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Explaining Heterogeneity in the Organization of Scientific Work

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Abstract. Prior studies of academic science have largely focused on researchers in life sciences or engineering. However, while academic researchers often work under similar institutions, norms, and incentives, they vary greatly in how they organize their research efforts across different scientific domains. This heterogeneity, in turn, has important implications for innovation policy, the relationship between industry and academia, the scientific labor market, and the perceived deficit in the relevance of social sciences and humanities research. To understand this heterogeneity, we model scientists as publication-maximizing agents, identifying two distinct organizational patterns that are optimal under different parameters. When the net productivity of 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 costs of research staff exceed their productivity benefits, the hands-on research approach is optimal. The model implies significant heterogeneity across the two modes of organizing in research funding, supply of scientific workforce, team size, publication output, and stratification patterns over time. Exploratory empirical analysis finds consistent patterns of time allocation and publication in a prior survey of faculty in U.S. 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—due to visa or health problems, for example—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). Large American corporations have increasingly stepped back from investing directly in basic research and rely more on academia as the source of basic science for their R&D activities (Arora et al. 2015). Scientific research, largely done in academia, also spurs economic growth and produces considerable societal benefits (Polanyi 1962, Rosenberg 1974, Romer 1990, Narin et al. 1997, Mokyr 2002). 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 (Merton and Zuckerman 1973, Dasgupta and David 1994, McPherson and Schapiro 1999, Diamond 2005). This picture of academia, largely based on American scientific enterprise, has provided valuable insight for firms and policy makers seeking to incentivize and steer academic research (Dasgupta and David 1994).

However, despite the fundamental interest of organizational scholars 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 incentives and organizational structures. In fact, what we know of scientists' behavior in academia comes largely from studies focused on life sciences or engineering (e.g., Fox 2005; Azoulay et al. 2009, 2011; Li and Agha 2015; Vakili et al. 2015; Vakili and McGahan 2016). Yet there is ample evidence of heterogeneity in academia even within the U.S. research universities (Moses 1990, Becher 1994). Consider, for example, two star scientists at a top U.S. 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 laboratory employing over 80 people, brings in millions of dollars of funding each year to support this laboratory, 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.[1] 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. Similarly, large variations are also observable in national data across more aggregate categories and diverse institutions (see Table S1 in Online Appendix A for details).

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. In this paper we develop a formal theoretical model to partially explain the observed heterogeneity in research processes and outcomes across academic fields and scientists in the U.S. research universities. We then empirically explore some of our model's predictions and discuss the practical and policy implications.

One may intuitively expect a continuum of organizational patterns when it comes to scientists' use of research teams and external research funding. However, a simple model conceptualizing academic scientists as publication-maximizing agents shows that optimal organizational forms may bifurcate to distinct alternatives. 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 sizable 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 research projects, trains fewer graduate students and postdocs, works in smaller teams, and demands less funding. In fields where the hands-on research model dominates, publications per scientist are fewer than in fields where the funded model is optimal.

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 U.S. 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; 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.

Moreover, 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 the scientist's quality-adjusted publication productivity if she uses the funded research model, but not if she uses the hands-on model.

Focusing on the individual scientists' optimal time allocation problem, our model complements other accounts of scientific enterprise that explore historical path dependencies, the cumulative nature of knowledge, and institutional logics; and in doing so it offers novel 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 particularly 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.

Table 1. Faculty Statistics at Virginia Tech

Area[a]	Department[b]	Research staff per scientist[c]	External funding per scientist[d]	Publications per scientist[e]	Number of scientists[f]
Engineering	Mechanical engineering	2.82	258,573	4.00	66
	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	
Life sciences	Biomedical science	1.68	69,153	1.83	41
	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, physiology, & weed science	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	
Physical sciences	Chemistry	3.51	137,274	3.44	41
	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	
Social sciences	Public & international affairs	1.47	10,019	0.80	30
	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	
Humanities	School of education	0.87	9,702	2.40	47
	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	
Management	Accounting & information systems	0.82	7,245	0.09	22
	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	

[a]Area labels are assigned to be roughly consistent with the Higher Education Research Institute Faculty Survey used in the quantitative analysis.
[b]Only traditional departments that actively publish research findings are included.
[c]This number includes PhD students as well as senior research staff (postdocs 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.
[d]Average funding per faculty member for the 2011–2013 period.
[e]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.
[f]Includes both tenured/tenure-track and ranked research faculty based on Virginia Tech’s human resource data.

Multiple implications for firm strategy and policy follow. For example, where the funded model dominates, funding supply can be used as a lever to influence the direction of research. In contrast, project choice of hands-on researchers is not very sensitive to funding. The former areas enable firms to partially relegate their research activities to academia; the latter do not. 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. This mechanism informs a long-standing concern among management scholars about the impact of their research (Barley et al. 1988, Hambrick 1994, Mintzberg 2004, Markides 2007, Vermeulen 2007). Our findings also suggest that whereas 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 30-fold increase in research funding in the United States 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. In practice, scientists' time allocation is motivated by a host of factors, including institutional pressures, social norms, habits, and career motivations. While other drivers are certainly important, we simplify by assuming that the main goal of academic scientists is to generate scientific insights, typically measured in publication units. This assumption is in line with prior work showing that a scientist's impact and reputation depend on his or her publication record (Merton 1968, 1973; Bensman 1982), 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 (Kasten 1984, Fairweather 1993, 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 (Merton 1973, Fox 1983, Fox and Mohapatra 2007). 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 include surveys, mathematical calculations, computer coding, working with laboratory animals, conducting experiments, writing journal articles, presenting research results, installing and maintaining the research equipment, and other tasks.

Teaching includes all activities focused on helping others acquire knowledge and gain academic credentials but which do not primarily contribute 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 of 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 of 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 Online Appendix B2 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 quality-adjusted 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 research domains 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 that a scientist can choose, and lower case is used 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: (i) the number of research staff she should employ (P), (ii) how much research equipment she should acquire and maintain (E), and (iii) 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

$$T_r + Pt_f + Pt_a + Et_e = 1 \quad 0 \le T_r, t_f, t_a, t_e \le 1. \tag{1}$$

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 the constant returns to scale Cobb–Douglas production function. The scientist is typically a coauthor on all publications coming from her research group.[2] Therefore, the total publication output, O, for the scientist can be stated as

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

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

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

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

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 Online Appendix B1), 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 depending on the net productivity of research staff ($r_p - t_a - t_f$). Staff's net productivity compares the publication productivity benefits of a typical PhD student or postdoc (r_p) against their costs to the scientist in raising funds for the staff (t_f) and advising, training, and managing the staff (t_a). First, if research staff are productive enough ($t_a + t_f < r_p$), then the scientist spends her remaining time (after allocating what is needed to acquire funding for equipment) raising funds and managing the largest possible research group ($P = \alpha/(t_a + t_f)$), spending no time on research execution tasks. In such a setting the scientist's role is closer to that of an entrepreneur: she brings in money to sustain the research group, manages a relatively large research team, and participates more in the research design than in the execution. When this model dominates, publications are more numerous and a larger number of coauthors are typically listed than would be the case if the scientist had spent most of her time doing the research without a team. We call this mode of operation the "funded" research model.

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. We call this mode of operation the "hands-on" research model. Where this model dominates, 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.

Determinants of Dominant Research Model

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) 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. These three parameters vary for each scientist and depend on (a) the nature of research (field effect), (b) the institutional arrangement in which a faculty works (institution effect), and (c) the qualities and preferences of the scientist and her team members (individual effects). Given the potential importance of field effects (for which we provide evidence in the empirical section), our model predicts that scientists in the same field would on average follow the same research model (i.e., funded versus hands-on). Meanwhile, institution and individual effects can create heterogeneity in the adopted research model within the same field, the same institution, and over time.

The hands-on model dominates when a typical PhD student/postdoc cannot produce 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, staff productivity relative to scientist (r_p) may be small when learning the research concepts is time-consuming, delaying the time at which PhD students become productive (e.g., theoretical physics and mathematics, where reaching the conceptual frontiers requires sequences of multiple graduate courses), when scholarly writing is complex and calls for years of apprenticeship (e.g., sociology), or when there are few venues for raising research funds (e.g., anthropology). Such field effects often have a strong impact on the choice of research model and may thus provide a rational impetus for homogeneity in organizational practices among scientists in the same field.

Institution effects can also matter, for example when faculty at famous universities can attract very talented PhD students, increasing the r_p, and thus the viability of the funded model. Some universities offer generous internal funding packages to their scientists, which by reducing t_f, can tip the scale in favor of the funded model. Finally, individual effects can also be consequential. For example, very talented scientists may prefer the hands-on model (since they are relatively more productive in doing the research than their staff, thus reducing r_p). On the other hand, scientists with strong interpersonal and managerial skills may gravitate toward the funded model. Some may even create additional levels of management hierarchy in which postdoc researchers are hired to conduct the day-to-day training and supervision of PhD students, reducing t_a and making the funded model more attractive for their own group.

Extensions and Robustness

Focusing on a stylized representation of individual scientists' choices, our model excludes a host of relevant social and institutional factors and makes simplifying assumptions about the motivations and rationality of scientists. Before reporting empirical results, we explore three extensions of this model to provide a more nuanced view.

Heterogeneous Research Tasks

We modeled a single "research" activity, but in practice research tasks span a wide range, from designing studies to laboratory work to computer programming to data cleanup. Relative productivity of research staff may vary across different tasks. For example, staff may be inefficient in research design but be as productive as the scientist in data cleanup. Our model can capture such heterogeneity with a more complex output function with multiple types of research tasks, each with a distinct r_p value. We solve one such variant in which the research design (assumed to have an r_p of zero) is explicitly incorporated into the research output function and distinguished from research execution (see Online Appendix B2 for details). The results are very similar to the base model: the scientist is required to spend a fixed fraction of her time on research design, but otherwise the time allocation follows the baseline model. Extensions in which multiple task types are included (not formally modeled here) may lead to intermediate solutions between hands-on and funded modes in which research staff are worthwhile for a subset of tasks, but not others, and thus the scientist is partially involved in doing the research while supporting a smaller team.

Institutional Support and Internal Funding

In our baseline model, faculty are required to secure external funding to maintain a research team. In practice, host institutions may subsidize the scientist's fundraising overhead by offering salaried support staff, start-up funds, and teaching assistantships that, besides external research funding, could be used to recruit research staff. For example, principal investigators (PIs) at the National Institutes of Health are often provided with a number of research staff for whom the PIs do not secure funding. Top research universities may also offer multiple person-years of staff funding as part of their start-up package for new faculty. Similar arrangements may be even more common outside of the United States and can be explicitly incorporated in our model (see Online Appendix B3 for details). This consideration leads to an additional equilibrium in which the scientist uses only a few research staff who are funded through institutional support but does not seek external funding for additional staff. This intermediate mode dominates when such internal funding is available and staff are net productive when considering only their advising and management costs but become a net loss if the scientist had to secure external funding for them.

Behavioral Alternatives to Publication-Maximization: Effects of Norms and Social Learning

Publication-maximization, the organizing logic of our model, is a behaviorally strong assumption: even if incentivized based on publications, how would a scientist know the parameters (e.g., t_a, t_f, and r_p) that apply to them? And if aware of the parameters, do scientists really solve an optimization problem? What about the impact of institutional norms and social influence on their time allocation decisions? Indeed, publication-maximization in our model is not intended to provide a behaviorally realistic description of scientists' actual decision processes; rather, it is an analytical path to capturing forces that promote publications in a research community. The actual discovery and diffusion of those practices likely span multilevel dynamics of individual exploration, social influence, and institutionalization. Here we show how, despite its simplicity, our model can be useful for understanding the direction toward which those more intricate dynamics evolve.

Specifically, we build an agent-based model (see Online Appendix C for details) of a community of scientists who are exposed to the same research output function as our baseline model but are otherwise ignorant of the parameters of the model (e.g., t_a, t_f, and r_p, which are identical across scientists) and do not actively maximize their publications. Instead, these scientists are prone to adopting community norms [in deciding the number of staff (P), research time (T_r), and equipment (E)] when their output is below average and exploring modest changes in their practice when they are outperforming the average member in the community but lagging the best performers. In other words, scientists here are not publication-maximizing; rather, they are influenced by what others do and also experiment to organize their work more productively. Simulations of this community (reported in Online Appendix C) show that they will, over time, converge to the neighborhood of organizational forms predicted by our analytical model. The speed of this convergence, potential bias, and level of heterogeneity in community practices over time depend on the learning and exploration assumptions embedded in the model. Nevertheless, local adaptation and vicarious learning can provide a behaviorally plausible path for identification and diffusion of organizational forms indicated by our simple publication-maximizing model, a result resonating with a long tradition of research in organizational learning (Terlaak and Gong 2008, Argote 2012).

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 funded versus hands-on models. 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

$$\partial O/\partial T_a = \alpha\left(\frac{e_s r_p}{t_a}\right)^{\alpha}\left(\frac{1-\alpha}{T_a t_e}\right)^{1-\alpha} \geq 0 \text{ for } 1 \geq \alpha \geq 0).$$

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, even conditional on having funding, we expect the positive effect of time spent with research staff on research output to be stronger in domains in which, due to the field effect, the funded model strongly dominates. In domains where the hands-on model dominates, faculty may still acquire funding. They may seek funding for reasons other than publication-maximization or because of *individual effects* that justify the funded model for a few scientists despite field effects pointing to the hands-on model. Thus the effect of interaction between time spent with research staff and funding on research output would be weaker.

Prediction 2. *The effect of interaction between funding and 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 is more common.*

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

$$\partial O/\partial P = \alpha\left(e_s r_p\right)^\alpha \left(\frac{1-\alpha}{Pt_e}\right)^{1-\alpha},$$

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 U.S. universities. We then test Prediction 3 using data from a survey we administered at two U.S. research 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 (for details, see https://heri.ucla.edu/heri-faculty-survey). To focus on research-oriented faculty, we include in our analysis only assistant, associate, and full professors working at U.S. research universities. Our final sample includes 116,067 faculty working at 194 U.S. universities. The level of analysis in all regressions is the faculty-year.

We use the number of publications in the 2 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 2 years prior to each survey. Although HERI Faculty Surveys offer one of the few data sets 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 that 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 that each faculty member has received. Instead, we rely on whether they received any research funding in the 2 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 U.S. 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 2 presents summary statistics for our sample. The faculty in our sample produced on average about five publications in the 2 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 U.S. 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 2 also breaks down the summary statistics across seven major areas: engineering, life sciences, physical sciences, psychology, social sciences (other than psychology), humanities, and management. Consistent with National Science Foundation (NSF) reporting practice, we separate psychology from other social sciences. This separation is also indicated in the data from the Virginia Tech (in Table 1) and national surveys[3] that 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. 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, as well as the psychology faculty, reported having received research funding in the previous 2 years. They also spent on average more time advising and/or counseling students. The differences in these three variables between the faculty in engineering, life sciences, physical sciences, and psychology (except for publications) and the faculty in (other) social sciences, 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, the 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 pairwise correlations between these three variables. These graphs suggest a shift from the funded to the hands-on research model as we

Table 2. Summary Statistics by Major Area

Variables	All areas	Engineering	Life sciences	Physical sciences	Psychology	Other social sciences	Humanities	Management
2yr publications	5.158	6.957	6.051	6.202	5.547	5.62	4.182	3.697
	(7.210)	(8.597)	(7.365)	(8.649)	(6.757)	(6.296)	(4.669)	(4.540)
Hours per week advising and/or counseling students	4.172	4.987	4.382	4.228	4.342	4.157	4.056	3.749
	(3.678)	(3.773)	(3.918)	(3.538)	(3.616)	(3.389)	(3.189)	(3.238)
Received external or internal funding	0.680	0.813	0.901	0.719	0.718	0.701	0.569	0.567
	(0.466)	(0.390)	(0.299)	(0.449)	(0.45)	(0.458)	(0.495)	(0.495)
Hours per week spent on research & scholarly writing	11.617	13.163	17.196	14.374	14.261	13.774	10.830	11.587
	(11.210)	(10.560)	(14.006)	(12.154)	(11.702)	(12.266)	(9.785)	(10.519)
Hours per week spent on committee work & meeting	4.400	4.438	4.294	4.076	4.059	4.545	3.983	4.440
	(4.011)	(3.703)	(3.806)	(3.575)	(3.538)	(4.124)	(3.583)	(4.141)
Hours per week spent on other administration duties	4.825	4.853	4.305	4.169	4.276	5.046	4.437	4.284
	(7.722)	(7.247)	(6.983)	(6.965)	(6.851)	(7.132)	(7.239)	(7.525)
Hours per week spent on teaching responsibilities	15.584	14.873	13.236	15.402	14.915	13.839	18.890	17.286
	(10.420)	(8.941)	(10.045)	(9.502)	(9.067)	(9.541)	(10.237)	(9.688)
Gender (male = 0, female = 1)	0.297	0.105	0.227	0.158	0.26	0.401	0.345	0.225
	(0.457)	(0.306)	(0.419)	(0.365)	(0.438)	(0.49)	(0.476)	(0.418)
U.S. citizen (no = 0, yes = 1)	0.923	0.874	0.922	0.877	0.906	0.938	0.875	0.922
	(0.267)	(0.332)	(0.268)	(0.328)	(0.292)	(0.24)	(0.331)	(0.269)
Tenured (no = 0, yes = 1)	0.705	0.730	0.746	0.772	0.742	0.67	0.717	0.668
	(0.456)	(0.444)	(0.435)	(0.420)	(0.438)	(0.47)	(0.450)	(0.471)
Salary ($K)	73.189	84.283	75.613	72.266	73.058	78.27	63.631	91.801
	(35.656)	(39.473)	(32.921)	(33.340)	(33.67)	(38.672)	(32.108)	(39.075)
Age[a]	5.492	5.273	5.621	5.440	5.327	5.402	5.577	5.265
	(2.040)	(2.171)	(1.969)	(2.146)	(2.128)	(2.024)	(2.098)	(2.008)
Experience (years since last degree)	19.060	19.037	16.558	21.230	19.214	18.487	18.355	16.558
	(10.853)	(11.071)	(10.430)	(11.323)	(10.935)	(10.842)	(10.923)	(10.430)

Notes. Standard deviations are shown in parentheses. The full sample included 128,005 faculty-year data points.
[a]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, and (10) 70+.

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:

$$\begin{aligned} &Research\ Output_{it} \\ &\quad = \beta_0 + \beta_1.Funded_{it} + \beta_2.Advising\_Time_{it} \\ &\qquad + \beta_3.Advising\_Time_{it} \times Funded_{it} + \theta.X_{it} \\ &\qquad + Year_t + \alpha + \varepsilon_i, \end{aligned} \tag{4}$$

where $Research\ Output_i$ is the number of publications by faculty member i in the 2 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 field, 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 3 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

Figure 1. (Color online) The Correlations Between Funding, Hours Spent on Advising/Counseling Students, and Publications

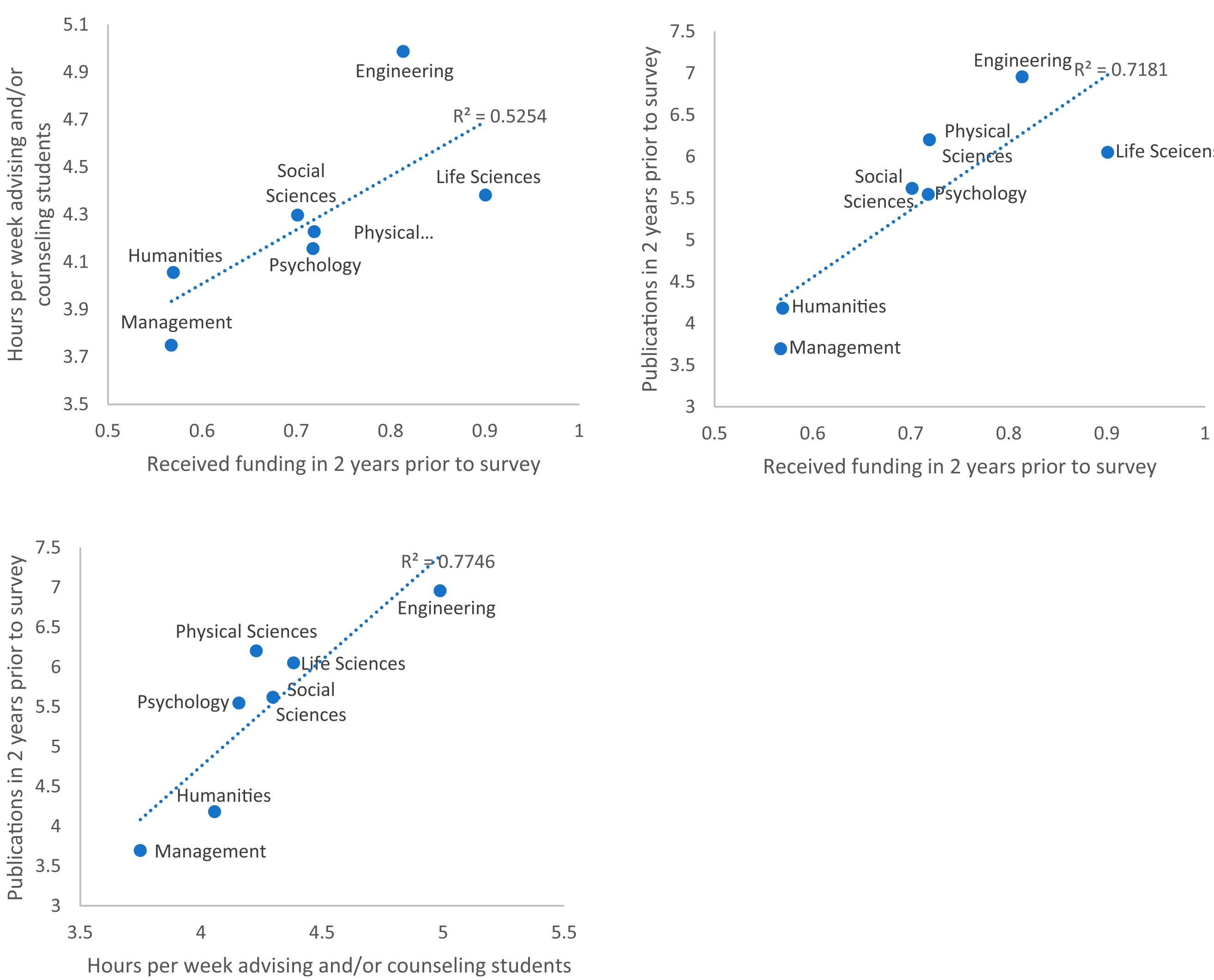

Table 3. The Interaction Between Funding, Advising/Counseling Students, and Research Output

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	0.079***	−0.003
	(0.008)	(0.009)
Received funding in 2 years prior to survey	1.326***	0.779***
	(0.056)	(0.083)
Received funding in 2 years prior to survey × Hours per week advising and/or counseling students		0.129***
		(0.014)
Hours per week spent on research and scholarly writing	0.102***	0.102***
	(0.003)	(0.003)
Hours per week spent on committee work and meetings	0.010	0.009
	(0.007)	(0.007)
Hours per week spent on other administration duties	−0.034***	−0.034***
	(0.003)	(0.003)
Hours per week spent on teaching responsibilities	−0.026***	−0.026***
	(0.003)	(0.003)
Gender (male = 0, female = 1)	−0.303***	−0.310***
	(0.056)	(0.056)
U.S. citizen (no = 0, yes = 1)	−0.738***	−0.737***
	(0.109)	(0.109)
Tenured (no = 0, yes = 1)	1.343***	1.332***
	(0.070)	(0.070)
Salary ($K)	0.028***	0.028***
	(0.002)	(0.002)
Age	−0.368***	−0.365***
	(0.022)	(0.022)
Experience (years since last degree)	0.018***	0.018***
	(0.005)	(0.005)
Survey year dummies	Yes	Yes
Institution dummies	Yes	Yes
Field dummies	Yes	Yes
Constant	2.144***	2.488***
	(0.225)	(0.229)
Observations	76,491	76,491
R^2	0.126	0.127

Notes. All estimates are from ordinary least squares (OLS) models. Robust standard errors are shown in parentheses.
***$p < 0.01$.

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 show a significant positive relationship between both funding and the time that a faculty member spends on advising/counseling students and her research output. Having funding is associated with 1.5 more publications in a 2-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 2-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 2-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 projects (Fox 2005). U.S. citizens also produced significantly fewer publications than did noncitizens working in the United States, which might be the result of lower incentives for U.S. 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).

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 4 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 of the areas and in line with those reported in Table 3. Consistent with Prediction 1, 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.[4] 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 psychology, and is negligible and insignificant in (other) social sciences, humanities, and management. These findings are consistent with Prediction 2. Figures in Online Appendix D are 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, and those in (other) social sciences, 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.

Finally, the HERI data provide an opportunity to better explore the relative contribution of field, institution, and individual factors to the observed variance in the organization of scientific work across fields. In introducing the model we distinguished between these factors and discussed how each can impact model parameters (such as relative productivity of staff and costs of advising and fundraising). Here we conduct variance decomposition analyses on HERI data, partitioning the observed standard deviation in publications, funding, and student advising time between field, institution, and other factors (residual). In the absence of panel data, the residual component will combine the contribution of individual effects with a host of stochastic or unobserved factors, and thus it is bound to have a larger effect. Nevertheless, across different specifications, field and institutions explain between 9.5% and 21.3% of the standard deviation of each measure of interest (see Online Appendix E for details). Overall, this analysis provides evidence on the significant effect of field and institutional factors on the organization and outputs of scientific research and provides a bridge between our individual-level model and the multilevel determinants of its parameters.

Causal Results. We use a different sample to test Prediction 3. The data were collected in two steps. First, we sent a survey to all faculty we could identify at MIT (964) and Virginia Tech (1,509), two major U.S. research universities. We collected the faculty names, department information, and email contacts from department websites and faculty directories. The survey was conducted over 4 months between December 2016 and April 2017. The survey questions are listed in Online Appendix F. The respondents were asked whether they have ever had a graduate student, postdoc, or research staff who had gone unexpectedly absent—for example, because of 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 member had been advising at the time of the incident. Out of 2,473 inquiries, we received 259

Table 4. 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:	Engineering	Life sciences	Physical sciences	Psychology	Other social sciences	Humanities	Management
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hrs./week advising students	−0.041	−0.050	0.079**	0.023	0.003	0.015	−0.008
	(0.043)	(0.050)	(0.039)	(0.034)	(0.049)	(0.018)	(0.042)
Received funding in 2 years prior to survey	0.479	1.131**	1.750***	1.660***	0.869*	1.287***	1.050***
	(0.407)	(0.477)	(0.313)	(0.317)	(0.459)	(0.193)	(0.214)
Funding × Hrs./week advising students	0.298***	0.155***	0.180***	0.156***	0.098	0.007	0.043
	(0.064)	(0.056)	(0.056)	(0.058)	(0.076)	(0.036)	(0.050)
Hrs./week spent on research and scholarly writing	0.118***	0.081***	0.125***	0.078***	0.095***	0.094***	0.076***
	(0.015)	(0.011)	(0.011)	(0.011)	(0.014)	(0.009)	(0.011)
Hrs./week spent on committee & meetings	−0.024	0.009	0.051	0.008	0.022	0.013	0.017
	(0.034)	(0.038)	(0.035)	(0.033)	(0.036)	(0.018)	(0.018)
Hrs./week spent on other admin duties	−0.035*	−0.047***	−0.041**	−0.006	−0.032*	−0.034***	−0.018*
	(0.018)	(0.018)	(0.016)	(0.019)	(0.018)	(0.008)	(0.010)
Hrs./week spent on teaching responsibilities	−0.054***	−0.019*	−0.058***	−0.029**	−0.020	−0.033***	−0.007
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.009)	(0.009)
Gender (male = 0, female = 1)	0.768	−0.623***	−0.443*	−0.047	−0.762***	0.007	−0.249
	(0.471)	(0.213)	(0.243)	(0.247)	(0.225)	(0.124)	(0.164)
U.S. citizen (no = 0, yes = 1)	−2.233***	−0.851**	−0.541*	−1.587***	−0.581	−0.460**	−0.136
	(0.455)	(0.395)	(0.317)	(0.592)	(0.510)	(0.196)	(0.316)
Tenured (no = 0, yes = 1)	2.377***	1.702***	1.263***	1.835***	1.621***	0.584***	0.461**
	(0.330)	(0.293)	(0.273)	(0.328)	(0.323)	(0.188)	(0.235)
Salary ($K)	0.031***	0.072***	0.053***	0.019**	0.027***	0.028***	0.006**
	(0.010)	(0.017)	(0.015)	(0.009)	(0.008)	(0.007)	(0.003)
Age	−0.512***	−0.179	−0.561***	−0.560***	−0.224**	−0.249***	−0.074
	(0.108)	(0.135)	(0.105)	(0.101)	(0.101)	(0.054)	(0.058)
Experience (years since last degree)	0.017	−0.039	0.056**	0.070***	−0.009	0.019	0.024*
	(0.024)	(0.050)	(0.024)	(0.025)	(0.022)	(0.013)	(0.014)
Survey year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.189***	7.867***	0.338	2.097*	2.434**	1.942***	1.388
	(1.211)	(1.488)	(0.751)	(1.248)	(1.204)	(0.569)	(0.951)
Observations	4,923	5,859	7,648	3,836	2,327	5,780	5,984
R^2	0.172	0.154	0.181	0.177	0.237	0.165	0.150

Notes. All estimates are from ordinary least squares (OLS) models. Robust standard errors are shown in parentheses.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

responses indicating no incidents, 58 reporting one incident, 30 reporting two, and 15 reporting three. Of those 103 reporting at least one 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 of the publications of each faculty member 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 member 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 et al. 2015, Vakili and McGahan 2016).

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 faculty were flagged as affiliated with the funded research model; they produced on 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 six to 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 the funded model because of the positive net productivity of research staff, and therefore the loss of one staff member would have a larger productivity cost for those following the funded model compared with 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 2 years for an absence to show its effect on research output. Below, we report the results for a 2-year lag between the incident and its effect on publication output. The estimates based on a 3-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 the time-independent idiosyncratic characteristics of each faculty member, 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 scientist 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 member uses the funded model.

Table 5 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 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.[5] 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 through 6 show the same results based on the panel Poisson estimates. The results are in line with those reported in Models 1–3, suggesting that the unexpected absence of research staff has a negative effect on research output for faculty using the funded model but little effect for those using the hands-on model. Overall, the results confirm Prediction 3.

Discussion and Conclusion

Using a parsimonious model, we showed that the variance in the net productivity of research staff—that

Table 5. 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*** (97.291)	25.196 (24.686)		−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			−253.57*** (69.954)			−0.800** (0.335)
Nonlinear 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^2 (within)	0.248	0.103	0.181			
Log-likelihood				−111,958.87	−111,715.51	−128,034.75

Notes. All estimates are from panel ordinary least squares (OLS) models with individual and year fixed effects. Robust standard errors are shown in parentheses.
$^{**}p < 0.05$; $^{***}p < 0.01$.

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 discuss the model's implications for two interrelated sets of considerations. First, our model offers a novel vantage point for understanding the organization of science, a topic of theoretical and personal interest to scholars of organizations. We discuss how our model can be a starting point in examining the economies of scale and scope and dynamics of stratification in research, role of equipment, patterns of collaboration, perceived relevance gap, and emergence of paradigmatic consensus. Second, we elaborate on some of the practical implications of our model spanning the organization of research outside U.S. academia, agenda-setting in research, dynamics of supply and demand in research funding, and labor market considerations for PhD graduates.

Model Extensions and Theoretical Implications

Our model is relatively parsimonious and could be extended on multiple fronts. In particular, the current model is static, predicting the overall organization of research based on fixed parameters for productivity and costs of research staff. Some underlying drivers of those parameters may indeed change very slowly. For example, the more fundamental features of a knowledge domain, such as paradigmatic consensus (e.g., in concepts, tools, and goals of research enterprise), can drive staff productivity and costs. Higher consensus increases the modularity of research, which reduces the costs of team-based science (Newman 2004, Wuchty et al. 2007) and increases benefits to specialization and the productivity of staff. Paradigmatic consensus also reduces writing complexity [e.g., compare the length and complexity of introductions across social and natural sciences (Strang and Siler 2015)] and through that increases the productivity of new staff, increasing the attractiveness of the funded model. On the other hand, growth in the available stock of knowledge (Jones 2009) adds to the cost of reaching the frontiers of knowledge, which reduces the productivity of new staff, promoting hands-on research in areas such as theoretical physics and pure mathematics.

Beyond these more immutable features of knowledge domain, there are various economies of scale, scope, and learning that can, over time, change the cost and productivity parameters and 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 6% in all subfields; see Online Appendix Table S1 (National Science Foundation 2015a)], equipment cost alone cannot explain the variations in funding (e.g., those in Tables 1 and S1). 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 (e.g., first-year PhD students) in simpler well-defined tasks (e.g., data cleanup), and thus increases the overall 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 et al. (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 horizontally collaborate with colleagues in order to complement one another's specialties (to compensate for the narrowness of their own expertise) in order to extend the knowledge frontier even further (Jones 2009). Our model highlights the organizational choices that regulate vertical collaboration between scientists and staff. A combination of these two theories may provide a more complete explanation for 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 among 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 6 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 HERI sample. The standard deviations in 2-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.

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, Mintzberg 2004, Markides 2007, 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

Table 6. 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%
Physical sciences	7.907	8.472	7%
Psychology	5.220	6.708	28%
Social sciences (excluding psychology)	6.183	5.479	−11%
Humanities	4.768	4.392	−8%
Management	4.957	4.132	−17%

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 portfolios 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 create pressure to adopt a well-defined common language across research subcommunities. In short, even the more fundamental features of knowledge domain could be endogenously changing with the choice of research mode.

Managerial and Policy Implications

Our focus in this paper is on U.S. academic research, but our results may be informative more broadly. For example, to the extent that research teams in industry are incentivized to maximize their research output and have the autonomy to assemble their teams, the results may apply to them as well. Research suggests that scientists in industry do indeed care about their contribution to open science (Stern 2004). Hence, ceteris paribus, scientists in funded domains in industry would also benefit from forming larger research groups and investing in securing more money to support their teams (either internally or through state or federal grants). The reinforcing loops regulating funded research may then become relevant for competitive dynamics in research-heavy industries. However, while leading scientists in firms usually have a say in hiring their research staff, the decision might also be influenced by other organizational factors beyond scientists' control. Moreover, scientists in industry may also pursue other objectives, such as cost minimization, that would influence the composition of their teams and their time allocation decision.

Beyond the workings of research teams inside firms, governments and private organizations are very much interested in shaping the pace and direction of scientific research. They often do so through changing the distribution and supply of research funding across various knowledge domains. 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 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 the more than 30-fold growth in the supply of funding in the United States 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 (R_0: "the mean number of new PhD's that a typical tenure-track faculty member will graduate during his or her academic career"; Larson et al. 2014, p. 246). 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 R_0 (because more students and postdocs can be accommodated by each scientist), so that demand will grow even more quickly. R_0s in hands-on fields are smaller and are not influenced by funding availability. Given the significantly different R_0s across fields (Larson et al. 2014), a balanced portfolio of basic research funding will skew over time toward favoring the fields with the highest R_0. 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 United States 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 (Stephan 2013, National Science Foundation 2015a). Overall, supply for funding would be quickly matched and exceeded by demand in funded fields, whereas 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. 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 underexplored—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 PhD's. The returns on basic science would justify increased funding, yet such increases would exacerbate the oversupply of PhD's. One might expect an excess of PhD's 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 U.S. engineering programs are foreigners (National Science Foundation 2015b). As a pro-immigration 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.

Limitations and Future Research

Our analysis focused only on a subset of relevant mechanisms. Future research can extend this work in multiple directions to shed light on the full richness of a phenomenon as complex as the organization of scientific work across heterogeneous scientists, institutions, communities of practice, and countries. First, from the joy of discovery to mentoring the next generation of scientists and making a difference, many factors beyond publications motivate scientists. Other incentives may also play a role in acquiring funding (e.g., to buy out courses or signal competence), working in a team (e.g., social interaction), or doing administrative work (e.g., income or status); where those factors are more prominent, the mechanisms we model have weaker explanatory value. Second, our analysis was limited to U.S. research universities. Understanding variations across other research settings in the United States, as well as significant cross-country heterogeneity, may require very different models. Third, in focusing on the incentives of a single scientist, our analysis excludes many relevant mechanisms spanning social norms and historical precedents, institutional and legal determinants, and administrative policies in each university, to name a few. Future research is needed to elaborate on these determinants and how they determine heterogeneity in the organization of science. Fourth, given that scientists following funded versus hands-on models have different day-to-day tasks (e.g., raising funds versus doing research) and different publication prospects, over time potential scientists may pick their field of study to align their tasks with their interests. Those sorting mechanisms offer interesting extensions in light of limited supply for different skills. Fifth, a deeper treatment of the field, institution, and individual effects driving the key model parameters will be very informative. For example, such multilevel analysis can shed light on heterogeneity within the same field and the same institution. Finally, the relevant parameters that regulate the research model are not known to new scientists and are dynamically changing because of endogenous mechanisms (some of which we briefly discussed) and others [e.g., the increasing burden of knowledge (Jones 2009)]. How scientists learn about those parameters and how much scientists account for the dynamics of key parameters in their choice of research model are important questions for future research.

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Endnotes

[1] Effort required for a single publication varies by field, and differences in the number of publications do not imply proportional differences in faculty productivity across departments. In fact, our model does not rely on any potential productivity differences to explain the large heterogeneity observed in the number of publications per faculty member.

[2] For simplicity, this analysis assumes equal credit to the scientist regardless of the number of coauthors. 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.

[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 versus 0.11 doctorate degrees were granted, respectively, per full-time academic faculty member (National Science Foundation 2015b).

[4] 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.

[5] Note that 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.

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