i = B_{\min} + G_i + \phi_i F_i \tag{7b}$$

$$R_i + F_i + D_i = H_i \tag{7c}$$

$$Q_i = \alpha_i B_i^{\gamma_i} R_i^{1-\gamma_i}, \tag{7d}$$

where $\theta_i = (\alpha_i, \gamma_i, \phi_i)$ is the vector of individual-specific attributes related to scientific activity and μ_i is a vector of parameters that govern the shape of $b_{1i}(\cdot)$, $b_{2i}(\cdot)$, and $c_i(\cdot)$. The functional forms of these benefit and cost functions are assumed to be:

$$b_{1i}(\cdot) = \omega \times \frac{M_i^{1-\sigma_i}}{1-\sigma_i} \tag{8a}$$

$$b_{2i}(\cdot) = \frac{Q_i^{1-\eta_i}}{1-\eta_i} \tag{8b}$$

$$c_i(\cdot) = \psi \times \frac{(R_i + F_i + D_i^{\xi_i})^{1+\zeta_i}}{1+\zeta_i}. \tag{8c}$$

The ξ_i parameter allows for additional disutility from duty-related work (e.g., administration or teaching), which improves the model's fit to the data. We also assume the following: $\eta_i \in (0,1)$, $\psi > 0$, $\xi_i > 0$, and $\zeta_i > 0$.

Solving the researcher's maximization problem (Equation (7)) yields optimal choices of research time, fundraising time, and total working hours as a function of states, attributes, and parameters. We represent these optimal choices as policy functions $\mathcal{R}(\mathbf{S}_i, \theta_i, \mu_i)$, $\mathcal{F}(\cdot)$, and $\mathcal{H}(\cdot)$. The derivations of these policy functions are described in Appendix C.1.

Ideally, we would have enough variation to estimate all researcher-specific attributes including the production-related parameters $(\alpha_i, \gamma_i, \phi_i)$ as well as all of the consumption-related parameters that govern researchers' utility from salary, output, and effort $(\sigma_i, \eta_i, \xi_i, \zeta_i)$. However, as shown below, we only have enough structural conditions to uniquely identify the production-related parameters $(\alpha_i, \gamma_i, \phi_i)$. Thus, we choose to specify each of the consumption-related parameters as a parametric function of researchers' observable features, whose common parameters we then estimate by GMM consistent with the framework of Section 2.

Fortunately, we have a large vector of observable features ($\mathbf{Z}_i$) that describe researchers' positions, their backgrounds, and their subjective descriptions of their scientific output (i.e., the features summarized in Table 2 and Appendix Tables B2). This is useful because it allows us to incorporate more heterogeneity into the consumption components of the model and limit the degree to which variation in the data might otherwise cause us to overstate the heterogeneity in the production parameters.

However, the computational demands of estimating the model limit the flexibility with which we can incorporate the dozens of features available. Thus, to balance the benefits of allowing for heterogeneity in consumption with the benefits of simpler estimation, we use k-means clustering to reduce the full set of observable features ($\mathbf{Z}_i$) into a one-dimensional index. We assume there are two clusters of researcher types ($k = 2$) and estimate each researcher's distance from these clusters with their Euclidean similarity score. This distance provides a one-dimensional description of all of the different ways researchers responded to questions that could plausibly be driven by heterogeneous preferences.

We refer to this resulting index as describing researchers' type, T_i. Appendix C.2 reports the results of the k-means estimation showing the distribution of researcher type T in the sample as well as a view of the mean differences in the features of researchers per their type.

We then specify each of the consumption-related parameters ($\sigma_i, \eta_i, \xi_i, \zeta_i$) to be simple, univariate functions of a researcher's type. For instance, the parameter that governs the utility from private consumption is parameterized as: $\sigma_i = \exp(\delta_{\sigma,0} + T_i\delta_{\sigma,1})$. We similarly parameterize ζ_i and ξ_i with exponential functions with intercept and slope, respectively. The curvature of utility in scientific output, η_i, is modeled with a logistic function bounded in the interval $(0, 1)$. Therefore, we express individual-specific parameters $\boldsymbol{\mu}_i(T_i, \boldsymbol{\mu})$ as a function of a researcher's type T_i and of the vector of common parameters to be estimated, denoted by $\boldsymbol{\mu} = (\omega, \psi, \boldsymbol{\delta})$, where $\boldsymbol{\delta}$ includes the deep parameters that govern the utility functions.

Allowing the $\boldsymbol{\mu}_i$ parameters to be type-specific is not a panacea, but it helps reduce the degree to which variation in the experimental data that is truly driven by heterogeneous preferences or heterogeneous demand for scientific output contaminates our productivity estimates.

2.3. Social Value

To incorporate the externalities of knowledge production, which we assume to be net positive, we define the social value produced by each researcher as:

$$\mathcal{W}(\mathbf{S}_i, \theta_i, \mu_i, \kappa) = b_{1i}(M_i) + \kappa b_{2i}(Q_i^*) - c_i(R_i^*, F_i^*, D_i), \tag{9}$$

where researchers' privately optimal choices and output are given by R_i^*, F_i^* and Q_i^*. κ reflects the size of the externalities associated with researchers' output. Thus, $1/\kappa$ gives the share of the social value generated by each researcher's output that they themselves capture and $1 - 1/\kappa$ is the size of the positive externality.

This formulation of externalities is an ad hoc way of implicitly modeling consumer surplus as some constant multiple of producer surplus. However, it has a clear economic interpretation as a measure of appropriation, and we can draw on prior studies that have sought to identify precisely this measure. Studies that focus on commercial innovators have found producers' value capture to be as large as 15% ($\kappa = 6.7$) and as low as 2% ($\kappa = 50$) (Nordhaus 2004; Jena and Philipson 2008; Lakdawalla et al. 2010). In our empirical analyses, our baseline assumption is $\kappa = 10$, which implies researchers capture 10% of the social value they create.

3. Survey and Data Overview

3.1. Survey Design

We use the National Survey of Academic Researchers (Myers et al. 2023) and provide a brief overview of the survey methodology here. The population target is U.S. professors who conduct research at major institutions of higher education. To construct the sampling frame, information on professors was collected from the 158 largest institutions in the US by total R&D funding using the National Science Foundation's 2019 Higher Education R&D survey (HERD; National Science Foundation 2023).

The population consisted of 264,036 unique e-mails. A total of 131,672 individuals were e-mailed and 4,388 (3.33%) completed the survey.[17] We then restrict the sample to the 4,003 individuals (91.2% of respondents) who reported being a professor, spending a

[17] The IRB approval permitted e-mailing only 50% of the population. The 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).

non-zero amount of time on research, and having a non-zero salary from their primary institution.

During recruitment, incentives and reminders were randomly assigned. 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 reminder arms were zero, one, or two follow-up emails. Each email was randomly assigned to one incentive arm and one reminder arm with equal probability, resulting in twelve possible combinations.

The randomized incentives and reminders provide us with instruments that we can use to implement a sample selection correction (i.e., Heckman 1979). The validity of this approach relies on having variables that cause entry into the sample (i.e., completing the survey) but do not affect the outcomes of interest. This allows us to adjust for unobservable differences between the population and our sample. Appendix Table B1 reports the results from a regression of an indicator for survey completion on the different incentive and reminder arms, showing that all arms had a statistically significant positive effect on researchers' propensity to complete the survey.

In addition to adjusting for unobservable differences, Myers et al. (2023) also checks the representativeness of the respondent sample by comparing it to the invited sample on observable characteristics. First, the authors explore a series of observable characteristics at the researcher level by comparing the grant and publication histories of respondents and non-respondents using the Dimensions database (Digital Science 2018), which collects and disambiguates scientific metrics for researchers worldwide.[18] Appendix Figure B1 (replicated from Myers et al. (2023)) shows invite-respondent overlap on various measures of scientific inputs and outputs. Overall, there is little difference between the respondents and non-respondents both economically and statistically speaking.

Looking at the institutional level, Appendix Figure B2 (replicated from Myers et al. (2023)) shows invite-respondent overlap on various measures of institution funding derived from the HERD survey. As in the case of the researcher-level comparison, the distributions overlap substantially. In this case, there are some statistically significant differences; on average, respondents come from institutions with slightly less research funding (4–6%).

[18] Using a fuzzy name matching process, Myers et al. (2023) are able to confidently match 87,000 (66%) of the researchers to their records in Dimensions.

3.2. Summary Statistics: Researchers and their Inputs

Table 1 reports the summary statistics of the key covariates in our analyses. See Myers et al. (2023) for a more detailed investigation of these summary statistics.

Fields of Study. Using the name of the professor's department, we assign them to a narrow set of twenty "minor" fields of study and aggregate those fields into five broader "major" fields: Humanities and related; Engineering, Math, and related; Medicine and Health Sciences; Natural Sciences; and Social Sciences. Unless otherwise noted, our counterfactual analyses constrain the reallocation of inputs to only occur *within* the major fields.

TABLE 1
Summary Statistics—Salary, Funding, Time, and Fields

	mean	*s.d.*	*p*50
Salary and research funds, $/year			
Total salary	159,028.23	74,516.13	140,000.00
Guaranteed & existing funding	52,223.08	83,420.47	5,000.00
Fundraising expectations	93,909.19	144,013.69	20,000.00
Work time, hrs./week			
Total work	48.55	10.00	48.00
Research	18.51	9.60	17.40
Fundraising	4.47	5.09	2.65
Administration	7.48	6.17	5.80
Teaching and other work	18.09	9.78	17.20
Major field, {0,1}			
Engineering, math, & related	0.17	0.37	
Humanities & related	0.19	0.39	
Medical & health sciences	0.28	0.45	
Natural sciences	0.16	0.37	
Social sciences	0.21	0.40	

Note: Reports summary statistics for 4,003 researcher-level observations. Unless otherwise noted, all variables are continuous and bound below by zero. *{0,1}* indicates binary variables.

Salaries and Research Inputs. The survey solicits a range of details regarding researchers' salary, their guaranteed funding (e.g., from prior grants or institutional guarantees), expected funds they will raise over the coming five years, and their time allocations. Importantly, most variables are elicited as expectations over the coming five years to ensure the responses span the same time horizon as the thought experiments described below. In the Appendix, we replicate a test of respondents' self-reporting by comparing their self-reported salaries to the publicly-reported salaries we are able to locate for a subset of researchers. Overall, there is a high degree of alignment (see Appendix Figure B3).

Position and Socio-demographics. Appendix Table B2provides a full summary of all other major features collected regarding researchers' positions (e.g., rank and tenure status) and their socio-demographics (e.g., gender, race/ethnicity, citizenship).

TABLE 2
Summary Statistics—Subjective Output

	mean	*s.d.*
Intended research outputs, {0,1,2}		
Journal articles	1.87	0.37
Books	0.52	0.68
Materials or methods	0.70	0.68
Products	0.47	0.64
Intended research audience, {0,1,2}		
Academic peers	1.88	0.36
Policymakers	0.84	0.69
Businesses	0.54	0.62
General public	0.83	0.62
Riskiness of own research, [0,10]		
Own belief	4.63	2.34
Belief of peers' beliefs	4.57	2.37
Theoretical vs. empirical, [0,10]		
Ask [0] or answer [10] questions	4.89	2.54

Note: Reports summary statistics for 4,003 researcher-level observations. The intended research outputs and audience variables are coded responses to questions of the form *How often are the following the intended output / audience of your research,* where responses are coded as follows: *Rarely*=0, *Sometimes*=1, *Very often*=2. The question about risk used a scale where 0 indicated no risk and 10 indicated very high risk. The question about theory versus empirics used a scale where 0 indicated that the researcher focused on asking new questions and 10 indicated that the researcher focsed on answering existing questions.

3.3. Summary Statistics: Subjective Output Measures

Our methodology for estimating productivity is explicitly designed to avoid the need to quantify the output produced by researchers' efforts. Still, it is useful to have a more qualitative understanding of what researchers are producing. Fortunately, the survey includes a number of subjective questions regarding researchers' output. Table 2 summarizes answers to these questions, which asked the frequency with which researchers intended to produce outputs of certain types (e.g., articles, books, materials, products) for certain types of audiences (e.g., peers, policymakers, businesses, general public) as well as other measures of riskiness and the degree to which the researcher focused on asking new questions or answering existing questions.

The traditional proxy for scientific output is peer-reviewed journal articles, and the data indicate that this is the most common output type that researchers intend to produce. However, there is a considerable amount of variation and a significant amount of attention focused on producing output of types and for audiences that may never be codified in a journal article. More importantly, these measures are often negatively correlated in a way that suggests strategic substitution (see Appendix Table B3). For instance, researchers who focus more on publishing articles for their academic peers are less likely to focus on publishing books or developing products intended for non-academic audiences. This highlights the limitation of observable output proxies.

4. Survey Experiment

Here, we describe the thought experiments in the survey (Subsection 4.1) and how they connect to the model (Subsection 4.2). We then report the distribution of responses and conduct tests for face validity, sample selection, and other potential concerns (Subsection 4.3).

4.1. Soliciting Willingness to Pay

WTP for Funding and Time. Respondents are presented with four hypothetical scenarios, each offering different trade-offs between salary and inputs. They are asked to imagine that their primary institution has offered them: (*i*) an increase of $250,000 in guaranteed funding in exchange for a lower salary, (*ii*) an increase of $1,000,000 in guaranteed funding in exchange for a lower salary, (*iii*) an elimination of all administrative duties in exchange for a lower salary, and (*iv*) an increase in duties by 20 hours per month over a five-year period in exchange for a higher salary.[19] All of these hypotheticals are posed over a five-year span to fix the time horizon for all respondents. In order to solicit the salary at which

[19] Researchers who report no administrative duties are not shown scenario (*iii*).

they are indifferent between the current position and each offer, respondents are asked to report the lowest offered salary at which they would be willing to accept the offer.[20] Importantly, the survey only solicits researchers' WTP for more funding. This matters because counterfactual reallocations will involve reducing some researchers' funding. In the case of time, the survey solicits both WTP (for more free time) and willingness to accept (WTA; for less free time) and we treat these as symmetric after being filtered through the model. Appendix Figure C2 displays examples of how these thought experiments appeared to the survey respondents.

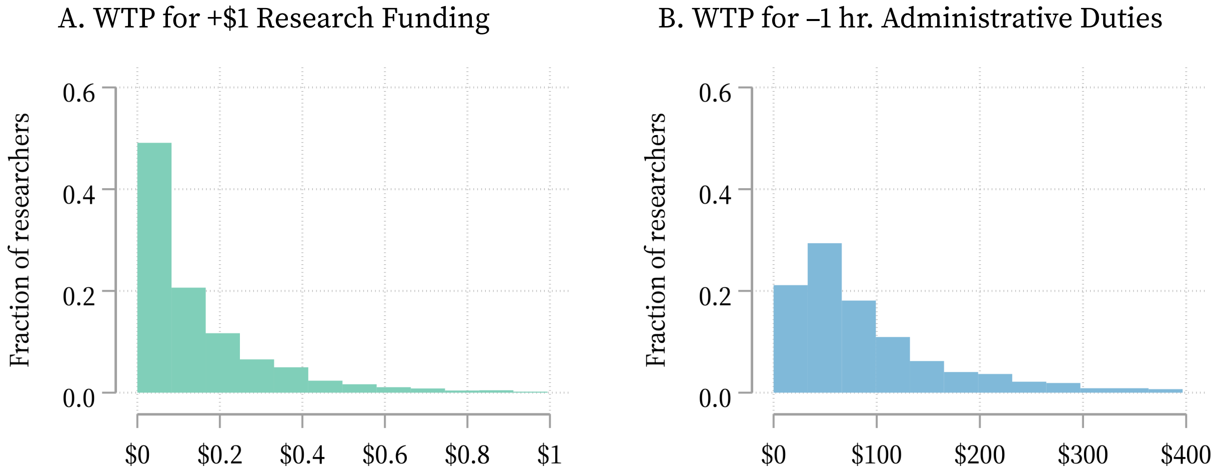
WTP for a Benchmark Good. When soliciting willingness to pay, especially in an unincentivized manner, it is always possible that respondents under- or overstate their price sensitivity. In order to test for this, we follow Dizon-Ross and Jayachandran (2022) and explore respondents' willingness to pay for a "benchmark good." Dizon-Ross and Jayachandran (2022) note that, if one solicits a subject's willingness to pay for a good whose value (to the subject) is plausibly uncorrelated with the value of the focal good, then any correlation between the two willingness-to-pay values can be attributed to systematic noise. The survey asks respondents to report the maximum amount they would be willing to pay per month for high-speed internet access at their primary residence. We use this as our benchmark good since researchers scientific productivity should plausibly be uncorrelated with their demand for high-speed internet access at home. In Appendix Table C1, we show that respondents' stated WTP for scientific inputs are rarely correlated with their stated WTP for the benchmark good, which suggests a small amount of variation in researchers' answers is attributable to systematic noise.

4.2. Connection to Model: WTP and Compensating Variation

Four survey thought experiments elicit the compensating variation of individual researchers in relation to (*i*) an increase of $250,000 in guaranteed funding G_i, (*ii*) an increase of $1,000,000 in guaranteed funding G_i, (*iii*) a reduction of duties D_i to 0, and (*iv*) an increase in duties by 20 hours per month over a 5-year period. In other words, we ask for income levels $\widehat{M}_{ij}$, where $j = \{1, 2, 3, 4\}$ indexes the four experiments, that would make the researcher's utility in the counterfactual scenario equal to their indirect utility $\mathcal{V}_i^*$ at current allocations. Formally, counterfactual guaranteed funding and duties in the four

[20] Pilot tests indicated that researchers could more easily report the lowest salary that could make them take the offer as opposed to the literal salary at indifference, and since indifference is a vanishingly small amount less than this reported value, we treat their answer as the amount at indifference.

FIGURE 1
Willingness to Pay Experiment Responses



Note: Shows the distribution of researchers' stated WTP for $1 more of additional research funds (Panel A) and 1 hour less of administrative duties (Panel B). Approximately 1% of the upper tails have been trimmed for visibility.

experiments are:

$$(\widetilde{G}_{i1}, \widetilde{D}_{i1}) = \big((G_i + \$250{,}000), D_i\big)$$
$$(\widetilde{G}_{i2}, \widetilde{D}_{i2}) = \big((G_i + \$1{,}000{,}000), D_i\big)$$
$$(\widetilde{G}_{i3}, \widetilde{D}_{i3}) = \big(G_i, 0\big)$$
$$(\widetilde{G}_{i4}, \widetilde{D}_{i4}) = \big(G_i, (D_i + 20 \text{ hours/month})\big),$$

where G_i and D_i represent actual states.

As noted in Section 2, the values of $\widehat{M}_{ij}$ reported in these four experiments make the researcher indifferent between all possibilities, and therefore we can write these reported values to be a known function of observable data and the unknown parameters to be estimated.

4.3. Survey Experiment Results

Figure 1 plots the distribution of WTP for guaranteed research funding and free time (in the form of WTP for less duties or WTA for more duties). The values shown are averaged over the two thought experiments for either factor and converted to a per-dollar basis. As evidenced by Figure 1, there is considerable variation in WTP responses across researchers. Some of this variation reflects different preferences and constraints, but another portion reflects heterogeneous productivity across researchers. The model described above allows us to separate these two forces.

Validating these WTP responses is a difficult but important task. They are the key ingredient of our entire exercise, but they may be driven in part by sample selection effects, behavioral biases, or noise. Although these are practical trade-offs that professors face throughout their careers, systematic data have not been collected in this way before to our knowledge. Thus, it is not clear what plausible variation would look like here. Still, we can conduct some tests motivated by economic and statistical theory to explore how reasonable these distributions of WTP are.

Motivated by the notion of opportunity costs, we test how WTP varies with researchers' implied hourly wage (per their annual salary divided by their total hours of work). Assuming this implied wage rate is a proxy for researchers' opportunity costs, it should be the case that researchers with higher hourly wages are willing to pay more for their free time. In Appendix Figure C3A, we see that this is indeed the case. Furthermore, it should be the case that, conditional on opportunity costs of time, researchers who expect to spend more time fundraising should have a higher WTP for guaranteed funding. In Appendix Figure C3B, we find this to be true.

As another test, Appendix Tables C1 and C2 describe analyses where we regress researchers' WTP responses on the variables in the model as well as (*i*) the large vector of observable features ($\mathbf{Z}_i$), (*ii*) an inverse Mills ratio constructed using the randomized survey participation incentives following Heckman (1979), and/or (*iii*) researchers' WTP for the benchmark good (high-speed internet) following Dizon-Ross and Jayachandran (2022). We find the variables in the model can explain 82–96% of the variation in WTP responses (see Appendix Table C1). This supports the model's ingredients as being key determinants of researchers' answers. When we include the large vector of observable features in addition as additional explanatory features, the R^2 statistics increase by only one to four percentage points. Residual variation in WTP responses (conditional on the variables of the model) are not well explained by these heterogeneous observables. This gives us confidence that we are not dramatically mis-specifying heterogeneity in the model.

We also find that the inverse Mills ratio is not a statistically significant predictor of responses (see Appendix Table C2). Under the assumptions outlined in Heckman (1979), this supports the notion that respondents did not differentially select into our sample as a function of their WTP for inputs and suggests some generalizability of our responses. Finally, we find that researchers' WTP for the benchmark good (high-speed internet at their house) is correlated with their WTP for inputs (see Appendix Table C2). Under the assumption that researchers' demand for home internet is truly uncorrelated with their productivity, this provides some evidence of systematic noise in how respondents are reporting their WTP in these experiments. However, the economic magnitude of this relationship is quite small. Furthermore, the benchmark good WTP is included in our vector of features we use to make the researcher type index (that determines heterogeneity in the consumption parameters), which allows us to control for this to some degree. Overall, despite not being incentivized experiments, researchers' responses behave as expected and are of plausible magnitudes.

5. Estimates for the Model of Science

5.1. A View of Researchers' Utility Functions

To illustrate our estimates of the utility function, Appendix Figure D1 shows how an average researcher's utility depends on the levels of the three state variables (salary, administrative duties, guaranteed research funding) and research output. The figure shows the percent change in a researcher's utility as the variable is increased from the 10^{th} percentile level to the 90^{th} percentile level while all other variables and parameters are held fixed at the sample averages.

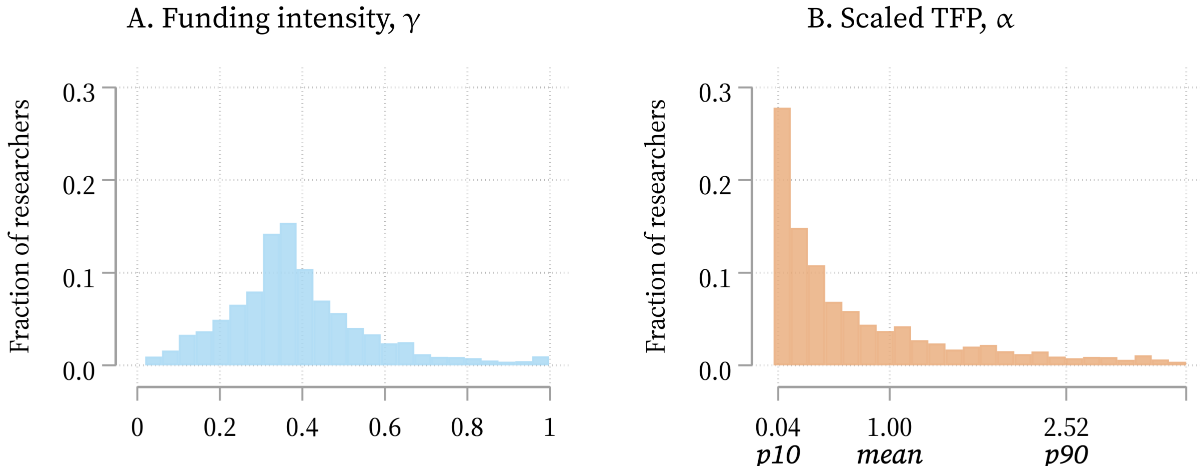
In terms of magnitude, salary and administrative duties are the most important for researchers' utility. Shifting the average researcher's salary from the 10^{th} percentile to the 90^{th} percentile increases their utility by roughly 60%. An equivalent relative increase in administrative duties reduces utility by about 20%. In contrast, similarly scaled increases in guaranteed funding or research output raise utility by only a few percentage points.[21]

5.2. Productivity Distributions

Figure 2 shows the unconditional distributions of the production function parameters γ_i (funding intensity) and α_i (TFP). Figure 2A displays the distribution of the γ_i parameter, which describes the relative weight of funding versus research time in researchers' production functions. The distribution highlights a significant degree of heterogeneity across

[21]As evidence of fit, the median absolute difference between a researcher's stated WTP and the model's prediction ranges from 6–12 percentage points across the four questions. The numerical estimates of the common parameters and more detailed descriptions of the model's fit are available from the authors upon request.

FIGURE 2
Production Function Parameters



Note: Shows the distribution of researcher-specific estimates of the production function parameters γ_i (funding intensity; Panel A) and α_i (productivity; Panel B). In Panel (A, larger values indicate more funding intensity and $\gamma \in [0, 1]$. In Panel (B), the top 5% of productivities have been trimmed for visibility and estimates are scaled into units where the mean is normalized to equal 1 (with the 10th and 90th percentiles of the distribution noted on the x axis).

researchers, with roughly 20% of our sample having a funding intensity either larger than 0.6 or smaller than 0.2.

As both an interesting exercise and test of face validity, Appendix Figure D2 plots the average funding intensity parameters (γ_i) for the twenty minor fields represented in the sample. We find that γ_i is highest in chemistry and engineering, where research is often capital intensive and involves the use of expensive lab equipment. In contrast, and in line with intuition, the social sciences (e.g., economics, political science) display the lowest funding intensity on average. Notably, Appendix Figure D2 highlights the heterogeneity in funding intensity across researchers even within these narrower fields of study.

Figure 2B displays the distribution of the α_i parameter, our measure of researchers' TFP. Our estimates reveal a large skew in researchers' beliefs about their productivity.

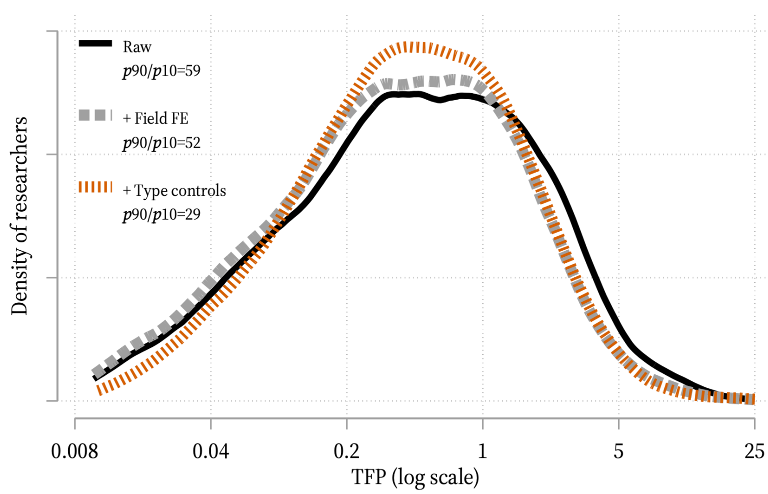
As one test of face validity, Appendix Table D1 reports regression results that test for associations between researchers' productivity (α_i) and their performance per traditional metrics of scientific productivity, which are often simply output levels (e.g., publications, citations). Under some reasonable assumptions, we expect a positive association between these metrics, and we find it.[22] Researchers with higher productivity beliefs are more

[22]Specifically, those assumptions are: (*i*) there is a positive correlation between researchers' input levels

likely to have more actual publication output whether that output is measured using recent publication counts or citation-weighted counts. This provides a signal that our estimates do in fact reflect real productivity differences across researchers.

To understand how variation in TFP affects output, we decompose the variance in log output into components attributable to TFP, input levels, and factor intensity. Note that the variance in log output due to the variance in log TFP is given by: $\text{Var}(\log(\alpha_i)) + 2\text{Cov}(\log(\alpha_i), \gamma_i \log(B_i)) + 2\text{Cov}(\log(\alpha_i), (1-\gamma_i)\log(R_i))$. Using this relationship, we estimate that 46% of the variance in output across researchers is due to the variance in TFP. Without adjusting for the covariances between TFP and the input levels and funding-intensity parameter, we obtain an estimate of 80%. This finding indicates that more productive researchers obtain more inputs that are well-suited to their production functions, and it motivates questions related to allocative efficiency that we return to in the next section.

FIGURE 3
TFP Distributions



Note: Shows the distribution of researchers' TFP (α_i) where units have been rescaled so the mean equals 1; note the log scale. In addition to (*i*) the distribution of the raw values, productivities are also shown after removing residual variation due to (*ii*) major field fixed effects, and (*iii*) the covariates used to construct the researcher type index. 90-10 percentile ratios are also shown.

While Figure 2B shows a substantial degree of heterogeneity, some fraction of this variation may be due to differences in the demand for their output or the nature of science within their fields of study; for a similar reason, most studies on the industrial organization of

and productivity; (*ii*) these traditional output metrics are positively correlated with researchers' true output; (*iii*) researchers' output levels are semi-persistent over time (since we can only work with pre-survey bibliographic data).

firms report productivity distributions based only on within-industry variation. Thus, Figure 3 shows the distribution of researcher productivity (α_i) after various controls for field-specific (or "industry-specific") variation are introduced.

First, Figure 3 shows the raw distribution of productivity levels, which mirrors the distribution shown in Figure 2B but now on a logarithmic scale. Next, we regress researchers' TFP estimates on a set of major-field fixed effects, and we report the distribution of residual productivity levels. Lastly, we also condition productivity on the full vector of covariates used to generate the researcher type index.

Figure 3 also reports the ratio of the 90^{th} and 10^{th} percentiles, the "90–10 TFP ratio" measure of variance commonly reported in traditional, firm-level studies. The 90–10 TFP ratio of the raw productivity estimates is substantial, but, even after conditioning on the additional controls, we still find a large dispersion. The 90^{th} percentile researcher believes they are roughly 30 times as productive as the 10^{th} percentile researcher.

It is difficult to benchmark this dispersion. Firm-level estimates are primarily from manufacturing sectors, which typically involve 90–10 TFP ratios on the scale of 1.5× to 5× (Syverson 2011). To date, most worker-level productivity estimates tend to be similarly dispersed (Hoffman and Stanton 2024); however, those estimates do not come from occupations as complex and creatively oriented as science. One notable example is Sackman, Erikson, and Grant (1968) who used direct observation to estimate software engineers' productivity and found that some individuals were as much as an order of magnitude faster on coding tasks than others. Interestingly, this is the same approximate scale that we identify with our sample of researchers.[23]

Motivated by the prevalence of power laws in the tails of distributions (Gabaix 2009), we examine the distribution of TFP among the most productive researchers. Appendix Figure D3 shows the traditional log rank versus log value plots along with the regression results following the approach described by Gabaix (2009). We find clear evidence of power laws when focusing on the top 20% or top 1% of researchers per their TFP. The regressions yield power law exponents of approximately 2–3, which are significantly larger than Zipf's law (exponent of 1) but are on the same scale as the power law exponents observed in income distributions and stock prices (Gabaix 2009). Future work that estimates high-skilled workers' productivity (and not simply their output) in other settings would be

[23] For more evidence of face validity, we note that the 90-10 ratio for field-normalized citations in our sample is 56, which is very similar to the degree of productivity dispersion we estimate.

worthwhile.

6. Counterfactuals and Allocative Efficiency

6.1. Overview

In this section, we use our productivity estimates to analyze allocative efficiency through the lens of our model. Specifically, we treat guaranteed funding (G) and duties (D) as policy levers a planner can adjust to maximize a given objective. Importantly, we search for the allocations of guaranteed funding and duties that maximize an objective after accounting for researchers' endogenous behavioral responses to the planner's decisions. The margins for behavioral responses are total hours worked, time spent fundraising (to obtain additional funds), and time spent on research (to directly produce output). In reality, researchers may endogenously adjust along many other margins (e.g., the types of projects they pursue), but these complexities are beyond the scope of our model. Still, adjustments to time allocations are likely a first-order response, and ignoring other margins allows us to keep the problem tractable.

Within the literature on misallocation, tests of efficiency are performed using either: (*i*) *relative* benchmarks, where allocative efficiency across multiple markets is equated, which reveals how much of the gap in aggregate output between markets is due to allocative frictions (e.g., Hsieh and Klenow 2009); and (*ii*) *absolute* benchmarks, which compare the actual output level to that which a social planner could achieve (e.g., Petrin and Sivadasan 2013; Asker, Collard-Wexler, and De Loecker 2019). Our approach allows us to perform both of these types of tests.[24]

We consider two alternative objectives. First, we estimate the allocation that maximizes total output. Second, we optimize for a utilitarian objective of maximizing researchers' aggregate utility. To aid interpretation, we conduct an exercise where we estimate how much additional guaranteed research funding must be increased under *actual allocations* in order to achieve the same growth in scientific output that we are able to achieve using the actual budget distributed under *alternative allocations*. Beyond this, we explore a range of alternative constraints on how inputs are reallocated to draw broader conclusions about the gains from reallocation. Appendix C contains further details on how we specify

[24] However, we do not explicitly model the sources of inefficiencies that give rise to wedges between actual an optimal input allocations. But, in Sections 6.3 and 6.4 we identify and investigate features of producers that are correlated with the size of their input wedge.

the optimization problems and constraints.

The externalities of science loom large in these counterfactuals. As noted, our approach assumes all researchers' production involves the same relative amount of externalities (per the common parameter κ that multiplies their private value from output into social value). In practice, externalities likely vary greatly across fields, which is why we primarily focus on reallocations *within* the five major fields of researchers in our sample (i.e., Engineering, Math and related; Humanities and related; Medical and Health Sciences; Natural Sciences; Social Sciences). We also report results where we condition researchers' actual and counterfactual outcomes (i.e., output, utility) on the large vector of covariates used in the researcher type index. This approach allows us to isolate gains from reallocation between researchers with similar observable features.

6.2. Summary of Counterfactuals

Table 3 details the changes we estimate after reallocating inputs to maximize total output (Cols. 2–3) or researchers' total utility (Cols. 4–5); Column (1) describes the actual allocation of inputs for reference. In all cases of Table 3, we hold the total amount of funding in each major field fixed, we only reallocate within fields, and social value is evaluated at $\kappa = 10$ (implying that scientists capture 10% of the value of their output). Given our limited ability to incorporate heterogeneous preferences into the model, Columns (3) and (5) report changes in output and welfare after removing variation in those metrics correlated with the covariates used to construct the researcher type index.[25]

Input Reallocation. The first four rows of Table 3 report how reallocation changes the equilibrium distribution of inputs. For these rows, Columns (2–3) are identical since they are based on the same counterfactual and we do not include any controls for these statistics; likewise for Columns (4–5). Compared to the status quo, the counterfactual allocations lead to more research time on average (approximately 20%), they increase the variance in research time (approximately 40%), and they decrease the variance in research budgets (approximately –20%).

In the Appendix, we illustrate the actual and optimal input distributions as well as Lorenz

[25]In those cases, we regress researcher-level output or welfare metrics on the model variables and the full vector of covariates used in the type index, and then we subtract out variation in the metric predicted by the covariates conditional on the model variables. We include the model variables as controls because the productivity parameters are (partially) determined by them and so we do not want to remove variation in outcomes due to productivity differences.

TABLE 3
Outcomes given Actual and Optimized Allocations

	Current allocation	Optimized allocations			
	(1)	(2)	(3)	(4)	(5)
Research inputs					
Research hrs./week, avg.	18.5	+27%	+27%	+14%	+14%
Research hrs./week, s.d.	9.6	+43%	+43%	+43%	+43%
Budget $-K/year, avg.	147.1	0%	0%	0%	0%
Budget $-K/year, s.d.	206.9	–18%	–18%	–20%	–20%
Research output					
Output, avg.	*n.r.*	+158%	+142%	+159%	+133%
Output, s.d.	*n.r.*	+44%	+53%	+44%	+56%
Output per hr.	*n.r.*	+103%	+91%	+128%	+105%
Welfare					
Researcher utility, avg.	*n.r.*	+4.5%	+3.3%	+4.7%	+3.2%
Researcher utility, s.d.	*n.r.*	–5.2%	–7.9%	–5.4%	–5.7%
Researcher utility per hr.	*n.r.*	+25%	+24%	+16%	+15%
Social value, avg.	*n.r.*	+16%	+5.7%	+16%	+5.2%
Social value, s.d.	*n.r.*	+21%	–6.5%	+20%	–3.4%
Social value per hr.	*n.r.*	+34%	+27%	+26%	+19%
Objective, max		Y	Y	$\mathcal{V}$	$\mathcal{V}$
Type controls			✓		✓

Note: Reports summary statistics for inputs under actualallocations (Col. 1). The first three sets of rows in Columns 2–5 report the percentage change in research inputs (*Research inputs*), outputs (*Research outputs*), and utility (*Welfare*) under alternative allocations; estimates are rounded to aid in comparison. The bottom sets of rows outline the objective of the counterfactuals explored in Columns 2–5. The two different objectives explored are maximizing output (Y) or researchers' private utility ($\mathcal{V}$). Models with *Type controls* report output and welfare changes after removing residual variation due to covariates used to construct the researcher type index. All optimized allocations allow for researchers' behavioral responses.

curves (see Figure D4) to show how more or less unequal the distributions are under actual and optimal allocations. In general, the model opts to make the distribution of duties more unequal, while the inequality of the distribution of guaranteed funding is relatively unchanged. After researchers' behavioral responses to these reallocations, there is little change in the inequality of the distribution of research time and total funding (see Figure D4).

Gains from Reallocations. Overall, the model suggests that there are large gains in output to be had from alternative allocations. Whether the objective is to maximize output or researchers' private utility, the new allocations yield roughly 130–160% more output. Given the changes in research time, this translates into significant welfare gains on the scale of 3–4% for researchers and 5–15% for society. The finding that both objectives yield qualitatively similar gains is primarily driven by the fact that researchers have control over their time. Whatever the planner hopes to maximize, the approach is to ensure that the most productive researchers are incentivized to spend more time working on their science.

To contextualize these gains, we estimate how much more funding under actual allocations would be necessary to achieve the same growth in scientific output that our counterfactual allocations achieve using current funding levels. For simplicity, we assume these additional funds are injected into the market as proportional increases in guaranteed funds (G) for all researchers. Specifically, we solve for the percentage increase in researchers' G that ultimately yields the same total growth in output reported in Table 3. Importantly, a 1% increase in G for all researchers can yield a $\lesseqgtr$1% increase in aggregate funding B and, in turn, output Y even in the absence of a behavioral response despite the fact that we have specified production as constant returns to scale. We formally describe this mechanical composition effect in Appendix D.2. In short, since guaranteed funding G is (weakly) less than total funding B, the percentage change in a scientists' total funding and output will vary across researchers depending on correlations between initial output shares, funding intensity parameters (γ_i), and the share of funding from guarantees (G_i/B_i); see Appendix D.2 for more discussion.

Table 4 reports these estimates under both a "*Mechanical*" scenario that does not incorporate researchers' behavioral responses and a "*Behavioral*" scenario that does. Allowing for the behavioral response, this exercise indicates that funding guarantees would need to grow by roughly 200% for the actual allocations to achieve the same growth in output that we observe in the counterfactuals. In the case allowing a behavioral response, this corresponds to total research budgets increasing by roughly 40%. On an annual basis this amounts to roughly \$60,000 per researcher. Scaling these results from our sample to the entire population of researchers targeted by the survey, this implies the gains from a more efficient allocation are equivalent to a funding increase of roughly \$14 billion per year.

Notably, allowing for the behavioral response is economically important. More guaran-

TABLE 4

Growth in Funding with Actual Allocations Needed to Produce the Same Output as Optimized Allocation of Actual Funding

	Mechanical	Behavioral
Relative growth in funding		
Guaranteed, G	210%	206%
Total, B	85%	41%
Absolute growth in total funding, B		
Sample average	+\$126K	+\$60K
Sample total	+\$503M	+\$240M
Population total	+\$30,186M	+\$14,444M

Note: Reports the increase in guaranteed (G) and total (B) research funding under actual allocations necessary to achieve the same growth in output achieved by the reallocation of actual input levels that maximizes researchers' utility. Sample averages on a per-researcher basis are reported in addition to sample totals (summing over all in-sample researchers) and implied population totals (scaling the sample up to the population size per the survey response rate). The *Mechanical* scenario does not allow researchers to re-optimize their time allocations and the *Behavioral* scenario does.

teed research funding (which substitutes for fundraising and complements researcher time) leads researchers to spend less time fundraising and more time on their research (approximately +25% in the aggregate). Without accounting for researchers' endogenous response to budget growth, we underestimate the impact of growing the budget by roughly two-fold.

Additional Results. In the Appendix, we report results from alternative counterfactual exercises (Appendix Table D2). There are a few findings of note. First, the allocation of duties is only meaningfully relevant for influencing researchers' utility, whereas the allocation of funding is what has the main influence on output.[26] Second, and rather interestingly, when we allow the total research budget to be unconstrained, and therefore only researchers' fundraising decisions constrain the size of the budget, the total research budget grows only about 15%. While we caution against interpreting this result too seriously, but it suggests that the total research budget is not far from the optimum given the (fixed) size of the research workforce. Of course, this ignores dynamic concerns which may certainly be relevant. In other unreported analyses, we find qualitatively similar

[26]When only duties are reallocated, researchers' utility increases by roughly 3%, but output only increases by roughly 1%. When only funding is reallocated, researchers' utility increases by only 1%, but output increases by 150%. Maximizing output or researchers' utility yield relatively similar outcomes

outcomes when we alter our assumptions about input caps, preference heterogeneity, and reallocation constraints, which suggest our results do not hinge on any specific modeling assumption.[27]

6.3. Input Wedges: Actual Versus Optimal

The results summarized thus far suggest that reallocating researchers' time and funding constraints can yield significant gains in output and welfare. In order to better understand how these gains are achieved, we now focus on a single counterfactual specification and compare the actual and optimized input levels. For simplicity, we focus for the remainder of this section on the scenario where duties and funding are jointly optimized to maximize output, which corresponds to the counterfactual described in Columns (2–3) of Table 3.

To better understand how actual and optimal input levels correlate at the individual level, we estimate a series of regressions of the following form:

$$\text{Actual Input Level}_i = a + \beta \text{Optimal Input Level}_i + \delta Z_i + \epsilon_i \,, \tag{10}$$

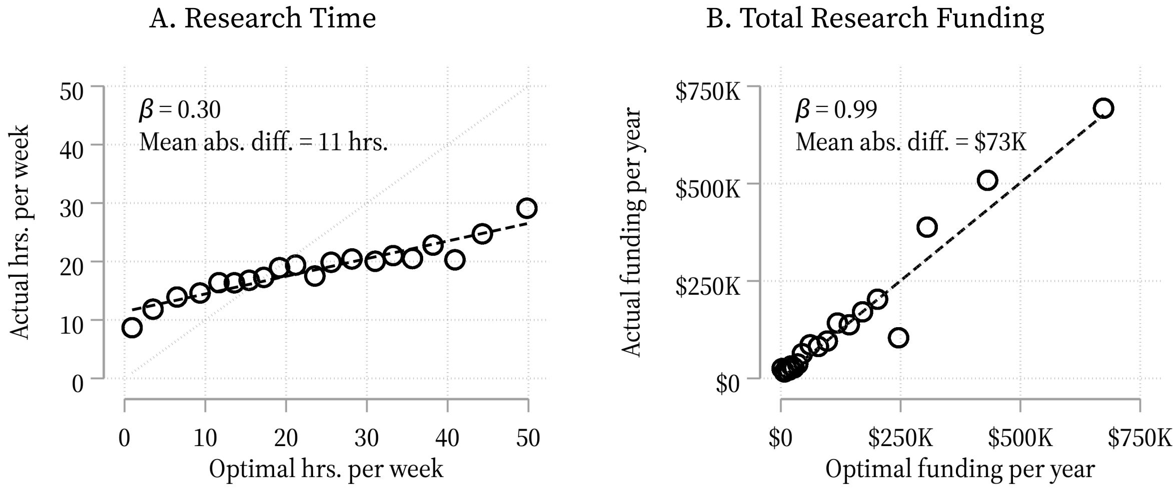
which relates researchers' actual and optimal input levels possibly conditioning on one (or more) covariate Z. If allocations were perfectly efficient, such a regression would yield an estimate $\widehat{\beta} = 1$ (with no standard error) since actual levels would equal optimal levels. If allocations are not efficient, then $\widehat{\beta} < 1$.

Focusing first on estimating Equation 10 with no covariates, Figure 4 reports estimates of β on a binned scatterplot of the data. For both inputs, there is a clear positive relationship between researchers' actual and optimal levels. For every hour a researcher *should* commit to research, they actually commit 0.3 hours on average. Interestingly, for every one dollar in total funding the researcher *should* have, they actually have nearly one dollar (0.987) on average. The figure also reports the mean absolute differences between actual and optimal levels, which are approximately 10 hours of research time and $70,000 in funding. For reference, these values are both roughly half the sample means.

Appendix Table D3 Column (1) replicates these univariate regressions, and then Columns (2–5) include additional sets of covariates, which are all subsets of the vector of covariates used in the researcher type index: researchers' professional positions (e.g., rank, tenure status); their subjective measures of their research output (i.e., as reported in Table 2);

[27]These additional specification tests are available from the authors on request.

FIGURE 4
Actual and Optimal Input Level Correlations



Note: Shows the binned scatterplot of actual and optimal input levels per an objective of maximizing output. Also reports the coefficient estimate from a regression of actual on optimal input levels and the mean absolute difference between actual and optimal input levels.

and their socio-demographic features (e.g., age, gender, household structure).

Examining the R^2 statistics reported in Table D3 Columns (2–5) as we include different sets of covariates generally reveals small increases in R^2 compared to Column (1). At most, the inclusion of the full vector of covariates increases the R^2 by 4–14 percentage points. We interpret this pattern as indicating that misallocation using these sorts of observable features is a challenging exercise, and that the degree of misspecification in the model (along these specific dimensions) is relatively small. The latter gives us confidence in our results, and the former has the interesting implication that predicting which researchers are over- or under-resourced based only on their observables may be a challenging exercise.

6.4. Case Studies of Potential Frictions

When estimating regressions of the form in Equation 10, it is important to be careful when interpreting the δ coefficient. A covariate Z may be a significant predictor of actual levels conditional on optimal levels (i.e., $\widehat{\delta} \neq 0$) for two reasons: (*i*) the feature truly is a predictor of misallocation as implied by the model, in which case a positive (negative) association indicates that the feature is predictive of a researcher being over-resourced (under-resourced) due to a friction; (*ii*) there is misspecification in the model and the feature describes some heterogeneous preferences or demand variation that we have failed to capture, which has led to bias in our productivity estimates. We cannot separate these two possibilities.

Here, we embrace the interpretation that our estimates of δ are indicative of a friction (and not misspecification) only for two features for which misspecification is unlikely to be a major concern, but these results should still be interpreted cautiously.

First, we focus on a highly scrutinized feature: gender. A large body of work has documented a wide range of biases and frictions facing female researchers when it comes to the acquisition of inputs (or credit) for their science.[28] But while the vast majority of this work rejects null hypotheses and finds female researchers are under-resourced, they typically cannot formally quantify *how much* female researchers are under-resourced. Our model and approach allow us to do just that.

In Appendix Table D3, Columns (4–5) report the results from estimating regressions of the form shown in Equation 10, where Z_i is an indicator for researchers who self-report as female. Whether we only include other socio-demographic covariates (Col. 4) or the full set of covariates (Col. 5), we estimate a statistically significant negative association indicating female researchers are under-resourced. They spend approximately 1 hour fewer on their research per week and have roughly $10,000 less in total research funding annually. Both of these wedges are approximately 10% of the sample mean.

Next, we focus on another question that has received much attention by meta-science scholars: the Matthew effect. In general, the Matthew effect posits that researchers amass resources beyond what their productivity warrants due to their social status (Merton 1968). The specific version of this effect that we can test for is the degree to which the use of grant dollars and publication outcomes as productivity proxies distorts the allocation of inputs (e.g., Lee et al. 2013; Gralka, Wohlrabe, and Bornmann 2019). Again, we run regressions of the form shown in Equation 10, now including a vector of variables describing researchers' recent grant funding and publication or citation output. As reported in Appendix Table D4, we find some evidence of statistically significant distortions whereby a one standard deviation increase in these traditional proxies leads to over-resourcing on the scale of roughly 0.1–0.2 standard deviations (approximately 5–10% relative to the sample means).

These two cases reveal statistically significant predictors of the input wedges that are plausibly due to frictions in the allocation process. Researchers are more likely to be

[28] See, for example, Witteman et al. (2019); Kim and Moser (2025).

under-resourced if they are female, and they are more likely to be over-resourced if their observable input and output measures are higher. Still, the R^2 statistics shown in Table D3 convey a seemingly novel point—these observable features, which have received so much attention thus far, explain a very small amount of the misallocation implied by the model. It appears difficult to use standard observable features to predict which researchers are over or under-resourced.

6.5. Output Differences across Major Fields

Our final exercise seeks to understand the determinants of scientific output differences across the major fields of researchers. Doing so takes a strong stance on the comparability of output across fields, which is debatable. Thus, we treat this exercise as more speculative.

In general, the aggregate output of a market depends on input levels (i.e., the number of researchers, their funding, and their time spent on research), productivity levels (i.e., researchers' TFP), and the market's allocative efficiency. Here, we explore the relative importance of these three dimensions.

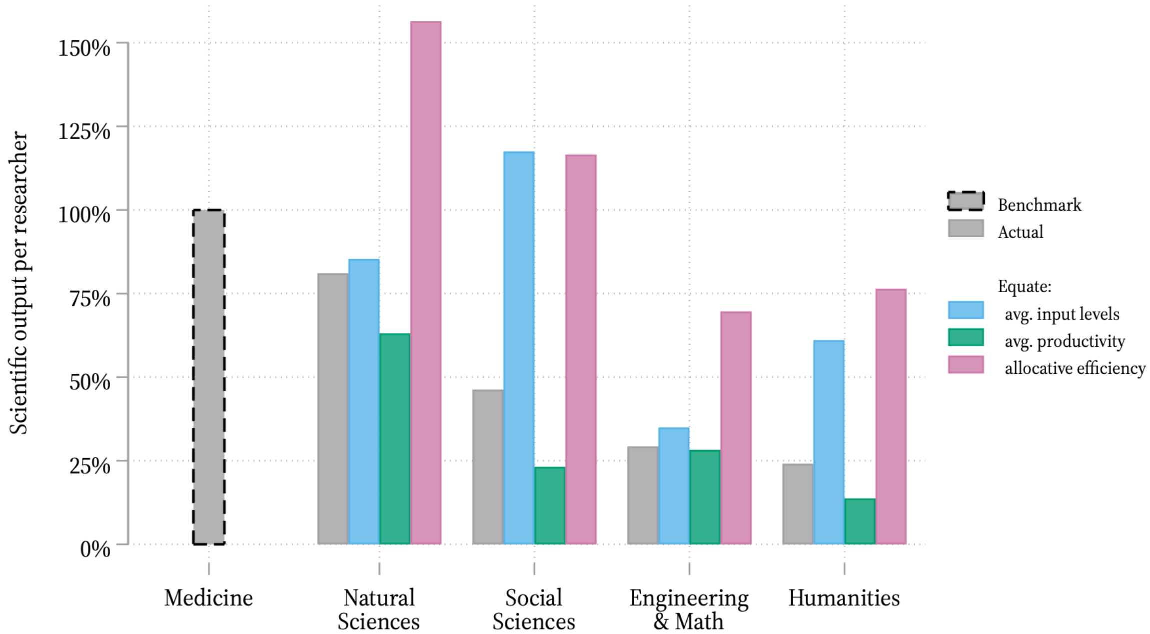
First, we divide all fields' total output by the number of researchers in that field in order to compare the per capita output only. Next, we use the field with the most output, Medicine, as a benchmark and consider the other fields' output in percentage terms relative to Medicine's actual total (per capita) output. The gray bars in Figure 5 plot the total scientific output implied by the data and our productivity estimates across the five major fields of study. The four comparison fields have aggregate output levels that are roughly 25–75% that of Medicine.

Medicine is the most resourced field, so our first test is to equate input levels across fields. In this case, aggregate output in the Social Sciences and the Humanities more than doubles. But, except for the Social Sciences most of the gap in aggregate output between each field and Medicine remains.

Average TFP levels across the fields are relatively similar such that equating productivity has little impact on differences in aggregate output. In fact, the average TFP level in Medicine is slightly lower than that of all other fields, which may be related to the size of the field.

Lastly, we use our estimates from the counterfactual where we maximize output within each of the five major fields to estimate aggregate output gaps in the scenario where

FIGURE 5
Across Field Output Comparisons



Note: Shows the per capita scientific output of each major field benchmarked to the field with the most output, Medicine. Actual output levels (in percentage terms relative to the benchmark) are shown alongside counterfactual output levels where all fields have the same average input levels per researcher, average productivity, and allocative efficiency.

all fields are equal in their allocative efficiency (i.e., output is maximized).[29] Here, we see a reordering of fields in terms of their per capita output. The Natural and Social sciences would produce more output than Medicine, and the other two fields would rise to producing nearly 75% the output of Medicine. In this sense, differences in allocative efficiency appear to be the most important determinant of differences in aggregate output across fields of science.

We can only speculate as to why, based on our sample of medical researchers, the field of medicine appears to be the best at allocating resources efficiently. One might think that medical researchers spend more time engaged in fundraising efforts and that process facilitates positive selection on productivity; however, medical researchers exhibit quite average levels of fundraising effort.[30] The mean duty level for medical researchers is

[29]Since this leads to output growth in all fields, we re-scale aggregate levels so that the level observed in the field of Medicine remains the benchmark at 100%.

[30]The field-specific averages for fundraising hours per week are as follows: Engineering & Math = 6.1; Humanities = 2.7; Medicine = 4.9; Natural sciences = 6.7; Social Sciences = 2.5.

slightly lower relative to other fields, and the variance is much larger. This sort of allocation is consistent with the logic of our model and results — in a world with highly dispersed productivity, the planner should move non-research duties onto as few, low productivity (in the scientific sense) researchers. Of course there are both practical constraints and unmodeled objectives. For example, high-productivity researchers could plausibly have the largest externalities from their other duties (e.g., teaching) and the allocations we observe are balancing social value from research with social value from those other duties. Further work on understanding across-field differences in allocation mechanisms in science seems warranted.

7. Discussion

By some measures, the market for science believes that the benefits from a more efficient allocation are low and declining (or, the costs are high and increasing). Consider the share of science committed to *meta-science* — efforts to improve the efficiency of science writ large: in recent years, approximately 0.1-1.0% of all publications relate to meta-science; furthermore, while US investments in science grew roughly 3-fold over the past fifty years, the number of meta-science studies per dollar declined by nearly 80% in that same period.[31] This could reflect a rational, fully-informed allocation of resources. Or, it may reflect significant uncertainty about the degree to which the aggregate productivity of the scientific enterprise could be improved. In this paper, we use a new approach to productivity estimation in order to shed new light on the benefits from improving allocative efficiency in science.

Our approach allows us to estimate researchers' productivity beliefs without observing output quantities or input prices. We find actual input allocations to be positively correlated with those that maximize plausible objectives, but we also find large gains to be had from more efficient allocations. In the counterfactuals we explore, total scientific output per research-hour or per research-dollar could be more than doubled.

Our model abstracts away from many important considerations that likely drive actual allocations (e.g., dynamic returns), and our data relies on researchers' stated preferences. These and other limitations of our approach motivate us to interpret these magnitudes as plausible upper bounds on the gains from more efficient use of scientific inputs. Still, these large potential gains provide a glimmer of hope amid declining R&D productivity

[31] See Appendix E for the methods used to produce these estimates.

across most sectors of the economy (Bloom et al. 2020b) and the persistently growing burden of knowledge that raises the cost of conducting frontier science (Jones 2009). Furthermore, our approach to identifying productive scientists may prove useful in talent selection processes more generally (e.g., Agarwal and Gaule 2020).

Our approach has deep roots in the economics of labor (i.e., surveys of time use and work-leisure trade-offs), industrial organization (i.e., production function estimation), marketing (i.e., using surveys to identify demand functions), and macroeconomics (i.e., models of factor misallocation). By drawing on insights from these fields, our methodology allows us to overcome many of the challenges that have long plagued our understanding of productivity and efficiency in science.

Our analyses reveal researchers' *beliefs* about their productivity and therefore their *beliefs* about how well inputs are allocated. This is a crucial limitation, since there are clearly many potential biases affecting these beliefs. Still, science is inherently about forecasting uncertain outcomes, and, therefore, the optimal mechanisms for identifying productive researchers and allocating them more inputs will need to tackle this challenge of engaging with researchers' forecasts of their productivity. Specifically, one important next step in this line of work will be to ensure that the producers being studied report their willingness-to-pay for inputs truthfully. Of course, the theoretical underpinnings of how to elicit true willingness-to-pay estimates have long been established (e.g., Becker, DeGroot, and Marschak 1964). However, the magnitudes of costs in our are on the scale of tens to hundreds of thousands of dollars. Thus, developing the practical details of incentivizing truthful responses from producers at this scale would be a fruitful endeavor.

More broadly, our approach may prove useful in other settings. There are many markets populated by a large number of producers acquiring inputs in a highly decentralized way to produce outputs that are not easy to observe. For example, in developing economies, accurate producer-level data on outputs can be difficult to obtain (e.g., Tybout 2000); in entrepreneurship, many organizations never produce observable output before exiting (e.g., Decker et al. 2014); and in nonprofit sectors, the output may be so high-dimensional that reaching consensus on a suitable proxy is challenging (e.g., Philipson and Lakdawalla 2001). In each of these examples, our methodology could provide a way forward to better understand the distribution and determinants of productivity and efficiency.

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Supplemental Appendix

A. Example Applications of Methodology

A.1. Application 1: Constant Returns to Scale and Convex Costs

Consider first the case of a firm that operates a linear production function in a single input, e.g., labor, and faces convex adjustment costs because, e.g., there are hiring and firing frictions. The optimization problem is:

$$\max_{l_i} \quad \alpha_i l_i - w l_i - c l_i^{\psi} \tag{A1}$$

with $b(\cdot) = \alpha_i l_i + m_i$ and $m_i = 0$, $c(\cdot) = w l_i + c l_i^{\psi}$ ($c > 0$ and $\psi > 1$), and $\boldsymbol{\mu}_i = \boldsymbol{\mu} = (w, c, \psi)$. The optimality condition of the problem is:

$$\alpha_i - w - c\psi l_i^{\psi-1} = 0 \tag{A2}$$

In the first step of the estimation procedure, we evaluate the optimality condition at observed allocations to characterize α_i as a function of parameters and observed allocations:

$$\alpha_i(\hat{l}_i, w, c, \psi) = w + c\psi \hat{l}_i^{\psi-1} \tag{A3}$$

where $\hat{l}_i$ denotes the observed input allocation. Moreover, conditional on attributes, parameters, and prices, the solution is determined by:

$$l_i^* = \left(\frac{\alpha_i - w}{\psi c}\right)^{\frac{1}{\psi-1}} \tag{A4}$$

In the second step, we implement the thought experiment and we offer to the firm $\Delta > 0$ extra units of labor, which the firm can hire by just paying WTP_i dollars and without incurring the convex adjustment cost. Of course, the firm can re-optimize the quantity of labor that hires at market conditions. Therefore, the problem is:

$$\max_{\tilde{l}_i} \quad \alpha_i(\tilde{l}_i + \Delta) - w\tilde{l}_i - c\tilde{l}_i^{\psi} - WTP_i \tag{A5}$$

and the solution:

$$\tilde{l}_i^* = \left(\frac{\alpha_i - w}{\psi c}\right)^{\frac{1}{\psi-1}} = l_i^* \tag{A6}$$

Replacing the solution in the profit function and equating profits at current allocations and in the thought experiment, we obtain:

$$WTP_i = \alpha_i(\hat{l}_i, w, c, \psi)(\tilde{l}_i^* + \Delta) - w\tilde{l}_i^* - c\left(\tilde{l}_i^*\right)^{\psi} - \alpha_i(\hat{l}_i, w, c, \psi)l^* + wl^* + c\,(l^*)^{\psi} \tag{A7}$$

Using the fact that $\tilde{l}_i^* = l_i^*$, we obtain:

$$WTP_i = \alpha_i(\hat{l}_i, w, c, \psi)\Delta = \left(w + c\psi\hat{l}_i^{\psi-1}\right)\Delta \tag{A8}$$

which allows the identification of w, c, ψ and thus $\alpha_i(\hat{l}_i, w, c, \psi)$, given $\hat{l}_i$ and Δ. The same logic applies to the case of decreasing returns to scale, namely:

$$\max_{l_i} \;\; \alpha_i l_i^{\beta} - wl_i - cl_i^{\psi}$$

with $v(\cdot) = \alpha_i l_i^{\beta} + m_i$ for $m_i = 0$ and $\beta \in (0,1)$, $c(\cdot) = wl_i + cl_i^{\psi}$ for $c > 0$ and $\psi > 1$, and $\mu_i = \mu = (\beta, w, c, \psi)$. In the general case, the optimal input choice does not admit a closed-form expression, but we can show that $\frac{\partial \tilde{l}_i^*}{\partial \Delta} \neq -1$, i.e., the additional input does not perfectly crowd out the quantity of input sourced in the market. This is a sufficient condition such that WTP_i does depend on α_i and thus on all estimands μ.

A.2. Application 2: Decreasing Returns to Scale and Linear Costs

Here, we show an example of how a linear cost schedule renders our approach unable to recover productivity. The setting is:

$$\max_{l_i} \;\; \alpha_i l_i^{\beta} - wl_i$$

i.e., the problem coincides with the previous application for $\psi = 0$. The first order condition is $\beta\alpha_i l_i^{\beta-1} = w$, which identifies:

$$\alpha_i(\hat{l}_i, \beta, w) = \left(\frac{w}{\beta}\right)\hat{l}_i^{1-\beta} \tag{A9}$$

and determines the optimal allocation as:

$$l_i^* = \left(\frac{\beta\alpha_i}{w}\right)^{\frac{1}{1-\beta}} \tag{A10}$$

Under the thought experiment, the optimization problem becomes:

$$\max_{\tilde{l}_i} \quad \alpha_i(\tilde{l}_i + \Delta)^\beta - w\tilde{l}_i$$

which implies:

$$\tilde{l}_i^* = \left(\frac{\beta\alpha_i}{w}\right)^{\frac{1}{1-\beta}} - \Delta = l_i^* - \Delta \tag{A11}$$

Replacing in the profit function and deriving WTP_i, we obtain:

$$\begin{aligned} WTP_i =& \alpha_i(\tilde{l}_i^* + \Delta)^\beta - w\tilde{l}_i^* - \alpha_i l_i^* + wl_i^* \\ =& \alpha_i(l_i^* - \Delta + \Delta)^\beta - w(l_i^* - \delta) - \alpha_i l_i^* + wl_i^* \\ =& w\Delta \end{aligned}$$

where from the first to the second line we replace $\tilde{l}_i^* = l_i^* - \Delta$. Because the willingness to pay just depends on w, β cannot be identified, which implies that also α_i is not pinned down.

A.3. Application 3: Individuals as Producers with Utility Function

Consider the problem of an agent that gets utility from income m_i and output $\alpha_i d_i^\beta l_i^{1-\beta}$—produced using a fixed input d_i and labor l_i—and gets disutility from working. The problem is:

$$\max_{l_i} \quad \ln m_i + \left(\alpha_i d_i^\beta l_i^{1-\beta}\right)^\eta - \phi l_i^\psi \tag{A12}$$

with $b(\cdot) = \ln mi_i + \left(\alpha_i l_i^\beta d_i^{1-\beta}\right)^\eta$ for $\beta \in (0,1)$ and $\eta \in (0,1)$, $c(\cdot) = \phi l_i^\psi$ for $\phi > 0, \psi > 1$, and $\mu_i = \mu = (\beta, \eta, \phi, \psi)$. The optimality condition is:

$$\eta(1-\beta)\alpha_i^\eta d_i^{\eta\beta} l_i^{(1-\beta)\eta-1} = \phi\psi l_i^{\psi-1} \tag{A13}$$

Therefore:

$$\alpha_i(\hat{l}_i, d_i, \beta, \eta, \phi, \psi) = \left(\frac{\phi\psi\hat{l}_i^{\psi-1}}{\eta(1-\beta)d_i^\eta \hat{l}_i^{\eta(1-\beta)-1}}\right)^{\frac{1}{\eta}} \tag{A14}$$

and

$$l_i^* = \left(\frac{\eta(1-\beta)\alpha_i^\eta d_i^{\eta\beta}}{\phi\psi}\right)^{\frac{1}{\psi-\eta(1-\beta)}} \tag{A15}$$

In the setting of a thought experiment where Δ additional units of the fixed input are offered to the agent, the problem becomes:

$$\max_{\tilde{l}_i} \ \ln(m_i - WTP_i) + \left(\alpha_i (d_i + \Delta)^{\beta} \tilde{l}_i^{1-\beta}\right)^{\eta} - \phi \tilde{l}_i^{\psi} \tag{A16}$$

with

$$\tilde{l}_i^* = \left(\frac{\eta(1-\beta)\alpha_i^{\eta}(d_i + \Delta)^{\eta\beta}}{\phi\psi}\right)^{\frac{1}{\psi - \eta(1-\beta)}}$$

Therefore, WTP_i solves:

$$\begin{aligned}
&\ln(m_i - WTP_i) + \alpha_i^{\eta}\left(\frac{\eta(1-\beta)}{\phi\psi}\right)^{\frac{\eta(1-\beta)}{\psi-\eta(1-\beta)}} (d_i + \Delta)^{\frac{\beta\psi\eta}{\psi-\eta(1-\beta)}} - \phi\left(\frac{\eta(1-\beta)\alpha_i^{\eta}(d_i + \Delta)^{\eta\beta}}{\phi\psi}\right)^{\frac{\psi}{\psi-\eta(1-\beta)}} + \\
&- \ln m_i - \alpha_i^{\eta}\left(\frac{\eta(1-\beta)}{\phi\psi}\right)^{\frac{\eta(1-\beta)}{\psi-\eta(1-\beta)}} d_i^{\frac{\beta\psi\eta}{\psi-\eta(1-\beta)}} - \phi\left(\frac{\eta(1-\beta)\alpha_i^{\eta} d_i^{\eta\beta}}{\phi\psi}\right)^{\frac{\psi}{\psi-\eta(1-\beta)}} = 0
\end{aligned} \tag{A17}$$

and depends on all parameters.

B. Additional Survey Statistics and Comparisons

Table B1 shows the effects of the randomized participation incentives and reminders on survey completion. Figures B1–B2 illustrate sample representativeness and Figure B3 documents the alignment between self- and publicly-reported salaries (see Myers et al. (2023) for more on the sample). Table B2 describes the summary statistics for the sample on numerous dimensions. Table B3 shows the pairwise correlations of the subjective output measures.

TABLE B1
Survey Completion per Randomized Treatments

	(1)
Either incentive	0.00297**
	(0.00117)
Both incentives	0.00797***
	(0.00141)
1 reminder	0.0112***
	(0.00114)
2 reminders	0.0188***
	(0.00119)
Constant	0.0197***
	(0.00107)
N obs.	131,672

Note: Reports estimates from a regression of a binary indicator of survey completion on binary indicators for the randomized incentives and reminders including observations for all researchers emailed. Robust standard errors reported; $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

TABLE B2

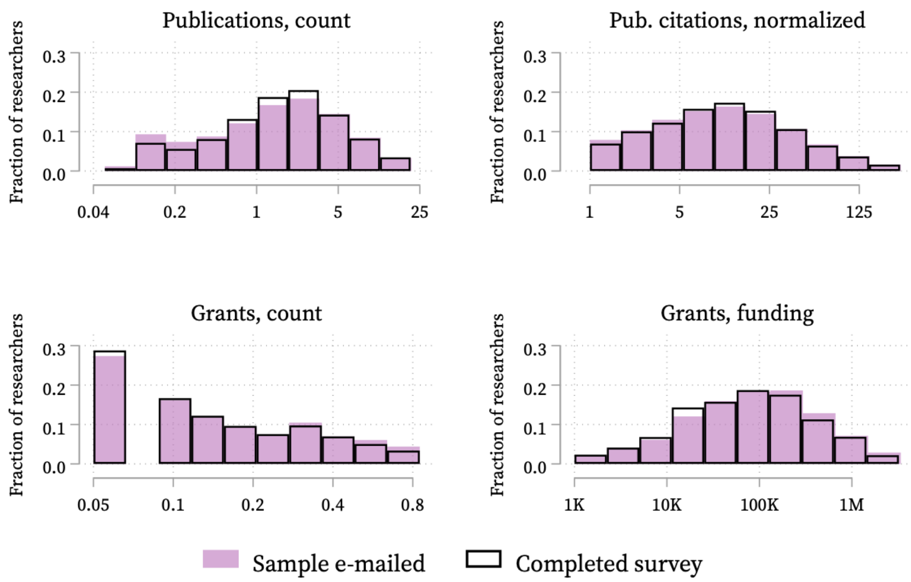
Summary Statistics of Other Variables

	mean	*s.d.*
From HERD: Institution-level R&D		
Total R&D, $M	611.32	451.18
R&D per researcher, $M	0.61	0.86
Share federal gov.'t R&D, [0,1]	0.52	0.12
Share basic R&D, [0,1]	0.63	0.20
From Dimensions: Research output		
Publications per year	5.28	7.09
Citations per year	23.07	49.10
Co-authors per publication per year	9.09	68.40
Position details		
Assistant professor, {0,1}	0.26	0.44
Associate professor, {0,1}	0.26	0.44
Full professor, {0,1}	0.41	0.49
Other rank, {0,1}	0.07	0.25
Not on tenure track, {0,1}	0.19	0.39
Pre-tenure, {0,1}	0.22	0.42
Tenured, {0,1}	0.58	0.49
Years until next contract eval.	3.68	1.82
Duration of contract	2.45	1.93
Gender identity, {0,1}		
Female	0.40	0.49
Male	0.55	0.50
Other or N.R	0.05	0.22
Racial/ethnic identity, {0,1}		
Asian	0.13	0.33
Black	0.03	0.18
Hispanic	0.06	0.23
White	0.77	0.42
Other or N.R	0.05	0.21
Citizenship, {0,1}		
Citizen, domestic-born	0.71	0.45
Citizen or perm resident, foreign-born	0.24	0.43
Other or N.R citizenship	0.05	0.21
1st–3rd generation in U.S.	0.30	0.46
Other or N.R generation in U.S.	0.70	0.46
Other covariates		
Age	48.78	12.05
Household total income	260,336.00	215,388.31
Married or domestic partnership, {0,1}	0.82	0.39
Single, {0,1}	0.13	0.34
Other or N.R relationship, {0,1}	0.05	0.22
Dependents in household	0.98	1.13
Risk-taking in personal life, [0,10]	5.26	2.13

Note: Reports summary statistics for 4,003 researcher-level observations. *From HERD* indicates variables from National Science Foundation (2023). *From Dimensions* indicates variables from the Digital Science (2018) dataset. *N.R.* stands for Not Reported.

FIGURE B1

Sample Representativeness per Publication and Grant Funding Measures



-NoValue- (*Note*: Shows the distribution of publication and grant outcomes split by whether the researcher was emailed (i.e., the full sample) versus those who completed the survey; note the log x axes. See Myers et al. (2023) for regression-based estimates of the differences.

TABLE B3

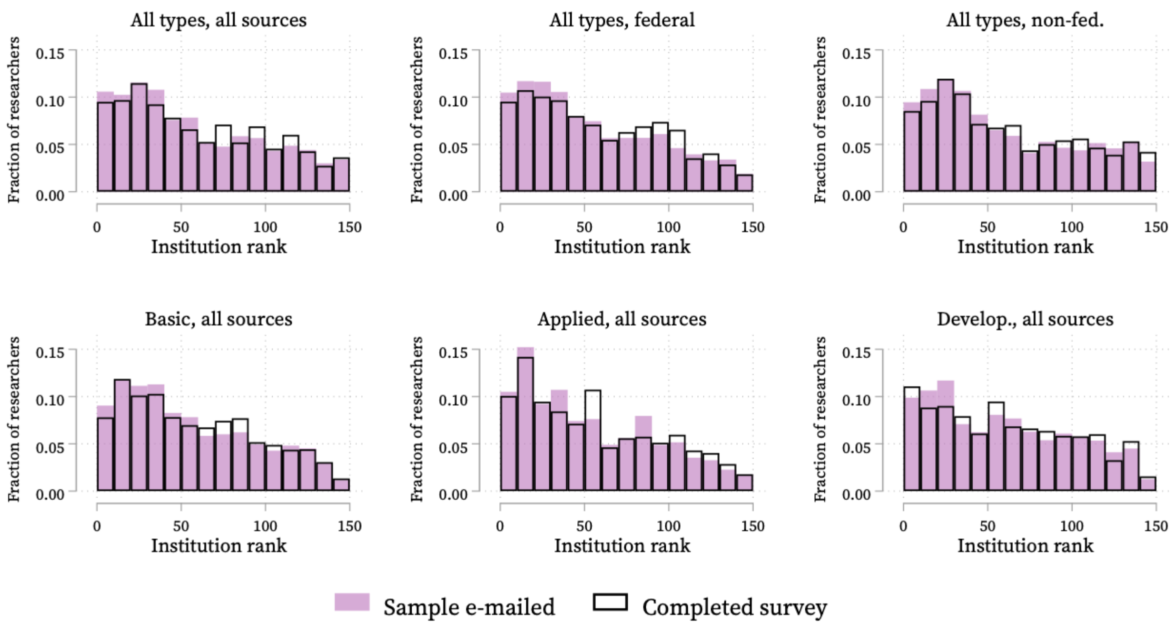
Pairwise Correlations of Subjective Output Measures

	Articles	Books	Methods	Products	Academic	Policy	Business	Public
Articles								
Books	-0.13^{s}							
Methods	0.08^{s}	-0.20^{s}						
Products	-0.13^{s}	-0.12^{s}	0.23^{s}					
Academic	0.48^{s}	-0.01	0.02	-0.24^{s}				
Policy	0.01	-0.00	0.10^{s}	0.25^{s}	-0.07^{s}			
Business	-0.03	-0.07^{s}	0.20^{s}	0.38^{s}	-0.12^{s}	0.24^{s}		
Public	-0.12^{s}	0.19^{s}	0.04	0.21^{s}	-0.20^{s}	0.28^{s}	0.13^{s}	

Note: Reports pairwise correlations for the four subjective measures of researchers' intended output types (Journal articles; Books; Materials or Methods; Products) and the four subjective measures of researchers' intended audiences (Academic peers; Policymakers; Businesses and organizations; General public); $^{s}\,p < 0.01$.

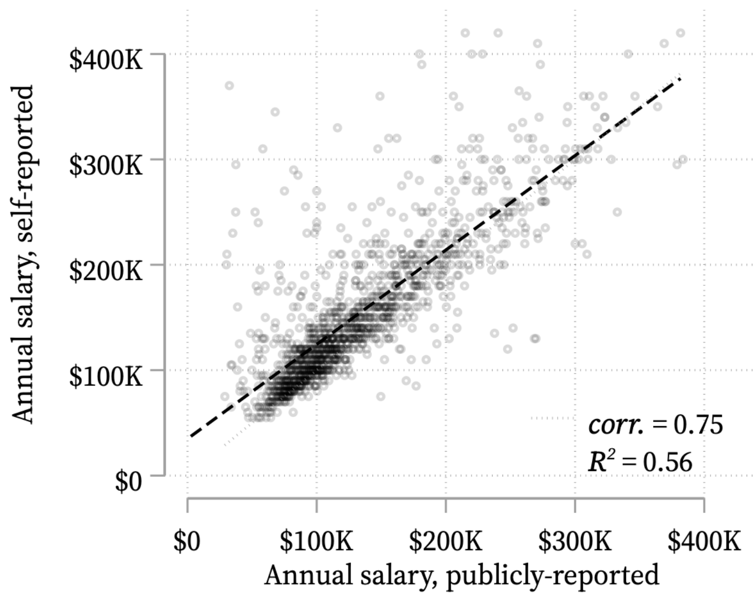
FIGURE B2

Sample Representativeness per Institutional Funding Measures



Note: Shows the distribution of institution-level funding split by whether the researcher was emailed (i.e., the full sample) versus those who completed the survey. See Myers et al. (2023) for regression-based estimates of the differences.

FIGURE B3
Correlation of Self- and Publicly-reported Annual Salaries



Note: Shows the publicly- and self-reported annual salaries for 1,369 in-sample researchers whose salaries were located in public reportings, and reports the pairwise correlation alongside the R^2 statistic from a regression of self-reported on publicly-reported salary.

C. Additional Model and Experiment Details

C.1. Derivation of Policy Functions

The policy functions $\mathcal{R}(\mathbf{S}_i, \theta_i, \mu_i)$, $\mathcal{F}(\mathbf{S}_i, \theta_i, \mu_i)$ and $\mathcal{H}(\mathbf{S}_i, \theta_i, \mu_i)$ characterize the solution (R_i^*, F_i^*, H_i^*) to problem (7) for each individual scientist i as a function of states $\mathbf{S}_i$, attributes θ_i, and parameters μ_i. They determine indirect utility $\mathcal{V}_i^* = \mathcal{V}(\mathbf{S}_i, \theta_i, \mu_i)$ at current allocations. Substituting the constraints, the utility maximization problem is:

$$\mathcal{V}(\cdot) = \max_{F_i, H_i} u_{1i}(M_i) + u_{2i}(\alpha_i \left(B_{\min} + G_i + \phi_i F_i\right)^{\gamma_i} \left(H_i - F_i - D_i\right)^{1-\gamma_i}) - u_{3i}(H_i, D_i) \,, \tag{C1}$$

with the policy functions $\mathcal{F}(\cdot,\cdot,\cdot)$ and $\mathcal{H}(\cdot,\cdot,\cdot)$ solving the optimality conditions:

$$\frac{\partial u_{2,i}(Y_i)}{\partial Y_i}\frac{\partial Y_i}{\partial F_i} + \lambda_{F,i} = 0 \tag{C2}$$

$$\frac{\partial u_{2,i}(Y_i)}{\partial Y_i}\frac{\partial Y_i}{\partial H_i} - \frac{\partial u_{3,i}(H_i, D_i)}{\partial H_i} - \lambda_{H,i} = 0 \,, \tag{C3}$$

and $\mathcal{R}(\cdot,\cdot,\cdot)$ being residually determined based on the time-constraint (7c). To derive the policy functions, we start from model's optimality conditions (C3) and (C3) and evaluate them using the functional forms described in the main text. We obtain the conditions:

$$Y_i^{1-\eta_i}\left[\gamma_i \phi_i (B_{\min} + G_i + \phi_i F_i)^{-1} - (1-\gamma_i)(H_i - D_i - F_i)^{-1}\right] + \lambda_{F,i} = 0 \tag{C4}$$

$$Y_i^{1-\eta_i}(H_i - D_i - F_i)^{-1}(1-\gamma_i) - \psi(H_i - D_i + D_i^{\xi_i})^{\zeta_i} - \lambda_{H,i} = 0 \,. \tag{C5}$$

We characterize the policy functions in two intervals of H_i. The first is $H_i \in (D_i, H_{i,F>0}]$ and the second is $H_i \in (H_{i,F>0}, H_{\max}]$, depending on whether the optimal fundraising time allocation is a corner solution ($F_i = 0$) or not ($F_i > 0$). We identify the threshold $H_{i,F>0}$ below which optimal fundraising is zero by solving (C5) for F_i as a function of H_i assuming that F_i is strictly positive, i.e., $\lambda_{F,i} = 0$:

$$F_i = \gamma_i (H_i - D_i) - \frac{1-\gamma_i}{\phi_i}(B_{\min} + G_i) \,. \tag{C6}$$

Therefore, (C6) implies that fundraising time is strictly positive as long as:

$$H_i > D_i + \frac{1-\gamma_i}{\gamma_i \phi_i}(B_{\min} + G_i) \,, \tag{C7}$$

which identifies the threshold $H_{i,F>0}$ that is strictly larger than D_i as long as $\gamma_i < 1$. As a consequence, we can solve for optimal hours H_i using equation (C5), which takes the piece-wise functional form:

$$\begin{cases} (1-\gamma_i)[\alpha_i(B_{\min}+G_i)^{\gamma_i}]^{1-\eta_i}(H_i-D_i)^{(1-\gamma_i)(1-\eta_i)-1} - \psi(H_i - D_i + D_i^{\xi_i})^{\zeta_i} - \lambda_{H,i} = 0 & \text{if } H_i \leq H_{i,F>0} \\ \left[\alpha_i(\phi_i\gamma_i)^{\gamma_i}(1-\gamma_i)^{1-\gamma_i}\right]^{1-\eta_i}\left(H_i - D_i\frac{B_{\min}+G_i}{\phi_i}\right)^{-\eta_i} - \psi(H_i - D_i + D_i^{\xi_i})^{\zeta_i} - \lambda_{H,i} = 0 & \text{if } H_i > H_{i,F>0} \end{cases} \tag{C8}$$

and defines an implicit solution $\mathcal{H}_i$ for H_i as a function of all parameters and state variables. (C8) is continuous but not differentiable at $H_{i,F>0}$. Moreover, the Lagrange multiplier $\lambda_{H,i}$ equals zero for $H_i < H_{\max}$ and H_i is always strictly larger than D_i because $\lim_{H_i \to D_i}$ (C8) $= +\infty$. Hence, the non-negativity constraint on research time is always met. Given the policy function $\mathcal{H}_i$ for hours, the functions defining optimal allocation to fundraising time and research time are:

$$\mathcal{F}_i = \begin{cases} 0 & \text{if } \mathcal{H}_i \leq H_{i,F>0} \\ \gamma_i(\mathcal{H}_i - D_i) - \frac{1-\gamma_i}{\phi_i}(B_{\min}+G_i) & \text{if } \mathcal{H}_i > H_{i,F>0} \end{cases} \tag{C9}$$

and

$$\mathcal{R}_i = \mathcal{H}_i - D_i - \mathcal{F}_i\ . \tag{C10}$$

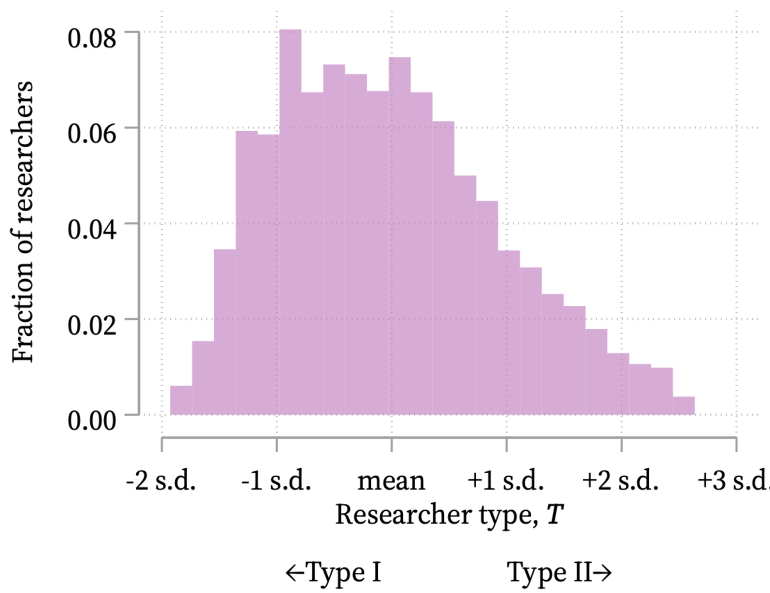
C.2. Reducing Dimensions of Heterogeneity: k-means Clustering Results

Ideally, our model would allow for rich heterogeneity in researchers' preferences (i.e., the $u_{1,i}(\cdot)$, $u_{2,i}(\cdot)$, and $u_{3,i}(\cdot)$ functions). This would help ensure that (true) variation in preferences would not mistakenly be attributed as (estimated) variation in productivity. We lack enough data to estimate researcher-specific preference functions, but we do have the large vector of observables from the survey $\mathbf{Z}_i$.[32] This motivates the approach outlined in Section **??**. We use k-means clustering to collapse the multi-dimensional heterogeneity from the observables $\mathbf{Z}_i$ into a single-dimensional index, T_i. Specifically, we assume there are two clusters of researcher types (k=2), and we use k-means clustering to estimate each researcher's euclidean distance from one of those groups; we use that distance as T_i, which provides a smooth, continuous measure of heterogeneity. Thus, for the preference function parameter σ_i, we assume that $\sigma_i = \exp(\delta_{\sigma,0} + T_i\delta_\sigma)$. Figure C1

[32] We could allow the parameters that govern the preference functions to depend on deep parameters and these observables. For example, for the preference function parameter σ_i, we could assume that $\sigma_i = \exp(\delta_{\sigma,0} + \sum_z Z_i\delta_{\sigma,Z})$. However, this presents some practical estimation challenges (i.e., estimating approximately (35×3=) 105 additional parameters; the $\delta_{\sigma,z}$ parameters in the previous example).

shows the distribution of the one-dimensional euclidean similarity scores. Researchers with larger values of T_i tend to be, among other things, older, white, males that are full professors in the humanities and natural sciences. A table reporting the mean differences between the two types of researchers is available upon request.

FIGURE C1
Researcher Heterogeneity



Note: Shows the distribution of the log-transformed and standardized euclidean similarity scores from the k-means cluster estimation with two k=I,II.

C.3. Estimation Outline

We infer individual attributes and parameters using a mix of calibration and estimation. First, we set minimum funding B_{min} = \$5,000 and fix total hours endowment H_{max} to 62 work hours per week (approximately the 90th percentile of the observed work hours). Second, we estimate individual attributes and common parameters of the utility function, including deep parameters that determine individual-specific parameters in μ_i as functions of researcher's type T_i. We use survey information on hours worked, research time, fundraising time, guaranteed funding, expected additional funds raised, duties, and the salaries reported in the alternative offer experiments, which we map to model counterparts $(H_i, R_i, F_i, G_i, \phi_i F_i, D_i, \{M_{ij}\}_{j=1}^4)$, respectively.

Conditional on some common parameters, we can infer individual-specific attributes θ_i from researchers' optimality conditions and model's structure. One important note is that we have separate estimation routines for inferring individual attributes θ_i among researchers with non-zero fundraising time ($F_i > 0$) and those at a corner solution ($F_i = 0$). For the former group, we first infer fundraising ability ϕ_i by exploiting the identity equating the observed, expected additional funding (EG_i) to $\phi_i F_i$. Therefore, $\forall i = 1, \ldots, N_F$:

$$\widehat{\phi}_i = \frac{EG_i}{F_i} \,. \tag{C11}$$

Expression (C11) is well-defined if and only if observed $F_i > 0$, which is why the inference strategy must differ for researchers with $F_i = 0$ at observed allocations.[33] As a second step, conditional on $\widehat{\phi}_i$, we infer factor shares $\widehat{\gamma}_i$ from researchers' first order condition in fundraising time, which we derive in Appendix C.1. For the chosen functional forms, this takes the expression:

$$\widehat{\gamma}_i = \frac{B_i}{B_i + \phi_i R_i} = \frac{B_{\min} + G_i + \widehat{\phi}_i F_i}{B_{\min} + G_i + \widehat{\phi}_i F_i + \widehat{\phi}_i R_i} \,. \tag{C12}$$

Equation (C12) states that γ_i constitutes the weight of total funding over the total dollar-value of inputs used in scientific activity, with the last term of the denominator being the dollar-valued opportunity cost of research time relative to fundraising. Finally, the optimality condition for total hours worked determines productivity $\widehat{\alpha}_i$ as a function of parameters, observed allocations, and $\widehat{\phi}_i$ and $\widehat{\gamma}_i$:

$$(1 - \widehat{\gamma}_i)\widehat{\alpha}_i^{1-\eta_i}(B_{\min} + G_i + \widehat{\phi}_i F_i)^{(1-\eta_i)\widehat{\gamma}_i} R_i^{(1-\eta_i)(1-\widehat{\gamma}_i)-1} = \psi(H_i - D_i + D_i^{\xi_i})^{\zeta_i} \,, \tag{C13}$$

This equation holds exactly if $H_i < H_{\max}$. Therefore, Equations (C11), (C12), and (C13) determine individual attributes as functions of parameters and observed allocations for researchers with positive fundraising time. Unfortunately, for the group of researchers reporting zero fundraising time, we can neither infer $\widehat{\phi}_i$ from Equation (C11), nor can we compute $\widehat{\gamma}_i$.[34] Therefore, we assume that ϕ_i and γ_i are parametric polynomial functions of state variables, and we estimate these functions using the other sub-sample of researchers with $F_i > 0$.[35]

[33] For numerical stability, we constrain $\widehat{\phi}_i \geq 1$.

[34] The Lagrange multiplier $\lambda_{F,i}$ is strictly positive and unknown.

[35] We use the following specifications: $\phi_i = \exp\left\{\sum_{p=1}^{3} \beta_{G,p} G_i^p + \sum_{p=1}^{3} \beta_{D,p} D_i^p + \sum_{p=1}^{3} \beta_{M,p} M_i^p\right\}$, and $\gamma_i = \left(1 + \exp\left\{\sum_{p=1}^{3} \iota_{G,p} G_i^p + \sum_{p=1}^{3} \iota_{D,p} D_i^p + \sum_{p=1}^{3} \iota_{M,p} M_i^p\right\}\right)^{-1}$, which we estimate using poisson and logistic regressions. Whenever the fitted $(\widehat{\phi}_i, \widehat{\gamma}_i)$ combination would imply, given the observed state variables and for a specific vector of parameters μ_i, that the optimal (observed) time allocation to fundraising would

Finally, given the estimates attributes $\widehat{\phi}_i$ and $\widehat{\gamma}_i$, the state variables, and the vector of common parameters $\widehat{\mu}$, we infer productivity beliefs $\widehat{\alpha}_i$ through Equation (C13). Given estimates of individual attributes $\widehat{\theta}_i = (\widehat{\alpha}_i, \widehat{\gamma}_i, \widehat{\phi}_i)$ as functions of parameters $\mu = (\omega, \psi, \delta)$, calibrated values $(B_{\min}, H_{\max})$, and observed allocations, we estimate the vector μ by generalized method of moments as:

$$\widehat{\mu} = \arg\min_{\mu} \mathcal{L}(\mu) = \arg\min_{\mu} \sum_{i=1}^{N} \sum_{j=1}^{4} \left(M_{ij}^{\text{obs}} - \widehat{M}_{ij}(\mathbf{S}_{ij}, \widehat{\theta}_i(\mu_i(\mu, T_i)), \mu_i(\mu, T_i)) \right)^2 , \tag{C14}$$

where M_{ij} is researcher i's answer to thought experiment j in the data and $\widehat{M}_{ij}$ is its model-based counterpart, which is itself an implicit function of the vector of counterfactual states $\mathbf{S}_i$, researcher's type T_i, and of the estimand μ which determines individual attributes $\widehat{\theta}_i$ and individual-specific parameters μ_i.[36] Parameter estimates $\widehat{\mu}$ solve (C14) conditional on parameter restrictions specified in Section 2.2. Appendix C.4 provides additional details on the search algorithm.

C.4. Estimation Algorithm

Here, we describe the estimation of the common parameters $\mu = (\omega, \psi, \delta_{\sigma,0}, \delta_{\sigma,1}, \delta_{\eta,0}, \delta_{\eta,1}, \delta_{\xi,0}, \delta_{\xi,1}, \delta_{\zeta,0}, \delta_{\zeta,1})$. First, we define a grid of parameter values at which we perform a preliminary evaluation of the loss function in (C14). The grid is defined by the Cartesian product of the following:

$$\begin{aligned}
&\omega^{(0)} = [0.1, 1, 10] , \quad \psi^{(0)} = [0.00001, 1, 10] , \\
&\delta_{\sigma,0}^{(0)} = [-100, 0] , \quad \delta_{\sigma,1}^{(0)} = [0] , \\
&\delta_{\eta,0}^{(0)} = [\ln(0.8) - \ln(0.2), 0, \ln(0.2) - \ln(0.8)] , \quad \delta_{\eta,1}^{(0)} = [0] \\
&\delta_{\xi,0}^{(0)} = [-11.5, \ln(2)] , \quad \delta_{\xi,1}^{(0)} = [0] , \\
&\delta_{\zeta,0}^{(0)} = [-11.5, 0] , \quad \delta_{\zeta,1}^{(0)} = [0] .
\end{aligned}$$

Second, we select the grid-points where the value of the loss function is within 0.5% of the minimum, and we use them as initial points for the numerical solution. We perform a preliminary "Nelder-Mead simplex direct search" with a high tolerance on the loss function and standard tolerance on parameter values. We then select the parameters

be strictly positive, we re-scale $\widehat{\phi}_i$ below the individual-specific lower bound below which the optimal fundraising time at observed states is indeed null.

[36] To save notation, we omit that $\widehat{M}_{ij}$ are also a function of calibrated $(B_{\min}, H_{\max})$.

vectors where the value of the loss function is within 1% of the minimum, and we use them as initial points with the same search algorithm and with lower loss function tolerance. We repeat this step twice until we are left with a single candidate optimal parameter vector.

C.5. Objectives and Constraints for Counterfactuals

We first analyze a setting where social planner's objective is to maximize field-specific aggregate scientist's utility by reallocating guaranteed funding G_i and administrative duties D_i within the major field. We define the output function

$$\mathcal{Y}_i(\widetilde{G}_i, \widetilde{D}_i, \pi_f) = \alpha_i \left(B_{\min} + G_i + \phi_i \mathcal{F}(\widetilde{G}_i, \widetilde{D}_i, \pi_f)\right)^{\gamma_i} \mathcal{R}(\widetilde{G}_i, \widetilde{D}_i, \pi_f)^{1-\gamma_i}$$

where the adjustment factor π_f to fundraising ability in field f enforces the constraint that additional funding in the counterfactual allocation must equal observed funding. For convenience, in this section we omit from the notation the dependence of the policy functions on attributes $\widehat{\theta}_i$ and parameters $\widehat{\mu}_i$. Therefore, the problem in field f is:

$$\begin{aligned}
&\max_{(\widetilde{G}_i, \widetilde{D}_i)_{i=1}^{N_f}} \sum_{i=1}^{N_f} \left(\kappa \frac{\mathcal{Y}_i(\widetilde{G}_i, \widetilde{D}_i, \pi_f)^{1-\eta_i}}{1-\eta_i} - \psi \frac{(\mathcal{H}_i(\widetilde{G}_i, \widetilde{D}_i, \pi_f) - \widetilde{D}_i + \widetilde{D}_i^{\xi_i})^{1+\zeta_i}}{1+\zeta_i} \right) \\
&\text{subject to} \\
&\sum_{i=1}^{N_f} \widetilde{G}_i = \widehat{G}^{tot} \quad [\text{Multiplier } \lambda_{G,f}] \\
&\sum_{i=1}^{N_f} \widetilde{D}_i = \widehat{D}^{tot} \quad [\text{Multiplier } \lambda_{D,f}] \\
&\sum_{i=1}^{N_f} EG_i = \pi_f \sum_{i=1}^{N_f} \widehat{\phi}_i \mathcal{F}_i(\widetilde{G}_i, \widetilde{D}_i, \pi_f) \ ,
\end{aligned} \tag{C15}$$

where N_f is the number of scientists in field f. We also impose non-negativity constraints on individual $\widetilde{G}_i$ and $\widetilde{D}_i$ allocations. The individual research output function $\mathcal{Y}_i = \widehat{\alpha}_i \mathcal{B}_i^{\widehat{\gamma}_i} \mathcal{R}_i^{1-\widehat{\gamma}_i}$ and hours $\mathcal{H}_i$ make explicit that both are functions of the considered instruments $(\widetilde{G}_i, \widetilde{D}_i)$. The last constraint requires that total additional funding in the observed allocations. Therefore, all the policy functions not only vary with policy levers $(\widetilde{G}_i, \widetilde{D}_i)$ but also with π_f, which can be interpreted as an endogenous adjustment to fundraising probability. When the new allocation violates the constraint, fundraising probability uniformly shrinks, thus reducing additional funding both directly and indirectly through the behavioral decline in fundraising hours.

In the optimal allocations, the planner seeks to equate the marginal utility of guaranteed funding and duties across individuals, conditional on the non-negativity constraint and the additional funding constraint. Therefore, the solution satisfies the following equations for each $i = 1, \ldots, N_f$:

$$\frac{d\mathcal{V}_i}{d\widetilde{G}_i} = \kappa \mathcal{Y}_i^{-\eta_i} \frac{d\mathcal{Y}_i}{d\widetilde{G}_i} - \psi(\mathcal{H}_i - \widetilde{D}_i + \widetilde{D}_i^{\xi_i})^{\zeta_i} \frac{\partial \mathcal{H}_i}{\partial \widetilde{G}_i} = \lambda_{G,f} - \lambda_{G^*,i} \tag{C16}$$

$$\frac{d\mathcal{V}_i}{d\widetilde{D}_i} = \kappa \mathcal{Y}_i^{-\eta_i} \frac{d\mathcal{Y}_i}{d\widetilde{D}_i} - \psi(\mathcal{H}_i - \widetilde{D}_i + D_i^{\xi_i})^{\zeta_i} \left(\frac{\partial \mathcal{H}_i}{\partial \widetilde{D}_i} - 1 + \xi_i \widetilde{D}_i^{\xi_i - 1} \right) = \lambda_{D,f} - \lambda_{D^*,i} \, , \tag{C17}$$

where the marginal product of guaranteed funds $\frac{d\mathcal{Y}_i}{d\widetilde{G}_i}$ and the (negative) marginal product of duties $\frac{d\mathcal{Y}_i}{d\widetilde{D}_i}$ are determined by equations (C18) and (C19), respectively:

$$\frac{d\mathcal{Y}_i}{dG_i} = \widehat{\alpha}_i \mathcal{B}_i^{\widehat{\gamma}_i} \mathcal{R}_i^{1-\widehat{\gamma}_i} \left(\widehat{\gamma}_i \mathcal{B}_i^{-1} \frac{\partial \mathcal{B}_i}{\partial \widetilde{G}_i} + (1 - \widehat{\gamma}_i) \mathcal{R}_i^{-1} \frac{\partial \mathcal{R}_i}{\partial \widetilde{G}_i} \right) \tag{C18}$$

$$\frac{d\mathcal{Y}_i}{dD_i} = \widehat{\alpha}_i \mathcal{B}_i^{\widehat{\gamma}_i} \mathcal{R}_i^{1-\widehat{\gamma}_i} \left(\widehat{\gamma}_i \mathcal{B}_i^{-1} \frac{\partial \mathcal{B}_i}{\partial \widetilde{D}_i} + (1 - \widehat{\gamma}_i) \mathcal{R}_i^{-1} \frac{\partial \mathcal{R}_i}{\partial \widetilde{D}_i} \right) . \tag{C19}$$

Total funding as a function of state variables is defined by $\mathcal{B}_i(G_i, D_i, \pi_f) = B_{\min} + G_i + \pi_f \widehat{\phi}_i \mathcal{F}_i(G_i, D_i, \pi_f)$.

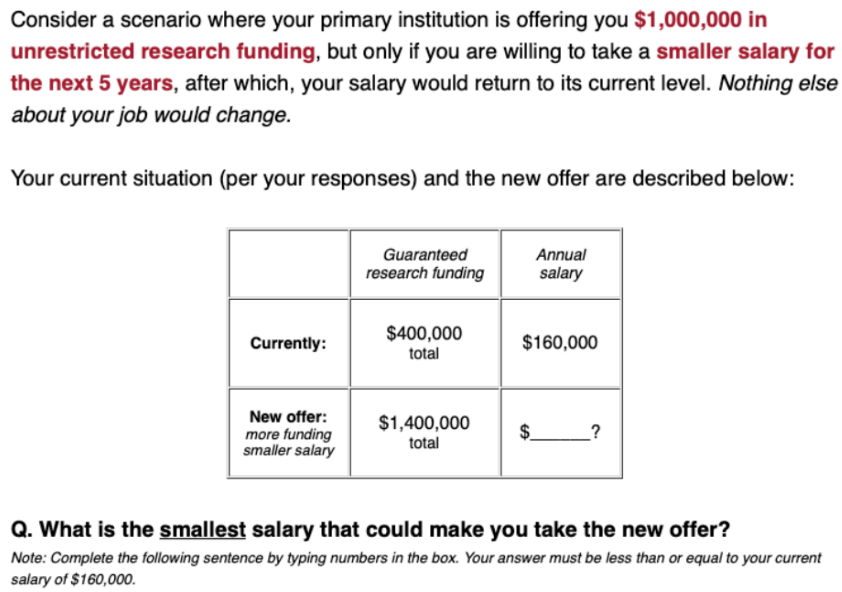
TABLE C1

Proportion of Response Variation Correlated with Model and Non-model Variables

	WTP +\$250K		WTP +\$1M		WTP +admin.		WTP –admin.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R^2	0.95	0.96	0.87	0.89	0.82	0.86	0.96	0.97
Model vars.	✓	✓	✓	✓	✓	✓	✓	✓
X		✓		✓		✓		✓
N obs.	4,003	4,003	4,003	4,003	4,003	4,003	4,003	4,003

Note: Reports the R^2 statistics from regressions of researchers' responses to the four experiments (i.e., their willingness to pay for the alternative scenarios) on different combinations of variables: *Model vars.* includes the state and choice variables of the model; **X** includes the full vector of variables that comprise the type index.

FIGURE C2
Example Image of Survey Experiment


Consider a scenario where your primary institution is offering you **$1,000,000 in unrestricted research funding**, but only if you are willing to take a **smaller salary for the next 5 years**, after which, your salary would return to its current level. *Nothing else about your job would change.*

Your current situation (per your responses) and the new offer are described below:

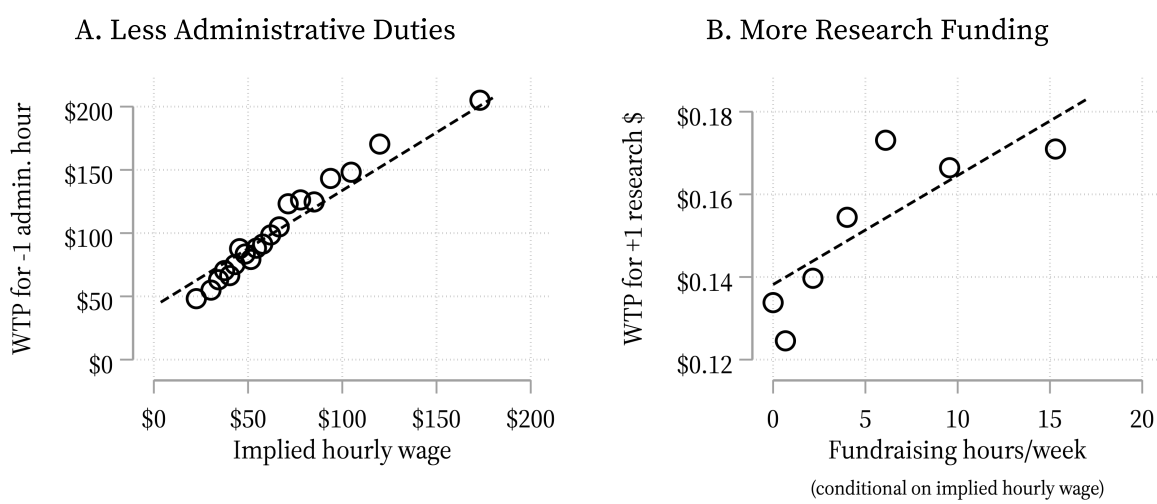
	Guaranteed research funding	*Annual salary*
Currently:	$400,000 total	$160,000
New offer: *more funding smaller salary*	$1,400,000 total	$______?

Q. What is the smallest salary that could make you take the new offer?

Note: Complete the following sentence by typing numbers in the box. Your answer must be less than or equal to your current salary of $160,000.

Note: Shows a screenshot of the survey experiment designed to solicit researchers' willingness to trade off their salary for additional guaranteed funding.

FIGURE C3
Correlations of Implied Valuations



Note: Shows a binned scatterplot and line-of-fit for the relationship between researchers' implied hourly wage and their willingness to pay for 1 less hour of administrative duties (Panel A), and the relationship between how many hours per week a researcher spends on fundraising and their willingness to pay for $1 more of additional research funds conditional on their implied hourly wage (Panel B).

TABLE C2
Potential Role of Non-response Bias and Stated Preference WTP Bias

	WTP +\$250K		WTP +\$1M		WTP +admin.		WTP –admin.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMR		–0.000858		–0.00391		–0.00466		–0.000835
		(0.00379)		(0.00593)		(0.00684)		(0.00327)
Benchmark		–0.0126***		–0.0258***		0.0134*		–0.0102***
		(0.00411)		(0.00644)		(0.00742)		(0.00355)
R^2	0.95	0.95	0.87	0.87	0.82	0.82	0.96	0.96
Model vars.	✓	✓	✓	✓	✓	✓	✓	✓
N obs.	4,003	4,003	4,003	4,003	4,003	4,003	4,003	4,003

Note: Reports the estimates from regressions of researchers' responses to the four experiments (i.e., their willingness to pay for the alternative scenarios) on a control for non-response bias in the form of the Inverse Mills Ratio (IMR) and a control for bias in individuals' stated WTP in the form of their WTP for the benchmark good (i.e., high-speed internet at home); all variables are standardized. *Model vars.* includes the state and choice variables of the model. Robust standard errors reported; $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

D. Additional Productivity and Efficiency Results

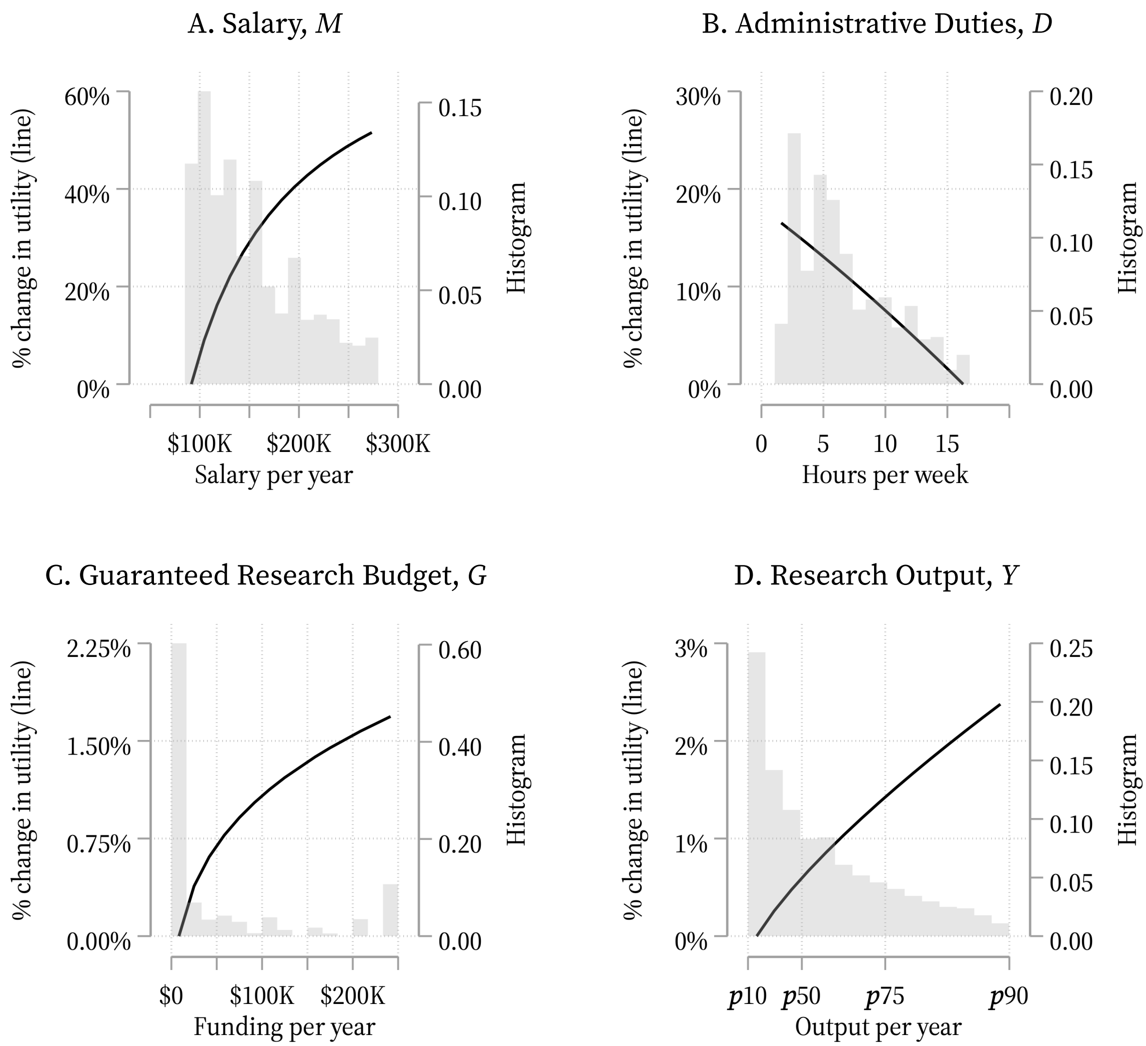
D.1. Additional Tables and Figures

TABLE D1
Observable Output Correlations

	Recent publications, count		Recent publications, cite-weighted	
	(1)	(2)	(3)	(4)
$\log(\alpha)$	0.201^{***}	0.176^{***}	0.276^{***}	0.254^{***}
	(0.0406)	(0.0397)	(0.0648)	(0.0648)
$\log(\text{recent grant }\$)$		0.0220^{***}		0.0174^{***}
		(0.00350)		(0.00525)
Field–FE, γ, ϕ, **X**–index	✓	✓	✓	✓
R^2	0.18	0.20	0.15	0.16
N obs.	2,703	2,703	2,703	2,703

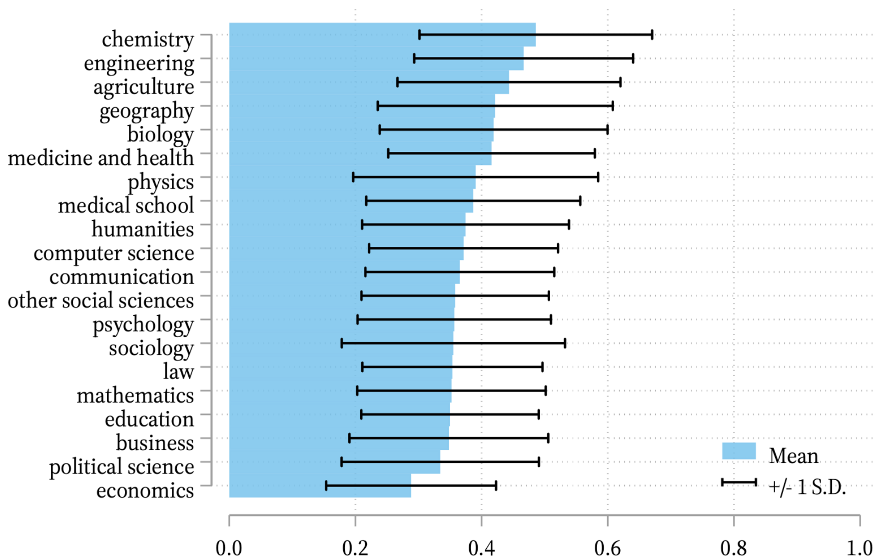
Note: Reports the estimates from regressions of researchers' publication measures (including publications from 2018–2022) on their estimated research productivity (α) as well as vector of controls that includes major field fixed effects (*Field-FE*) and the researchers' funding intensity (γ), fundraising efficiency (ϕ), their type (**X**-*index*), and, in some specifications, a control for their publicly observable research grant funding over the same period. Robust standard errors reported; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE D1
Utility Function Visualization



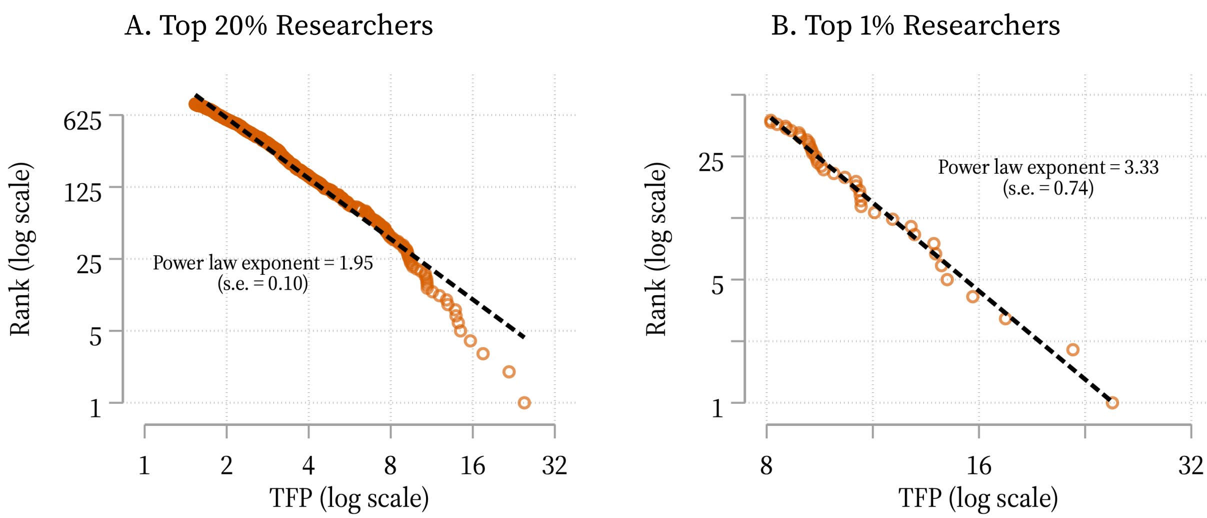
Note: Shows the percent change in utility in four of the key model variables (Panels A–D) holding all other variables and parameters fixed at the sample means. The black line (left y axis) shows the percent change in utility as the focal variable increases from the 10th percentile to the 90th percentile. The histogram (right y axis) shows the distribution of the focal variable in the sample. Note the different scales of all y axes. For simplicity, behavioral responses where researchers re-optimize are not incorporated here.

FIGURE D2
Research Funding Intensity (γ) by Minor Field of Study



Note: Shows the mean and standard deviations of researcher-specific estimates of the production function parameter γ_i (funding intensity) split by minor field of study.

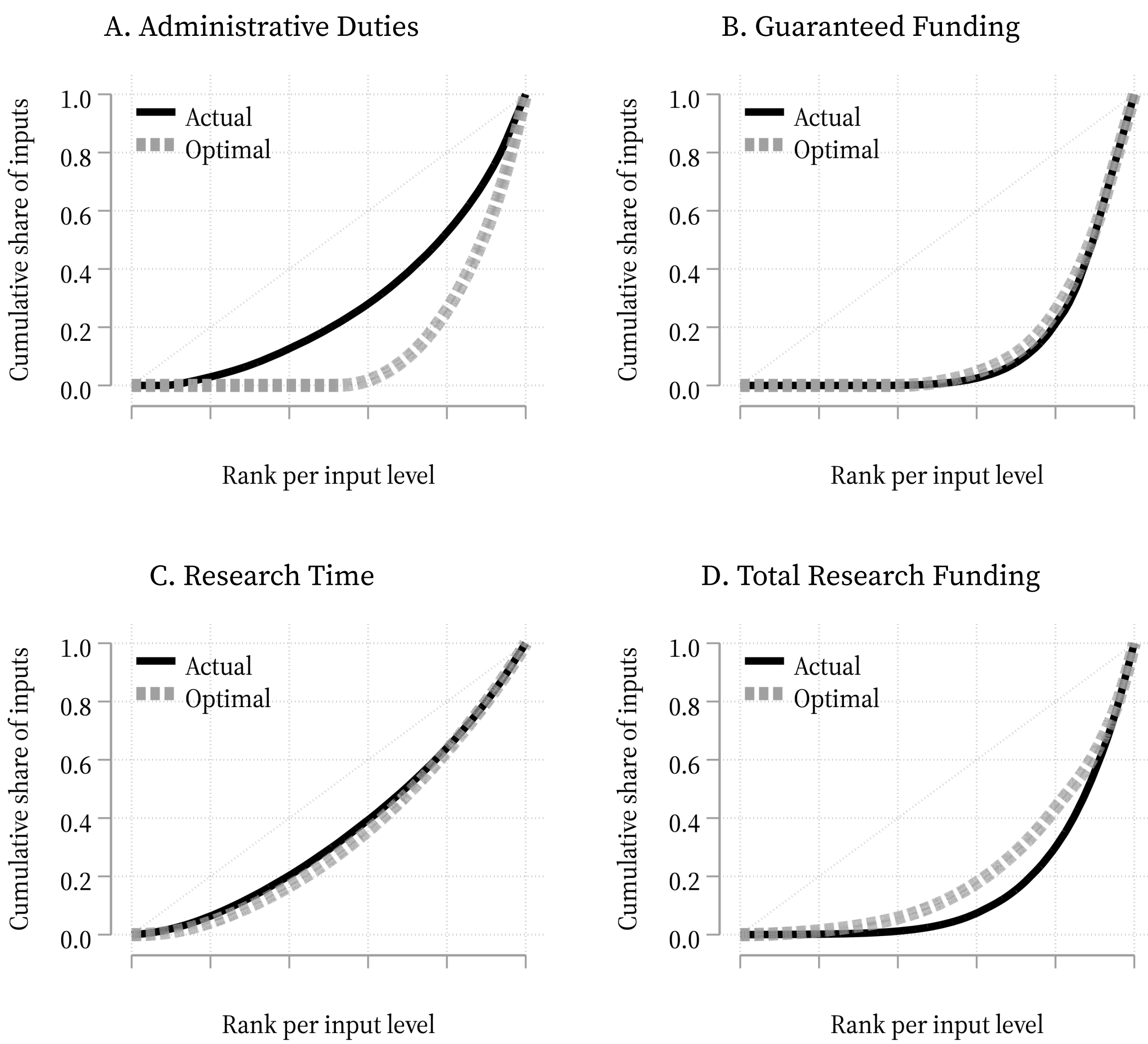
FIGURE D3
Power Laws in the TFP Tail



Note: Shows the log rank of researchers' TFP (α_i, where the sample mean is normalized to 1) versus the log of the TFP for either the top 20% of researchers (Panel a) or the top 1% (Panel b). The power law exponent reported is based on the linear regression of log rank on log TFP (see the dashed line) following Gabaix (2009).

FIGURE D4

Lorenz Curves for Actual and Optimal Input Levels



Note: Shows Lorenz curves for actual and optimal input levels. Researchers are sorted on the x axis per their ranking in terms of how much of each input they have, and the lines plot the cumulative share of total inputs (per the y axis) summing from the lowest- to highest-ranked researcher. Thus, plots closer to the 45^o line indicate input allocations closer to equality.

TABLE D2
Production with Actual and Optimized Allocations—Alternative Counterfactuals

	Current allocation	Optimized allocations				
	(1)	(2)	(3)	(4)	(5)	(6)
Research inputs						
Research hrs./week, avg.	18.5	–11%	+18%	+14%	+25%	+16%
Research hrs./week, s.d.	9.6	+6.0%	+18%	+43%	+39%	+41%
Budget $-K/year, avg.	147.1	0%	0%	0%	0%	+14%
Budget $-K/year, s.d.	206.9	+14%	–24%	–20%	–20%	–3.9%
Research output						
Output, avg.	*n.r.*	+1.3%	+149%	+159%	+158%	+161%
Output, s.d.	*n.r.*	+0.7%	+43%	+44%	+44%	+44%
Output per hr.	*n.r.*	+14%	+111%	+128%	+107%	+125%
Output per $	*n.r.*	+1.4%	+149%	+158%	+158%	+129%
Welfare						
Researcher utility, avg.	*n.r.*	+3.6%	+1.0%	+4.7%	+2.1%	+4.7%
Researcher utility, s.d.	*n.r.*	–5.7%	+0.3%	–5.4%	–2.4%	–5.4%
Researcher utility per hr.	*n.r.*	–8.3%	+16%	+16%	+21%	+18%
Researcher utility per $	*n.r.*	+3.6%	+1.0%	+4.8%	+2.3%	+16%
Social value, avg.	*n.r.*	+3.4%	+12%	+16%	+13%	+16%
Social value, s.d.	*n.r.*	–4.0%	+23%	+20%	+21%	+20%
Social value per hr.	*n.r.*	–8.5%	+25%	+26%	+30%	+28%
Social value per $	*n.r.*	+3.4%	+12%	+16%	+13%	+26%
Input reallocation						
Research hrs./week		9%	19%	27%	24%	25%
Budget $-K/year		14%	27%	28%	25%	25%
Objective, max		$\mathcal{V}$	$\mathcal{V}$	$\mathcal{V}$	Y	$\mathcal{V}$
Reallocate D		✓		✓	✓	✓
Reallocate G			✓	✓	✓	✓
Unconstrained B						✓

Note: Reports summary statistics for inputs under actual allocations (Col. 1). The first three sets of rows in Columns 2–6 report the percentage change in research inputs (*Research inputs*), outputs (*Research outputs*), and utility (*Welfare*) under alternative allocations; estimates are rounded to aid in comparison. The *Input Reallocation* rows report the amount of inputs reallocated expressed as a percentage of the total level of the input (e.g., 50% implies that half of all dollars are moved from one researcher to another). The bottom sets of rows outline the objective and constraints of the five different counterfactual allocations explored in Columns 2–6. The two different objectives explored are maximizing researchers' private utility ($\mathcal{V}$) or output (Y). D refers to administrative duties, and G refers to guaranteed research funding. *Unconstrained B* indicates the scenario when the total research budget is left unconstrained and so the total amount of funding in the market is limited only by researchers' fundraising choices. All optimized allocations allow for researchers' behavioral responses after D and/or G have been reallocated.

TABLE D3
Input Wedges and Gender Differences

	(1)	(2)	(3)	(4)	(5)
Panel (a): Actual research time					
Optimal level	0.301***	0.294***	0.300***	0.352***	0.349***
	(0.00970)	(0.00989)	(0.00991)	(0.00985)	(0.0102)
Female				−1.333***	−0.885***
				(0.286)	(0.279)
R^2	0.18	0.22	0.26	0.24	0.32
X: position		✓			✓
X: output			✓		✓
X: socio–demog.				✓	✓
N obs.	4,003	4,003	4,003	4,003	4,003
Panel (b): Actual research funding					
Optimal level	0.987***	0.982***	0.928***	0.985***	0.932***
	(0.00856)	(0.00883)	(0.0102)	(0.00939)	(0.0109)
Female				−12111.4***	−7907.5**
				(3950.8)	(3872.1)
R^2	0.65	0.65	0.67	0.67	0.69
X: position		✓			✓
X: output			✓		✓
X: socio–demog.				✓	✓
N obs.	4,003	4,003	4,003	4,003	4,003

Note: Reports results from regressions of actual input levels on optimal input levels and as described in Equation 10. Robust standard errors reported; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D.2. Mechanical Composition Effect in the Counterfactual

In Section 6.2, we estimate the growth in funding using current allocations that is necessary to achieve the same growth in output that we achieve using alternative allocations of the current funding. We choose guaranteed funding (G) as our policy lever for injecting funding into the market because it is exogenous in the model.[37] In the main counterfactual, we find that a 210% increase in guaranteed funding for all researchers—equivalent

[37]The other component of funding, which researchers obtain via fundraising, is the product of an exogenous component (researchers' fundraising productivity, ϕ_i) and an endogenous component (researchers' time spent fundraising, F_i). Practically, it is much easier to engage with simulations that manipulate G, especially when behavioral responses are allowed.

to a 210% increase in *aggregate* guaranteed funding ($G \equiv \sum_i G_i$)—translates into an 85% increase in total aggregate funding ($B \equiv \sum_i B_i$), which then yields a 160% increase in aggregate output ($Y \equiv \sum_i Y_i$). This may seem counterintuitive given that our specification of the scientific production function features decreasing returns to funding ($\gamma_i < 1$ for all i). Below, we explain how this can occur.

Recall the production functions is: $Y_i = \alpha_i B_i^{\gamma_i} R_i^{1-\gamma_i}$, where B_i is researcher i's total funding and R_i is their time spent on research. A researcher's total budget is:$B_i = G_i + B_{min} + \phi_i F_i$. Given these functional forms, the marginal change in a researchers' log-output ($d\ln(Y_i)$) given a change to their total budget, holding their time spent on research (R_i) fixed, is: $d\ln(Y_i) = \gamma_i d\ln(B_i)$. Next, define a researcher's share of total funding due to their guarantees as: $s_i \equiv G_i/B_i$.

This allows us to approximate the marginal change in a researcher's log-output given a change to their guaranteed funding: $d\ln(Y_i) \approx \gamma_i s_i d\ln(G_i)$, which holds as an approximation because it keeps s_i fixed to its value before the change. Define a researcher's share of total budget as: $t_i \equiv B_i/B$, and their share of total output under initial allocations as: $z_i \equiv Y_i/Y$. Thus, the relative change in aggregate budget and aggregate output given a change in each individual researcher's output are: $d\ln B \approx \sum_i t_i d\ln(B_i)$ and $d\ln Y \approx \sum_i z_i d\ln(Y_i)$. Combining these last two equations with previous derivations gives us two expressions for the relative change in aggregate budget and in aggregate output given an average relative change in funding guarantees: $d\ln(B) \approx \sum_i t_i s_i d\ln(G_i) \approx \sum_i t_i d\ln(B_i)$ and $d\ln(Y) \approx \sum_i z_i \gamma_i s_i d\ln(G_i) \approx \sum_i z_i \gamma_i d\ln(B_i)$.

If there is a positive covariance between the $d\ln(B_i)$ and γ_i terms, *then the relative growth in aggregate output (Y) can exceed the relative growth in the total budget (B)*. This is what we find in practice. Furthermore, note that the change in aggregate budget never exceeds the change in funding guarantees ($d\ln(G_i)$), because it is a convex combination of individual $d\ln(B_i)$, and the latter never exceed $d\ln(G_i)$ because the weights s_i are smaller than one. In contrast, $d\ln(Y)$ is not a convex combination of variations in individual budget $d\ln(B_i)$, because the sum of $z_i\gamma_i$ weights may exceed one. Therefore, a positive covariance between γ_i and $d\ln(B_i)$ inflates $d\ln(Y)$.

TABLE D4
Input Wedges per Common Productivity Proxies

	(1)	(2)	(3)	(4)
Panel (a): Actual research time				
Optimal level	0.508***	0.506***	0.509***	0.508***
	(0.0164)	(0.0166)	(0.0162)	(0.0163)
Recent research funding, own	0.130***			
	(0.0311)			
Recent research funding, institution		−0.0137		
		(0.0139)		
Recent publications			0.177***	
			(0.0197)	
Recent citations				0.148***
				(0.0223)
R^2	0.32	0.30	0.33	0.32
X: position, output, socio–demog.	✓	✓	✓	✓
N obs.	3,072	3,057	3,072	3,072
Panel (b): Actual research funding				
Optimal level	0.746***	0.763***	0.744***	0.753***
	(0.0110)	(0.00974)	(0.0106)	(0.0101)
Recent research funding, own	0.0767***			
	(0.0264)			
Recent research funding, institution		0.00202		
		(0.00958)		
Recent publications			0.0760***	
			(0.0153)	
Recent citations				0.0592***
				(0.0142)
R^2	0.70	0.69	0.69	0.69
X: position, output, socio–demog.	✓	✓	✓	✓
N obs.	3,072	3,057	3,072	3,072

Note: Reports results from regressions of actual input levels on optimal input levels and common proxies for researchers' productivities. All variables are standardized. All proxies are based on data from one to two years prior to the survey. Robust standard errors reported; * $p < 0.10$,** $p < 0.05$,*** $p < 0.01$.

E. Trends in Science and Meta-science

Data on total US R&D spending is sourced from the National Center for Science and Engineering Statistics (NCSES).[38] Data on meta-science studies is sourced from (*i*) the *OpenAlex* publication database, which covers virtually all fields of science,[39] and (*ii*) the *PubMed* publication database, which focuses primarily on the life and biomedical sciences.[40]

OpenAlex is valuable in that its coverage spans a tremendous range of scientific fields; however, the categorization scheme used to index publications by topics is relatively coarse and lacks a clear set of topic codes for meta-science. In order to identify meta-science publications in OpenAlex, we restrict our focus to all journal-article publications flagged with the following topic codes: *scientometrics and bibliometrics research; scientific research and philosophical inquiry; philosophy and history of science; academic writing and publishing; science and science education; international science and diplomacy; innovation, technology, and society; research, science, and academia*.

PubMed is clearly a strict subset of scientific fields; however, publications are indexed with relatively fine-grain topic codes that facilitate the identification of meta-scientific studies. In order to identify meta-science publications in PubMed, we restrict our focus to all journal-article publications flagged with the following topic codes: *efficiency; research personnel; research support as topic; grants peer review; knowledge discovery; scholarly communication; allocative efficiency; grants; funding, capital*.

Clearly, in both cases, the set of topics we use to flag meta-science will include some false positives, and we surely have a non-trivial number of false negatives. However, we have no reason to suspect these error rates should be evolving significantly over time.

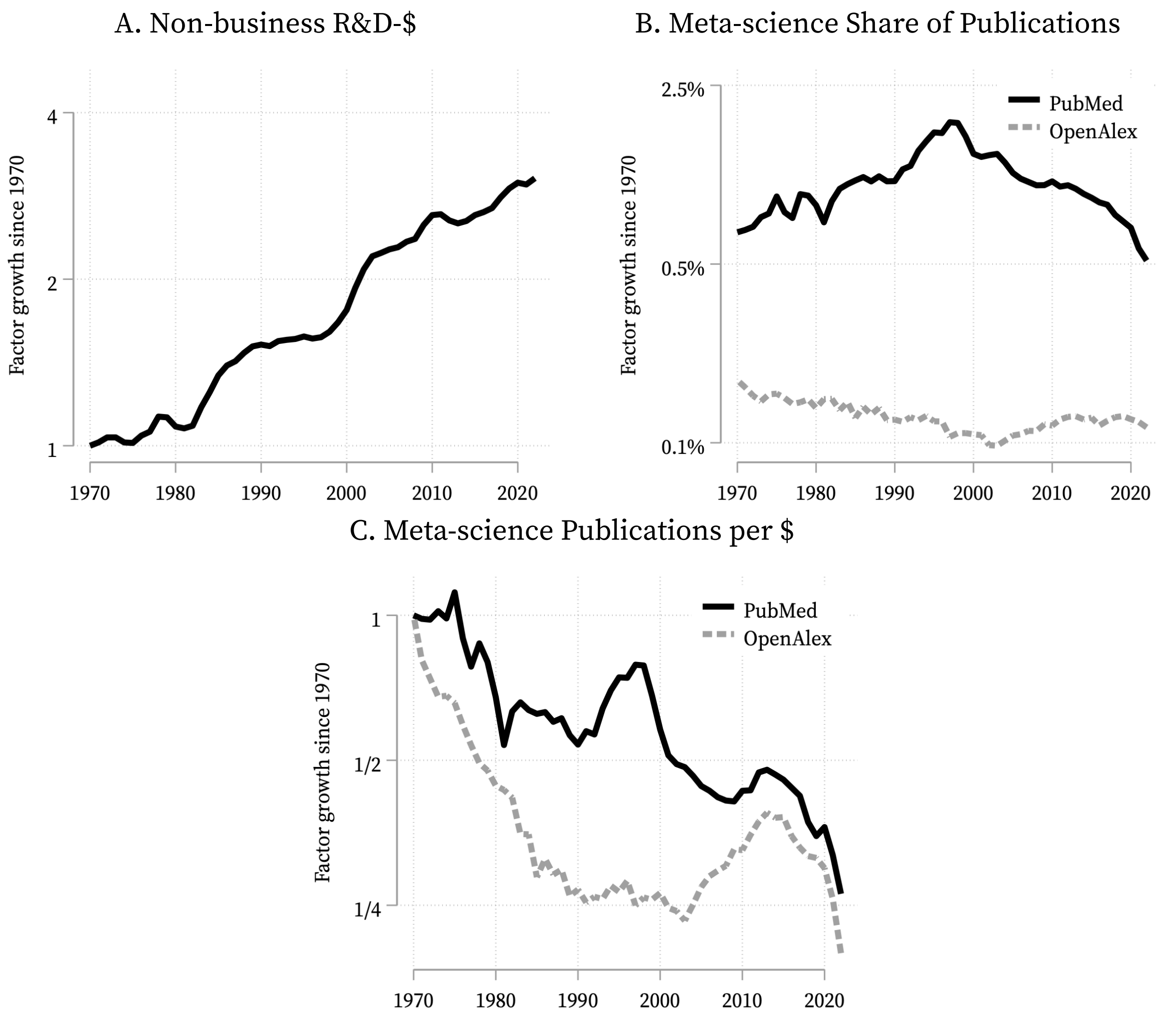
Figure E1 reports the trends for the past 50 years for total non-business R&D in real-$ (see Panel A), the share of all publications focused on meta-science (see Panel B), and the count of meta-science studies per $ shown in Panel A (see Panel C).

[38] See: National Center for Science and Engineering Statistics (NCSES). 2025. *U.S. R&D Totaled $892 Billion in 2022; Estimate for 2023 Indicates Further Increase to $940 Billion*. NSF 25-327. Alexandria, VA: U.S. National Science Foundation. Available at https://ncses.nsf.gov/pubs/nsf25327/.

[39] See: Priem, J., Piwowar, H., & Orr, R. (2022). OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts. ArXiv. https://arxiv.org/abs/2205.01833.

[40] See: PubMed [Internet]. Bethesda (MD): National Library of Medicine (US), National Center for Biotechnology Information; 2004 – 2025. Available from: https://pubmed.ncbi.nlm.nih.gov.

FIGURE E1
Relative Growth in Science and Meta-science since 1970



Note: Shows the relative growth in real, non-business R&D spending in the US since 1970 (Panel A), the share of publications focused on meta-science (Panel B), and the count of meta-science publications per non-business R&D dollar (Panel C), using either the OpenAlex or PubMed publication databases.