New facts and data about US research professors

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Abstract

We introduce the National Survey of Academic Researchers, a new survey of professors at roughly 150 of the most research-intensive institutions of higher education in the US. We document six new features of how research professors are compensated, their socio-demographics, how they spend their time, and how they perceive their research pursuits: (1) There is more inequality in earnings within fields than there is across fields. (2) Differences in tasks, income sources, fields, and institutions can account for roughly 40% of the total variation in earnings. (3) There is significant variation across fields in the correlations between earnings and different kinds of research output. (4) There are substantial differences between professors' gross research output and their average productivity in terms of output per hour worked. (5) Researchers' willingness to take risks in their personal lives is highly predictive of their willingness to take risks in their research. (6) Personal risk-taking is also highly predictive of researchers being orientated towards more applied science. An anonymous version of the individual-level responses are publicly available at: [data preparation still in progress].

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1 Introduction

Researchers are at the core of economic growth. The quantity and quality of their new ideas are what enable technological change (Jones 2022). In the U.S., the most common employer of researchers is academic institutions,[1] and a long body of evidence has documented the importance of academic science for industrial progress.[2] Amidst concerns of declining R&D productivity (Jones 2009; Bloom et al. 2020) and an increasing division of labor between industry and academia (Arora et al. 2020), it has become increasingly important to understand the academic research workforce.

While historically dominated by philosophers (e.g., Popper 1934; Kuhn 1962; Godfrey-Smith 2009), the "science of science" has become increasingly populated by quantitative analyses by economists, sociologists, physicists, and other scholars looking to turn their empirical tool-kits inwards (Azoulay et al. 2018; Fortunato et al. 2018). But most of these empirical studies make use of a small number of data sources that were assembled as a byproduct of conducting science, not as intentional sources of data to study science. Scientific inputs are usually measured using federal grant databases, which covers only some fraction of funding flows and leaves unobserved arguably the most important input in the scientific production function, researchers' time. Outputs are usually measured using publication databases, which generates serious measurement error for any researcher whose output is not codified in print. Many other important aspects of researchers' work and lives are left only partly visible at best: their professional position (e.g., tenure status, administrative duties); their incentives (e.g., sources of income); and the objectives of their research (e.g., their intended audience).[3]

In this paper, we document a new nationally representative survey of research professors at the, roughly, 150 largest institutions of higher education in the US. The population and sample includes professors from all fields of science, broadly construed: humanities and related fields; medicine and health; natural, social, and mathematical, sciences. The survey instrument includes a number of novel elements related to researchers' rank and tenure status, time use, funding, salaries and sources thereof, the nature of their research, in addition to a battery of socio-demographic and household-related factors.

[1] According to the 2021 National Science Foundation Survey of Doctoral Recipients: 42% of Ph.D. scientists and engineers work at educational institutions; 37% work at private, for-profit businesses; 15% work at non-profit or government agencies; and the remainder are employed by other organization types or are self-employed (National Science Foundation 2021).

[2] See, for example, Cohen (2010) or Perkmann et al. (2021) for excellent reviews on this topic.

[3] Still, impressive efforts are still underway to improve the fidelity and interoperability of existing meta-science datasets (e.g., Marx and Fuegi 2020; Lin et al. 2023, UMETRICS at https://iris.isr.umich.edu/, and the Innovation Information Initiative at https://iii.pubpub.org/datasets).

Our approach follows a long line of prior work that has used surveys of researchers to uncover their otherwise unobservable features, choices, preferences, or beliefs (e.g., Levin and Stephan 1991; Fox and Stephan 2001; Stern 2004; Sauermann and Cohen 2010; Curty et al. 2017; Levecque et al. 2017; Shortlidge and Eddy 2018; Ganguli and Gaulé 2019; Cohen et al. 2020; Philipps 2022). However, unlike many prior surveys of researchers, a guiding principle of our effort was "breadth over depth" such that many design choices reflect an objective of shedding new light on features of this market that have been largely ignored by empiricists in hopes that the summary statistics and correlations in this survey might spark more detailed, focused, and rigorous investigations into the causal effects underlying the patterns we see.

Before reporting the major findings of the survey, we describe the population, sampling methodology, recruitment protocol, and summary statistics. To test for representativeness, we use multiple dimensions of data that are observable for respondents and non-respondents. At the institutional level, we use data from the National Science Foundation's HERD survey (National Science Foundation 2023) to show that respondents come from institutions that receive relatively equal amounts of research funding from a variety of sources. At the individual level, we use data from publication and grant records to show a high degree of similarity in these metrics between respondents and non-respondents. Additionally, as one test of attention and honesty, we match a sub-sample of respondents to their publicly reported salaries and find a high degree of alignment

We document six key new findings about the research professor workforce:

Finding 1: There are significant differences in earnings across fields at the individual- and household-level, and professors exhibit positive assortative matching, but there is much more inequality in earnings within fields than there is across fields.

Finding 2: There are significant differences in the implied wages of professors' work and their earnings across fields and institutions, and these differences can account for roughly 40% of the total variation in earnings across all professors.

Finding 3: There are significant differences across fields in the implied returns to producing research outputs (e.g., earnings per publication), and these differences can roughly 10% of the total variation in earnings across all professors.

Finding 4: There is substantial variation in professors' time allocations, which can lead to large differences between professors' gross output (i.e., annual publications) relative to their average productivity (i.e., publication per research hour).

Finding 5: Three of the strongest predictors of perceptions about how risky a professor's research are: (1) the share of their time spent fundraising; (2) their willingness to take risks in their personal lives; and (3) an orientation towards asking questions with their research (as opposed to answering questions).

Finding 6: Professors' position on the basic–applied spectrum can be proxied with the intended output and audience of their research; more applied "Edison-like" researchers, whose output is more likely to be tools and products and whose audience is more likely to be businesses and policymakers, report a higher willingness to take risks in their personal lives.

We do not report any causal effects in this paper, taking all equilibrium correlations as representative of some combination of treatment and selection effects. In some cases, we report decompositions based on the R^2 and partial-R^2 statistics based on some simple linear models of focal outcomes and some covariates. Our goal with these exercises is to determine how much the variation in the focal outcome can be described by the covariates, which indicates the extent to which any treatment or selection effects are important along those dimensions. We also report the results of "hedonic earnings regressions", a term which we will summarily use to describe regressions of professors' earnings on a set of (possibly endogenous) covariates such as professors' time spent on different tasks. We cannot guarantee that the variation in covariates across professors is exogenous (e.g., uncorrelated with unobservable differences in preferences or abilities). Still, the broad patterns that emerge provide useful views of equilibrium relationships and motivate new hypotheses about the incentives facing academic researchers.

An anonymous version of the individual-level data is publicly available here: [data preparation still in progress]. We hope the results reported in this paper, and the public data, will prove useful as sparks for further investigation into the academic research workforce. The rest of the paper is organized as follows: Section 2 describes the survey methodology and some summary statistics; Section 3 walks through our key new findings; Section 4 concludes with a discussion.

2 Methodology: Population, sampling, and survey

2.1 Population and sampling

Our target population is U.S. professors who conduct research at major institutions of higher education. We identify this population by selecting the 154 largest institutions in the U.S.

per their total R&D funding reported in the National Science Foundation's 2019 Higher Education R&D (HERD) survey (National Science Foundation 2023). We hired individuals to manually collect the emails of professors from these universities' websites (i.e., people listed on the website with the word "professor" in their position title) as well as information on each professor's name, program and/or department and/or college, and professorial rank.

Table 1 reports summary statistics for the institutions included in the population based on variables sourced from websites as well as the HERD survey.

Our sampling process was as follows. Based on the information gathered, we classified these emails into one of 22 fields of study and one of four ranks (assistant, associate, full or emeritus, and adjunct or other). We then sent an e-mail invitation to a randomly-selected half of the e-mails within each field-rank cell. These e-mails were distributed from October 2022 to March 2023.

The population consisted of 262,343 unique e-mails. We e-mailed a total of 130,785 individuals and 4,357 (3.33%) completed the survey.[4] We then restrict the sample to the 4,145 individuals (95.1% of respondents) who reported being a professor and spending a non-zero amount of time on research. Our final sample consists of professors from the natural sciences (1,017; e.g., biology, chemistry, engineering, physics), social and mathematical sciences (1,169; e.g., computer science, economics, math, psychology), humanities (814; e.g., communications, education, linguistics), and health or medical sciences (1,145; e.g., schools of medicine or public health). We use these four aggregate groupings of fields throughout our discussion and empirical analyses given the small sample sizes within narrower field definitions.

2.2 Sample summary statistics

Table 2 reports summary statistics for a majority of the components solicited in the survey. The majority of respondents are full professors (41%) followed by roughly equal proportions of assistant (27%) and associate professors (23%) with the remainder being adjunct, clinical, or other types of professors (9%). The distribution across aggregate fields is relatively even, although we imposed these field groupings in a way that sought approximate balance in subsample sizes. Most respondents are tenured (59%), with another 22% still on the tenure-track and 20% not on the tenure track at all. The average number of years since tenure for those who are tenured is approximately 15 years. For those not on the tenure track, the average contract length is about 2.5 years, and for those pre-tenure, the average years until their tenure evaluation is about 2.6 years.

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

On average, individuals work roughly 50 hours per week, which is nearly eight hours more than the national average for full-time workers (US Bureau of Labor Statistics 2023). The average annual income is approximately $165,000, which is approximately the 93rd percentile in the US (US Census Bureau 2023). The standard deviation is nearly $100,000, indicating a significant amount of heterogeneity, which we return to below.

The average 5-year guaranteed research funding is roughly $85,000 per year, but with a very high standard deviation ($200,000 per year), suggesting tremendous heterogeneity across researchers. The same is true of researchers' expected fundraising, which is on the same order of magnitude as their current guarantees.

The majority of the individuals are White (79%), followed by Asian (12%), with these groups being slightly (Whites) and substantially (Asians) over-represented relative to their shares of the full US population (US Census Bureau 2023). The representation of Black, Hispanic, and other ethnicities is relatively low at 3%, 6%, and 4% respectively. Nearly 25% of professors are non-US born, nearly double the rate of the full US population (US Census Bureau 2023), which is yet another signal of the importance of immigration for the US research enterprise (e.g., Kerr 2020).

To get some initial sense of heterogeneity across fields, Tables 3–4 report field-level averages of researchers' time allocations (Table 3) and the fraction of their own earnings due to different sources (Table 4). Table 5 reports the summary statistics for the "nature of research" questions, which solicited researchers' intended outputs and audience of their work.

3 Findings

> **Finding 1**: *There are significant differences in earnings across fields at the individual- and household-level, and professors exhibit positive assortative matching, but there is much more inequality in earnings within fields than there is across fields.*

Variation within and across fields in academic researchers' salaries is a regular conversation topic within the halls of most universities. But the difficulties of systematically matching researchers' fields to their salaries has limited the number of systematic observations of this variation except in specific cases (e.g., Mohanty et al. 1986; Hamermesh 1988; Bellas 1997; Baker et al. 2023). Furthermore, most existing data on researchers' earnings leave the remainder of the household (e.g., spouses' earnings) untouched despite the importance of the household as an economic unit (Chiappori and Mazzocco 2017).

Figure 1 reports field-level average self-reported total annual earnings for individuals (Panel a) as well as households (Panel b). Professors' individual earnings span lower values

of approximately $130,000 per year in fields such as the humanities, communication, agriculture, and education. Earnings in the highest-paying fields, economics, medicine, law and business, span $200,000–250,000. As evidenced by the strong positive relationship between individual and household earnings (Panel c), there is clear evidence of positive assortative matching amongst research professors. Furthermore, it appears that the degree of this matching is relatively similar across most fields as evidence by most field-level averages lying relatively close to the linear fit of the relationship between own and household earnings.

This sort of matching can have some effect on earnings inequality. For comparison, Greenwood et al. (2014) study the full US population and observe a household-level Gini coefficient of 0.43, which would be 0.34 in the absence of positive assortative mating. We observe a similar pattern here, albeit to a lesser degree, where the observed household Gini coefficient within the sample is 0.32, which would be 0.28 in the absence of similar matching.

To get a sense as to the variation in earnings across and within fields, Panel (d) of Figure 1 plots the household-level Gini coefficients within each field, which span roughly 0.25 to 0.36, as well as the Gini coefficient across the field-level averages, which is roughly 0.1. These differences indicate that there is much more inequality in incomes within fields than there is within fields, a novel fact of inherent and policy relevance to the market for academic research labor. Furthermore, this motivates a need for a better understanding of what drives heterogeneity in earnings across professors, which we turn to next.

> **Finding 2** *There are significant differences in the implied wages of professors' work and their earnings across fields and institutions, and these differences can account for roughly 40% of the total variation in earnings across all professors.*

What explains the heterogeneity within and across fields shown in Figure 1? More generally, how much of the variation in professors' earnings can be explained by observable differences in their work? Research efforts may be a key difference, but is only one of professors' many tasks that could influence their earnings.

To better understand earnings differences, we estimate two hedonic earnings regressions that relate professors' earnings to either their time spent on six different tasks (research, fundraising, teaching, administration, clinical, or other) or the source of their earnings (base salaries, grant-covered, supplemental income from their primary institution, clinical work, or other). The results of these two regressions are presented in Table 2, Panels (a) and (b), respectively.

There are substantial differences in the implied returns to different tasks (Figure 2, Panel a). Clinical work is associated with the most earnings, nearly $90 per marginal hour, which is intuitive given the fact that most of this clinical work is done by professors at academic

medical systems where these efforts are typically directly compensated. Research, administration, and "other" tasks are all associated with roughly \$30–50 per hour of additional earnings. More fundraising is less positively associated with earnings, while additional time spent on teaching activities is associated with negative marginal earnings. Clearly, this reflects some significant selection effect whereby positions with larger teaching responsibilities also have lower salaries. But this hedonic regression makes this negative premium clear.

Overall, Figure 2 Panel (b) illustrates that professors who have a larger share of their earnings coming from sources other than their base salary also tend to have higher total earnings, especially for those undertaking clinical work. Figure 2 Panel (c) shows that there is considerable variation in earnings across institutions. Notably, the distribution appears to be slightly right-skewed, which is consistent with a few institutions offering particularly large salaries for all fields.

We decompose the variation in earnings across professors more formally in Figure 2 Panel (d). Field-level averages and differences in time spent on tasks each account for slightly more than 10% of the variation across professors. Earnings sources do not seem important compared to other differences across professors, while institutions account for the largest amount of variation (roughly 20%). Altogether, these four forces can explain roughly 40% of the variation in earnings across professors. This suggests that nearly two-thirds of the variation may be due to idiosyncratic differences. We focus on one of those differences, research output, below.

> **Finding 3** *There are significant differences across fields in the implied returns to producing research outputs (e.g., earnings per publication), and these differences can roughly 10% of the total variation in earnings across all professors.*

And how do different fields (implicitly) reward different types of research progress? Understanding researchers' behavior requires understanding the incentives they face. Being able to combine salary data with grant and bibliometric data allows us to uncover new patterns about how researchers are rewarded by their universities and the profession at large.

Figure 3 Panel (a) reports the results of a hedonic regression of earnings on research inputs and outputs (i.e., grants, publications and citations). In this regression, we interact the research metrics with indicators for each of the four aggregate fields in our sample. For each of the three metrics, we standardize the variation within each aggregate field so that a unit increase in each metric corresponds to a one s.d. increase per the distribution within the aggregate field.

We find substantial differences across fields in terms of the implied earnings per research metric. All fields implicitly reward grant funding, with a one s.d. increase being associated

with somewhere between $7,500–15,000 in additional annual earnings. There are positive implied returns to publications across all fields as well, although there are dramatic differences in magnitudes and the differences between publications and citations. Humanities, social, mathematical, and related sciences appear to put a much larger value on citations relative to publications — the returns to citations are 2–3× the returns to publication counts. The "hard" sciences appear to operate in the opposite way — there, there are roughly zero (or negative) returns to citations while there are large returns to publication counts. Overall, these point to very different norms across fields in terms of how researchers are rewarded for output.

We more formally decompose earnings heterogeneity again, focusing on these research metrics, in Figure 3 Panel (b). Differences in these research metrics appear roughly equally as important as field-level differences; including all three research metrics in the model with the field indicators doubles the R^2.

> **Finding 4**: *There is substantial variation in professors' time allocations, which can lead to large differences between professors' gross output (i.e., annual publications) relative to their average productivity (i.e., publication per research hour).*

Time is a key input into knowledge production and an advantage of a survey is being able to delve more deeply into researchers allocate their time. Professors generally balance multiple roles in a university, only one of them being research. In grant-intensive fields, for example, many have raised concerns that scientists devote too much time to unproductive activities in order to win grants (Gross and Bergstrom 2019; Collison et al. 2021).[5]

We ask respondents how many hours they expect to work on average in a given week over the next five years, and then how they expect to allocate that time across six categories of activities: Research (including supervising others), fundraising for research, teaching or advising (not as a part of their own research), service, clinical or medical practice, and all other activities.[6]

Figure 4 Panel (a) shows the distribution of time spent on the six categories. Research and teaching take up the most time. There is a wide spread of hours allocated to research – the average respondent spends 19 hours per week on research, with a standard deviation of 10 hours.

The wide spread in time spent on research means that measures of researchers' "productivity" that rely only on output levels may be biased because of unobservable differences in

[5]See Ayoubi et al. 2019 and Myers 2022 for why not all time and effort devoted to fundraising is wasteful.

[6]Technically we ask this as a prospective question so that it is consistent with later questions in the survey where we investigate how respondents trade off time with other inputs. However, in practice we expect a high degree of correlation between past time allocation and future time allocation.

input levels. How large of a problem might this be? We find that the correlation between publications per research hour and gross output is 0.5, suggesting that gross output measures are still informative, but may be misleading. To further investigate this issue, Figure 4 Panel (b) plots the rank of researchers in our sample using their gross output level (publication counts) compared to their rank based on their output per hour. We find that only for about 40% of professors is their gross output rank within 10% their output-per-research-hour rank. This suggests the existence of many researchers who are more productive than standard bibliometric measures (when not adjusted for differences in input levels) would suggest. Understanding who these researchers are and whether more resources ought to be allocated to them is a key policy question.

> **Finding 5** *Three of the strongest predictors of perceptions about how risky a professor's research are: (1) the share of their time spent fundraising; (2) their willingness to take risks in their personal lives; and (3) an orientation towards asking questions with their research (as opposed to answering questions).*

Discourse about innovation and science policy often asserts that the system overly discourages scientists from taking risks, causing society to miss out on high-impact scientific discoveries and inventions (e.g. Alberts et al. 2014). To explore this issue, most empirical work has focused on generating ex-post measures of risk based on bibliometric measures (e.g. Greenblatt et al. 2022).[7] These ex-post measures of publications are clearly limited in their ability to proxy for ex-ante risk-taking by researchers.

In this survey, we take a new step towards better understanding risk preferences amongst researchers by asking respondents for self-reported measures of risk-taking. Following Falk et al. (2018), we ask respondents to report how much risk they take in their personal lives, in their research, and how risky their peers think the respondent's research is.[8] Figure 5 shows the results from a Lasso regression of research risk-taking on the full set of covariates from our sample. While personal risk-taking is one of the strongest predictors of research risk-taking, it is also far from a perfect predictor, with a pairwise correlation of 0.21. While much more work needs to be done into understanding the determinants of risk-taking behavior and its relation to science, this may be an indication that risk-taking in research is context dependent and can be affected by policy.

Time spent fundraising also strongly predicts research risk-taking , with a pairwise correlation of 0.22. This could be a reflection that if a researcher does work that requires grant

[7] See Carson et al. (2022) and Carson et al. (2023) for exceptions.

[8] Falk et al. (2018) ask about risk-taking in respondents' personal lives. We adapt their question to ask about risk in research.

funding, in addition to uncertainty about whether a project will "succeed", there is an additional layer of uncertainty of whether funding will be successfully obtained that is separate from the project's likelihood of success conditional on sufficient resources, and researchers may interpret this as being more risky. Alternatively, it may be that, on average, projects that are more ambitious and risky tend to be projects that also require more resources and hence fundraising. This points to the need for more work on understanding what risk means to researchers: What are the outcomes they care about? How do they perceive risk (Holzmeister et al. 2020)?.

Another strong predictor of research risk-taking is whether respondents say their work is more about "asking questions" (basic) versus "answering questions" (applied). Research risk-taking is negatively correlated with more applied work. This highlights that risk in the personal domain and risk in research are distinct concepts to researchers. It is not immediately clear why researchers doing more basic work perceive their research to be riskier than researchers doing applied work. It is possible that basic research is inherently more uncertain (or feels more uncertain) than applied research, since it is by definition done without a specific application in mind.

> **Finding 6**: *Professors' position on the basic–applied spectrum can be proxied with the intended output and audience of their research; more applied "Edison-like" researchers, whose output is more likely to be tools and products and whose audience is more likely to be businesses and policymakers, report a higher willingness to take risks in their personal lives.*

Understanding the selection of research topics by researchers and the rewards for these choices is crucial to understanding how the direction of science and innovation is determined. One approach of characterizing research is on a spectrum of "basic" to "applied". However, creating a quantitative measure solely based on existing data is challenging. For example, bibliometric measures such as patent citations may have limited validity in some fields where patenting is rare.

Our survey allows us to directly ask scientists how they view their own research. We do so in three ways. First, we asks the respondents to rate on a scale of 1 to 10 whether their research is more about "generating new theories" (basic) or "testing existing theories and hypotheses" (applied).[9] In addition, we ask respondents about their intended outputs and audiences for their research.[10]

[9] "Use the scale below to rate whether the overall objective of your current research is more (A) to generate new theories and hypotheses, or is more (B) to test existing theories and hypotheses, or is somewhere in between."

[10] Options for intended output are: publications, books, tools (e.g. data, software, instruments), or prac-

To combine the information contained in all of these nature-of-research questions, we use Principal Components Analysis (PCA) to estimate a single index, which we term the "Bohr-Edison index". More negative values of this index indicate more "Bohr" like research where the objective is to ask questions, write academic papers, and speak to an academic audience. Converseley, more positive values of the index indicate more "Edison" like research where the objective is to answer questions, develop tools and products, and speak to an audience of businesses and policymakers. Figure 6 Panel (a) reports the results from the PCA. Panel (b) of the same figure reports the field-level average scores. The ranking is intuitive, with traditionally "theoretical" fields like mathematics and physics scoring more towards the Bohr end of the spectrum, and more applied and technically-oriented fields like agriculture, law, and medicine scoring more towards the Edison end of the spectrum.

One way to conceptualize basic-vs.-applied research is the ability of the researcher to appropriate the value of their outputs. The value of more basic research is more fundamental in nature and may be harder to appropriate, and vice versa as the research becomes more applied. In this vein, Figure 6 Panel (c) plots researchers' earnigns as a function of their Bohr-Edison score, and we do find a strong positive correlation except for the most applied researchers in the sample.

To understand what variables are most predictive of the Bohr-Edison score, we run a Lasso regression of the Bohr-Edison index on our full set of covariates. Figure 6 (d) shows the 10 variables that are most frequently selected out of 100 bootstrap sub-samples (the "stability selection share"), and the univariate correlation of each of those variables with the Bohr-Edison index. A noteworthy finding here is that personal risk-taking is associated with doing more applied work with a correlation coefficient of 0.21. This is an example of a pattern that would be difficult to find using ex-post measures of risk aversion (e.g. based on citations or text of publications and patents) because it is difficult to know whether cross-field differences in such measures are due to underlying researcher characteristics or simply reflect field differences (e.g. different citation norms). There are also no obvious ex-ante theories for why such a correlation might exist. One possibility could be related to the correlation the Bohr-Edison index and time spent fundraising (correlation coefficient of 0.22). Since fundraising is likely to be more important in more applied fields, and fundraising is an endeavor with some uncertainty, then risk-tolerant people may be more likely to select into such fields.

tical applications (products, patents, policies). Options for intended audience are: other academics, policymakers, businesses, or the general public. Respondents whether each of these options is their intended audience or output "Never or rarely", "Sometimes", or "Most or all of the time". Options are coded as 0, 1 or 2.

4 Discussion

The emergence of large, curated datasets derived from publication and grant records has facilitated a surge of new empirical studies of science. However, there are many important variables that even high-quality administrative datasets do not capture (Stantcheva 2022). In this paper, we document our survey efforts to solicit and codify some of these important but hard-to-observe variables: researchers' time allocations, their earnings sources, the nature of their research, and their risk aversion. This new survey data, combined with existing datasets, yields new insights into variation in the population of US researchers both *within* and *across* fields at a national scale.

We are certainly not the first to use survey methods to learn about the academic research workforce. But our approach provides one of the first broad views across the full spectrum of science in modern research universities. We do not report any causal effects here, and we are limited in our ability to precisely disentangle sources of heterogeneity across researchers in many dimensions. But we have highlighted a number of novel features of this workforce. Future survey work can build on this by investing more resources into recruiting respondents, eliciting preferences with more precise methods, or eliciting a wider spectrum of preferences. Likewise, our results provide new guideposts for empirical work using other large datasets to investigate the science of science.

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Tables and Figures

Table 1: Institution-level summary statistics

	type	count	mean	sd
prof. share, by rank				
assistant	$[0, 1]$	158	0.25	0.10
associate	$[0, 1]$	158	0.23	0.06
full	$[0, 1]$	158	0.37	0.11
adjunct, clinical, other	$[0, 1]$	158	0.15	0.11
prof. share, by field				
humanities & related sciences	$[0, 1]$	158	0.18	0.11
medicine & health sciences	$[0, 1]$	158	0.36	0.30
social sciences	$[0, 1]$	158	0.23	0.16
natural sciences	$[0, 1]$	158	0.23	0.12
num. prof., total	$[0, \infty)$	158	843.60	555.92
num. schools	$[0, \infty)$	158	11.73	5.76
num. departments	$[0, \infty)$	158	80.28	40.55
HERD data				
total R&D funding, M-$	$[0, \infty]$	158	469.55	414.93
federal R&D funding, M-$	$[0, \infty)$	158	249.60	273.42
non-federal R&D funding, M-$	$[0, \infty)$	158	219.96	182.89
total wage bill, M-$	$[0, \infty)$	158	205.98	183.85
num. principal investigators	$[0, \infty)$	158	862.89	729.41

Note: All variables are from the NSAR population, except for the last rows, which are sourced from HERD.

Table 2: Professor-level summary statistics, professional & socio-demographic

	type	count	mean	sd
rank				
assistant	$\{0,1\}$	4,145	0.27	0.44
associate	$\{0,1\}$	4,145	0.23	0.42
full	$\{0,1\}$	4,145	0.41	0.49
adjunct, clinical, other	$\{0,1\}$	4,145	0.09	0.29
aggregate field				
humanities & related sciences	$\{0,1\}$	4,145	0.20	0.40
medicine & health sciences	$\{0,1\}$	4,145	0.28	0.45
social sciences	$\{0,1\}$	4,145	0.25	0.43
natural sciences	$\{0,1\}$	4,145	0.28	0.45
tenure status				
not on tenure track	$\{0,1\}$	4,145	0.20	0.40
contract length (non tenure track)	$[1,\infty)$	788	2.51	2.02
pre-tenure	$\{0,1\}$	4,145	0.22	0.41
years until tenure eval.	$[1,\infty)$	875	2.63	1.93
tenured	$\{0,1\}$	4,145	0.59	0.49
years since tenure	$(-\infty,0)$	2,364	14.86	11.51
work hrs., income, research funding				
work hours per week	$[1,\infty)$	4,145	49.88	13.05
own annual income	$[1,\infty)$	4,145	164,717.73	99,650.72
5-year guaranteed research funding	$[0,\infty)$	4,145	431,378.17	1,087,730.32
5-year fundraising expectations	$[0,\infty)$	4,145	549,068.76	1,056,442.72
socio-demographics				
asian	$\{0,1\}$	4,081	0.12	0.33
black	$\{0,1\}$	4,081	0.03	0.18
hispanic	$\{0,1\}$	4,081	0.06	0.23
other	$\{0,1\}$	4,081	0.04	0.19
white	$\{0,1\}$	4,081	0.79	0.41
US born	$\{0,1\}$	4,060	0.73	0.45
non-US born	$\{0,1\}$	4,060	0.25	0.43
married or in partnership	$\{0,1\}$	4,015	0.84	0.36
num. dependents	$\{0,1\}$	4,075	0.99	1.13
household annual income	$[0,\infty)$	4,016	260,740.79	215,542.31

Note: All variables are from the NSAR sample. Any counts that do not equal the sample size (4,145) are due to the question either being not applicable (i.e., the tenure status questions) or were socio-demographic questions where respondents were not forced to answer.

Table 3: Average share of time allocation per task, by aggregate field

	Research	Fundraising	Teaching	Administration	Clinical	Other
Humanities & related sciences	0.35	0.05	0.35	0.18	0.00	0.07
Medical & health sciences	0.41	0.10	0.18	0.13	0.13	0.05
Natural sciences	0.38	0.14	0.26	0.14	0.00	0.07
Social & mathematical sciences	0.41	0.06	0.30	0.16	0.00	0.06
Full sample	0.39	0.09	0.27	0.15	0.04	0.06

Table 4: Average share of income per source, by aggregate field

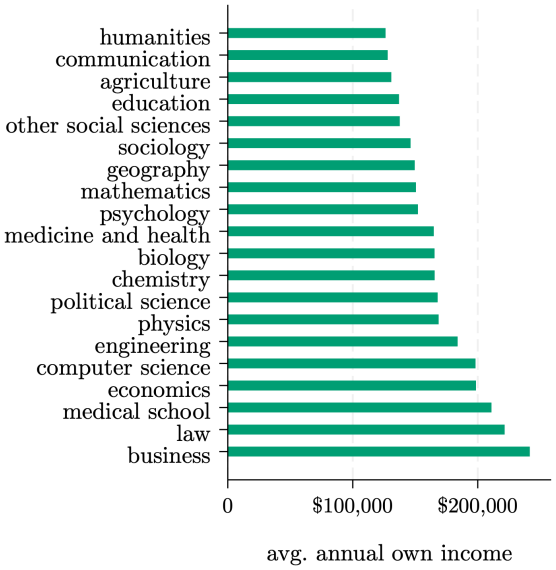
	Base	Grants	Supplemental	Clinical	Other
Humanities & related sciences	0.87	0.05	0.03	0.00	0.05
Medical & health sciences	0.58	0.28	0.03	0.07	0.04
Natural sciences	0.78	0.16	0.02	0.00	0.04
Social & mathematical sciences	0.84	0.08	0.03	0.00	0.04
Full sample	0.76	0.15	0.03	0.02	0.04

Table 5: Nature of research summary statistics

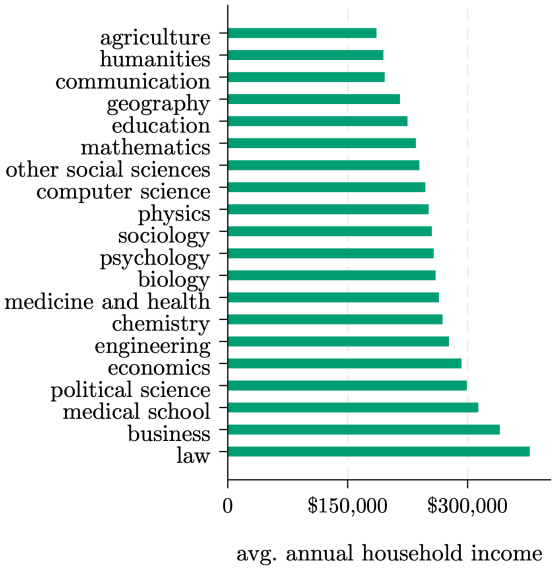
	type	count	mean	sd
intended output				
journal articles	$\{0, 1, 2\}$	4,145	1.87	0.37
books	$\{0, 1, 2\}$	4,145	0.53	0.69
research materials, tools, etc.	$\{0, 1, 2\}$	4,145	0.70	0.68
products	$\{0, 1, 2\}$	4,145	0.47	0.64
intended audience				
academics	$\{0, 1, 2\}$	4,145	1.88	0.36
policymakers	$\{0, 1, 2\}$	4,145	0.84	0.69
businesses and organizations	$\{0, 1, 2\}$	4,145	0.54	0.62
general public	$\{0, 1, 2\}$	4,145	0.83	0.62
other				
objective is to answer (vs. ask) questions	$[0, 10]$	4,145	4.85	2.57
risk of research	$[0, 10]$	4,145	4.59	2.25
matched to Dimensions data	$\{0, 1\}$	4,145	0.77	0.42

Figure 1: Individual and household earnings across fields

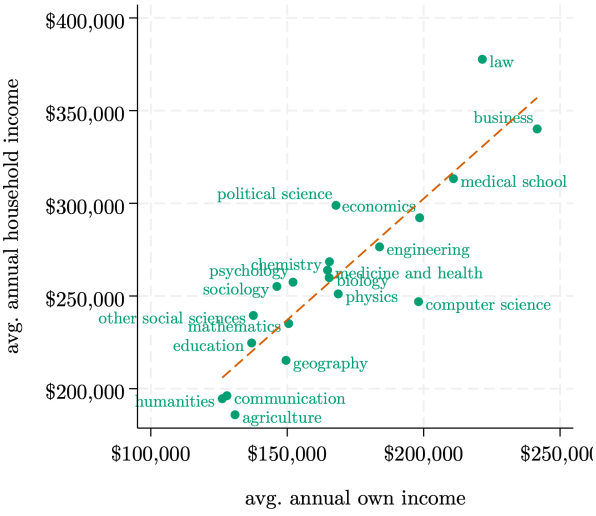
(a) Own income



(b) Household earnings



(c) Correlation: Own & household earnings



(d) Inequality in household earnings

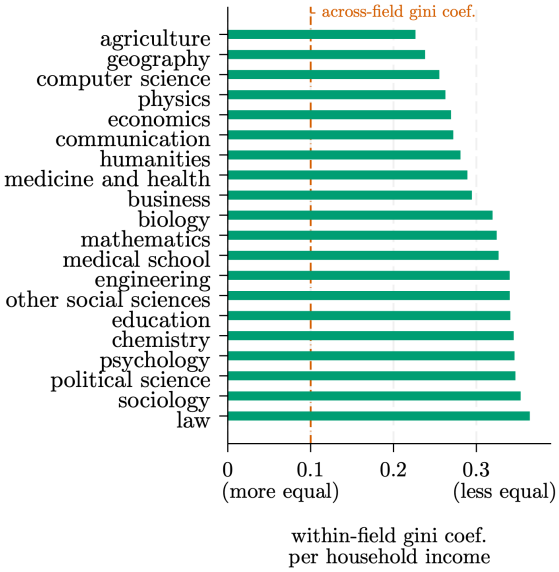
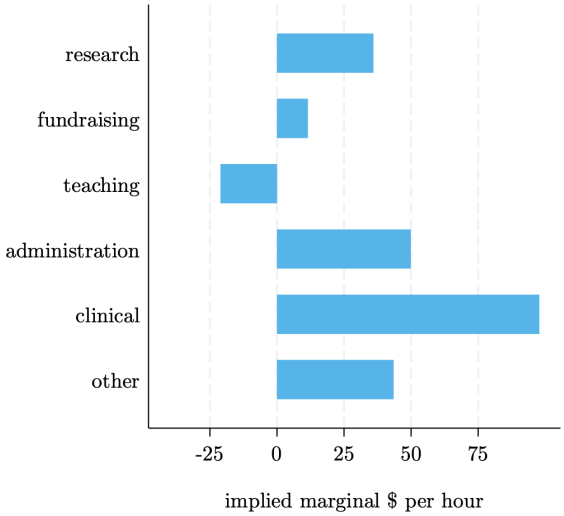
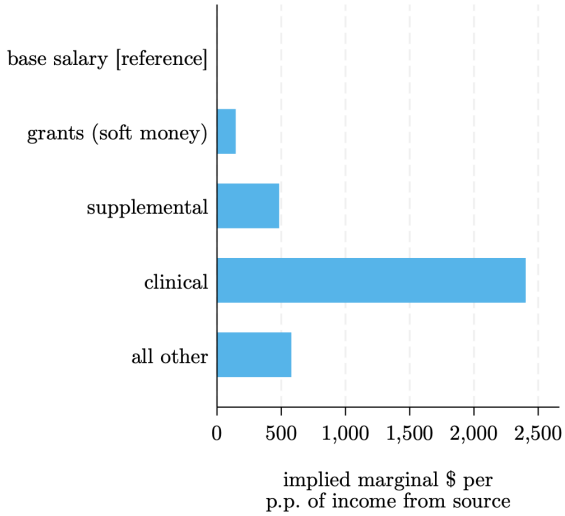


Figure 2: Earnings per tasks, sources, and institutions

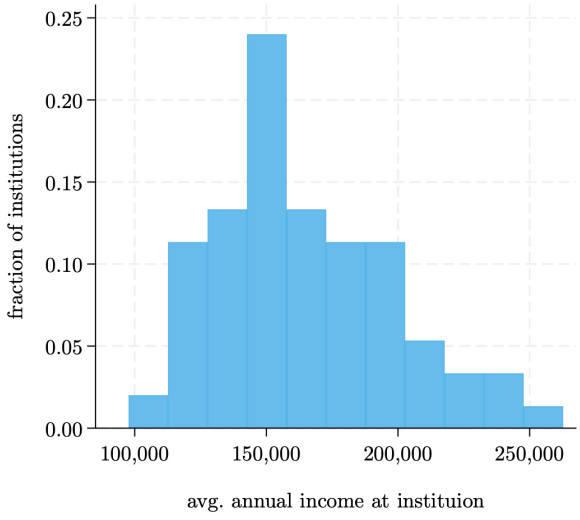
(a) Hedonic earnings regression, by task



(b) Hedonic earnings regression, by source



(c) Earnings across institutions

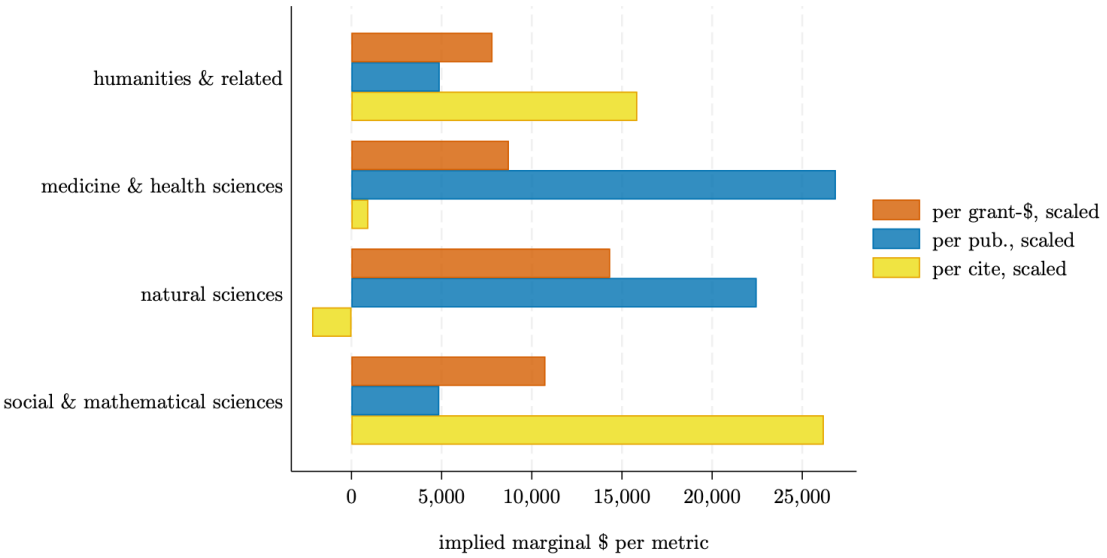


(d) Decomposing heterogeneity

	(1)	(2)	(3)	(4)
partial R^2:				
field	0.13	0.11	0.16	0.12
tasks		0.20	0.19	0.14
sources			0.06	0.02
institution				0.19
total R^2	0.13	0.27	0.32	0.40
N obs.	3958	3958	3958	3958

Figure 3: Earnings per research inputs and outputs

(a) Hedonic earnings regression, by metric

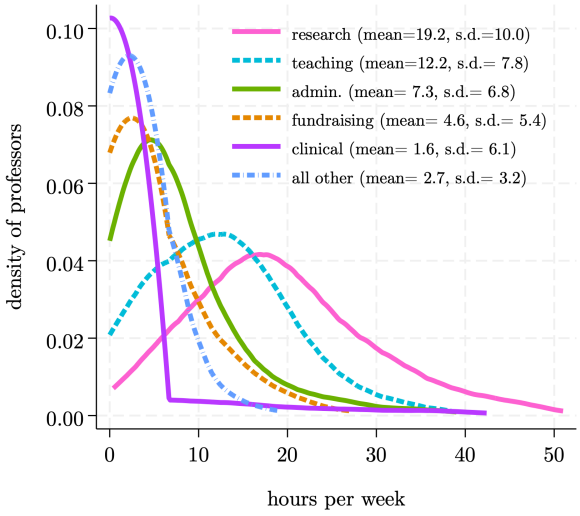


(b) Decomposing heterogeneity

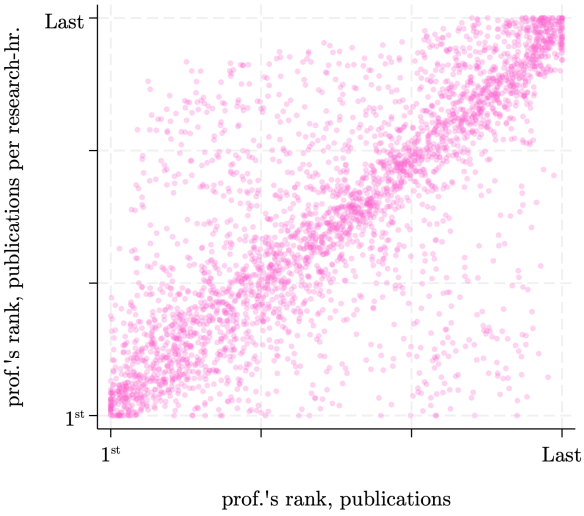
	(1)	(2)	(3)	(4)
partial R^2:				
field	0.09	0.10	0.10	0.11
pub. count		0.09	0.02	0.02
pub. wgt.			0.00	0.01
grant $				0.01
total R^2	0.09	0.16	0.16	0.18
N obs.	3115	3115	3115	3115

Figure 4: Time use distributions and correlations

(a) Distribution of time allocations



(b) Rankings per gross publication output and publications per research-hour



(c) Pairwise correlations, unconditional

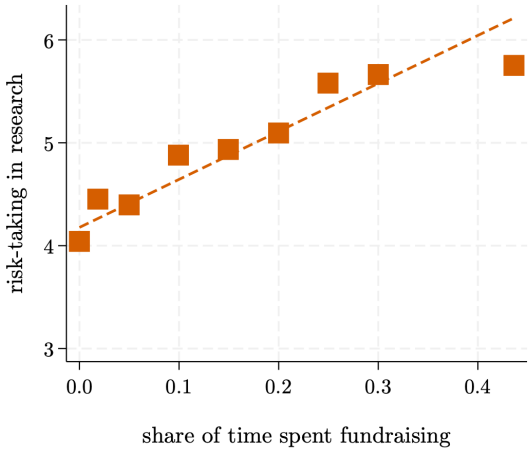
	research	fundraising	teaching	administ.	clinical	other
research	1					
fundraising	0.09***	1				
teaching	–0.22***	–0.12***	1			
administ.	–0.27***	–0.07***	0.03*	1		
clinical	–0.23***	–0.14***	–0.18***	–0.06***	1	
other	–0.10***	0.03	–0.00	–0.06***	–0.09***	1

Figure 5: Correlates of research risk-taking

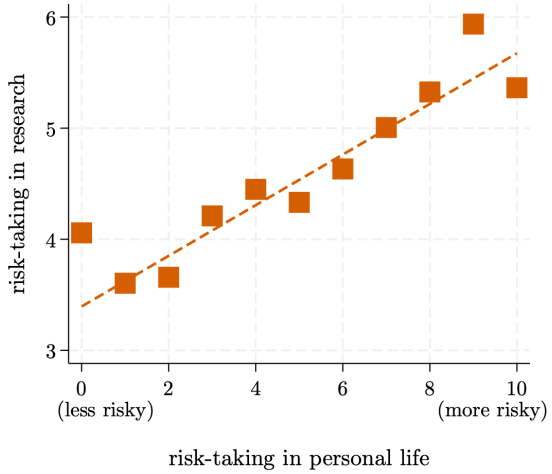
(a) Lasso-selected predictors of research risk-taking

	stability selection share	univar. corr.
share of hrs., fundrais.	1.00	0.22
risk-taking in personal life	1.00	0.21
answer (vs. asking) questions	1.00	–0.20
share of hrs., research	1.00	0.17
non-tenure-track	1.00	–0.14
female	1.00	–0.13
output: materials, methods, etc.	1.00	0.13
total work hrs.	1.00	0.11
household income	0.99	0.07
fundraising expectations	0.98	0.17

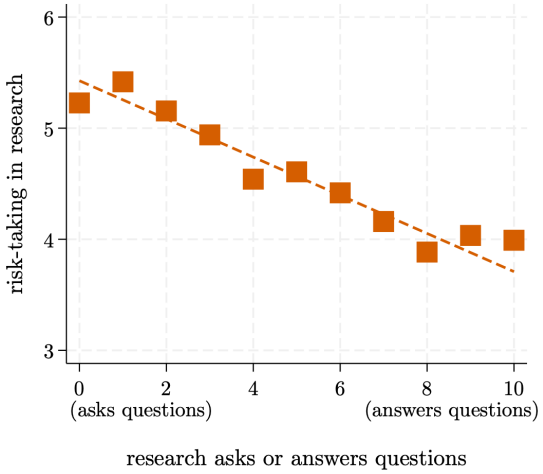
(b) Research risk and fundraising



(c) Research risk and personal risk-taking



(d) Research risk and strategy



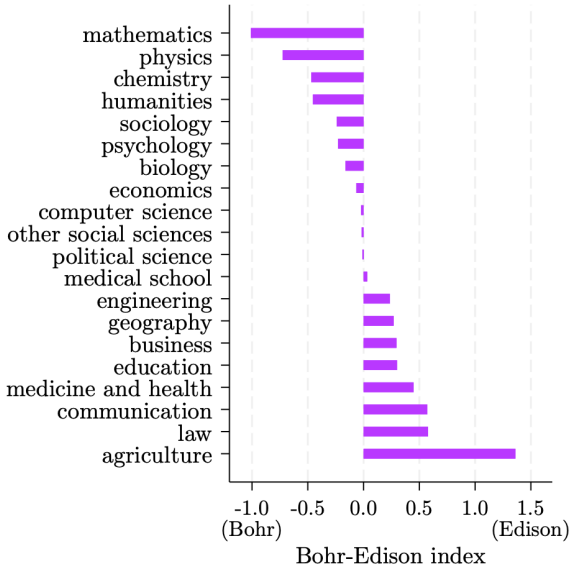
Note: Panel (a) shows a binned scatterplot relating researchers' perceptions of the riskiness of their research (y-axis) and the amount of risk-taking in their personal lives (x-axis). Panel (b) reports the results from lasso regressions predicting research risk with the full set of covariates from the sample; the stability selection share column reports the share of 100 bootstrap subsamples that the covariate is selected in, and the univariate correlation column reports that correlation for the full sample.

Figure 6: Correlates of the Bohr ("basic") – Edison ("applied") spectrum

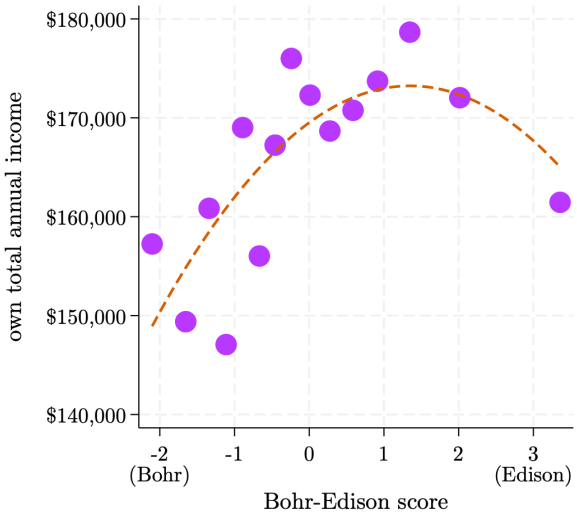
(a) Principal component analysis of nature-of-research questions

	loading
objective is to ask (0) versus answer questions (10)	0.18
intended output	
journal articles	–0.25
books	–0.06
research materials, tools, etc.	0.24
products	0.51
intended audience	
academics	–0.37
policymakers	0.38
businesses and organizations	0.42
general public	0.35

(b) Bohr-Edison scores, by field



(c) Bohr-Edison scores and earnings



(d) Lasso-selected predictors of Bohr-Edison score

	stability selection share	univar. corr.
personal risk-taking	1.00	0.21
share of hrs., research	1.00	0.17
non-tenure-track	1.00	–0.14
share of hrs., other	1.00	–0.04
has dependents	1.00	–0.01
income, other sources	1.00	0.01
share of hrs., fundrais.	0.99	0.22
tenured	0.99	0.08
age	0.99	0.01
funding guarantees	0.97	0.13

Note: Panel (a) shows a binned scatterplot of researchers' annual income and their Bohr-Edison score. Panel (b) reports the results from lasso regressions predicting the Bohr-Edison score with the full set of covariates from the sample; the stability selection share column reports the share of 100 bootstrap sub-samples that the covariate is selected in, and the univariate correlation column reports that correlation for the full sample.

A Additional information on methods

A.1 Self- and publicly-reported salary comparisons

One limitation of our survey-based methodology is that respondents do not report truthfully due to inattention or some bias such social desirability or an experimenter demand effect. Testing for such issues is notoriously challenging. But one of the survey questions, which solicits respondents' annual salary, provides one test of the degree to which respondents are reporting truthfully since a sub-sample of respondents' salaries are publicly observable.

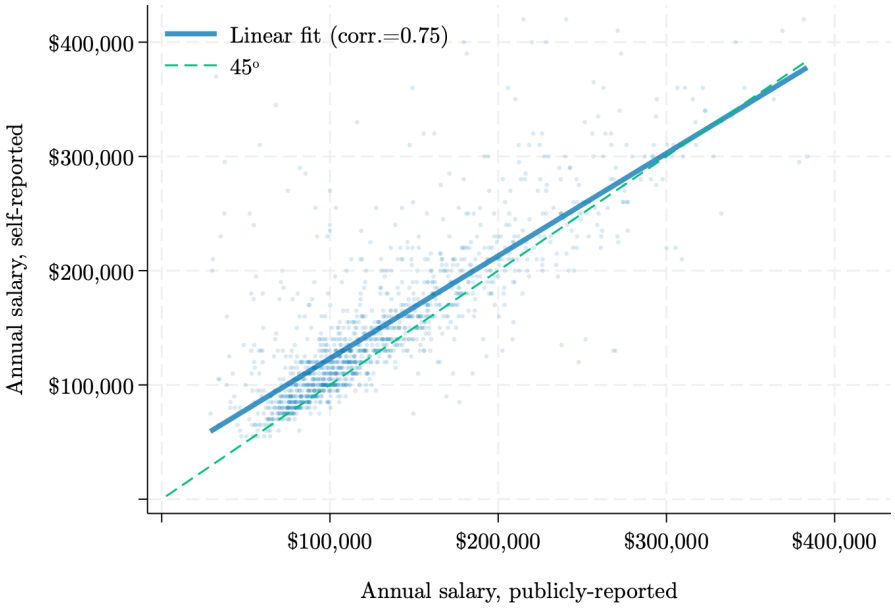
A number of, primarily publicly owned, institutions in our population publicly post the salaries of their workforce. Using this data we can estimate the extent to which researchers' self- and publicly-reported salaries align.

We used a manual approach to match respondents to their public records (when possible), relying on researchers' names and affiliations to make as high-fidelity of a match as possible. Across and within the 89 institutions that had public salary data, there was a significant amount of heterogeneity in how salaries were reported. In the matching process we made note of any irregularities or confusion for each record matched. Below, we focus only on matches where both we had a high degree of confidence that both (1) the respondent was in fact the individual listed in the public record, and (2) the salary listed represented the full annual salary of that individual.

We expect a high degree of alignment between these two measures, but not perfect alignment. Beyond the traditional concern of misreporting by the respondents, misalignment may occur for three other possible reasons: (1) human error in the matching process; (2) the publicly reported salary was for a different fiscal- or calendar-year than what the respondent was reporting or did not in fact reflect the individuals' full annual salary; or (3) we solicited salaries in the survey using a pre-populated menu of discrete values to minimize effort, which in turn creates "lumpiness" in the self-reported values.

Figure A1 reports a scatterplot of respondents self- and publicly-reported salaries, which have a correlation of approximately 0.75. Overall, the figure indicates a high degree of alignment between the two measures, suggesting that respondents are answering this question truthfully. Given the traditional sensitivity surrounding salaries amongst this population, especially relative to the questions asked in our thought experiments, this alignment suggests that most respondents were in fact attentive and truthful.

Figure A1: Self- and publicly-reported salaries



Note: Shows a scatterplot of salaries by source along with a linear fit and 45^o line for comparison.

A.2 Population and sample comparisons

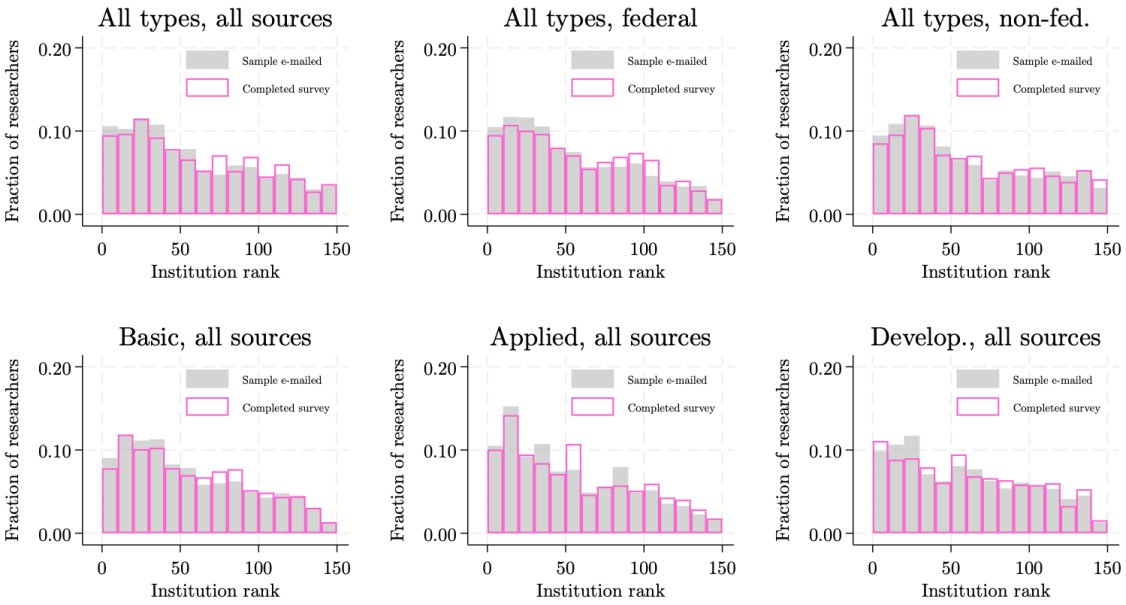
A key challenge for all surveys is ensuring representativeness. Here we report two tests of representativeness using data that is observable for both respondents and non-respondents. First, A2 shows this comparison based on data from the National Science Foundation's HERD survey (National Science Foundation 2023), which reports institutional-level data on the total amount of funding flows into all of the institutions in our population (recall, our population was constructed using the HERD, which is why this data is available for the full population).

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

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

Figure A2: Recruitment versus completion sample comparison per HERD metrics

(a) Distributions per HERD R&D measures



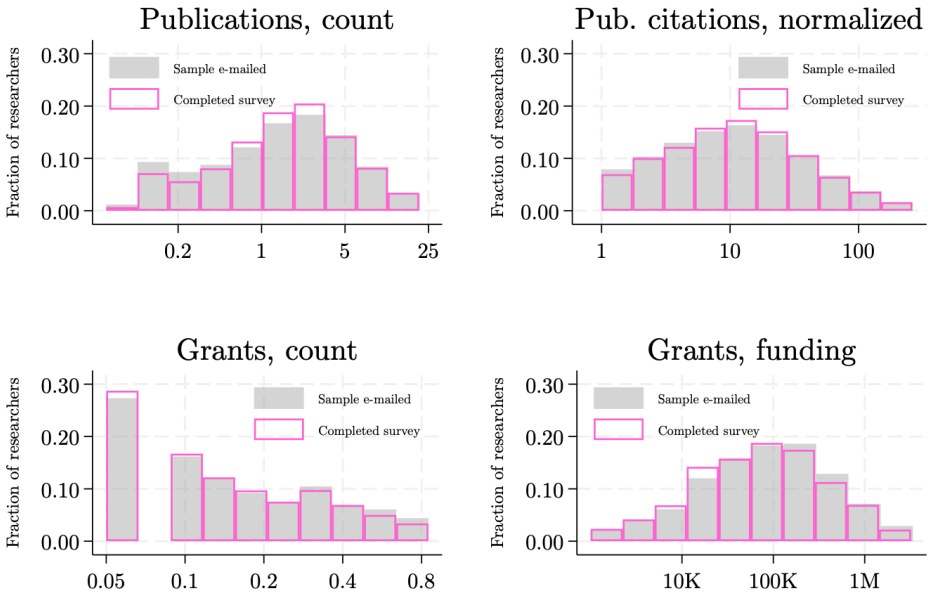
(b) Regression estimates of mean differences

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

Note: Panel (a) compares the distributions of e-mailed professors and respondents per the rank of their institution along each dimension of R&D funding. Panel (b) reports estimates from a regression of each sampled professor's institutional R&D funding (in 2019 $-M) on a dummy for whether the sampled individual completed the survey; the "% diff." row reports the mean difference in the measure as a percentage of the non-respondent average (i.e., it is the ratio of the two coefficients); robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All institutional data is from the 2019 NSF HERD (National Science Foundation 2023).

Figure A3: Recruitment versus completion sample comparison per Dimensions metrics

(a) Distributions per Dimensions publications and grants



(b) Regression estimates of mean differences

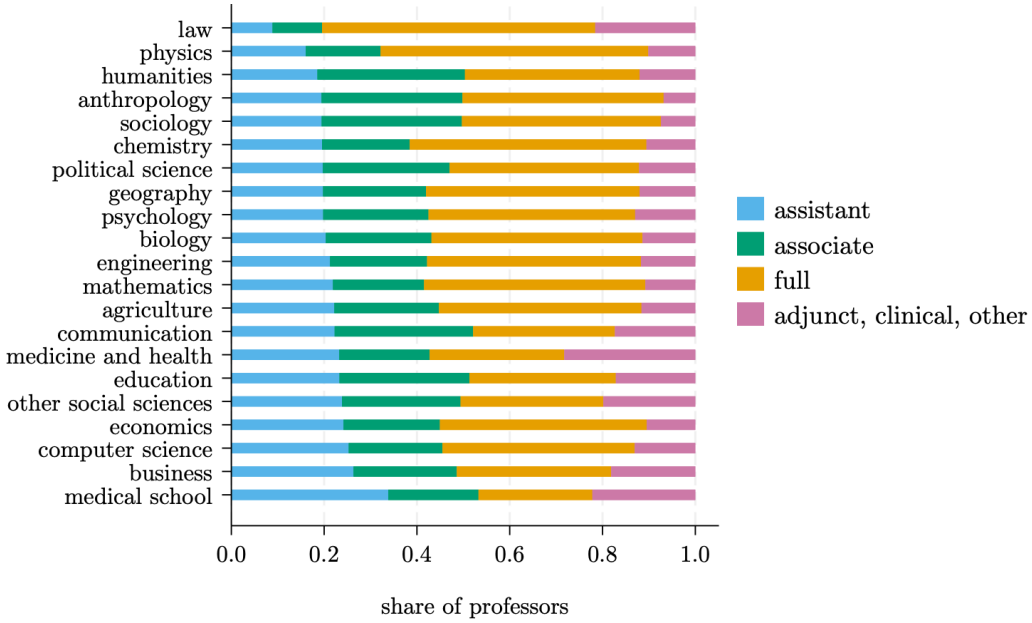
	Pub., count (1)	Pub. cites, normalized (2)	Grant, count (3)	Grant, total $ (4)
Completed survey	–0.116*	–0.573	0.00857**	–5250.7
	(0.0689)	(0.810)	(0.00344)	(8556.2)
Constant	2.902***	20.56***	0.117***	121115.1***
	(0.0158)	(0.186)	(0.000717)	(2100.2)
% diff.	–4.0%	–2.8%	7.3%	–4.3%
N obs.	86,504	86,504	86,504	86,504

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

B Additional results

B.1 Additional summary statistics

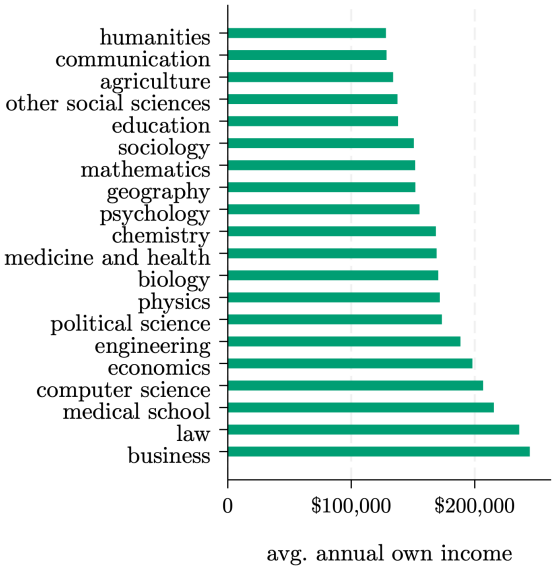
Figure B1: Rank distribution, by field



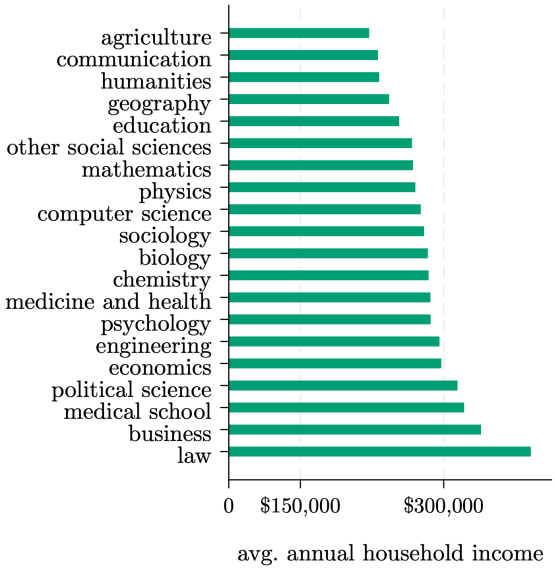
B.2 Additional salary comparisons

Figure B2: Individual and household earnings across fields, excluding single individuals

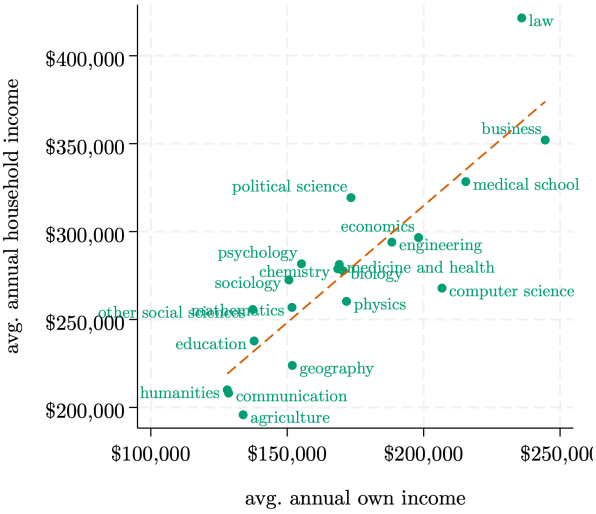
(a) Own income



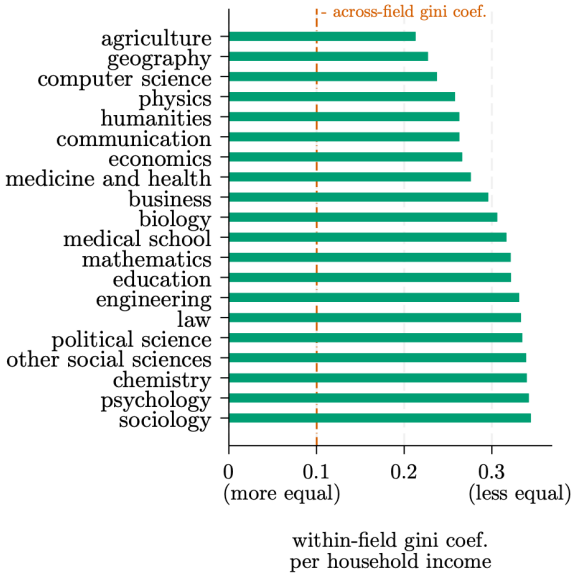
(b) Household income



(c) Correlation: Own & household incomes



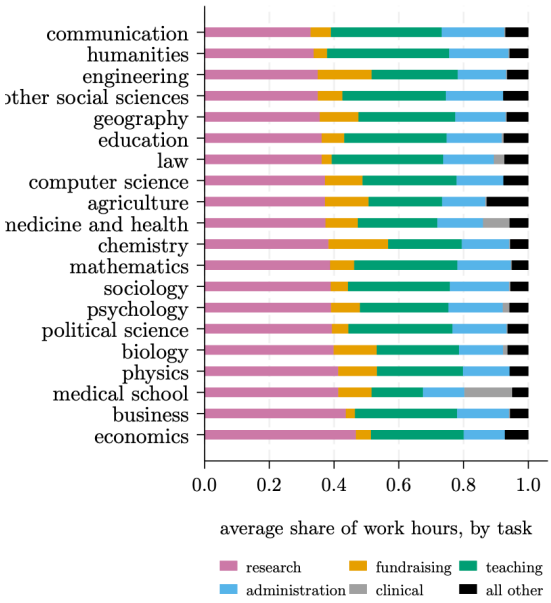
(d) Inequality in household incomes



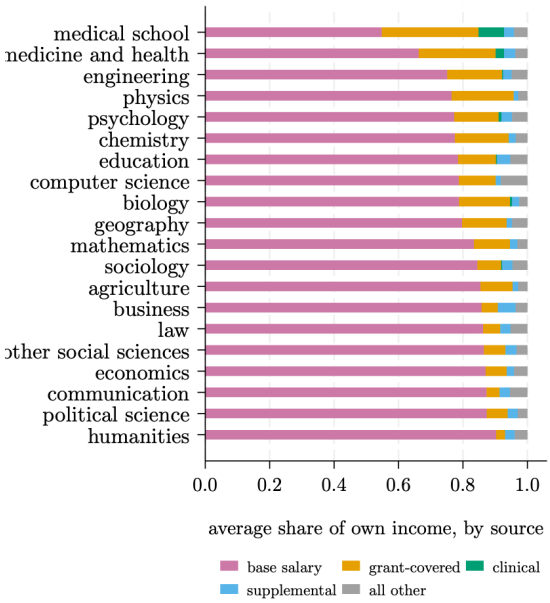
B.3 Additional field comparisons

Figure B3: Field compositions

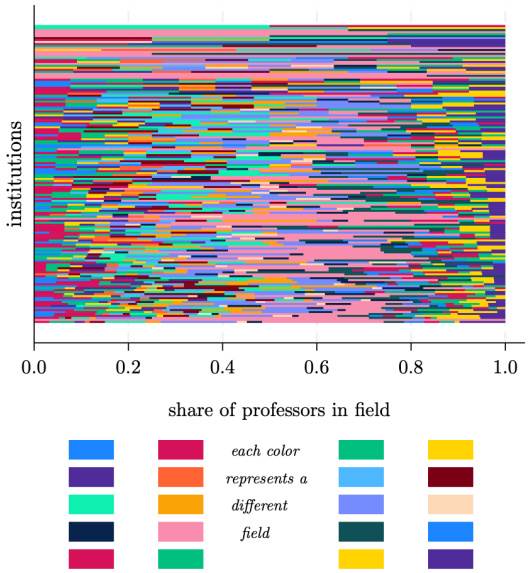
(a) Field-level averages, by work tasks



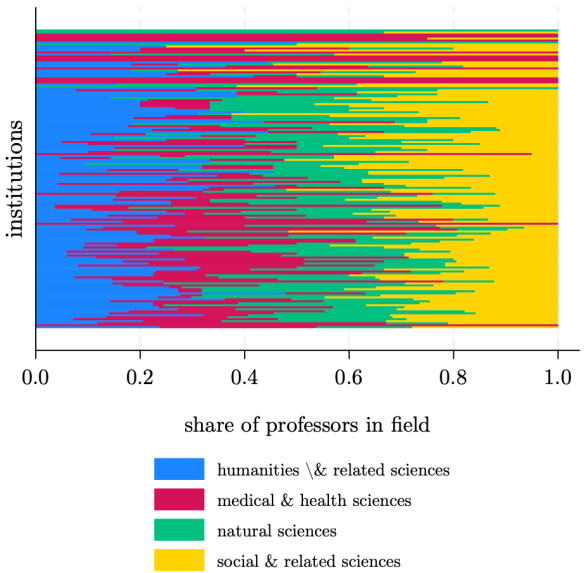
(b) Field-level averages, by source of income



(c) Distribution of fields across institutions



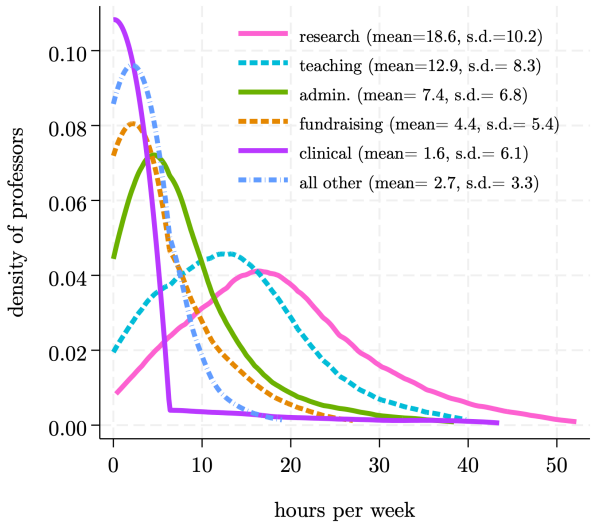
(d) Distribution of aggregate fields across institutions



B.4 Additional time-use results

Figure B4: Time use distributions and correlations

(a) Distribution of time use, full sample



(b) Unconditional pairwise correlations, full sample

	research	fundraising	teaching	administ.	clinical	other
research	1					
fundraising	0.11***	1				
teaching	–0.25***	–0.16***	1			
administ.	–0.26***	–0.07***	0.03*	1		
clinical	–0.22***	–0.14***	–0.18***	–0.08***	1	
other	–0.09***	0.03*	–0.03**	–0.06***	–0.09***	1