Task Mismatch and Salary Penalties: Evidence from the Biomedical PhD Labor Market*

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Abstract

Researchers seeking to estimate the returns to postdoctoral training face a unique challenge unanswered by classical human capital theory: should postdoctoral ("postdoc") training be treated as schooling or employment experience? In this paper, we find that the answer to this question has great bearing on the estimated effect of postdoc training on the future salary of biomedical doctorates as estimated by a Mincerian specification. If postdoc training is treated as employment experience, the estimated effects are uniformly negative across sectors, including in academia (-6%) and industry (-21%). If postdoc training is instead treated as schooling, the estimated effects are typically found to be insignificantly different from zero, but with a positive and significant effect in academia (10%) driven by those employed after their postdoc as academic non-tenure-track researchers (23%). Due to this disparity, we propose a unified framework for explaining the acquisition of human capital through both schooling and on-the-job-experience which recognizes the existence of a multiplicity of skills and views the acquisition of human capital as task-specific. Using a nationally-representative and longitudinal sample of biomedical doctorates graduating in the US, we find this framework to be salient in explaining the pay-disparity between postdoc-trained and nonpostdoc-trained biomedical doctorates: a positive postdoc salary premium emerges when postdoc skill-job task congruity is high and a negative postdoc premium when it is low. Augmenting a Mincer salary regression with individual-level measures of accumulated task-specific human capital reduces the estimated biomedical postdoc salary penalty in industry by 65%, eliminating its statistical significance. In contrast, we find no evidence to suggest that general ability bias, compensating differentials for tasks performed as part of current employment, seniority, and a limited set of employer characteristics explains the postdoc salary penalty in industry. (*JEL* J24, J31, I26, J44)

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1 Introduction

Since the work of Schultz (1960), Mincer (1958, 1974), and Becker (1962, 1964), the theory of human capital has played a central role in explaining differences in wages by education and experience. Human capital theory views the formation of skills as emanating from durable investments, typically in the form of schooling and experience on-the-job. While schooling and experience may differ in their returns, increases in either are expected to increase the earnings prospects of workers by increasing their skills, holding pre-existing ability constant. While schooling and experience are typically viewed as distinct concepts, the notion of postdoctoral ("postdoc") training, which is especially prevalent in the biomedical sciences, provides an interesting case: should postdoctoral training be viewed as schooling or employment experience?[1] Is postdoctoral training like other forms of employment available to biomedical doctorates at the time of graduation, such as jobs as scientists in private industry, or is the decision whether to pursue postdoc training more like the investment decision facing newly-graduated Bachelor's degree holders choosing between industry employment or investing in doctoral education?[2]

The case of postdoctoral training in the biomedical sciences also provides an empirical puzzle: despite evidence that biomedical doctorates who pursue postdoctoral ("postdoc") training are of higher ability (Sauermann and Roach, 2016), previous research finds that postdoc-trained biomedical doctorates typically earn persistently *less* than their nonpostdoc-trained counterparts regardless of employment sector, a finding which suggests that postdoctoral training is inconsistent with a model of human capital investment (Kahn and Ginther, 2017).[3] In this paper, we find that the choice of whether to categorize postdoctoral training as employment or schooling has a direct bearing on whether the returns to postdoctoral training in biomedical science are estimated as uniformly negative across sectors. When postdoctoral training is treated as employment experience and employment sector is defined as that at 10 years post-PhD, we are able to broadly replicate the findings in Kahn and Ginther (2017), finding a postdoc salary penalty across employment sectors, including those going on to careers in academia (-6%) and industry (-21%). When postdoctoral training is instead treated as schooling, the effect of this training on future salary, rather than being estimated as negative and significant across all sectors, is typically found to be insignificantly different from zero, but with a positive and significant effect in academia (10%) driven by those

[1]In a Mincer earnings equation, schooling and experience enter separately as regressors to explain variations in the logarithm of earnings, with estimated coefficients giving the semi-elasticity of earnings with respect to schooling and experience. However, the definitions of experience and schooling are intertwined: in Mincer's (1974) classic case, potential labor market experience is defined by subtracting years of schooling and the age one began schooling from an individual's age. Years of work experience are included in the Mincer equation to capture the effect of "productivity-augmenting investments in human capital" that continue *after* the completion of schooling and result in the accrual of skills on-the-job (Mincer).

[2]Like doctoral training, postdoctoral training (typically) takes place at a US university, is tuition free (from the perspective of the student), and in the case of biomedical science, typically pays the student/worker a stipend to work in the lab under the mentorship of a senior academic researcher.

[3]Sectors of employment include academic tenure-track research, academic non-tenure-track research, academic nonresearch, industry, and government/nonprofits. Kahn and Ginther (2017) find that the postdoc penalty on salary persists for up to 15 years post-PhD.

employed after their postdoc as academic non-tenure-track researchers (23%).[4]

Given the disparity in results depending on whether postdoc training in biomedicine is treated as schooling or experience, how can we judge whether this training is consistent with the theory of human capital?[5] By itself, the classical version of human capital theory is silent on whether postdoctoral training should be treated as schooling or experience, which suggests the value of a more general and unified theory that explains the way in which skills are accumulated both through schooling and on-the-job experience. Such a theory has gained prominence in the last decades with the emergence of an increasing number of studies in labor economics which view skill as multidimensional, jobs as sets of tasks to be performed ("task requirements"), and the accumulation of human capital as task-specific.[6] The performance of tasks, either on-the-job or through formal educational training, leads to the accumulation in human capital specific to the skills utilized in the tasks performed. In this framework, the returns to both education and experience can be boiled down into returns associated with the tasks performed as part of schooling and past employment, providing a unified theory of human capital acquisition.[7]

In this paper, we offer a simple conceptual framework relating task-specific human capital to wage determination. Applying this framework to the labor market for biomedical doctorates, we find that within-cohort salary differences between postdoc-trained and nonpostdoc-trained biomedical doctorates follow as a likely result, even after controlling for differences in ability at time of PhD graduation. A key prediction is that worker wages are correlated with the history of tasks performed as part of previous employment, with wage growth increasing in the similarity of tasks

[4]We also find evidence that the mobility of biomedical doctorates into and out of academic non-tenure-track positions may lead to a substantial bias in specifications defining the employment sector of workers at a single point in time. When treating postdoc training as experience and excluding salary observations for years when a biomedical PhD is employed as a postdoc, we are able to associate each person-year observation with the actual sector of employment held by the biomedical doctorate in that year. When doing so, we detect a 15.9% positive postdoc premium on after-postdoc salary among biomedical doctorates in academic non-tenure-track research positions.

[5]If treated as experience, postdoc training produces a negative effect on future salary regardless of employment sector, including in academia. This seems to rule out an explanation that postdoctoral training produces only "specific" human capital, unless one is willing to argue that this human capital is not specific to academic research, but to the specific lab where the training itself takes place—a view which would call into question whether postdoc "training" could usefully be viewed as training at all. If treated as schooling, postdoc training instead looks as if it builds human capital specific to academic research.

[6]See Sanders and Taber (2012) for a review of this literature and the related literature on industry-specific (or sector-specific) and occupation-specific human capital. Previous research finds that job task requirements are predictive of worker wages even when controlling for education and occupation (Autor and Handel, 2013; Deming and Kahn, 2018) and that task-specific human capital accumulation is a key source of wage growth over the life-cycle (Gathmann and Schönberg, 2010; Sanders, 2016; Lise and Postel-Vinay, 2020; Guvenen et al., 2020). In related work, Deming and Noray (2020) find that that the rate of change in the task requirements of jobs is important in explaining differences in the age-earnings profiles of STEM workers in different fields.

[7]Becker (1962) differentiates between "general" and (firm-) "specific" human capital, where general human capital is comprised of skills valuable to other firms beyond the employer where on-the-job training takes place, and specific human capital is comprised of skills that increase the productivity of a worker at the firm where a workers is trained. The notion of task-specific human capital moves the focus away from the firm where training takes place and towards the job tasks that comprise on-the-job training. Task-specific human capital is general in the sense that workers are able to increase their productivity in jobs at other firms that require the performance of the same tasks as the worker's current employer, but is also specific in that a worker's productivity in jobs requiring a different set of tasks will not be increased, even if these jobs are with the same employer (Gibbons and Waldman, 2004).

performed as part of previous and current employment. In support of this framework, we find that postdoc salary premia are higher the more correlated job tasks are with postdoc skills: when postdoc skill-job task congruity is high, the postdoc premium is positive and when it is low, the premium is negative.[8] We also find that including individual-level measures of the history of tasks performed by postdoc-trained and nonpostdoc-trained biomedical doctorates working in industry as mediating regressors in a Mincer salary regression reduces the estimated postdoc salary penalty by 65%, eliminating its statistical significance.[9] In contrast, we find no evidence to suggest that general ability bias, compensating differentials for tasks performed as part of current employment, seniority, and a limited set of employer characteristics explains the postdoc salary penalty in industry.

Our paper is one of few in the task-specific human capital literature able to associate workers with both their labor market outcomes and the actual tasks they perform on the job rather than having to rely on external occupation- or job-level survey data to infer what tasks are performed for each job title held by the worker; with the exception of Stinebrickner, Stinebrickner, and Sullivan (2019), ours is the only paper to our knowledge to track both the outcomes and tasks performed by the same workers longitudinally.[10] Tasks ascribed to any particular worker in a job classification based on surveys of workers in that job classification are liable to be inaccurate and possibly biased.[11] Our measure of tasks share the fine granularity of the occupation-level measures utilized in other papers in the literature, but has the advantage of being specific to the focal worker's employment environment. To our knowledge this is the first work relating the skills workers acquire during academic training to activities performed in employment where the skills embodied by the worker can be directly linked to the tasks performed: in other work exploring education-job match quality, educational background is often measured crudely—whether the worker has a college degree—and the education-job match is determined by whether the worker's job is held mostly by workers in the same broad educational category.[12] Previous task-based studies typically analyze

[8] In this specification, postdoc training is treated as contributing to overall labor market experience, but we also allow for an intercept shift due to postdoc training and an interaction between this level shift and a measure of the degree of mismatch between tasks performed as part of current employment and those performed early in one's career (including during postdoc training).

[9] This Mincer specification directly follows from our conceptual framework where we approximate an individual's stock of accrued task-specific human capital with their history of tasks.

[10] Autor and Handel (2013) utilize cross-sectional data with individual-level measures of wages and tasks, finding that job task requirements are predictive of worker wages even when controlling for education and occupation—a finding also supported by the job-level analysis in Deming and Kahn (2018) which uses data from online job postings collected by Burning Glass Technologies. Stinebrickner, Stinebrickner, and Sullivan (2019) use longitudinal worker-level data on the amount of time workers spend on different types of tasks in each of their jobs to examine how current and past tasks performed at work impact wages, find strong evidence for learning-by-doing for "high-skilled" (but not low-skilled) tasks. A limitation of Stinebrickner, Stinebrickner, and Sullivan is that they are only able to examine workers graduating from a single school (Berea College), but a strength of their data is the inclusion of detailed time allocation measures for each task in each year.

[11] Job tasks are likely to vary within each occupation (Autor and Handel, 2013; Deming and Kahn, 2018), and so workers may tend to match to jobs within a given occupations that minimizes the activity-skill distance. Thus, assigning tasks to a worker based on O*NET's description for the job title will tend to overstate the distance between the worker's skill set and the employment tasks s/he performs.

[12] Nordin, Persson, and Roof (2010) examine the consequence of mismatches among the college-educated, measuring

workers across a broad spectrum of occupations and categorize tasks into coarse categories such as abstract, routine, and manual.[13] We show that skill-job mismatch is important even within a narrow education category (doctoral degree holders in the biomedical sciences) and within job classifications that make nearly exclusive use of abstract/analytical ability.

The structure of biomedical science gives a natural setting for exploring if differences in abstract/analytical task histories are important to wage determination: the subsidization of postdoc positions focused on basic research in academia paired with the limited number of permanent basic research positions in academia thereafter (such a tenure-track research positions) leads to a significant share of this labor force moving into jobs outside academia which emphasize a different set of abstract tasks beyond basic research. We find that three-fourths of all postdocs are engaged in basic research as their primary task, regardless of their subsequent sector of employment (i.e., academia, industry, or government/nonprofits), confirming that basic research skills are the dominant skill type acquired; in contrast, post-postdoc employment shows considerable heterogeneity in tasks, even within sectors, with basic research being the most important task only in academic jobs. In the industry jobs taken by biomedical PhDs, managing people or projects, applied research, development, and professional services are reported as more important activities, with only 10% of postdoc-trained industry workers primarily engaged in basic research. When comparing the tasks performed by postdocs with those carried out by nonpostdoc-trained early-career biomedical PhDs working in industry, we find that the tasks performed by the latter line up quite closely with the those performed later in their industry career. This suggests that postdoc training and on-the-job training in industry build-up a distinct set of skills, giving plausibility to the view that the postdoc salary penalty in industry is explained by a deficit in types of task-specific human capital highly-valued by industry employers.[14]

Beyond the task-specific human capital literature, our study contributes to the literature on postdoctoral training in biomedical science and future career outcomes (e.g., Jacob and Lefgren, 2011; Su, 2013; Kahn and Ginther, 2017; Heggeness et al., 2018; Hayter and Parker, 2019).[15]

the quality of the match by whether the worker's job is typical of persons who share the worker's major. Other works (e.g., Robst (2007)) use the worker's self-reported subjective measure of job match.

[13]For example, Autor and Handel (2013) categorize tasks as abstract, routine, or manual, Gathmann and Schönberg (2010) categorize tasks as analytical, interactive, or manual, and Stinebrickner, Stinebrickner, and Sullivan (2019) categorize tasks as relating to people, information, or objects.

[14]See Hayter and Parker (2019) for a survey-based qualitative study of the difficulties faced by postdocs transitioning to nonacademic positions, and see section 5.1.3 therein for a discussion of the differences in the skills possessed by postdocs (e.g., knowledge of scientific concepts and research methods) and the other skills valuable in industry employment (e.g., applying research to product development, skills needed to work in teams that integrate multiple functions such as research, management, manufacturing, and sales).

[15]Jacob and Lefgren (2011) find that receipt of an NIH postdoctoral fellowship is associated with a 20% increase in publications relative to non-recipients in the five years following fellowship receipt; Heggeness et al. (2018) find that securing a postdoc fellowship improves a biomedical doctorate's chances of receiving future NIH funding (including R01 research project funding which signifies achievement of an independent research career); and Su (2013) finds that tenure-track or tenured faculty at more prestigious universities were more likely to have completed postdocs relative to faculty from less prestigious institutions. Both Jacob and Lefgren (2011) and Heggeness et al. (2018) utilize variation in NIH postdoctoral fellowship application scores to produce their findings, with Jacob and Lefgren (2011) utilizing a fuzzy regressions discontinuity design and Heggeness et al. (2018) utilizing a matching approach.

Utilizing longitudinal microdata from the Survey of Doctorate Recipients (SDR) linked to the Survey of Earned Doctorates (SED), we find that postdoc-trained biomedical doctorates are more likely to obtain research positions in the employment sectors they enter following the postdoc but that postdoc training comes at the expense of on-the-job learning in industry which manifests in a 15.8% within field-by-cohort industry salary penalty which persists for up to 15 years post-PhD.[16] However, we do not find a postdoc salary penalty in academia as a whole, and instead find that postdoc training leads to a substantial salary premium (15.9%) for those that go on to work as non-tenure-track researchers.[17] We show that both the estimated benefits (i.e., increased likelihood of obtaining future research jobs) and costs (i.e., the industry postdoc salary penalty) associated with postdoc training appear robust to plausible levels of selection bias, and that our estimates of the benefits of postdoc training are likely upper-bounds while the estimated magnitude of the postdoc salary penalty in industry is likely a lower-bound.[18] We find evidence that a task-specific model of human capital acquisition explains the heterogeneity in the returns to biomedical postdoc training across sectors and that differences in accumulated task-specific human capital are largely responsible for the postdoc salary penalty in industry.

The remainder of the paper is structured as follows: Section 2 gives a quick description of the labor market for biomedical doctorates that focuses on the role of postdoctoral training, and presents descriptive evidence of a persistent life-cycle postdoc salary penalty for biomedical doctorates working in industry. Section 3 presents a model where salary differences between workers emanate from differences in both endowed and accrued task-specific human capital, the latter of which is a function of employment history. Section 4 describes the survey microdata used for the empirical analysis and lays out our baseline empirical approach, including a discussion of the

[16] Salary results discussed in this paragraph are for specifications where postdoc training is treated as experience, the sample is limited to observations which exclude years when a biomedical doctorate is employed as a postdoctoral researcher, and when each doctorate is associated with the actual employment sector where they work in each given year. We find that biomedical doctorates with postdoc training are 26.5 percentage points more likely to work in an academic research job and 21.3 percentage points more likely to obtain a tenure-track research position. Meanwhile, for biomedical doctorates working in industry, we find that postdoc-trained biomedical doctorates are about 12.3 percentage points more likely to obtain a research position within industry compared to their counterparts without postdoc training. "Research job" includes jobs where the primary activity is one of the following: basic research, applied research, development, or design.

[17] The difference in our finding for non-tenure-track academic researchers from that in Kahn and Ginther (2017) is due to a difference in research questions which leads to differences in empirical approaches. The analysis in Kahn and Ginther (2017) seeks to describe the overall price in terms of career salary that biomedical doctorates pay (on average) when choosing to enter postdoc employment, which includes the salary foregone from alternative employment during postdoc training. We study a related but distinct topic, namely how postdoc training impacts future (i.e., after-postdoc) salary specifically. This leads Kahn and Ginther to include salary observations for years when a biomedical PhD is employed as a postdoc in their analytical sample and to associate biomedical PhDs with their sector of employment at a single point in time (i.e., ten years post-PhD). In our main specification, we exclude salary observations for years when a biomedical PhD is employed as a postdoc and associate each person-year observation with the actual sector of employment held by the biomedical doctorate in each year. When estimating regression specifications similar to those found in Kahn and Ginther (2017), we find that their results replicate, with postdoc-trained biomedical PhDs who work as non-tenure-track academic researchers at ten years post-PhD earning approximately 10% less than their nonpostdoc-trained counterparts over their career.

[18] This direction of selection bias is consistent with previous research suggesting that biomedical doctorates who pursue postdoc training are typically of higher ability at time of graduation (Sauermann and Roach, 2016).

construction of our individual-level task-based variables. Section 5 reports our baseline results which exclude task-based variables from the specification, supplemented by Appendix B.1 which estimates Oster (2019) bias-adjusted treatment effects to test the robustness of results to selection on unobservable ability at time of PhD graduation. Section 6 gives our results when including our task-based variables as part of the regression specification, either in the form of the inclusion of measures of the history of tasks performed by workers as part of previous employment or as measures of the degree of mismatch between the tasks performed as part of current employment and those performed early in one's career (including as a postdoctoral researcher).[19] Section 7 considers other mechanisms that could plausibly lead to a postdoc salary penalty in industry and Section 8 concludes.

2 Postdoc Training: Apprenticeship or Lottery Ticket?

Every year, a new crop of talented young PhDs graduate in the US and enter the job market in search of academic careers. In the case of the biomedical sciences, the number of newly-graduated PhDs per cohort has doubled since 1980 (Figure A.1), with around 70% of each cohort going on to work as postdoctoral researchers ("postdocs") for an average of five years (Figure A.2).[20] The classic view of postdoc training—as espoused by the National Institutes of Health (NIH) and the National Science Foundation (NSF)—is as an academic apprenticeship for doctorates with "a temporary and defined period of mentored advanced training to enhance the professional skills and research independence needed to pursue his or her chosen career path" (Bravo and Olsen, 2007). Like an apprenticeship, postdoc positions are known for their relatively low pay, and also for their relatively long work hours: between 1995 and 2013, biomedical postdocs typically worked about 10% more hours per week for 50% of the salary compared to industry-employed biomedical doctorates of the same age (Figure A.3). Also like an apprenticeship, postdoc training is all but necessary for those who wish to fill their mentors shoes, with 90% of both new tenure-track and newly-tenured biomedical research faculty having received training as postdocs (Figure A.4 and Figure A.5, respectively).

However, most biomedical postdocs are unlikely to obtain a tenure-track research position in academia, with less than 20% of biomedical PhDs who graduated in 2005 working as a tenure-track researcher by 2015 (Figure A.6). This growth in the number of biomedical postdocs, pared with declining rates in the share eventually obtaining tenure-track positions, has attracted much concern from economists and biomedical researchers alike.[21] While postdoc training is much like an appren-

[19]The former approach follows from the conceptual framework in Section 3 and is similar to the empirical approach in Stinebrickner, Stinebrickner, and Sullivan (2019) while the latter is similar to the approach taken by Gathmann and Schönberg (2010).

[20]Descriptive figures are based on data from the National Science Foundation's (NSF's) Survey of Doctorate Recipients (SDR) linked with the NSF's Survey of Earned Doctorates. See Section 4.1 for additional details. A single postdoc position may only last for two or three years, but a biomedical PhD may seek a subsequent postdoc position at another lab.

[21]For example, see Freeman et al. (2001*a*,*b*), and see Stephan (2012) for a recent and comprehensive view of the

ticeship for academic researchers, for many biomedical doctorates it may be an apprenticeship for the wrong job: between 1993 and 2015, the share of early-career postdoc-trained biomedical doctorates working outside academia has remained above 40% (Figure A.7), and 40% of those employed in academia find themselves in jobs where research is not the primary focus (Figure A.8). Rather than entering an apprenticeship for one's future vocation, entering postdoc employment might more usefully be viewed as purchasing a lottery ticket whose value is the enhanced probability of securing a rare tenure-track academic research position (the lottery prize) and where the price of the ticket includes two instances of foregone earnings: 1) the foregone earnings from alternative employment not undertaken during the postdoc and 2) lower future earnings when the skills acquired during the postdoc do not match the requirements of the job obtained thereafter.

In Figure 1 we plot the median salary of biomedical doctorates in academia and industry by postdoc-trained status and years since PhD graduation.[22] As expected, postdoc-trained biomedical doctorates in industry and academia have similar median salary and are paid less than nonpostdoc-trained biomedical doctorates in their first three years after PhD as this is when most would be employed as postdocs. Industry salary profiles are steeper than academic salary profiles, indicating stronger salary growth in industry. Interestingly, it appears that the median salary of ex-postdocs catches up with and then begins to exceed the median salary of nonpostdocs in the academic sector 10 years after graduation, which may be due to ex-postdocs being more likely to obtain higher-paying tenure-track research positions after postdoctoral training. In industry, it appears that the gap between the median salary of postdoc-trained and nonpostdoc-trained biomedical doctorates is persistent.[23] This suggests that the cost of doing a postdoc for those that end up going to industry is indeed not just forgone salary during their years as a postdoc, but also lower after-postdoc salary possibly due to deferred task-specific human capital accumulation in tasks that are valued in industry but not emphasized as part of postdoctoral training. To formalize this intuition, in Section 3 we offer a simple task-specific human capital model of wage determination to serve as a conceptual framework for analyzing salary differences between postdoc-trained and nonpostdoc-trained biomedical doctorates working in industry.

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scientific research environment, including the role played by postdoctoral researchers. Members of the biomedical research community have expressed concern that the small chance of a young biomedical scientist achieving a career as an independent researcher in academia, even after a prolonged period of postdoctoral training, hampers their ability to attract the best and brightest students to the field (National Research Council, 1998, 2005; National Academies of Sciences, Engineering, and Medicine, 2018; National Academy of Sciences, 2014; Alberts et al., 2014, 2015; Kimble et al., 2015; Daniels, 2015; Pickett et al., 2015).

[22] For this figure, biomedical doctorates are associated with the employment sector (academia or industry) that they occupy at 10 years post-PhD. Observations are for biomedical doctorates first appearing in the SDR 1993, 1995, and 1997 waves and who graduated no earlier than 1990; due to the biennial nature of the SDR, we plot salary in 3-year intervals to ensure sufficient cell size for disclosure.

[23] In Appendix C.2 we describe the demographic differences between postdocs and nonpostdocs and further details on the differences between the career paths of postdoc-trained and nonpostdoc-trained biomedical doctorates.

3 A Task-Based Framework of Wage Determination

We first consider a general model with J tasks, K sectors, and I worker types.[24] In this model, differences in wages between different types of workers in a given sector result from two sources: 1) differences in endowed task-specific human capital and 2) differences in accrued task-specific human capital arising from differences in the employment history of different worker types. We then apply the results from this model to a special case with 2 tasks (research and nonresearch), 2 sectors (academia and industry), and 2 worker types (postdoc-trained and nonpostdoc-trained biomedical doctorates). We find that researchers estimating salary regressions are likely to find that postdoc-trained and nonpostdoc-trained biomedical doctorates are paid differently in industry, even if able to adequately control for differences in pre-existing abilities, due to differences in the tasks performed and skills learned as part of postdoctoral training versus industry employment.

3.1 Model with *J* Tasks, *K* Sectors, and *I* Worker Types

We construct a model similar to Autor and Handel (2013) and Gathmann and Schönberg (2010) to motivate a task-based analysis of wage determination. We write worker i's stock of skills at time t as $\Phi_{it} = \{\phi_{it}^1 \ldots \phi_{it}^J\}$ where each $\phi_{it}^j > 0$ gives worker i's stock of task j specific human capital at time t which is measured in the units of task j that worker i can perform in a unit of time ("task efficiency"). Assume worker i produces output in sector $k \in \{1, \ldots, K\}$ by utilizing task-specific skills ϕ_{it}^j for $j \in \{1, \ldots, J\}$ as follows:

$$Y_{ikt} = e^{\alpha_k + \sum_j \lambda_k^j \phi_{it}^j}, \tag{1}$$

where $\lambda_k^j \geq 0 \ \forall \ j, k$ measures the productivity of task j in producing output in sector k. As in Autor and Handel (2013), we normalize the output price for each sector to unity, and also note that α_k is not constrained to be positive, thus allowing for a worker's marginal productivity in sector k to be negative in the case of insufficient skills (e.g., an untrained air pilot).

If workers are paid their marginal product, then the log wage of worker i in sector k is:

$$w_{ikt} = \alpha_k + \sum_j \lambda_k^j \phi_{it}^j. \tag{2}$$

We write task j specific human capital as the sum of endowed task j specific ability and task j specific human capital accrued over time (through training or labor market experience):

$$\phi_{it}^j = H_i^j + H_{it}^j. \tag{3}$$

[24] More generally, K could represent the number of jobs or occupations in an economy. We use K to represent the number of employment sectors since our empirical analysis involves estimating separate salary regressions by employment sector, rather than by jobs or occupations.

Then plugging (3) into (2) we get:

$$w_{ikt} = \alpha_k + \sum_j \lambda_k^j H_{it}^j + \sum_j \lambda_k^j H_i^j. \tag{4}$$

which shows that wage differences across workers in sector k is the result of differing levels of endowed and/or accrued task-specific human capital.[25]

As in Gathmann and Schönberg (2010), we assume that task j specific human capital accrual is the result of passive learning-by-doing as part of previous employment, with the rate of task j specific human capital accrual varying by sector such that:

$$H_{it}^j = \sum_{k'} H_{ik't}^j \quad \text{where} \quad H_{ik't}^j \equiv \theta_{k'}^j t_{ik't} \tag{5}$$

where $k' \in K$ indexes sectors of *previous* employment and thus $t_{ik't}$ denotes worker i's previous years of experience working in sector k' and $\theta_{k'}^j$ denotes the amount of task j specific human capital accrued per each unit of time previously employed in sector k'.[26] Substituting (5) into (4), we get:

$$w_{ikt} = \alpha_k + \sum_j \lambda_k^j \sum_{k'} \theta_{k'}^j t_{ik't} + m_{ik}. \tag{6}$$

where $m_{ik} = \sum_j \lambda_k^j H_i^j$ represents worker-sector match quality.[27] Equation (6) implies that workers with greater levels of accumulated task-specific human capital in those tasks that are most productive to their current employer will tend to be paid more. This suggests that the more similar the tasks performed as part of previous and current employment, the higher the wage.

3.2 Example with 2 Tasks, 2 Sectors, and 2 Worker Types

Suppose that there are two tasks: research (R) and nonresearch (N). Also suppose there are two sectors: academia (A) and industry (I). Then equation (6) can be written as:

$$w_{ikt} = \alpha_k + \lambda_k^R \left[\theta_{A'}^R t_{iA't} + \theta_{I'}^R t_{iI't}\right] + \lambda_k^N \left[\theta_{A'}^N t_{iA't} + \theta_{I'}^N t_{iI't}\right] + m_{ik}. \tag{7}$$

[25] We note that it is possible that differences in task-specific human capital do not lead to differences in wages, depending on the relative productivity of each task j in production of output in sector k; that is, differences in task-specific human capital could be perfectly offset by differences in the productivity of each task.

[26] Previous employment could include one's time as student or, in the case of PhDs, one's time as a postdoc.

[27] This simple model treats sector-specific task j productivity, λ_k^j, and the rate at which workers accrue task j specific human capital when employed in sector k, θ_k^j, as exogenous (and time-invariant). However, some minimal assumptions can be made relating these two rates for sake of clarification. Let $\mathcal{J}$ denote the set of all tasks $\{1, \ldots, J\}$. There may exist some set of tasks $\mathcal{J}_k^- \subset \mathcal{J}$ that are not useful in production in sector k, and so for each $j^- \in \mathcal{J}_k^-$ we have $\lambda_k^{j^-} = 0$. Assume that if $\lambda_k^{j^-} = 0$, then $\theta_k^{j^-} = 0$; that is, if a task j^- is not useful in production in sector k, then workers do not perform task j^- when employed in sector k. Likewise, let $\mathcal{J}_k^+ \subseteq \mathcal{J}$ denote the set of tasks that are useful for production in sector k (i.e., where $\lambda_k^{j^+} > 0$). Assuming that all tasks $j^+ \in \mathcal{J}_k^+$ are performed simultaneously to produce output in sector k at time t, then $\theta_k^{j^-} = 0$ for all $j^- \in \mathcal{J}_k^-$ and $\theta_k^{j^+} > 0$ for all $j^+ \in \mathcal{J}_k^+$.

Now, as an example, suppose there are two different types of workers p and n of the same level of overall experience (i.e., $t_{pt} = t_{nt} \equiv t_t$) who both work in industry. Suppose worker p spent all previous years in the academic sector in postdoc training, whereas worker n has worked in industry ever since graduation. Then we have the following:

$$w_{pIt} = \alpha_I + \lambda_I^R \theta_{A'}^R t_t + \lambda_I^N \theta_{A'}^N t_t + m_{pI},$$
$$w_{nIt} = \alpha_I + \lambda_I^R \theta_{I'}^R t_t + \lambda_I^N \theta_{I'}^N t_t + m_{nI},$$

where $m_{ik} = \lambda_k^R H_i^R + \lambda_k^N H_i^N$. Then wage differences across workers is either due to differences in endowed task-specific human capital or differences in accrued task-specific human capital caused by $\theta_{A'}^R \neq \theta_{I'}^R$ or $\theta_{A'}^N \neq \theta_{I'}^N$.[28]

Let $\Delta^j \equiv \theta_{A'}^j - \theta_{I'}^j$ and $m_{\Delta I} \equiv m_{pI} - m_{nI}$. Then wages for both types of workers can be written as the following:

$$w_{iIt} = \alpha_I + \lambda_I^R \theta_{I'}^R t_t + \lambda_I^N \theta_{I'}^N t_t + m_{nI} + 1[i = p] * \left\{\lambda_I^R \Delta^R t_t + \lambda_I^N \Delta^N t_t + m_{\Delta I}\right\} \tag{8}$$

where $1[i = p] = 1$ if worker i is type p and $1[i = p] = 0$ if worker is type n. Equation (8) implies that industry wage differences between postdoc-trained (type p) and nonpostdoc-trained (type n) workers of the same cohort are due to differences in worker-sector match quality $m_{\Delta I}$—which is governed by differences in endowed ability in each task (i.e., differences in H_i^j)—and between-sector differences in the rate of task j specific human capital accumulated as part of production (Δ^j). In this simplified example, we considered the case where a postdoc-trained doctorate is entering the first year of employment in industry. However, under the assumption that θ_k^j and λ_k^j remain fixed over time for each sector and do not differ by worker type, differences in task-specific human capital, and thus wage differences, will persist between postdoc-trained and nonpostdoc-trained workers in industry.[29]

4 Empirical Analysis

4.1 Data

To construct a longitudinal dataset of biomedical doctorates, we append all waves of the NSF's Survey of Doctorate Recipients from 1993-2017. The SDR is a biennial survey of a representative

[28]A reasonable assumption might be that $\theta_{A'}^R > \theta_{I'}^R$ and $\theta_{A'}^N < \theta_{I'}^N$.

[29]Note that the magnitude and direction of the difference is an empirical question: if pure research abilities are more valuable than other types of abilities in industry, then postdoc training could potentially lead to postdoc-trained biomedical doctorates earning more than their nonpostdoc-trained counterparts, assuming that postdoc training is primarily focused on pure research. However, it could be the case that nonresearch skills are sufficiently valued in industry that nonpostdoc-trained workers in industry tend to earn more; allowing for more than 2 tasks, it could be that the type of research conducted in academia is qualitatively different from that in industry. Lastly, differences in task-specific human capital accrual between postdoc-trained and nonpostdoc-trained biomedical doctorates working in industry could be perfectly offset by differences in the productivity of each task, resulting in equal wages.

sample of Science, Engineering, and Health (SEH) doctorates under the age of 76 and contains information on each doctorate's salary, employment sector, and whether their current employment is as a postdoc, in addition to many demographic and economic variables.[30] A unique aspect of SDR data is that it also includes, for each doctorate, the primary and secondary tasks associated with current employment, as well as tasks performed for at least 10% of work time, allowing us to track the tasks performed by each biomedical doctorate over their career.[31] For doctorates in the constructed longitudinal SDR 1993-2017 dataset, we pull any additional information regarding postdoc employment available in earlier SDR waves (1973-1991) using the 1991 SDR Longitudinal File. We then merge this dataset with the NSF's Survey of Earned Doctorates (SED), which is an annual survey given to all PhD recipients from US institutions and which contains, among other information, each PhD recipient's field of study and whether he/she intended to take a postdoc position after graduation.[32] We follow a similar strategy to that of Kahn and Ginther (2017) in determining whether an individual has ever been employed as a postdoc and for how many years.[33] We limit the sample to biomedical doctorates obtaining a PhD sometime between 1981 and 2007, who were first surveyed in the SDR prior to 2010, and for whom we could identify, for each year, whether they were employed as a postdoc.[34] We use these data to produce the descriptive figures discussed above in Section 2.

In addition to the sample restrictions above, we limit our analytical sample to biomedical doctorates that are observed at least once after their first six years post-PhD, and at least once in a job after completing postdoc training (if applicable) to ensure the consistency of sample members across regression specifications, some of which, by design, exclude observations corresponding to

[30]The SDR only contains information on doctorates graduating from US universities. Stephan (2012) reports that almost five out of ten postdocs in the US earned a doctorate in another country—we are unable to analyze the impact of postdoc-training for these doctorates using the SDR. For more information about the SDR see: `https://www.nsf.gov/statistics/srvydoctoratework/#sd`.

[31]The list of activities/tasks that respondents may select are as follows: 1) Accounting, finance, contracts, 2) Applied research— study directed toward gaining scientific knowledge to meet a recognized need, 3) Basic research—study directed toward gaining scientific knowledge primarily for its own sake, 4) Computer programming—including systems or applications development, 5) Development—using knowledge gained from research for the production of materials, devices, 6) Design—of equipment, processes, structures, models, 7) Human resources—including recruiting, personnel development, training, 8) Managing or supervising people/projects, 9) Production, operations, maintenance—including chip production, operating lab equipment, 10) Quality or productivity management, 11) Sales, purchasing, marketing—including customer service and public relations, 12) Professional services—including health care, counseling, financial services, legal services, 13) Teaching, and 14) Other.

[32]The microdata described here are restricted-use and so were accessed remotely through the National Opinion Research Center (NORC) data enclave.

[33]See Appendix C.1 for details.

[34]See Table A.1 for a list of the biomedical fields included in the analytical sample. In 2010, the SDR began sampling US-trained PhDs who reside outside of the United States, whereas previous waves only included US-trained PhDs residing in the US after graduation. Due to this sampling change, the NSF recommends caution when analyzing and interpreting pre- and post-2010 trends. Also, the SDR 2010 introduced new sample members that had graduated as far back as 2001; we are not able to reliably identify whether these individuals were ever employed as postdocs given that they are first sampled in the SDR many years after graduation and were not part of the SDR 2006 wave where doctorates were asked whether they had previously worked as a postdoc. We therefore restrict the sample to those first appearing in the SDR data prior to 2010. We also limit the sample to individuals who appear in the SDR in 1993 at the earliest due to survey format changes in 1993 and sampling changes in 1991. See `https://nsf.gov/statistics/srvydoctoratework/#micro&tabs-1&sd` for more details.

the first six years post-PhD as well as any years when a doctorate is employed as a postdoc.[35] We group observations into one of three employment sectors: academia, industry, or government and nonprofits. As in Kahn and Ginther (2017), we also consider subsectors within academia and industry: academic tenure-track research, academic non-tenure-track research, academic nonresearch, industry research, and industry nonresearch.[36] Table 1 breaks down the analytical sample by sector and subsector of employment and whether biomedical doctorates within each sector are postdoc-trained. As we can see, postdoc-trained biomedical doctorates make up the majority of biomedical doctorates working in each sector and subsector, reflecting the high prevalence of postdoc training in biomedical science. Differences in the person counts in the third and last column show that there is a nontrivial level of mobility of doctorates across sectors over time: for example, 1468 biomedical doctorates in our sample are employed in industry at ten years post-PhD, which reflects only 82% of the 1786 sample members who work in industry for at least one year post-PhD; similarly, only 58% of sample members who ever work in academic non-tenure-track research do so at ten years post-PhD, indicating strong mobility in and out of this subsector over time.[37]

Table 2 reports summary statistics for the analytical sample broken down by postdoc-trained status and current employment sector (academia and industry).[38] We find that postdoc-trained biomedical doctorates are more likely to be foreign-born and to be temporary residents compared to nonpostdoc-trained biomedical doctorates. They also tend to be younger at time of PhD graduation and less likely to be married and to have children living at home. Additionally, postdoc-trained biomedical doctorates are more likely to have been funded by research assistantships as graduate students and to have finished the PhD more quickly. Due to these differences between postdoc-trained and nonpostdoc-trained biomedical doctorates, we include the characteristics in Table 2 among the controls used in the regression analyses that follow.

4.2 Empirical Specification

Our baseline empirical model for examining the effect of postdoc training on salary is given by the following person-year level Mincer equation:

$$\log(earn_{ifct}) = \boldsymbol{X_i}\boldsymbol{\beta} + \theta Postdoc_i + \boldsymbol{Exp_{it}}\boldsymbol{\lambda} + \boldsymbol{\gamma_f} + \boldsymbol{\gamma_c} + \boldsymbol{\gamma_t} + \varepsilon_{ifct}, \tag{9}$$

where $earn_{ifct}$ is the year t inflation-adjusted annualized salary of doctorate i who graduated with a PhD in field f in year c, $\boldsymbol{X_i}$ is a vector of pre-determined individual-level controls, $Postdoc_i$ is

[35]This ensures that differences between results discussed in Section 5 are not due to changes in the underlying sample members.

[36]We define a job as research-based if respondents report basic research, applied research, development, or design as their primary work activity/task. Tenure-track workers include those on the tenure-track and those who have received tenure.

[37]The sample counts in the last three columns exclude observations corresponding to years when a biomedical doctorate is employed as a postdoc.

[38]Summary statistics for the full sample and "Gov't/Nonprofit" sector are reported in Table A.3. A given doctorate who switches employment sector during their career will appear in multiple employment sector samples.

an indicator variable for if doctorate i is postdoc-trained, $\boldsymbol{Exp_{it}}$ is a vector containing a quartic polynomial in experience, $\boldsymbol{\gamma_f}$ are field fixed effects, $\boldsymbol{\gamma_c}$ are PhD graduation year/cohort fixed effects, $\boldsymbol{\gamma_t}$ are normalized year fixed effects, and ε_{ifct} is an idiosyncratic error term.[39] We cluster standard errors at the person-level as each biomedical doctorate may appear more than once in the estimation sample and the regressor of interest, $Postdoc_i$, is fixed for each doctorate. For each person-year observation, we use the sample weight associated with the SDR wave in which the observation appears and include the controls listed in Table A.2 which includes race, sex, age at PhD, number of years spent in graduate school, source of PhD study financial support, whether completed professional degree in conjunction with PhD, marital status at time of graduation, whether had child at home at time of graduation, foreign-born status, and whether the individual was a temporary resident.[40]

Our preferred specification augments (9) with field-by-cohort fixed effects ($\boldsymbol{\gamma_{fc}}$) to control for field-cohort specific shocks that could influence both a doctorate's decision to pursue a postdoc and future career outcomes.[41] Our preferred specification also includes PhD institution (i.e., *alma mater*) fixed effects ($\boldsymbol{\gamma_s}$) to capture the impact of PhD institution—and any unobserved characteristics of the doctorate that led to his or her acceptance into that PhD institution and that may be correlated with the decision to do a postdoc—on future career outcomes. In addition to the full sample, we conduct regression analyses on three subsamples based on employment sector—academia, industry, or government/nonprofit—since the return to doing a postdoc likely varies by employment sector.

We first estimate the impact of postdoc training on salary using all observations in the estimation sample, including those corresponding to years when a doctorate is employed as a postdoc. For these regressions, we follow Kahn and Ginther (2017) in associating each doctorate with the sector in which they are employed at 10 years after graduation and treat postdoctoral training as adding to labor market experience.[42] As it is well-known that postdocs get paid less than nonpostdocs throughout the duration of their postdoc employment, we subsequently consider a separate analysis where, for postdoc-trained doctorates, we include only observations for years after their

[39] Salary is adjusted using the CPI-U with base years 1982-84. We follow Murphy and Welch (1990) and Lemieux (2006) by including a quartic polynomial in experience. To address the issue of collinearity between cohort fixed effects, year fixed effects, and experience, we normalize year fixed effects as in equation 2.95 of Deaton (1997) which, as discussed in Aguiar and Hurst (2013) and Lagakos et al. (2018), results in salary growth over time being attributed to experience and cohort effects, and restricts year fixed effects to capture only cyclical fluctuations in salary.

[40] See Table A.4 for results from a person-level regression of the postdoc indicator on the time-invariant controls.

[41] Such shocks include the number of PhDs and postdocs in one's own field of study, the level of NIH funding allocated to one's field, and field-specific research agendas and breakthroughs (e.g., the Human Genome Project, the use of MRI and fMRI), as well as technological and methodological progress (e.g., advances in semiconductor technology leading to both increases in computational power and decreases in cost, emergence of AI and machine learning methods in biomedical research) that open up both new avenues for research and new economic opportunities. For example, see the large increases in the number of NIH-supported PhD recipients in neuroscience and neurobiology since the 1990s: `https://report.nih.gov/nihdatabook/report/267`.

[42] Since the SDR is biennial, a doctorate may not be observed in the data at exactly 10 years post-PhD. Therefore, for those who are not in the data 10 years post-PhD, we impute their employment sector using 11 years, 12 years, and then 9 years post-PhD. We also restrict that the imputed employment sector not come from an observation when the person is employed as a postdoc since we are interested in the after-postdoc employment sector.

postdoc training has ended.[43] This allows us to explicitly estimate the effect of postdoc training on *future* salary in the absence of its effect on current salary and also allows us to group person-year observations by the employment sector associated with each observation, rather than with the employment sector of the doctorate at a single point in time. In this way we generate an estimate of the impact of postdoc training on *after-postdoc* salary that is less susceptible to possible bias caused by doctorates switching between employment sectors over the course of their career. For each specification, we then allow the dummy on postdoc training to interact with the quartic polynomial in experience and plot predicted salary profiles for postdoc-trained and nonpostdoc-trained biomedical doctorates by employment sector.[44]

We then consider an alternative specification where postdoctoral training is treated as schooling such that labor market experience, rather than being defined as the number of years since PhD graduation for all biomedical doctorates, is instead defined as years of nonpostdoc employment—for postdoc-trained biomedical doctorates, this reflects the number of years since exiting one's (last) postdoc position, while for nonpostdoc-trained biomedical doctorates, this reflects the number of years since PhD gradation (as before).[45] As with the other specifications, we plot predicted salary profiles by employment sector, allowing the shape of the predicted salary profiles to vary based on one's postdoc-trained status as before.

If differences in task-specific human capital are a main driver of the industry postdoc salary penalty, then we would expect this penalty to be greatest for those who spend the most years employed as postdocs and thus defer on-the-job task-specific human capital acquisition in industry the longest. To see if this is indeed the case, we estimate specifications where we partition $Postdoc_i$ into three separate indicator variables based on the number of years that we observe a doctorate employed as a postdoc: an indicator for if a doctorate did a postdoc 1) no longer than three years, 2) for greater than three years but less than six years, and 3) exceeding six years.

We also analyze the impact of postdoc training on the ability of biomedical doctorates to obtain research jobs in academia and industry. Our empirical model for examining the effect of postdoc training on the likelihood of obtaining research jobs is given by the following person-level linear probability model (LPM) specification:

$$job_{ifcs} = \boldsymbol{X_i \beta} + \theta Postdoc_i + \boldsymbol{\gamma_{fc}} + \boldsymbol{\gamma_s} + \varepsilon_{ifcs}, \tag{10}$$

where job_i is an indicator variable for if doctorate i ever obtains a given research job and all other variables are defined as before. We consider four different indicator variables: The first is

[43] Given that the average postdoc duration is between five and six years in biomedical science (see Figure A.2), for these specifications, we drop observations corresponding to a doctorate's first six years post-PhD regardless of postdoc status, in addition to dropping any other observations from years when a doctorate is employed as a postdoc, so that postdoc and nonpostdoc observations are comparable.

[44] This allows the shape of the predicted salary profiles to vary based on one's postdoc-trained status.

[45] In regressions using this definition of experience, we do not remove observations corresponding to the first six years post-PhD for nonpostdoc-trained biomedical doctorates as there will now be a sufficient number of postdoc observations with experience less than seven years.

for whether a doctorate ever finds a nonpostdoc research position in academia ("academic"), the second is for whether a doctorate ever lands a tenure-track research job in academia ("tenure-track"), the third is for whether an individual obtains tenure in an academic research position ("tenured") conditional on having obtained a tenure-track research position, and the fourth is an indicator variable for if a doctorate ever obtains a research position in industry conditional on ever working in industry ("industry").[46] The analytical sample members for these regressions are the same as those in the salary regressions and robust standard errors are computed allowing for clustering at the field-cohort level.

Of course, since postdoc-trained status is clearly endogenous, our estimates for the impact of postdoc training on future salary and the likelihood of obtaining future research jobs are unlikely to represent the true causal effect of postdoc training: the choice to pursue postdoc training is likely correlated with unobserved factors such as skill endowments not fully captured by the observed controls. Therefore, we estimate Oster (2019) bias-adjusted treatment effects to test the sensitivity of our results to plausible selection on unobservable ability at time of PhD graduation. See Appendix B.1 for a discussion of this method, followed by the estimation of bias-adjusted versions of the results that follow.

5 Baseline Results

5.1 Salary Regressions: Postdoc as Experience vs. Schooling

In this section, we carry out three different strategies for estimating the returns to postdoc training. The first strategy treats postdoc training as experience and estimates the effect of postdoc training on salary, including those years when a biomedical doctorate is employed as a postdoc. As in Kahn and Ginther (2017), we associate each worker with their sector of employment at 10 years post-PhD so that we can estimate different effects for each sector. The second strategy treats postdoctoral training as experience, but explicitly focuses on the impact of postdoc training on future (i.e., after-postdoc) salary by excluding observations corresponding to years when a biomedical doctorate is employed as a postdoc. This allows us to then associate each doctorate with their actual sector of employment held in each year for purposes of estimating different effects for different sectors. The results from this strategy form the basis of our subsequent analysis of the degree to which a task-specific human capital model can explain (after-postdoc) salary differences between postdoc- and nonpostdoc-trained biomedical doctorates across sectors and within industry. Our third strategy treats postdoc training as a form of schooling so that experience is measured as the number of years since postdoc training for those biomedical doctorates that pursue postdoc training.

[46] "Research job" includes jobs where the primary activity is reported as one of the following: basic research, applied research, development, or design. We also include regressions where we do not restrict the job to being a research position.

5.1.1 Postdoc Training as Experience, Postdoc Salary Observations Included

Table 3 reports regression results where an indicator variable for if a biomedical doctorate ever received postdoc training serves as the main variable of interest and where, as in Kahn and Ginther (2017), we include all person-year observations in the analytical sample including observations corresponding to years when a biomedical doctorate is employed as a postdoc. We focus attention to specification (2) as it is the more general specification. The estimates in Panel A suggest that, on average, postdoc training results in a 13.8% decrease in annual salary. However, the returns to doing a postdoc are likely to vary by sector of employment. Therefore, we break the observations into three groups based on the employment sector of the biomedical doctorate at 10 years post-PhD. The results in Panel B suggest that postdoc-trained biomedical doctorates in academia earn about 6.0% less than nonpostdoc-trained biomedical doctorates. In contrast, a postdoc-trained biomedical doctorate who works in industry faces a 21.3% postdoc salary penalty, as shown in Panel C. Panel D suggests that postdocs may face a penalty when entering government or nonprofit organizations, but this penalty is not statistically significant in the preferred specification. The difference in the magnitude of the estimates between the industry and academic employment sectors is likely driven in part by the higher starting salaries in industry as evidenced in Figure 1.

Since the impact of postdoc training on salary likely varies over a person's career, we consider an augmented version of specification (2) that allows for interactions between the indicator variable for postdoc training and the quartic polynomial in years since PhD graduation. Figure 2 plots the average predicted salary profile for biomedical doctorates with and without postdoc training for each of the first 20 years post-PhD as implied by the augmented version of specification (2) for academia and industry.[47] As we can see, postdoc training leads to lower salary early in a biomedical doctorate's career regardless of employment sector at 10 years post-PhD. For postdocs that find after-postdoc employment in academia, we find an initial postdoc salary gap that dissipates over time. In contrast, postdoc-trained biomedical doctorates in industry suffer a greater gap in salary that persists longer into their career. These results suggest that biomedical postdocs not only experience lower salary while employed as postdocs, but also suffer an after-postdoc salary penalty if entering industry.

5.1.2 Postdoc Training as Experience, Postdoc Salary Observations Excluded

To explicitly test whether postdoc training impacts after-postdoc salary, we estimate the effect of postdoc training on *future* salary in the absence of its effect on current salary by keeping only those person-year observations corresponding to years after a biomedical doctorate's completion of

[47] The plots are generated by the following process: For each doctorate in the given employment sector sample, we generate two predictions (fitted values) of log(salary) in each year since PhD. The first prediction gives the log(salary) predicted if the doctorate is assumed to have done a postdoc and the second prediction gives the log(salary) predicted if the doctorate is assumed to have not done a postdoc. Then, we average the predicted log(salary) across individuals in the given employment sector in each year since PhD and apply the exponential function to translate log(salary) into salary. We then plot these average predicted salary profiles in Figure 2.

any and all postdoc positions.[48] Table 4 reports the regression results for this analysis where an indicator variable for if a biomedical doctorate ever received postdoc training serves as the main variable of interest. We first focus attention to specification (2) where we define experience as years since PhD graduation and where we include field-by-cohort fixed effects as well as PhD university fixed effects.[49] The result for the full estimation sample suggests that, on average, postdoc training results in a 11.7% decrease in annual salary following the completion of one's postdoc position. As before, we break the observations into three groups based on the employment sector of the biomedical doctorate, but we assign each person-year observation to a subsample based on the actual sector of employment for the doctorate in the given year, rather than the employment sector of the doctorate 10 years post-PhD.[50] We find that if a postdoc lands a position in academia, then he or she does not face a postdoc penalty; in contrast, we find that postdocs working in industry face a 15.8% penalty on after-postdoc salary, and that postdocs in government/nonprofits face a 10.6% salary penalty.

As before, we plot average predicted salary profiles by postdoc-trained status and employment sector, allowing the shape of the predicted salary profiles to vary based on one's postdoc-trained status. Figure 3 shows that, when limiting the sample to exclude observations for years when biomedical doctorates are employed as postdocs and associating each observation with the current sector of employment, postdoc training is associated with a persistent salary penalty in industry, whereas in academia postdoc training appears to have a slight negative impact on salary early in a doctorate's after-postdoc career, but enhances salary growth such that the salary of postdoc-trained biomedical doctorates catches up and then exceeds that of nonpostdoc-trained doctorates after about 15 years post-PhD. These results are consistent with the view that postdoc training primarily builds skills valued by academia and thus increases one's chances of obtaining a subsequent higher-paying research-based academic job.[51]

[48]For specifications (1) and (2) where experience is defined as the number of years since PhD graduation, we also drop observations corresponding to a person's first six years post-PhD so that postdoc and nonpostdoc observations are comparable.

[49]Specifications (1) and (3) are included for comparison purposes and demonstrate the importance of controlling for field-by-cohort fixed effects and PhD university fixed effects.

[50]See Table A.5 for results where we use the employment sector at 10 years post-PhD for subsampling. The results remain similar to what we find in Table 4 except for the government and nonprofit subsample in specifications (2) and (4) where we control for field-cohort fixed effects.

[51]The negative impact early in a postdoc-trained biomedical doctorate's career may be due to nonpostdoc-trained doctorates of the same cohort being promoted to a higher academic rank sooner than those who enter a tenure-track position after spending multiple years as a postdoc. Agarwal and Ohyama (2013) find a similar criss-crossing pattern when comparing the salary of those in academia primarily focused on basic science versus applied science, with those in basic science starting with lower salary but having a steeper salary profile. In Figure C.4, we show that a greater share of postdoc-trained biomedical doctorates are engaged in basic research as opposed to those in academia without postdoc training. However, Agarwal and Ohyama (2013) include observations corresponding to years when doctorates are employed as postdocs, as well as including doctorates outside of biomedical science, and so their results are not directly comparable to ours.

5.1.3 Postdoc Training as Schooling, Postdoc Salary Observations Excluded

The estimates reported in columns (1) and (2) of Table 4 are the result of specifications where postdoctoral training is treated as contributing to general labor market experience: for example, biomedical doctorates who spend six years in postdoc training and first enter industry at seven years post-PhD are treated as having the same level of labor market experience as a biomedical doctorate of the same cohort who has worked in industry ever since graduation. Since postdoc training and on-the-job training in industry likely emphasize different sets of skills, we might expect within-cohort differences in task-specific human capital between ex-postdocs and nonpostdocs working in industry conditional on years since PhD, resulting in salary differences. If postdoc training is instead treated as a type of schooling and experience is defined as the number of years in post-PhD nonpostdoc employment, we would not expect such differences. Therefore, we estimate specifications (3) and (4) which are identical to specifications (1) and (2), respectively, except that experience is defined as the number of years in post-PhD nonpostdoc employment. Focusing on specification (4), we find that the postdoc penalty on salary in industry is no longer statistically significant when experience is defined in this way, and we also find that postdoc training is associated with a statistically significant 9.8% increase in salary in academia. Plotting average predicted salary profiles by postdoc-trained status and employment sector, Figure 4 shows that, when postdoc training is treated as schooling, postdoc training is associated with a persistent increase in salary for academic jobs, whereas postdoc training does not significantly impact salary in industry. These findings are consistent with the view that postdoc training in biomedical science is specialized academic training, and so the postdoc penalty in industry that we observe in column (2) of Table 4 is driven by differences in the accumulation of industry-relevant human capital between postdoc-trained and nonpostdoc-trained biomedical doctorates early in their career. These results also suggest that, for biomedical doctorates working in academia, postdoc training improves one's chances of obtaining a higher-paying research-based job.

5.2 Postdoc Training and Obtaining a Future Job in Research

To test the extent to which postdoc training enhances a biomedical doctorate's chances of working in research-focused jobs, we estimate the impact of postdoc training on ever obtaining a nonpostdoc academic research job, a tenure-track research position, ultimately attaining tenure in a research position, and obtaining a research position in industry conditional on ever working in industry. Panel B of Table 5 reports the results using the LPM specification given by (10).[52] To measure the impact of doing a postdoc on ever obtaining a (nonpostdoc) academic research job, we regress an indicator variable for if a biomedical doctorate ever works in an after-postdoc research job in academia on an indicator variable for if the individual has postdoc training. We find that doing a postdoc increases the likelihood of working in an academic research position by about

[52]For comparison purposes, Panel A reports the results when we omit restricting the position to being one where research is the primary work activity.

26.5 percentage points.[53] Next, we find that postdoc training increases the chances of landing a tenure-track position by about 21.5 percentage points. Lastly, among those that ever take a tenure-track job and whom we observe after they are up for their tenure decision, we estimate the impact postdoc training on obtaining tenure.[54] We find that postdoc training does not significantly impact the ability of tenure-track researchers to obtain tenure. Lastly, we estimate the impact of postdoc training on the ability to ever obtain a research position in industry among doctorates ever working in industry. The last column in Panel B of Table 5 shows that postdoc training raises the probability of obtaining a research position in industry by about 12.3 percentage points.

5.3 Salary Regressions by Academic and Industry Subsectors

The positive association between postdoc training and the likelihood of obtaining a research-focused job in industry suggests that postdoc training might enhance one's research skills. If this is the case, we would expect the industry postdoc salary penalty to be smaller among biomedical doctorates employed in research-focused positions. Therefore, we estimate subsector salary regressions for "industry research" and "industry nonresearch" and report results in Table 6. These results suggest that the industry postdoc salary penalty is indeed smaller for those in industry research jobs—the estimated magnitude is just over half that for industry nonresearch jobs, and only marginally significant. For both subsectors, we find no statistically significant postdoc salary penalty when postdoc training is treated as a form of schooling (i.e., when experience is defined as years of post-PhD nonpostdoc employment).

We also estimate subsector regressions for academia, breaking academia down into three subsectors: "academic tenure-track (TT) research", "academic non-tenure-track (non-TT) research", and "academic nonresearch." When postdoc training is treated as a form of employment experience, postdoc-trained biomedical doctorates appear to earn less in TT research positions, no differently in nonresearch positions, and earn more than their nonpostdoc-trained counterparts in non-TT research positions. When redefining experience so as to treat postdoc training as a form of schooling, we find no substantial differences in salary between ex-postdocs and nonpostdocs in TT research and nonresearch positions, but find a substantial postdoc *premium* in non-TT research positions (23.2%). This suggests that previous postdoc training increases the productivity of non-TT researchers, which could be due to similarities in the set of tasks emphasized in both types of jobs.[55]

[53] In results not shown, we find that postdoc training is associated with a 24.2 percentage-point increase in the likelihood of working in any research-focused job (i.e., regardless of employment sector).

[54] This sample includes individuals who report being on the tenure track at some point and then later report either 1) being in a tenured position or 2) not in a tenured position and no longer on the tenure track.

[55] See Table A.6 for subsector regressions where, as in Table 3 and Kahn and Ginther (2017), we include observations for years when doctorates are employed as postdocs and where employment sector is defined as that at 10 years post-PhD. Our findings broadly replicate those of Kahn and Ginther, with negative point estimates for all subsectors except academic nonresearch for which we estimate an effect close to zero. Table 1 shows that only 58% of sample members who ever work in academic non-tenure-track research do so at ten years post-PhD, indicating strong mobility in and out of this subsector over time, which might explain the sensitivity of results for the non-tenure-track research

5.4 Does the Duration of the Postdoc Spell Matter?

The results reported in Table 4 estimate the impact of postdoc training on future salary, regardless of the length of postdoc training. If differences in salary between ex-postdocs and nonpostdocs in industry are driven by differences in task-specific human capital, we would expect ex-postdocs who spent the longest time in postdoc training—and therefore deferred on-the-job training in industry for the longest—to suffer the largest salary penalties. To test this, we repeat the analysis in Table 4 after replacing the single indicator variable for if a biomedical doctorate ever did a postdoc with three indicator variables: an indicator for if a doctorate did a postdoc 1) no longer than three years, 2) for greater than three years but less than six years, and 3) exceeding six years. Table A.7 reports the results. We first focus attention to specification (2) where postdoc training is treated as employment experience. The results suggest that postdocs finding a job in academia do not suffer a salary penalty regardless of how long they are employed as a postdoc. However, biomedical doctorates who spend any number of years employed as a postdoc experience a salary penalty in excess of 10% in industry, with those who spend the most time working as a postdoc suffering the largest penalty. In specification (4) we treat postdoc training as a form of schooling and find that the postdoc penalty in industry is no longer statistically significant for postdocs of any length. We also detect increases in after-postdoc salary for biomedical doctorates that spend greater than three years in postdoc positions and who find employment in academia; those with the longest postdocs tend to earn more, possibly due to postdoc employment serving as a holding position as one waits for an academic position at a research-intensive university, which are typically higher-paying than other entry-level positions in academia.[56]

To test whether the chances of obtaining a research job in academia, including a tenure-track research position, are increasing in the length of postdoc training, we repeat the analysis in Table 5 after replacing the single indicator variable for if a biomedical doctorate ever did a postdoc with the three indicator variables based on postdoc length. Panel B of Table A.8 shows that biomedical doctorates employed in postdoc positions of any length have greater chances than nonpostdocs in obtaining academic research and tenure-track research positions, with those with postdoc lengths exceeding three years having the greatest chances on landing these positions. Additionally, biomedical doctorates with postdoc lengths greater than three years are also more likely to obtain a research position in industry than those without any postdoc experience. The likelihood that a tenure-track researcher obtains tenure does not appear to be impacted by postdoc length. In general, doing a postdoc longer than three years leads to significantly greater chances of landing an academic research position, a tenure-track research position, and an industry research position.

subsector.

[56] Andalib, Ghaffarzadegan, and Larson (2018) model postdoc positions using a queuing model. Cheng (2020) finds that remaining in postdoc training for longer periods increases the chances of securing a non-tenure-track academic position at research-intensive institutions.

5.5 Robustness Check: Selection on Unobservables

In Appendix B.1, we estimate Oster (2019) bias-adjusted treatment effects to test the sensitivity of our results to plausible selection on unobservable ability at time of PhD graduation. Specifically, we examine the sensitivity of the salary regression results reported in columns (2) and (4) of Table 4 and Table 6 and the research job results in Table 5. We find that both the estimated benefits (i.e., increased likelihood of obtaining future research jobs) and costs (i.e., the industry postdoc salary penalty) associated with postdoc training appear robust to plausible levels of selection bias, and that our estimates of the benefits of postdoc training are likely upper-bounds while the estimated magnitude of the postdoc salary penalty in industry is likely a lower-bound.[57]

6 Evidence For a Task-Specific Human Capital Explanation

In this section, we compare the tasks performed during postdoc training versus with those performed on-the-job by nonpostdoc-trained doctorates in their career, focusing on those biomedical doctorates who go on to work in industry after their PhD or postdoc.[58] The SDR is relatively unique in that it provides individual-level, longitudinal measures of tasks which can be directly linked to the salary of the job for which these tasks are performed.[59] For the analysis in this section, we limit our analytical sample to those doctorates whose tasks we observe at least two times during the first six years of post-PhD employment (including postdoc training).[60] Motivated by the task-based framework of wage determination laid out in Section 3, we construct measures of the history of tasks performed by each doctorate as part of previous employment and postdoc training—a proxy for accumulated task-specific human capital—and test the extent to which differences in accumulated task-specific human capital can explain the 15.8% within field-by-cohort industry postdoc salary penalty.[61] We then construct a measure of task mismatch between the tasks performed as part of current employment and the tasks performed earlier in one's post-PhD career to explore whether task mismatch can explain the heterogeneity in the impact of postdoc training across sectors.

[57] This direction of selection bias is consistent with previous research suggesting that biomedical doctorates who pursue postdoc training are typically of higher ability at time of graduation (Sauermann and Roach, 2016).

[58] See Footnote 31 for the list of 14 work activities/tasks included in the SDR.

[59] Studies typically rely on obtaining occupation-level measures of tasks from external data sources, which may vary in their ability to accurately measure the tasks actually performed by an individual worker.

[60] Since SDR 1993 is the first survey wave of our analytical sample, this restriction implicitly excludes doctorates graduating prior to 1989, as these doctorates would only be observed at most once in their first six years post-PhD in the SDR.

[61] This estimate can be found in column (2) of Panel C in Table 4 and is the result of a regression where we treat postdoc training as experience and limit the sample to exclude observations for years when biomedical doctorates are employed as postdocs. This empirical approach follows directly from our conceptual framework where we approximate an individual's stock of accrued task-specific human capital with their history of tasks.

6.1 Task Differences Between Postdoc Training and Other Employment

In Table 7, we find substantial differences between postdocs and nonpostdocs in the tasks reported as primary work activities at least once in the first six years post-PhD. Approximately three-fourths of all postdocs report basic research as their primary work activity within the first six years after graduation regardless of their subsequent sector of employment; in contrast, only 6%-15% of nonpostdocs are primarily engaged in basic research focused depending on employment sector.[62] Applied research, professional services, development, and management are much more likely to be reported as the primary work activity of nonpostdocs as opposed to postdocs early in their career, especially in industry. Since jobs typically require the performance of multiple tasks, we also consider a broader measure of task-content to characterize the jobs of postdocs and nonpostdocs early in their career. In Table 8, we calculate, for both postdoc-trained and nonpostdoc-trained biomedical doctorates that work in industry at 10 years post-PhD, the percentage of each that, in any of the first six years post-PhD, report working in a job where they spend at least 10% of their time engaged in each given task.[63] Table 8 shows that biomedical postdocs are much more likely to be engaged in basic research and slightly more likely to be engaged in applied research during their postdoc employment compared to nonpostdoc-trained biomedical doctorates working in industry during their first six years post-PhD. Meanwhile, postdocs are considerably less likely to be engaged in the other activities which may be considered more industry-relevant, which include development, design, management, and professional services (among other tasks). The stark differences in job tasks performed by biomedical postdocs and nonpostdoc-trained biomedical doctorates working in industry during their first six years after graduation indicates that postdoc training and on-the-job learning in industry act as distinct training regimens which are likely to develop different types of skills.

One empirical implication of a task-specific model of human capital is that, other things equal, a worker who moves to a new job that requires substantially different tasks than their previous job will typically experience a greater salary change than a worker whose previous job had more similar task-requirements (Gathmann and Schönberg, 2010). Thus, in Table 8 we report the percentage of postdoc-trained and nonpostdoc-trained biomedical doctorates working in industry who, in any year *after* the first six years post-PhD, report working in a job where they spend at least 10% of their time engaged in each given task. We then subtract from these calculations the percentage of each that, in any year *within* the first six years post-PhD, report working in a job where they spend at least 10% of their time engaged in each given task, and report this percentage-point difference as the "Task

[62] For the comparisons in Table 7, we restrict the sample to biomedical doctorates that are employed in the given sector of employment at 10 years post-PhD. For postdocs, we only consider observations in the first six years post-PhD that correspond to years employed as a postdoc; after six years post-PhD, we only consider observations corresponding to years after any and all years employed as a postdoc, and where the doctorate is employed in in the given employment sector. For nonpostdocs, we only consider observations corresponding to years where the person is employed in the given employment sector.

[63] See Table A.10 for comparable data on biomedical doctorates working in the academic and government/nonprofit sectors at ten years post-PhD.

Change." Table 8 shows that postdoc-trained biomedical doctorates in industry experience larger changes in each task relative to nonpostdoc-trained biomedical doctorates (except for computer applications), with these differences often substantially larger than those for nonpostdoc-trained biomedical doctorates in many cases. The comparative postdoc deficit in the types of task-specific human capital highly-valued by industry employers (as shown by the relatively large task changes faced by postdocs transitioning to industry employment) are likely to explain some part of the 15.8% postdoc salary penalty in industry.

6.2 Task-Specific Human Capital and the Industry Postdoc Salary Penalty

Given the differences in tasks performed by postdoc-trained and nonpostdoc-trained biomedical doctorates in industry, we would expect those with the longest spells as postdocs to experience the largest postdoc penalty on after-postdoc salary in industry. This is what we found in column (2) of Table A.7 where biomedical doctorates with postdoc lengths exceeding six years experienced the largest postdoc penalty in industry. Additionally, we would expect the magnitude of the estimated postdoc penalty in industry to decrease when we redefine experience as years of post-PhD employment in nonpostdoc positions rather than as years since PhD graduation; this shifts the focus to comparing the salary of postdoc-trained biomedical doctorates in their first year employed in industry with the pay of nonpostdocs in their first year employed in industry, a time where both would be likely to have similar levels of industry-relevant task-specific human capital. We carried out this exercise in column (4) of both Table 4 and Table A.7 and found that, in both cases, redefining experience in this way shrinks the magnitude of the estimated postdoc penalty in industry to such an extent that the effect is no longer statistically significant.

To directly test the plausibility of a task-specific human capital explanation of salary differences between postdoc-trained and nonpostdoc-trained biomedical doctorates, we construct measures of the history of tasks performed by biomedical doctorates in previous jobs as a proxy for task-specific human capital accrued as part of previous employment to include and include these as mediating controls in industry salary regressions. Given the biennial nature of the SDR, we are not able to measure the precise task tenure for each doctorate, and so we instead approximate each doctorate's task tenure by calculating the percentage of previous jobs that we observe where the doctorate reports performing the given task and multiplying this value by the number of years since PhD minus one. We calculate three sets of task history variables used to proxy for task-specific human capital accumulation: one set for the number of years where a given work activity was performed as the primary job task, another set for the number of years where a given work activity was performed as the primary or secondary job task, and another set for the number of years where a given task was performed for at least 10% of work time.[64] We estimate specifications using different combinations of these three sets of task history variables as a robustness check. Despite the absence of data on the exact proportion of time spent on each task, including the primary or secondary

[64]Each set of task history variables is comprised of 14 variables (i.e., one for each task).

task history with the history of tasks performed for at least 10% of work time allows us to account in some way for the difference in the time allocated to different tasks.

Table 9 reports estimates of the industry postdoc salary penalty when including alternative sets of task tenure variables as mediating controls.[65] We see that the magnitude of the industry postdoc salary penalty is substantially reduced when including measures of the history of tasks performed by biomedical doctorates in previous jobs as mediating controls: when controlling for both the history of primary tasks performed and those tasks performed for at least 10% of work time in column (6), we obtain a statistically insignificant estimate of the industry postdoc salary penalty that is roughly one-third the magnitude of the baseline estimate reported in column (1). This lends plausibility to a task-based explanation of our results where the postdoc salary penalty in industry is caused by differences in the task-specific human capital accumulation of postdoc-trained and nonpostdoc-trained biomedical doctorates.

Table A.12 gives coefficient estimates for the primary task history controls included in the specification reported in column (2) of Table 9. We include these estimates rather than those for column (6) for ease of interpretation: each coefficient represents the effect of spending an additional year engaged in the given primary task relative to if one spent an additional year primarily engaged in applied research. We find that substituting a year where one could primarily be engaged in applied research with a year where one is primarily engaged in basic research results in a an approximate 4% decline in salary. This implies that a postdoc primarily engaged in basic research for five years stands to lose 20% of their industry earnings capacity compared to the case where they obtain an applied research-focused job in industry.

6.3 Task Mismatch and Postdoc Salary Premia Across Sectors

Next, we construct a measure of task mismatch between the tasks performed as part of current employment and those performed during the first six years of post-PhD employment to explore whether task mismatch can explain the heterogeneity in the impact of postdoc training across sectors. We construct our measure of task mismatch (or task distance) as follows: 1) We identify any tasks performed for at least 10% of work time in any year during the first six years of post-PhD employment (including any postdoc training). 2) We calculate the percent of time spent on each task during the first six years under the simplifying assumption that the doctorate spends equal time on each task mentioned in each year during the first six years.[66] 3) We calculate the proportion

[65] For comparison purposes, Table A.11 reports estimates for the same sample when including controls for current job tasks; we find that current job tasks do not explain much (if any) of the industry postdoc salary penalty.

[66] For example, suppose we observe a doctorate two times during their first six years post-PhD. Suppose in the first year they report spending at least 10% of time on basic research and applied research, and then assume that in the second year they report spending 10% of time on basic research, applied research, and teaching. We would thus calculate that they spent 2/5 of their time during first six years post-PhD engaged in basic research, 2/5 of their time engaged in applied research, 1/5 of their time engaged in teaching, and no amount of time on any other task. While this measure of task distance is admittedly prone to error, it has the benefit of being based on tasks actually performed by each respondent—measures of task distance such as the one utilized in Gathmann and Schönberg (2010) utilize the percentage of workers in one's occupation who perform a given task (for any amount of time) as a proxy

of time spent on each task as part of current employment by identifying each task performed as part of current employment and allocating equal time to each task. 4) We calculate the distance between tasks performed in the first six years of post-PhD employment versus those performed as part of the current job using the same angular separation measure as Gathmann and Schönberg (2010) subtracted from one.[67] The constructed measure of task distance thus ranges from zero to one, with a value of zero for doctorates whose proportion of time spent on each task during their first six years post-PhD exactly matches the percentage of time spent on each task as part of current employment.

To test whether task mismatch might explain the difference in the effect of postdoc training across sectors, we estimate a regression for all sectors as in Column (2) in Panel A of Table 4 but where we add 1) sector fixed effects to control for average salary differences between academia, industry, and gov't/nonprofits and 2) an interaction between the postdoc indicator and our measure of task mismatch/distance. The coefficient associated with postdoc training then represents the effect of postdoc training on salary if the tasks performed as part of that training are identical to those performed as part of future employment (i.e., where there is no task mismatch). The coefficient on the interaction between the postdoc indicator and task mismatch indicates the degree to which task mismatch drives heterogeneity in the returns to postdoc training across sectors; if task mismatch drives this heterogeneity, we would expect the effect of postdoc training in the absence of task mismatch to be positive and the interaction between postdoc training and task mismatch to be negative.[68]

Table 10 report our results. In column (1) of the "All Sectors" regression results, we find that postdoc-trained doctorates tend to earn 8.2% less than their nonpostdoc-trained counterparts after controlling for average differences across sectors but excluding measures of task distance from the specification. When we allow the impact of postdoc training to vary by task distance, we find that postdoc-trained biomedical doctorates who perform a set of tasks identical to those performed during postdoc training earn 9.0% more than their nonpostdoc-trained counterparts; however, this postdoc premium decreases as task mismatch increases such that it becomes negative given a sufficient level of task mismatch. Column (2) results for academia are qualitatively similar, while those for industry and government/nonprofits indicate that postdoc-trained biomedical doctorates

for one's own time spent on a task.

[67] Letting θ_{i1}^{j} and θ_{it}^{j} denote the share of time biomedical doctorate i spends performing task j as part of employment in their first six years post-PhD and as part of current employment, respectively, the degree of task mismatch (or task distance) between the two measures is calculated as

$$1 - \frac{\sum_{j=1}^{J}\left(\theta_{i1}^{j} * \theta_{it}^{j}\right)}{\left\{\left[\sum_{j=1}^{J}(\theta_{i1}^{j})^2\right] * \left[\sum_{j=1}^{J}(\theta_{it}^{j})^2\right]\right\}^{1/2}}.$$

[68] We would expect the coefficient on the postdoc indicator to be positive since we find positive returns to postdoc training in academic non-tenure-track research. We would then expect increases in task mismatch to push the returns to postdoctoral training in a negative direction to account for the negative or null effects estimated for other sectors and subsectors.

who perform a set of tasks identical to those performed during postdoc training are paid the same as their nonpostdoc-trained counterparts, but that task mismatch pushes the effect of postdoc training in a negative direction, yielding a postdoc salary penalty for the average postdoc-trained biomedical doctorate in industry as shown in column (1) of the industry results.

Next, we add the task distance measure itself—rather than just its interaction with the postdoc indicator—to the specification, the results of which appear as specification (3) in Table 10. In this specification, the coefficient on task distance shows the effect of task mismatch on nonpostdoc-trained biomedical doctorates while the coefficient on the interaction between task distance and the postdoc indicator tells us whether the effect of task distance varies by postdoc-trained status. The coefficient on the postdoc indicator then gives the residual difference in salary between postdoc-trained and nonpostdoc-trained biomedical doctorates, holding task distance constant. Column (3) for "All Sectors" indicates that task mismatch is associated with a decrease in salary—while the coefficient on the interaction between task distance and postdoc training is negative, it is statistically insignificant, suggesting that postdoc-trained and nonpostdoc-trained pay a similar salary penalty for task mismatch. We find that after controlling for task mismatch, there is no residual difference in salary between postdoc-trained and nonpostdoc-trained biomedical doctorates. Similarly, only the coefficient on task distance is significant and negative for academic jobs. For industry and government/nonprofits, it appears that task mismatch does not have a sizable effect on nonpostdoc-trained biomedical doctorates, but has a significant negative impact on postdoc-trained doctorates in particular, leaving no residual difference to be picked up by the postdoc indicator.

7 Exploring Alternative Mechanisms for the Industry Postdoc Salary Penalty

7.1 Compensating Differentials for Research and Other Job Tasks

Autor and Handel (2013) and Deming and Kahn (2018) find that job task requirements are predictive of worker wages even when controlling for education and occupation, and so it could be that industry salary differences between postdoc-trained and nonpostdoc-trained biomedical doctorates arise from differences in the types of job tasks performed as part of *current* (rather than past) employment. Previous research also finds that biomedical doctorates are willing to trade-off salary for the opportunity to participate in research: Stern (2004) finds that postdoctoral biologists pay a negative compensating differential to participate in science after their postdoc and Sauermann and Roach (2014) find that the PhD candidates most likely to pursue jobs in industrial R&D differ in the price that they are willing to pay to be allowed to publish. Table 5 shows that postdoc training enhances a biomedical doctorate's ability to obtain a research position in industry, and so one may wonder whether the industry postdoc salary penalty is explained by a greater willingness of postdocs to pay to do science.[69] However, in column (2) of Table 6 we find that postdoc-trained biomedical doctorates working in industry tended to earn less than their nonpostdoc-trained counterparts, regardless of whether their job was primarily focused on research or nonresearch tasks.[70] The lesser pay of postdoc-trained biomedical doctorates in industry jobs where research is the primary task suggests that a compensating differential does not explain the industry postdoc salary penalty.

However, industry-employed ex-postdocs might differ in terms of other job tasks that they perform on-the-job as part of current employment, or it might be that the type of research (i.e., basic, applied, development, or design) matters when trying to explain the industry postdoc salary penalty. Table 11 reports estimates of the industry postdoc salary penalty when controlling for alternative sets of indicator variables reporting whether or not a given task is performed 1) as the primary job task, 2) as the primary or secondary job task, or 3) for at least 10% of work time. as part of *current* employment.[71] As we can see, inclusion of mediating controls for current job tasks increases the magnitude of the estimated industry postdoc salary penalty, which suggests that differences in current job tasks do not explain the the postdoc salary penalty in industry.

7.2 Sorting by Occupation or Employer

Another possible explanation is that industry-employed biomedical doctorates with postdoc training tend to sort into different firms or occupations than biomedical doctorates without postdoc training. The SDR contains information on occupation, as well as a limited set of employer characteristics including size, location (state/country code), and type. We therefore estimate regressions where worker occupation, employer size, employer location, and employer type are included as controls.[72] Column ($2''$) of Table 12 reports the results.[73] As we can see, inclusion of these controls does not eliminate the industry postdoc salary penalty. While we find no evidence that employer

[69]However, these previous studies also provide rationale casting doubt on this mechanism as explaining pay disparity between doctorates. First, Stern (2004) notes that his finding a negative compensating differential to participate in science depends critically on the inclusion of individual fixed effects made possible by the structure of his survey data which include the observation of multiple job offers for each postdoc at a given point in time. Second, Sauermann and Roach (2014) note that the scientists who report being willing to pay the highest price to be able to publish in industry are scientists of perceived higher ability and from top-tier institutions, and so tend to be more expensive to hire even if publishing is allowed.

[70]Research jobs, as elsewhere, is defined as jobs where the primary task is either basic research, applied research, development, or design. The postdoc salary penalty in research-focused industry jobs is about half the size of that in nonresearch jobs, which makes sense as postdoc training is more heavily emphasizes research compared to nonresearch-based tasks.

[71]Each of the three sets consists of 14 indicator variables (i.e., one for each task).

[72]Employer types in the industry employment sector include the following: 1) Private-for-profit, 2) Self-employed, not incorporated, 3) Self-employed, incorporated, and 4) Other. See SDR survey questionnaire for list of occupation codes. We use occupation-by-year fixed effects to control for occupation as this both allows the impact of a given occupation to change over time and also is robust to changes in occupational codes in the SDR that have occurred over time.

[73]Column ($2'$) adds two indicator variables for the reported primary work activity of industry-employed biomedical PhDs—one for if the job is primarily research-focused and a second for if the job is primarily managerial/administrative—as controls to the regression specification, and are also included in columns ($2''$) and ($2'''$).

characteristics are a driver of the industry postdoc salary penalty, we cannot rule out this mechanism entirely as employer information in the SDR is limited, and so a linked employer-employee dataset of the doctoral workforce is necessary for a stronger test of this mechanism.[74]

7.3 Seniority Pay

Even if biomedical doctorates in industry with and without postdoc training sort into similar firms and occupations, those who forgo postdoc training to enter industry directly after graduation can build up seniority at the firm where they work, unlike their postdoc counterparts. The existence of a return to employer-specific seniority would mean that when postdoc-trained biomedical doctorates enter a firm, they will tend to be paid less than nonpostdoc-trained colleagues, even if they are otherwise identical in terms of skill.[75] In each SDR wave, respondents are asked if they have the same employer as in the last SDR wave. Using responses to these questions, we construct a variable that measures seniority (i.e., how many years an individual has been at their current employer as of the given year). We therefore augment the specification once more by including a quartic polynomial in seniority. Column ($2'''$) of Table 12 gives the results: we find that including seniority as a control in the regressions does not diminish the estimated postdoc penalty in industry. However, this exercise may be of limited value as the SDR does not have firm identifiers, and it is plausible that returns to seniority differ substantially across firms. Again, a linked employer-employee dataset of the doctoral workforce is necessary for a stronger test of this mechanism.

8 Conclusion

Using a Mincer specification that treats postdoc training as experience and controls for individual-level characteristics, a quartic polynomial in experience, PhD university (i.e., *alma mater*) fixed effects, and field-by-cohort fixed effects, we find that industry-employed biomedical doctorates with postdoc training earn 15.8% less in terms of inflation-adjusted annual salary compared to their nonpostdoc-trained counterparts. We find no evidence that this industry postdoc salary penalty is explained by selection on unobservable ability at time of PhD, differential sorting into firms and occupations, or compensating differentials for conducting research or other tasks as part of current employment. Instead, we find evidence consistent with a task-specific human capital model of wage determination where differences in salary between postdoc-trained and nonpostdoc-trained biomedical doctorates is the result of differences in the history of tasks performed as part of

[74] Davis et al. (2021) uses American Community Survey (ACS) and Longitudinal Employer-Household Dynamics (LEHD) data to create a new employer-employee linked dataset of the doctoral workforce. Davis et al. (2021) contains a preliminary analysis of the returns to postdoc training for biomedical doctorates and finds that the postdoc salary penalty for nonacademic jobs remains after including both firm fixed effects and occupation fixed effects, although the magnitude of the penalty is reduced relative to specifications not including these controls. Given the differences in the data sources, and thus samples, used in this paper and in Davis et al. (2021), the results are not directly comparable—see Davis et al. (2021) for a fuller discussion.

[75] Barth (1997) finds evidence of within-firm seniority pay not explained by firm-specific human capital accumulation using Norwegian microdata.

previous employment. First, we find substantial differences in the tasks emphasized as part postdoc training and industry employment: postdoc training is primarily focused on basic research, with little focus on development, design, management, professional services, and other tasks that are valued in industry employment. Second, inclusion of task history measures as mediating controls substantially reduces the magnitude of the estimated postdoc salary penalty in industry, rendering the estimate statistically insignificant. Third, those that participate in postdoc training the longest appear to suffer the largest postdoc salary penalty in industry, which is expected if differences in salary are largely due to postdocs deferring accrual of industry-relevant task-specific human capital while employed as a postdoc. In addition, we find that a task-based human capital model does well to explain the differences in estimated effects of postdoc training across sectors, which range from a positive postdoc premium of 15.9% in academic non-tenure-track research to a postdoc salary penalty (or negative premium) of 15.8% in industry.

A task-specific human capital explanation is also consistent with the views of those within the biomedical community who argue that postdoc training is specialized academic training,[76] and that, in lieu of the growing number of biomedical doctorates working outside academia, initiatives to broaden the types of training and career preparation available to postdocs is much needed. Towards this end, in 2013, the NIH initiated the Broadening Experiences in Scientific Training (BEST) grant aimed at supporting institutions seeking to provide biomedical doctorates with career development opportunities to facilitate an easier (and quicker) transition from postdoc employment to nonacademic jobs.[77] Programs designed to expose biomedical doctoral students to other career paths before graduation, such as research funding for graduate students that requires participation in a two to three month industrial internship, may better prepare biomedical doctorates for the road ahead.[78] Our results suggest that increasing the exposure of biomedical doctorates to skills valued in industry may be effective at lessening the postdoc salary penalty in industry.

[76] "The focus of young scientists on securing an academic research faculty position can lead them to overlook opportunities as independent researchers in other areas, such as in start-up and established industries, foundations, and government. Significantly, these opportunities may require training experience different from those associated with traditional academic careers. Yet too many postdoctoral researchers pursue training experiences with the objective of later securing an academic position, rather than enhancing their ability to compete for the range of fulfilling, independent careers that exist outside of academia, where the majority will be employed" (National Academies of Sciences, Engineering, and Medicine, 2018).

[77] For more information, see `https://commonfund.nih.gov/workforce`, Meyers et al. (2016), and Lenzi et al. (2020).

[78] As mentioned in National Academy of Sciences (2014), the National Institute of General Medical Sciences (NIGMS) biotechnology predoctoral training program requires recipients to participate in a two to three month industrial internship.

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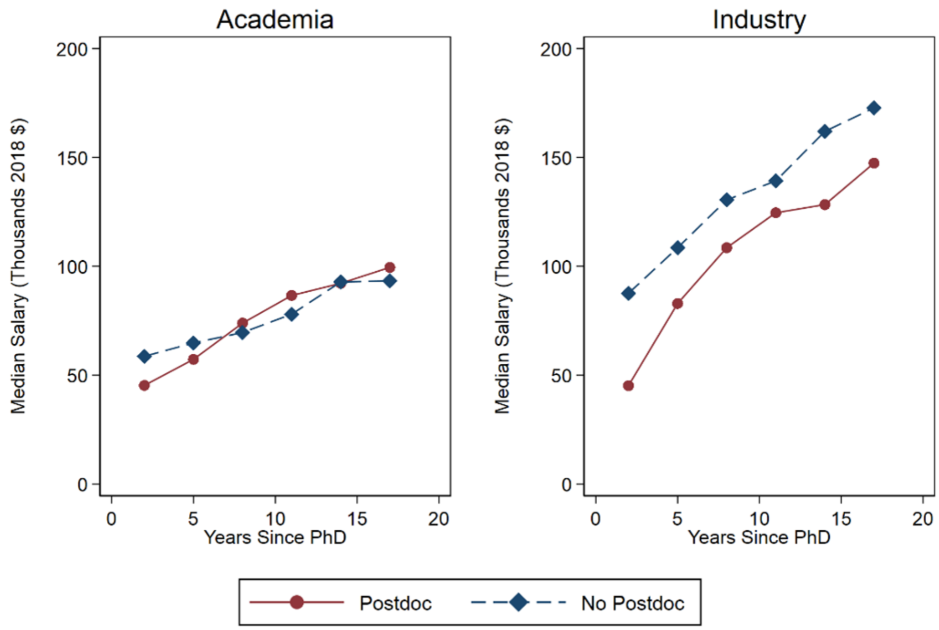
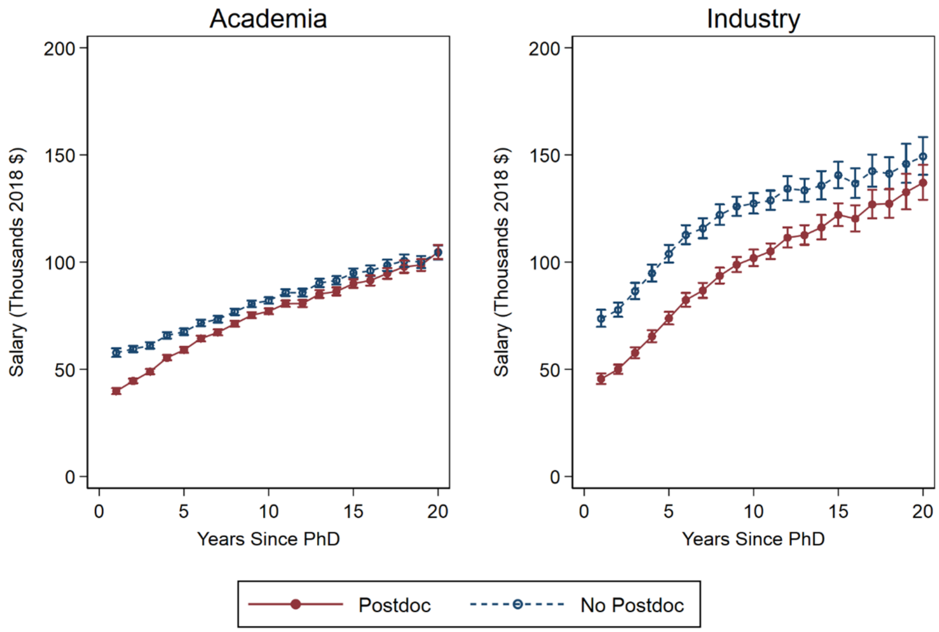
Figures

Figure 1: Median Salary of Biomedical Doctorates over Career by Prior Postdoc Status



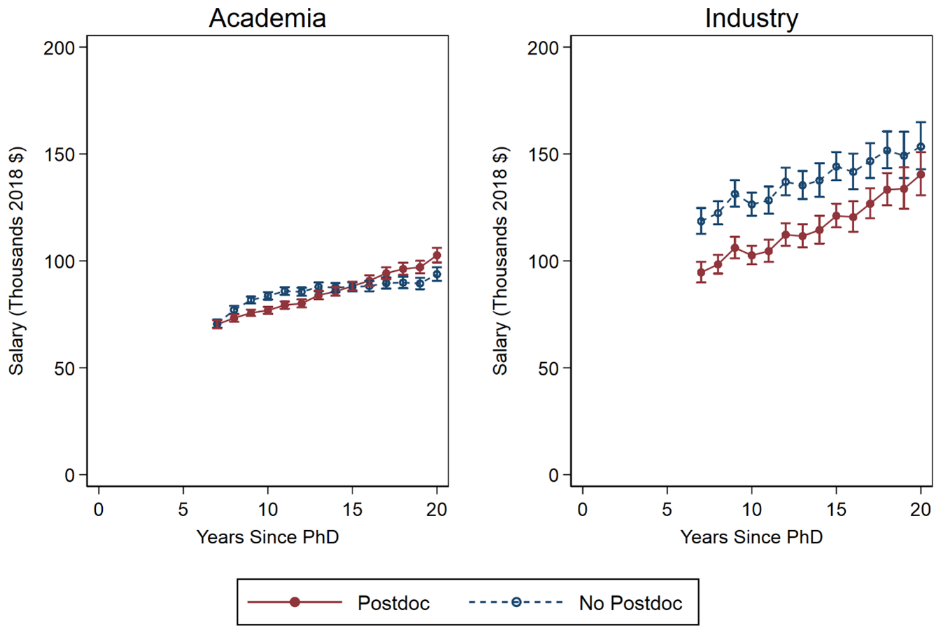
Notes: Figure 1 shows the median salary in each 3-year interval since PhD for biomedical doctorates first appearing in the SDR 1993, 1995, or 1997 waves and who graduated no earlier than 1990. Biomedical doctorates are associated with the employment sector (academia or industry) that they occupy at 10 years post-PhD. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure 2: Average Predicted Salary Over Career by Postdoc-Trained Status:
Postdoc Training as Experience, Postdoc Salary Observations Included



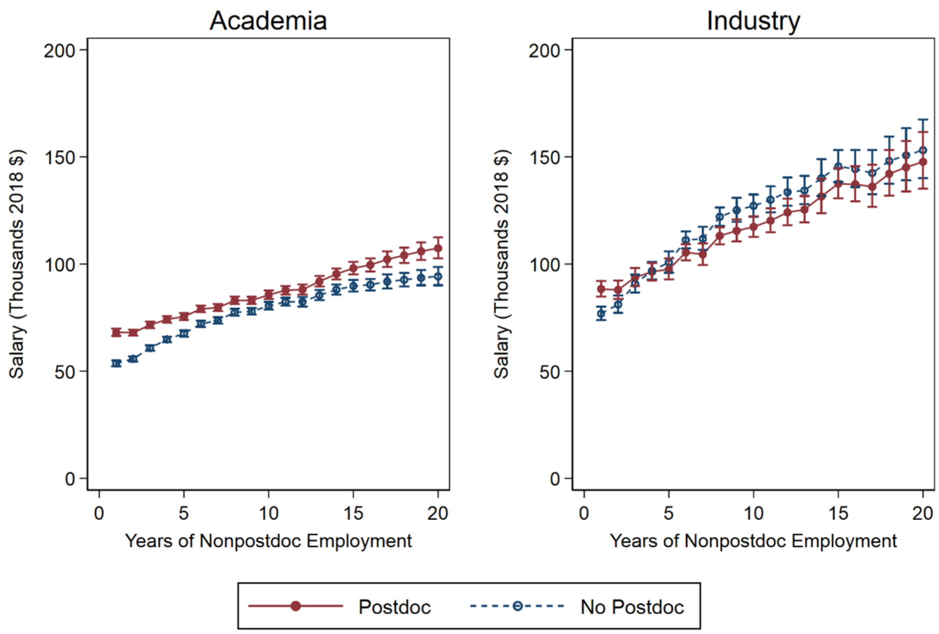
Notes: Figure 2 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the regression model found in Column (4) of Table 3 where we allow for interactions between the indicator variable for postdoc training and quartic polynomial in experience. The plots are generated by the following process: For each doctorate in the given employment sector sample, we generate two predictions of log(salary) in each year since PhD. The first prediction gives the log(salary) predicted if the person is assumed to have done a postdoc and the second prediction gives the log(salary) predicted if the person did not do a postdoc. Then, we average the predicted log(salary) across individuals in the given employment sector in each year since PhD and apply the exponential function to translate log(salary) into salary. We then plot these average predicted salary profiles in Figure 2. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure 3: Average Predicted After-Postdoc Salary Over Career by Postdoc-Trained Status: Postdoc Training as Experience, Postdoc Salary Observations Excluded



Notes: Figure 3 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the regression model found in Column (4) of Table 4 where we allow for interactions between the indicator variable for postdoc training and quartic polynomial in experience. The plots are generated by the following process: For each doctorate in the given employment sector sample, we generate two predictions of log(salary) in each year since PhD. The first prediction gives the log(salary) predicted if the person is assumed to have done a postdoc and the second prediction gives the log(salary) predicted if the person did not do a postdoc. Then, we average the predicted log(salary) across individuals in the given employment sector in each year since PhD and apply the exponential function to translate log(salary) into salary. We then plot these average predicted salary profiles in Figure 3. The employment sector subsamples are based on each doctorate's sector of employment in the given year, rather than the sector of employment at ten years post-PhD, in the underlying regression models used to generate the predictions Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure 4: Average Predicted After-Postdoc Salary Over Career by Postdoc-Trained Status: Postdoc Training as Schooling, Postdoc Salary Observations Excluded



Notes: Figure 4 shows the average of predicted salary profiles for biomedical doctorates with and without postdoc training generated by an augmented version of the regression model found in Column (4) of Table 4 where we allow for interactions between the indicator variable for postdoc training and quartic polynomial in experience. The plots are generated by the following process: For each doctorate in the given employment sector sample, we generate two predictions of log(salary) in each year since PhD. The first prediction gives the log(salary) predicted if the person is assumed to have done a postdoc and the second prediction gives the log(salary) predicted if the person did not do a postdoc. Then, we average the predicted log(salary) across individuals in the given employment sector in each year since PhD and apply the exponential function to translate log(salary) into salary. We then plot these average predicted salary profiles in Figure 4. The employment sector subsamples are based on each doctorate's sector of employment in the given year, rather than the sector of employment at ten years post-PhD, in the underlying regression models used to generate the predictions. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Tables

Table 1: Analytical Sample Observations by Employment Sector

Employment Sector	In Sector at 10 years post-PhD			In Sector in Year of Observation*		
	Postdoc	Non-Postdoc	Total	Postdoc	Non-Postdoc	Total
All Sectors	21604 (3420)	7984 (1358)	29598 (4778)	16325 (3420)	6187 (1358)	22512 (4778)
Academia	12463 (1961)	3604 (593)	16067 (2554)	9221 (2192)	2720 (674)	11941 (2866)
TT Research	5092 (789)	529 (81)	5621 (870)	3630 (1111)	366 (132)	3996 (1243)
Non-TT Research	2422 (395)	494 (80)	2916 (475)	1625 (675)	363 (146)	1988 (821)
Nonresearch	4949 (777)	2581 (432)	7530 (1209)	3966 (1321)	1991 (577)	5957 (1898)
Industry	5964 (961)	2835 (507)	8799 (1468)	4519 (1193)	2189 (593)	6708 (1786)
Research	3179 (521)	1121 (188)	4300 (709)	2260 (805)	857 (292)	3117 (1097)
Nonresearch	2785 (440)	1714 (319)	4499 (759)	2259 (820)	1332 (474)	3591 (1294)
Gov't/Nonprofits	3187 (498)	1545 (258)	4732 (756)	2582 (809)	1278 (360)	3863 (1169)

Notes: This table lists the number of observations and (unique individuals) in each employment sector for the analytical sample by whether each observation is associated with a biomedical doctorate with postdoctoral training.
* = excludes observations for years when employed as a postdoc. Since a single worker may show up in different sectors at different times, the sum of the person counts associated with the last three columns exceed the total number of persons included in the analytical sample.

Table 2: Summary Statistics by Postdoc-Trained Status: Academia and Industry

Employment Sector:	Academia		Industry	
Group:	Postdoc	Nonpostdoc	Postdoc	Nonpostdoc
Foreign-born	0.25	0.17	0.27	0.22
Temp. Resident	0.13	0.06	0.14	0.09
Age at PhD	30.53	33.19	30.26	31.55
Female	0.39	0.40	0.39	0.36
Asian	0.17	0.10	0.21	0.17
Minority	0.08	0.09	0.06	0.11
PhD Length	6.77	7.97	6.57	7.45
Married at PhD	0.55	0.66	0.53	0.60
Child at PhD	0.32	0.47	0.28	0.41
Fellowship during PhD	0.17	0.17	0.15	0.15
RA during PhD	0.30	0.21	0.33	0.27
TA during PhD	0.12	0.16	0.11	0.10
Mother's Highest Education: BA	0.22	0.19	0.22	0.20
Mother's Highest Education: $>$ BA	0.20	0.16	0.18	0.18
Father's Highest Education: BA	0.24	0.20	0.22	0.21
Father's Highest Education: $>$ BA	0.34	0.30	0.32	0.30
N	2192	674	1193	593

Notes: This table reports weighted means for postdoc-trained and nonpostdoc-trained biomedical doctorates in the analytical sample by employment sector, where the weights used for each doctorate are those from the most recent SDR wave wherein each doctorate is observed. Sample counts are unweighted. For each cell, approximately 10% of PhD length calculations were imputed at the mean value (seven years) for the analytical sample. Individuals who work in both industry and a nonpostdoc job in academia are included in both subsamples to be consistent with the samples underlying the results in Table 4. Summary statistics for the full sample and "Gov't/Nonprofit" sector are reported in Table A.3.

Table 3: Impact of Postdoc Training on Salary

Dependent Variable: log(salary)	(1)	(2)
Panel A. All Sectors	$N = 29598$	
Postdoc Training	-0.115***	-0.138***
	(0.0202)	(0.0201)
R^2	0.181	0.272
Panel B. Academia	$N = 16067$	
Postdoc Training	-0.0201	-0.0602**
	(0.0256)	(0.0277)
R^2	0.232	0.363
Panel C. Industry	$N = 8799$	
Postdoc Training	-0.138***	-0.213***
	(0.0377)	(0.0376)
R^2	0.176	0.381
Panel D. Gov't/Nonprofit	$N = 4732$	
Postdoc Training	-0.135***	0.00392
	(0.0404)	(0.0542)
R^2	0.201	0.409
Postdoc Training Treated As:		
Experience	✓	✓
Schooling		
Fixed Effects		
Field + Cohort + Year	✓	
Field-Cohort + PhD University + Year		✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1980 and 2007. We include all person-year observations, including those associated with years when a doctorate is employed as a postdoc. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates. Subsamples are based on the employment sector of the biomedical doctorate at ten years after PhD graduation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) and (2) include all controls listed in Table A.2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of Postdoc Training on After-Postdoc Salary

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)
Panel A. All Sectors	N = 22512		N = 26312	
Postdoc Training	-0.0842***	-0.117***	0.0253	0.000956
	(0.0236)	(0.0235)	(0.0209)	(0.0210)
R^2	0.130	0.246	0.143	0.244
Panel B. Academia	N = 11941		N = 13947	
Postdoc Training	0.0318	-0.00836	0.126***	0.0983***
	(0.0307)	(0.0337)	(0.0270)	(0.0294)
R^2	0.159	0.314	0.159	0.301
Panel C. Industry	N = 6708		N = 7898	
Postdoc Training	-0.103**	-0.158***	-0.0102	-0.0450
	(0.0423)	(0.0410)	(0.0380)	(0.0385)
R^2	0.132	0.400	0.141	0.376
Panel D. Gov't/Nonprofit	N = 3863		N = 4467	
Postdoc Training	-0.0867**	-0.106**	0.0318	0.0177
	(0.0349)	(0.0450)	(0.0322)	(0.0396)
R^2	0.201	0.540	0.224	0.528
Postdoc Training Treated As:				
Experience	✓	✓		
Schooling			✓	✓
Fixed Effects				
Field + Cohort + Year	✓		✓	
Field-Cohort + PhD University + Year		✓		✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1980 and 2006. For each doctorate, we keep only those person-year observations corresponding to years after any and all years employed as a postdoc. When postdoc training is treated as experience, experience is defined as years since PhD graduation for all biomedical doctorates. When postdoctoral training is treated as schooling, experience is instead defined as years of nonpostdoc employment—for postdoc-trained biomedical doctorates, this reflects the number of years since exiting one's (last) postdoc position, while for nonpostdoc-trained biomedical doctorates, this reflects the number of years since PhD gradation (as before). For specifications (1) and (2), we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. In specifications (3) and (4), we do not remove observations corresponding to the first six years post-PhD for nonpostdoc-trained biomedical doctorates as there is a sufficient number of postdoc observations with experience less than seven years when experience is defined so that postdoc training is treated as schooling. Subsamples are based on the employment sector associated with each person-year observation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) - (4) include all controls listed in Table A.2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Impact of Postdoc Training on Securing Job Type

	Any	Academic	Tenure-Track	Tenured	Industry
Panel A. Any Job					
Postdoc Training	···	0.169***	0.167***	-0.0149	···
	···	(0.0206)	(0.0198)	(0.0526)	···
R^2	···	0.249	0.267	0.459	···
N	···	4778	4778	1583	···
Panel B. Research Job					
Postdoc Training	0.242***	0.265***	0.213***	-0.0634	0.123***
	(0.0198)	(0.0193)	(0.0147)	(0.168)	(0.0435)
R^2	0.296	0.269	0.263	0.680	0.492
N	4778	4778	4778	798	1786
Fixed Effects					
Field-Cohort	✓	✓	✓	✓	✓
PhD University	✓	✓	✓	✓	✓

Notes: This table reports regressions results where the dependent variable for each column is an indicator variable for the type of job given by the column name. Observations are person-level. The samples used for the "Academic" and "Tenure-Track" columns include biomedical doctorates in the SDR graduating between 1980 and 2007 for whom we have observed for at least 10 years post-PhD. The sample used for the "Tenured" column includes biomedical doctorates in the SDR graduating between 1980 and 2006 who report being on the tenure track at some point and then later report either 1) being in a tenured position or 2) not in a tenured position and no longer on the tenure track. The sample used for the "Industry" column includes biomedical doctorates in the SDR graduating in or after 1980 who ever report working in industry. For each column, Panel B adds an additional restriction that the type of job be one where the doctorate's primary work activity is R&D in order for the indicator variable to equal 1. Robust standard errors clustered at the field-cohort level are in parentheses. Specifications (1) - (4) include all controls listed in Table A.2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Impact of Postdoc Training on After-Postdoc Salary by Employment Subsector

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)
Panel A. Academic TT Research	$N = 3996$		$N = 4394$	
Postdoc Training	-0.0941*	-0.174***	0.00601	-0.0500
	(0.0495)	(0.0557)	(0.0455)	(0.0533)
R^2	0.168	0.349	0.169	0.349
Panel B. Academic NonTT Research	$N = 1988$		$N = 2408$	
Postdoc Training	-0.0244	0.159**	0.115**	0.232***
	(0.0584)	(0.0788)	(0.0541)	(0.0678)
R^2	0.189	0.531	0.165	0.498
Panel C. Academic Nonresearch	$N = 5957$		$N = 7145$	
Postdoc Training	0.00369	-0.0416	0.0812**	0.0481
	(0.0396)	(0.0476)	(0.0346)	(0.0397)
R^2	0.189	0.453	0.174	0.419
Panel D. Industry Research	$N = 3117$		$N = 3801$	
Postdoc Training	-0.00865	-0.0832*	0.0714*	0.0162
	(0.0490)	(0.0446)	(0.0430)	(0.0440)
R^2	0.138	0.482	0.149	0.453
Panel E. Industry Nonresearch	$N = 3591$		$N = 4097$	
Postdoc Training	-0.160***	-0.155***	-0.0701	-0.0707
	(0.0570)	(0.0762)	(0.0520)	(0.0722)
R^2	0.177	0.499	0.180	0.473
Postdoc Training Treated As:				
Experience	✓	✓		
Schooling			✓	✓
Fixed Effects				
Field + Cohort + Year	✓		✓	
Field-Cohort + PhD University + Year		✓		✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1980 and 2006. For each doctorate, we keep only those person-year observations corresponding to years after any and all years employed as a postdoc. When postdoc training is treated as experience, experience is defined as years since PhD graduation for all biomedical doctorates. When postdoctoral training is treated as schooling, experience is instead defined as years of nonpostdoc employment—for postdoc-trained biomedical doctorates, this reflects the number of years since exiting one's (last) postdoc position, while for nonpostdoc-trained biomedical doctorates, this reflects the number of years since PhD gradation (as before). For specifications (1) and (2), we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. In specifications (3) and (4), we do not remove observations corresponding to the first six years post-PhD for nonpostdoc-trained biomedical doctorates as there is a sufficient number of postdoc observations with experience less than seven years when experience is defined so that postdoc training is treated as schooling. Subsamples are based on the employment subsector associated with each person-year observation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) - (4) include all controls listed in Table A.2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Primary Tasks Performed by Doctorates Before and After the First Six Years Post-PhD by Postdoc-Trained Status

Employment Sector:	**Academia**				**Industry**				**Gov't/Nonprofits**			
Period (Years Post-PhD):	**First Six Years**		**After Six Years**		**First Six Years**		**After Six Years**		**First Six Years**		**After Six Years**	
Work Activity	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc
Acct., Finance, and Contracts	NA	NA	NA	1.50%	NA	NA	4.21%	4.21%	NA	NA	NA	3.91%
Applied Research	17.65%	21.58%	20.45%	22.28%	45.98%	28.86%	40.23%	52.91%	40.58%	28.52%	47.83%	41.02%
Basic Research	14.85%	79.32%	18.21%	64.34%	5.75%	75.15%	4.21%	10.22%	9.42%	75.00%	15.22%	40.63%
Computer Applications	NA	NA	NA	1.20%	6.90%	2.00%	7.28%	6.21%	NA	NA	NA	NA
Development	NA	NA	NA	1.70%	18.39%	NA	27.59%	25.85%	NA	NA	10.14%	8.59%
Design	NA	NA	NA	NA	NA	NA	NA	4.61%	NA	NA	NA	NA
Human Resources	NA	NA	3.36%	1.00%	NA	NA	NA	NA	NA	NA	NA	NA
Managing People or Projects	8.40%	1.20%	21.29%	23.48%	19.16%	NA	38.70%	37.27%	23.19%	NA	49.28%	40.23%
Production, Operations, Maint.	NA	NA	NA	NA	NA	NA	NA	3.81%	NA	NA	NA	NA
Quality or Productivity Mgmt.	NA	NA	NA	NA	NA	NA	4.60%	5.81%	NA	NA	NA	NA
Sales, Purchasing, Marketing	NA	NA	NA	NA	4.98%	NA	8.05%	8.82%	NA	NA	NA	NA
Professional Services	13.73%	5.00%	13.45%	6.49%	24.90%	4.21%	31.80%	20.64%	25.36%	5.86%	23.19%	15.23%
Teaching	62.18%	4.30%	64.43%	33.67%	NA	NA	NA	NA	NA	NA	NA	NA
Other	3.08%	1.30%	7.56%	3.70%	7.28%	NA	10.34%	9.02%	15.22%	NA	15.22%	17.58%
N	357	1001	357	1001	261	499	261	499	138	256	138	256

Notes: In this table, we calculate the proportion of postdoc-trained and non-postdoc trained biomedical doctorates that report each given task as their primary work activity at least once 1) in their first six years post-PhD and 2) after their first six years post-PhD. We restrict the sample to biomedical doctorates that are employed in each employment sector at 10 years post-PhD and for whom we observe at least two times in their first six years post-PhD. For postdocs, we only consider observations in the first six years post-PhD that correspond to years employed as a postdoc; after six years post-PhD, we only consider observations corresponding to years after any and all years employed as a postdoc, and where the doctorate is employed in the given employment sector. For nonpostdocs, we only consider observations corresponding to years where the person is employed in the given employment sector. "NA" reported in cells of insufficient size to be disclosed. N reports person counts.

Table 8: Tasks Performed by Doctorates Working in Industry Before and After the First Six Years Post-PhD by Postdoc-Trained Status

Employment Sector:	**Industry**					
Period (Years Post-PhD):	**First Six Years**		**After Six Years**		**Task Change**	
Work Activity	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc
Accounting, Finance, and Contracts	22.61%	2.61%	47.13%	39.68%	24.52	37.07
Applied Research	67.82%	73.95%	72.03%	78.76%	4.21	4.81
Basic Research	33.33%	90.98%	37.93%	53.31%	4.60	-37.68
Computer Applications	32.95%	28.66%	28.35%	30.66%	-4.60	2.00
Development	55.56%	21.64%	65.13%	69.94%	9.58	48.30
Design	33.72%	18.64%	38.31%	48.30%	4.60	29.66
Human Resources	44.83%	23.25%	53.26%	51.10%	8.43	27.86
Managing People or Projects	72.41%	40.68%	85.06%	85.17%	12.64	44.49
Production, Operations, Maintenance	11.11%	7.01%	14.94%	30.06%	3.83	23.05
Quality or Productivity Management	29.12%	5.61%	39.85%	42.08%	10.73	36.47
Sales, Purchasing, Marketing	26.44%	4.01%	38.70%	35.67%	12.26	31.66
Professional Services	37.16%	8.82%	47.51%	35.67%	10.34	26.85
Teaching	21.07%	19.64%	25.29%	27.86%	4.21	8.22
Other	12.26%	3.61%	21.46%	21.24%	9.20	17.64
N	261	499	261	499	261	499

Notes: In this table, we calculate the proportion of postdoc-trained and non-postdoc trained biomedical doctorates that report spending at least 10% of their work time engaged in the given activity at least once 1) in their first six years post-PhD and 2) after their first six years post-PhD. We restrict the sample to biomedical doctorates that are employed in industry at 10 years post-PhD and for whom we observe at least two times in their first six years post-PhD. For both postdoc-trained and nonpostdoc-trained biomedical doctorates, we then report the percentage-point difference between the fraction of each performing each task within and after their first six years post-PhD, and refer to this measure as the "task change" of each group. For postdocs, we only consider observations in the first six years post-PhD that correspond to years employed as a postdoc; after six years post-PhD, we only consider observations corresponding to years after any and all years employed as a postdoc, and where the doctorate is employed in industry. For nonpostdocs, we only consider observations corresponding to years where the person is employed in industry.

Table 9: Adding Task History Controls

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Employment Sector: Industry				$N = 3104$		
Postdoc Training	-0.228***	-0.126*	-0.112*	-0.130**	-0.0917	-0.0781
	(0.0634)	(0.0666)	(0.0633)	(0.0629)	(0.0641)	(0.0664)
R^2	0.498	0.518	0.527	0.524	0.536	0.537
Postdoc Training Treated As:						
Experience	✓	✓	✓	✓	✓	✓
Schooling						
Task History Controls						
Primary Activity		✓				✓
Primary or Secondary Activity			✓		✓	
Activity $\geq$ 10% of Work Time				✓	✓	✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1993 and 2006 who are observed in at least two of their first six years post-PhD. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates. For each doctorate, we keep only those person-year observations corresponding to years after any and all years employed as a postdoc, and we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. Subsamples are based on the employment sector associated with each person-year observation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) - (6) include all controls listed in Table A.2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of Task Mismatch on Postdoc Salary Premia

Sector:	All Sectors			Academia		
Dependent Variable: log(salary)	(1)	(2)	(3)	(1)	(2)	(3)
Postdoc Training	-0.0815***	0.0898***	-0.0194	-0.0185	0.102**	-0.0453
	(0.0313)	(0.0339)	(0.0497)	(0.0415)	(0.0447)	(0.0569)
Postdoc Training * Task Distance		-0.467***	-0.163		-0.369***	-0.435***
		(0.0509)	(0.120)		(0.0671)	(0.113)
Task Distance			-0.309***			0.0581
			(0.109)			(0.126)
R^2	0.323	0.336	0.338	0.422	0.430	0.433
N	10215	10215	10215	5442	5442	5442
Postdoc Training Treated As:						
Experience	✓	✓	✓	✓	✓	✓
Schooling						

Sector:	Industry			Gov't/Nonprofit		
Dependent Variable: log(salary)	(1)	(2)	(3)	(1)	(2)	(3)
Postdoc Training	-0.228***	-0.00708	-0.0290	-0.103	-0.00235	0.00314
	(0.0634)	(0.0709)	(0.111)	(0.0789)	(0.0830)	(0.110)
Postdoc Training * Task Distance		-0.515***	-0.459*		-0.343***	0.0140
		(0.107)	(0.246)		(0.123)	(0.165)
Task Distance			-0.0577			-0.357*
			(0.226)			(0.200)
R^2	0.498	0.508	0.508	0.703	0.707	0.707
N	3104	3104	3104	1669	1669	1669
Postdoc Training Treated As:						
Experience	✓	✓	✓	✓	✓	✓
Schooling						

Notes: For "All Sectors" regressions, we include sector fixed effects to control for average salary differences between academia, industry, and gov't/nonprofits. This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1993 and 2006 who are observed in at least two of their first six years post-PhD. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates. For each doctorate, we keep only those person-year observations corresponding to years after any and all years employed as a postdoc, and we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. Subsamples are based on the employment sector associated with each person-year observation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications include all controls listed in Table A.2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Adding Current Job Tasks as Controls

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Employment Sector: Industry			$N = 6708$			
Postdoc Training	-0.158***	-0.171***	-0.167***	-0.179***	-0.170***	-0.174***
	(0.0410)	(0.0407)	(0.0402)	(0.0398)	(0.0396)	(0.0397)
R^2	0.400	0.419	0.422	0.421	0.428	0.431
Postdoc Training Treated As:						
Experience	✓	✓	✓	✓	✓	✓
Schooling						
Current Job Task Controls						
Primary Activity		✓				✓
Primary or Secondary Activity			✓		✓	
Activity $\geq$ 10% of Work Time				✓	✓	✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1993 and 2006 who are observed in at least two of their first six years post-PhD. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates. For each doctorate, we keep only those person-year observations corresponding to years after any and all years employed as a postdoc, and we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. Subsamples are based on the employment sector associated with each person-year observation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) - (6) include all controls listed in Table A.2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Impact of Postdoc Training on After-Postdoc Salary when Including Possible Mechanisms as Controls

Dependent Variable: log(salary)	(2)	(2′)	(2′′)	(2′′′)
Panel A. All Sectors	$N = 22512$		$N = 21339$	
Postdoc Training	-0.117***	-0.141***	-0.0941***	-0.0895***
	(0.0235)	(0.0236)	(0.0206)	(0.0207)
R^2	0.246	0.258	0.397	0.399
Panel B. Academia	$N = 11941$		$N = 11272$	
Postdoc Training	-0.00836	-0.0533	-0.0554*	-0.0488*
	(0.0337)	(0.0335)	(0.0295)	(0.0292)
R^2	0.314	0.331	0.432	0.436
Panel C. Industry	$N = 6708$		$N = 6392$	
Postdoc Training	-0.158***	-0.180***	-0.193***	-0.190***
	(0.0410)	(0.0426)	(0.0400)	(0.0402)
R^2	0.400	0.403	0.522	0.522
Panel D. Gov't/Nonprofit	$N = 3863$		$N = 3675$	
Postdoc Training	-0.106**	-0.108**	-0.0819	-0.0811
	(0.0450)	(0.0453)	(0.0547)	(0.0549)
R^2	0.540	0.541	0.625	0.625
Postdoc Training Treated As:				
Experience	✓	✓	✓	✓
Schooling				
Controls				
Baseline	✓	✓	✓	✓
Research and Management Job indicators		✓	✓	✓
Firm Characteristics & Occupation FE			✓	✓
Seniority				✓

Notes: See notes for Table 4. Here we add controls for potential mechanisms that could drive the relationship between postdoc training and after-postdoc salary. All specifications include field-cohort fixed effects, year fixed effects, and PhD university fixed effects. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

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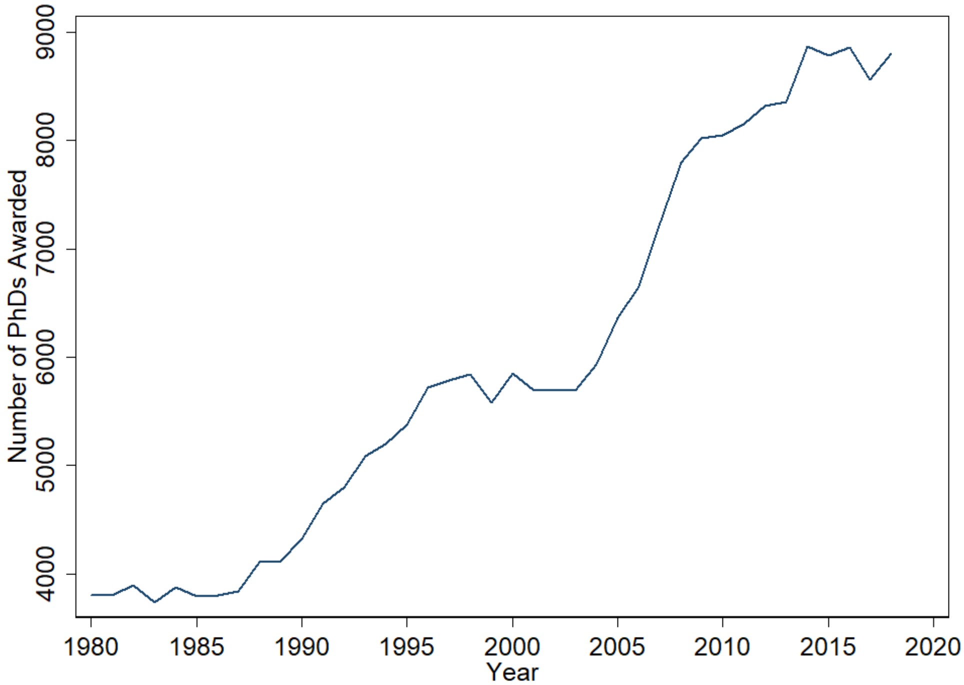
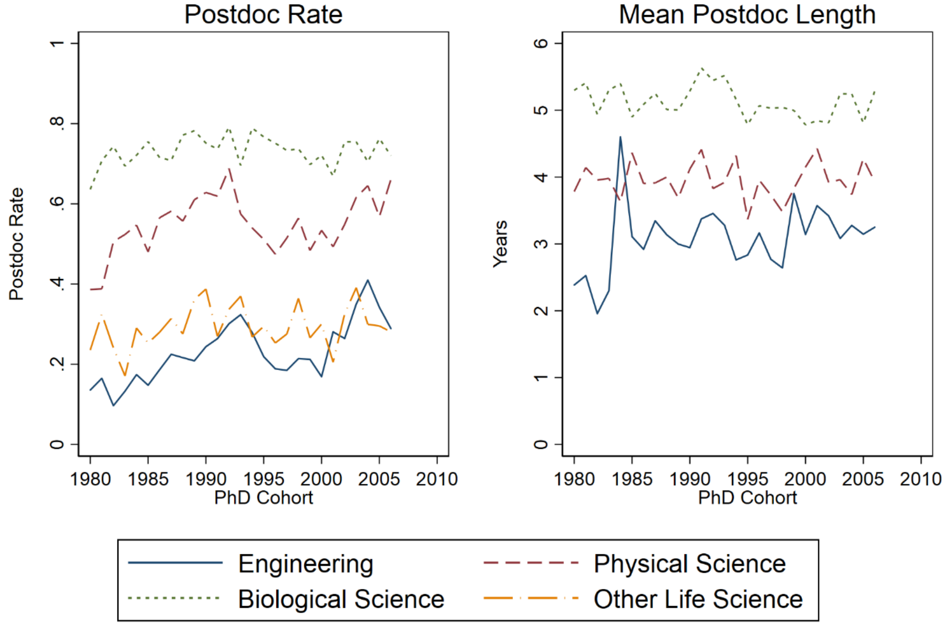
A Appendix Figures and Tables

Figure A.1: Number of PhDs Awarded in Biomedical Fields by Year



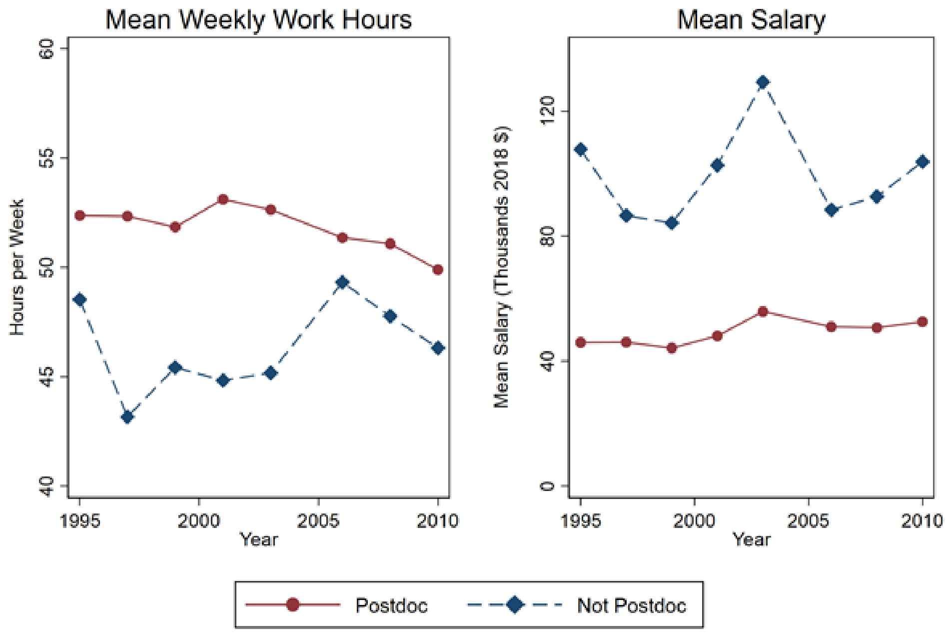
Notes: Figure A.1 shows the number of PhDs awarded in Biological and Biomedical Sciences in each year. Data is from the NSF's Survey of Earned Doctorates (SED).

Figure A.2: Postdoc Rate and Length by S&E Field



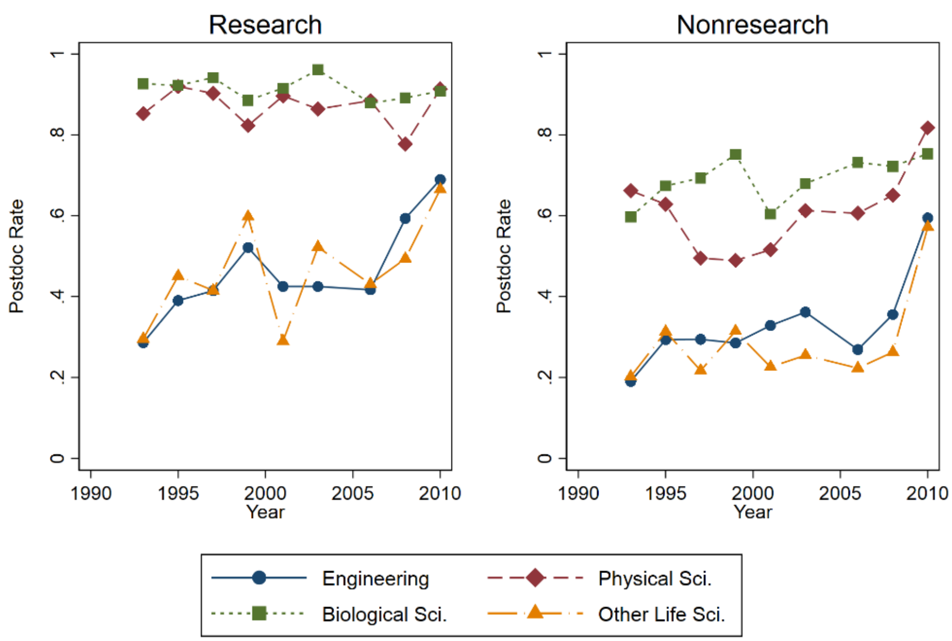
Notes: The left panel of Figure A.2 shows the proportion of doctorates in each PhD cohort that ever take a postdoc by broad field of study. The right panel show the mean length of postdoc training for all postdoc-trained PhD cohort members by broad field of study. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure A.3: Work Hours and Pay by Postdoc Employment Status



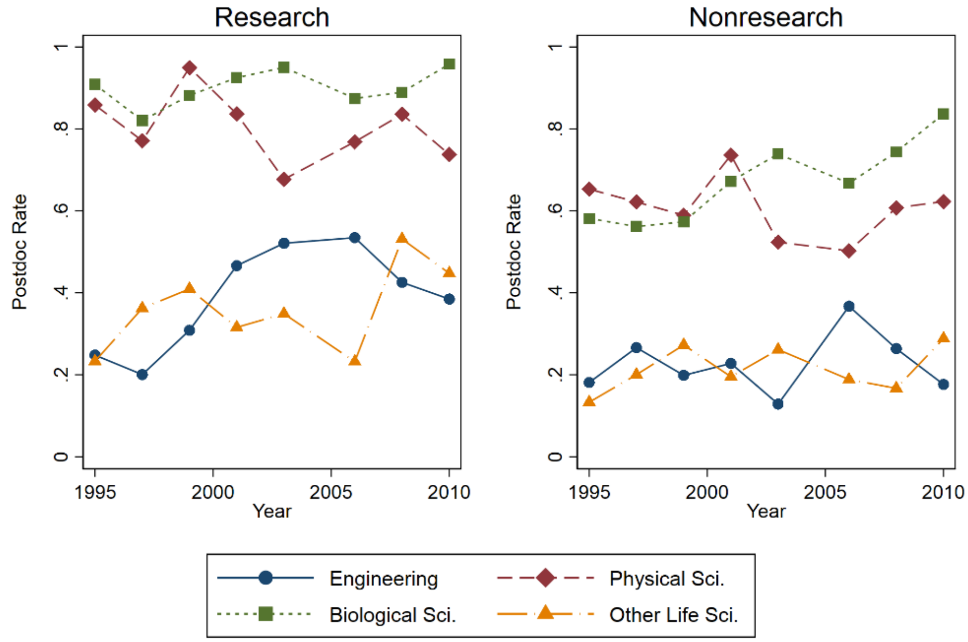
Notes: Figure A.3 shows the average work hours and salary for biomedical doctorates age 28-32 employed as postdocs in the given year compared to biomedical doctorates of the same age employed in industry in the same year. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure A.4: Postdoc Rate of New Tenure-Track Faculty by S&E Field



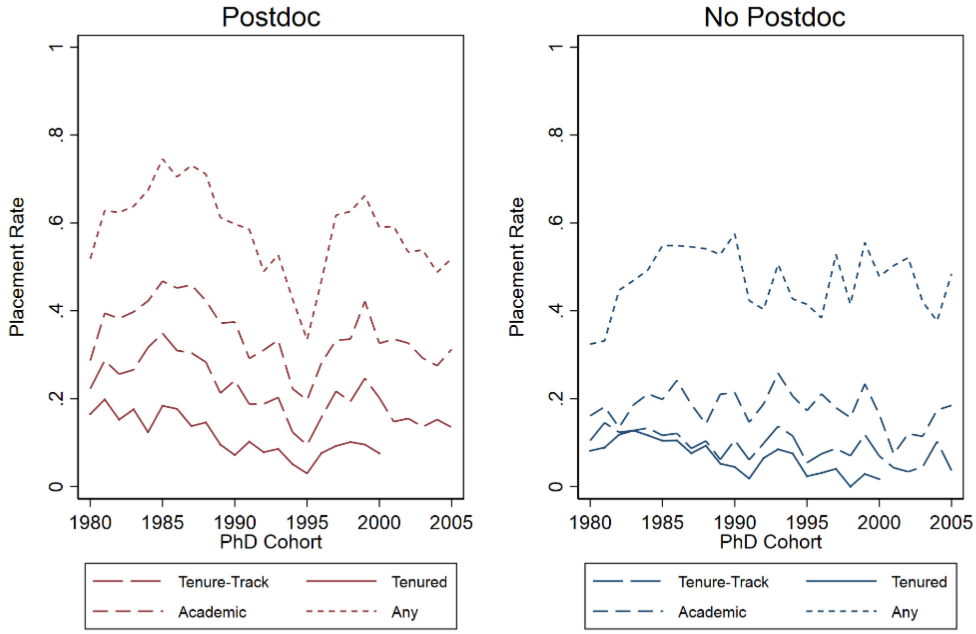
Notes: Figure A.4 shows proportion of individuals that first report being employed in a tenure-track position in a given SDR wave by broad field of study. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure A.5: Postdoc Rate of Newly Tenured Faculty by S&E Field



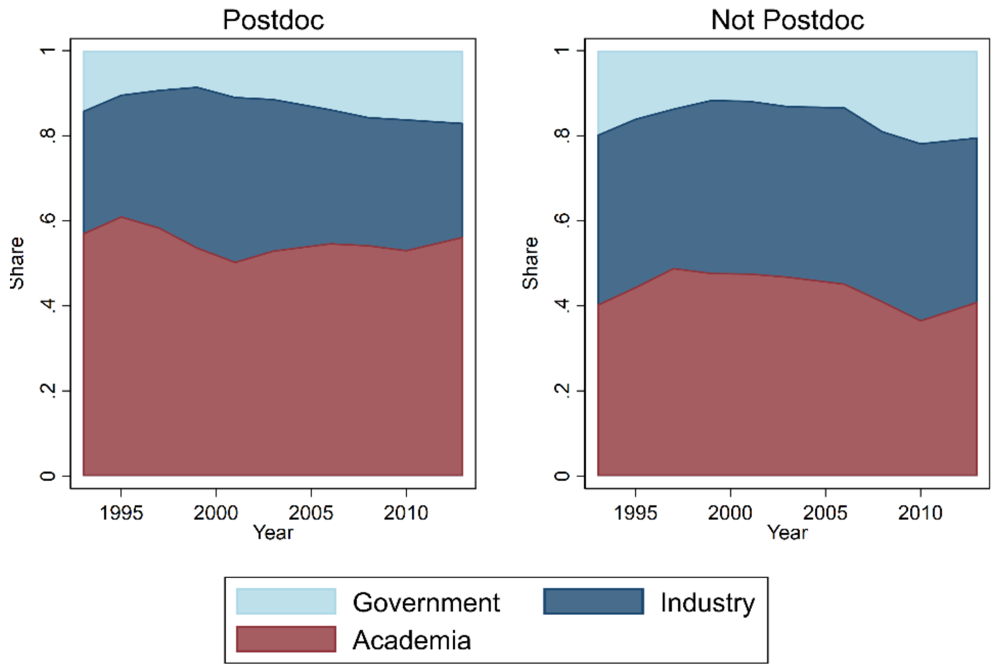
Notes: Figure A.5 shows proportion of individuals that first report being employed in a tenured position in a given SDR wave by broad field of study. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure A.6: Research Job Placement Rates by Prior Postdoc Status



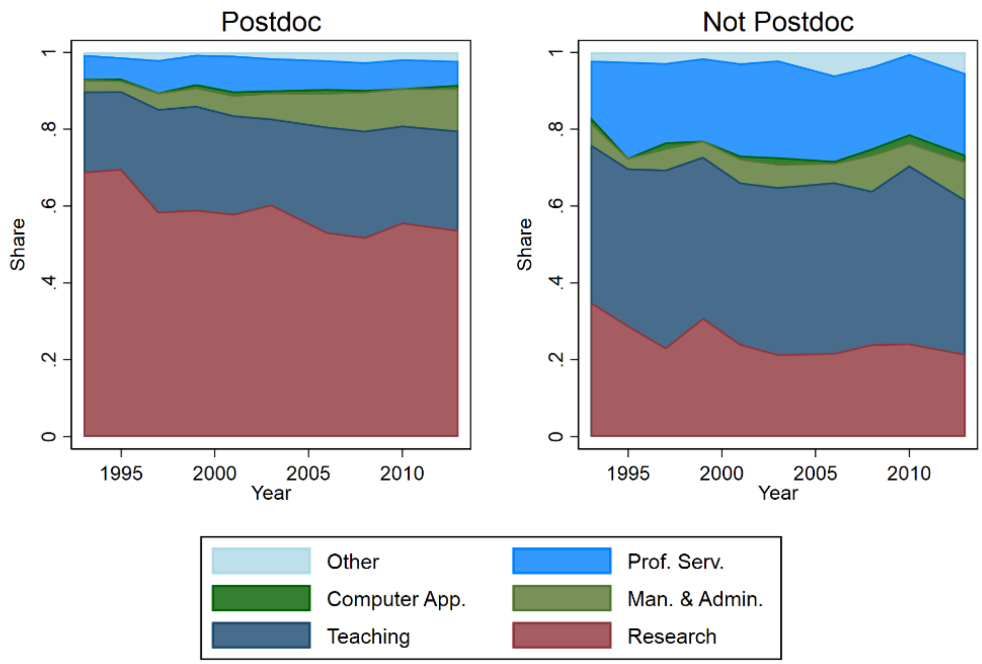
Notes: Figure A.6 shows proportion of biomedical doctorates who take the indicated academic research position (excluding postdoc positions) within 15 years post-PhD by PhD cohort and whether individual has postdoc training. We require that we observe an individual for the full 15 years post-PhD for "Tenured" calculations, but only require at least 10 years of observations for the other positions since these positions typically take less time to obtain relative to a tenured position. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure A.7: Share of Biomedical Doctorates Working in Each Employment Sector



Notes: Figure A.7 shows the share of biomedical doctorates age 30 to 40 working in each employment sector by year and whether they have previous postdoc training; those employed as postdocs in the given year are excluded. "Government" sector includes both government and nonprofits. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure A.8: Share of Biomedical Doctorates in Academia by Primary Work Activity



Notes: Figure A.8 shows the share of academia-employed biomedical doctorates age 30 to 40 in different reported primary job tasks by year and whether they have postdoc training; those employed as postdocs in the given year are excluded. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Table A.1: Biomedical SED Fine Fields of Study in Analytical Sample

SED Fine Field of Study	Year field first appears in SED
Anatomy	Before 1980
Bacteriology	1983
Biochemistry	Before 1980
Biology/Biomedical Sciences, General	Before 1980
Biology/Biomedical Sciences, Other	Before 1980
Biomedical Sciences	1995
Biometrics & Biostatistics	Before 1980
Biophysics	Before 1980
Biotechnology & Bioinformatics	1993
Botany/Plant Biology	Before 1980
Cell/Cellular Biology & Histology	Before 1980
Developmental Biology/Embryology	Before 1980
Ecology	Before 1980
Endocrinology	1983
Entomology	Before 1980
Evolutionary Biology	2007
Genetics/Genomics, Human & Animal	Before 1980
Immunology	Before 1980
Microbiology	Before 1980
Molecular Biology	Before 1980
Neurosciences & Neurobiology	1982
Nutrition Sciences	Before 1980
Parasitology	Before 1980
Pathology, Human & Animal	Before 1980
Pharmacology, Human & Animal	Before 1980
Physiology, Human & Animal	Before 1980
Plant Genetics	1983
Plant Pathology/Phytopathology	1983
Plant Physiology	Before 1980
Toxicology	1983
Zoology	Before 1980

Notes: This table lists the biomedical fields that are represented in our analytical sample, meaning that fields introduced in SDR 2010 or later are excluded.

Table A.2: Regression Controls

Variable Name	Variable Definition
female	Indicator variable for if reported as a female
age_phd	Age when earned PhD
asian	Indicator variable for if race reported as "Asian"
race_minority	Indicator variable for if race reported as non-Asian minority
foreign	Indicator variable for if reported as foreign-born
temp_res	Indicator variable for if reported being a temporary resident when earned PhD
married_phd	Indicator variable for if reported being married when earned PhD
child_phd	Indicator variable for if reported any children living at home when earned PhD
married_child_phd	Indicator variable for if reported being married and having children at home when earned PhD
female_interactions	A set of two-way interaction terms between female and all controls listed above
phd_length	Number of years between entering PhD program and earning PhD
phd_length_miss	Indicator variable for if PhD length missing — phd_length assigned average value when phd_length_miss=1
fellow	Indicator variable for if primary source of support during PhD was a fellowship or scholarship
TA	Indicator variable for if primary source of support during PhD was a teaching assistantship
RA	Indicator variable for if primary source of support during PhD was a research assistantship
edmother_ba	Indicator variable for if mother's highest level of education is Bachelor's degree
edmother_ma	Indicator variable for if mother's highest level of education is Master's degree
edmother_prof	Indicator variable for if mother's highest level of education is Professional degree
edmother_phd	Indicator variable for if mother's highest level of education is PhD
edfather_ba	Indicator variable for if father's highest level of education is Bachelor's degree
edfather_ma	Indicator variable for if father's highest level of education is Master's degree
edfather_prof	Indicator variable for if father's highest level of education is Professional degree
edfather_phd	Indicator variable for if father's highest level of education is PhD
profmd	Indicator variable for if earning or have already earned a professional degree such as MD
yrs_since_phd	Number of years since earned PhD
yrs_since_phd_sq	(Number of years since earned PhD)^2
yrs_since_phd_cub	(Number of years since earned PhD)^3
yrs_since_phd_quart	(Number of years since earned PhD)^4
year	A set of normalized year fixed effects
phdfy	A set of PhD cohort (i.e. graduation year) fixed effects
phdfield	A set of SED fine field of study fixed effects

Notes: This table lists the controls used in the salary regressions. These controls are also used in the research job regressions (excluding yrs_since_phd, yrs_since_phd_sq, yrs_since_phd_cub, yrs_since_phd_quart, and year).

Table A.3: Summary Statistics by Postdoc-Trained Status: Full Sample and Government/Nonprofit Subsample

Employment Sector:	Full Sample		Gov't/Nonprofit	
Group:	Postdoc	Nonpostdoc	Postdoc	Nonpostdoc
Foreign-born	0.25	0.20	0.23	0.17
Temp. Resident	0.13	0.07	0.10	0.06
Age at PhD	30.47	32.69	30.75	33.26
Female	0.39	0.38	0.40	0.36
Asian	0.18	0.13	0.17	0.10
Minority	0.08	0.10	0.07	0.10
PhD Length	6.69	7.75	6.81	7.96
Married at PhD	0.53	0.63	0.51	0.59
Child at PhD	0.30	0.45	0.30	0.40
Fellowship during PhD	0.17	0.17	0.19	0.15
RA during PhD	0.31	0.23	0.30	0.22
TA during PhD	0.12	0.14	0.11	0.15
Mother's Highest Education: BA	0.22	0.20	0.21	0.19
Mother's Highest Education: > BA	0.19	0.16	0.21	0.19
Father's Highest Education: BA	0.23	0.21	0.20	0.24
Father's Highest Education: > BA	0.34	0.30	0.35	0.27
N	3420	1358	809	360

Notes: This table reports weighted means for postdoc-trained and nonpostdoc-trained biomedical doctorates in the analytical sample by employment sector, where the weights used for each doctorate are those from the most recent SDR wave wherein each doctorate is observed. Sample counts are unweighted. For each cell, approximately 10% of PhD length calculations were imputed at the mean value (seven years) for the analytical sample.

Table A.4: LPM Estimates of Possible Postdoc Determinants

Dependent Variable: Postdoc Training		
temp_res	0.112***	(0.0417)
foreign	0.0335	(0.0338)
age_phd	-0.0108***	(0.00270)
asian	0.0167	(0.0318)
race_minority	-0.0119	(0.0282)
phd_length	-0.0178***	(0.00364)
phd_length_miss	0.00882	(0.0251)
married_phd	-0.0215	(0.0266)
child_phd	-0.0905	(0.0939)
married_child_phd	0.0305	(0.0974)
fellow	-0.000562	(0.0220)
TA	-0.00501	(0.0254)
RA	0.0269	(0.0183)
edmother_ba	0.0205	(0.0201)
edmother_ma	0.0112	(0.0246)
edmother_prof	0.0419	(0.0467)
edmother_phd	0.0213	(0.0520)
edfather_ba	-0.00435	(0.0188)
edfather_ma	-0.00252	(0.0236)
edfather_prof	0.0105	(0.0364)
edfather_phd	0.0113	(0.0260)
profmd	-0.155***	(0.0344)
female	-0.148	(0.104)
female_asian	0.000567	(0.0487)
female_minor	-0.0239	(0.0411)
female_age_phd	0.00458	(0.00342)
female_foreign	-0.0517	(0.0496)
female_tempres	0.0398	(0.0641)
female_married_phd	0.0168	(0.0381)
female_child_phd	0.0653	(0.122)
female_married_child_phd	-0.0710	(0.132)
Fixed Effects		
Field-Cohort	✓	
PhD University	✓	
N	4778	
R^2	0.352	

Notes: Table A.4 reports coefficient estimates of a LPM regression of an indicator variable for if a doctorate ever is employed as a post-doc on our salary regression controls. Observations are person level. Robust standard errors clustered on field-cohort in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Impact of Postdoc Training on After-Postdoc Salary Using Alternative Sector Subsamples

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)
Panel A. All Sectors	N = 22512		N = 26312	
Postdoc Training	-0.0842***	-0.117***	0.0253	0.000956
	(0.0236)	(0.0235)	(0.0209)	(0.0210)
R^2	0.130	0.246	0.143	0.244
Panel B. Academia	N = 12295		N = 14149	
Postdoc Training	0.00100	-0.0507	0.106***	0.0725**
	(0.0297)	(0.0322)	(0.0263)	(0.0284)
R^2	0.188	0.355	0.194	0.347
Panel C. Industry	N = 6640		N = 7943	
Postdoc Training	-0.0965**	-0.165***	0.0135	-0.0596
	(0.0443)	(0.0439)	(0.0389)	(0.0400)
R^2	0.129	0.382	0.138	0.362
Panel D. Gov't/Nonprofit	N = 3577		N = 4220	
Postdoc Training	-0.106**	0.0815	-0.00612	0.179***
	(0.0469)	(0.0652)	(0.0432)	(0.0524)
R^2	0.162	0.440	0.161	0.409
Postdoc Training Treated As:				
Experience	✓	✓		
Schooling			✓	✓
Fixed Effects				
Field + Cohort + Year	✓		✓	
Field-Cohort + PhD University + Year		✓		✓

Notes: See notes for Table 4. The only change relative to Table 4 is that we define the employment sector subsamples based on each doctorate's sector of employment at ten years post-PhD.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Impact of Postdoc Training on Salary by Employment Subsector

Dependent Variable: log(salary)	(1)	(2)
Panel A. Academic TT Research	$N = 5621$	
Postdoc Training	-0.176***	-0.381***
	(0.0515)	(0.0409)
R^2	0.358	0.56
Panel B. Academic NonTT Research	$N = 2916$	
Postdoc Training	-0.102*	-0.130
	(0.0591)	(0.130)
R^2	0.242	0.491
Panel C. Academic Nonresearch	$N = 7530$	
Postdoc Training	-0.0253	0.0114
	(0.0333)	(0.0399)
R^2	0.208	0.445
Panel D. Industry Research	$N = 4300$	
Postdoc Training	-0.101*	-0.176***
	(0.0540)	(0.0598)
R^2	0.183	0.390
Panel E. Industry Nonresearch	$N = 4499$	
Postdoc Training	-0.153***	-0.207***
	(0.0499)	(0.0644)
R^2	0.221	0.522
Postdoc Training Treated As:		
Experience	✓	✓
Schooling		
Fixed Effects		
Field + Cohort + Year	✓	
Field-Cohort + PhD University + Year		✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1980 and 2007. We include all person-year observations, including those associated with years when a doctorate is employed as a postdoc. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates. Subsamples are based on the employment subsector of the biomedical doctorate at ten years after PhD graduation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) and (2) include all controls listed in Table A.2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Impact of Postdoc Length on After-Postdoc Salary

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)
Panel A. All Sectors	$N = 22512$		$N = 26312$	
0 years < Postdoc Length $\leq$ 3 years	-0.0245	-0.0535*	0.0142	-0.00439
	(0.0293)	(0.0291)	(0.0259)	(0.0262)
3 years < Postdoc Length $\leq$ 6 years	-0.0728***	-0.115***	0.0430*	0.00877
	(0.0252)	(0.0254)	(0.0225	(0.0228)
Postdoc Length > 6 years	-0.222***	-0.231***	-0.0135	-0.0134
	(0.0290)	(0.0293)	(0.0270)	(0.0277)
Panel B. Academia	$N = 11941$		$N = 13947$	
0 years < Postdoc Length $\leq$ 3 years	0.0609*	0.00406	0.0904***	0.0466
	(0.0361)	(0.0404)	(0.0323)	(0.0358)
3 years < Postdoc Length $\leq$ 6 years	0.0453	0.00226	0.155***	0.122***
	(0.0327)	(0.0360)	(0.0290)	(0.0314)
Postdoc Length > 6 years	-0.0537	-0.0517	0.133***	0.156***
	(0.0361)	(0.0408)	(0.0333)	(0.0395)
Panel C. Industry	$N = 6708$		$N = 7898$	
0 years < Postdoc Length $\leq$ 3 years	-0.0435	-0.122**	-0.0129	-0.0628
	(0.0523)	(0.0482)	(0.0459)	(0.0451)
3 years < Postdoc Length $\leq$ 6 years	-0.0942**	-0.139***	0.00540	-0.0238
	(0.0468)	(0.0458)	(0.0428)	(0.0433)
Postdoc Length > 6 years	-0.264***	-0.283***	-0.0791	-0.0736
	(0.0587)	(0.0620)	(0.0565)	(0.0595)
Panel D. Gov't/Nonprofit	$N = 3863$		$N = 4467$	
0 years < Postdoc Length $\leq$ 3 years	-0.0713	-0.112*	-0.0216	-0.0412
	(0.0483)	(0.0678)	(0.0440)	(0.0586)
3 years < Postdoc Length $\leq$ 6 years	-0.0329	-0.0762	0.0945***	0.0450
	(0.0370)	(0.0480)	(0.0347)	(0.0432)
Postdoc Length > 6 years	-0.267***	-0.171**	-0.00833	0.0918
	(0.0548)	(0.0681)	(0.0544)	(0.0616)
Postdoc Training Treated As:				
Experience	✓	✓		
Schooling			✓	✓
Fixed Effects				
Field + Cohort + Year	✓		✓	
Field-Cohort + PhD University + Year		✓		✓

Notes: See notes to Table 4. The only change relative to Table 4 is that we replace a single indicator variable for postdoc training with a set of three indicator variables based on a doctorate's length of postdoc training.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Impact of Postdoc Length on Securing Job Type

	Any	Academic	Tenure-Track	Tenured	Industry
Panel A. Any Job					
0 years $<$ Postdoc Length $\leq$ 3 years	$\cdots$	0.0867***	0.111***	-0.0231	$\cdots$
	$\cdots$	(0.0258)	(0.0251)	(0.0634)	$\cdots$
3 years $<$ Postdoc Length $\leq$ 6 years	$\cdots$	0.199***	0.201***	-0.00460	$\cdots$
	$\cdots$	(0.0232)	(0.0223)	(0.0533)	$\cdots$
Postdoc Length $>$ 6 years	$\cdots$	0.234***	0.177***	-0.0299	$\cdots$
	$\cdots$	(0.0275)	(0.0298)	(0.0728)	$\cdots$
R^2	$\cdots$	0.256	0.270	0.460	$\cdots$
N	$\cdots$	4778	4778	1583	$\cdots$
Panel B. Research Job					
0 years $<$ Postdoc Length $\leq$ 3 years	0.138***	0.139***	0.105***	0.106	0.0578
	(0.0253)	(0.0245)	(0.0180)	(0.182)	(0.0518)
3 years $<$ Postdoc Length $\leq$ 6 years	0.285***	0.321***	0.260***	-0.0286	0.165***
	(0.0215)	(0.0228)	(0.0179)	(0.177)	(0.0487)
Postdoc Length $>$ 6 years	0.312***	0.340***	0.281***	-0.0949	0.131**
	(0.0260)	(0.0282)	(0.0248)	(0.197)	(0.0609)
R^2	0.308	0.285	0.280	0.682	0.496
N	4778	4778	4778	798	1786
Fixed Effects					
Field-Cohort	✓	✓	✓	✓	✓
PhD University	✓	✓	✓	✓	✓

Notes: See notes to Table 5. The only change relative to Table 5 is that we replace a single indicator variable for postdoc training with a set of three indicator variables based on a doctorate's length of postdoc training.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Task Regression Sample Observations by Employment Sector

Employment Sector	In Sector in Year of Observation*		
	Postdoc	Non-Postdoc	Total
All Sectors	7541 (1804)	2674 (675)	10215 (2479)
Academia	4186 (1134)	1256 (333)	5442 (1467)
TT Research	1466 (509)	133 (58)	1599 (567)
Non-TT Research	776 (358)	185 (74)	961 (432)
Nonresearch	1944 (692)	938 (284)	2882 (976)
Industry	2211 (638)	893 (271)	3104 (909)
Research	1077 (412)	363 (137)	1440 (549)
Nonresearch	1134 (437)	530 (212)	1664 (649)
Gov't/Nonprofits	1144 (416)	525 (165)	1669 (581)

Notes: This table lists the number of observations and (unique individuals) in each employment sector for the analytical sample by whether each observation is associated with a biomedical doctorate with postdoctoral training. Regressions including measures of worker task histories or the degree of mismatch between tasks performed as part of current employment and those performed early in their career restrict to those biomedical doctorates in the analytical sample who are observed at least two times during the first six years post-PhD.
* = excludes observations for years when employed as a postdoc. Since a single worker may show up in different sectors at different times, the sum of the person counts associated with the last three columns exceed the total number of persons included in the analytical sample.

Table A.10: Tasks Performed by Doctorates Before and After the First Six Years Post-PhD by Postdoc-Trained Status

Employment Sector:	**Academia**						**Gov't/Nonprofit**					
Period (Years Post-PhD):	**First Six Years**		**After Six Years**		**Task Change**		**First Six Years**		**After Six Years**		**Task Change**	
Work Activity	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc	No Pdoc	Pdoc
Accounting, Finance, and Contracts	10.92%	5.99%	27.73%	33.07%	16.81	27.07	33.33%	6.64%	42.03%	39.06%	8.70	32.42
Applied Research	56.02%	67.73%	66.39%	71.93%	10.36	4.20	77.54%	75.00%	75.36%	73.83%	-2.17	-1.17
Basic Research	64.15%	94.41%	66.11%	90.91%	1.96	-3.50	40.58%	92.97%	48.55%	68.36%	7.97	-24.61
Computer Applications	23.53%	29.77%	23.25%	21.88%	-0.28	-7.89	36.96%	34.38%	31.16%	28.91%	-5.80	-5.47
Development	18.21%	15.38%	22.69%	26.27%	4.48	10.89	28.26%	19.92%	47.83%	43.36%	19.57	23.44
Design	10.08%	21.18%	19.05%	24.08%	8.96	2.90	23.19%	19.53%	33.33%	36.72%	10.14	17.19
Human Resources	32.21%	26.17%	44.54%	57.74%	12.32	31.57	38.41%	22.27%	55.07%	50.39%	16.67	28.13
Managing People or Projects	63.03%	49.45%	84.03%	90.01%	21.01	40.56	71.74%	48.05%	90.58%	89.06%	18.84	41.02
Production, Operations, Maintenance	8.40%	10.89%	15.41%	17.58%	7.00	6.69	9.42%	8.59%	18.84%	16.02%	9.42	7.42
Quality or Productivity Management	9.52%	5.00%	14.57%	19.98%	5.04	14.99	23.19%	4.30%	40.58%	35.94%	17.39	31.64
Sales, Purchasing, Marketing	8.12%	3.10%	14.85%	14.19%	6.72	11.09	21.74%	6.64%	31.16%	26.95%	9.42	20.31
Professional Services	33.05%	9.99%	43.70%	26.97%	10.64	16.98	37.68%	10.55%	48.55%	35.94%	10.87	25.39
Teaching	90.48%	36.46%	92.72%	86.11%	2.24	49.65	30.43%	26.56%	41.30%	40.23%	10.87	13.67
Other	19.33%	4.40%	33.61%	28.07%	14.29	23.68	26.09%	5.86%	31.88%	31.25%	5.80	25.39
N	261	499	261	499	261	499	138	256	138	256	138	256

Notes: In this table, we calculate the proportion of postdoc-trained and non-postdoc trained biomedical doctorates that report spending at least 10% of their work time engaged in the given activity at least once 1) in their first six years post-PhD and 2) after their first six years post-PhD. We restrict the sample to biomedical doctorates that are employed in the given employment sector at 10 years post-PhD and for whom we observe at least two times in their first six years post-PhD. For both postdoc-trained and nonpostdoc-trained biomedical doctorates, we then report the percentage-point difference between the fraction of each performing each task within and after their first six years post-PhD, and refer to this measure as the "task change" of each group. For postdocs, we only consider observations in the first six years post-PhD that correspond to years employed as a postdoc; after six years post-PhD, we only consider observations corresponding to years after any and all years employed as a postdoc, and where the doctorate is employed in industry. For nonpostdocs, we only consider observations corresponding to years where the person is employed in industry.

Table A.11: Adding Current Job Tasks as Controls for Observations where Task History Available

Dependent Variable: log(salary)	(1)	(2)	(3)	(4)	(5)	(6)
Employment Sector: Industry			$N = 3104$			
Postdoc Training	-0.228***	-0.237***	-0.233***	-0.249***	-0.236***	-0.242***
	(0.0634)	(0.0644)	(0.0639)	(0.0645)	(0.0641)	(0.0643)
R^2	0.498	0.511	0.512	0.507	0.516	0.517
Postdoc Training Treated As:						
Experience	✓	✓	✓	✓	✓	✓
Schooling						
Current Job Task Controls						
Primary Activity		✓				✓
Primary or Secondary Activity			✓		✓	
Activity $\geq$ 10% of Work Time				✓	✓	✓

Notes: This table reports regressions results based on the specification given in equation (9) where our sample includes all biomedical doctorates in the SDR graduating between 1993 and 2006 who are observed in at least two of their first six years post-PhD. Postdoc training is treated as experience such that experience is defined as years since PhD graduation for all biomedical doctorates. For each doctorate, we keep only those person-year observations corresponding to years after any and all years employed as a postdoc, and we drop all observations within the first six years after Ph.D. so that postdoc and nonpostdoc observations are comparable. Subsamples are based on the employment sector associated with each person-year observation. Robust standard errors clustered at individual-level are in parentheses. Estimates produced using survey weights. Specifications (1) - (6) include all controls listed in Table A.2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Coefficient Estimates on Task History Controls

Dependent Variable: log(salary)		
Postdoc Training	-0.126*	(0.0666)
Accounting Experience	-0.0898**	(0.0394)
Basic Research Experience	-0.0394***	(0.0108)
Computer App Experience	-0.00224	(0.0116)
Development Experience	0.00149	(0.0125)
Design Experience	0.0202	(0.0293)
HR Experience	0.0295	(0.0118)
Management Experience	0.0204**	(0.0103)
Production Experience	-0.0286	(0.0273)
Quality/Productivity MGMT Experience	0.00277	(0.0309)
Sales/Marketing Experience	-0.0351**	(0.0152)
Professional Services Experience	0.00652	(0.00873)
Teaching Experience	-0.0641**	(0.0264)
Other Experience	-0.0268	(0.0237)
N	3104	
R^2	0.518	

Notes: Table A.4 reports coefficient estimates on the (primary) task history controls included in the regression whose main results are report in column (2) of Table 9. Applied research is base case so estimates can be interpreted as value of spending an additional year in a job with the given primary task relative to a job where applied research is the primary task. Robust standard errors clustered at individual-level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Bias-Adjusted Estimates of the Effect of Postdoc Training

B.1 Method for Estimating Bias-Adjusted Treatment Effects

Oster's (2019) bias-adjusted treatment effect estimator is motivated by the following data generating process:

$$Y = \beta X + \Psi\omega^0 + W_2 + \varepsilon,$$

where Y is the outcome of interest, X is a scalar treatment variable, ω^0 is a vector of observed controls, and W_2 and ε are unobserved.[79] Letting $W_1 \equiv \Psi\omega^0$, a proportional selection relationship can be defined as $\delta\frac{\sigma_{1X}}{\sigma_1^2} = \frac{\sigma_{2X}}{\sigma_2^2}$, where $\sigma_{iX} \equiv \text{cov}(W_i, X)$ and $\sigma_i^2 \equiv \text{var}(W_i)$ for $i \in \{1, 2\}$, and where δ measures the level of selection on unobservables relative to observables. Let the coefficient and the R^2 obtained from a regression of Y on X ("uncontrolled regression") be denoted $\mathring{\beta}$ and $\mathring{R}$, respectively. Let the coefficient and the R^2 obtained from a regression of Y on X and ω^0 ("controlled regression") be denoted $\tilde{\beta}$ and $\tilde{R}$, respectively. Lastly, let the R^2 obtained from a hypothetical regression of Y on X, ω^0, and W_2 ("fully-specified regression") be denoted as R_{max}. Then, under some additional assumptions, Oster (2019) shows that a consistent bias-adjusted treatment effect (β^*) can be approximated by the following:

$$\beta^* \approx \tilde{\beta} - \delta\left[\mathring{\beta} - \tilde{\beta}\right]\frac{R_{max} - \tilde{R}}{\tilde{R} - \mathring{R}}.$$

Oster (2019) subsequently develops a consistent bias-adjusted treatment effect estimator that relaxes the additional restrictions used to derive the above approximation, and we use this more robust estimator to measure the sensitivity of our results to selection on unobservables.[80]

B.2 Bias-Adjusted Salary Regression Results

If postdoc-trained biomedical doctorates have lower ability at the time of PhD completion than those who forgo postdoc employment, then the postdoc salary penalty in industry reported in column (2) of Table 4 could potentially be explained by selection on unobserved ability at time of graduation. This explanation is unlikely for two reasons: First, Sauermann and Roach (2016) find that higher-ability biomedical doctorates plan on pursuing postdoc training, which would point to our estimates of a postdoc penalty being too conservative rather than too extreme.[81] Second, we include controls that are likely correlated with ability at time of graduation; these include field-by-cohort fixed effects, PhD university fixed effects, the education level of each biomedical doctorates'

[79] A key assumption in what follows is that W_2 is orthogonal to W_1; therefore, W_2 should be viewed as the *residualized portion* of the unobservables after a hypothetical regression of the unobservables on ω^0. See Appendix A.1 of Oster (2019) for a discussion of this assumption.

[80] This method is implemented using the user-created Stata command `psacalc` accessible via Emily Oster's website.

[81] Ability is proxied by four measures in Sauermann and Roach (2016): 1) number of peer-reviewed publications, 2) fellowships from a federal agency, 3) their PhD program's National Research Council (NRC) ranking, and 4) respondent's assessment of their own research ability relative to peers.

mother and father, length of time in a graduate program, graduate program funding source, and various background characteristics that are likely related to ability.[82]

Nevertheless, we test whether residual variation in unobserved ability at time of graduation might explain the postdoc salary penalty in industry by estimating bias-adjusted treatment effects as formulated in Oster (2019) and report the results of this, and the results for other sectors (and subsectors), as a robustness check in Panel A of Table B.1 (and Table B.2). We find that the inclusion of controls, which are plausibly correlated with ability, pushes the estimated impact of postdoc training on future salary in a negative direction for all sectors in Table B.1, which is consistent with postdoc-trained biomedical doctorates having higher ability than their nonpostdoc-trained counterparts. While we are not able to pinpoint the causal impact of postdoc training in the absence of a valid instrument for postdoc attainment, under the plausible assumption that selection on unobservables acts in the same direction as selection on observables, we can bound the value for the causal impact by using the Oster (2019) method for estimating bias-adjusted treatment effects. To do so, we must select an upper-bound for the level of selection on unobservables relative to selection on observables (δ) and the R^2 that we would expect from a fully-specified model that we would be able to estimate if the unobservables were instead observable (R_{max}). We follow Altonji, Elder, and Taber (2005) and Oster (2019) in treating $\delta = 1$ as an upper-bound for the level of selection on unobservables relative to observables.[83] Oster (2019) suggests that researchers arguing for the stability of their results consistent with that of randomized treatment should consider an upper bound value of $1.3\tilde{R}^2$ for R_{max}, where $\tilde{R}^2$ is the R^2 obtained from the controlled regression. Thus, we use this R_{max} and $\delta = 1$ to calculate an upper-bound value for the impact of postdoc training on after-postdoc salary in each employment sector and subsector, which we report as θ^* in Table B.1 and Table B.2.

We find that each point estimate in Panel A of Table B.1 is negative and of greater magnitude compared to the estimate in the corresponding controlled regression, suggesting that, under the plausible assumption that selection on unobservables runs in the same direction as selection on observables, the magnitude of each estimate in column (2) of Table 4 is a lower-bound for the causal impact of postdoc training on after-postdoc salary, while each estimate reported as θ^* represents an upper-bound.[84] Altogether, these results suggest that ability bias is unlikely to explain the

[82] Field-by-cohort fixed effects will be correlated with ability if individuals sort into different biomedical fields based on ability. PhD university fixed effects will be correlated with ability insofar as universities admit students to biomedical PhD programs based on individual ability (e.g., as measured by application materials including GRE scores and GPA) and insofar as different universities have different impacts on the human capital accumulation of PhD students. Parent's education level may proxy for socioeconomic background and possibly inherited traits impacting educational performance.

[83] As argued in Oster (2019), δ represents the relative degree of selection on the *residualized portion* of the unobservables (i.e., the variation in the unobservables unrelated to variation in the observables).

[84] The calculated upper-bounds all lie outside the 95% confidence interval of the corresponding estimate in column (2) of Table 4, indicating that correcting for selection on unobservables is potentially important. Altonji, Arcidiacono, and Maurel (2016) note that in the context of evaluating the impact of college field choice on future earnings, "much of the variance in earnings at a point in time is due to measurement error or permanent and transitory shocks that occur after college decisions have been made" and thus are not a source of selection bias. The same argument can be made for the postdoc decision. It is important to note that the analysis in this section evaluates the sensitivity

existence of a postdoc penalty in industry, and that the true salary penalty in industry caused by postdoc training is somewhere between 15.8% and 26.2%, depending on the level of selection on unobservables and the degree to which inclusion of the unobservables as controls would increase the R^2 of the model.

When treating postdoc training as schooling in Panel B of Table B.1 and Table B.2, we find that the direction of selection bias is in the same direction as the results in Panel A when postdoc training is treated as experience. Of all the results in Table B.1 and Table B.2, only academic non-tenure-track research yields bias-adjusted estimates of the effect of postdoc training which push the estimate in a positive direction. This suggests that biomedical doctorates choosing a job in non-tenure-track research directly after graduation may be of higher ability compared to those who take a postdoc position, but our results suggest that postdoc training ultimately leads to higher earnings for those in this sector, which is consistent with postdoc training being an effective way to augment skills relevant to academic research.

B.3 Bias-Adjusted Research Job Regression Results

As with the impact of postdoc training on salary, unobservable ability at the time of graduation could potentially explain the impact of postdoc training on the ability of biomedical doctorates to obtain different types of research-focused jobs. Therefore, we test the robustness of our research job regression results reported in Panel B of Table 5 to selection on unobservables using the Oster's (2019) method as before and report the results in Table B.3. We find that the results in Panel B of Table 5 represent upper-bound estimates of the true impact of postdoc training on the likelihood of obtaining tenure-track and industry research jobs, whereas the bias-adjusted treatment effects represent lower-bounds. This finding, in conjunction with the direction of bias detected in the salary regressions in Panel A of Table B.1, is consistent with postdoc-trained biomedical doctorates having greater ability at the time of graduation compared to their nonpostdoc-trained counterparts, assuming that high-ability doctorates are more likely to obtain tenure-track and industry research positions. On the other hand, we find that correcting for selection on unobervables increases the positive effect of postdoc training on the chances that a biomedical doctorate works in any academic research job after-postdoc. This may indicate that doctorates of lower ability at time of graduation sort into postdoc training to augment their academic research skills in hopes of increasing their chance at nontenure-track research positions in academia, such as staff scientist positions. However, we find that, in all cases, the bias-adjusted treatment effect lies within one standard error of the estimates reported in Table 5, indicating that the results are not especially sensitive to selection

of our results to selection on unobserved ability *at the time of PhD graduation*, with the results based on movements in coefficients when controls determined by the time of PhD graduation are added to the regression specifications. It is not meant to test sensitivity to variables not determined by the time of PhD, such as tasks to be performed as part of future employment or as part of postdoc training that lead to the accumulation of task-specific human capital (which is the focus of Section 6).

on unobservables.[85]

[85] We use the standard errors reported in Table 5. The results for tenured positions are quite sensitive to selection on unobservables — this makes sense given the sensitivity of the results to selection on observables, paired with the fact that inclusion of the observable controls increases the R^2 drastically relative to the uncontrolled regression.

Table B.1: Sensitivity of Salary Regression Results to Selection on Unobservables by Sector

Sector:	All		Academia		Industry		Gov't/Nonprofit	
	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2
Panel A. Postdoc Training as Experience								
Uncontrolled	-0.0164	0.000	0.0815	0.003	-0.0675	0.001	0.0252	0.000
Controlled	-0.117	0.246	-0.00836	0.314	-0.158	0.400	-0.106	0.540
R_{max}	0.320		0.408		0.521		0.702	
θ^*	-0.174		-0.0775		-0.262		-0.510	
N	22512		11941		6708		3863	
Panel B. Postdoc Training as Schooling								
Uncontrolled	0.0212	0.000	0.118	0.006	-0.0384	0.000	0.0524	0.002
Controlled	0.001	0.245	0.0983	0.301	-0.0450	0.376	0.0177	0.528
R_{max}	0.317		0.391		0.488		0.686	
θ^*	-0.004		0.0835		-0.0518		-0.0835	
N	26312		13947		7898		4467	

Notes: We test if the results in columns (2) and (4) of Table 4 are robust to allowing for selection on unobservables using the methods developed in Oster (2019) in Panel A and Panel B, respectively; see notes to Table 4. We report both the estimated impact of postdoc training on log(salary) and the R^2 for regressions without any controls ("uncontrolled") and with all of the controls ("controlled") in our most general regression specification. We then calculate the estimated effect of postdoc training on after-postdoc salary (θ^*) given an equal degree of selection on unobservables as selection on observables ($\delta = 1$) and where we select R_{max} as equal to $1.3 * \tilde{R}^2$ where $\tilde{R}^2$ is the R^2 obtained from the controlled regression.

Table B.2: Sensitivity of Salary Regression Results to Selection on Unobservables by Subsector

Sector:	Academia						Industry			
Subsector:	TT Res.		Non-TT Res.		Nonres.		Res.		Nonres.	
	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2	$\hat{\theta}$	R^2
Panel A. Postdoc Training as Experience										
Unctrld.	-0.0962	0.002	-0.00343	0.000	0.0318	0.001	-0.0254	0.000	-0.101	0.002
Ctrld.	-0.174	0.349	0.159	0.531	-0.0416	0.453	-0.0832	0.482	-0.155	0.499
R_{max}	0.454		0.611*		0.589		0.626		0.649	
θ*	-0.339		0.546*		-0.135		-0.232		-0.273	
N	3996		1988		5957		3117		3591	
Panel B. Postdoc Training as Schooling										
Unctrld.	-0.00721	0.001	0.0364	0.000	0.0632	0.002	-0.00163	0.000	-0.0680	0.001
Ctrld.	-0.0500	0.0349	0.232	0.498	0.0481	0.419	0.0162	0.453	-0.0707	0.473
R_{max}	0.454		0.572*		0.544		0.589		0.615	
θ*	0.00102		0.573*		0.0316		0.0519		-0.0756	
N	4394		2408		7145		3801		4097	

Notes: We test if the results in columns (2) and (4) of Table 6 are robust to allowing for selection on unobservables using the methods developed in Oster (2019) in Panel A and Panel B, respectively; see notes to Table 6. We report both the estimated impact of postdoc training on log(salary) and the R^2 for regressions without any controls ("uncontrolled") and with all of the controls ("controlled") in our most general regression specification. We then calculate the estimated effect of postdoc training on after-postdoc salary (θ^*) given an equal degree of selection on unobservables as selection on observables ($\delta = 1$) and where we select R_{max} as equal to $1.3 * \tilde{R}^2$ where $\tilde{R}^2$ is the R^2 obtained from the controlled regression. * = we set $R_{max} = 1.15 * \tilde{R}^2$ since $1.3 * \tilde{R}^2$ exceeds the R^2 obtained from a controlled regression with person fixed effects.

Table B.3: Sensitivity of Research Job Regression Results to Selection on Unobservables

Research Job Type:	Any		Academic		Tenure-Track		Tenured		Industry	
	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{R^2}$	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{R^2}$	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{R^2}$	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{R^2}$	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{R^2}$
Uncontrolled	0.258	0.062	0.258	0.056	0.228	0.060	0.0811	0.071	0.153	0.023
Controlled	0.242	0.296	0.265	0.269	0.213	0.263	-0.0634	0.680	0.122	0.492
$\boldsymbol{R_{max}}$	0.384		0.349		0.342		0.884		0.640	
$\boldsymbol{\theta^*}$	0.231		0.271		0.202		-1.47		0.090	
$\boldsymbol{N}$	4778		4778		4778		798		1786	

Notes: We test if the results in Panel B of Table 5 are robust to allowing for selection on unobservables using the methods developed in Oster (2019); see notes to Table 5. We report both the estimated impact of postdoc training on obtaining research jobs and the R^2 for regressions without any controls ("uncontrolled") and with all of the controls ("controlled"). We then calculate the estimated effect of postdoc training (θ^*) given an equal degree of selection on unobservables as selection on observables ($\delta = 1$) and where we select R_{max} as equal to $1.3 * \tilde{R}^2$ where $\tilde{R}^2$ is the R^2 obtained from the controlled regression.

C Supplementary/Online Appendix

C.1 Identifying Postdocs and Postdoc Length in SDR-SED Data

Our dataset is made up of three different sources that contain information about a doctorate's postdoc status. The first source is the SED, wherein respondents are asked "What best describes your (within the next year) postgraduate plans?" and "What is the status of your postgraduate plans (in the next year)?" Starting in the SED in 2004, respondents are also asked "Do you intend to take a 'postdoc' position?". Using these questions, we assign a person as doing a postdoc if the respondent says that, post-graduation, he/she plans to do either a: 1) postdoc fellowship, 2) postdoc research associateship, 3) traineeship, or 4) internship/ clinical residency, and also states that he/she 1) will be either returning to present employment, 2) has accepted a position, or 3) is in negotiation with one or more specific organizations.

The second source containing information on postdoc status is the SDR. In each SDR wave, doctorates are asked whether they are currently working and whether their current job is a "post-doc." If a doctorate reports being in a postdoc job in any SDR wave, then we consider them to have done a postdoc. The third source comes from the Special Topic Module included on the SDR 1995 and 2006 waves wherein respondents are asked how many postdoc positions they have ever held and the starting and ending dates for their last three postdoc positions. We follow Kahn and Ginther (2017) in referring to these as the SDR Retrospective Surveys. If a doctorate reports having done at least one postdoc on either SDR Retrospective Survey, then we count that person as having done a postdoc. If a doctorate reports never having done a postdoc on the Retrospective Surveys, then we label the person as having never done a postdoc. In rare cases, sources disagree about whether a person has ever done a postdoc. If SED states that a person plans to do a postdoc, but then they never report doing a postdoc in any SDR wave and they claim to have never taken a postdoc position in the SDR Retrospective Surveys, then we label the person as never having done a postdoc. If a doctorate ever claims to have done a postdoc in any SDR wave (including the SDR Retrospective Surveys), then we label them as having done a postdoc.

Next, we seek to determine which years a person was employed as a postdoc. We create a variable ("pdoc_year") that equals one if the doctorate was in a postdoc in the given year and equals zero if the doctorate was not in a postdoc in the given year. Once we form this variable, we will take its sum across years for each doctorate to measure each doctorate's duration (or "length") of postdoc training. If a person was found to have never done a postdoc (pdoc==0), then we label the person as not being employed in a postdoc for all years for which they appear (i.e., pdoc_year==0 for all years). If the person could be identified as a postdoc based solely on information from the SED, then we labeled the year of PhD receipt as being a year that the doctorate was employed as a postdoc. For those who report currently being in a postdoc position in an SDR wave, we have the year that they began that current employment and so label all years from the start of employment to that SDR wave as years in a postdoc. For doctorates in the SDR

1995 and/or 2006 wave ("SDR Retrospective Surveys"), we have information on the start and end dates of a person's last three postdoc positions, and so label any years within any of the reported postdocs as postdoc years. Additionally, we consider all years after the end of the last reported postdoc on the SDR Retrospective Surveys as being years where a doctorate was not in a postdoc, assuming we have no other evidence to suggest the person took up an additional postdoc after that time. Similarly, for doctorates who report having done at most three postdocs throughout their career in the SDR Retrospective Surveys, we label years preceding the start of their first reported postdoc as years that the person was not in a postdoc, assuming no additional evidence to suggest otherwise. Additionally, we label any years 1) between the end of the 2nd most recent postdoc and the start of the most recent postdoc or 2) between the end of the 3rd most recent postdoc and the start of the 2nd most recent postdoc as "non-postdoc" years. Lastly, we label as non-postdoc years any SDR year where a doctorate reports not being currently employed in a postdoc position.

In addition, we impute whether a year is or is not a postdoc year in special cases to avoid sample attrition. The need for imputation is due to two features of the SDR. First, the SDR is typically biennial, and so there is usually one year in between SDR waves, although there are two cases where there are two-year gaps: between SDR 2003 and 2006 and between SDR 2010 and 2013. Second, new sample members to the SDR have typically been added between one and three years after PhD receipt. This means that some doctorates may have one or two years between their PhD graduation year and entry into the SDR where postdoc status is missing.[86]

Our imputation strategy is as follows: if a doctorate reports not being in a postdoc in both the SDR wave before and after the gap year(s), then those gaps years are considered as non-postdoc years. Similarly, if a person reports being in a postdoc in both the SDR wave before and after the gap year(s), then those gap years are considered postdoc years. If a doctorate reports doing a postdoc in the SDR wave before a gap year, but reports not doing a postdoc in the SDR wave after the gap year, then we split the difference for gap years by assigning a value of 0.5 to our postdoc year variable. If a doctorate is surveyed in the SDR within three years, but has gap years preceding appearance in the SDR, then we assign a value of 0.5 if the person reports a postdoc position in his/her first SDR wave and assign a value of 0 if the person reports no postdoc position in his/her first SDR wave.[87] For biomedical doctorates first sampled in the SDR prior to SDR 2010, we are able to identify if a doctorate was ever a postdoc in 99% of cases. In 86% of cases, we are able to identify or impute whether or not a biomedical doctorate is employed as a postdoc in each year

[86]Starting with SDR 2010, doctorates obtaining PhDs more than three years prior to the survey date were newly sampled; for these cases, there are many years where we cannot determine postdoc status, and so we will exclude these doctorates from our analytical sample.

[87]After our imputation strategy, the majority of doctorates who ever have a year where we fail to determine postdoc status are those who first appear in the SDR in the 2015 wave. The SDR 2015 wave was unique in that 80% of the SDR 2015 sample members were new to the survey, whereas in past cycles around 10% of the sample members were new. This was due to the SDR being expanded from 47,000 to 120,000 members, with members being added even when having graduated much earlier than 2015. Given this large increase in the number of new SDR members, it would be valuable for the SDR to once again include questions about previous postdoc experience, as was done for the 1995 and 2006 waves.

since PhD graduation.[88]

C.2 Biomedical Postdocs: Who They Are, Where They Work, and What They Do

Among biomedical doctorates, who are the most likely to pursue postdoc training? Figure C.1 breaks down biomedical postdocs and nonpostdocs by their foreign-born status, sex, race, marital status at time of PhD, and whether a child was present at home at time of PhD.[89] Since 1980, the female-shares of biomedical doctorates taking and not taking postdoc positions have both risen, although a recent gap has emerged with the female share of nonpostdocs exceeding that of postdocs. The foreign-born shares of postdocs and nonpostdocs have both risen over time, with postdocs tending to have a higher concentration of foreign-born doctorates compared to nonpostdocs.[90] The trends in the Asian-share of postdocs and nonpostdocs roughly mirrors the foreign-born trends, and these two trends are likely related as Asian countries including China, India, South Korea, and Taiwan make up the top countries-of-origin for foreign biomedical PhD students in the US (National Science Board, 2018). Postdocs appear less likely than nonpostdocs to be married at time of PhD and to have a child at home at time of PhD, and Figure C.2 shows that the average age at PhD graduation for nonpostdocs has consistently exceeded that of postdocs. Altogether, these trends make intuitive sense — individuals that are younger and have potentially fewer financial responsibilities (nonmarried with no children) at the time of graduation are more likely to do postdocs, as are foreign-born individuals whose ability to remain in the United States may be enhanced by taking an academic postdoc position exempt from H-1B quotas.[91]

Postdoc employment involves working long hours for low pay: Figure A.3 shows that between 1995 and 2013, biomedical doctorates age 28-32 employed in postdoc positions typically worked about 10% more hours a week for 50% of the salary compared to their counterparts in industry. These demanding working conditions have typically been justified by the traditional view that postdoc positions are apprenticeships that provide researchers training in skills necessary to become

[88] In the analytical sample used in this study, we find that 77% of postdoc person-years occur in academia, 17% occur in government/nonprofits, and only 6% occur in industry.

[89] Here postdoc refers to biomedical doctorates in a given cohort who ever go on to do postdocs. Similarly, nonpostdocs refers to those biomedical PhDs in a given cohort that never receive postdoc training.

[90] These data are for individuals first appearing in the SDR prior to 2010. In 2010, the SDR began sampling US-trained PhDs who reside outside of the United States, whereas previous waves only included US-trained PhDs residing in the US after graduation. Due to this sampling change, the NSF recommends caution when analyzing and interpreting pre- and post-2010 trends. Also, the SDR 2010 introduced new sample members that had graduated as far back as 2001; we are not able to reliably identify whether these individuals were ever employed as postdocs given that they are first sampled in the SDR many years after graduation and were not part of the SDR 2006 wave where doctorates were asked whether they had previously worked as a postdoc. We therefore restrict the graphs to pre-SDR 2010 data. We also limit the sample to individuals who appear in the SDR in 1993 at the earliest due to survey format changes in 1993 and sampling changes in 1991. (https://nsf.gov/statistics/srvydoctoratework/#micro&tabs-1&sd).

[91] Jobs at academic institutions have been exempt from H-1B visa caps since fiscal year 2001. Additionally, there are no statutory caps on J-1 visas which are a popular alternative to the H-1B visa for foreign-born postdocs working in the US.

independent researchers.[92] However, as Figure A.6 shows, only a small fraction of biomedical postdocs actually become independent researchers in the traditional academic setting.

After completing a postdoc, where do biomedical doctorates work? Figure A.7 shows that postdoc-trained biomedical doctorates between the ages of 30 and 40 are slightly more concentrated in academic jobs than those of the same age with no postdoc training, and that a significant fraction of both occupy jobs in industry, with only a small fraction in government and nonprofits.[93] Figure C.3 shows that, on average, biomedical doctorates age 30 to 40 working in industry have higher salary compared to their counterparts in academia.[94] While the share of biomedical doctorates going into each sector are similar regardless of postdoc-trained status, the tasks performed by each significantly differ. Figure A.8 shows that most postdoc-trained biomedical doctorates age 30 to 40 in academia report their primary work activity as research, and that this share is roughly double that of biomedical doctorates without postdoc training. Meanwhile, the plurality of nonpostdocs in academia are primarily engaged in teaching. These results suggest that postdoc training improves one's chances of securing a research job in academia, but that a postdoc is not necessary for an academic teaching position.[95] As may be expected, Figure C.6 shows that research positions in academia tend to pay more than teaching positions, meaning that taking a postdoc position may increase a biomedical doctorate's after-postdoc salary in academia through an enhanced ability to find an after-postdoc research position.[96]

Figure C.7 shows the primary work activities performed by postdoc-trained and non-postdoc-trained biomedical doctorates age 30 to 40 working in industry. In any given year, biomedical doctorates with postdoc training are more heavily concentrated in research positions in industry, while nonpostdoc-trained individuals are more likely to be performing professional services (e.g., healthcare services). Furthermore, Figure C.8 shows that the number of biomedical PhDs in research-oriented jobs is growing and that, unlike researchers in other fields, a majority of biomedical PhDs conducting research in industry have postdoc training. These findings suggest that postdoc training may not only improve one's chances of acquiring a research job in academia but may also improve one's chances at securing a research job in industry.[97]

[92] The NSF and NIH define a postdoctoral scholar as "an individual who has received a doctoral degree (or equivalent) and is engaged in a temporary and defined period of mentored advanced training to enhance the professional skills and research independence needed to pursue his or her chosen career path" (Bravo and Olsen, 2007).

[93] Throughout this paper, we focus on academia and industry as these are the two main sectors employing biomedical doctorates.

[94] For purposes of Figure C.3, individuals employed as postdocs in the given year are excluded from the calculation of the average salary for that year.

[95] Figure C.4 shows that among biomedical doctorates working in research-focused jobs in academia, postdoc-trained biomedical doctorates are much more likely to be working in jobs focused on basic research rather than applied research compared to nonpostdoc-trained counterparts. See Figure C.5 for comparable results for those employed in industry research jobs, where jobs focused on basic research are much more rare.

[96] Figure C.6 excludes salary observations for those that are employed as a postdoc in the given year.

[97] This finding is notable: Sauermann and Roach (2016) survey PhD students from 39 research-intensive universities and find that 78% of respondents in the biological sciences believed that at least 1 year of postdoc training was required for a PhD-level R&D position in industry. The authors lament that "unfortunately, there is little empirical evidence showing whether the postdoc benefits graduates pursuing nonacademic careers."

Among biomedical doctorates whom acquire a research position in academia or industry, do postdoc trained individuals perform any differently than those without postdoc training? Figure C.10 shows that among biomedical doctorates age 30 to 55 working in research jobs, those with postdoc training are more likely to produce — and tend to produce more — peer-reviewed papers in both academia and industry. Figure C.11 shows that postdocs in industry are more likely to be named as an inventor on patent applications and granted patents. Figure C.12 shows that postdocs have more patents granted on average, although the rate at which granted patents result in commercial products is higher for nonpostdocs.[98] Nonetheless, the fact that postdocs are more likely to publish peer-reviewed research — and publish more of it — and are more likely to engage in patenting activity, suggests that the research positions occupied by postdoc trained doctorates in industry may either be more research-intensive than nonpostdoc research positions, or that postdocs are more scientifically productive than nonpostdocs in similar industry research positions.

How do the earnings in research-oriented industry jobs compare to nonresearch industry jobs? Figure C.13 shows that, on average, research jobs in industry pay less in terms of salary compared to nonresearch jobs, and Figure C.14 shows that this relationship holds for both postdoc-trained and nonpostdoc-trained biomedical doctorates age 30 to 40. This pattern is consistent with the finding in Stern (2004) that PhD biologists pay a compensating differential to participate in science. However, Figure C.14 also shows that the average salary for postdocs is less than that of their nonpostdoc counterparts in most years regardless of the research orientation of the job, which is consistent with a postdoc penalty on after-postdoc salary in industry that cannot be explained by a compensating differential for research jobs.

How do earnings evolve over a postdoc's career compared to that of a nonpostdoc? Figure 1 shows the median earnings over time for biomedical doctorates by employment sector and whether they take a postdoc position.[99] We find that postdoc-trained biomedical doctorates in industry and academia have similar median earnings in their first three years after PhD, which is when most would be employed as postdocs. We can see that postdoc-trained biomedical doctorates in academia and industry both start at a lower salary than their nonpostdoc-trained counterparts, but that nonpostdoc-trained biomedical doctorates attract a higher starting salary in industry as compared to academia. Industry earnings profiles are steeper than academic earnings profiles, indicating stronger earnings growth in that sector. Interestingly, it appears that postdoc median earnings catch up with and then begin to exceed the median earnings of nonpostdocs in the academic

[98]The SDR asks individuals about the number of patent applications, patents granted, and granted patents resulting in a commercial product in the last 5 years. If postdocs are more likely than nonpostdocs to be named as an inventor on longer-term projects, this could explain why the commercialization rate for postdocs is lower than nonpostdocs. It might not be that patents associated with postdocs are not able to be commercialized, but that it takes longer than five years for this to occur. Patenting information is only available for four waves of the SDR: 1995, 2001, 2003, and 2008.

[99]Biomedical doctorates are associated with the employment sector (academia or industry) that they occupy at 10 years post-PhD.

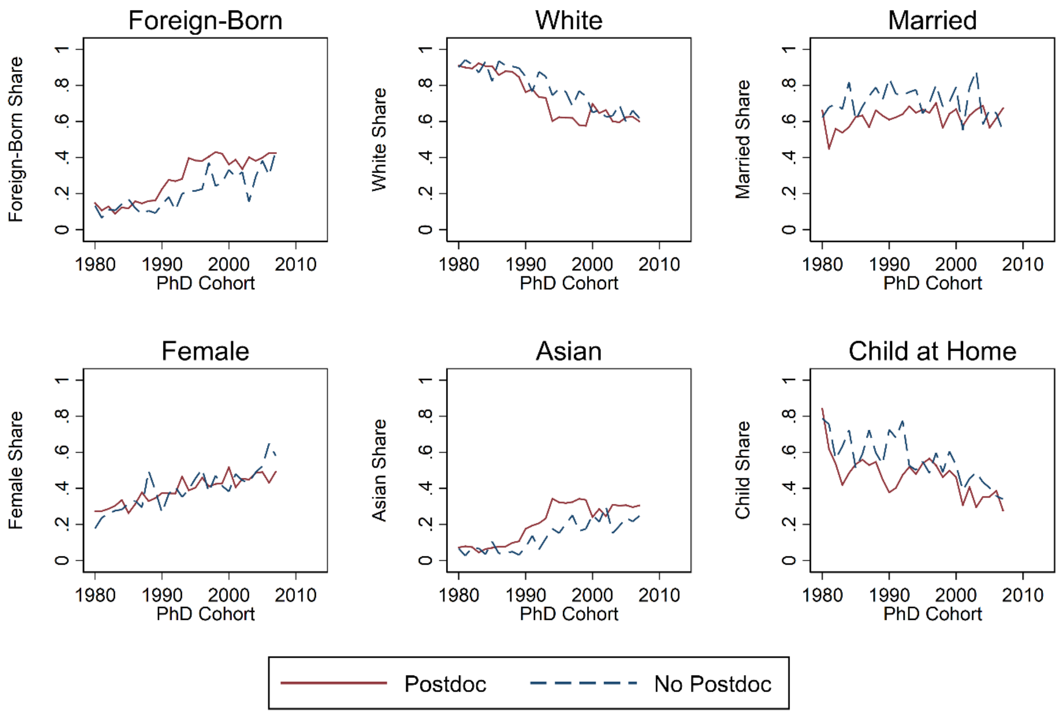
sector 10 years after graduation. In industry, it appears that the gap between the median earnings of postdoc-trained and nonpostdoc-trained biomedical doctorates is persistent. This suggests that the cost of doing a postdoc for those that end up going to industry is not just forgone earnings during their years as a postdoc, but also lower after-postdoc salary possibly due to deferred on-the-job training in industry.

In summary, the trends in the data show the following: Postdoc-trained biomedical doctorates are more heavily concentrated in research positions both in academia and industry compared to their nonpostdoc-trained counterparts. Biomedical doctorates working in industry earn more than those in academia, and those in industry (academic) research jobs tend to make less (more) than those in industry (academic) nonresearch jobs. Nonpostdoc-trained biomedical doctorates in both research and nonresearch positions in industry tend to earn more than their postdoc-trained counterparts. Postdoc-trained biomedical doctorates working in industry are more likely to publish peer-reviewed research, publish more papers, and are more likely to engage in at least some patenting activity compared to nonpostdoc-trained biomedical doctorates in industry.[100] Postdoc-trained biomedical doctorates in industry consistently earn less than their nonpostdoc-trained counterparts, while postdoc-trained biomedical doctorates in academia start with a lower salary than their nonpostdoc-trained counterparts, but catch up and then exceed them in terms of salary by 10 years after PhD. Altogether, these facts suggest that postdoc training holds value for obtaining a research-oriented career, whether that be in academia or industry, but that there is a persistent postdoc penalty on after-postdoc salary in industry for biomedical doctorates.

[100]In addition to these facts, Figure C.15 and Figure C.16 show that postdocs may be more likely to work in industry jobs closely related to their field of study and to work in larger firms, respectively. Figure C.15 allays concerns that postdoc-trained biomedical doctorates might earn less due to "educational (field) mismatch" as proxied by the job-relatedness to dissertation field in Bender and Heywood (2009).

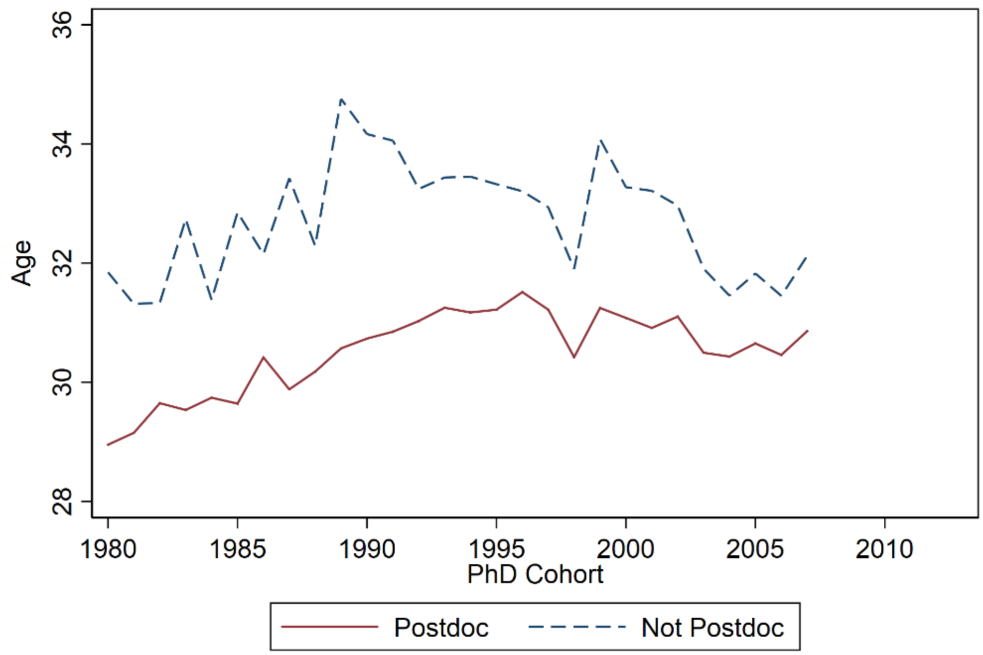
C.3 Supplementary Figures

Figure C.1: Demographics by Postdoc Status and Cohort



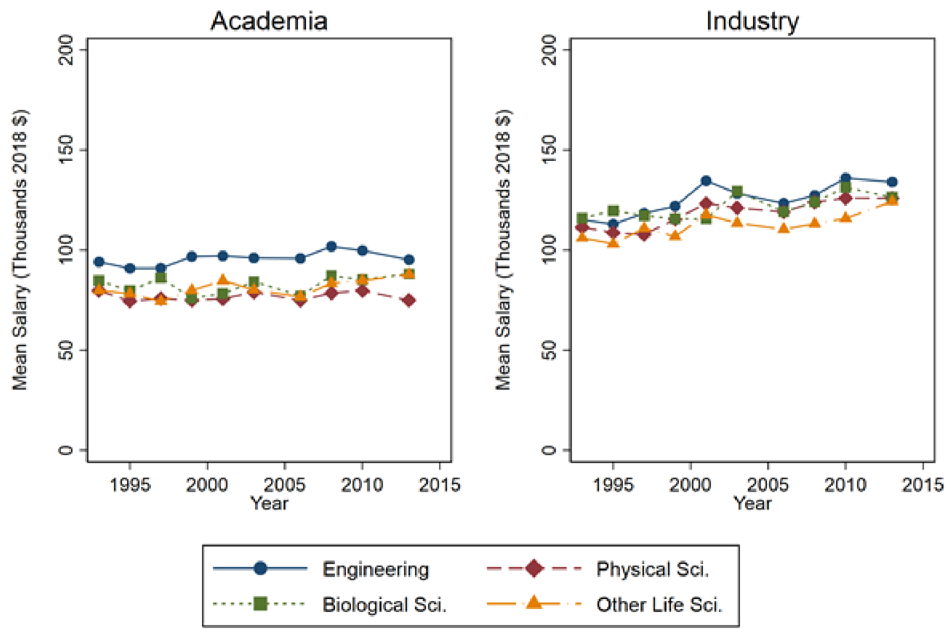
Notes: Figure C.1 shows the proportion of biomedical doctorates with various background characteristics by PhD cohort and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.2: Average Age at PhD Receipt by Postdoc Status



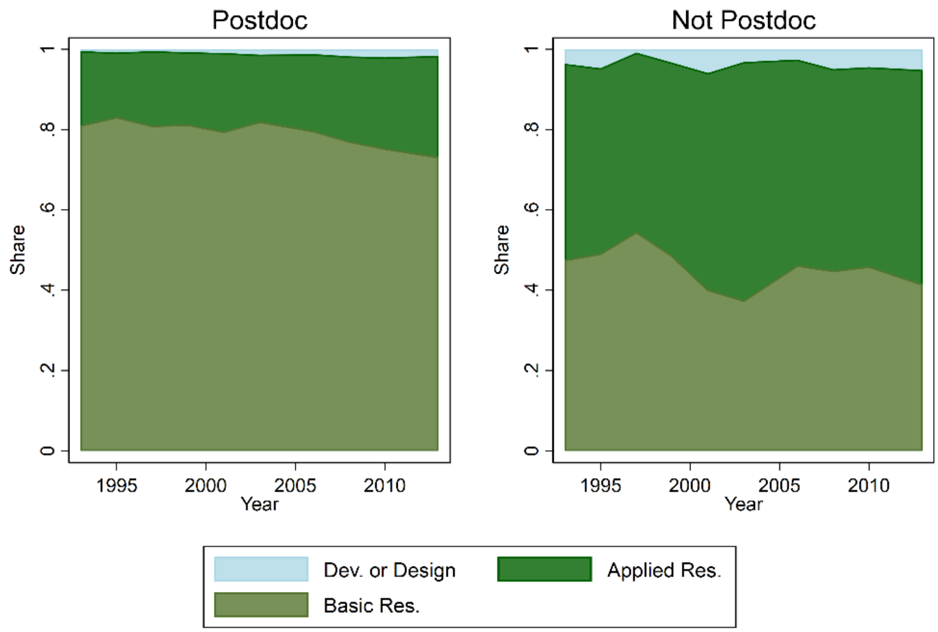
Notes: Figure C.2 shows the average age of biomedical doctorates at time of PhD completion by PhD cohort and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.3: Mean Salary by Employment Sector and S&E Field



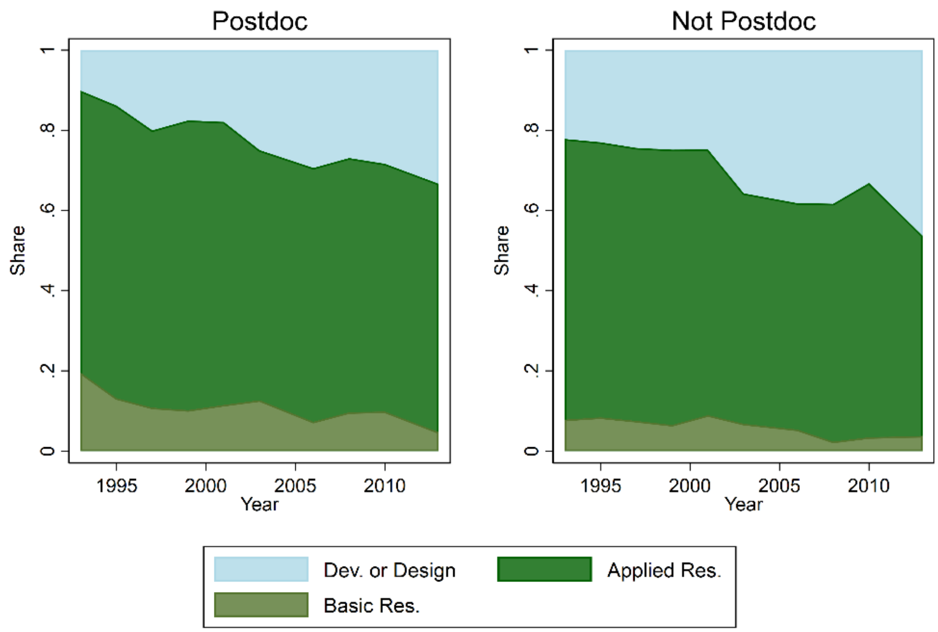
Notes: Figure C.3 shows the average salary of doctorates age 30 to 40 working in each employment sector by year and broad field of study. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure C.4: Share of Biomedical Doctorates in Academic Research Jobs by Primary Research Activity



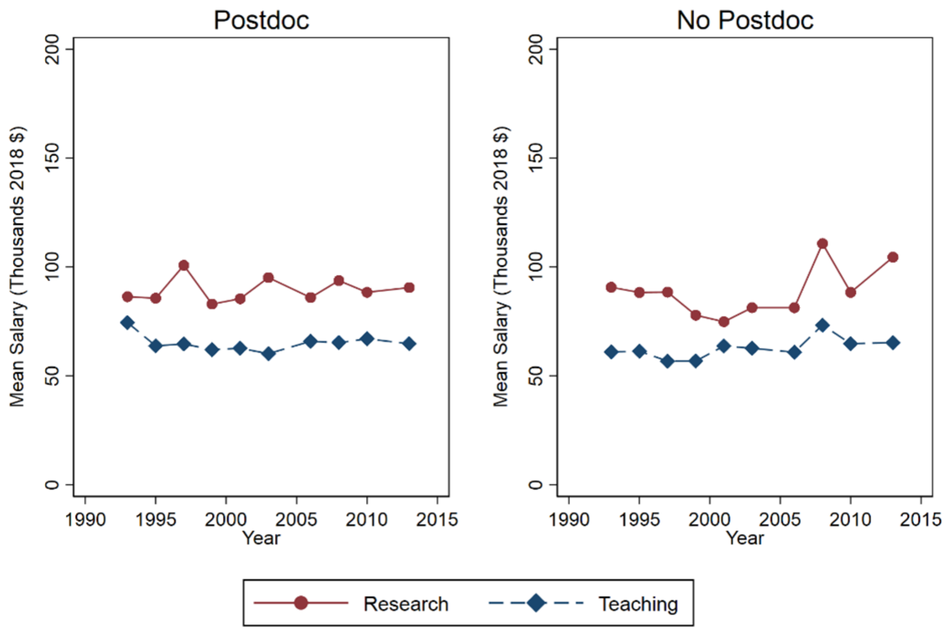
Notes: Figure C.4 shows the share of biomedical doctorates age 30 to 40 who are employed in academic research jobs broken down by the different types of research activities and whether they have postdoc training; those employed as postdocs in the given year are excluded. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.5: Share of Biomedical Doctorates in Industry Research Jobs by Primary Research Activity



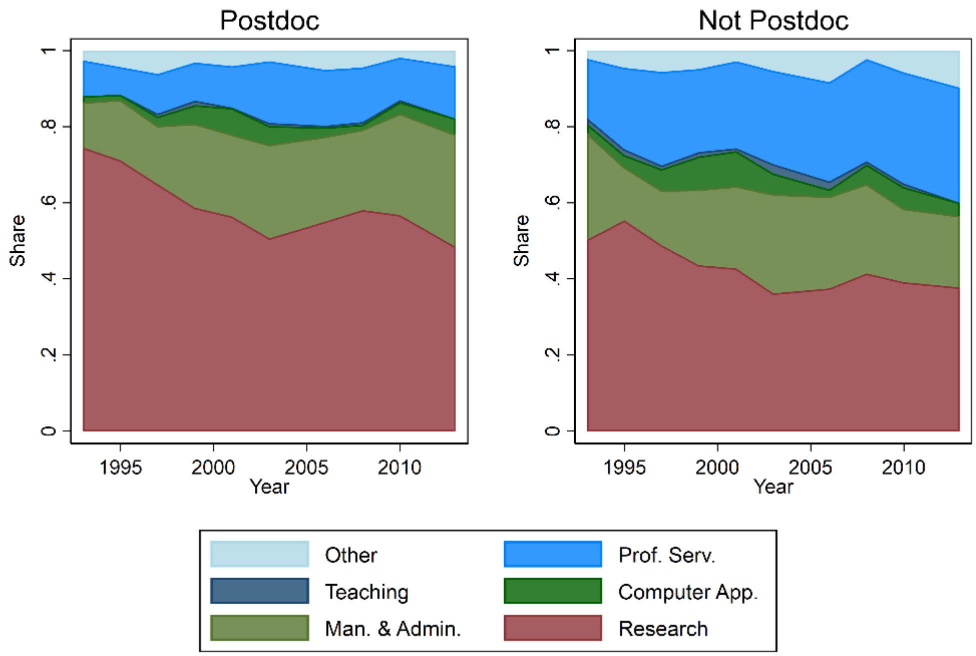
Notes: Figure C.5 shows the share of biomedical doctorates age 30 to 40 who are employed in industry research jobs broken down by the different types of research activities and whether they have postdoc training; those employed as postdocs in the given year are excluded. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.6: Mean Salary of Biomedical Doctorates in Academia



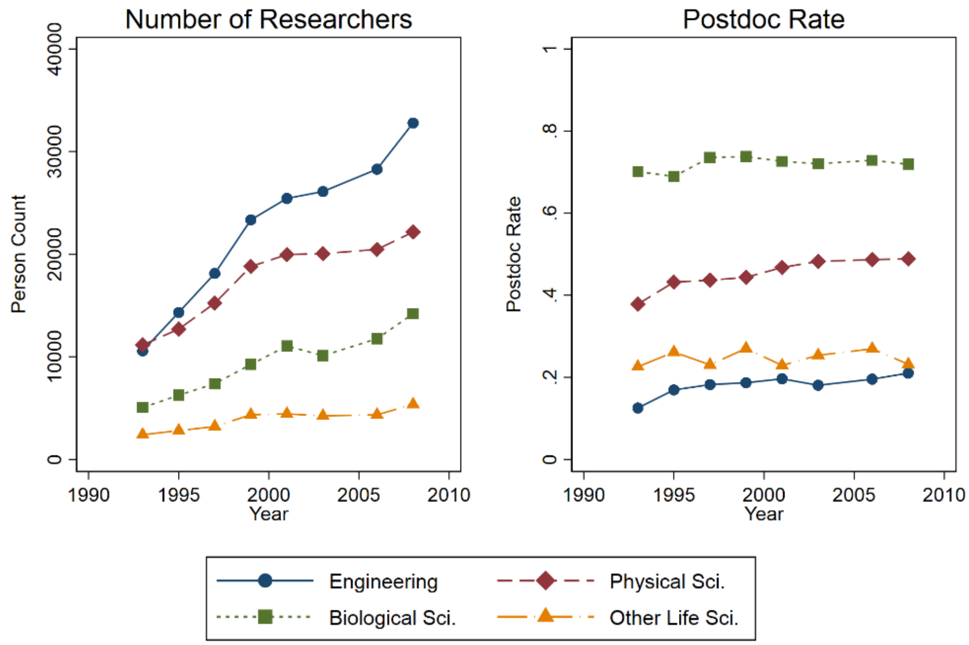
Notes: Figure C.6 shows the average salary of doctorates age 30 to 40 working in research and teaching jobs in academia by year and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure C.7: Share of Biomedical Doctorates in Industry by Primary Work Activity



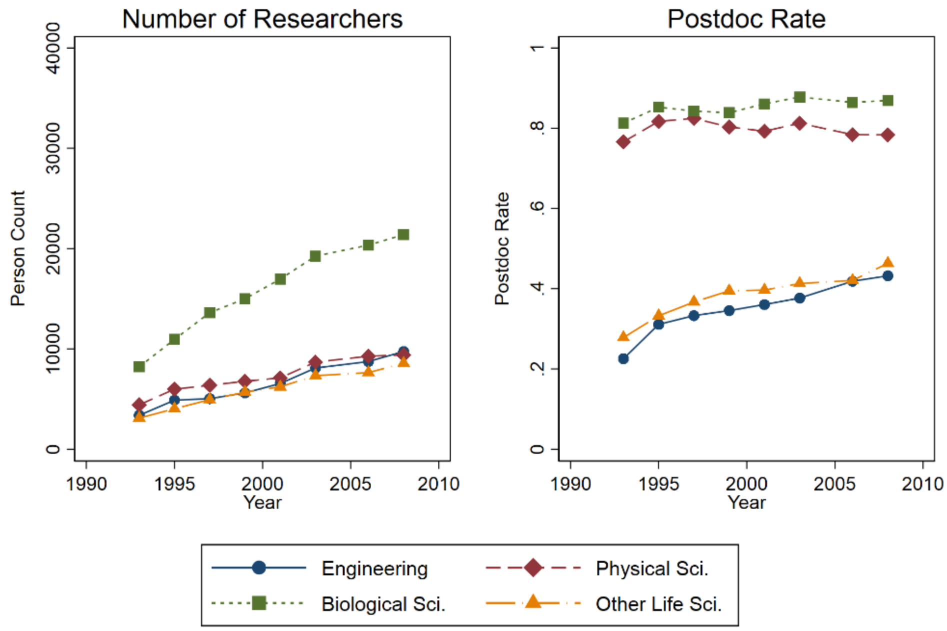
Notes: Figure C.7 shows the share of industry-employed biomedical doctorates age 30 to 40 in different reported primary job tasks by year and whether they have postdoc training; those employed as postdocs in the given year are excluded. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.8: Number and Postdoc Rate of Industry Researchers by S&E Field



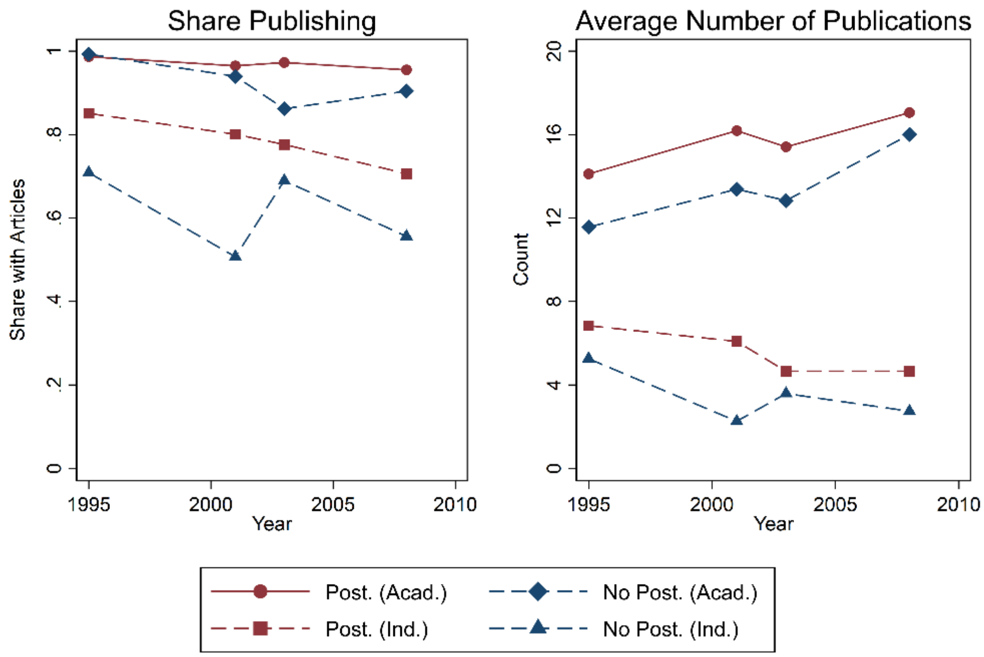
Notes: Figure C.8 shows the number and postdoc-trained share ("postdoc rate") of doctorates working in research jobs in industry by year and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.9: Number and Postdoc Rate of Academic Researchers by S&E Field



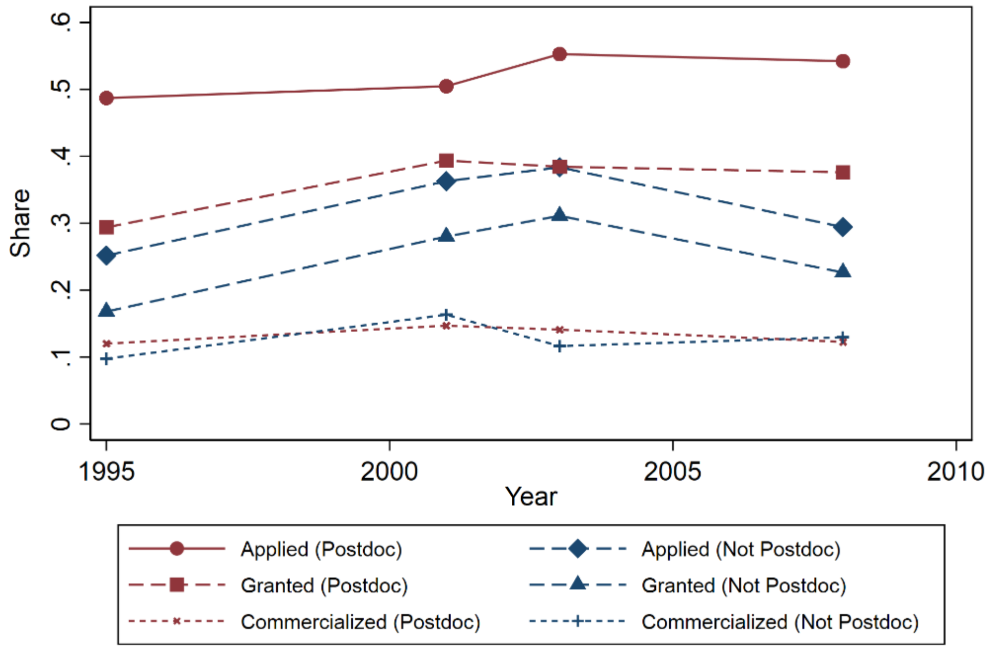
Notes: Figure C.9 shows the number and postdoc-trained share ("postdoc rate") of doctorates working in research jobs in academia by year and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.10: Publishing Activity by Employment Sector and Prior Postdoc Status



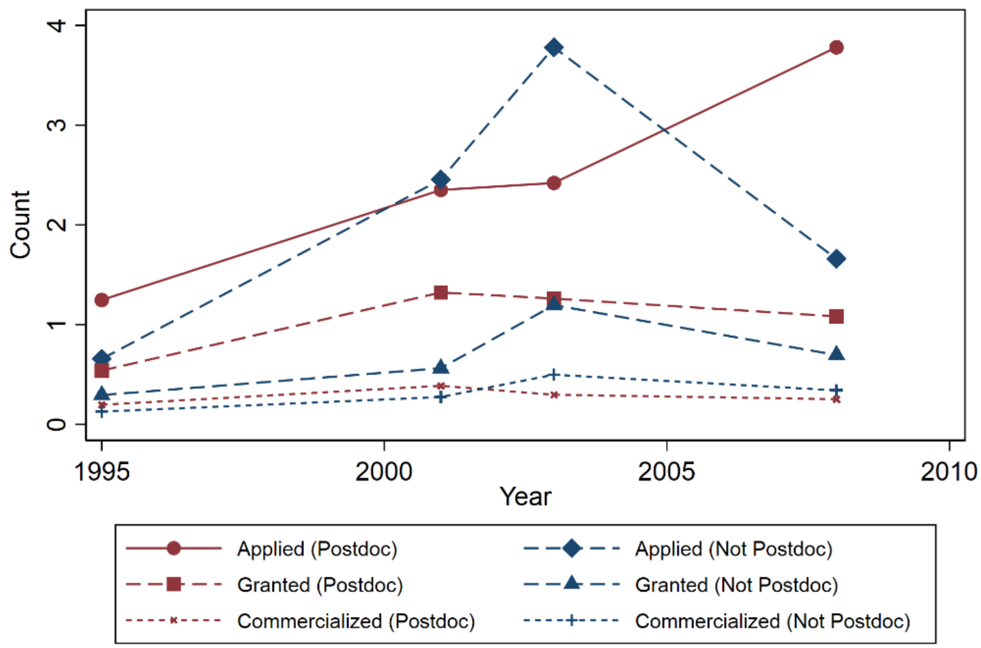
Notes: Figure C.10 shows the share of biomedical doctorates age 30 to 55 with peer-reviewed publications in the five years preceding the given SDR wave, and shows the average number of peer-reviewed publications in the last 5 years, by SDR survey wave and whether they have postdoc training. Require that individuals had finished postdoc seven or more years prior to survey wave or had graduated with a PhD seven or more years prior if did not do a postdoc; this restriction is so that we avoid counting papers authored during a postdoc or graduate school. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.11: Share of Industry Biomedical Doctorates by Patenting Activity



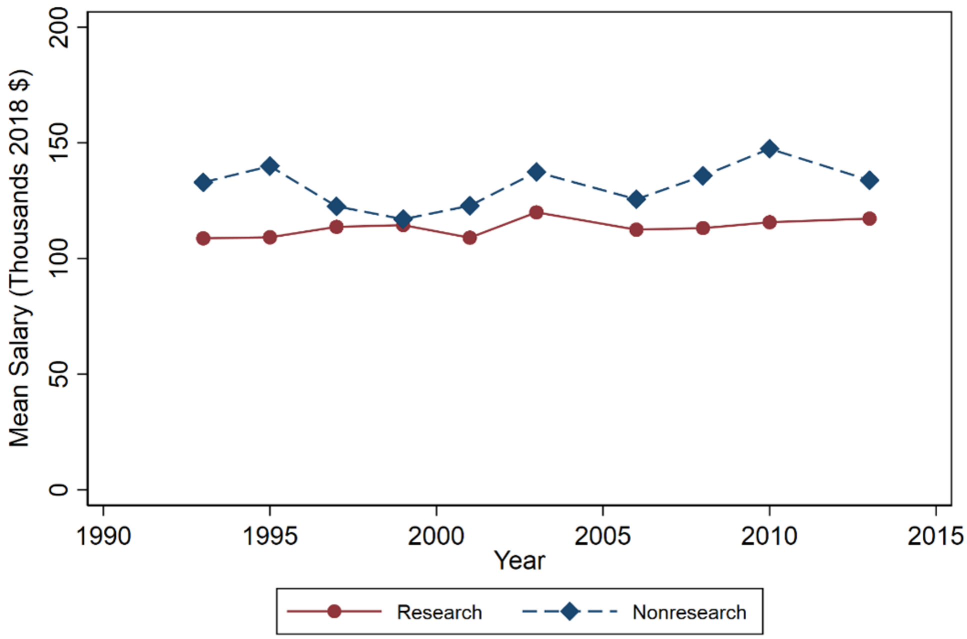
Notes: Figure C.11 shows the share of industry-employed biomedical doctorates age 30 to 55 named as an inventor on a patent application, granted patent, and/or granted patent that resulted in a commercial product in the five years preceding the given SDR by whether they have postdoc training. Require that individuals had finished postdoc seven or more years prior to survey wave or had graduated with a PhD seven or more years prior if did not do a postdoc; this restriction is so that we avoid counting patents resulting from research conducted as a postdoc or graduate school. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.12: Average Number of Patents per Industry Biomedical Doctorate



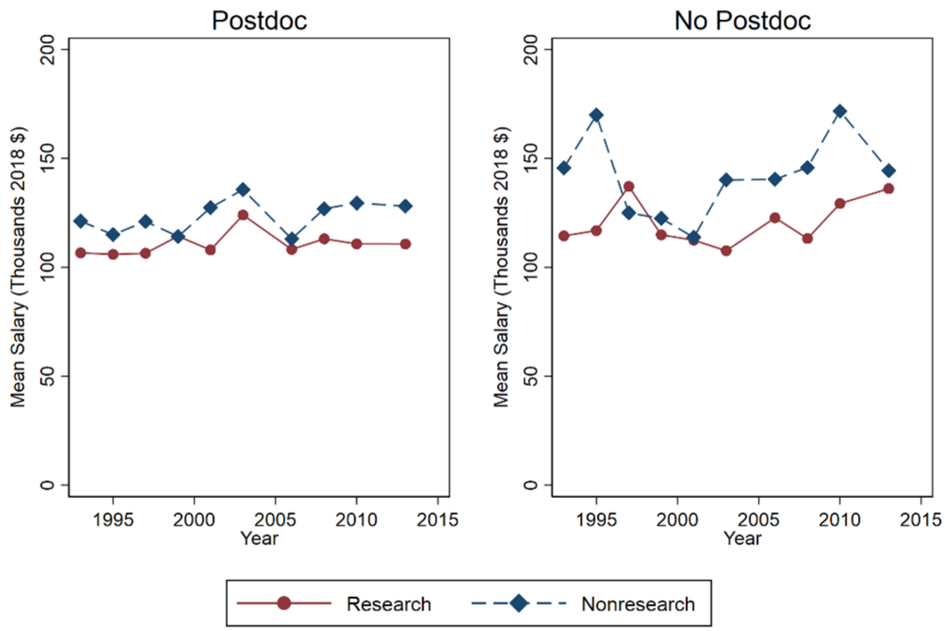
Notes: Figure C.12 shows the average number of patent applications, granted patents, and/or granted patents that resulted in a commercial product in the five years preceding the given SDR for industry-employed biomedical doctorates age 30 to 55 by whether they have postdoc training. Require that individuals had finished postdoc seven or more years prior to survey wave or had graduated with a PhD seven or more years prior if did not do a postdoc; this restriction is so that we avoid counting patents resulting from research conducted as a postdoc or graduate school. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.13: Mean Salary of Biomedical Doctorates in Industry by Job Type



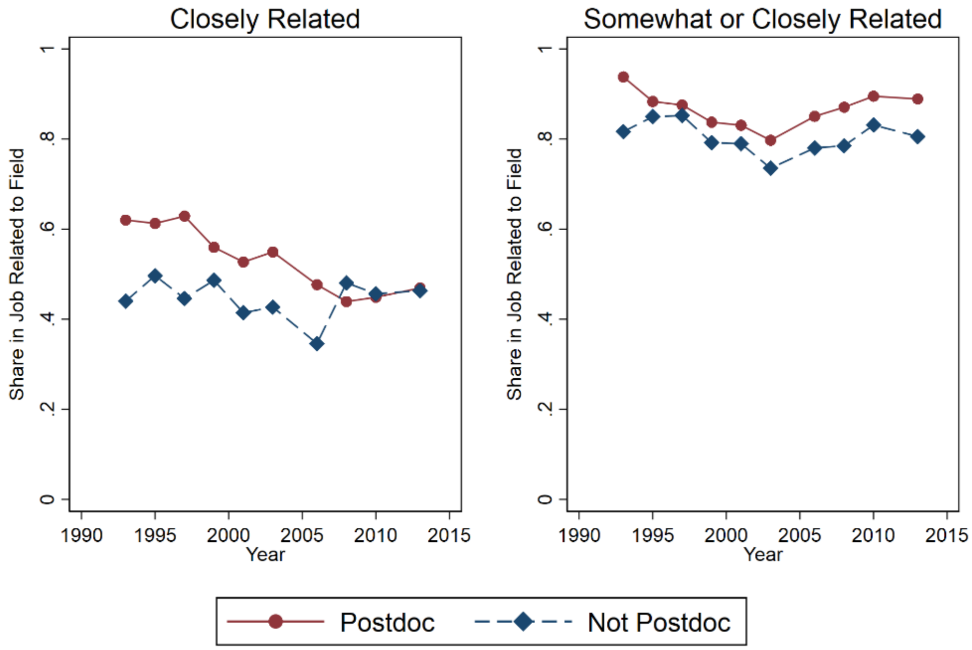
Notes: Figure C.13 shows the average salary of biomedical doctorates age 30 to 40 working in research and nonresearch jobs in industry by year. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure C.14: Mean Salary of Biomedical Doctorates in Industry by Job Type and Prior Postdoc Status



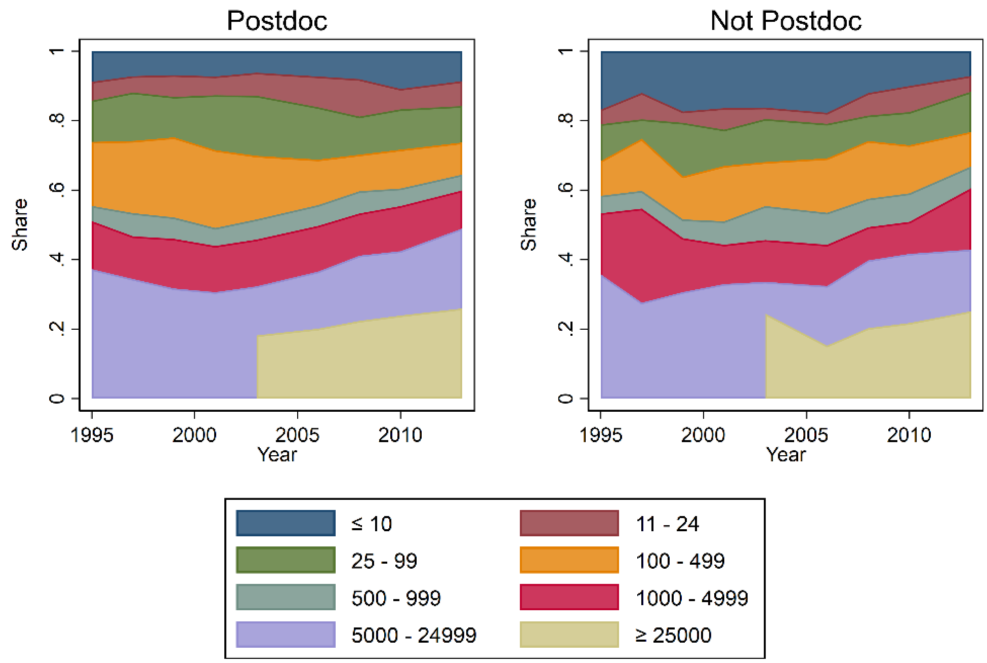
Notes: Figure C.14 shows the average salary of biomedical doctorates age 30 to 40 working in research and nonresearch jobs in industry by year and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year. Salary adjusted for inflation using the CPI-U with base years 1982-84.

Figure C.15: Share of Industry Biomedical PhDs by Job-Relatedness to Field



Notes: Figure C.15 shows proportion of industry-employed biomedical doctorates age 30 to 40 working in jobs related to their field by year and whether they have postdoc training. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.

Figure C.16: Share of Industry Biomedical PhDs by Firm Size



Notes: Figure C.16 shows proportion of industry-employed biomedical doctorates age 30 to 40 working in firms of different size by year and whether they have postdoc training. The SDR did not include a category for firms with more than 25,000 employees until 2003. Sample restricted to doctorates appearing in the NSF's Survey of Doctorate Recipients in any wave(s) between 1993 and 2015 and graduating as early as 1980. We restrict sample to doctorates who first appear in the SDR prior to 2010 due to SDR sampling changes starting in that year.