An Inside Look: Modeling Heterogeneity in the Organization of Scientific Work

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ABSTRACT

Although academic scientists work under similar institutions, norms, and incentives, they vary greatly in how they organize their research efforts and in their outputs. To understand this heterogeneity, we model scientists as publication-maximizing agents and identify two distinct organization patterns that are optimum under different parameters. When the net productivity of a research staff (e.g., PhD students and postdocs) is positive, the funded research model with an entrepreneurial scientist and a large team dominates. When the research staff's costs exceed its productivity benefits, the hands-on research approach is optimal. Our model provides an explanatory framework for significant heterogeneity of scientists across fields in research funding, supply of scientific workforce, team size, publication output, perceived relevance gap, and stratification patterns over time. Exploratory empirical analysis finds consistent patterns of time allocation and publication in a survey of faculty in US universities. Using data from an original survey, we also find causal effects consistent with the model's prediction on how negative shocks to research staff—for example, due to visa or health problems—differentially impact research output under the two modes of organization.

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INTRODUCTION

Access to academic research plays a significant role in shaping firms' competitive advantage. Scientific research can help firms overcome technological barriers, improve their R&D efficiency, and identify new market opportunities (McMillan et al. 2000). Recent research suggests that large corporations have increasingly outsourced more of their investment in science to academia (Arora et al. 2015). Scientific research, largely done in academia, also spurs economic growth and produces considerable societal benefits (Mokyr 2002; Narin et al. 1997; Polanyi 1962; Romer 1990; Rosenberg 1974). Accordingly, a large stream of research has explored the incentive structures and social norms of academia, depicting it as an institution in which scientists typically race for scientific credit, assess each other through peer review, and follow the academic norms of openness, universalism, originality, and skepticism (Dasgupta and David 1994; Diamond 2005; McPherson and Schapiro 1999; Merton and Zuckerman 1973). This picture of academia has provided valuable insight for firms and policy makers seeking to incentivize and steer academic research (Dasgupta and David 1994).

However, despite organizational scholars' fundamental interest in the sources of heterogeneity across organizations, they have uncharacteristically overlooked the sources of heterogeneity across academic fields. Academia is theoretically understood as one important organizational form with a set of shared norms and incentives. In fact, what we know of the dynamics of scientists' behavior in academia comes largely from studies focused on life sciences or engineering (e.g. Azoulay et al. 2009; Azoulay et al. 2011; Fox 2005; Li and Agha 2015; Vakili and McGahan 2016; Vakili et al. 2015). Yet there is ample evidence of the heterogeneity in academia (Becher 1994; Moses 1990). Consider, for example, two star scientists at a top research university. The first, a Nobel laureate economist, typically works alone or with a handful of senior collaborators, rarely seeks research funding, and only occasionally works with PhD students. He has published over 60 articles, mostly solo or with one coauthor, with over 12,000 citations and an H-index of 33. The second, a biological engineer, runs a 1,300-square-meter lab employing over 80 people, brings in millions of dollars of funding each year to support this lab, and has published over 1,400 papers—with hundreds of coauthors—earning over 138,000 citations and an H-index of 183. He is also named on more than 1,200 patents licensed to over 300 firms. Such significant differences across fields, not only in output but also in inputs and organization, are the norm rather than the exception. Table 1 provides some examples of this heterogeneity, based on data obtained from Virginia Tech between 2011 and 2013. While a typical scientist in the physical sciences, engineering, and life sciences produced more than two papers per year, a typical social scientist produced one and the scientist in humanities only half that. Similarly, the average number of PhD students and senior research staff per faculty member ranged from 3.04 in engineering to about 0.51 in management (with a maximum of 7.4 in biomedical engineering). Furthermore, a typical faculty member in engineering or life sciences brings in, on average, more than 10 times the funding of her counterpart in the humanities or management.

-- Insert Table 1 around here --

Given such variance, our understanding of research processes and outcomes based on studies of life sciences or engineering may leave us uninformed about much of the scientific community. In turn, implications and policies based on such studies may not apply to other areas of science. We take a step towards addressing this issue by developing a formal theoretical model that can explain, at least partially, the observed heterogeneity in research processes and outcomes across academic fields. We then empirically explore some of our model's predictions and discuss the practical and policy implications.

Conceptualizing academic scientists as publication-maximizing agents, our formal model shows that they may organize the research process according to two distinct patterns. When net productivity of research staff—that is, their research output minus the opportunity cost of raising funds to support, train, and advise them—is positive, the funded research model dominates. The scientist acts as team manager and entrepreneur, obtaining funding to sustain a sizeable research team. Scientists using the funded research model often do not execute the actual research but rather oversee those who do. This model leads to a large supply of scientific workforce per scientist, large research teams, and high demand for external funding. On the other hand, when the research staffs' costs exceed their productivity benefits, the hands-on research model dominates. The scientist is highly engaged in executing a research project, trains fewer graduate students and postdocs, works in smaller teams, and demands less funding. This hands-on research model leads to fewer publications per scientist than the funded research model does.

We use our model to generate a series of testable hypotheses and explore them using two data sources. Analyzing data from a national survey of US university faculty, we find two patterns consistent with our model predictions. First, whether spending time interacting with students contributes to a scientist's publication output is contingent on having funding. Those who have funding end up benefiting from student interaction, while those who don't will not. Second, the extent of this benefit is contingent on the viability of the funded model in a given research domain. In domains in which the funded model is common, scientists benefit more from interacting with students.

Second, we use an original survey of scientists at two major universities to track the causal impact of unexpected losses of research staff (e.g., due to visa or health problems) on a scientist's research productivity. Consistent with our model predictions, such incidents lower scientist's quality-adjusted publication productivity if she uses the funded research model, but not if she uses the hands-on model.

Beyond identifying one of the drivers of heterogeneity in academia, the mechanisms we discuss have notable implications for innovation research. Our model can complement current theories that explain the growing dominance of teams in knowledge creation (Agrawal et al. 2016; Jones 2009). Prior literature underlines the increasing cost of reaching the knowledge frontier as an important factor contributing to greater specialization and hence to more teamwork being needed to advance that frontier. The basic principles of our model combined with the reinforcing mechanisms that are particularly to be found in funded research can explain the differential in team size and productivity between areas that use the funded research model (such as engineering and life sciences) and those that use the hands-on research model (such as humanities and management). Moreover, the same reinforcing dynamics in the funded research model can also explain the concentration of research impact in a few top research institutes. Finally, our model's mechanisms interact with the plurality of theoretical views in hands-on domains or with paradigmatic consensus in funded domains to reinforce each other over time, further sustaining the observed heterogeneity.

Multiple implications for firm strategy and policy follow. Our model suggests that the effectiveness of the supply of research funding as a strategic lever to influence research direction, is moderated by a field's dominant research model. Funding may have limited impact on the research trajectories and portfolios of academic scientists in fields in which the hands-on model dominates. This has a direct implication for the extent to which firms can outsource their research activities to academia. Moreover, by endogenizing the demand for external funding, our model can provide an additional explanation for why research in funded areas is perceived to be more aligned with the needs of industry and society than research in areas using the hands-on model. Our findings also suggest that while scientists in funded fields are typically selected into their position based on their research skills, they require managerial skills to thrive as group heads. Investment in the development of scientists' managerial skills can thus improve their long-term productivity and success. Finally, our model might explain a puzzling imbalance: despite a more than thirty-fold increase in research funding in the US over the last 60 years, demand has grown even more quickly. This could be a natural outcome of the funded model, in which PhD students, having been trained by supplied funding, go on to demand funding for their own research. This mechanism might also contribute to the imbalance between supply and demand for PhD graduates in the labor market for scientists.

A MODEL OF PUBLICATION-MAXIMIZING SCIENTISTS

In this section, we develop a parsimonious model of time allocation by an academic scientist who aims to maximize her publication output. Scientists' time allocation represents their day-to-day motivations. While other motivations are certainly important, we simplify by assuming the main goal of academic scientists is to maximize their publication output and scientific impact. This assumption is in line with prior work showing that a scientist's impact and reputation depend on his or her publication record (Bensman 1982; Merton 1968; Merton 1973), while a university's reputation is determined by its faculty's research productivity (Porter and Toutkoushian 2006). Therefore, promotion, tenure, and salary at research universities are based largely on publication productivity (Fairweather 1993; Kasten 1984; Tien 2007). We use the maximization of research output as the organizing principle to model scientists' time allocation across different activities.

In their race for priority, scientists openly share their findings through journal articles, books, patents, and other artifacts. Different output types are valued differently across different fields (Huang and Chang 2008); overall, however, publications are the primary output of academic research (Fox 1983; Fox and Mohapatra 2007; Merton 1973). Publication quality is another significant factor in evaluating research output, although measuring it is complex (van Raan 1988). Our model defines research output in terms of an effort-adjusted unit of publication; for example, an article in a leading journal. Other types of output, such as books, could be expressed in terms of this unit, based on the amount of research time they require from a scientist compared with the time required to research and publish a unit output.

We group an academic scientist's various activities into the following categories:

Research includes all activities that contribute to the design, production, and dissemination of scientific knowledge and artifacts. Here we distinguish between research activities that only the lead scientist can engage in (which we label "research design") and tasks that could be undertaken by both the scientist and her research staff (which we label "research execution"). The latter includes surveys, mathematical calculations, computer coding, working with laboratory animals, conducting experiments, writing journal articles, presenting research results, and installing and maintaining the research equipment, among others.

Teaching includes all activities focused on helping others acquire knowledge and gain academic credentials but not primarily contributing to the scientist's research program. Examples include lecturing in class, preparing for the lectures, grading, holding office hours, and offering academic advice to undergraduate students.

Advising includes all interactions intended to train students, postdocs, and research staff or to manage the research projects and teams of researchers in the research group the scientist leads.

Raising funds includes all the activities related to acquiring the funds needed to sustain the scientist's research program; for example, meeting with research sponsors, communicating within a proposal team, and writing a research proposal.

Service includes all the activities that do not fall into the previous categories, such as administrative tasks and work on committees not related to research and funding.

This section focuses on analytically modeling the tradeoffs that a scientist faces in allocating her time across the activities just described. For the sake of simplicity, we assume that teaching and service activities make a limited contribution to research output and are exogenously imposed on the scientist by her institution (institutional effect). Moreover, since scientists have to spend the requisite time on "research design" (research activities they cannot delegate to team members), the time corresponding to research design can be excluded from their allocation problem (see Appendix A2 for explicit treatment of research design). Given these assumptions, consider a single scientist (and her research group) distributing her flexible time (time not dedicated to research design, teaching, and service) between research execution, raising funds, and advising. She is assumed to allocate her effort between these activities to maximize her publication rate.

The time allocated to different activities depends on how the scientist structures her research group; that is, how much equipment and how many research staff (typically PhD students and postdocs) are employed. Different academic disciplines require different physical artifacts and experimental setups for research. Research equipment influences this analysis in two ways: first, because equipment enables research, the amount of equipment influences research output. Second, a scientist must spend time raising the funds needed to acquire and maintain the research equipment. Specifically, calling the level of equipment E (upper-case is used for variables a scientist can choose and lower-case for model parameters) and the fraction of the scientist's total time required to raise funds for a single unit of equipment t_e, the scientist should spend a fraction of her time amounting to Et_e on raising funds for her research group's equipment.

On the other hand, the research staff require a scientist's time for supervision and advising, as well as for raising funds to pay them if they are not funded by external scholarships or salaried positions (we return to this possibility later in the analysis). Consider a research group consisting of P research staff, besides the scientist. Call the fraction of the scientist's time needed for raising funds to sustain one staff member t_f and the fraction of time to advise and manage one staff member t_a. The time spent on management and fundraising related to the staff is $P(t_f+t_a)$.

The scientist spends a fraction, T_r, of her time on research. As a result, three interrelated decisions shape the scientist's choices: (a) the number of research staff she should employ (P); (b) how much research equipment she should acquire and maintain (E); and (c) the fraction of her time she should spend on research execution (T_r).

These decisions are interrelated because the total time available to the scientist is limited. So the amount of equipment and the number of staff she can have are constrained by the time she has available to sustain and manage them. Normalizing the total flexible time available to the scientist to 1, we have:

$$T_r + Pt_f + Pt_a + Et_e = 1 \qquad 0 \le T_r, t_f, t_a \le 1 \qquad (1)$$

Publication output depends on the research execution time spent by the scientist (T_r) and other members of the group, weighted by their productivity (e_s for the scientist and $e_s r_p$ for other group members, where r_p is the productivity of research staff relative to that of the scientist). Research output also depends on the availability of proper research equipment (E). The combination of these two factors (research labor and equipment) is assumed to produce research output (O), based on a constant return to scale Cobb-Douglas production function. The scientist is typically a co-author on all publications coming from her research group.[1] Therefore, the total publication output, O, for the scientist can be stated as:

[1] For simplicity, this analysis assumes equal credit to the scientist regardless of the number of co-authors. Given the evidence on limited discounting of credit (i.e., proportional to the inverse of the logarithm of the number of coauthors (Bikard et al. 2015)), this assumption does not change the results qualitatively. Moreover, the hands-on research model does not lead only to solo-authored papers. In practice, horizontal collaboration among peers leverages the unique capabilities and assets of each scientist and is common among those using the hands-on research model. Those horizontal collaborations do not change the core mechanisms in our model and thus are not included explicitly.

$$O = (e_s T_r + e_s r_p P)^{\alpha} E^{1-\alpha} \quad (2)$$

where α, between 0 and 1, represents the significance of human actors in producing research output, relative to the significance of technology.

In solving the resulting time allocation problem, the number of PhDs and postdocs (*P*), the amount of equipment (*E*), and the time spent on research execution (T_r) are chosen to maximize research output. Formally:

$$\underset{T_r, P, E}{Maximize}: (e_s T_r + e_s r_p P)^{\alpha} E^{1-\alpha} \quad (3)$$

Subject to: $T_r + Pt_f + Pt_a + Et_e = 1;\ 0 \le T_r \le 1;\ 0 \le P, E$

Solving this problem (see Appendix A1), optimum research equipment is found to be $E = (1-\alpha)/t_e$. With respect to research time and the size of the team, two significantly different possibilities emerge. First, if research staff are productive enough ($t_a + t_f < r_p$), then the scientist spends her remaining time raising funds and managing the largest possible research group $(P = \alpha/(t_a + t_f))$, spending little time on research execution tasks. In contrast, if research staff are not productive enough to justify their costs ($t_a + t_f > r_p$), then the scientist will prefer to have no staff and instead spend much of her flexible time executing the research herself, with the remaining time spent raising funds for the required equipment. Table 2 summarizes the characteristics of the two alternative modes of organizing research groups. The model could be extended to include fellowships, scholarships, and teaching assistantships that, besides research funding, could be used to fund research staff. This extension (see Appendix A3) leads to additional equilibria in which fewer PhD students and postdocs, funded through scholarships and teaching assistantships, may work with the scientist, but otherwise does not change the model's basic predictions.

-- Table 2 about here --

The results suggest that (a) the fractional advising (t_a) and fundraising (t_f) times for sustaining a staff member and (b) his productivity relative to the scientist (r_p) are enough to explain significant differences in the size of the scientist's research group and her allocation of time to conducting research versus raising funds and training the research team. In some settings, the scientist is better off spending most of her time conducting the research alone, because what a typical PhD student/postdoc can produce is not the equivalent of the scientist's research publication output during the time spent on raising funds for, and advising, that student/postdoc. Multiple factors could contribute to this. For example, learning the research concepts could be time-consuming, delaying the time at which PhD students become productive (e.g. theoretical physics and mathematics), scholarly writing may be complex (e.g. sociology), or raising research funds may be hard (e.g., anthropology). Our model predicts that, in such fields of inquiry, the most successful scientists have little demand for external funding, they fund few PhD students or postdocs, fewer authors are listed on their publications, and they are often doing the day-to-day research tasks. We call this mode of operation the "hands-on" research model. In contrast, where research staff save the scientist more time (by doing research tasks) than it costs (for advising, managing, and fundraising) to support them, the number of PhD students/postdocs is larger and the scientist's role is closer to that of an entrepreneur: she brings in money to sustain the research group, manages the relatively large research team, and participates more in the research design than in the execution. In this situation, publications are more numerous and a larger number of co-authors are typically listed. We call this mode of operation the "funded" research model. The scientist can streamline her effort allocation by creating additional levels of management hierarchy in which postdoc researchers are hired to conduct the day-to-day training and supervision of PhD students.

EMPIRICAL EXPLORATION

In the next two sections, we provide empirical evidence for our theoretical model. First, we generate empirically testable predictions based on the model. We test them using two samples. To complement our empirical tests, we provide additional statistical evidence for some of the model's assumptions.

Empirical Predictions

There are two sets of empirical predictions we can make based on our model: equilibrium outcomes and causal relationships. The first two predictions describe the bifurcated relationship between research inputs and outputs in equilibrium. These predictions are not causal and simply explain what we should expect in each model of team organization. The third prediction pertains to the causal relationship between changes in one of the inputs (research staff) and changes in research output.

A scientist's time spent on advising research staff has different repercussions depending on whether she uses the funded model or not. In the funded model, time spent on advising research staff increases research output. Mathematically, the partial derivative of output with respect to time spent by the scientist in advising and managing the research staff (T_a=Pt_a) is always positive in the funded model ($\partial O / \partial T_a = \alpha(\frac{e_s r_p}{t_a})^{\alpha}(\frac{1-\alpha}{T_a t_e})^{1-\alpha}$ ≥0 for 1≥α≥0). In the hands-on model, the time spent on research staff has no effect on research output. This has two empirical implications. First, if we assume that using the funded model is positively correlated with funding at the individual level, we expect the impact of time spent with research staff on research output to be fully moderated by having funding.

Prediction 1: The positive effect of time spent with research staff on research output is fully moderated by having funding.

Second, we expect the positive effect of time spent with research staff on research output to be stronger where the funded model is dominant. In domains where the hands-on model dominates, faculty may still acquire funding but the relationship between time spent with research staff and research output would be weaker.

Prediction 2: The effect of time spent with research staff on research output is larger in domains in which the funded model dominates than in domains in which the hands-on model dominates.

Finally, we expect that an exogenous change in the number of research staff will directly affect a scientist's research output only if she uses the funded model. For faculty using the funded model, the partial derivative of output with respect to number of staff is $\partial O / \partial P = \alpha (e_s r_p)^{\alpha} (\frac{1-\alpha}{Pt_e})^{1-\alpha}$, which is always positive. It is zero, however, for scientists using the hands-on model.

Prediction 3: A negative (positive) exogenous shock to research staff would have a measurable negative (positive) impact on the productivity of scientists who use the funded model, but would have little impact on those using the hands-on approach.

Empirical Evidence

We first provide empirical evidence for Predictions 1 and 2 using a longitudinal, cross-sectional survey of research-oriented faculty at a large number of US universities. We then test Prediction 3 using data from a survey we administered at two top US universities, MIT and Virginia Tech, combined with publication data extracted from the Scopus database.

Equilibrium results: The first set of data to test Predictions 1 and 2 comes from six Higher Education Research Institute (HERI) Faculty Surveys administered in 1989, 1992, 1995, 1998, 2001, and 2010. We excluded the 2004 and 2007 survey waves because they did not include any questions on research funding. The survey asks faculty about their appointment and rank, department, highest degree held, major, tenure status, demographic information (including gender, education, citizenship status, language, and age), salary, research output, whether they have received funding for their research, and weekly time allocation to teaching, research, advising/counseling students, and administrative tasks, among other topics. The aggregated sample of surveys contains data from 385,414 faculty working at 1,261 colleges and universities in the United States (see https://heri.ucla.edu/heri-faculty-survey/ for details). To focus on research-oriented faculty, we include in our analysis only assistant, associate, and full professors working at universities. Our final sample includes 116,067 faculty working at 194 US universities. The level of analysis in all regressions is the faculty-year.

We use the number of publications in the two years prior to each survey wave as the main indicator of faculty research output—our main dependent variable. Our main independent variables are the average number of hours a faculty member allocated to advising and counseling students and whether she received any funding for her research in the two years prior to each survey. Although HERI Faculty Surveys offer one of the few datasets that include scientists' time allocation, some of their measures are imperfect matches for variables in our theoretical model. The data do not include the time each faculty member spends supervising research staff. Instead, it includes the "time spent on advising and/or counseling students." However, we expect a positive correlation between these two variables. We also do not observe the amount of funding each faculty member has received. Instead, we rely on whether they received any research funding in the two years prior to each survey wave. While this measure is far from perfect, we expect it to capture the basic variance in funding per faculty member across different departments.

We further control for the number of hours per week that a faculty member allocated to research, to teaching, to committee work and meetings, and to other administrative tasks; their gender; whether they had tenure; and whether they were US citizens at the time of the survey. We also include a set of year dummies to control for the macro factors (such as a financial crisis) that might have affected the research productivity of all faculty members in a given survey year. Finally, we include a full set of university dummies to control for the idiosyncratic characteristics of each institution that might influence the research productivity of its faculty across all departments.

Table 3 presents summary statistics for our sample. The faculty in our sample produced on average about five publications in the two years prior to each survey. Approximately 68% of them received funding during that period. On average, they spent about 11.6 hours per week on research and scholarly writing, 15.6 hours on teaching, 4.2 hours on advising and/or counseling students, 4.4 hours on committee work and meetings, and 4.8 hours on other administrative tasks. About 30% were female, 92% were US citizens, and 70% had tenure. Their average salary was approximately $78,000 (2009 dollars), their average age was about 47, and they had an average of 19 years of experience.

-- Table 3 about here --

Table 3 also breaks down the summary statistics across six major areas: engineering, life sciences, physical sciences, social sciences, humanities, and management. Consistent with the figures reported for Virginia Tech in Table 1, faculty in engineering, life sciences, and physical sciences on average produced more publications than faculty in social sciences, humanities, and management. Moreover, a higher proportion of the former group reported having received research funding in the previous two years. They also spent on average more time advising and/or counseling students, with the exception of faculty in physical sciences, who spent slightly less time with students than those in social sciences did. If we exclude the faculty in psychology, the statistics for faculty in social sciences look more like those in humanities and management. The statistics for faculty in psychology are more like those in physical sciences. As we show later in our econometric analysis, the faculty in psychology are indeed more likely to show the characteristics of the funded research model. The differences in these three variables between the faculty in engineering, life sciences, and physical sciences and the faculty in social sciences (excluding psychology), humanities, and management are all significant at the 99% level (using a t-test comparison of means).

Together, the summary statistics suggest a positive correlation between the number of publications, percentage of faculty who received funding, and the number of hours per week spent advising/counseling students across these six areas. The three graphs in Figure 1 illustrate the pair-wise correlations between these three variables. Following the typology introduced in the theoretical model, these graphs suggest a shift from the funded to the hands-on research model as we move from engineering and life sciences to humanities and management. However, the summary statistics cannot reveal the more nuanced interactions between funding, time spent on advising/counseling students, and research output as modeled in our theory section.

Next, we test the first two predictions using econometric analysis. We use the following linear ordinary least squares (OLS) regression with robust standard errors to estimate the association between funding, time allocated to advising/counseling students, and research output:

$$Research\ Output_{it} = \beta_1.Funded_{it} + \beta_2.Advising\_Time_{it} + \beta_3.Advising\_Time_{it} \times Funded_{it} + \ \theta.X_{it} + Year_t + \ \alpha + \varepsilon_i \quad (4)$$

where $Research\ Output_i$ is the number of publications by faculty member i in the two years prior to each survey, as reported in the survey administered in year t; $Advising\_Time_{it}$ is the number of hours per week spent by i on advising and/or counseling students, reported in year t; $Funded_{it}$ is equal to 1 if faculty member i indicated that she had received funding in year t, and 0 otherwise; X_{it} contains the set of control variables and includes i's institution, gender, tenure status, citizenship status, salary, age, experience (in years since last degree), and number of hours per week spent on research, committee work and meetings, and other administrative duties; and $Year_t$ includes the set of year dummies corresponding to each survey wave.

Model 1 of Table 4 shows the estimation results without the interaction between funding and the time spent on advising/counseling. Following our theoretical model, we expect both β_1 and β_2 to be positive and significant. Moreover, we expect β_2 to be positive and significant only in areas that use the funded research model and to be smaller and insignificant in areas that use the hands-on research model. We add the interaction term in Model 2. After controlling for the moderating role of funding, we expect β_2 to turn insignificant and the positive effect of time spent on advising/counseling students on research output to be largely captured by β_3 (Prediction 1).

The results in Model 1 shows a significant positive relationship between both funding and the time a faculty member spends on advising/counseling students and her research output. Having funding is associated with 1.5 more publications in a two-year window, a 30% increase over the baseline. Moreover, an extra hour spent on advising/counseling per week is associated with about 0.1 more publications in a two-year window. Put differently, a one-standard-deviation increase in time spent advising/counseling is associated with about 0.2 extra publications per year. Not surprisingly, the time spent on research is also strongly and positively correlated with the two-year research output. A one-standard-deviation increase in time spent on research leads to about 0.5 additional publications per year. In contrast, the number of hours spent on teaching and administrative activities is negatively and significantly associated with research productivity. The impact of time spent on committee work and meetings is not significant. Moreover, female faculty produce on average 0.16 fewer publications per year, which is consistent with previous findings in the literature and may be due to family demands or to sorting into different types of project (Fox 2005). US citizens also produced significantly fewer publications than did non-citizens working in the US, which might be due to lower incentives for US citizens, to sorting into different departments and research trajectories, and/or to selection on quality (Hur et al. 2015). A higher salary is on average associated with greater research productivity. Tenured faculty and more experienced faculty are on average significantly more productive, but age is negatively associated with research output. The estimates associated with the control variables are in line with prior findings and anecdotal observations (Fox 1983).

-- Table 4 about here --

Results in column 2 are for the interaction model. The coefficient of time spent advising/counseling students is now close to 0 and is insignificant. Instead, the positive significant coefficient of the interaction term suggests that there is a positive effect of advising/counseling on research output only for faculty who received funding prior to the survey. The estimates are broadly consistent with Prediction 1. However, the aggregation of data across all areas masks the heterogeneity in the modes of research across departments (hands-on or funded). In other words, it is not clear whether the positive interaction effect is driven by faculty in areas that use the funded research model (our Prediction 2) or is instead driven homogenously by funded faculty across all departments.

Table 5 repeats the interaction model for each major area in the sample separately. The effects of control variables on research output are largely similar across all the areas and in line with those reported in Table 4. Consistent with Prediction 2, in the absence of funding there is little relationship between spending time on advising/counseling students and research output. The only exception is in the physical sciences, where spending time on advising/counseling in the absence of funding is still positively and significantly associated with research productivity.[2] When interacted with funding, the estimated effect of spending time on advising/counseling is large, positive, and significant in engineering, life sciences, physical sciences, and social sciences and negligible and insignificant in humanities and management. In Table 6, we further break down the social sciences into psychology and non-psychology areas. The data from the Virginia Tech (in Table 1) and national surveys[3] suggest that faculty in psychology on average supervise larger groups of research staff and receive more funding for their research than faculty in the other social sciences do. The estimates in Table 6 show that, whereas in psychology spending time on advising/counseling is significantly associated with research productivity when faculty have received funding, in the other social sciences there is no significant relationship between allocating time to students and research output, independent of funding status. Figure S1 in Appendix B is a graphical summary of interaction effects across fields. The regression results are completely robust to a split-sample analysis, based on whether faculty received funding, within each department.

In short, faculty in engineering, life sciences, physical sciences, and psychology largely use the funded research model, while those in social sciences (excluding psychology), humanities, and management largely use the hands-on research model. These findings support Predictions 1 and 2 and highlight the different roles of funding and research staff in the funded and hands-on research models.

-- Tables 5 and 6 about here --

Causal results: We use a different sample to test Prediction 3. The data was collected in two steps. First, we sent a survey to all faculty we could identify at MIT (964) and Virginia Tech (1,509), two top US research universities. We collected the faculty names, department information, and email contacts from department websites and faculty directories. The survey was conducted over four months between

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[2] Further analysis shows that the effect of time spent on students on research output in the physical sciences becomes insignificant once we exclude faculty in statistics departments. Our qualitative interviews with statistics faculty in a small sample of universities suggest that they can maintain a relatively large number of students without much funding, since students usually are supported by doing work for faculty in other departments.

[3] In 2010, for example, 36.5% of psychology faculty had federal funding, compared with 20.6% in the other social sciences, and 0.17 vs. 0.11 doctorate degrees were granted, respectively, per full-time academic faculty member (National Science Foundation 2015b).

December 2016 and April 2017. The survey questions are listed in Appendix C. The respondents were asked whether they have ever had a graduate student, postdoc, or research staff who had gone unexpectedly absent; for example, due to visa or health issues. If the respondents answered yes, the survey then asked how many times it had happened and asked for more details about each incident. The questions included the timing of the incident, the length of the absence, the reason for it, how the student was funded, how much research funding the faculty had at the time of the incident, and how many other students the faculty had been advising at the time of the incident. Out of 2,473 inquiries, we received 259 responses indicating no incidents, 58 reporting one incident, 30 reporting two, and 15 reporting three. Of those 103 reporting an incident, 83 provided detailed data on at least one incident. All incidents had occurred between 1996 and 2016. Since we focus on identifying rare events, we do not have a clear measure of true response rate among faculty experiencing at least one incident. Nevertheless, our focus here is on the differential effect of unexpected absence of research staff on scientists' productivity between the two research models. While scientists who had experienced a negative effect in their productivity might be more likely to report the incidents, we do not expect this bias to be systematically different between those who use the funded research model and those who use the hands-on model. In fact, such a response bias may lead to an estimated negative effect of staff absence on productivity for scientists using the hands-on model, which would work against our theoretical model. As we report below, our estimates suggest that staff absences had no significant effect on the research output of scientists using the hands-on model.

In the second step, we collected from the Scopus database all the publications of each faculty who reported at least one unexpected absence of a research team member. Scopus is one of the most comprehensive databases of academic research, covering almost all major domains of knowledge. We used the faculty name and institutional affiliation to identify each faculty on Scopus. For each publication, we also collected the number of citations it had received. Following previous research, we use the citation impact of each publication to adjust for its quality (Azoulay et al. 2009; Vakili and McGahan 2016; Vakili et al. 2015).

After excluding the most recent incidents (the impact of which cannot yet be tracked) and scientists with incomplete publication data, the final sample is a panel of 71 scientists reporting a total of 100 incidents. A typical scientist in our sample has an average of 201.2 citation-weighted publications per year. The sample includes 1,752 scientist-year observations. For each scientist, we coded his or her research model as either hands-on or funded, based on the department affiliation. Fifty-four were flagged as affiliated with the funded research model; they produced an average 270.5 citation-weighted publications yearly during the sample period. Seventeen were flagged as affiliated with the hands-on research model; they produced on average 31.5 citation-weighted publications yearly during the sample period. The difference in publication output between the two groups is significant at the 99% level (based on t-test analysis). The median scientist assigned to the hands-on model reported having below $50,000 in annual funding and fewer than three team members at the time of the absence incident. The median scientist assigned to the funded model reported having between $200,000 and $500,000 in funding and between six and eight team members at the time of the absence incident. Given the larger teams in the funded model, one might intuitively have predicted a *smaller* negative impact of an absence on the productivity of faculty using the funded model; after all, they have more people to make up the slack. Our model predicts the opposite: teams are larger in funded model because of the positive net productivity of research staff, and therefore the loss of one staff would have a larger productivity cost for those following the funded model compared to the hands-on faculty. Thus this setup provides a rather conservative test for our model.

For each scientist, we estimate the impact of the unexpected absence of a student on her research output in subsequent years. Each absence incident is coded based on its length, ranging from 0 to 1: 0.25, 0.5, 0.75, and 1 for the absence lengths of 2-4 months, 5-8 months; 9-12 months, and more than 12 months, respectively. Based on our interviews with faculty, we assumed that it can take about two years for an absence to show its effect on research output. Below, we report the results for a two-year lag between the incident and its effect on publication output. The estimates based on a three-year lag are in line with those reported here, but the effects are smaller. All estimations have individual and year fixed effects. The individual fixed effects control for time-independent idiosyncratic characteristics of each faculty, such as their innate quality. The time fixed effects control for the macro events that would affect the productivity of all faculty in the sample. We also control for the nonlinear effect of experience on productivity, using a fifth-degree polynomial function of experience.

Our estimation method is in principle similar to a difference-in-differences method. For each scientists who experienced an absence incident at time *t*, those who have not experienced an incident by then act as controls. We estimate the effect of absence on research output using both conditional fixed-effect panel Poisson models and panel OLS with individual fixed effects. In both cases, we use robust standard errors. We also report the results using both a split sample analysis—estimating the effect separately for faculty using the hands-on model and the funded model—and an interaction model in which the absence is interacted with whether the faculty uses the funded model.

Table 7 reports the results. Model 1 shows the estimated impact, based on the OLS model, of the unexpected absence of a graduate student or postdoc on the citation-weighted publication output of scientists using the funded model. Model 2 shows the same estimated effects for faculty using the hands-on model. A sudden decline in the research staff has a significant, large negative effect on the research output of faculty using the funded model. The results suggest that a one-standard-deviation increase in the absence of a research staff member is associated with a decline of 31 citation-weighted publications per year for faculty using the funded model.[4] Put differently, the unexpected absence of a research staff member for a year can lead to a 0.4-standard-deviation decline in citation-weighted output of faculty using the funded model. In contrast, the absence of research staff seems to have a very small, positive, and statistically insignificant effect on the research output of faculty using the hands-on research model. The estimations based on the interaction model in Model 3 are in line with those based on the split-sample analysis. Models 4 to 6 show the same results based on the panel Poisson estimates. The results are in line with those reported in Models 1 to 3, suggesting that the unexpected absence of research staff has a negative effect on research

[4] Note that the faculty who use the funded model in the sample produced on average 270 citation-weighted publications per year during the sample period. The standard deviation is also relatively large at 731. While the estimated coefficient is large, it is equivalent to 37% of the observed standard deviation in citation-weighted publication output of this faculty group.

output for faculty using the funded model but little effect for those using the hands-on model. Overall, the results confirm Prediction 3.

-- Table 7 about here --

Discussion and Conclusion

Using a parsimonious model, we showed that the variance in the net productivity of research staff—that is, their productivity relative to the focal scientist minus the opportunity costs to the scientist of advising and of raising funds for the staff—brings about two different organizations for scientific research. The hands-on research model dominates where research staff are less productive or require extensive training and supervision or where raising research funds is very time-consuming. This model leads to smaller research groups, with the main scientist doing many day-to-day research tasks, and to limited demand for research funding. In contrast, where PhD students and postdocs could be net contributors, the most successful scientists (in terms of publication) have large teams and spend most of their time securing research funding. We explored some empirical implications of this model using survey data and provided exploratory evidence in support of the analytical model. In this section, we first explain possible extensions to our model and then lay out its broader theoretical, managerial, and policy implications.

Model extensions and theoretical implications

Our model is relatively parsimonious and could be extended on multiple fronts. In particular, the current model is static and does not capture some of the reinforcing dynamics that can lead to further differentiation in the organization of scientific work and productivity across and within knowledge domains. There are indeed various economies of scale, scope, and learning that can, over time, particularly reinforce a scientist's reliance on the funded research model. Once a scientist trains a group of research staff, she can use them across multiple projects that share similar tasks, which would lower the per-project cost of training and managing them. Also, in the funded model, to the extent that research staff can train one another, scientists can allocate relatively less time to training and advising per staff person and instead spend more time raising funds to support a larger group, which would in turn increase the viability of the funded research model in the next period. In addition, scientists involved in raising funds can build their funding networks, learn about funding opportunities, and influence funding directions, thus reducing the cost of fundraising for themselves and making the funded model more advantageous in the future. Greater reliance on the funded research model can also lead to relatively more publications and hence greater reputation, which in turn increases the chances of attracting funding and of acquiring the strongest, most productive research staff. In fact, in the short run, total capacity for publication in each field is capped by the space in the relevant journals. Hence, reinforcing dynamics may increase skewness of publication distribution in a zero-sum game. Refinements to our model could also capture how growth in team size increases organizational complexity and thus could cap the team size and funding demand before scientist's time becomes a binding constraint.

Research equipment can also influence these dynamics. At 3% of total academic R&D costs (and below 8% in all subfields) (National Science Foundation 2015a), equipment cannot explain the observed magnitude of variations in funding (for example, those in Table 1). However, equipment needs require faculty to engage in fundraising, with the aforementioned learning effects. A more subtle impact of equipment is on modularizing research tasks into concrete interactions with physical artifacts. This organizing effect allows for more efficient division of labor, engages novice research staff (for example, first-year PhD students) in simpler well-defined tasks, and thus increases the relative productivity of the research staff and the viability of the funded model. These synergies between equipment use and use of the funded model may lead to significant correlation between them, beyond what is predicted based on equipment costs alone.

Learning and economies of scale and scope are likely less pronounced, though not absent, in areas using the hands-on research model. Hence, we expect to see an increase over time in the gap in the team size and research productivity of scientists using the funded model and those using the hands-on model. This expectation is consistent with some of the empirical evidence reported by Wuchty, Jones, and Uzzi (2007): whereas the average team size in sciences and engineering almost doubled between 1960 and 2000 (from 1.9 to 3.6), it increased more slowly in the social sciences (from 1.2 to 2) and remained almost unchanged in the arts and humanities. According to the knowledge burden theory, as the knowledge frontier moves outward, scientists must become more specialized in order to reach it, which in turn increases their need to collaborate in order to complement one another's specialties (that is, to make up for the narrowness of their own expertise) in order to extend the knowledge frontier even further (Jones 2009). A dynamic extension of our model can complement the knowledge burden theory by explaining the heterogeneous rates of increase in team size and productivity across knowledge domains.

The same reinforcing dynamics can also result in significant stratifications across scientists within an area, particularly where the funded research model dominates. The reinforcing mechanisms behind the funded research model combined with the competition amongst scientists to obtain funding and acquire the best talent can create a dynamic whereby "the rich get richer"—a few labs at top research universities attract much of the available funds and many of the high-quality PhD students and produce much of the high-impact work. Table 8 shows the standard deviations of research output across scientists in the six main areas plus psychology for the first two (aggregated) and the last two (aggregated) surveys in our sample. The standard deviations in two-year research output within engineering, life sciences, physical sciences, and psychology grew by 31%, 27%, 7%, and 28%, respectively, between the periods 1989–1991 and 2007–2010, suggesting an increase in the gap between the research outputs of high performers and low performers in the field. In contrast, the standard deviations in research output in social sciences (excluding psychology), humanities, and management dropped by 11%, 8%, and 17%, respectively, during the same period, suggesting a convergence in productivity for scientists in these areas.

-- Table 8 about here --

Our model can also provide a theoretical basis for the differences in perceived relevance gap between academia and industry. For example, several management scholars have worried about the disconnect between management research and management practice (Barley et al. 1988; Hambrick 1994; Markides 2007; Mintzberg 2004; Vermeulen 2007). This perception is not limited to management researchers, though. Becher (1994) observes that, unlike those in engineering and natural sciences, researchers in social science and the humanities areas—who also use the hands-on research model—

perceive limited connection between their work and the outside world. Our framework provides one potential explanation for this perceived gap. In areas using the funded research model, the significant need for funding leads to considerable interaction between the scientists, public funding agencies mandated to serve the public interest, and industry as a potential source of research grants. Consequently, the research questions in these areas are actively aligned with the needs of supporting constituencies, be it industry or the public. These relationships would also lead scientists to build capabilities that are in greater demand by the research clients, not only because they are engaged in writing grants and justifying the research in terms of various benefits for the clients, but also because they have to adopt concepts that the industry or public interest audience can relate to. In contrast, the hands-on model's lower demand for external funding leads to fewer such relationships and fewer such attempts to align with external stakeholders. In the absence of external feedback, research questions may diverge from the public's interest, contributing to the perceived disconnect in hands-on areas between research and the needs of industry and society.

Our model also sheds light on the central role of funding in shaping the research portfolio and trajectory of scientists in areas using the funded research model. In particular, the rise and fall of particular funding opportunities requires scientists to adjust their research portfolio accordingly. Thus, we expect the research portfolios of scientists in these areas to be not only more homogenous at any given time but also more volatile over time than the research portfolios of hands-on scientists. For the latter, we expect the changes in research trajectories to follow more closely the individual scientist's interests and the socially constructed view of the field about what the important questions are at any time. In the absence of the homogenizing pressures of external funding in hands-on research areas, various research communities with different research trajectories—and hence different tools and constructs—can emerge and coexist (Scherer 1998), increasing the plurality in the field at the expense of paradigmatic consensus (Pfeffer 1995; van Maanen 1995). The lack of paradigmatic consensus may in turn increase the cost of training research staff and further solidify the hands-on research model in these areas. In contrast, the adoption of the funded research model and the resulting requirement for collaboration among larger groups of (potentially less-experienced) research staff creates pressure to adopt a well-defined common language across research subcommunities. The paradigmatic consensus in funded research areas can be observed, for example, in shorter introductions in published research (compared with papers coming from the hands-on research model (Strang and Siler 2015)) and more collaborations that span more distant disciplines (Newman 2004; Wuchty et al. 2007).

Managerial and policy implications

Changing the distribution and supply of research funding across various knowledge domains is one of the most common strategic levers by which governments and private organizations try to shape the pace and direction of scientific research. Our model provides insight into the effectiveness of funding as a strategic lever. Whereas the dominant narrative suggests a simple linear relationship between funding and research output (Furman et al. 2012), our findings suggest a more nuanced and nonlinear relationship. At low levels of funding supply (which significantly raise the costs of securing funding) or in fields in which the hands-on research model dominates, the demand rather than the supply would be the binding constraint on funding use. Thus, increases in funding may have limited impact on the direction and production of scientific output. Therefore, if national basic research programs and private funding grants are to have a notable impact on academic scientific production, they need to be large and to focus on fields with potential to adopt the funded model. More particularly, in areas where the hands-on research model dominates, the distribution of funding may prove inadequate to regulate the research direction and outputs. In the absence of a clear strategic lever to influence research in these fields, the basic contract underlying external funding of research—where funding agencies set the direction and fund the research and academic scientists work on those priorities—starts to break down. Policy makers and managers of organizations may see a need for research in those domains (because there are many unanswered questions that can benefit from basic research) while also finding the output of existing research wanting. Indeed, over the past decades, several attempts have been made to increase federal support for social science research, yet the total share for social sciences in federal research funds declined from 4.3% in 1970 to 1.9% in 2014 (National Science Foundation 2015a). The challenge to hands-on research increases further when we consider that teaching loads are a function of a university's business model. In the absence of research funding, declining state and federal spending on higher education (Hovey 1999) may be putting a disproportionate pressure on social sciences and humanities, leading many administrators to squeeze out research time by increasing teaching loads in order to balance university budgets (Summers 2005).

Our findings also address another puzzle regarding the supply and demand of funding. Despite more than thirty-fold growth in the supply of funding in the US over the last 60 years, demand has grown even more quickly. Whereas in the 1950s, the acceptance rate of typical National Institutes of Health (NIH) and National Science Foundation proposals was over 50%, it is now below 20% (Stephan 2013). These conflicting trends have fueled a policy debate on the merits of additional public research funding. At the heart of this puzzling imbalance is a reinforcing feedback whereby each scientist, using research funding, trains more than one other scientist, leading to an even larger pool of scientists who eventually demand more funding, and the cycle continues. Our model sheds light on the strength of this reinforcing loop, which has been called the basic reproduction number of academia (R0) (Larson et al. 2014). Where the funded model dominates, each scientist trains many PhD students, increasing future demand for research funding several-fold if those trainees decide to pursue basic research. In fact, increasing the availability of funding counterintuitively leads to an increase in R0 (because more students and postdocs can be accommodated by each scientist), so that demand will grow even more quickly. R0's in hands-on fields are smaller and are not influenced by funding availability. Given the significantly different R0's across fields (Larson et al. 2014), a balanced portfolio of basic research funding will skew over time towards favoring the fields with the highest R0. Those fields endogenously generate increasing demand, getting a higher share of the overall funding, and thus calling for even more funding. Even if those demands for additional funding are granted, those fields continue to see a reduced funding rate as supply-generated demand always remains ahead of supply. The distribution of funding across fields in the US may show some of this crowding-out effect; the share of the NIH budget for life sciences research has increased significantly over the past 50 years (National Science Foundation 2015a; Stephan 2013). Overall, supply for funding would be quickly matched and exceeded by demand in funded fields, while in hands-on fields, demand for funding may take much longer to catch up to an increase in supply. Therefore, metrics of the balance of supply and demand, such as funding rate, are noisy and imprecise in assessing the actual societal return on marginal additional supply of funding. Yet, in the absence of better measures of the economic value of scientific output, easily measured metrics, such as funding rate, may hold sway in policy debates.

Our model also addresses the potential mismatch in the skills of scientists hired into academic positions. The funded model calls for scientists who spend most of their time seeking funding, promoting their research, and managing their groups. These activities call for managerial and public relations skills as much as for scientific research aptitude. However, at the time of appointment into a faculty position, little is known about whether the candidate has those skills; decisions are largely based on research skills. In fact, some candidates who secure a tenure-track position in a funded field may find it more satisfying to act as research staff, while others with the skills best fitted to managing a research group may never get to lead one. Academic departments conducting funded research may find it valuable to more systematically consider managerial skills when hiring faculty.

Finally, our results have important implications for the scientific labor market. An important—yet under-explored—output of the scientific enterprise is the training of the scientific workforce. Where the funded model dominates, PhD students are the workhorses of producing science and the capacity to train them scales directly with the funding supply for basic research. This creates a policy dilemma when an increase in basic research is called for based on its societal returns but there is already an oversupply of PhDs. The returns on basic science would justify increased funding, yet such increases would exacerbate the oversupply of PhDs. One might expect an excess of PhDs to be balanced by reduced demand for applying to PhD programs in funded research areas in response to low or negative returns to pursuing a PhD. However, this balancing mechanism is dampened and delayed because a significant part of demand for PhD programs in top research universities can come from foreign applicants with limited knowledge of—and sensitivity to—labor markets in the host country. For example, more than half of all PhD graduates of US engineering programs are foreigners (National Science Foundation 2015b). In fact, as a proimmigration policy, subsidizing PhD programs may prove very effective for attracting skilled immigrants to countries with strong basic research programs that could use the funded model. On the other hand, the supply of scientific workforce in fields dominated by hands-on research would be less sensitive to funding policy. Overall, we expect that the viability of policy levers and their impact on scientific research and scientific workforce output are highly contingent on where the research domain stands on the funded–hands-on continuum. A more nuanced understanding of the organization of science is thus important for the design and implementation of effective science policy.

References

Agrawal, A., A. Goldfarb, F. Teodoridis. 2016. Understanding the Changing Structure of Scientific Inquiry. *American Economic Journal: Applied Economics* **8**(1) 100-128.

Arora, A., S. Belenzon, A. Patacconi. 2015. Killing the Golden Goose? The Decline of Science in Corporate R&D. National Bureau of Economic Research.

Azoulay, P., W. Ding, T. Stuart. 2009. The Impact of Academic Patenting on the Rate, Quality and Direction of (Public) Research Output. *J Ind Econ* **57**(4) 637-676.

Azoulay, P., J.S.G. Zivin, G. Manso. 2011. Incentives and creativity: evidence from the academic life sciences. *Rand J Econ* **42**(3) 527-554.

Barley, S.R., G.W. Meyer, D.C. Gash. 1988. Cultures of Culture - Academics, Practitioners and the Pragmatics of Normative Control. *Admin Sci Quart* **33**(1) 24-60.

Becher, T. 1994. The significance of disciplinary differences. *Studies in Higher Education* **19**(2).

Bensman, S.J. 1982. Bibliometric Laws and Library Usage as Social Phenomena. *Library Research* **4**(3) 279-312.

Bikard, M., F. Murray, J.S. Gans. 2015. Exploring Trade-offs in the Organization of Scientific Work: Collaboration and Scientific Reward. *Management Science*.

Dasgupta, P., P.A. David. 1994. Toward a New Economics of Science. *Research Policy* **23**(5) 487-521.

Diamond, A.M. 2005. Measurement, incentives and constraints in Stigler's economics of science. *European Journal of the History of Economic Thought* **12**(4) 635-661.

Fairweather, J.S. 1993. Faculty Reward Structures - toward Institutional and Professional Homogenization. *Research in Higher Education* **34**(5) 603-623.

Fox, M.F. 1983. Publication Productivity among Scientists - a Critical-Review. *Social Studies of Science* **13**(2) 285-305.

Fox, M.F. 2005. Gender, family characteristics, and publication productivity among scientists. *Social Studies of Science* **35**(1) 131-150.

Fox, M.F., S. Mohapatra. 2007. Social-organizational characteristics of work and publication productivity among academic scientists in doctoral-granting departments. *Journal of Higher Education* **78**(5) 542-+.

Furman, J.L., F. Murray, S. Stern. 2012. Growing Stem Cells: The Impact of Federal Funding Policy on the US Scientific Frontier. *J Policy Anal Manag* **31**(3) 661-U151.

Hambrick, D.C. 1994. What If the Academy Actually Mattered. *Academy of Management Review* **19**(1) 11-16.

Hovey, H.A. 1999. State Spending for Higher Education in the Next Decade: The Battle To Sustain Current Support.

Huang, M.-h., Y.-w. Chang. 2008. Characteristics of Research Output in Social Sciences and Humanities. *Journal of American Society for Information Science and Technology* **59**(11) 1819-1828.

Hur, H., N. Ghaffarzadegan, J. Hawley. 2015. Effects of Government Spending on Research Workforce Development: Evidence from Biomedical Postdoctoral Researchers. *Plos One* **10**(5).

Jones, B.F. 2009. The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder? *Rev Econ Stud* **76**(1) 283-317.

Kasten, K.L. 1984. Tenure and Merit Pay as Rewards for Research, Teaching, and Service at a Research University. *Journal of Higher Education* **55**(4) 500-514.

Larson, R.C., N. Ghaffarzadegan, Y. Xue. 2014. Too Many PhD Graduates or Too Few Academic Job Openings: The Basic Reproductive Number R-0 in Academia. *Syst Res Behav Sci* **31**(6) 745-750.

Li, D., L. Agha. 2015. Big names or big ideas: Do peer-review panels select the best science proposals? *Science* **348**(6233) 434-438.

Markides, C. 2007. In search of ambidextrous professors. *Academy of Management Journal* **50**(4) 762-768.

McMillan, G.S., F. Narin, D.L. Deeds. 2000. An analysis of the critical role of public science in innovation: the case of biotechnology. *Research Policy* **29**(1) 1-8.

McPherson, M.S., M.O. Schapiro. 1999. Tenure issues in higher education. *Journal of Economic Perspectives* **13**(1) 85-98.
Merton, R.K. 1968. The Matthew effect in science. *Science* **159**(3810) 56-63.
Merton, R.K. 1973. *The sociology of science : theoretical and empirical investigations*. University of Chicago Press, Chicago.
Merton, R.K., H. Zuckerman. 1973. Institutionalized patterns of evaluation in science. *The sociology of science: Theoretical and empirical investigations* 461–496.
Mintzberg, H. 2004. *Managers not MBAs : a hard look at the soft practice of managing and management development*. Financial Times Prentice Hall, London ; New York.
Mokyr, J. 2002. *The gifts of Athena : historical origins of the knowledge economy*. Princeton University Press, Princeton, N.J.
Moses, I. 1990. Teaching, Research and Scholarship in Different Disciplines. *Higher Education* **19**(3) 351-375.
Narin, F., K.S. Hamilton, D. Olivastro. 1997. The increasing linkage between US technology and public science. *Research Policy* **26**(3) 317-330.
National Science Foundation. 2015a. Federal Funds for R&D survey data series.
National Science Foundation. 2015b. Science and Engineering Doctorates.
Newman, M.E.J. 2004. Coauthorship networks and patterns of scientific collaboration. *P Natl Acad Sci USA* **101** 5200-5205.
Pfeffer, J. 1995. Mortality, reproducibility, and the persistence of styles of theory. Organization Science **6** 681-686.
Polanyi, M. 1962. The Republic of Science - Its Political and Economic-Theory. *Minerva* **1**(1) 54-73.
Porter, S.R., R.K. Toutkoushian. 2006. Institutional research productivity and the connection to average student quality and overall reputation. *Economics of Education Review* **25**(6) 605-617.
Romer, P.M. 1990. Endogenous Technological-Change. *Journal of Political Economy* **98**(5) S71-S102.
Rosenberg, N. 1974. Science, Invention and Economic Growth. *Econ J* **84**(333) 90-108.
Scherer, A.G. 1998. Pluralism and incommensurability in strategic management and organization theory: A problem in search of a solution. *Organization* **5**(2) 147-168.
Stephan, P. 2013. The Endless Frontier: Reaping what Bush Sowed? National Bureau of Economic Research.
Strang, D., K. Siler. 2015. Revising as Reframing: Original Submissions versus Published Papers in Administrative Science Quarterly, 2005 to 2009. *Sociol Theor* **33**(1) 71-96.
Summers, D. 2005. Prospects for the Humanities as Public Research Universities Privatize Their Finances *Tracking Changes in the Humanities- Essays on finance and education*, 47-79.
Tien, F.F. 2007. To what degree does the promotion system reward faculty research productivity? *British Journal of Sociology of Education* **28**(1) 105-123.
Vakili, K., A.M. McGahan. 2016. Health Care's Grand Challenge: Stimulating Basic Science on Diseases That Primarily Afflict the Poor. *Academy of Management Journal* **59**(6) 1917-1939.
Vakili, K., A.M. McGahan, R. Rezaie, W. Mitchell, A.S. Daar. 2015. Progress in Human Embryonic Stem Cell Research in the United States between 2001 and 2010. *Plos One* **10**(3).
van Maanen, J. 1995. Style as theory. *Organ Sci* **6** 133-143.
van Raan, A.F.J. 1988. *Handbook of Quantitative Studies of Science and Technology*. North Holland Publishing Co., Amsterdam.
Vermeulen, F. 2007. "I shall not remain insignificant": Adding a second loop to matter more. *Academy of Management Journal* **50**(4) 754-761.
Wuchty, S., B.F. Jones, B. Uzzi. 2007. The increasing dominance of teams in production of knowledge. *Science* **316**(5827) 1036-1039.

Figure 1 – the correlations between funding, hours spent on advising/counseling students and publications

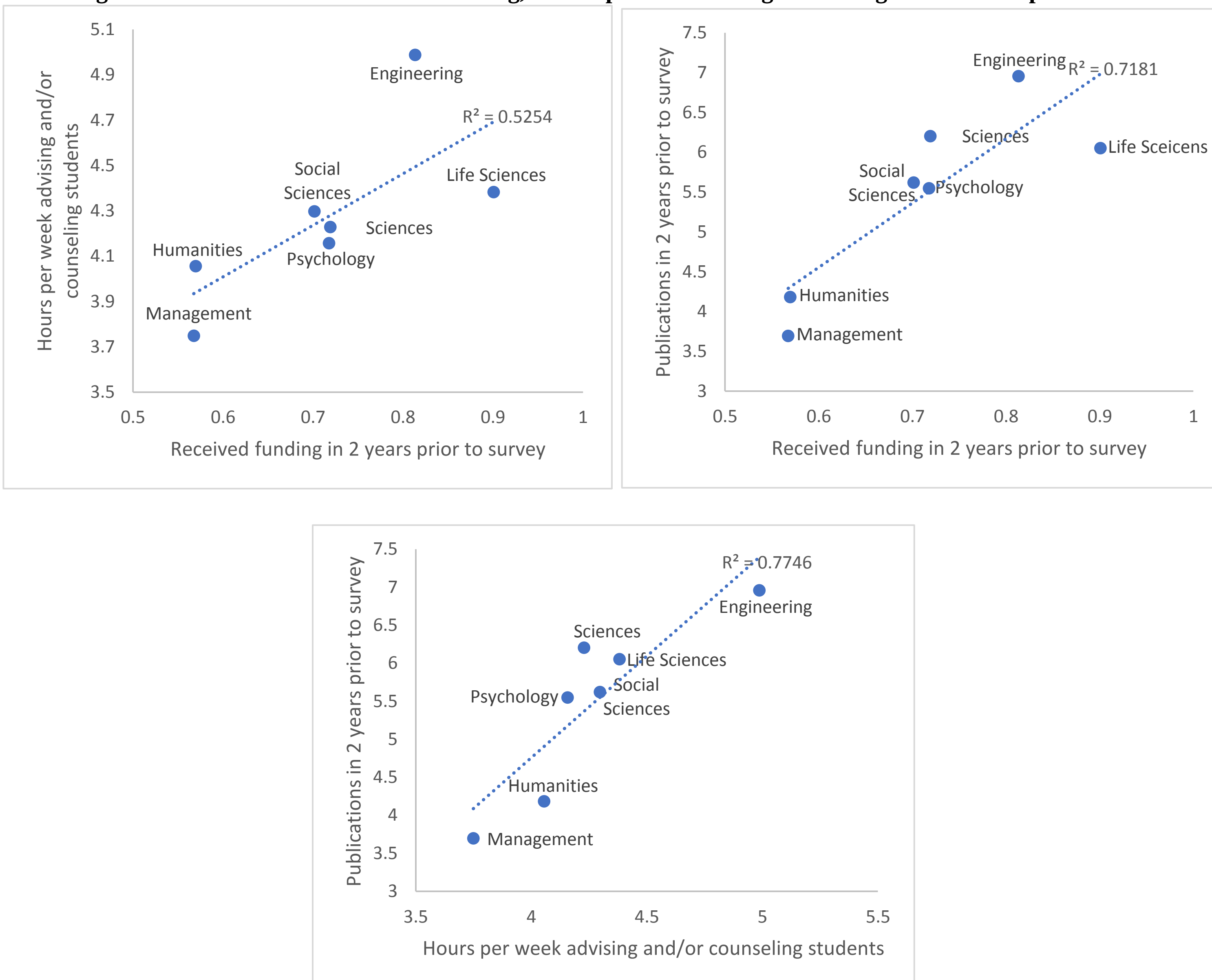

Table 1 – Faculty statistics at Virginia Tech

Department[1]	Research Staff per Scientist[2]	External Funding per Scientist[3]	Publications per Scientist[4]	# of Scientists[5]	Area[6]
Mechanical Engineering	2.82	258,573	4.00	66	Engineering
Civil & Environmental Engineering	2.66	158,815	2.17	64	
Computer Science	4.61	216,526	2.63	41	
Industrial and Systems Engineering	2.52	91,045	1.71	31	
Aerospace and Ocean Engineering	2.69	169,169	1.21	29	
Biological Systems Engineering	1.40	67,686	1.84	25	
Engineering Science & Mechanics	3.21	112,824	1.04	24	
Materials Science & Engineering	4.27	120,831	2.95	22	
Biomedical Engineering	7.38	102,744	4.90	21	
Mining and Minerals Engineering	0.41	160,765	0.24	17	
Chemical Engineering	3.00	138,967	3.60	15	
Electrical & Computer Engineering	2.71	132,035	2.63	103	
Average (Weighted by the number of faculty)	**3.04**	**156,045**	**2.55**		
Biomedical Science	1.68	69,153	1.83	41	Life Sciences
Biological Sciences	1.55	84,654	3.96	55	
Human Nutrition, Foods & Exercise	1.41	183,294	1.15	39	
Crop & Soil Environmental Science	1.06	100,769	1.06	35	
Biochemistry	1.18	124,007	1.97	31	
Animal and Poultry Sciences	1.15	106,423	2.63	27	
Entomology	1.26	142,183	1.50	26	
Plant Pathology, Phys, & Weed Sci.	1.49	138,703	1.75	24	
Horticulture	1.30	91,600	1.19	16	
Food Science and Technology	1.38	81,794	1.08	13	
Average (Weighted by the number of faculty)	**1.37**	**112,178**	**2.02**		
Chemistry	3.51	137,274	3.44	41	Physical Sciences
Mathematics	0.87	15,607	1.73	40	
Physics	2.20	89,130	3.43	40	
Geosciences	1.59	101,797	2.97	34	
Statistics	3.05	27,607	2.63	19	
Average (Weighted by the number of faculty)	**2.18**	**79,330**	**2.86**		
Public & International Affairs	1.47	10,019	0.80	30	Social Sciences
Sociology	1.22	2,797	0.81	27	
Psychology	2.92	56,407	1.88	26	
Agricultural & Applied Economics	2.03	44,058	0.83	23	
Political Science	0.63	0	0.37	19	
Economics	0.94	2,056	1.25	12	
Hospitality and Tourism	1.10	9,156	1.90	10	
Average (Weighted by the number of faculty)	**1.59**	**20,219**	**1.05**		
School of Education	0.87	9,702	2.40	47	Humanities
English	0.50	932	0.14	36	
Foreign Languages and Literatures	0.00	4,552	0.12	26	
Human Development	2.38	34,791	0.96	24	
History	0.45	3,103	0.14	22	
Communication	0.00	1,818	0.45	11	
Average (Weighted by the number of faculty)	**0.76**	**9,224**	**0.92**		
Accounting & Information Systems	0.82	7,245	0.09	22	Management
Business Information Technology	0.05	0	0.63	19	
Finance, Insurance & Business Law	0.59	588	0.18	17	
Management	0.38	0	0.56	16	
Marketing	0.80	950	1.20	10	
Average (Weighted by the number of faculty)	**0.51**	**2,130**	**0.45**		

Notes: 1) Only traditional departments that actively publish research findings are included. 2) This number includes PhD students as well as senior research staff (post-doctoral and research associates typically employed by senior scientists) in each department. For interdisciplinary PhD programs, the number of students is distributed across departments proportional to the faculty from those departments active in the interdisciplinary center. 3) Average funding per faculty member for the 2011-2013 period. 4) Publications from 2013 with author address terms including "Blacksburg" and "Virginia Tech" (and other spelling variations such as "Virginia Polytech Inst") listed in Web of Science are matched using author address information against departments in Virginia Tech. A satisfactory match is found for more than 95% of 3,154 identified publications. 5) Includes both tenured/tenure-track and ranked research faculty based on Virginia Tech's human resource data. 6) Area labels are assigned to be roughly consistent with the Higher Education Research Institute Faculty Survey used in the quantitative analysis.

Table 2 – Metrics for the extent of relationship between a research group and external clients.

	Funded Research Model If $r_p > t_a + t_f$	Hands-on research Model If $r_p \le t_a + t_f$
Number of funded PhD Students (P)	$\alpha/(t_a + t_f)$	0
Equipment (E)	$(1-\alpha)/t_e$	
Scientist's Research Execution Time (T_r)	0	α
Research Output (O)	$(e_s r_p P)^{\alpha}(\frac{1-\alpha}{t_e})^{1-\alpha}$	$(e_s \alpha)^{\alpha}(\frac{1-\alpha}{t_e})^{1-\alpha}$
Scientist time on raising funds (T_f)	$1-\alpha t_a/(t_a + t_f)$	$1-\alpha$
Scientist time advising and managing the team (T_a)	$\alpha t_a/(t_a + t_f)$	0
Research fraction labored by funding (O_F)	1	0

Table 3 – Summary statistics by major area

Variables	All Areas	Engineering	Life Sciences	Sciences	Social Sciences	Humanities	Management
2yr publications	5.158 (7.210)	6.957 (8.597)	6.051 (7.365)	6.202 (8.649)	5.575 (6.588)	4.182 (4.669)	3.697 (4.540)
Hours per week advising and/or counseling students	4.172 (3.678)	4.987 (3.773)	4.382 (3.918)	4.228 (3.538)	4.273 (3.534)	4.056 (3.189)	3.749 (3.238)
Received external or internal funding	0.680 (0.466)	0.813 (0.390)	0.901 (0.299)	0.719 (0.449)	0.712 (0.453)	0.569 (0.495)	0.567 (0.495)
Hours per week spent on research & scholarly writing	11.617 (11.210)	13.163 (10.560)	17.196 (14.006)	14.374 (12.154)	14.079 (11.917)	10.830 (9.785)	11.587 (10.519)
Hours per week spent on committee work & meeting	4.400 (4.011)	4.438 (3.703)	4.294 (3.806)	4.076 (3.575)	4.240 (3.774)	3.983 (3.583)	4.440 (4.141)
Hours per week spent on other administration duties	4.825 (7.722)	4.853 (7.247)	4.305 (6.983)	4.169 (6.965)	4.563 (6.967)	4.437 (7.239)	4.284 (7.525)
Hours per week spent on teaching responsibilities	15.584 (10.420)	14.873 (8.941)	13.236 (10.045)	15.402 (9.502)	14.513 (9.261)	18.890 (10.237)	17.286 (9.688)
Gender (male=0, female=1)	0.297 (0.457)	0.105 (0.306)	0.227 (0.419)	0.158 (0.365)	0.312 (0.463)	0.345 (0.476)	0.225 (0.418)
US Citizen (no=0, yes=1)	0.923 (0.267)	0.874 (0.332)	0.922 (0.268)	0.877 (0.328)	0.918 (0.274)	0.875 (0.331)	0.922 (0.269)
Tenured (no=0, yes=1)	0.705 (0.456)	0.730 (0.444)	0.746 (0.435)	0.772 (0.420)	0.714 (0.452)	0.717 (0.450)	0.668 (0.471)
Salary ($K)	73.189 (35.656)	84.283 (39.473)	75.613 (32.921)	72.266 (33.340)	75.002 (35.706)	63.631 (32.108)	91.801 (39.075)
Age[1]	5.492 (2.040)	5.273 (2.171)	5.621 (1.969)	5.440 (2.146)	5.355 (2.090)	5.577 (2.098)	5.265 (2.008)
Experience (years since last degree)	19.060 (10.853)	19.037 (11.071)	16.558 (10.430)	21.230 (11.323)	18.943 (10.906)	18.355 (10.923)	16.558 (10.430)

Note: Standard deviations are shown in parentheses. The full sample included 128,005 faculty-year data points.

1) The survey asks participants to mark the age bracket they belong to. There are 10 age brackets: (1) Under 30, (2) 30 to 34, (3) 45 to 39, (4) 40 to 44, (5) 45 to 49, (6) 50 to 54, (7) 55 to 59, (8) 60 to 64, (9) 65 to 69, (10) 70+.

Table 4 – The interaction between funding, advising/counseling students, and research output

DV:	Publications in 2 years prior to Survey	
Model:	OLS with Robust Standard Errors	
Area:	All Areas	
	(1)	(2)
Hours per week advising and/or counseling students	0.085***	0.004
	(0.008)	(0.009)
Received funding in 2 years prior to survey	1.499***	0.959***
	(0.003)	(0.082)
Received funding in 2 years prior to survey × Hours per week advising and/or counseling students		0.128***
		(0.014)
Hours per week spent on research and scholarly writing	0.101***	0.101***
	(0.003)	(0.003)
Hours per week spent on committee work and meetings	0.011	0.011
	(0.007)	(0.007)
Hours per week spent on other administration duties	-0.031***	-0.031***
	(0.003)	(0.003)
Hours per week spent on teaching responsibilities	-0.027***	-0.028***
	(0.003)	(0.003)
Gender (male=0, female=1)	-0.322***	-0.324***
	(0.053)	(0.053)
US Citizen (no=0, yes=1)	-0.761***	-0.758***
	(0.108)	(0.108)
Tenured (no=0, yes=1)	1.270***	1.258***
	(0.068)	(0.068)
Salary ($K)	0.025***	0.026***
	(0.002)	(0.002)
Age	-0.392***	-0.388***
	(0.022)	(0.022)
Experience (years since last degree)	0.034***	0.034***
	(0.005)	(0.005)
Survey year dummies	Yes	Yes
Institution dummies	Yes	Yes
Constant	2.119***	2.281***
	(0.178)	(0.267)
Observations	79,682	79,682
R-squared	0.112	0.113

Note: All estimates are from ordinary-least-squares (OLS) models. Robust standard errors are shown in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5 – The interaction between funding, advising/counseling students, and research output across major areas

DV:	**Publications in 2 years prior to Survey**					
Model:	**OLS with Robust Standard Errors**					
Area:	**Eng.**	**Life Sci.**	**Sciences**	**Social Sci.**	**Humanities**	**Management**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hrs./week advising students	-0.041 (0.043)	-0.050 (0.050)	0.079** (0.039)	0.015 (0.026)	0.015 (0.018)	-0.008 (0.042)
Received funding in 2 years prior to survey	0.479 (0.407)	1.131** (0.477)	1.750*** (0.313)	1.461*** (0.246)	1.287*** (0.193)	1.050*** (0.214)
Funding × Hrs./week advising students	0.298*** (0.064)	0.155*** (0.056)	0.180*** (0.056)	0.146*** (0.045)	0.007 (0.036)	0.043 (0.050)
Hrs./week spent on research and scholarly writing	0.118*** (0.015)	0.081*** (0.011)	0.125*** (0.011)	0.088*** (0.009)	0.094*** (0.009)	0.076*** (0.011)
Hrs./week spent on committee & meetings	-0.024 (0.034)	0.009 (0.038)	0.051 (0.035)	0.016 (0.024)	0.013 (0.018)	0.017 (0.018)
Hrs./week spent on other admin duties	-0.035* (0.018)	-0.047*** (0.018)	-0.041** (0.016)	-0.013 (0.013)	-0.034*** (0.008)	-0.018* (0.010)
Hrs./week spent on teaching responsibilities	-0.054*** (0.013)	-0.019* (0.012)	-0.058*** (0.012)	-0.020 (0.012)	-0.033*** (0.009)	-0.007 (0.009)
Gender (male=0, female=1)	0.768 (0.471)	-0.623*** (0.213)	-0.443* (0.243)	-0.304* (0.167)	0.007 (0.124)	-0.249 (0.164)
US Citizen (no=0, yes=1)	-2.233*** (0.455)	-0.851** (0.395)	-0.541* (0.317)	-1.134** (0.448)	-0.460** (0.196)	-0.136 (0.316)
Tenured (no=0, yes=1)	2.377*** (0.330)	1.702*** (0.293)	1.263*** (0.273)	1.704*** (0.230)	0.584*** (0.188)	0.461** (0.235)
Salary ($K)	0.031*** (0.010)	0.072*** (0.017)	0.053*** (0.015)	0.021*** (0.006)	0.028*** (0.007)	0.006** (0.003)
Age	-0.512*** (0.108)	-0.179 (0.135)	-0.561*** (0.105)	-0.413*** (0.068)	-0.249*** (0.054)	-0.074 (0.058)
Experience (years since last degree)	0.017 (0.024)	-0.039 (0.050)	0.056** (0.024)	0.040** (0.017)	0.019 (0.013)	0.024* (0.014)
Survey year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Institution dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.189*** (1.211)	7.867*** (1.488)	0.338 (0.751)	2.133*** (0.568)	1.942*** (0.569)	1.388 (0.951)
Observations	4,923	5,859	7,648	6,163	5,780	5,984
R-squared	0.172	0.154	0.181	0.169	0.165	0.150

Note: All estimates are from ordinary-least-squares (OLS) models. Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6 – Research mode differences between psychology and the other social sciences

DV:	**Publications in 2 years prior to Survey**	
Model:	**OLS with Robust Standard Errors**	
Area:	**Social Sciences excluding Psychology**	**Psychology**
	(1)	**(2)**
Hrs./week advising students	0.003 (0.049)	0.023 (0.034)
Received funding in 2 years prior to survey	0.869* (0.459)	1.660*** (0.317)
Funding × Hrs./week advising students	0.098 (0.076)	0.156*** (0.058)
Hrs./week spent on research and scholarly writing	0.095*** (0.014)	0.078*** (0.011)
Hrs./week spent on committee & meetings	0.022 (0.036)	0.008 (0.033)
Hrs./week spent on other admin duties	-0.032* (0.018)	-0.006 (0.019)
Hrs./week spent on teaching responsibilities	-0.020 (0.012)	-0.029** (0.013)
Gender (male=0, female=1)	-0.762*** (0.225)	-0.047 (0.247)
US Citizen (no=0, yes=1)	-0.581 (0.510)	-1.587*** (0.592)
Tenured (no=0, yes=1)	1.621*** (0.323)	1.835*** (0.328)
Salary ($K)	0.027*** (0.008)	0.019** (0.009)
Age	-0.224** (0.101)	-0.560*** (0.101)
Experience (years since last degree)	-0.009 (0.022)	0.070*** (0.025)
Survey year dummies	Yes	Yes
Institution dummies	Yes	Yes
Constant	2.434** (1.204)	2.097* (1.248)
Observations	2,327	3,836
R-squared	0.237	0.177

Note: All estimates are from ordinary-least-squares (OLS) models. Robust standard errors are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7 – the impact of unexpected absence of research staff on faculty productivity

DV:	Citation-weighted publication					
Model:	Panel OLS			Panel Poisson		
Sample:	Funded model	Hands-on model	Full sample	Funded model	Hands-on model	Full sample
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected absence of research staff	-290.302*** (7.989)	25.196 (24.686)	-0.008 (0.042)	-0.808** (0.338)	0.638 (1.195)	
Unexpected absence of research staff × hands-on model			-14.719 (119.426)			0.406 (0.940)
Unexpected absence of research staff × funded model			-0.254*** (69.954)			-0.800** (0.335)
Non-linear experience controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,244	508	1,752	1,242	501	1,743
Number of faculty	54	17	71	53	16	59
R-squared (within)	0.248	0.103	0.181			
Log-likelihood				-111958.87	-111715.51	-128034.75

Notes: Note: All estimates are from panel ordinary-least-squares (OLS) models with individual and year fixed effects. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8 – Change in the standard deviations of research output across scientists in the six main areas plus psychology from the first two surveys (aggregated) to the last two

	Standard deviation of research output for 1989 and 1992 surveys (aggregated)	Standard deviation of research output for 2007 and 2010 surveys (aggregated)	Percent change in standard deviations
Engineering	7.355	9.639	31%
Life sciences	6.019	7.650	27%
Sciences	7.907	8.472	7%
Psychology	5.220	6.708	28%
Social sciences (exc. psychology)	6.183	5.479	-11%
Humanities	4.768	4.392	-8%
Management	4.957	4.132	-17%

ONLINE APPENDIX TO ACCOMPNAY:

An Inside Look: Modeling Heterogeneity in the Organization of Scientific Work

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A-Analytical solutions

The model notations are summarized below:

Parameters (assumed constant):

r_p : The productivity of staff relative to scientist in contributing to labor component of research

t_a : The fraction of faculty time spent on training and advising one staff member

t_f : The fraction of faculty time spent on bringing the funding needed to sustain one staff member

t_e : The fraction of faculty time spent on bringing the funding needed to sustain one unit of equipment

e_s : The productivity of scientist in contributing to labor component of publication production

Decisions and Outcomes:

P: Number of funded research staff

E: Equipment

T_r: Scientist's Research Execution Time

O: Research Output

T_f: Scientist time on raising funds

T_a: Scientist time advising and managing the team

O_F: Research fraction labored by funding

1-Baseline model

To solve the first optimization model (equation 3), the Karush-Kuhn-Tucker conditions are used:

Defining: $\Lambda = (e_s T_r + e_s r_p P)^{\alpha} E^{1-\alpha} + \lambda(T_r + Pt_f + Pt_a + Et_e - 1) + \mu_1 T_r + \mu_2 E + \mu_3 P$

The following equations will hold at the local extremums for the original problem:

$$\frac{\partial \Lambda}{\partial T_r} = 0; \frac{\partial \Lambda}{\partial E} = 0; \frac{\partial \Lambda}{\partial P} = 0; \quad (4)$$

$$T_r + Pt_f + Pt_a + Et_e - 1 = 0 \quad (5)$$

$$\mu_1 T_r = 0; \mu_2 E = 0; \mu_3 P = 0; \quad (6)$$

This system of seven equations and seven unknowns can be solved by using the first three equations to find μ_1, μ_2, μ_3 in terms of other unknowns, and then solving the remaining four equations to find T_r, P, and E. This procedure provides two possible answer sets that maximize the original objective function depending on the parameter settings in the model. These results are summarized in Table 2 in the text.

2- Variable research design time

In the main analysis we distinguish between research design (research activities that the scientist is uniquely capable of undertaking) and research implementation (research activities that could be completed both by the scientist and her research team), and focused on the latter, making the assumption that the former is a constant. We can however explicitly capture research design time (T_D) as a variable the scientist can change, and consider its impact on the research output by moderating the scientist's time allocation problem to:

$$\underset{T_r, P, E, T_D}{Maximize} : (e_s T_r + e_s r_p P)^{\alpha} T_D{}^{\beta} E^{1-\alpha-\beta} \quad (8)$$

Subject to:

$$T_r + Pt_f + Pt_a + T_D + Et_e = 1$$

$$0 \le P, E, T_r, T_r$$

Solving this problem, using a similar method, leads to very similar results, where a fixed fraction of scientist's time ($T_D=\beta$) will be allocated to research design, and the optimum equipment level is $E=1-\alpha-\beta$. This solution is consistent with our original assumption, so we used the simpler model in the text.

3- Fellowships and assistantships

Finally, the possibility of using fellowships and teaching assistantships to fund research staff can be included. The resulting system of equations is thus modified to:

$$\underset{T_r, P, E, G}{Maximize} : (e_s T_r + e_s r_p (P + G(1-t_g)))^{\alpha} E^{1-\alpha} \quad (9)$$

Subject to:

$$T_r + Pt_f + Pt_a + Gt_a + Et_e = 1$$

$$G \le g$$

$$0 \le P, E, T_r, G$$

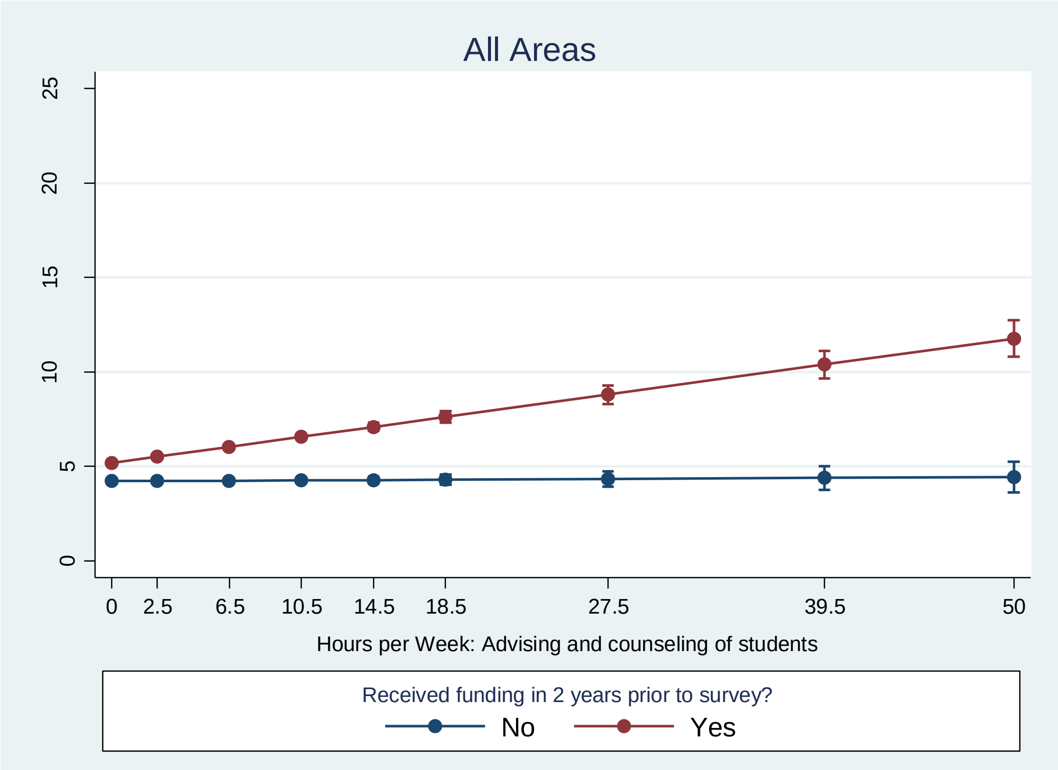
Here G is the number of scholarship/assistantship positions used by the group. Similar to the previous problems, the Lagrangian for this problem is formed and Karush-Kuhn-Tucker conditions applied, leading to the following feasible solutions:

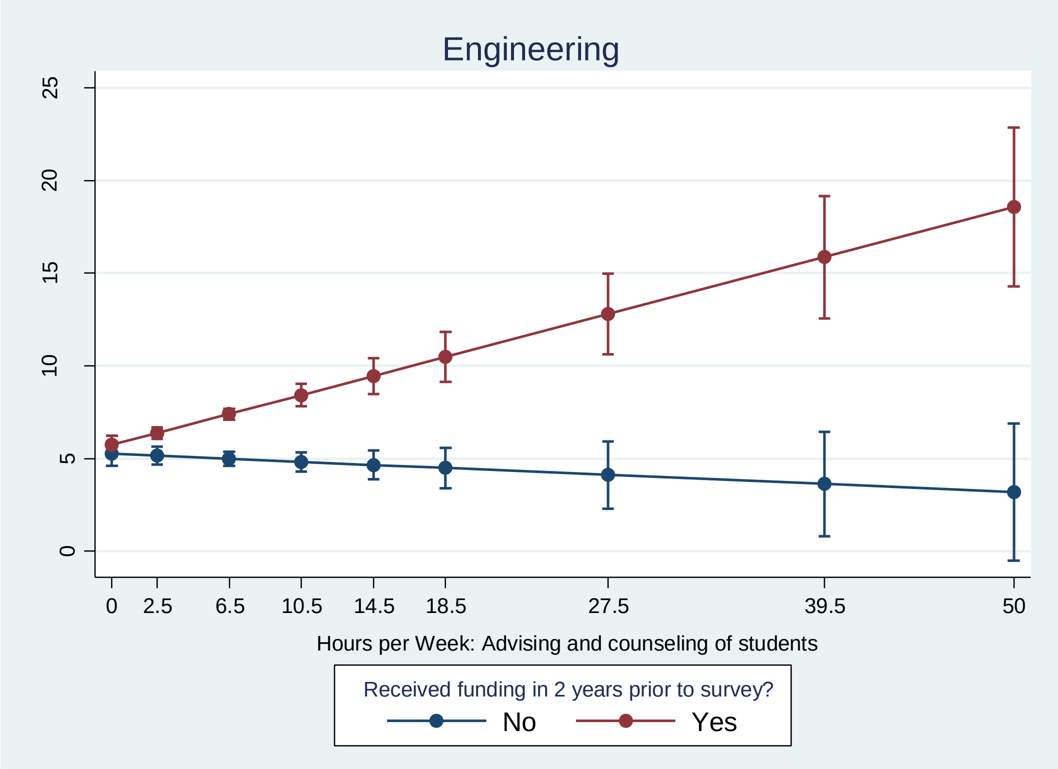
Conditions	Equipment (E)	Scientist's Research Execution Time (T_r)	Number of PhD Students Funded by Research Money (P)	Number of PhD Students Funded by Scholarships and Assistantships (G)
$r_p \le t_a + t_f$ & $r_p \le t_a/(1-t_g)$	$(1-\alpha)/t_e$	α	0	0
$r_p \le t_a + t_f$ & $r_p > t_a/(1-t_g)$ & $1 > gt_a$	$\frac{(1-\alpha)}{t_e.\alpha}(T_r + r_p g(1-t_g))$	$\alpha.(1-gt_a - \frac{(1-\alpha)}{\alpha} r_p g(1-t_g))$	0	g
$r_p \le t_a + t_f$ & $r_p > t_a/(1-t_g)$ & $1 \le gt_a$	$(1-\alpha)/t_e$	0	0	α/t_a
$r_p > t_a + t_f$ & $r_p \le t_a/(1-t_g)$	$(1-\alpha)/t_e$	0	$\frac{\alpha}{t_a + t_f}$	0
$r_p > t_a + t_f$ & $r_p > t_a/(1-t_g)$	$\frac{(1-\alpha)}{t_e.\alpha}(P + g(1-t_g))(t_f + t_a)$	0	$\frac{\alpha(1-gt_a) - g(1-t_g)(t_f + t_a)(1-\alpha)}{(t_f + t_a)}$	g

B-Funding and student advising interaction graphs

The eight graphs below further depict the relationship between time spent advising/counseling students and predicted research output in the presence and absence of funding across all areas and within each area separately. The graphs for engineering, life sciences, sciences, and psychology show a clear increase in research output as funded faculty spend more time advising/counseling students. Few research productivity benefits accrue, however, from allocating time to advising/counseling students in the absence of funding in these areas. In comparison, in social sciences (excluding psychology), humanities, and management, spending more time with students has little effect on research output regardless of whether faculty received funding over the 2 years prior to each survey.

Figure S1- The interaction between funding, advising/counseling students, and research output across major areas (bars on graphs indicate 95% confidence intervals)


All Areas
0
5
10
15
20
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes


Engineering
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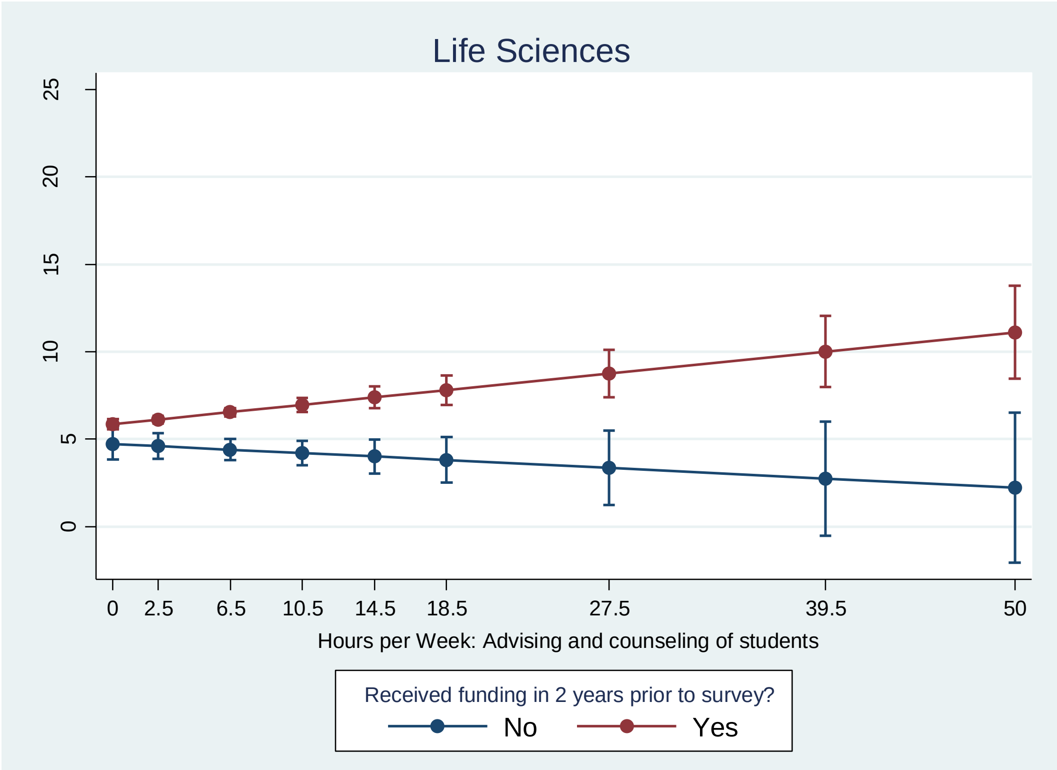
5
10
15
20
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes


Life Sciences
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5
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15
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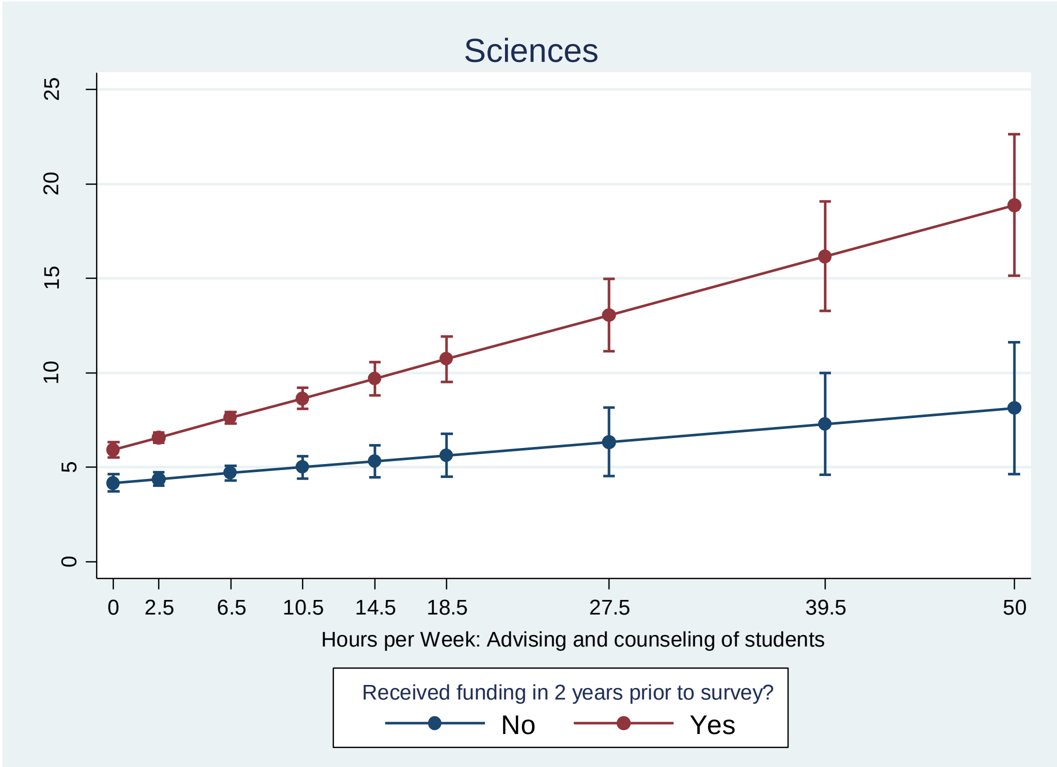
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes


Sciences
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5
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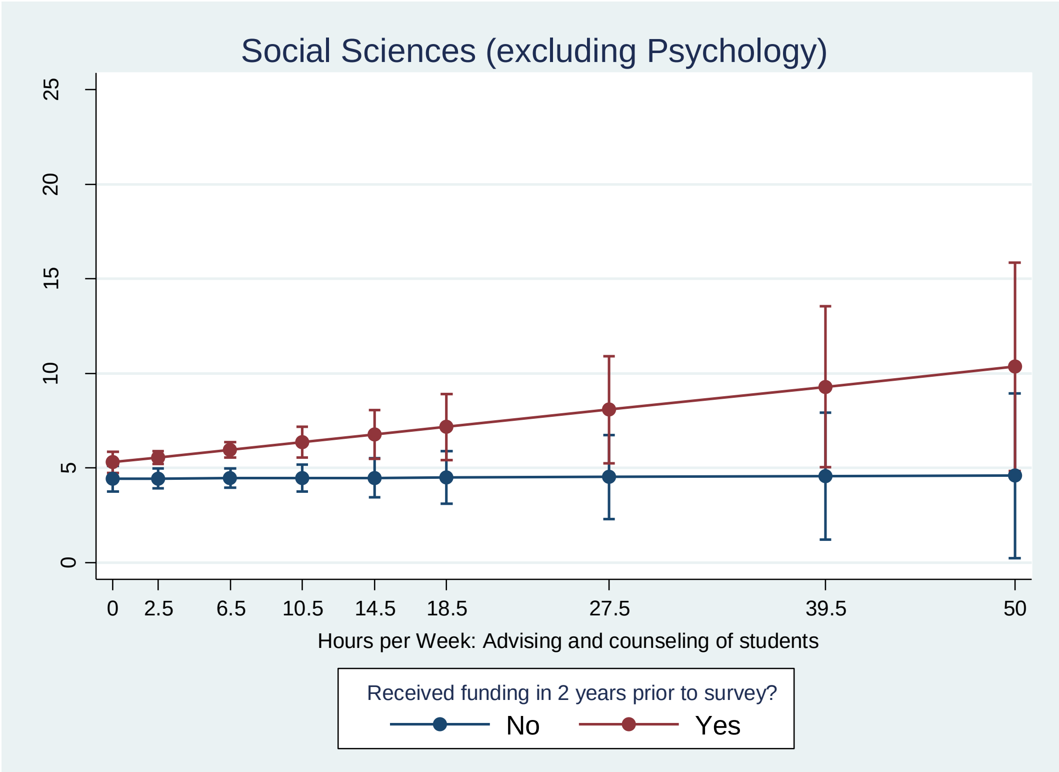
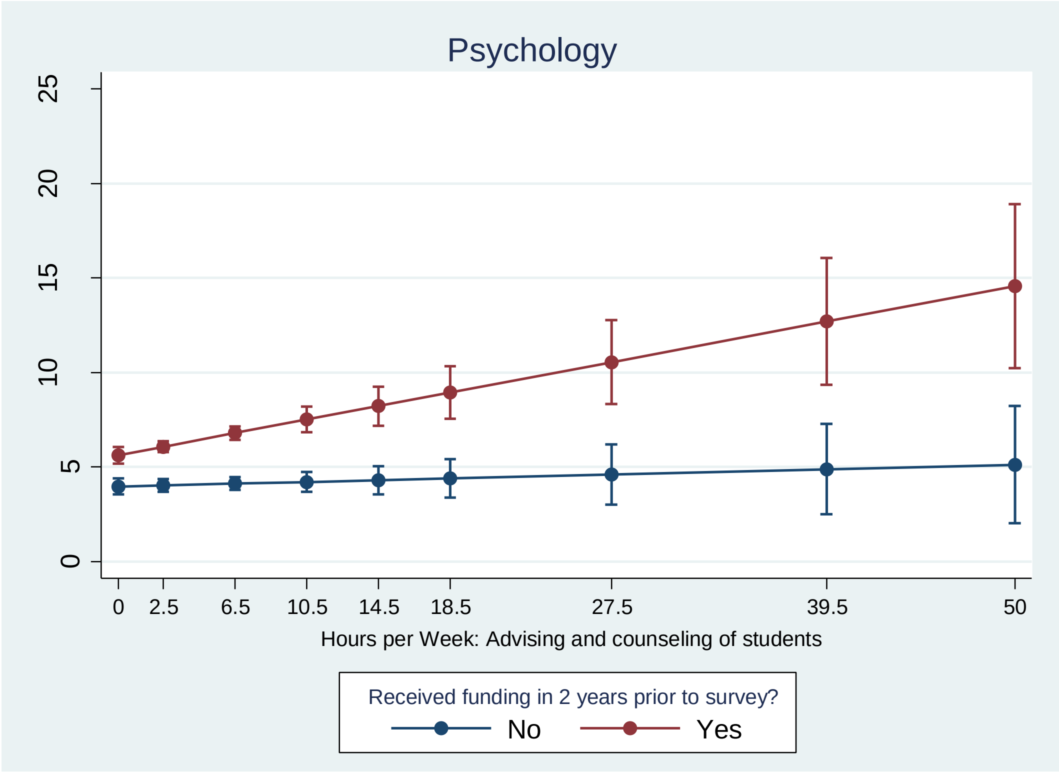
15
20
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes


Social Sciences (excluding Psychology)
0
5
10
15
20
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes


Psychology
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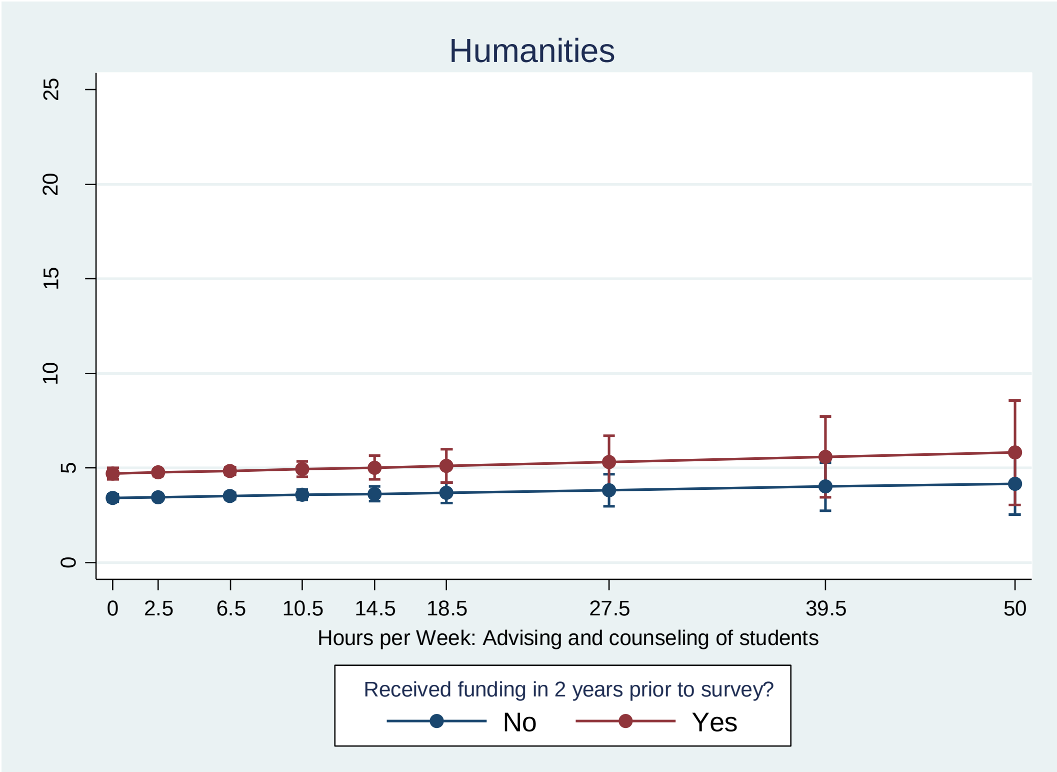
5
10
15
20
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes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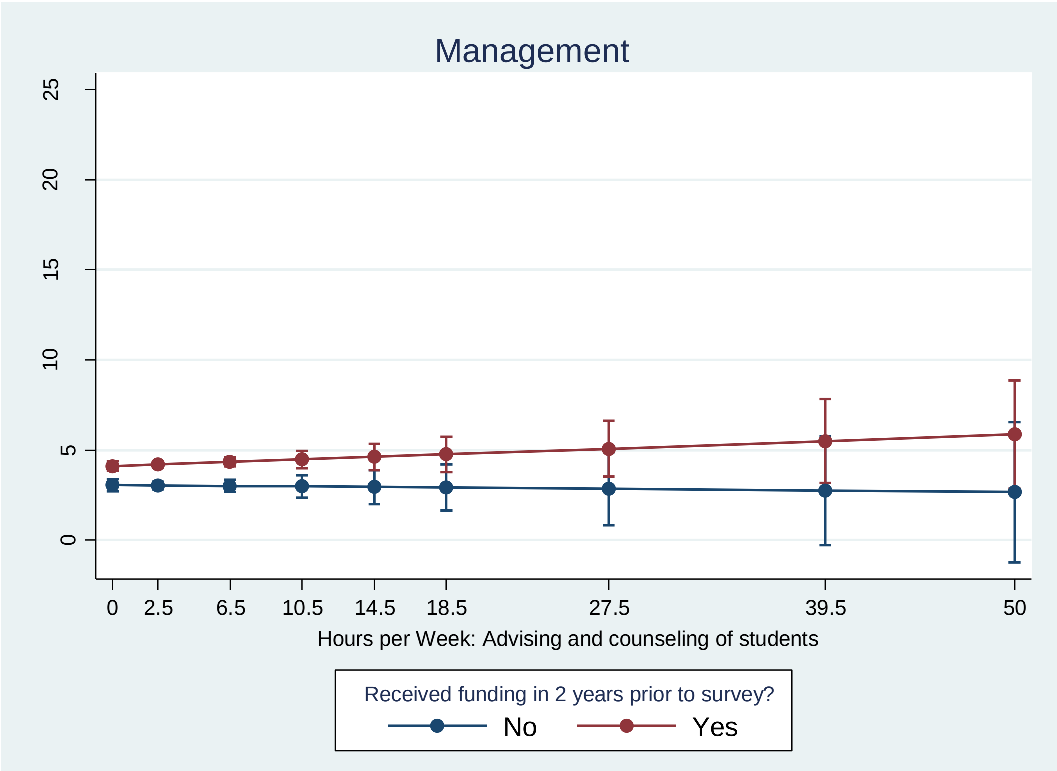
5
10
15
20
25
0
2.5
6.5
10.5
14.5
18.5
27.5
39.5
50
Hours per Week: Advising and counseling of students
Received funding in 2 years prior to survey?
No
Yes


Management
0
5
10
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14.5
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27.5
39.5
50
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C-Survey questions

The survey below was distributed to all faculty at the Massachusetts Institute of Technology and Virginia Tech. If a scientist wanted to report more than one incident, the questions on block 2 were repeated for each incident.

BLOCK 1

Your First Name ____________

Your Last Name ____________

On the following page please share instances in the past 20 years (1996-2016) when one or more of your direct advisees (a Ph.D. student, post-doc, or lab technician who was working under your supervision) went on leave/departed for an extended period of time (more than 2 months), or joined the team significantly later than expected, due to unforeseeable events (e.g. visa delays, family commitments, health problems).

How many instances would you like to report (please limit to the most notable 3 instances)

BLOCK 2

Consider the instance when one of your advisees/research staff was absent unexpectedly and answer these questions based on that instance.

In what year this instance started?

▼ 1996 ... 2016

Starting Month (mark the closest month you remember)

▼ January ... December, Can't Remember

How long did this absence last?

- ◯ 2-4 Months
- ◯ 5-8 Months
- ◯ 9-12 Months
- ◯ More than 12 Months
- ◯ Can't Remember

Advisee type

- ◯ early stage PhD student
- ◯ late stage PhD student
- ◯ post-doc associate
- ◯ technician or lab staff
- ◯ Other ____

Advisee gender

- ◯ Male
- ◯ Female

Advisee primary source of funding at the time

- ◯ Research funding I supplied
- ◯ Teaching assistantship
- ◯ Fellowships or other funding
- ◯ No Funding/ Self-funded
- ◯ Can't Remember

What is your subjective evaluation of the quality, research wise, of that advisee compared to her/his peers?

- ◯ Below average
- ◯ Typical
- ◯ Above average

Reason for absence

- ◯ Visa or immigration issues
- ◯ Health
- ◯ Family
- ◯ Other/Unknown

Do you think the underlying reason for absence impacted your advisee’s performance before their absence?

- ◯ No
- ◯ Probably not
- ◯ Maybe
- ◯ Yes

How many active PhD students, post-docs, and other research staff did you advise and manage at the time?

- ◯ Fewer than 3
- ◯ 3-5
- ◯ 6-10
- ◯ More than 10

Approximately how much research funding did you have at the time on an annual basis?

- ◯ Under $20,000
- ◯ $20k-50k
- ◯ $50k-100k
- ◯ $100-200k
- ◯ $200-500k
- ◯ More than $500k

What was your rank at the time?

- ◯ Assistant Professor
- ◯ Associate Professor
- ◯ Full Professor
- ◯ Other

Your institution at the time of this instance?

- ◯ MIT
- ◯ Virginia Tech
- ◯ Other