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The (Changing) Knowledge Production Function
Evidence from the MIT Department of Biology for 1970–2000

Annamaria Conti and Christopher C. Liu

2.1 Introduction

Knowledge has been recognized as a major contributor to technological change and to economic growth (Romer 1990). In the knowledge production function, one of the most important inputs is knowledge created by university researchers. Indeed, a report by the National Science Board (2008) has revealed that university researchers are responsible for more than 70 percent of all scientific articles. Moreover, scholars have shown that academic knowledge is responsible for a large percentage of industrial innovations (Jaffe 1989; Mansfield 1995).

Academic knowledge has increasingly become a collective phenomenon. Seminal studies have documented the increase in the size of scientific collaborations, with special focus on the evolution of the geographic dispersion of team members (e.g., Adams et al. 2005; Wuchty, Jones, and Uzzi 2007). Even though university scientists collaborate more and more across research institutions, the scientific laboratory remains the major locus of knowledge production (Stephan 2012a). These laboratories are largely populated by graduate students and postdocs, whose contributions to their laboratory's knowledge stock have been recognized in a number of studies

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(see, for instance, Stephan 2012a; Conti, Denas, and Visentin 2014). These research trainees have coauthored an important percentage of their laboratory's papers and, moreover, have produced a considerable share of the articles published in highly ranked journals (Black and Stephan 2010).

In this study, we use a unique database that allows us to examine the productivity, training duration, and the collaborative behavior of graduate students and postdocs as well as the extent to which these aspects have changed over time. We interpret the patterns we find in light of two paradigms: the increased burden of knowledge that successive generations of scientists face (Jones 2009, 2010a) and the limited availability of permanent academic positions (Stephan 1996; Freeman et al. 2001).

Our data encompass the complete set of laboratories in the MIT Department of Biology, observed from 1970 to 2000. This department has been a major locus of basic and applied discoveries in the life sciences for the latter half of the twentieth century. Through the time frame of our data set, the scientists working at the MIT Department of Biology made discoveries as varied as the molecular mechanisms underpinning recombinant DNA (e.g., the discovery of splicing and introns), cell death, aging, and the progression of cancer. This work has resulted in six Nobel Laureates and forty-three members of the National Academy of Sciences between 1966 and 2000. MIT's Department of Biology has roughly doubled in size, from twenty-seven laboratories in 1966 to forty-nine laboratories in the year 2000. Given this department's elite status, the findings in this chapter may be difficult to extend beyond other elite North American laboratories. With this caveat in mind, we follow in the footsteps of other scholars and trade analytical depth with a focus on an elite setting (Azoulay, Zivin, and Wang 2010; Zuckerman 1977).

We collected a detailed set of information on the graduate students and postdocs who populated these laboratories, including their publication output. For the purposes of this study, we use this information to analyze the evolution over time of four fundamental aspects of their productivity: (a) training duration, (b) time to a first publication, (c) productivity over the training period, and (d) collaboration with other scientists.

We identified four main trends that are common to graduate students and postdocs. First, training periods have increased for later cohorts of graduate students and postdocs. Second, recent cohorts tend to publish their first article later than the earlier cohorts. Third, they produce fewer first-author publications. Finally, collaborations with other scientists, as measured by the number of coauthors on a paper, have increased. This increase is driven by collaborations with scientists outside of a trainee's laboratory.

The remainder of this study is organized as follows. Section 2.2 describes the empirical setting. Section 2.3 presents the scientific productivity trends for graduate students and postdocs. Section 2.4 concludes and discusses policy implications.

Table 2.1 **Personnel composition of Professor Baltimore's laboratory**

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

2.2 Empirical Setting

Our core data source is the MIT Department of Biology's series of annual reports. The primary purpose of the annual report was to document, on a yearly basis, the department's internal activities. This information was then distributed to each member of the department, allowing individuals to be cognizant of their peers' scientific activities. To serve this purpose, the reports included both a roster of laboratory members that comprised the department, as well as technical summaries of ongoing projects. From 1966 to 1989, technical summaries were at the project level, which included both laboratory members affiliated with the project as well as a short project summary. The size of the annual report grew in accordance with the size of the department. After the annual report reached 629 pages in 1987, project summaries were condensed to two pages per laboratory, regardless of its size. In the year 2001, annual reports were no longer published, and our data set ceases at this point.

The annual report documents a roster of each laboratory's members. We know the names of every individual in each laboratory as well as the individual's personnel type (e.g., postdoc, graduate student, technician). As a result, we know the characteristics of the department, its laboratories, and its individual members over the duration of our data set. Table 2.1 provides an example of the roster data available for any given laboratory-year. We know of no other data source that provides as detailed a view into the organization of scientific work as this one.

We supplemented this departmental personnel roster with a number of other data sources. To examine scientific outputs, we hand collected each laboratory head's (i.e., principal investigator [PI]) paper output from Medline. We then matched each laboratory's extracted publication-author list with our personnel roster to examine the extent to which individual laboratory members contributed to the scientific output. In instances where matching

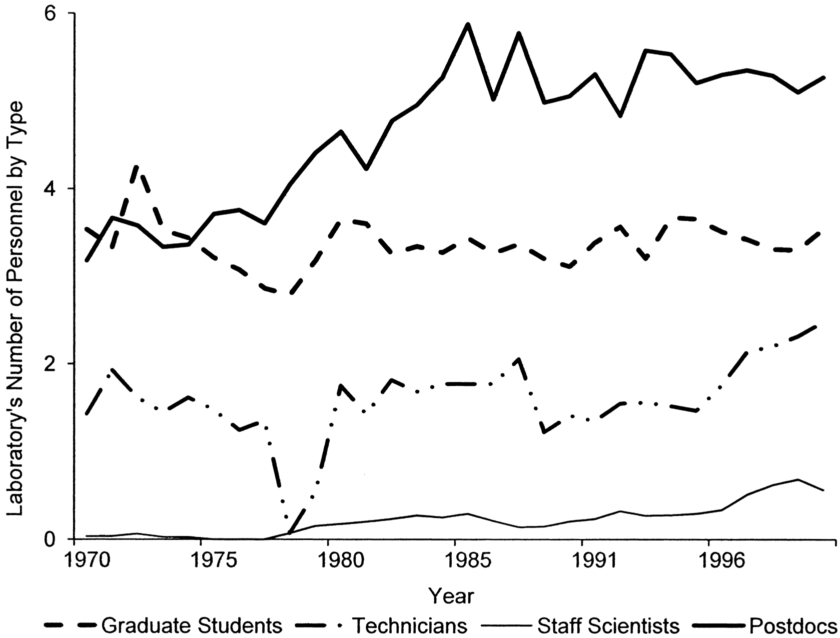

Fig. 2.1 Number of laboratory's personnel by type

was ambiguous (e.g., Liu), we examined the article directly. It is exceedingly rare for laboratory members to publish scientific papers without their PI listed as an author. Hence we do not believe we are missing any publications.

Overall, our data set comprises 1,494 laboratory-years and 20,324 laboratory member-years that span the period 1966–2000. Within this data set, there are 120 unique professors and 6,938 laboratory members who collectively produced 7,553 journal publications (in Medline).

We restrict our analysis to the years 1970–2000 as there was ambiguity in personnel categories prior to 1970. We begin with a description of the laboratories and their changes over time. We then turn our attention to examine the laboratory members with a particular emphasis on the two dominant personnel types, postdocs and graduate students, who comprise more than half of our personnel roster.

Within our data set, the average laboratory has ten members of whom five are postdocs, three are graduate students, and two are technicians. Staff scientists are rare, but their prevalence has increased over time. As shown in figure 2.1, laboratories have grown in size through the latter part of the twentieth century, and this increase has been driven by an increase in the number of postdoctoral scientists. There is no change in the number of graduate students or technicians over time, although the number of salaried staff (i.e., technicians and staff scientists) appears to have increased in the late 1990s.

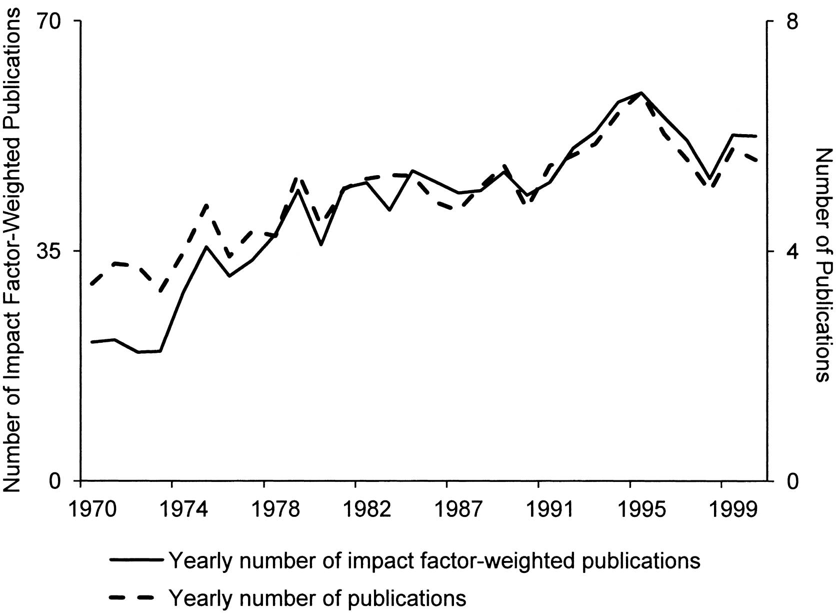

Fig. 2.2 Number of laboratory's publications and impact factor-weighted publications

Figure 2.2 presents trends in scientific output for our laboratories. As shown, the average number of articles has steadily increased over time, from an average of four articles per laboratory-year in the 1970s to six articles per laboratory-year in the 1990s. We observe a very similar trend in the number of impact factor-weighted publications.

We focus our analysis of laboratory members on graduate students and postdocs for a number of reasons. First, these individuals make large contributions to a PI's publication output (Conti and Liu forthcoming). Their purpose is to directly produce scientific publications, rather than to play a supporting role (e.g., technicians). Second, these two types are the most prevalent personnel categories within the roster. Together they make up more than half of the laboratory. Third, these two personnel types have been the focus of recent interest in the literature because of their contributions to knowledge and technology production (e.g., Dasgupta and David 1994; Waldinger 2010). Lastly, we note that graduate students and postdocs are easily and unambiguously identified from one another, suggesting that the distinction in these roles may be salient (e.g., Azoulay, Liu, and Stuart 2014).

Our sample is composed of 991 graduate students and 2,427 postdocs. Figures 2.3A and 2.3B provide descriptive results of the distribution of graduate students and postdocs by their publication count. Interestingly, a significant proportion of them (about 35 percent) did not publish any articles during

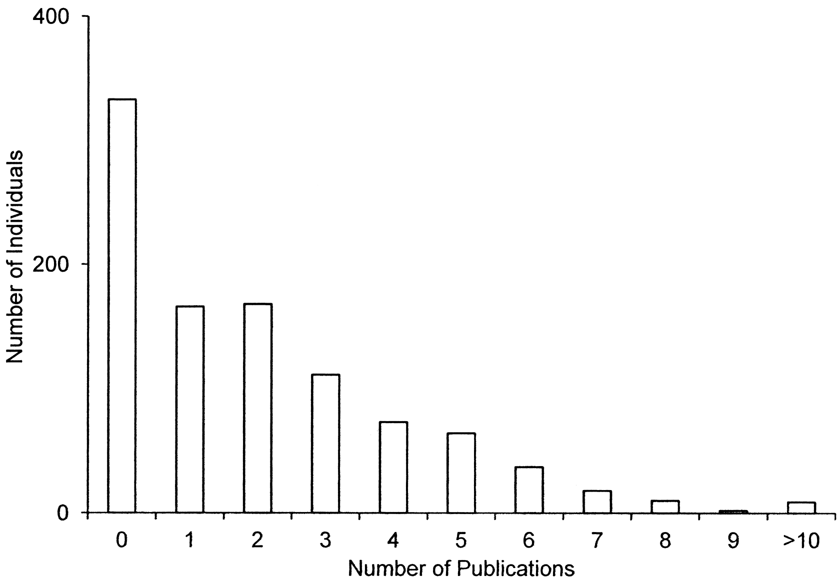

Fig. 2.3A Distribution of graduate students by their number of papers

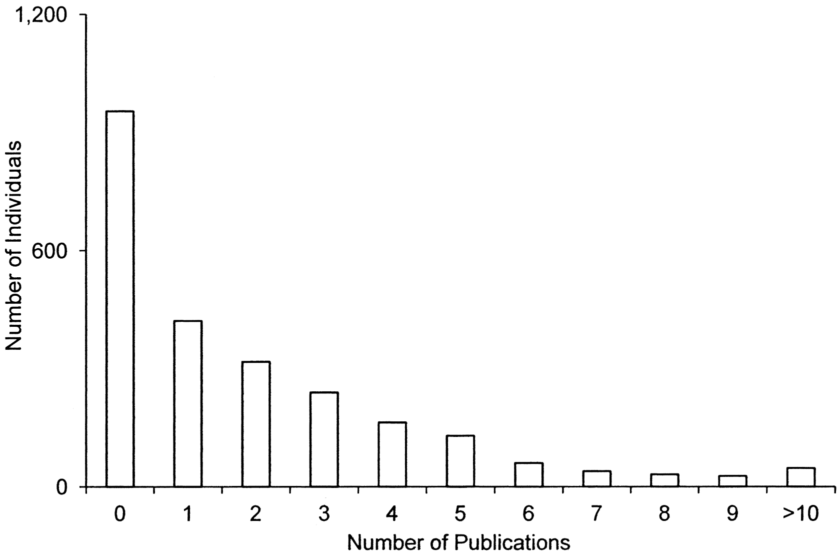

Fig. 2.3B Distribution of postdocs by their number of papers

their training period. Conditioned upon having published, the mean number of papers is about three articles for both graduate students and postdocs.

2.3 Trends in Scientific Productivity of Graduate Students and Postdocs

This section explores the trends in four major dimensions of graduate student and postdoc scientific productivity. First, we look at training duration. Second, we investigate the timing to a first publication. Third, we examine scientific output. Finally, we explore collaboration patterns.

In analyzing these trends, we should keep in mind that while both postdocs and graduate students are formally considered laboratory trainees, they fundamentally differ in a number of aspects. Postdocs are more experienced than graduate students and have accumulated a greater wealth of knowledge and skills. As a consequence, matching between postdocs and PIs is based upon prior ability and experience, rather than the future expectation of productivity as in the case of graduate students (Stephan 2012a).

2.3.1 Training Duration

We begin this section by presenting descriptive statistics for the average training duration of postdoc and graduate students over our sample period. We then investigate whether the length of training has changed over time. Figures 2.4A and 2.4B show the distribution of graduate students and postdocs by their training duration. That the training period for graduate students is longer than postdoctoral training is clearly evident. Indeed, the majority of graduate students in our sample completed their training between five and seven years, while postdocs tended to spend between two and four years in a PI's laboratory.[1]

Figure 2.5 documents training periods for graduate students (dotted line) and postdocs (solid line) over the period 1970–1995. We exclude the years 1996 through 2000 since students who enrolled in these years might not have completed their training by the end of 2000, when our data set is right-censored. Consistent with previous studies,[2] we find that training periods for recent cohorts of students are approximately one year longer than those for the earliest cohorts. The training period increases from three to approximately four years for postdocs and from five to six years for graduate students over our data set.

There are at least three reasons that can explain these trends. The first reason is that as knowledge accumulates, earlier trainee cohorts face a greater

1. It is possible for postdocs to have worked in more than one PI's laboratory before they are offered a faculty position. However, from discussions with MIT PIs as well as from an examination of a CV sample, it is evident that, at least for the period we examine, this is rarely the case for MIT postdocs.

2. See, for instance, the findings by Tilghman (1998), Jones (2009), Jones and Weinberg (2011), and Freeman et al. (2001).

Fig. 2.4A Distribution of graduate students by their training duration

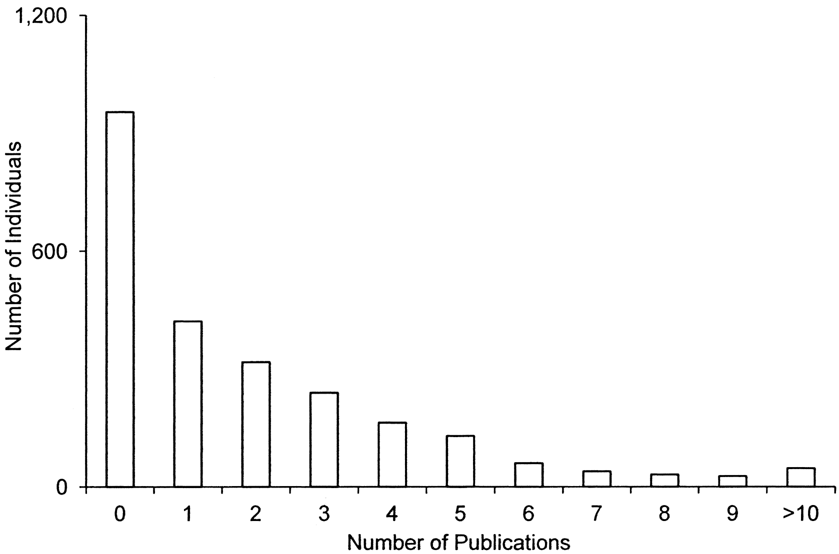

Fig. 2.4B Distribution of postdocs by their training duration

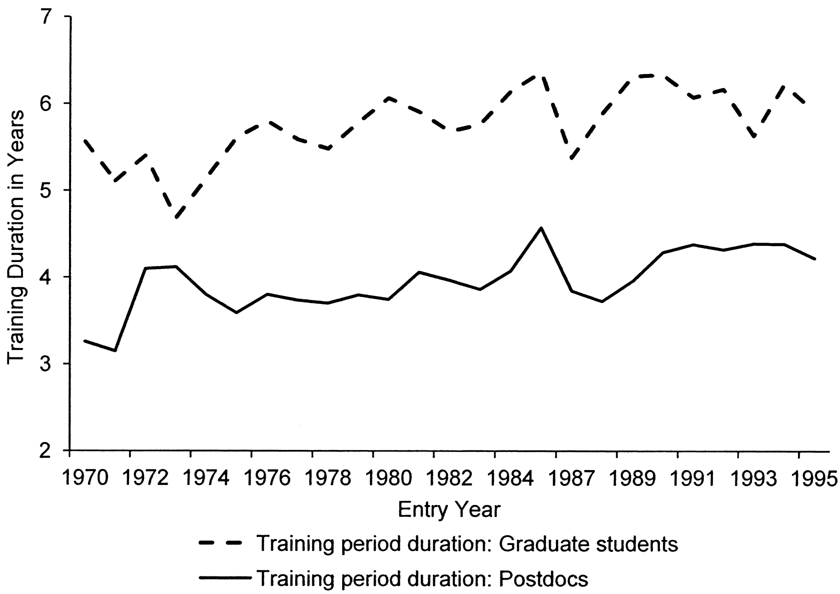

Fig. 2.5 Training duration for graduate students and postdocs over time

educational burden than do the older cohorts (Jones 2009, 2010a). Second, it is also possible that the recent cohorts of postdocs and graduate students tend to stay longer in their positions because of the increased mismatch between the trainees' supply and the availability of permanent academic positions (Stephan 1996; Freeman et al. 2001). Finally, one cannot exclude the possibility that the increased pressure on PIs to publish and apply for grants has led them to impose longer training periods on their students (Freeman et al. 2001).

To more formally assess the evolution of training periods over time, we estimate Poisson regression models, with robust standard errors, in which we relate the training duration of graduate students and postdocs to whether these trainees had enrolled during the following periods: (a) 1970–1979, (b) 1980–1989, and (c) 1990–1995. The distribution of students across enrollment periods is reported in table 2.2.

The equation we estimate is:

$$(1) \qquad y_i = \exp(\beta_1 \mathrm{D}1980\text{–}1989 + \beta_2 \mathrm{D}1990\text{–}1995 + \nu_i + \theta_i + \varepsilon_i),$$

where y_i is training duration, measured in number of years. Moreover, D1980–1989 is an indicator variable that equals one if trainee i enrolled during 1980–1989 and equals zero otherwise. D1990–1995 equals one if trainee i enrolled during 1990–1995 and, similarly, equals zero otherwise. We omit the 1970–1979 indicator variable and use it as a reference. Hence,

Table 2.2 Distribution of graduate students and postdocs by enrollment period

	Graduate students	Postdocs
1970–1979	289	560
1980–1989	334	868
1990–1995	247	565
1996–2000	121	434

Table 2.3 Regression results for graduate student and postdoc training duration

	Graduate students		Postdocs	
	Coeff.	Coeff.	Coeff.	Coeff.
D1980–1989	0.103***	0.075**	0.111***	0.065*
	(0.028)	(0.033)	(0.032)	(0.036)
D1990–1995	0.128***	0.055	0.209***	0.143***
	(0.029)	(0.039)	(0.034)	(0.041)
Field FE	Yes	Yes	Yes	Yes
PI FE		Yes		Yes
R^2	0.01	0.04	0.01	0.03
N	870		1993	

Note: We estimated Poisson models. Robust standard errors are in parentheses. For these analyses we only consider trainees who had enrolled before 1996.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

the coefficients of β_1 and β_2 should be interpreted as the change in training duration relative to the duration of trainees enrolled in 1970–1979. When investigating training duration, it is important to consider the scientific field in which a laboratory operates. Different scientific fields use different tools and it is likely that trends in training durations vary across fields (Galison 1997). To account for field effects, we include a series of indicator variables, ν_i, corresponding to the modal experimental organism used in each laboratory. Specifically, we generated indicators for protein biochemists, bacteriologists, unicellular systems (e.g., HeLa cells), genetic systems (e.g., yeast), rodents, and others (e.g., frogs). Finally, we include a set of PI dummies, θ_i, to control for variations in duration trends across laboratory heads (i.e., laboratory fixed effects).[3]

Table 2.3 presents the regression results for graduate student and postdoc training duration. For each trainee category, we first include biology field

3. In an alternative specification, we substituted the PI dummies with the PI five-year, presample stock of publications to compare cohorts of trainees from supervisors with similar characteristics.

fixed effects (column [1]) and, subsequently, we add PI fixed effects (column [2]). We begin by describing the results for graduate students and then for postdocs.

As table 2.3 shows, in the baseline model the dummies D1980–1989 and D1990–1995 have a positive and statistically significant coefficient. These results confirm the descriptive evidence that later cohorts of students take longer to complete their PhD than earlier cohorts (cohorts who enrolled during the 1970–1979 period). In the second column, we add PI effects and the magnitude of the coefficients declines, together with their statistical significance. This last result suggests that PI characteristics are a source of positive correlation between period dummies and training duration.

We find similar results for postdocs. The coefficients of the 1980–1989 and 1990–1995 period dummies are positive and statistically significant in both model specifications, although the magnitude and significance is, again, reduced with the inclusion of PI fixed effects.

To summarize, the results in this section suggest that training periods have increased in recent years for both graduate students and postdocs. While we cannot precisely disentangle the mechanisms behind these trends, we believe that increasing challenges imposed on recent trainees, in terms of increased educational burden or reduced availability of permanent academic positions, play an important role.

2.3.2 Time to a First Publication

A singular advantage to our data set is the ability to discern the year in which graduate students or postdocs *enter* their training, and begin to be at "risk" for being an author on an article. In this section, we use this aspect of the data set to focus on the time it takes trainees to publish their *first* article. We considered the time interval between a trainee's enrollment and first publication as the time it takes to acquire the knowledge to develop publishable findings. This interval then becomes a measure of trainee distance to the existing knowledge frontier. Figure 2.6 presents Kaplan-Meier estimates of the time to a first publication for postdocs and graduate students. As shown, the probability of publishing a paper in each training year appears to be higher for postdocs than for graduate students. This holds true even when we focus exclusively on first-author publications, which we take as a proxy for those projects to which trainees have given their greatest contribution.[4]

Once more, we are interested in the evolution of time to a first publication over our sample period, for both graduate students and postdocs. If the knowledge burden for the more recent cohorts is larger than that for the oldest ones, then we should expect that the time it takes to publish a first

4. For the sake of brevity, we do not show the results for first-author publications, but they are available upon request.

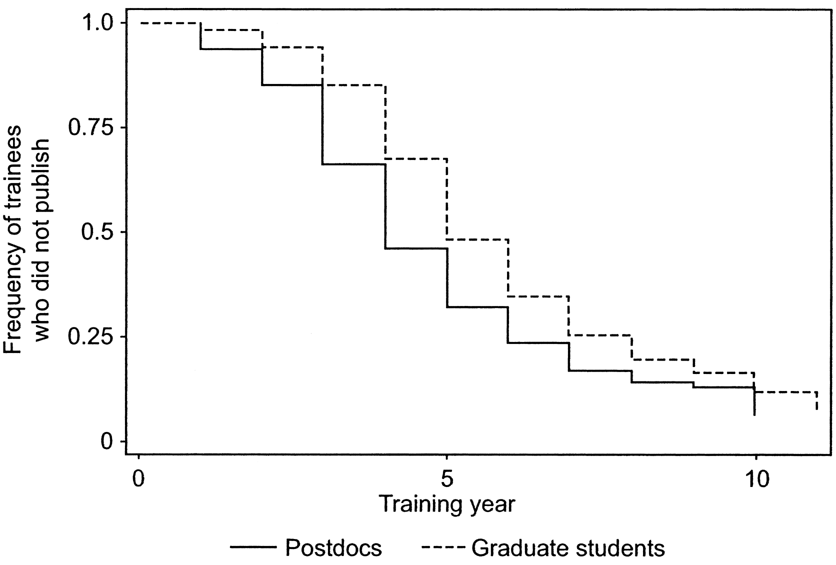

Fig. 2.6 Kaplan-Meier estimates of the time to a first publication: Graduate students and postdocs

article has increased for the most recent cohorts. There are other reasons to expect such a trend. One of these could be a lengthening of the review process at scientific journals. While this is a documented trend in the economic field (Ellison 2002), there are grounds for believing that this phenomenon is not confined to economic journals. As one example, statistics available for the *EMBO* journal reveal an increase over time in the number of days from submission to final decision.[5]

Figures 2.7 and 2.8 display Kaplan-Meier estimates of the time it takes to publish a first article, distinguishing between the following periods: (a) 1970–1979, (b) 1980–1989, and (c) 1990–2000. They provide evidence that the probability of publishing a paper at any given period is higher for the oldest cohorts than for the more recent ones. These trends seem to be more accentuated for postdocs than for graduate students. Moreover, for graduate students, they are more evident in first-author publications than they are in other publications.

Do these trends persist once we take into account field or PI characteristics, which are likely to be a source of correlation between enrollment periods and time to a first publication? Formally, we estimate a series of Cox proportional hazard models in which the hazard of publishing a first article is conditioned on a number of control variables (including period, field, and PI indicators) as above.

5. Statistics are available from http://www.nature.com/emboj/about/process.html.

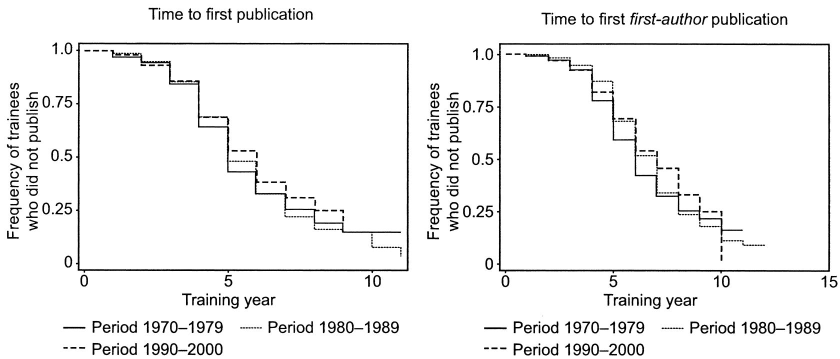

Fig. 2.7 Kaplan-Meier estimates of the time to a first publication: Graduate students over time

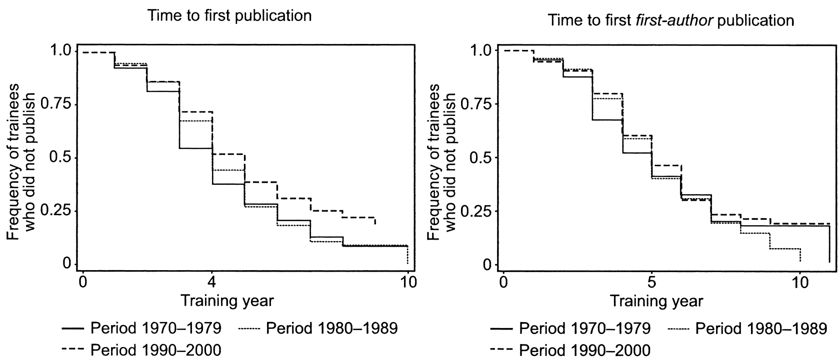

Fig. 2.8 Kaplan-Meier estimates of the time to a first publication: Postdocs over time

Specifically, we estimate the following equation:

$$h(t|x_i) = h_0(t)\exp(x_i\beta_x), \tag{2}$$

where $h(t|x_i)$ is the hazard of publishing a first article, $h_0(t)$ is the baseline hazard (i.e., the hazard when all covariates are equal to zero), and x_i is a matrix of covariates. As in our previous equation, x_i includes period indicator variables as well as field and PI dummies. This time we also include in the sample trainees who had enrolled after 1995. Hence, the last period indicator variable equals one for trainees who had enrolled during 1990–2000 and zero otherwise. The results for graduate students are presented in table 2.4, while those for postdocs are in table 2.5. Standard errors are clustered around PI.

We begin by presenting the results for graduate students, distinguishing between the time to a first publication and the time to an initial first-author publication in table 2.4. Estimates are presented in terms of their effect on

Table 2.4 **Hazard models for the time to a first publication: Graduate students over time**

	Any publication		First-author publications	
	Hazard ratios	Hazard ratios	Hazard ratios	Hazard ratios
D1980–1989	0.969	0.768**	0.888	0.718***
	(0.121)	(0.095)	(0.110)	(0.091)
D1990–2000	0.837	0.650***	0.780*	0.613***
	(0.110)	(0.103)	(0.099)	(0.081)
Field FE	Yes	Yes	Yes	Yes
PI FE		Yes		Yes
Log likelihood	–4,121	–4,042	–3,467	–3,380
N		991		

Note: We estimate Cox proportional hazards models with standard errors clustered around PI. We report hazard ratios.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 2.5 **Hazard models for the time to a first publication: Postdocs over time**

	Any publication		First-author publications	
	Hazard ratios	Hazard ratios	Hazard ratios	Hazard ratios
D1980–1989	0.850***	0.788***	0.862	0.795**
	(0.061)	(0.056)	(0.083)	(0.075)
D1990–2000	0.665***	0.615***	0.658***	0.602***
	(0.061)	(0.061)	(0.071)	(0.062)
Field FE	Yes	Yes	Yes	Yes
PI FE		Yes		Yes
Log likelihood	–10,583	–10,478	–8,626	–8,517
N		2,427		

Note: We estimate Cox proportional hazards models with standard errors clustered around PI. We report hazard ratios.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

the odds of publishing a first paper. Hence, a coefficient smaller (larger) than one reflects a negative (positive) effect. When we only include field fixed effects, the coefficients of the 1980–1989 and 1990–2000 period dummies are smaller than one, as expected, but not statistically significant. With the inclusion of PI fixed effects, the odds ratio of publishing a first paper decreases in magnitude (relative to the excluded reference category, 1970–1979) and is now statistically significant. This result, which is our preferred specification, indicates that trends in the time to a first publication vary across PIs.

When we examine first-author publications, we find additional evidence that the time to a first publication has increased for later cohorts of graduate students relative to earlier ones. Indeed, the coefficients of both period dummies are smaller than one and the coefficient for the 1990–2000 indicator is statistically significant. The coefficient magnitudes suggest that the hazard of publishing an initial first-author paper, for graduate students who enrolled in the 1980–1989 period, is 0.9 times the hazard of those who enrolled in the 1970–1979 period. It declines to 0.8 times for graduate students who enrolled during 1990–2000. As before, once we introduce PI fixed effects the significance of the coefficients improves and the magnitude declines.

In the case of postdocs, both the time to a first publication and that to an initial first-author publication appear to have increased for later cohorts relative to earlier ones. Across multiple regression specifications, the hazard of publishing a first paper is lower for postdocs who started in the 1980–1989 period, than for postdocs who enrolled during 1970–1979. And this downward, temporal shift in the hazard of publishing continues for those postdocs who started during 1990–2000. Moreover, the coefficients tend to be statistically significant with and without PI fixed effects.[6]

Taken together, we provide evidence that the time to an initial first-author publication has increased for both graduate students and postdocs and this trend line shows no evidence of leveling off. Moreover, in the case of postdocs, results indicate that the time to a first publication has increased even for non-first-author articles. As a complement to our prior results, that overall training periods have increased over time, increasing times to first publication suggest that, at least in part, recent cohorts of trainees require extra training time to "ramp-up" to the productive training periods.

2.3.3 Publication Trends

In this section, we turn our attention to trends in the overall publication output of graduate students and postdocs. The question we want to explore is whether recent cohorts of graduate students and postdocs have become less productive than older ones. Indeed, if one posits that recent cohorts of scientists face a larger learning burden or that the reviewing process at scientific journals has increased over time, then we should observe a declining trend in the publication output of graduate students and postdocs.

To investigate this hypothesis, we estimate count regression models in which we relate publication outputs that graduate students and postdocs had produced during their training as a function of whether their enrollment year falls within the 1970–1979, 1980–1989, or 1990–1995 periods. We adopt a Poisson specification with robust standard errors. We measure publication

6. In column (3) the coefficient for the 1980–1989 period dummy is not significant. However, a test of joint significance of period dummies rejects the null hypothesis that they are (jointly) equal to zero with a p-value of 0.00.

Table 2.6 Regression results for graduate student publications

	No. publications		No. first-author publications		Probability of publishing a first-author publication	
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
D1980–1989	0.022	–0.103	–0.114	–0.241**	–0.009	0.071
	(0.083)	(0.103)	(0.087)	(0.104)	(0.038)	(0.048)
D1990–1995	–0.071	–0.257**	–0.221**	–0.499***	–0.084**	–0.203***
	(0.090)	(0.120)	(0.096)	(0.130)	(0.041)	(0.059)
Duration	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes
PI FE		Yes		Yes		Yes
R^2	0.05	0.15	0.03	0.12	0.105	0.28
N				870		

Note: Standard errors are in parentheses. For the Poisson models we use robust standard errors, while for the linear probability model we cluster standard errors around PI. For these analyses we only consider trainees who had enrolled before 1996.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

output by counting the number of publications from the moment a trainee joins a PI laboratory until two years after the trainee was last observed in the laboratory. In this way, we account for the fact that there are lags between the moment a research project is completed and the moment its results are published. As for the analysis of training durations, we exclude the latest years because graduate students and postdocs who enrolled in these years might not have completed their training by the end of our sample period.

The equation we estimate is:

$$(3)\quad y_i = \exp(\beta_1 \text{D1980–1989} + \beta_2 \text{D1990–1995} + \beta_3 \text{Duration}_i + \nu_i + \theta_i + \varepsilon_i),$$

where y_i is either the total count of trainee i's publications or the count of their first-author publications. D1980–1989 is an indicator variable that equals one if trainee i enrolled during 1980–1989 and equals zero otherwise. D1990–1995 equals one if trainee i enrolled during 1990–1995 and, similarly, equals zero otherwise. Duration_i is defined as the number of years a trainee has spent in a laboratory. Finally, ν_i and θ_i are field and PI fixed effects, respectively.

The results for graduate students are displayed in table 2.6, while those for postdocs are presented in table 2.7. When we consider the total publication count (column [1]), we find that graduate students who enrolled in more recent periods are no less productive than their colleagues who enrolled during 1970–1979. In fact, none of the coefficients for the 1989–1990 and 1990–1995 period dummies are statistically significant. Once we include

Table 2.7 **Regression results for postdoc publications**

	No. publications		No. first-author publications		Probability of publishing a first-author publication	
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
D1980–1989	–0.160**	–0.250***	–0.174**	–0.255***	–0.018	0.019
	(0.067)	(0.071)	(0.068)	(0.074)	(0.026)	(0.029)
D1990–1995	–0.173**	–0.314***	–0.238***	–0.384***	–0.064**	–0.076**
	(0.075)	(0.086)	(0.076)	(0.089)	(0.028)	(0.035)
Duration	Yes	Yes	Yes	Yes	Yes	Yes
PI FE	Yes	Yes	Yes	Yes	Yes	Yes
Entry Year FE		Yes		Yes		Yes
R^2	0.10	0.18	0.08	0.14	0.22	0.23
N			1993			

Note: Standard errors are in parentheses. For the Poisson models we use robust standard errors, while for the linear probability model we cluster standard errors around PI. For these analyses we only consider trainees who had enrolled before 1996.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

supervisor fixed effects, the coefficient of the dummy for student enrollment during 1990–1995 becomes statistically significant and has a negative sign. While this last result suggests that there are some supervisor characteristics that are correlated with productivity trends, we cannot conclude that there is a general declining tendency in the graduate student paper count. In support of this conjecture, descriptive evidence reported in figure 2.9 does not reveal a decreasing trend for the annual publication count. In regressions not reported here (but available upon request), we find very similar results when we use the impact-factor weighted publication count as the output measure.

We show different findings when analyzing first-author publications. In this case, both period dummies have a negative coefficient and the coefficient for the 1990–1995 period variable is significant, regardless of whether we include PI fixed effects. One might wonder whether this effect is driven by the fact that fewer graduate students are publishing first-author papers in recent years. To investigate this possibility, we estimate a linear probability model in which the dependent variable is an indicator that takes a value of one if graduate students have published at least one article during their training. The results are displayed in the last column of table 2.6. The coefficient for the 1990–1995 period dummy is negative and statistically significant, independent of the regression specification. These results suggest that at least part of the declining output trend is explained by a lower publishing probability for the most recent cohorts. Overall, we find that later graduate student cohorts

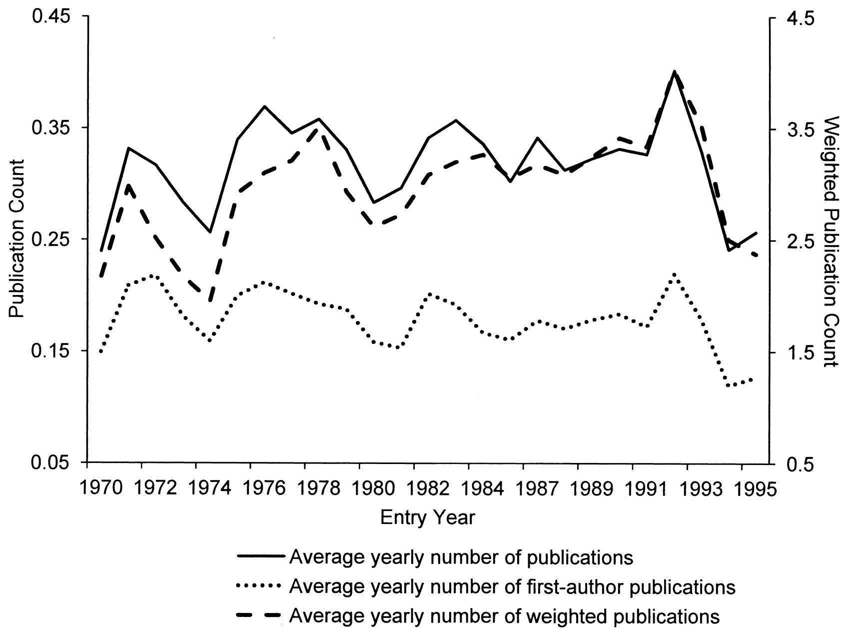

Fig. 2.9 Publication output of graduate student cohorts
Note: Counts normalized by duration.

produce fewer first-author articles than earlier ones and, this time, regression results seem to be supported by descriptive evidence reported in figure 2.9.

When we turn our attention to postdocs (table 2.7), we find strong evidence that the postdoc cohorts enrolled during 1980–1989 and 1990–1995 produce fewer articles than cohorts enrolled during 1970–1979. This result holds true regardless of whether we look at total or first-author publication counts. Indeed, the coefficients of our period dummies are negative and statistically significant, with and without PI fixed effects. When we analyze the probability of publishing at least one first-author paper, we find that part of the declining trend for the first-author paper count is explained by a lower publishing probability for the most recent cohorts. Overall, these findings are consistent with the descriptive trends presented in figure 2.10, which shows an over-time decline in publication outputs by postdoc students.

In analyses not presented here for the sake of brevity, we attempted to analyze whether the decline in the number of first-author graduate student publications was correlated with larger time intervals between papers, for subsequent publications. Thus we estimated hazard models for publishing a second first-author paper, conditioned on having published an initial one, and for publishing a third first-author paper, conditioned on having published a second. Because we have annual data, we cannot analyze the time

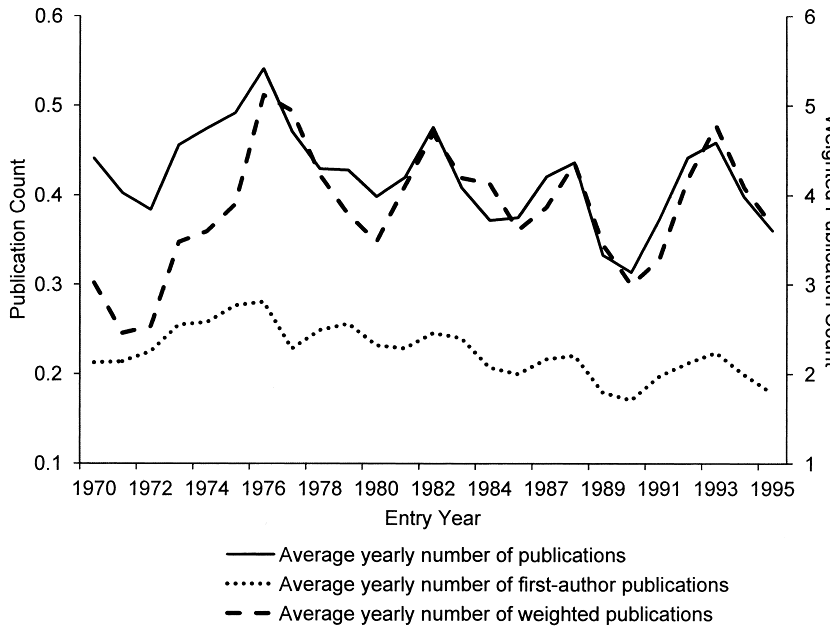

Fig. 2.10 Publication output of postdoc cohorts
Note: Counts normalized by duration.

interval between two papers published in the same year. With this caveat in mind, we find that the time intervals between first-author publications, subsequent to the first, are not larger for the most recent graduate student cohorts. This seems to suggest that the decline in the number of first-author papers for graduate students could be explained by the fact that trainees take longer to publish a first article or they publish fewer articles per year. Similar results were obtained when we estimated the hazard that postdoc students publish a paper or a first-author paper, conditioned on an initial publication.

To summarize, the results from this section lead us to infer that when we measure graduate student productivity by their first-author publication count, later cohorts appear to be less productive than earlier ones. As for postdocs, recent cohorts appear to be less productive in terms of both first-author and total paper counts.

2.3.4 Collaboration Trends

We have analyzed changes in both the training periods and scientific productivity of postdoc and graduate students from the 1970s through the 1990s. Although an array of mechanisms may explain these trend lines, a final question we pose is whether trainees have reacted to these challenges by working in larger teams, in a similar fashion to other researchers.

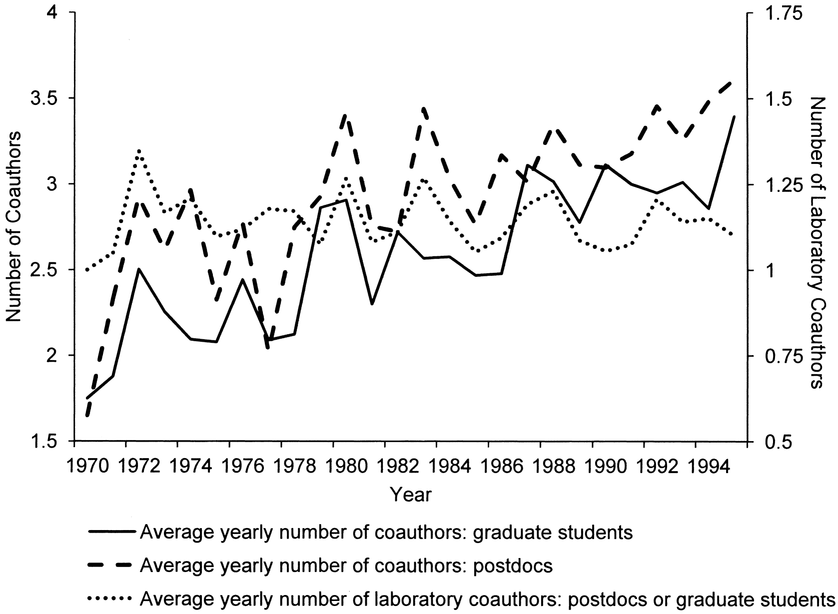

Fig. 2.11 Average yearly number of coauthors per paper

The benefits of teamwork have been extensively discussed in the economics literature and include output gains derived from labor specialization (Becker and Murphy 1992) and from the circulation of new ideas among team members (Adams et al. 2005). In the economics of science, scholars have found that scientists increasingly work in teams (Wuchty, Jones, and Uzzi 2007)[7] and that team size has expanded over time (Adams et al. 2005), largely due to an intensification of multiuniversity collaborations (Jones, Wuchty, and Uzzi 2008).

Figure 2.11 reports trends over time in the average number of coauthors per paper, distinguishing between postdocs and graduate students. In line with previous studies, we observe that for both trainee categories the average number of coauthors per paper has increased over time from approximately 1.5 at the beginning of the 1970s to approximately 3.5 by the second half of the 1990s. Interestingly enough, we also observe that the increased collaboration size was mainly driven by an increase in the number of outside laboratory coauthors.[8]

7. See also Agrawal and Goldfarb (2008) and Forman and Van Zeebroeck (2012).

8. In this case, we do not report regression results. The reason is that regression analyses must be conditioned on the sample of trainees who published at least one paper. The resulting sample size is quite limited and, thus, if we add PI and field fixed effects the regression estimates become imprecise. Nevertheless, the signs of the interest coefficients are the ones expected. Particularly, in the regression for the average number of coauthors on a paper, the coefficients of the dummies for the most recent decades are positive. Moreover, in the regression for the number of laboratory coauthors, the magnitude of the decade indicators' coefficients is almost zero, reflecting the trend that appears in figure 2.11.

Overall, this suggests that trainees, similar to other scientists across a broad range of disciplines, are increasingly working in teams and these teams tend to encompass authors from outside the focal trainees' laboratories.

2.4 Conclusions and Policy Implications

2.4.1 Summary

Knowledge production is widely considered to be one of the main determinants of economic growth. Within this domain, scientific knowledge production centered at universities, which results in codified outputs designed largely for dissemination and replication, is particularly important.

This study focuses on the contributions to academic knowledge by postdocs and graduate students. Using data from the MIT Department of Biology from 1970 to 2000, we looked at the evolution of four fundamental aspects of their productivity: (a) training duration, (b) time to a first publication, (c) productivity over the training period, and (d) collaboration with other scientists.

We identified four main trends that are common to both graduate students and postdocs. First, training periods have increased for later cohorts of research trainees. Second, recent cohorts tend to publish their initial first-author article later than the earlier cohorts. Third, they produce fewer first-author publications. Finally, collaborations with other scientists, as measured by the number of coauthors on a paper, have increased over time. This increase is driven by collaborations with scientists outside of a trainee's laboratory.

2.4.2 Interpreting the Results

What are the mechanisms that drive our results? Our findings are consistent with Jones's educational burden story (Jones 2009, 2010a), which states that as knowledge accumulates, future generations of scientists require greater effort (or more time) to absorb and build upon this accumulated knowledge base. To offset this trend, one possibility is for individuals to specialize, narrowing their field of expertise. A second consequence of specialization may be the need to broaden patterns of collaboration with other scientists. Our first three results—longer training periods, longer time to publish, lower productivity for later trainee cohorts—could be interpreted as an indication that the knowledge burden has increased, particularly for recent trainees. The final result regarding increased trainee collaboration provides an indication that these cohorts have become more specialized, although other possibilities abound.

While the educational burden story is a compelling explanation, we nevertheless think that other mechanisms might also be responsible for our results. One of these mechanisms is the mismatch between the supply of trainees and the availability of posttraining academic positions that scholars have discussed in recent decades (Stephan 2012b; Freeman et al. 2001). Data from the NSF-NIH Graduate Students and Postdoctorates in Science and Engineering survey shows that enrollment into PhD life science programs has increased by 80 percent between 1972 and 2005.[9] While we do not have information on the availability of posttraining positions, it is plausible that selection into (desirable) postdoctoral positions has become harder over time. Lastly, we also should note that longer training periods certainly benefit and are encouraged by PIs. Specifically, many PIs are reluctant to allow their most productive laboratory members (i.e., high-tenure trainees) to depart. In fact, a PI's compensation is, increasingly, linked to a tournament model in which seminal laboratory member (i.e., trainee) contributions are essential (Freeman et al. 2001).

If market frictions were to be responsible for longer training periods, should we also expect them to explain the lower productivity of recent trainee cohorts and their increased propensity to work in collaboration with other scientists? Is it plausible to posit that market disequilibria last for decades? Why is the market not redirecting the excess supply of trainees to other fields?

To answer the first question, one might consider that the excess supply of scientists has led to an increase in academic journal submissions, without a corresponding increase in the number of publications. If there is an excess supply of submissions, then the direct consequence is that publishing becomes more difficult, which might explain the lower productivity of recent trainee cohorts. Moreover, specialization and collaboration become ways of dealing with market disequilibria and one wonders whether the reduction in recent cohort productivity could have been even more accentuated had recent trainees not worked with other scientists. This mechanism is not necessarily in contrast with the educational burden explanation; rather, it offers a complementary perspective. In fact, market imbalances might act as a stimulus for scientists to expand the knowledge frontier in order to publish, thus increasing the burden on future generations.

While the mechanisms we have highlighted seem to be plausible, one cannot exclude the possibility that the mismatch between the supply of trainees and the availability of academic positions has led the brightest students to shy away from careers in the life sciences. Thus, the increase in training periods and the reduced productivity of the most recent cohorts is a reflection of their lower quality skills. With our current data set, we cannot disentangle these possibilities.

To answer the second and third questions regarding the duration of market imbalances, we should refer to studies by Freeman et al. (2001) and Stephan (2012a) and mention that, increasingly, PhD programs in life science, among others, tend to be populated by foreign students. Indeed, while some domes-

9. Data is available from https://webcaspar.nsf.gov/.

tic students might be discouraged from continuing their studies in the life sciences PhD programs, American PhD programs remain attractive to foreign students not only because of their prestige, but also because salary differentials between foreign countries and the United States are typically large. To verify that the proportion of foreign graduate students in the MIT Department of Biology has increased over time, we examined our trainees' first and last names. We then codified those who had a Chinese last name as well as those with an Italian or French first and last name.[10] We found that the proportion of Asian, Italian, or French trainees has increased from 17 percent in 1970 to 27 percent in 1995. While these figures are only suggestive, given that we cannot distinguish between foreign or native-born students, they provide some indication that foreign trainees have recently become an increasingly large proportion of the trainee population.

2.4.3 Policy Implications

Ultimately, this chapter has served to document the mechanisms underlying two important trends in the scientific community: the increasing duration of scientist trainees and an increasing propensity for collaborative activity (e.g., Agrawal, McHale, and Oettl [chapter 3, this volume]; Tilghman 1998). Additionally, we have provided evidence of a decline in the scientific output of recent trainees. What implications do these trends have for the scientific community?

First, we note the remarkable consistency linking changes in graduate students and postdocs training with an array of outcomes (i.e., training duration, time to first publication, and productivity). It is very possible that the act of doing science has become more difficult over time. To be productive, there is more knowledge that must be learned. It is possible that few policy changes can offset these trends, and that longer training durations are a necessary byproduct of scientific advances in the twentieth century.

Second, institutional constraints may be at play. Even for established scientists (i.e., PIs), increasing difficulties in acquiring funding may cascade through the scientific system in multiple ways. To increase efficiency, PIs may hold on to their productive students longer. Faced with increasing uncertainty over funding, universities may hire only the most experienced and productive postdocs. And lastly, each of these processes may feed back on one another over time.

Third, regardless of the reasons for the observed trends, it is important to note that the costs of science have increased (Jones 2010b). These costs are paid by the individual, who must endure longer training and uncertain future prospects, as well as by society at large, which does not recuperate the returns from its investment. As previous scholars have highlighted (Jones 2010b; Stephan 2012b), costs can be reduced by ensuring that graduate

10. Given the authors' backgrounds, we found it easiest to codify these student ethnicities.

students and postdocs receive adequate pedagogical support during their training period. This, in turn, improves the efficiency of trainee learning and may serve to offset increases in learning burdens. Moreover, decision makers could cap the trainee teaching load, thereby ensuring that the majority of their time is dedicated to research.

It is also worth mentioning that, as the pre-PI career path for life scientists has become incredibly long, talented scientists may increasingly choose to opt out. Our data illustrate that total trainee duration has crested ten years and this evidence is not unique to the MIT Department of Biology and to elite institutions (Stephan 2012a). Longer training duration raises the opportunity costs of a scientific career and makes other occupations more attractive. Thus, if employment in other fields entails shorter training periods, lower uncertainty and higher salaries, we may increasingly see a shift from the careers where graduate training is the passkey to the profession, such as the life sciences, toward other, equally rewarding careers (e.g., engineering).

Given fecundity differentials across the sexes, increasing training durations may affect women more severely than men, further exacerbating issues of female participation in the sciences (Ding, Murray, and Stuart 2006). As training increasingly comes to dominate individuals in their thirties, work-life balance issues, including considerations such as family constraints and career uncertainty (Kaminski and Geisler 2006) may come to dominate. Certainly, longer training durations do not help ease these concerns.

We conclude with a final important issue that has attracted the attention of recent scholars, namely the allocation of research credit in collaborations (Bikard, Murray, and Gans 2013). Working in teams entails a trade-off. On the one hand, teamwork seems to produce more knowledge breakthroughs than solo work (Singh and Fleming 2010). On the other, it involves costs, some of which are related to the assessment of the team members' contributions (Dasgupta and David 1994). This trade-off is especially relevant for trainees given that access to tenure-track positions requires that they be able to prove their ability to conduct impactful independent research.

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