Research Policy 44 (2015) 1633–1644

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Bringing the lab back in: Personnel composition and scientific output at the MIT Department of Biology☆

Annamaria Conti[a], Christopher C. Liu[b,*]

[a] Scheller College of Business, Georgia Institute of Technology, United States
[b] Rotman School of Management, University of Toronto, Canada

ARTICLE INFO

Article history:
Received 31 December 2014
Accepted 1 January 2015
Available online 28 January 2015

Keywords:
Innovation
Scientific productivity
Scientific laboratories
University funding
Postdocs
Graduate education
Technical work
Personnel composition

ABSTRACT

We study the link between a laboratory's personnel composition, its number and types of graduate students and postdocs, and the laboratory's productive output. Building upon a fine-grained dataset with full personnel lists from the MIT Department of Biology from 1966–2000, we find that while postdocs account for the large majority of publication outputs, graduate students and postdocs with external funding contribute equally to breakthrough publications. Moreover, technicians are key contributors to breakthrough publications, but not to overall productivity. Taken together, this study contributes to our understanding of knowledge work, as well as reinforcing the importance of a laboratory's personnel composition.

1. Introduction

> "... if the scientists we shadow go inside laboratories, then we too have to go there, no matter how difficult the journey." (Latour, 1988, p. 63)

The past two decades have witnessed an unprecedented advancement in a researcher's ability to collect and analyze large datasets. An exponential rise in computer storage and power, coupled with ready access to an ever increasing array of online data sources has enabled researchers to analyze datasets numbering in the millions of data points. Large-scale patent data have been used to study knowledge spillovers (Jaffe et al., 1993; Audretsch and Feldman, 1996; Breschi and Lissoni, 2001), inventor mobility (Marx et al., 2009; Singh and Agrawal, 2011), and inventor networks (Fleming and Sorenson, 2004), to name a few recent examples. More recently, a parallel easing of access to data on academic publications (e.g., Azoulay et al., 2006) has enabled the study of collaborative teams (Wuchty et al., 2007) and spillovers across individuals (Azoulay et al., 2010). Whether using patent or publication data, large-scale datasets allow the documentation of temporal trends across multiple fields, as well as the discovery of exogenous variation or the use of matched samples to aid in causal inference. Lastly, these empirical changes have been particularly pertinent for scholarship focused on the innovation economy, where the highly skewed distribution of productive individuals has been recognized for some time (Lotka, 1926). In short, the ability to access large datasets has engendered a revolution in the social studies of innovation, changing what questions social scientists might ask, as well as the way in which these new questions might be answered.

Despite the incontrovertible advantages of larger datasets (we doubt that any scholars would argue for fewer, rather than more data points), we fear that during this shift in the size and scope of data, critical supporting structures that underpin scientific productivity – in the context of this paper, the scientific laboratory – have fallen by the wayside. This oversight is remarkable given the central role of the laboratory in foundational studies ranging from the social construction of technology (Latour and Woolgar, 1979), mentorship and training (Zuckerman, 1977; Dasgupta and David, 1994), organizational structure and boundary spanning (Allen, 1984), as well as the coordination of innovative activities (Pelz

☆ Authorship is alphabetical. The authors give special thanks to the MIT Department of Biology for access to archival materials. We also thank Paula Stephan, Pierre Azoulay, Nico Lacetera, Jacques Mairesse, Fabiana Visentin, editor Martin Kenney and two anonymous reviewers, as well as participants at the NBER Changing Frontier Conference and the NSF Workshop on Science of Science Policy for their thoughtful comments. Chris Liu is thankful to the Kauffman Foundation for Dissertation Fellowship funding and support. The usual disclaimers apply. Direct all correspondence to Chris Liu at chris.liu@rotman.utoronto.ca.

* Corresponding author. Tel.: +1 416 978 5268.
E-mail addresses: annamaria.conti@scheller.gatech.edu (A. Conti), chris.liu@rotman.utoronto.ca (C.C. Liu).

http://dx.doi.org/10.1016/j.respol.2015.01.001
0048-7333/

and Andrews, 1976). More recently, burgeoning literatures on differences across scientists (Roach and Sauermann, 2010; Pezzoni et al., 2012) and incentive structures within firms (Cockburn et al., 1999; Liu and Stuart, 2014), as well as scientific careers and differences between graduate and postdoctoral stages (Stephan and Levin, 1992; Azoulay et al., 2009) reinforce the notion that there is considerable heterogeneity across scientists. As Stephan (2012) notes in her recent book, "Collaboration in science often occurs in a lab. The lab environment not only facilitates the exchange of ideas. It also encourages specialization. . ." (p. 67).

This paper's central goal is not to overturn laudable advances in data collection and analysis, but to urge greater attention to the study of scientific laboratories. As one avenue of motivation, in this paper we examine the personnel composition within laboratories. Specifically, we focus on laboratory members of varying characteristics and link changes in the number of these personnel types to the laboratory's scientific output. In particular, we ask the following set of related questions. First, in the biological sciences, how have laboratory personnel compositions changed as this field has grown in prominence through the twentieth century? Second, to what extent do laboratory members with different scientific experience (e.g., graduate students vs. postdocs), funding, or position (e.g., trainee vs. technician) affect the laboratory's scientific output? And in our examination of the laboratory's personnel composition, what might we learn about how different types of personnel members affect incremental versus breakthrough publications?

To answer these questions, we examine the laboratory compositions and scientific outputs for one elite set of scientists: principal investigators (PIs) running laboratories at the MIT Department of Biology. Using a complete personnel roster, we document an increase in the prevalence of postdoctoral scientists for the period 1966–2000, while the number of graduate students and technicians remained largely constant. Consistent with prior research, our analysis suggests that personnel are a critical determinant of laboratory productivity: larger laboratories have more publication outputs. Moreover, we find that experienced scientists (i.e., postdocs), particularly those with external funding (i.e., postdocs with fellowships), make greater contributions to the laboratory's publication outcomes, suggesting that both experience and funding are critical determinants of laboratory productivity.

However, when we focus solely on high-profile publications (i.e., publications in Science, Nature, or Cell), we present three unexpected findings. First, graduate students, who make only nominal contributions to overall publication counts, contribute as much to breakthroughs as postdocs with external funding. Second, postdocs without fellowships have no observable impact on breakthrough publications. In a final intriguing finding, technicians are instrumental to high-profile publications, but have no observable impact on lower impact publication output.

These results speak to the importance of composition, not just size, in a laboratory manager's consideration of potential laboratory members. Although larger laboratories result in more publications, only a subset of these personnel types appears to contribute to breakthrough publications. Moreover, our results have implications for the use of large-scale bibliometric data to study productivity. Our results suggest that the sole use of publication author lists to construct laboratory size may lead to severe biases in estimating a laboratory's productive resources. Coupled with recent, exponential advances in the collection of large datasets, our findings on laboratory composition provide motivation to revisit these ubiquitous social groups. We believe that the time is ripe for a large-scale examination of scientific laboratories.

This paper proceeds as follows. Section 2 reviews the literature on laboratories and their importance to knowledge production, as well as posing our research questions. In Section 3, we describe our setting and data, and Section 4 describes our measures and empirical strategy. Section 5 presents our findings. A final section concludes and discusses the implications of our findings for the current trend toward large bibliometric datasets.

2. Background and research questions

2.1. History of industrial and academic laboratories

Across both commerce and the academe, laboratories are central organizational structures in the production of knowledge. Laboratories enable the division of scientific labor (e.g., Jones, 2009), serve as repositories of scientific materials (Furman and Stern, 2011), and transmit tacit knowledge to scientific novitiates (Latour, 1988), to name a few roles among many. Historically, laboratories have been physical spaces that serve both to separate potentially dangerous chemicals and reagents away from the general population, as well as providing a controlled environment to foster reproducibility. From Leeuwenhoek's construction of microscope lenses in the 17th century through Marie Curie's toil to isolate radium in the early 1900s, work in a laboratory was often a solitary affair.

Only with the advent of the dye industry and advances in organic chemistry in late 19th century Germany did industrial laboratories, as we now conceive of them, first begin to appear (Mowery and Rosenberg, 1999; Murmann, 2003). Ranging from Thomas Edison's invention factory at Menlo Park, New Jersey to laboratories at General Electric, AT&T, or Dupont, industrial laboratories have been a wellspring of new ideas and technologies (Mowery, 1990). In the pharmaceutical industry, a large number of industrial laboratories were founded in the early 20th century, and have been linked to spillovers from geographically proximate university labs (Furman and MacGarvie, 2007), primarily in the corridor between Philadelphia and New York City (Feldman & Schreuder, 1996). In turn, large firms, and the R&D resources embodied in these firms, may "anchor" knowledge in the local community, resulting in localized knowledge spillovers (Agrawal & Cockburn, 2003; Feldman, 2003).

On the flip side, university research is responsible for a large percentage of industrial innovations (Jaffe, 1989; Mansfield, 1998). Academic laboratories are often thought of as a complement to industrial research, and access to academic laboratories is an essential component to the development of absorptive capacity (Cohen and Levinthal, 1990; Cockburn and Henderson, 1998). As a consequence, both academic and industry science are thought to be the twin engines that drive technological change and, ultimately, economic growth (Romer, 1990). For the biotechnology industry, university linkages were a critical component of success (cf., Kenney, 1986). There are often tight linkages between academic and industrial scientists (e.g., Balconi et al., 2004; Murray, 2004), and these linkages often occur through geographic collocation (e.g. Zucker et al., 1998; Breschi and Lissoni, 2001; Audretsch and Feldman, 1996).

Academia not only serves as a source of early-stage innovative ideas, it also serves as a source of knowledge workers for the industry. University labs are the major venue for training scientists, especially for positions that require specialized, tacit skills (e.g., a Ph.D.). Moreover, it has been proposed that universities serve a critical function in screening potential employees. As Dasgupta and David (2004; p. 511) suggest, "disclosure and peer evaluations make available, at very low cost to managers of company R&D laboratories, a great deal of information about the qualities of scientists who they might want to recruit as employees."

Both the scale and the scope of university research have changed dramatically throughout the 20th century. For example, Stephan (2013) notes that US research expenditures in 1940 were at less than one percent of current (i.e., year 2010) levels. In 1930, just 895 doctorates were awarded across all the sciences and engineering, and much of this was directed at basic research.

By comparison, in the life sciences alone, more than 8000 doctorates were awarded in 2010. The bulk of this growth has been driven by the post-war recognition of the importance of science and technology in innovative growth, and a push by Vannevar Bush's Endless Frontier campaign to "build research capacity by training new researchers" (Stephan, 2013, p. 32). Although a significant body of research is done by industry scientists, a report by the National Science Board (2008) has noted that university researchers are responsible for more than 70% of all scientific articles.

2.2. Laboratory studies

Given the central role that laboratories play in the production of knowledge, it comes as no surprise that there is significant interest in laboratories in the social sciences. In recent years, much of this work has bifurcated across methodological lines, with one body of work emphasizing depth through a series of qualitative case studies, and a second stream of work tapping into large bibliometric datasets. One of the goals of this paper is to provide an intermediary approach, bridging the benefits of large-scale quantitative approaches with the contextual nuances within laboratory structures.

Much of our fine-grained knowledge of laboratories comes through a series of case studies, primarily conducted from the 1970s. In a groundbreaking study, Bruno Latour conducted a deep ethnography to examine the social construction of knowledge within the context of an endocrinology laboratory (Latour and Woolgar, 1979; Latour, 1988). Over the course of a year, Latour illuminated the social environment within which data is collected and "facts" are established. Although not the central element in his examination of communication patterns, Allen (1984) also devoted a significant amount of effort to R&D laboratories. More recently, scholars have used qualitative analyses of laboratories to examine expert systems (Knorr-Cetina, 1999; Conti et al., 2014), managerial control (Owen-Smith, 2001), interactions with technology licensing offices (Colyvas, 2007), reward structures (Liu and Stuart, 2014), and geographic layouts (Kabo et al., 2014; Liu, 2014).

By contrast, large-scale quantitative studies of university laboratories have traded depth for breadth. These studies primarily focus on the laboratory head (i.e., professor or PI) and relationships between PIs rather than the microanalysis of laboratory structures. Building on the growing availability of bibliometric data sources (e.g., Azoulay et al., 2006), social scientists have begun to examine differences across PIs, often in studies across thousands of laboratory heads.

It comes as no surprise that a small number of scientists make a disproportionately large contribution to knowledge production (Lotka, 1926). As a consequent of this skewed distribution, researchers have typically focused on "stars", rather than the median scientist (Zuckerman, 1977). With the advent of larger databases, it has been possible to increase sample sizes, examining a more representative sample of scientists. Consistent with a skewed distribution, there is considerable heterogeneity across scientists, whether this heterogeneity is across individuals' orientation to commercial endeavors (Azoulay et al., 2009), their preferences (Roach and Sauermann, 2010), their institutional status (Azoulay et al., 2014), or their helpfulness to others (Oettl, 2012).

Moreover, the collection of sufficiently large datasets has enabled researchers to illustrate that the social context within which a university scientist works is a critical determinant of their rate and direction of innovative activity. For example, individuals with university colleagues and coauthors who have transitioned to entrepreneurship (Stuart and Ding, 2006) are more likely to transition to entrepreneurship themselves. Although Waldinger (2012), in examining the dismissal of scientists in Nazi Germany, did not find evidence for peer effects, Mairesse and Turner (2005) have shown that increases in the publication output of an individual's colleagues lead to higher productivity on the part of the focal individual. More recently, it has been shown that evolutionary biology departments who hire "stars" get nearly a 50% boost to departmental productivity, after accounting for the direct contribution of the star (Agrawal et al., 2013). In a study of geographic proximity, Catalini (2012) draws from over fifty thousand publications at a French university to examine how collocation drives innovative outcomes. As a final example, scholars have also mined hundreds of thousands of articles to examine how a scientist's death affects his or her peers (Azoulay et al., 2010; Oettl, 2012). Taken together, these studies have leveraged the availability of large-scale bibliometric data to provide more precise answers to important questions on knowledge production.

At the same time, left behind are the laboratory structures that case studies emphasize are critical determinants of productivity. Undergirding the thousands of scientists (i.e., professors) examined in these studies are tens, if not hundreds of thousands of laboratory members. Thus, we complement the quantitative body of work on scientific productivity by "bringing back in" the academic laboratory. As we have noted, one of the most robust patterns in social studies of science is the skewed distribution of productive workers. Our suspicion is that this skewed distribution applies not just to laboratories as a whole, but permeates into the laboratory itself: some laboratory members contribute more to laboratory productivity than others (also see Section 6). As a consequence, we examine the personnel composition of laboratories, and link how personnel with different characteristics have divergent effects on laboratory productivity.

2.3. Experience, funding, and positions in laboratory personnel

To link different types of personnel to laboratory output, we examine laboratory members across three dimensions: their experience, their external funding structure, and the positions the individuals occupy within the laboratory. We focus on these three dimensions because we believe that they are both salient and that they map onto characteristics of the lab members in our dataset. We do not suggest that these dimensions are exhaustive.

2.3.1. Experience

One of the central theories in the social studies of science is that knowledge production is a craft (Fujimura, 1996; Simonton, 2004). Given its tacit nature, the practice of science is most often acquired through hands-on apprenticeships to masters of the craft (Zuckerman, 1977). Consistent with the notion that there is a significant learning component to the mastery of science, scientific productivity increases over time, reaching an apex at mid career (Levin and Stephan, 1991).

In the life sciences, training commonly occurs across two stages: graduate, and then postdoctoral training (Nerad and Cerny, 1999), and the duration of these stages is increasing (Stephan and Ma, 2005; Conti and Liu, 2014). One explanation is that, to become active contributors, budding scientists need to accrue a significant amount of knowledge before they reach the scientific frontier (Jones, 2009). Alternatively, increasing competition for a limited number of positions may require longer resumes. Regardless of the mechanism, there is reason to suspect that laboratory members with greater age and experience may be positively correlated with the laboratory's research output.

2.3.2. Funding

A second dimension is the funding status of the laboratory member. Although many laboratory members receive funding (e.g., a salary stipend, conference travel, etc.) directly from the laboratory head's grants, a number of individuals receive significant funding from external sources. In the life sciences, the presence of external funding agencies (e.g., the Helen Hay Whitney Foundation) that want to identify and support scientists-in-training, particularly at the postdoctoral stage of their careers are common. These foundations want to identify promising young individuals, to mediate the cross-fertilization of ideas across sub-disciplines, and to promote greater autonomy and risk-taking on the part of trainees (Owen-Smith, 2001).

For postdocs, and most external funding within the laboratory occurs at the postdoctoral stage of training, gaining a fellowship is an important milestone. Funding provides external validation of the individual's research potential, as well as the individual's ability to write a grant and to raise external funds. Moreover, funding often enables the funded individual to take on riskier projects. Lastly, from the laboratory's perspective, the gain of external funding by a postdoc may spillover to free up financial resources for other purposes (e.g., hiring another postdoc), linking external funding to laboratory productivity.

2.3.3. Positions

A final dimension that may differentiate laboratory members is the position that the individuals occupy within the laboratory (Liu and Stuart, 2014). We focus on laboratory positions because of the divergence in roles expected from trainees (i.e., graduate students and postdocs) and permanent, salaried employees (i.e., technicians).

Graduate students and postdocs are apprentices within the laboratory. During their stay, they are expected to carry out independent research, striving to acquire the research skills of the master (i.e., laboratory head). Freeman et al. (2001) have characterized the career structure of these trainees as a tournament, with "winner-take-all" competition where the most successful candidates at one training stage advance to the next. Framed in this light, graduate students strive to advance to be postdocs, and postdocs strive for more permanent employment (e.g., tenure-track professorships). Thus, the primary role of a trainee is to conduct primary research, preparing him or her for a successful transition out of the current laboratory toward the next career stage.

By contrast, the roles undertaken by graduate students and postdocs diverge dramatically from individuals in the position of technicians. The role of the technician is to provide support (Barley, 1996; Kaplan et al., 2012). Technicians are not seen as researchers conducting independent work but, as Shapin (1989) states in his examination of Boyle's laboratory, "at one extreme, technicians might be seen as mere sources of physical energy and as muscular extensions of their master's will." Consistent with this view, technicians may also serve to ease and accelerate the workload for individuals in trainee positions, and technicians often lack autonomy within the laboratory (Owen-Smith, 2001). Lastly, technicians may act as knowledge repositories within the laboratory (Furman and Stern, 2011).

Taken together, there is strong reason to suspect that different types of laboratory members may make differential contributions to the knowledge output of the laboratory. The perspectives outlined above lead us to the first research question addressed in this paper: *to what extent do laboratory members who differ in their experience, funding, and positions contribute to the publication output of an academic laboratory?*

2.4. Incremental vs. breakthrough publications

However, not all scientific outputs are equal, and experience, funding, and positions may have varying effects across different segments of the scientific impact distribution. Just as a minority of individuals dominate the knowledge production function, a minority of publications have disproportionate impact, and it is plausible that a different subset of laboratory personnel are correlated with these high-impact outcomes. For example, in an examination of patent outliers, Singh and Fleming (2010) suggest that teams are more likely to result in highly cited patents than lone inventors. Lone inventors are disproportionately represented in the tails of the creativity distribution (Dahlin et al., 2004), while others have suggested that teams result in greater variation in outcomes (Taylor and Greve, 2006).

Although a positive relationship between experience and overall scientific output should come as no surprise, there is more doubt about a positive relationship between experience and outlier publications. For breakthroughs, a healthy dose of naiveté may be useful. For example, inexperienced graduate students may elect different projects than their more experienced counterparts. In Knorr-Cetina's words "Compared with postdocs and senior researchers, they [grad students] are (still) under less pressure to publish quickly, copiously, and in good journals. . .Also, doctoral students were considered to be more willing to take risks – out of sheer lack of knowledge about the kinds of trouble they would encounter, and perhaps out of greater confidence in a laboratory leader who tends to be enthusiastic about risky research." (Knorr-Cetina, 1999, p 230).

By contrast, we suspect that the link between external (postdoctoral) funding and breakthrough publications is likely to be positive. If funding agencies have the ability to identify talented individuals, and we suspect that talent is correlated with breakthroughs, funded researchers are more likely to achieve breakthroughs. Moreover, as noted above, external funding may give greater autonomy, enabling postdocs to engage in riskier types of research (Owen-Smith, 2001).

Lastly, laboratory technicians may also enable breakthroughs. Given their lack of independent projects, we equate technicians to "slack" resources, and their efforts can be brought to bear on particularly competitive projects. Defined by Nohria and Gulati (1996) as "the pool of resources in an organization that is in excess of the minimum necessary to produce a given level of organizational output," Cyert and March (1963) also state that, "organizational slack absorbs a substantial share of the potential variability in the firm's environment. As a result, it plays both a stabilizing and an adaptive role (p. 43)." As winning a competitive race often enables a paper to be published in a prominent journal, a laboratory's ability to rapidly mobilize technician resources may equate to breakthrough publications. Lastly, it is also probable that the impact of technicians may proxy for capital equipment, which has been found to mediate breakthroughs (Barley, 1996; Stephan, 2012). And, to the extent that technicians have different "hands-on experiences" from trainees, their contextual understanding of materials, instruments, and techniques may lead to different publication outcomes (Barley and Bechky, 1994).

This discussion leads us to ask a second, interrelated question: to what extent do laboratory members who differ in their experience, funding, and positions contribute to breakthrough publications?

3. Setting and data

To address these topics, this paper presents a quantitative case study examining a dataset comprised of laboratories at the Massachusetts Institute of Technology (MIT) Department of Biology between 1966 and 2000. Although focused on one scientific department at a specific university, this setting has a number of advantages. First, it is an elite biology department that has consistently contributed to scientific breakthroughs since the 1960s. Mirroring other studies that focus on scientific elites (Zuckerman, 1977; Azoulay et al., 2010), this set of laboratories is particularly

Professor:	David Baltimore
Visiting Scientists:	Samuel Latt and Richard Van Etten
Postdoctoral Associates:	Brygida Berse, Mark Feinberg, Michael Lenardo, Jing-Po Li, Shiv Pillai, Louis Staudt and Xiao-Hong Sun
Postdoctoral Fellows:	Raul Andino, Patrick Baeuerle, Andre Bernards, Lynn Corcoran, Sunyoung Kim, Towia Libermann, Ricardo Martinez, Mark Muesing, Cornelis Murre, Jacqueline Pierce, Stephen Smale, Didier Trono, Anna Voronova and Astar Winoto
Technical Assistants:	Ann Gifford, Carolyn Gorka, Patrick McCaw, Michael Paskind and Gabrielle Rieckhof
Graduate Students:	George Daley, Peter Jackson, Marjorie Oettinger, David Schatz and Dan Silver
Undergraduate Student:	Anna Kuang

Fig. 1. Representative example of MIT Biology Annual Report. *Note*: A representative personnel list from David Baltimore's laboratory. Within our study, we excluded visiting scientists and undergraduate students, as there was evidence that the reporting of these laboratory personnel types was incomplete.

important: their scientific discoveries have been critical to the emergence of the biotechnology industry. As an illustration, our dataset, which encompasses 119 laboratories in total, contains six Nobel Laureates and 43 members of the National Academy of Sciences. Second, within this elite cohort of scientists, we have access to a particularly rich data source: the department's internal Annual Report, which provides an unparalleled window into laboratory structures over the course of almost four decades. These Annual Reports present both a fine-grained illustration of the laboratory's internal activities and, perhaps even more importantly, a complete one. Lastly, a member of our research team received a doctorate from this department, providing rich insight into technical and organizational aspects of this particular department.

The centerpiece of our dataset is data culled from the Annual Reports. The purpose of these reports was to foster the internal dissemination of information between laboratories. As a consequence, from 1966, when the current departmental structure was adopted, through the year 2000, when the Annual Reports were moved online, a yearly report of the department's internal activities was compiled, printed and distributed to each member of the department.[1] The Annual Reports carefully documented a complete list of laboratory members, including their professional role in the department (i.e., graduate student, postdoctoral associate, technician, etc.) (Figure 1). We use the reports to measure the year in which an individual began working in a specific laboratory, in addition to the date (if applicable) when he or she left. Moreover, from the years 1966 through 1989, the reports included project level data documenting each individual's projects-in-progress. In 1989, the reports became so cumbersome, in excess of 650 pages, that each laboratories' activities were limited to a two-page summary. Although we do not use the project level data in this paper, the annual reports allow us to generate a complete roster of each laboratory's members, as well as their membership type.

We supplemented these personnel rosters with a hand-collected dataset of each laboratory's publication outputs, compiled from the Medline database (Azoulay et al., 2006). This collection resulted in a dataset of 7848 scientific papers. We supplemented this bibliometric data with a listing of all NIH funding awarded to the professors in our dataset.

4. Measures and empirical strategy

4.1. Publication outcomes

In this paper, we link a laboratory's personnel composition to its publication output. To do so, we examined two dependent variables. The first variable is simply a laboratory's yearly number of publications. An alternative measure of overall productivity, the impact-factor weighted publication count, did not affect this set of results.

A second set of regressions examines a laboratory's likelihood of achieving a "breakthrough" discovery. Specifically, we chose to focus on publications in Science, Nature, or Cell for three reasons. First, in multiple conversations with life scientists, these three venues were cited as the most prestigious journals. Second, excluding journals that don't publish original research (e.g., Annual Reviews of Biochemistry), these journals have the highest journal-impact factors. Lastly, as our dataset begins in the 1960s, these journals were publishing articles throughout the timeframe of our data. One exception is Cell, which began publishing only in 1974. Using just Science and Nature publications yielded similar results.[2] Thus, for our second set of regressions, we generate an indicator variable set to 1 if a publication occurred in Science, Nature, or Cell and 0 otherwise. We did not use a publication count as fewer than 20% of laboratories published more than one article in the journals within a given year.

4.2. Laboratory composition

Our key independent variables are the number of different personnel types that populate the laboratory. For these measures, we did not consider undergraduates or visiting scientists, as there was evidence that these personnel types were both infrequent and idiosyncratically underreported. As an initial point of entry, we

[1] See http://libraries.mit.edu/mithistory/research/schools-and-departments/school-of-science/department-of-biology/; accessed November 20, 2013.

[2] Another plausible journal to include is PNAS. However, given the large number of National Academy of Science members in our dataset, many laboratories have direct submission privileges to this journal. Thus, the competitiveness of this journal is diluted for our sample population.

simply generated the total number of personnel in the laboratory, a measure we call laboratory size. We also included the square of this measure, as well as of the personnel counts described below, to account for the possibility that our variables have a non-linear impact on a laboratory's output.

To distinguish between personnel types, we broke laboratory members into the following categories: (a) postdoctoral scientists with external funding, (b) postdoctoral scientists without external funding, (c) graduate students, and (d) technicians.[3]

In the life sciences, almost all scientists-in-training undergo two training stages: graduate education to obtain a doctorate, and then one or more postdoctoral appointments. This two-stage training is almost unavoidable if the trainee wishes to practice research, whether in the public or private sector. For "alternative" careers, such as management consulting or patent law, a postdoctoral stage can sometimes be bypassed. For the timeframe of our dataset, alternative career paths were not very prevalent. Lastly, given the elite nature of our setting, the vast majority of postdocs are doing their first postdoc.

Unlike many graduate programs in Europe, life science graduate students in elite US programs apply to the university program, not directly to a professor. After a year or two of coursework, concurrent with sequential apprenticeships (called rotations) in different laboratories, junior graduate students and professors simultaneously choose one another in a two-sided match. In the (exclusive) case of MIT Biology, graduate students attend a seminar by each and every professor in January of their first year (i.e., the Inter-Activities Period), and choose a laboratory at the end of their first year. Thus, graduate students at MIT are able to choose from a diverse array of laboratories, and only begin specialized training within one laboratory at the end of their first year.

Unlike graduate training, postdocs apply for a training position directly with the laboratory head. As the graduate student finishes doctoral training, strong disciplinary norms encourage the student to choose a new laboratory for postdoctoral training. Often, the graduate student will use postdoctoral training to shift research trajectories to complement his or her existing skills.[4] For the typical graduate student, a Ph.D. defense only occurs after matching to a postdoc position. Only after a postdoctoral laboratory is selected, does the graduating student apply for external funding. The external funding application requires the nomination of the trainee's postdoctoral advisor, as the "suitability" of the postdoc training environment is a key determinant of funding success. Many fellowships come with a boost to the postdoc's salary, as well as nominal research funds (e.g., to buy a laptop). For universities, postdoctoral fellowships are salient enough that postdocs are separated into those with external funding, called fellows, and those without, called associates, within our dataset.

A last category of laboratory personnel is technicians. Technicians are salaried staff that have an important role in supplementing the research efforts of trainees, and in providing all of the required technical support that enables a laboratory to function effectively. As Barley (1996; p. 430) states, "graduate students and postdoctoral fellows in the molecular biology labs we studied learned empirical procedures largely from technicians." In general, technicians do not have a doctorate. They are often overseers of essential equipment (e.g., a Nuclear Magnetic Resonance machine) or skills that are only acquired over time (e.g., tissue sectioning).

As a control variable, we include the amount of NIH funding a laboratory has received within a given year, deflated to 1982 dollars. Conditioned on the number of each laboratory's personnel types, NIH funding captures the residual impact of financial capital, net of salaries, on the productivity of the laboratory. As we have each laboratory professor's complete publishing history, including when he or she was a trainee, we include the years since first publication to proxy for the laboratory's "age".

4.3. Empirical strategy

To test our hypotheses that different personnel types have a differential impact on a laboratory's productive output, we estimate a dynamic panel model that follows a methodology proposed by Wooldridge (2005). We use a Poisson specification with robust standard errors, which takes into account the fact that the dependent variable, the number of articles per laboratory, can only take discrete and positive values. This model has several desirable properties, including consistency in the coefficient estimates and in the standard errors (Griliches and Hausman, 1986). Formally, our regression equation can be expressed as:

$$E[y_{it+2}|y_{it-1}, y_{i0}, \mathbf{z}_{it}, c_i] = c_i \exp(\mathbf{z}_{it}\boldsymbol{\gamma} + y_{it-1\rho}+) \quad (1)$$

where our dependent variable, y_{it+2}, is the number of articles per laboratory *i*. Using a count of laboratory articles that were published in $t+2$ accounts for the lags between the time at which an individual joins the laboratory and the time at which the resulting findings are published (Levin and Stephan, 1991).[5] Wooldridge (2005) suggests that we include y_{it-1}, the number of laboratory articles lagged by one year to control for omitted variable bias. As one example, productive labs might attract a different set of individuals than less productive laboratories. Lastly, a dynamic panel model allows, at least partially, to address problems of reverse causality, that laboratory productivity may drive laboratory structure.[6]

In the equation, $\mathbf{z}_{it}$ is a vector which includes the following covariates: the number of (a) postdoctoral scientists with external funding, (b) postdoctoral scientists without external funding, (c) graduate students, and (d) technicians, as well as the square of each term to control for nonlinearities. In addition, as controls, we include the amount of NIH funding (deflated to 1982 US dollars). We control for the experience of a principal investigator with the number of years since she published her first scientific article. Finally, we use year-fixed effects to capture dynamics unrelated to the personnel composition of the laboratory.

Lastly, we also include the pre-sample value of the dependent variable in our regressions, y_{i0}, because the unobserved effect c_i is conditioned on $(y_{i0}, \mathbf{z}_{it})$ in Eqs. (1) and (2).[7] Note that with a lagged dependent variable as a regressor, the usual within estimator (i.e., laboratory fixed effects) would be inconsistent and severely biased (Wooldridge, 2005). Thus, we opt for a random effect model, which allows the unobserved effect to be correlated with the initial condition, y_{i0}, and $\mathbf{z}_{it}$. Although not our preferred model, regressions with laboratory fixed effects yield similar results (not shown).

To evaluate the likelihood that a laboratory made a "breakthrough" discovery, we estimate a probit model, in which the dependent variable is a dummy that takes on the value of one if the laboratory has published either in Science, Nature, or Cell in a

[3] We excluded staff scientists because their numbers were few and limited to the latter years of our dataset.

[4] The major determinants of postdoc laboratory selection are research focus, as well as geographic proximity to the graduate laboratory. For a detailed examination of these selection factors, including both quantitative and qualitative evidence, see Azoulay et al. (2009).

[5] The results remain invariant if the dependent variable is observed in $t+1$ rather than in $t+2$.

[6] Summary statistics indicate considerable variability in our dependent variable, confirming the importance of estimating a dynamic panel model. Indeed, the between (i.e., 3.2) and the within (i.e., 2.9) standard deviation of a laboratory's publication output are large and similar to one another.

[7] The pre-sample value of the dependent variables is measured in the year preceding the moment in which a laboratory is observed for the first time.

Table 1
Descriptive statistics.

Variable	Mean	Std. dev.	Min.	Max.
Dependent variables				
Laboratory's publication count ($t+2$)	5.293	4.432	0	24
Laboratory published one or more articles in Science, Nature or Cell ($t+2$)	0.392	0.448	0	1
Independent variables				
Number of postdocs with fellowships	2.794	3.193	0	17
Number of postdocs w/o fellowships	1.890	2.199	0	13
Number of graduate students	3.357	2.615	0	15
Number of technicians	1.561	1.488	0	6
NIH grant dollars (in '000s)	340.7	495.1	0	7790
Number of laboratory publications ($t-1$)	4.867	4.387	0	24
Number of laboratory publications (in the pre-sample year)	2.685	2.329	0	17
Laboratory published one or more articles in Science, Nature or Cell ($t-1$)	0.391	0.488	0	1
Laboratory published one or more articles in Science, Nature or Cell (pre-sample)	0.323	0.468	0	1
Number of years elapsed since a principal investigator published his/her first article	19.318	11.103	0	51

Note: 1482 observations.

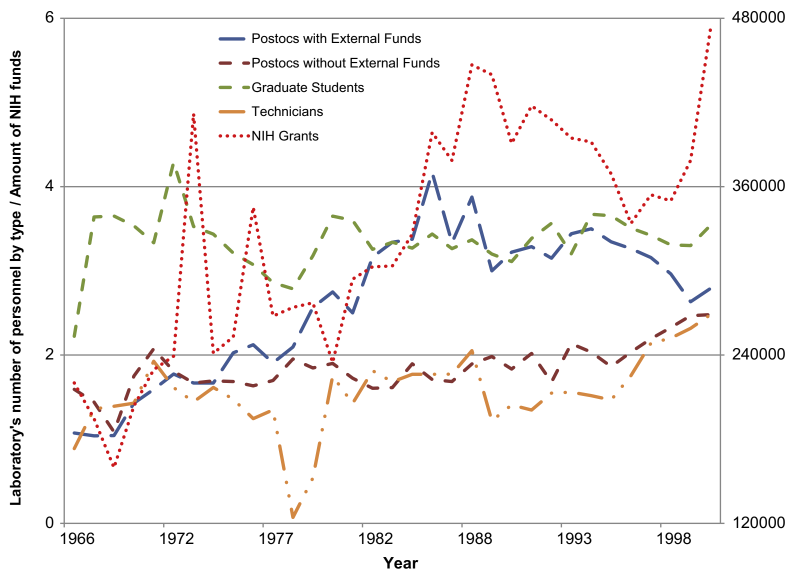

Fig. 2. Laboratory personnel-by type. *Note*: These are each laboratory's number of personnel by type (on the left axis). We also include the year amount of NIH grants (in 1982 US Dollars) on the right axis.

given year. As before, we estimate a dynamic panel model, which includes the one-year lagged value of the dependent variable as a regressor. Formally, the probability that a laboratory published a breakthrough can be expressed as:

$$P[y_{it+2} = 1 | y_{it-1}, y_{i0}, \mathbf{z}_{it}, c_i,] = F(\mathbf{z}_{it}\gamma + y_{it-1}\rho + c_i) \quad (2)$$

where the dependent variable, y_{it+2} is a dummy set to 1 if a laboratory publishes either in Science, Nature, or Cell in $t+2$. As before, we include y_{it-1}, the one-year lagged value of the dependent variable, and y_{i0}, the dependent variable measured in the pre-sample year. The coefficients we report for the probit models are marginal effects, evaluated at the means of the regressors.

5. Results

We begin our results section with a description of the dataset (Table 1). Overall, our dataset includes 1482 laboratory-year observations, and 20,324 laboratory member-years that span 1966–2000.[8] Within this dataset, there are 119 principal investigators and 5694 laboratory members, which include 1798 postdocs with fellowships, 1328 postdocs without fellowships, 1395 graduate students, and 1173 technicians. Over this time period, the laboratories resulted in 7844 journal publications, of which approximately 15% are breakthrough publications in Science, Nature or Cell.

From the 1960s to the year 2000, the number of laboratories in MIT Department of Biology grew from 27 to 49. Concomitantly, the number of incumbent graduate students increased from 42 to 86 and the number of postdoctoral assistants increased from 59 to 146. Finally, the overall number of technicians increased from 24 to 119 in total.

Not only did the overall size of the department increase over this decade, the average laboratory size increased as well (see Fig. 2). Over the thirty-five years encompassed in our dataset, laboratory size increased from 6 to 12 individuals (excluding the laboratory's head). This size increase was primarily driven by greater numbers of postdocs, particularly postdocs with external funds, although both types of postdocs increased steadily over the years. This rise in the number of postdocs parallels an increase in NIH funding per lab, which rose from 220 to 473 thousand dollars (in constant, 1982 dollars) over the course of the dataset. By contrast, the number of graduate students and technicians were largely stable over this time period.

[8] We excluded Eric Lander's laboratory, which was working on the Human Genome Project, as it was an extreme outlier.

Table 2
Laboratory composition determinants of publication count (Poisson models).

	1	2	3	4	5
Number of publications (lag 1)	0.019** (0.005)	0.012** (0.004)	0.012* (0.005)	0.011* (0.004)	0.011** (0.004)
Number of publications (pre-sample)	0.092** (0.016)	0.080** (0.014)	0.084** (0.014)	0.082** (0.013)	0.082** (0.014)
NIH grant dollars (log)	0.017* (0.008)	0.006 (0.007)	0.006 (0.007)	0.009 (0.008)	0.011 (0.008)
Elapsed years since first publication (log)	0.460** (0.104)	0.150* (0.072)	0.158* (0.073)	0.107 (0.071)	0.148* (0.073)
Lab size		0.101** (0.014)			
Lab size2̂		−0.002** (0.000)			
Technicians			0.011 (0.022)	0.009 (0.021)	0.008 (0.021)
Technicians2̂			−0.000 (0.002)	−0.000 (0.002)	−0.000 (0.002)
Trainees (postdocs + graduate students)			0.102** (0.016)		
Trainees2̂ (postdoc + graduate students)			−0.003** (0.001)		
Postdocs				0.108** (0.015)	
Postdocs2̂				−0.004** (0.001)	
Postdocs with fellowship					0.094** (0.015)
Postdocs with fellowship2̂					−0.004** (0.001)
Postdocs without fellowship					0.057** (0.021)
Postdocs without fellowship2̂					−0.002 (0.002)
Graduate students				0.035+ (0.021)	0.029 (0.022)
Graduate students2̂				0.000 (0.002)	0.001 (0.002)
Year FE	YES	YES	YES	YES	YES
Observations	1482	1482	1482	1482	1482
No. of lab clusters	119	119	119	119	119
Log-likelihood	−3423.33	−3346.70	−3346.54	−3346.37	−3352.90

Notes: All personnel types are count variables. The pre-sample number of publications is included, but not shown. Robust standard errors are in parentheses; +significant at 10%, *significant at 5%; **significant at 1%.

On average we observe a laboratory over twelve years. In a typical laboratory-year, the laboratory published 5.3 publications, although the range in this output varies widely (Table 1). Each laboratory's scientific output has steadily increased over time, from an average of three papers per laboratory-year in the 1960s to six papers per laboratory-year in the 1990s. By contrast, the yearly number of breakthrough papers has held steady over our studied timeframe, with a possible dip appearing in the 1970s (Fig. 3).

Within our dataset, the average laboratory has ten members, of which 5 are postdoctoral scientists, 3 are graduate students, and 2 are technicians. However, laboratories vary greatly in their composition of personnel types. For example, the average laboratory has 5 postdoctoral scientists, although this number ranges from zero to 30. Although the average laboratory received 341 thousand dollars from the NIH, the most highly funded laboratory received nearly eight million dollars.

To examine the links between different personnel types and laboratory productivity, we first turn our attention to a laboratory's yearly publication count (Table 2). In a baseline regression (Model 1), we see that a lagged publication count has a positive correlation with subsequent laboratory productivity, consistent with the notion of inertia in laboratory productivity. NIH funding also has a positive, significant effect on laboratory output. When we include laboratory size, a composite measure of laboratory personnel types, in our regressions, we observe a positive, significant effect (Model 2). The relationship between a laboratory's size and its productivity is characterized by diminishing returns, consistent with a negative and highly significant coefficient on the squared term of laboratory size. For the average-sized laboratory, adding one additional member is correlated with an increase in the number of a laboratory's publications by 0.24.[9] Given the magnitude of the laboratory size coefficients, the inflection point is reached at 25 members and thus lies in the 98th percentile of the distribution of laboratories by their size.

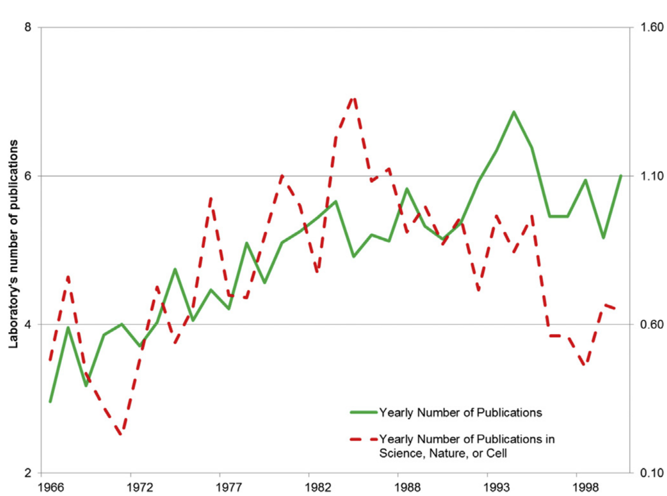

Fig. 3. Laboratory publication output-over time. *Note*: The year number of publications (on the left axis) and the yearly count of publications in Science, Nature or Cell (on the right axis) over the time period of our dataset.

In Models 3–5, we decompose the laboratory size measure into its constituent parts. In Model 3, we see that the bulk of personnel effects is due to the presence of laboratory trainees (i.e., postdocs and graduate students). Surprisingly, technicians do not have a significant impact on a laboratory's publication count, reinforcing the importance of positions and roles within the laboratory. This result is particularly noteworthy as the cost of a technician to the laboratory, in terms of salary and compensation, is comparable to a trainee. Digging deeper into trainee types (Model 4), the magnitude of the coefficients indicates that adding one member to the mean count of postdocs and graduates students increases a laboratory's publication output by 0.31 and 0.14, respectively. In line with the results from the previous Models, the relationship between the number of postdocs and a laboratory's output is concave. The inflection point is reached at 13 postdocs and thus lies in the 95th percentile of the distribution of laboratories by their postdoc count.

In Model 5, we distinguish between postdocs with and without external funding. Adding one member to the mean number of postdocs with external funding increases a laboratory's publication count by 0.29. Adding one member to the mean number of postdocs without external funding increases a laboratory's publication count

[9] This value was computed holding constant at the means the remaining controls.

Table 3
Laboratory composition determinants of the likelihood of publishing in Science, Nature, or Cell (Probit models).

	6	7	8	9	10
Published in Science, Nature, or Cell (lag 1)	0.123** (0.041)	0.095** (0.037)	0.094** (0.037)	0.094** (0.035)	0.091** (0.035)
Published in Science, Nature, or Cell (pre-sample)	0.249** (0.059)	0.174** (0.052)	0.173** (0.050)	0.175** (0.048)	0.162** (0.046)
NIH grant dollars (log)	0.011** (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.005 (0.004)
Elapsed years since first publication (log)	−0.051 (0.040)	−0.113** (0.033)	−0.108** (0.032)	−0.106** (0.033)	−0.082* (0.032)
Lab size		0.048** (0.011)			
Lab size2̂		−0.001* (0.000)			
Technicians			0.054** (0.019)	0.054** (0.019)	0.058**
Technicians2̂			−0.007* (0.003)	−0.006* (0.003)	−0.007*
Trainees (postdocs + graduate students)			0.049** (0.011)		
Trainees2̂ (postdocs + graduate students)			−0.001* (0.001)		
Postdocs				0.049** (0.014)	
Postdocs2̂				−0.002* (0.001)	
Postdocs with fellowships					0.046** (0.015)
Postdocs with fellowships2̂					−0.002 (0.001)
Postdocs without fellowships					−0.001 (0.020)
Postdocs without fellowships2̂					−0.000 (0.002)
Graduate students				0.044* (0.018)	0.040* (0.018)
Graduate students2̂				−0.001 (0.002)	−0.001 (0.002)
Year FE	YES	YES	YES	YES	YES
Observations	1482	1482	1482	1482	1482
No. of lab clusters	119	119	119	119	119
Log-likelihood	−757.28	−733.49	−730.20	−726.57	−721.80

Notes: Coefficients are marginal effects evaluated at the means of the independent variables. All personnel types are count variables. Robust standard errors are in parentheses below; +significant at 10%, *significant at 5%; **significant at 1%.

by only 0.19. Postdocs, regardless of their external funding status, are greater contributors to laboratory productivity than graduate students.

The effects of laboratory personnel types change considerably when we consider only "breakthrough" publications in the journals Science, Nature, or Cell (Table 3). In our baseline (Model 6), we find a significant role of NIH funding in breakthrough publications, although this effect does not hold with the inclusion of laboratory personnel. As before, larger laboratories have more breakthroughs, although, once again, there is evidence for diminishing returns to scale (Model 7). Adding one member to the mean laboratory's size increases the likelihood of breakthroughs by 0.03. Considering that the average probability of breakthroughs is 0.39, an increment by 0.03 of this value corresponds to an 8% increase. The inflection point is reached at 22 members and thus, it is similar to the one we found for the total publication count.

When we parse laboratory members into multiple personnel types, we see, contrary to the results with overall publication counts, that *both* technicians and trainees make contributions to breakthrough output (Model 8). Most surprisingly, the effect size of these two personnel types is significant and of equal magnitude. Adding one member to the mean number of trainees or technicians increases a laboratory's publication count by about 0.03, regardless of the laboratory member's position. The inflection point is reached at 19 members in the case of trainees and at 4 members in the case of technicians.

Moreover, our results on breakthrough pubs also diverge from our results on overall publication counts when we consider graduate students (Model 9). Mirroring our results with technicians, we find that graduate students make substantial contributions to laboratory breakthroughs, on par with postdocs, while only making marginal contributions to overall productivity. In a final finding, we find no correlation between postdoctoral scientists *without* external funding and the likelihood of breakthrough publications, suggesting that external funding is a key correlate of a postdoc's contribution to laboratory productivity (Model 10).

Two further aspects of our results are worth noting. First, we note that older vintage laboratories, while having greater overall publication output (Table 2, Model 2), appear to have fewer breakthroughs (Table 3, Model 2), consistent with a link between organizational age and obsolescence (Sorenson and Stuart, 2000). Second, consistently across both Table 2 and Table 3, we find, after controlling for the number and types of laboratory personnel, no effect on the level of NIH funding to a laboratory. This suggests, to our eyes, that a significant role of NIH funding is to allow the recruitment of laboratory personnel, presumably through the hiring of postdocs. First, this is a stark illustration of how the NIH funding structure is intimately intertwined with the market for scientists-in-training (Stephan, 2012). Second, this suggests that NIH funding is effective only to the extent by which a professor has the ability to recruit talented individuals into the lab. We discuss this in more detail in later sections.

6. Discussion and conclusion

This study links the number of personnel types with varying experience, external funding, and positions to a laboratory's publication output. We suggest that for incremental publications, postdocs (i.e., those with experience), regardless of their funding level, dominate. However, for breakthrough publications, graduate students and postdocs with external funding make equally significant contributions. By contrast, postdocs without fellowships do not correlate with breakthroughs. Lastly, we suggest that technicians, who have no observable effect on overall publication counts, are correlated with a laboratory's likelihood of breakthrough publications. Taken together, this study provides motivation for moving beyond aggregate measures of laboratory size, to suggest that the personnel composition of laboratories is an important determinant of laboratory productivity.

Three implications of our results are worthy of further elaboration. First, our results speak to the importance of personnel composition, and not just size, in a principal investigator's consideration of potential laboratory members. Although larger laboratories result in more publications, individuals with different levels of experience contribute differently to overall laboratory productivity. Moreover, only a subset of laboratory members contributes to breakthrough publications. Our analysis illustrates the critical importance to a laboratory of attracting personnel, especially postdocs that are able to garner external funding, who contribute not

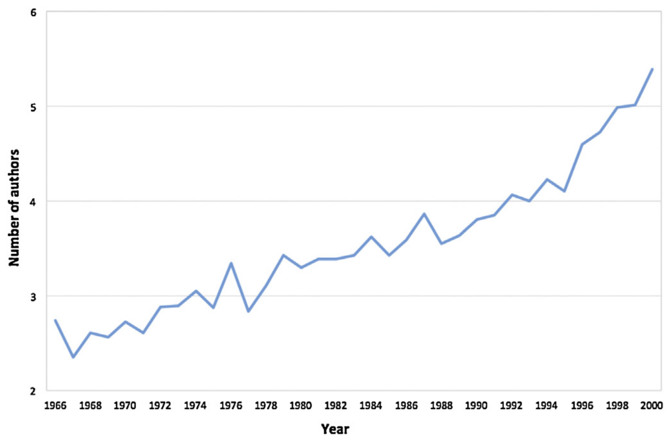

Fig. 4. Laboratory publication author numbers-over time. *Note*: For each year in our dataset, we tabulate the total number of authors on each paper.

only to the volume of a laboratory's publications but also to the laboratory's ability to foster breakthrough publications.

Second, our results suggest that the necessary personnel inputs for incremental versus breakthrough publications may be different. Although experienced personnel are a critical input for doing normal science, they are a less perfect correlate for the generation of breakthroughs, at least in this setting. Coupled with Singh and Fleming's (2010) finding that collaborations yield a greater likelihood of breakthroughs, it may be especially interesting to move from laboratory-level productivity down to the project-level (i.e., paper-level) of analysis. Our initial analysis of paper co-authorship patterns suggests two findings. First, the number of coauthors per project has increased over time (Fig. 4), but the proportion of papers that are coauthored with other laboratories, measured as the ratio of papers with the focal professor (i.e., one of 119 laboratory heads in our dataset) as last author to laboratory papers with a different last author, has not changed dramatically (Fig. 5). This finding, counter to Jones et al. (2008) finding of greater cross-laboratory collaboration for "typical" laboratories may reinforce the notion that laboratories operating at different positions in the status hierarchy have different resource constraints. Alternatively, MIT laboratories

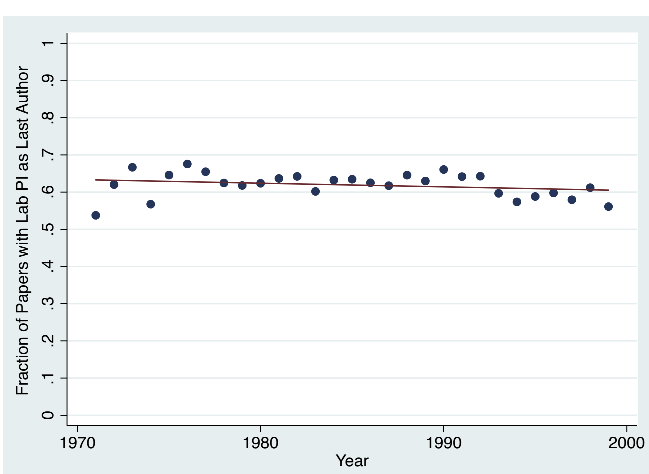

Fig. 5. Cross-laboratory collaboration patterns-over time. *Note*: Strong norms within the life sciences dictate that laboratory heads (PIs) are the last authors on publications. For the publications in our dataset, we parsed each laboratory's publication count into those with the laboratory head as the last author, as well as those where a different individual was the last author. This plot presents the ratio of the two counts, over time, which we interpret as an indicator of the extent of cross-laboratory collaboration. A line indicates the predicted linear trendline.

may be collaborating more over time, but using their superior (relative to their collaborator) negotiating position to extract a greater and unequal proportion of prestigious last author positions. Although preliminary, these findings reinforce the promise of a more fine-grained analysis of laboratories.

Lastly, our results juxtapose the role of technicians with that of trainees. In contrast to trainees, we are not able to pick up the impact of technicians (i.e., permanent staff) on overall laboratory publication counts. At first blush, this would suggest that a recent push for the creation of research scientist positions (e.g., a permanent "postdoc") would be both costly and non-productive for the laboratories, counter to policy implications called for by a number of prominent scholars (e.g., Stephan, 2013). However, although the number of technicians is small, we *are* able to link technical staff to breakthrough publications, and this effect appears to be significant in magnitude. In the ongoing conversation about the changing scientific workforce, a greater understanding of the relationship between attributes of different personnel types and the volume and kinds of scientific output is critical to shaping future policy changes.

Although our results are suggestive, there remain multiple caveats. For example, there are reasons to avoid a direct comparison between graduate students and postdocs in the dataset. First, postdocs may be of different quality than graduate students. Although MIT is an elite graduate institution with high-quality Ph.D. students, postdocs are, by definition, graduate students who have successfully made it through their dissertation. Moreover, given the mission surrounding university training, graduate students may be treated differently from postdocs and may receive greater supervision than postdocs. As we can not separate out these explanations in this paper, we urge caution in the mechanisms that may underlie differential contributions of graduate and postdoc personnel to overall laboratory productivity. Nonetheless, a closer examination of these mechanisms may also be a particularly fruitful avenue of future study.

This paper is not without empirical concerns. First, we emphasize that our results are suggestive correlations, and are not dispositive. To the extent possible, we have chosen an empirical approach that minimizes the likelihood of reverse causality (i.e., personnel members drawn to laboratories in anticipation of future output). Alternatively, the inclusion of laboratory fixed effects regressions, which correct for (time-invariant) unobservable characteristics of laboratories but do not address reverse causality, yielded consistent results. However, our analysis falls short of a natural experiment, such as an (truly) unexpected funding windfall or random assignment of fellowships to some postdocs and not to others. One possibility, if the goal is to examine comparable postdocs with and without fellowships, is to obtain the "scorecards" of fellowship applications and adopt a regression discontinuity approach (for an empirical example on grant applications, see Li, 2012). However, the identification of random variation, especially in elite contexts such as the one examined in this paper, is few and far between. Thus, a central goal of this paper is to motivate further work by the corpus of scholars interested in innovation and productivity.

We have chosen to study the MIT Department of Biology because it is an elite setting that has repeatedly made important contributions to modern biology. Although our results are likely to be relevant to other elite biology departments, it is not possible to predict how far down the status hierarchy of life science departments our results will extend. At less elite universities, it is more difficult to recruit top-level graduate students and postdocs. As a consequence, one might expect to find significant attenuation of our coefficients for these settings, but we cannot speculate as to the magnitude of this attenuation or on whether this attenuation would vary across different personnel types at this time. Lastly, given significant differences across knowledge production disciplines, parallels between our setting and others, such as physics laboratories, are tenuous (Knorr-Cetina, 1999).

This study also has significant implications for laboratory managers. Of little surprise is that experienced trainees make significant contributions to laboratory productivity. As a consequence, labs with a greater number of postdocs, particularly those able to garner external funding, correlate with greater productive output. More surprising are our results concerning breakthroughs. To the extent that the number of postdocs able to attract external funding are limited in number (and a quick perusal of fellowship websites suggests a strong correlation between fellowships and elite institutions), this result suggests that the skewed distribution of resources permeates not only across the professorial ranks, but also into each professor's access to skilled labor. For laboratories at less elite settings than MIT, we have little doubt that the ability to tap into productive personnel members is severely circumscribed. Rather than status hierarchical arguments for the stratification of laboratories, and Merton's (1968) Matthew effect comes to mind, we speculate that the lack of personnel resources may serve to limit the productivity of peripheral laboratories, even when they are able to obtain funding from NIH.

From the perspective of a central funding agency, the skewed distribution of talent also suggests that there is a limit to the productive expansion of the scientific training enterprise in the United States. Although Stephan (2013) has emphasized the lack of demand, in the form of academic jobs for students as they finish training, this paper suggests that there are limits to the supply of potentially productive applicants, especially those who hope to make breakthrough discoveries. Looking toward new sources of talent, such as emerging economies, may mitigate this constraint.

Although this paper has focused on the internal context (e.g., personnel composition) of laboratories, the external context within which the laboratory is situated is no doubt important (cf Autio et al., 2014). Laboratories are almost never standalone entities and may be embedded within universities, for-profit firms of varying types (e.g., small entrepreneurial firm, large biotech firm, industry consortium) or government entities (e.g., NIH). A future avenue of study may be to examine not only the effects of personnel composition in these varying context, but also the interactions and fit between different external contexts and the internal characteristics of laboratories.

We began this paper by urging greater attention to the study of scientific laboratories, organizational structures that underpin almost every facet of modern scientific work. It is our belief that insufficient attention to laboratories is not due to intellectual oversight, but rather the limited availability of fine-grained data. Indeed, collection of the dataset utilized in this paper only came about through many years of hand-coding, coupled with technological advances such as optical character recognition (OCR) software. Replicating this process to generate other datasets of comparable detail and quality is a non-trivial exercise.

And yet, circa 2015, we believe that the pieces may be in place for the large-scale reconstruction and examination of laboratory profiles. For example, over the past 10 years, there have been astonishing advances in curated, large, bibliometric datasets focused on scientists (e.g., Azoulay et al., 2006). Building upon these advances, scholars have used machine-learning techniques (Smalheiser and Torvik, 2009), structural equivalence ideas from network analysis (Tang and Walsh, 2010), or atypical citation patterns (Agrawal et al., 2013) to disambiguate seemingly equivalent names from the corpus of scientific authors. In the life sciences, coupling name disambiguation advances with NIH grant-funding (Li, 2012) or the scraping of university websites (Sheltzer and Smith, 2014), may yield the identification of a discrete set of primary investigators, or laboratory heads. And, coupled with strong norms to list laboratory heads as the last-author, publication coauthorships may enable the reconstruction of laboratory personnel lists (Bercovitz and Feldman, 2011). Once time-varying personnel lists are derived, and here we enter uncharted waters, it may be possible to use the ProQuest Dissertation Database and transitions from one lab to another to track graduate students as they transition to postdocs and, ultimately, to last-author, grant-holding positions as laboratory heads.

The laboratory reconstruction strategy sketched out above is both nontrivial and imperfect. Thus, the goal of this perambulation is not to provide a definitive roadmap toward the reconstruction of laboratories, but merely to suggest that the large-scale reconstruction of laboratories, at least for those built upon the Medline database, appears plausible at this point in time. Regardless of the technical manner in which it is executed, it is our strongly held belief that the large-scale analysis of laboratories and their constituent personnel types would serve as an important resource in the social studies of science. Even limited to fields with well-organized bibliometric sources (i.e., the life sciences), a more comprehensive examination of the universe of laboratories would be an important complement to existing ethnographic work (e.g., Owen-Smith, 2001).

Moreover, just as the study of individual scientists working in the knowledge economy has lent insights into broader phenomena, such as stratification processes (Merton, 1968), geographic spillovers (Zucker et al., 1998), and social construction (Latour and Woolgar, 1979), we suspect that the examination of scientific laboratories may yield insights into broader organizational phenomena. For example, we could imagine laboratory studies yielding insights into demographic studies of personnel turnover (Pfeffer, 1983), the integration of newcomers (Moreland et al., 2002), the management of knowledge scope and scale (Henderson and Cockburn, 1996) to name a few examples among myriad possibilities.

Ultimately, the goal of this paper has been to peer deeper into the social structures that underlie the productivity of individual PIs. And in so doing, we present a series of results that have implications for laboratory managers, policy makers, as well as social scientists studying scientists. We see our contribution as a complement to existing bibliometric studies, and hope to "bring laboratories back in", reinforcing the importance of individuals on the laboratory shop floor.

References

Agrawal, A., Cockburn, I.M., 2003. The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems. Int. J. Ind. Organ. 21, 1227–1253.

Agrawal, A., McHale, J., Oettl, A., 2013. Collaboration, Stars, and the Changing Organiation of Science: Evidence From Evolutionary Biology. NBER Working Paper Series #19653.

Allen, T.J., 1984. Managing the Flow of Technology. The MIT Press, Cambridge, MA.

Audretsch, D.B., Feldman, M.P., 1996. R&D spillovers and the geography of innovation and production. Am. Econ. Rev. 86, 630–640.

Autio, E., Kenney, M., Mustar, P., Siegel, D., Wright, M., 2014. Entrepreneurial innovation: the importance of context. Res. Policy 43, 1097–1108.

Azoulay, P., Graff Zivin, J.S., Wang, J., 2010. Superstar extinction. Q. J. Econ. 25, 549–589.

Azoulay, P., Liu, C.C., Stuart, T.E., 2009. Social Influence Given (Partially) Deliberate Matching: Career Imprints in the Creation of Academic Entrepreneurs. Harvard Business School Working Paper 09-136.

Azoulay, P., Stellman, A., Graff Zivin, J.S., 2006. Publication Harvester: an open-source software tool for science policy research. Res. Policy 35, 970–974.

Azoulay, P., Stuart, T.E., Wang, Y., 2014. Matthew: effect or fable? Manag. Sci. 60, 92–109.

Balconi, M., Breschi, S., Lissoni, F., 2004. Networks of inventors and the role of academia: an exploration of Italian patent data. Res. Policy 33, 127–145.

Barley, S.R., 1996. Technicians in the workplace: ethnographic evidence for bringing work into organizational studies. Adm. Sci. Q. 41, 404–441.

Barley, S.R., Bechky, B.A., 1994. In the backrooms of science: the work of technicians in science labs. Work Occup. 21, 85–126.

Bercovitz, J., Feldman, M.P., 2011. The mechanisms of collaboration in inventive teams: composition, social networks, and geography. Res. Policy 40, 81–93.
Breschi, S., Lissoni, F., 2001. Knowledge spillovers and local innovation systems: a critical survey. Ind. Corpor. Change 10, 975–1005.
Catalini, C., 2012. Microgeography and the Direction of Inventive Activity. Working Paper.
Cockburn, I.M., Henderson, R.M., 1998. Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. J. Ind. Econ. 46, 157–182.
Cockburn, I.M., Henderson, R.M., Stern, S., 1999. Balancing Incentives: The Tension Between Basic and Applied Research. NBER Working Paper Series w6882.
Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35, 128–152.
Colyvas, J.A., 2007. From divergent meanings to common practices: the early institutionalization of technology transfer in the life scences at Stanford University. Res. Policy 36, 456–476.
Conti, A., Liu, C.C., 2014. The (changing) knowledge production function: evidence from the MIT Department of Biology 1966–2000. In: Jones, B., Jaffe, A.B. (Eds.), NBER Changing Frontiers Volume. NBER, Cambridge, MA.
Conti, A., Denas, O., Visentin, F., 2014. Knowledge specialization in PhD student groups. IEEE Trans. Eng. Manage. 61, 52–67.
Cyert, R.M., March, J.M., 1963. A Behavioral Theory of the Firm. Blackwell Publishing, Englewood Cliffs, NJ.
Dahlin, K., Taylor, M., Fichman, M., 2004. Today's Edisons or weekend hobbyists: technical merit and success of inventions by independent inventors. Res. Policy 33, 1167–1183.
Dasgupta, P., David, P.A., 1994. Toward a new ecoomics of science. Res. Policy 23, 487–521.
Feldman, M.P., 2003. The locational dynamics of the US biotech industry: knowledge externalities and the anchor hypothesis. Ind. Innov. 10, 311–329.
Feldman, M.P., Schreuder, Y., 1996. Initial advantage: the origis of the geographic concentration of the pharmaceutical industry in the mid-Atlantic region. Ind. Corp. Change 5, 839–862.
Fleming, L., Sorenson, O., 2004. Science as a map in technological search. Strateg. Manag. J. 25, 909–928.
Freeman, R., Weinstein, E., Marincola, E., Rosenbaum, J., Solomon, F., 2001. Competition and careers in biosciences. Science 294, 2293–2294.
Fujimura, J.H., 1996. Crafting Science: A Sociohistory of the Quest for the Genetics of Cancer. Harvard University Press, Cambridge, MA.
Furman, J.L., MacGarvie, M.J., 2007. Academic science and the birth of industrial research laboratories in the U.S. pharmaceutical industry. J. Econ. Behav. Organ. 63, 756–776.
Furman, J.L., Stern, S., 2011. Climbing atop the shoulders of giants: the impact of institutions on cumulative research. Am. Econ. Rev. 101, 1933–1963.
Griliches, Z., Hausman, J.A., 1986. Errors in variables in panel data. J. Econom. 31, 93–118.
Henderson, R.M., Cockburn, I.M., 1996. Scale, scope, and spillovers: the determinants of research productivity in drug discovery. RAND J. Econ. 27, 32–59.
Jaffe, A.B., 1989. Real effects of academic research. Am. Econ. Rev. 79, 957–970.
Jaffe, A.B., Trajtenberg, M., Henderson, R.M., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108, 577–598.
Jones, B.F., 2009. The burden of knowledge and the "death of the renaissance man": is innovation getting harder? Rev. Econ. Stud. 76, 283–317.
Jones, B.F., Wuchty, S., Uzzi, B., 2008. Multi-university research teams: shifting impact, geography, and stratification in science. Science 322, 1259–1262.
Kabo, F.W., Cotton-Nessler, N., Hwang, Y., Levenstein, M.C., Owen-Smith, J., 2014. Proximity effects on the dynamics and outcomes of scientific collaborations. Res. Policy 43, 1469–1485.
Kaplan, S., Milde, J., Cowan, R.S., 2012. Interdisciplinarity in Practice: A Case of a Nanotechnology Research Center. Working Paper.
Kenney, M., 1986. The University-Industrial Complex. Yale University Press, New Haven, CT.
Knorr-Cetina, K., 1999. Epistemic Cultures: How the Sciences Make Knowledge. Harvard University Press, Cambridge, MA.
Latour, B., 1988. Science in Action: How to Follow Scientists and Engineers Through Society. Harvard University Press, Cambridge, MA.
Latour, B., Woolgar, S., 1979. Laboratory Life: The Construction of Scientific Facts. Princeton University Press, Princeton, NJ.
Levin, S.G., Stephan, P.E., 1991. Research productivity over the life cycle: evidence for academic scientists. Am. Econ. Rev. 81, 114–132.
Li, D., 2012. Expertise vs. Bias in Evaluation: Evidence from the NIH. Working Paper.
Liu, C.C., 2014. Brokerage by Design: Formal Struture, Geography, and Crosscutting Ties. Working Paper.
Liu, C.C., Stuart, T.E., 2014. Positions and rewards: the allocation of resources within a science-based entrepreneurial firm. Res. Policy 43, 1134–1143.
Lotka, A.J., 1926. The frequency distribution of scientific productivity. J. Wash. Acad. Sci. 16, 317–323.
Mairesse, J., Turner, L., 2005. Measurement and Explanation of the Intensity of Copublication in Scientific Research: An Analysis at the Laboratory Level. NBER Working Paper Series #11172.
Mansfield, E., 1998. Academic research and industrial innovation: an update of empirical findings. Res. Policy 26, 773–776.
Marx, M., Strumsky, D., Fleming, L., 2009. Mobility, skills, and the Michigan noncompete experiment. Manag. Sci. 55, 875–889.
Merton, R.K., 1968. The Matthew effect in science. Science 159, 56–63.
Moreland, R.L., Argote, L., Krishnan, R., 2002. Training people to work in groups. Theory and Research on Small Groups, vol. 4., pp. 37–60.
Mowery, D.C., 1990. The development of industrial research in US manufacturing. Am. Econ. Rev. 80, 345–349.
Mowery, D.C., Rosenberg, N., 1999. Paths of Innovation: Technological Change in 20th Century America. Cambridge University Press, Cambridge, UK.
Murmann, J.P., 2003. Knowledge and Competitive Advantage: The Coevolution of Firms, Technology, and National Institutions. Cambridge University Press, Cambridge, UK.
Murray, F., 2004. The role of academic inventors in entrepreneurial firms: sharing the laboratory life. Res. Policy 33, 643–659.
Nerad, M., Cerny, J., 1999. Postdoctoral patterns, career advancement, and problems. Science 285, 1533–1535.
Nohria, N., Gulati, J., 1996. Is slcak good or bad for innovation? Acad. Manag. J. 39, 1245–1264.
Oettl, A., 2012. Reconceptualizing stars: scientist helpfulness and peer performance. Manag. Sci. 58, 1122–1140.
Owen-Smith, J., 2001. Managing laboratory work through skepticism: processes of evaluation and control. Am. Sociol. Rev., 66.
Pelz, D.C., Andrews, F.M., 1976. Scientists in Organization. University of Michigan Press, Ann Arbor, MI.
Pezzoni, M., Sterzi, V., Lissoni, F., 2012. Career progress in centralized academic systems: social capital and institutions in France and Italy. Res. Policy 41, 704–719.
Pfeffer, J., 1983. Organizational demography. Res. Organ. Behav. 5, 299–357.
Roach, M., Sauermann, H., 2010. A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. Res. Policy 39, 422–434.
Romer, P.M., 1990. Endogeneous technological change. J. Polit. Econ., S71–S102.
Shapin, S., 1989. The invisible technician. Am. Sci. 77, 554–563.
Sheltzer, J.M., Smith, J.C., 2014. Elite male faculty in the life sciences employ fewer women. PNAS 111, 10107–10112.
Simonton, D.K., 2004. Creativity in Science: Change, Logic, Genius, and Zeitgeist. Cambridge University Press, Cambridge, UK.
Singh, J., Agrawal, A., 2011. Recruiting for ideas: how firms exploit the prior inventions of new hires. Manag. Sci. 57, 129–150.
Singh, J., Fleming, L., 2010. Long inventors as sources of breakthroughs: myth or reality? Manag. Sci. 56, 41–56.
Smalheiser, N.R., Torvik, V.I., 2009. Author name disambiguation. Annu. Rev. Inf. Sci. Technol. 43, 1–43.
Sorenson, J.B., Stuart, T.E., 2000. Aging, obsolescence, and organizational innovation. Adm. Sci. Q. 45, 81–112.
Stephan, P.E., 2012. How Economics Shapes Science. Harvard University Press, Cambridge, MA.
Stephan, P.E., 2013. The Endless Frontier: Reaping What Bush Sowerd? NBER Working Paper Series #19687.
Stephan, P.E., Levin, S.G., 1992. Striking the mother lode in science. The importance of age, place and time. Oxford University Press, Oxford, UK.
Stephan, P.E., Ma, J., 2005. The increased frequency and duration of the postdoctorate career stage. Am. Econ. Rev. 95, 71–75.
Stuart, T.E., Ding, W.W., 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. Am. J. Sociol. 112, 97–144.
Tang, L., Walsh, J.P., 2010. Bibliometric fingerprints: name disambiguation based on approximate structure equivalence of cognitive maps. Scientometrics 84, 763–784.
Taylor, A., Greve, H.R., 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. Acad. Manag. J. 49, 723–740.
Waldinger, F., 2012. Peer effects in science: evidence from the dismissal of scientists in Nazi Germany. Rev. Econ. Stud. 79, 838–861.
Wooldridge, J.M., 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. J. Appl. Econom. 20, 39–54.
Wuchty, S., Jones, B.F., Uzzi, B., 2007. The increasing dominance of teams in production of knowledge. Science 316, 1036–1039.
Zucker, L.G., Darby, M.R., Brewer, M.B., 1998. Intellectual human capital and the birth of U.S. Biotechnology Enterprises. Am. Econ. Rev. 88, 290–306.
Zuckerman, H., 1977. Scientific Elite: Nobel Laureates in the United States. The Free Press, New York City, NY.